## Clase 4

# Redes Neuronales Convolucionales


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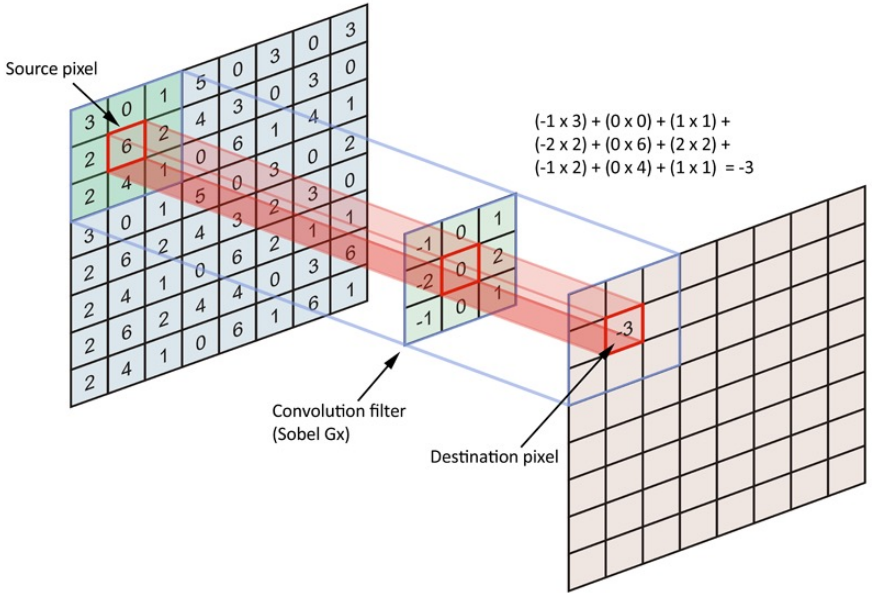



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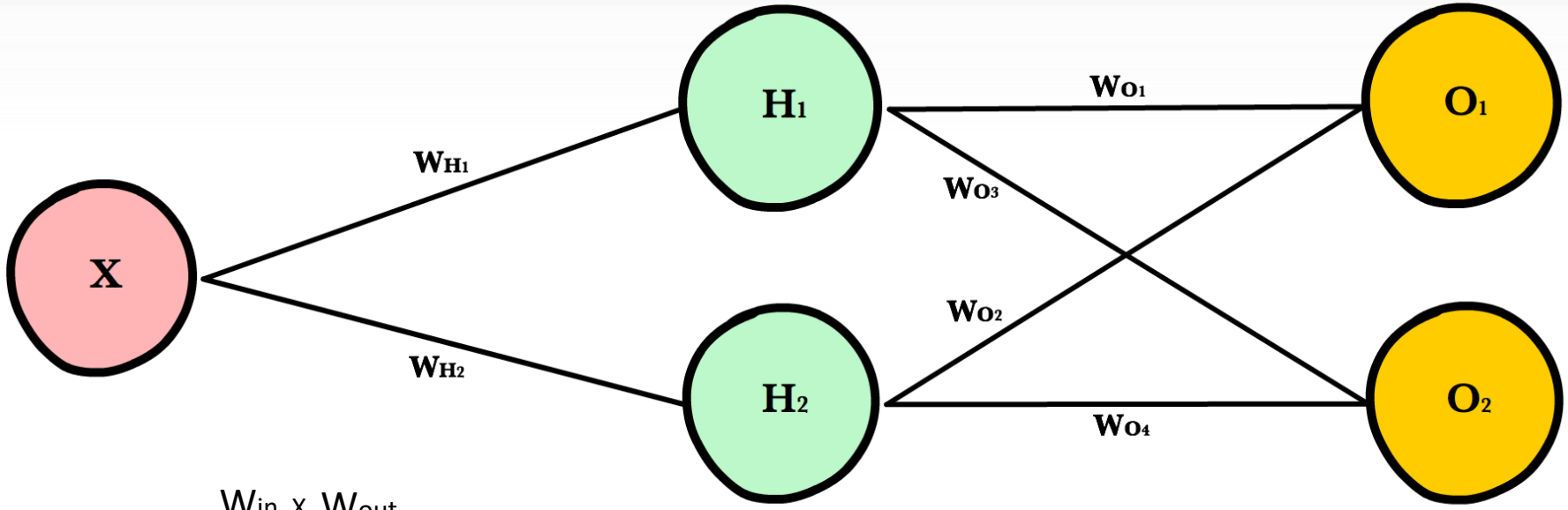
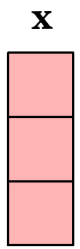
# Repaso de percetrón




Perceptrón
con 2 neuronas
de salida




3 muestras
con solo una feature
cada una

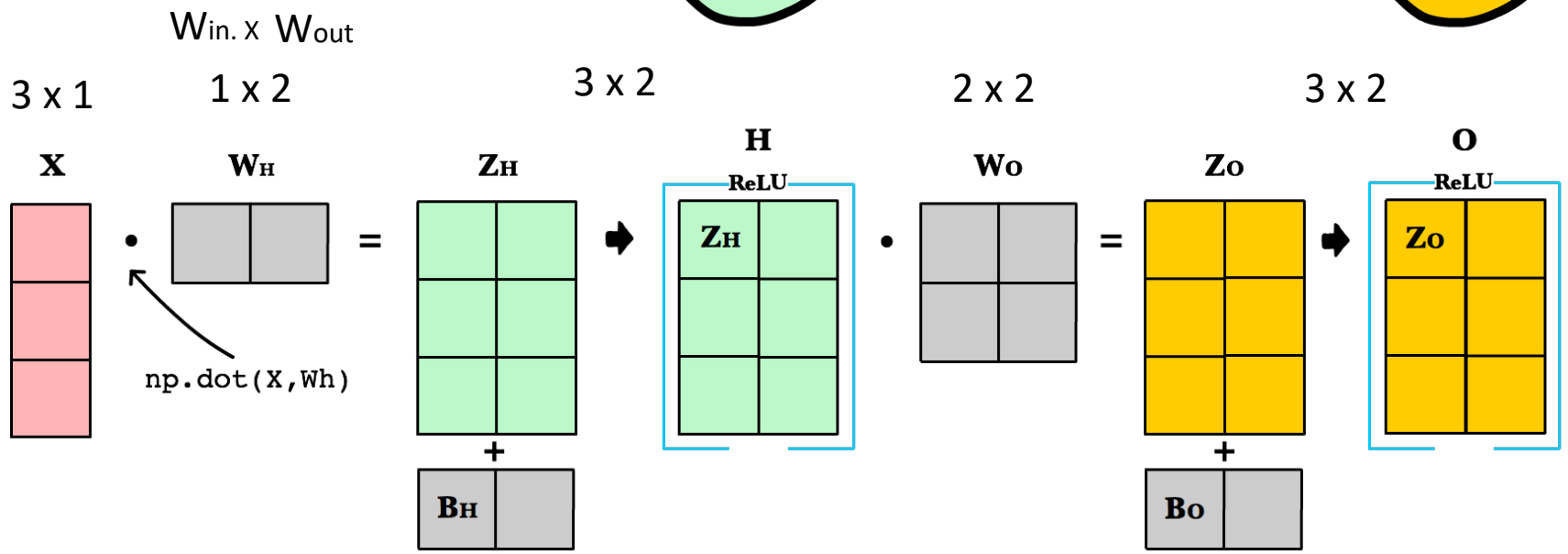
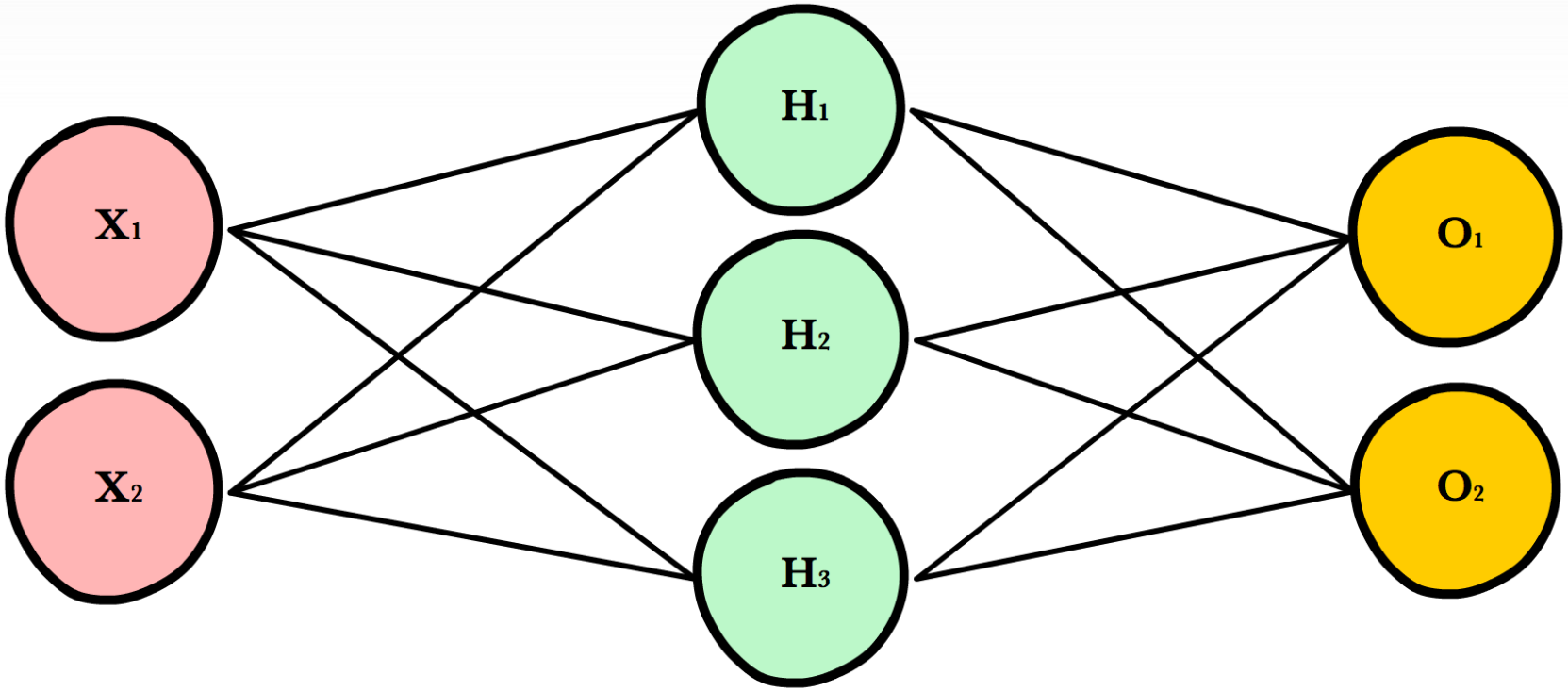
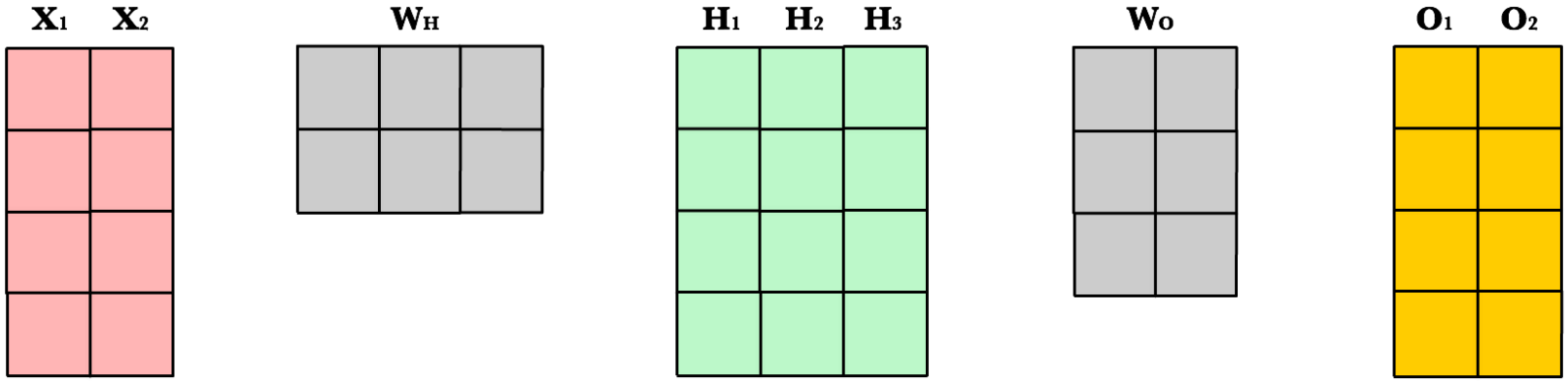



Imagen extraída de: https://ml-cheatsheet.readthedocs.io/en/latest/forwardpropagation.html

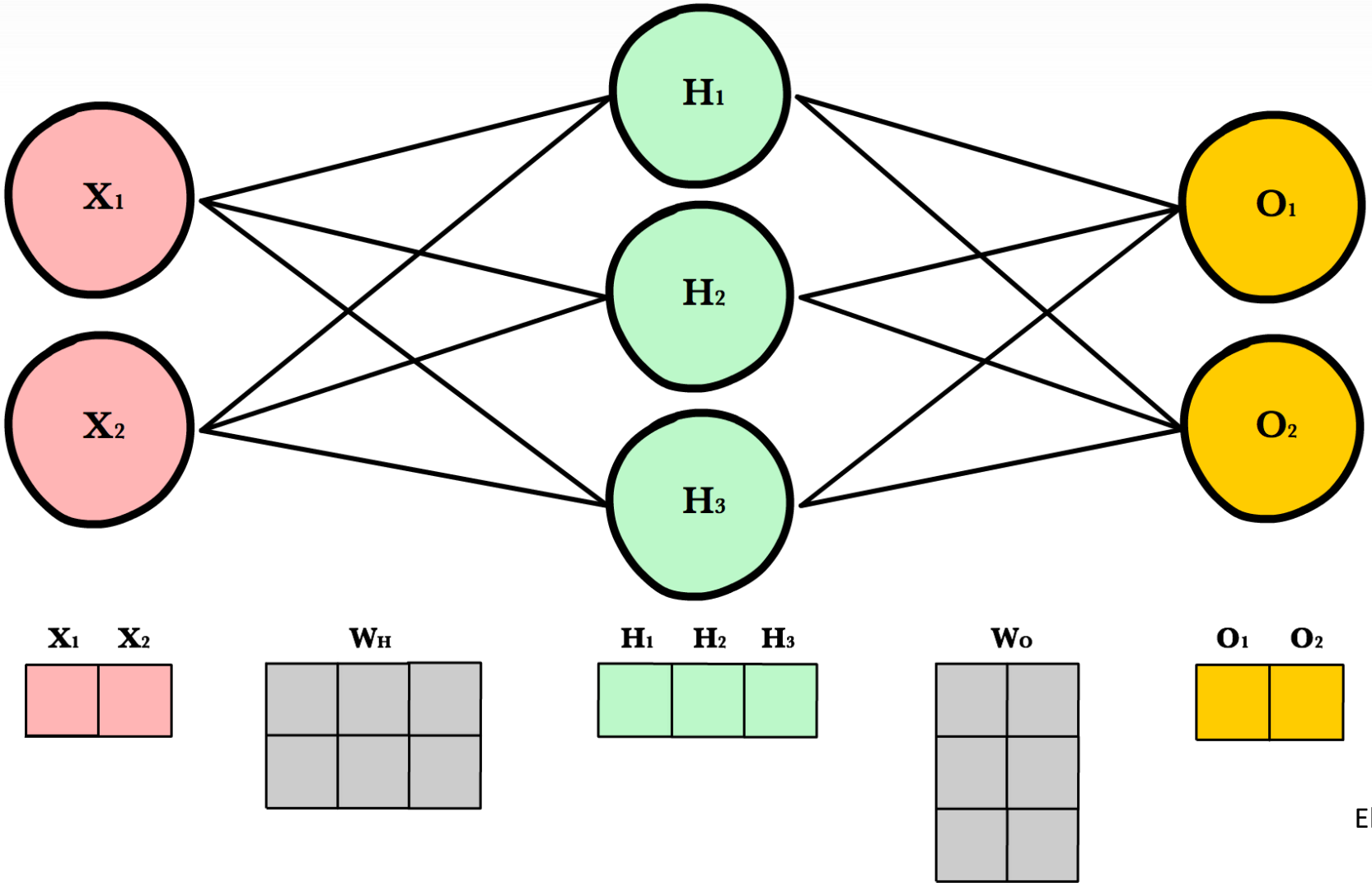
# Repaso de percetrón




3 muestras
con 2 features
de entrada cada una



# Repaso de percetrón




1 muestras
con 2 features
de entrada

El tamaño de las matrices
W es independiente
de la cantidad de
elementos en el batch!

# Cómo procesamos una imagen con un perceptrón?

N X N

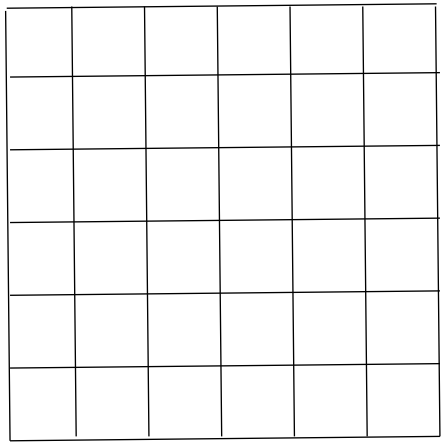
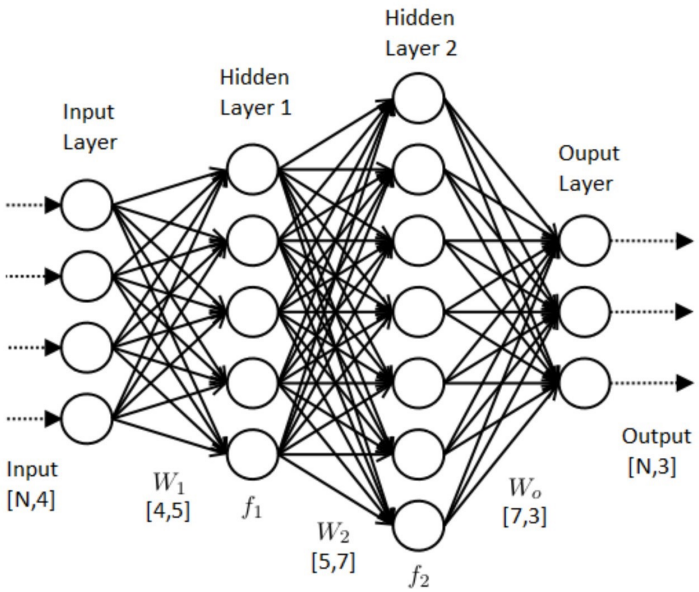


Imagen vectorizada
o extracción manual de
características

$N^2$ (img vect) o M (features)




Capas totalmente conectadas
(Fully connected layers)

# Cómo procesamos una imagen con un perceptrón?

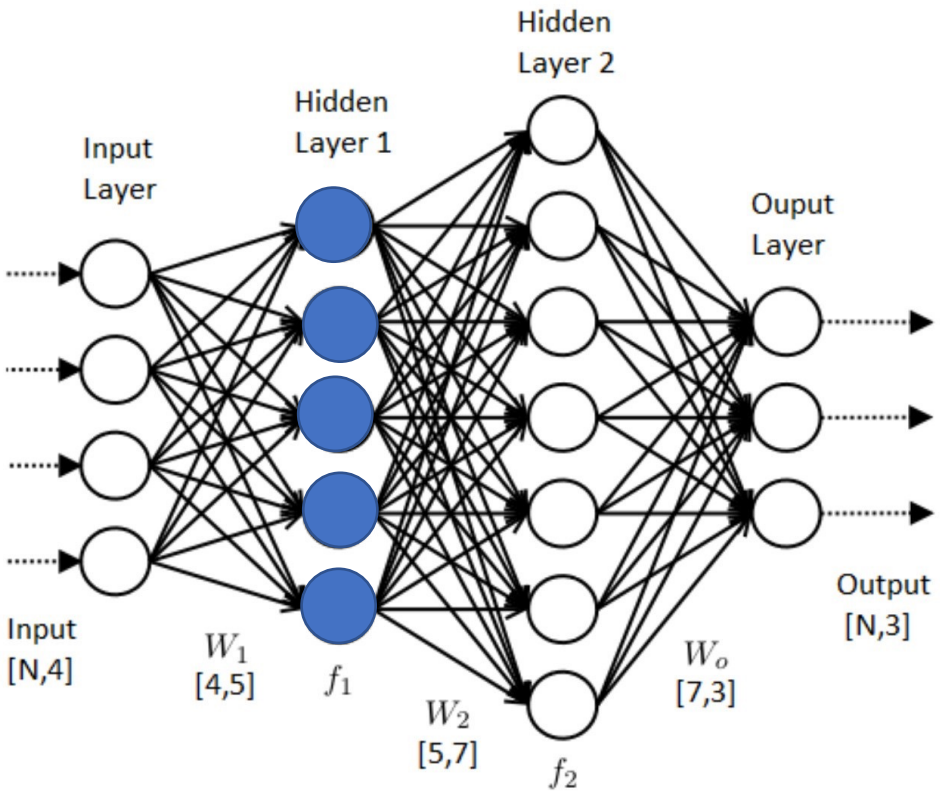
~ 1 Millón de conexiones

x

1024 neuronas ocultas

---

~ 1024 Millones de parámetros



# Cómo procesamos una imagen con un perceptrón?

## Desventajas

- Se pierde la estructura original de los datos
- Para grandes imágenes, la cantidad de neuronas (y sus consecuentes conexiones) crece exponencialmente
- No tenemos una noción clara de análisis multi-escala/multi-resolución (algo que resulta útil en general en análisis de imágenes)

# Redes neuronales inspiradas en el sistema visual

# Arquitectura de la corteza visual del gato

(Hubel & Wiesel, 1962)

*J. Physiol.* (1962), **160**, *pp.* 106–154
*With* 2 *plates and* 20 *text-figures*
*Printed in Great Britain*



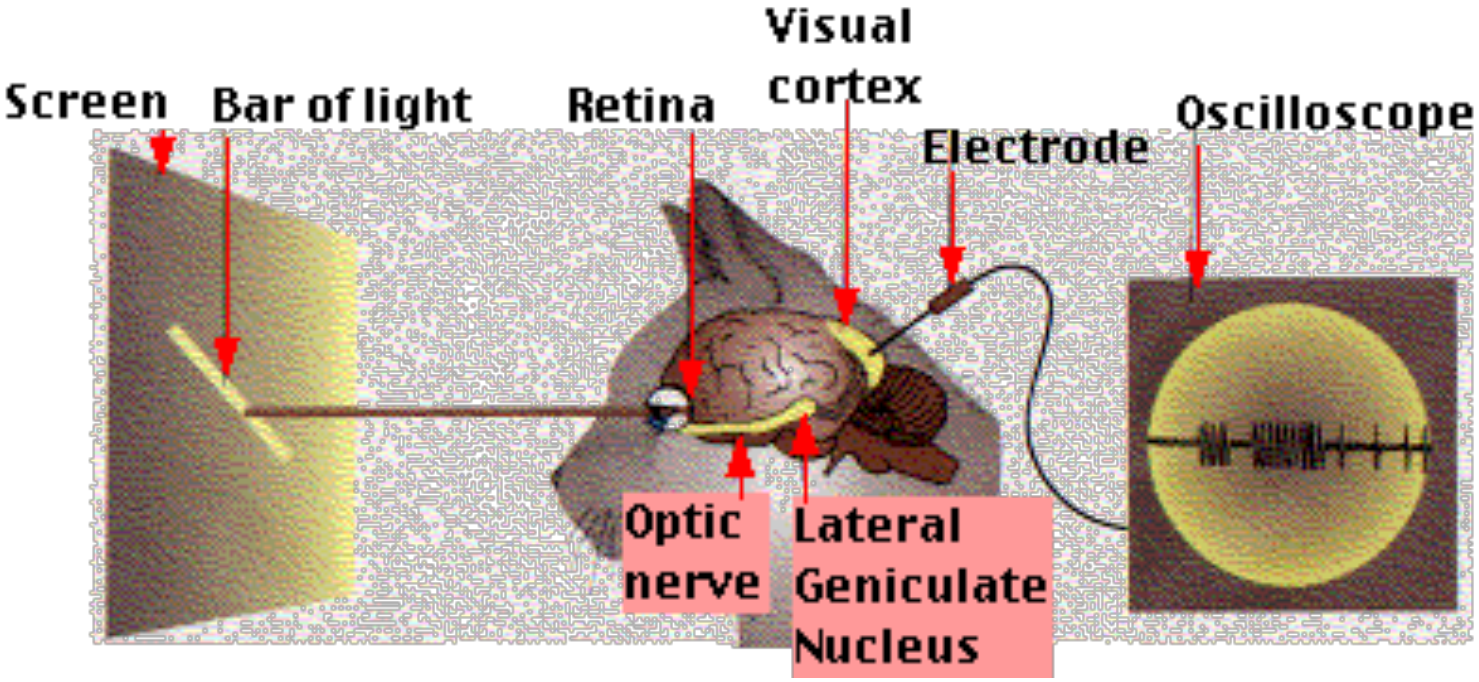
## RECEPTIVE FIELDS, BINOCULAR INTERACTION AND FUNCTIONAL ARCHITECTURE IN THE CAT'S VISUAL CORTEX

BY D. H. HUBEL AND T. N. WIESEL
*From the Neurophysiology Laboratory, Department of Pharmacology Harvard Medical School, Boston, Massachusetts, U.S.A.*

(*Received* 31 *July* 1961)

What chiefly distinguishes cerebral cortex from other parts of the central nervous system is the great diversity of its cell types and interconnexions. It would be astonishing if such a structure did not profoundly modify the response patterns of fibres coming into it. In the cat's visual cortex, the receptive field arrangements of single cells suggest that there is a level of complexity far exceeding anything yet seen at lower

# Redes neuronales inspiradas en el sistema visual



# Redes neuronales inspiradas en el sistema visual

- Midieron la respuesta eléctrica en el cerebro de un gato estimulándolo con patrones simples en una pantalla.

- Encontraron que las **neuronas de la corteza visual** temprana se organizan de **forma jerárquica**, donde las **primeras** reaccionan a **patrones simples como líneas**, y las **posteriores** capas responden a **patrones más complejos** combinando las activaciones que reciben.

- En el modelo propuesto, las neuronas en las capas superiores tienen un mayor **campo receptivo** y son **menos sensibles a la posición desde la cual proviene dicho estímulo**.

# Neocognitrón: red neuronal artificial inspirada en (Hubel & Wiesel, 1962)

(Fukushima 1980)

Biol. Cybernetics 36, 193–202 (1980)

Biological Cybernetics
© by Springer-Verlag 1980

## Neocognitron: A Self-organizing Neural Network Model for a Mechanism of Pattern Recognition Unaffected by Shift in Position

Kunihiko Fukushima

NHK Broadcasting Science Research Laboratories, Kinuta, Setagaya, Tokyo, Japan

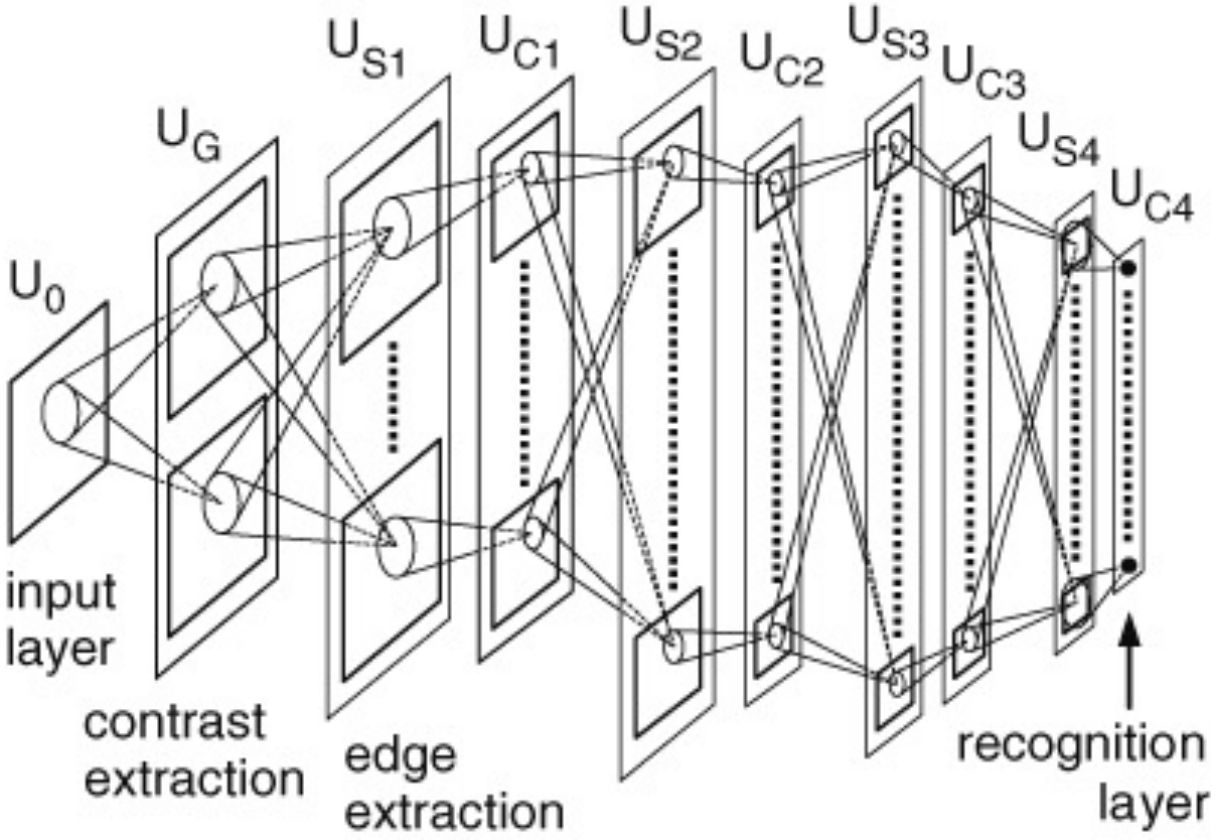
**Abstract.** A neural network model for a mechanism of visual pattern recognition is proposed in this paper. The network is self-organized by "learning without a teacher", and acquires an ability to recognize stimulus patterns based on the geometrical similarity (Gestalt) of their shapes without affected by their positions. This network is given a nickname "neocognitron". After completion of self-organization, the network has a structure similar to the hierarchy model of the visual nervous system proposed by Hubel and Wiesel. The network consists of an input layer (photoreceptor array) followed by a cascade connection of a number of modular structures, each of which is composed of two

reveal it only by conventional physiological experiments. So, we take a slightly different approach to this problem. If we could make a neural network model which has the same capability for pattern recognition as a human being, it would give us a powerful clue to the understanding of the neural mechanism in the brain. In this paper, we discuss how to synthesize a neural network model in order to endow it an ability of pattern recognition like a human being.

Several models were proposed with this intention (Rosenblatt, 1962; Kabrisky, 1966; Giebel, 1971; Fukushima, 1975). The response of most of these models, however, was severely affected by the shift in

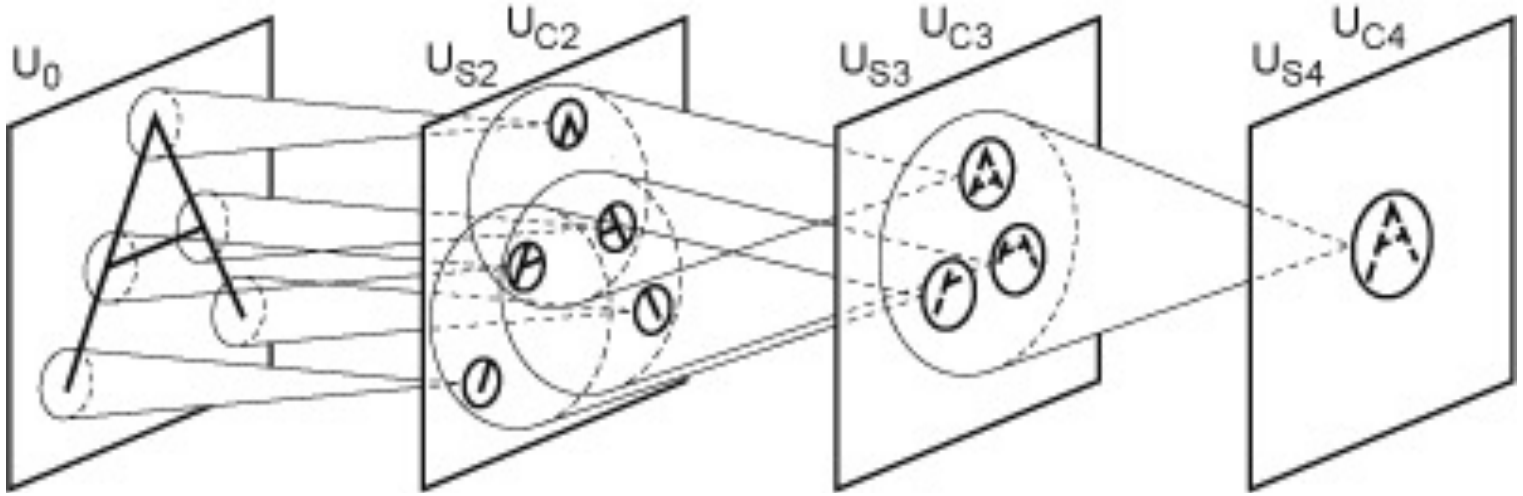
# Neocognitrón: red neuronal artificial inspirada en (Hubel & Wiesel, 1962)

(Fukushima 1980)



# Neocognitrón: red neuronal artificial inspirada en (Hubel & Wiesel, 1962)

(Fukushima 1980)

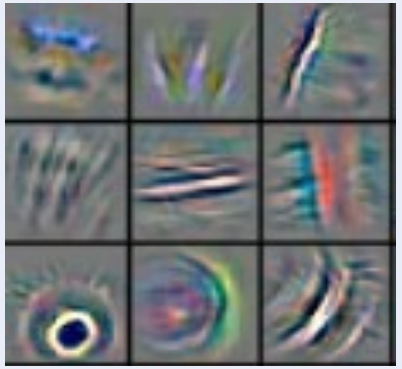


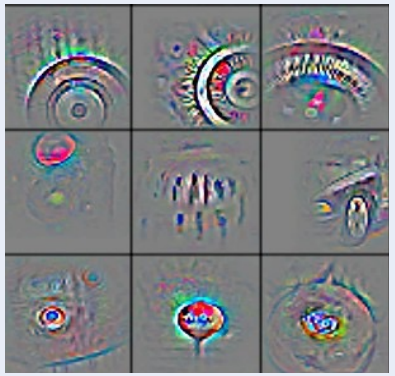
# Deep Learning

Multiples niveles de abstracción

Único modelo entrenado ”end to end”

Bordes → Formas → Partes → Clasificador → ¿Bicicleta?





# Redes neuronales convolucionales

(Lecun 1998)

# Gradient-Based Learning Applied to Document Recognition

YANN LECUN, MEMBER, IEEE, LÉON BOTTOU, YOSHUA BENGIO, AND PATRICK HAFFNER

*Invited Paper*

*Multilayer neural networks trained with the back-propagation algorithm constitute the best example of a successful gradient-based learning technique. Given an appropriate network architecture, gradient-based learning algorithms can be used to synthesize a complex decision surface that can classify high-dimensional patterns, such as handwritten characters, with minimal preprocessing. This paper reviews various methods applied to handwritten character recognition and compares them on a standard handwritten digit recognition task. Convolutional neural networks, which are specifically designed to deal with the variability of two dimensional (2-D) shapes, are shown to outperform all other techniques.*

*Real-life document recognition systems are composed of multiple modules including field extraction, segmentation, recognition, and language modeling. A new learning paradigm, called graph transformer networks (GTN's), allows such multimodule systems trained with gradient-based methods so as to*

| | |
|---|---|
| NN | Neural network. |
| OCR | Optical character recognition. |
| PCA | Principal component analysis. |
| RBF | Radial basis function. |
| RS-SVM | Reduced-set support vector method. |
| SDNN | Space displacement neural network. |
| SVM | Support vector method. |
| TDNN | Time delay neural network. |
| V-SVM | Virtual support vector method. |

## I. Introduction

Over the last several years, machine learning techniques, particularly when applied to NN's, have played an increasingly important role in the design of pattern recognition systems. In fact, it could be argued that the availability

# Redes Neuronales Convolucionales

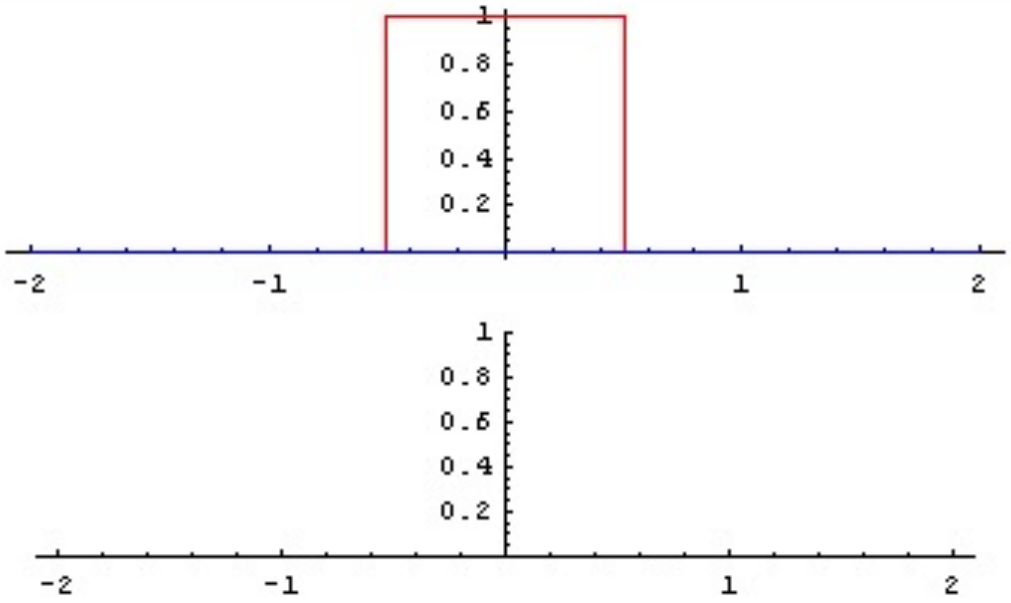
*”Convolutional networks are simply neural networks that use convolution in place of general matrix multiplication in at least one of their layers”*

Deep Learning, MIT Press, Goodfellow et al, 2016

# Convolución

# Convolución 1D

Representa la integral del producto de una función ***x*** con una versión trasladada y reflejada de otra ***w***



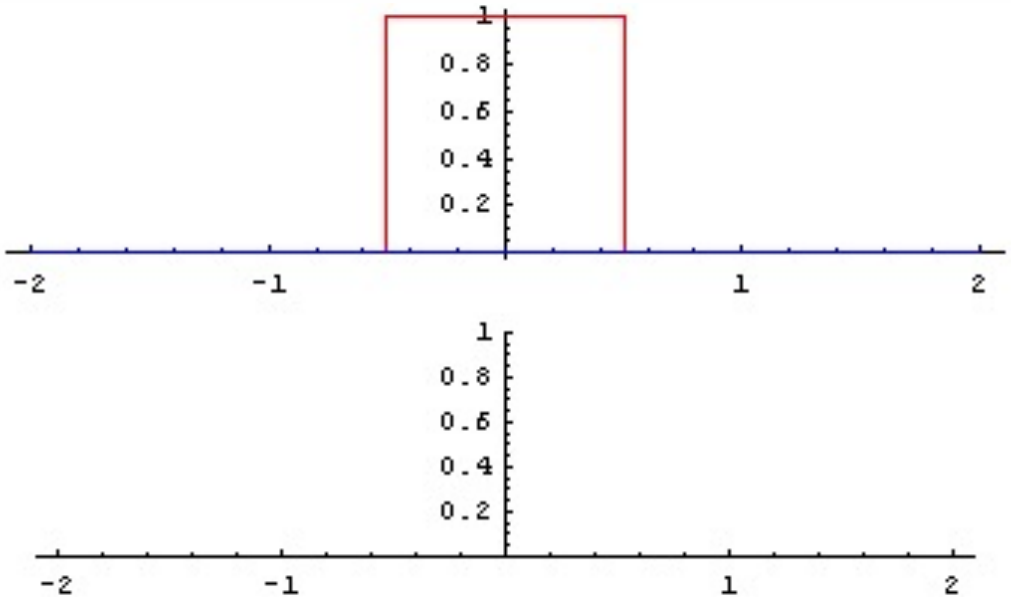

$$\boxed{s(t)} = \int \boxed{x(a)}\boxed{w(t-a)}da$$

Señal convolucionada

Señal de entrada

Filtro

# Convolución 1D




$$s(t) = (x * w)(t)$$

# Convolución 1D

Discretización de la señal

$$s(t) = \int x(a)w(t-a)da$$

**Señal Continua**

$$s(t) = (x * w)(t) = \sum_{a=-\infty}^{\infty} x(a)w(t-a)$$

**Señal Discreta**

# Convolución 2D

$$S(i,j) = (I * K)(i,j) = \sum_m \sum_n I(m,n)K(i-m, j-n)$$

La convolución es conmutativa

$$S(i,j) = (K * I)(i,j) = \sum_m \sum_n I(i-m, j-n)K(m,n)$$

Propiedad útil ya que el rango de valores válidos de m,n de una imagen es mayor en general que el del kernel.

# Correlación cruzada

$$S(i,j) = (K * I)(i,j) = \sum_m \sum_n I(i-m, j-n) K(m,n)$$

En el contexto de redes neuronales convolucionales se suele utilizar **la correlación cruzada** en lugar de la convolución para evitar el flipping del kernel.

$$S(i,j) = (I * K)(i,j) = \sum_m \sum_n I(i+m, j+n) K(m,n)$$

# Convolución 1D

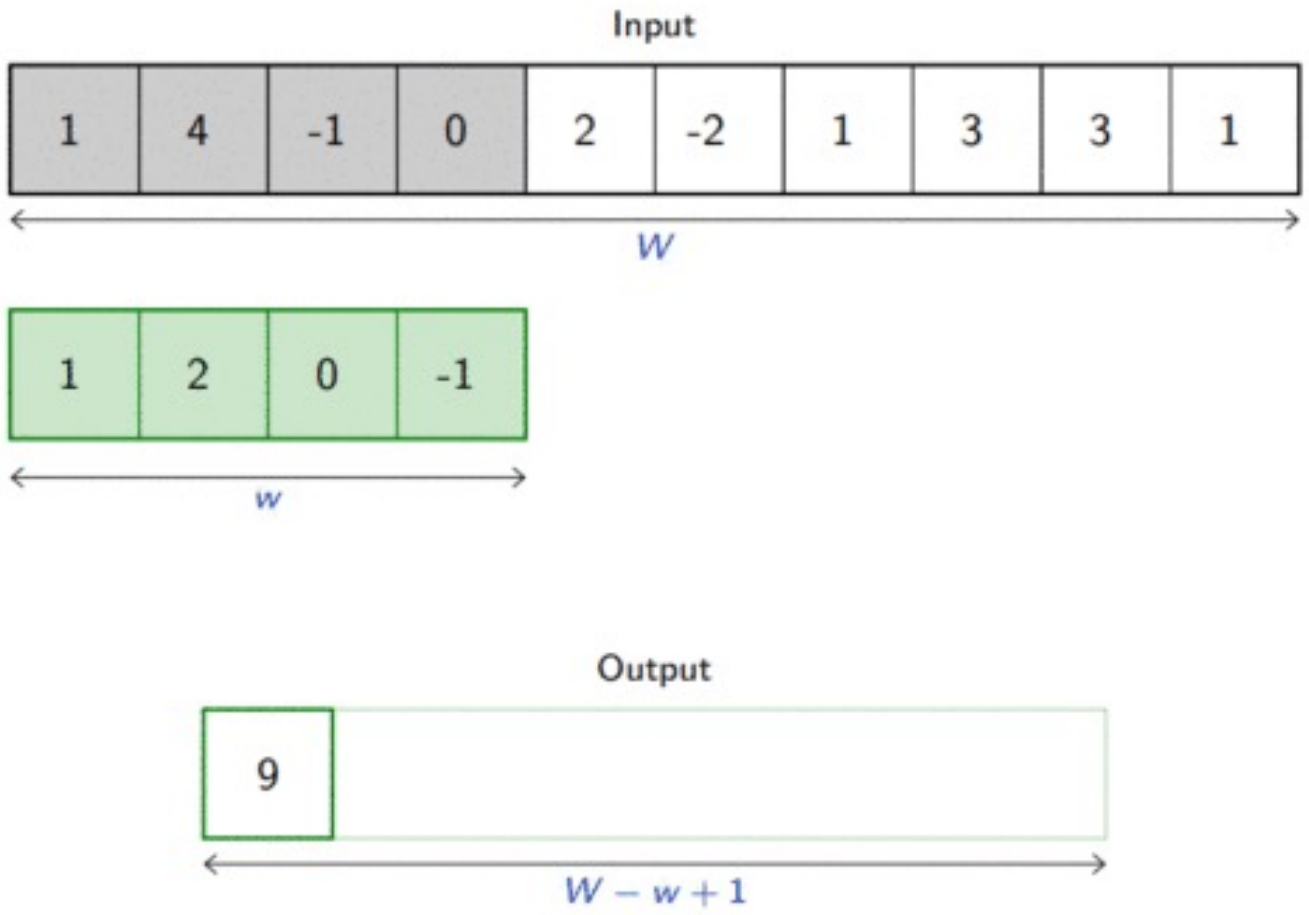



Imagen extraída de: https://glouppe.github.io/infoxxxx-deep-learning/?p=lecture3.md#10

# 2D Convolution

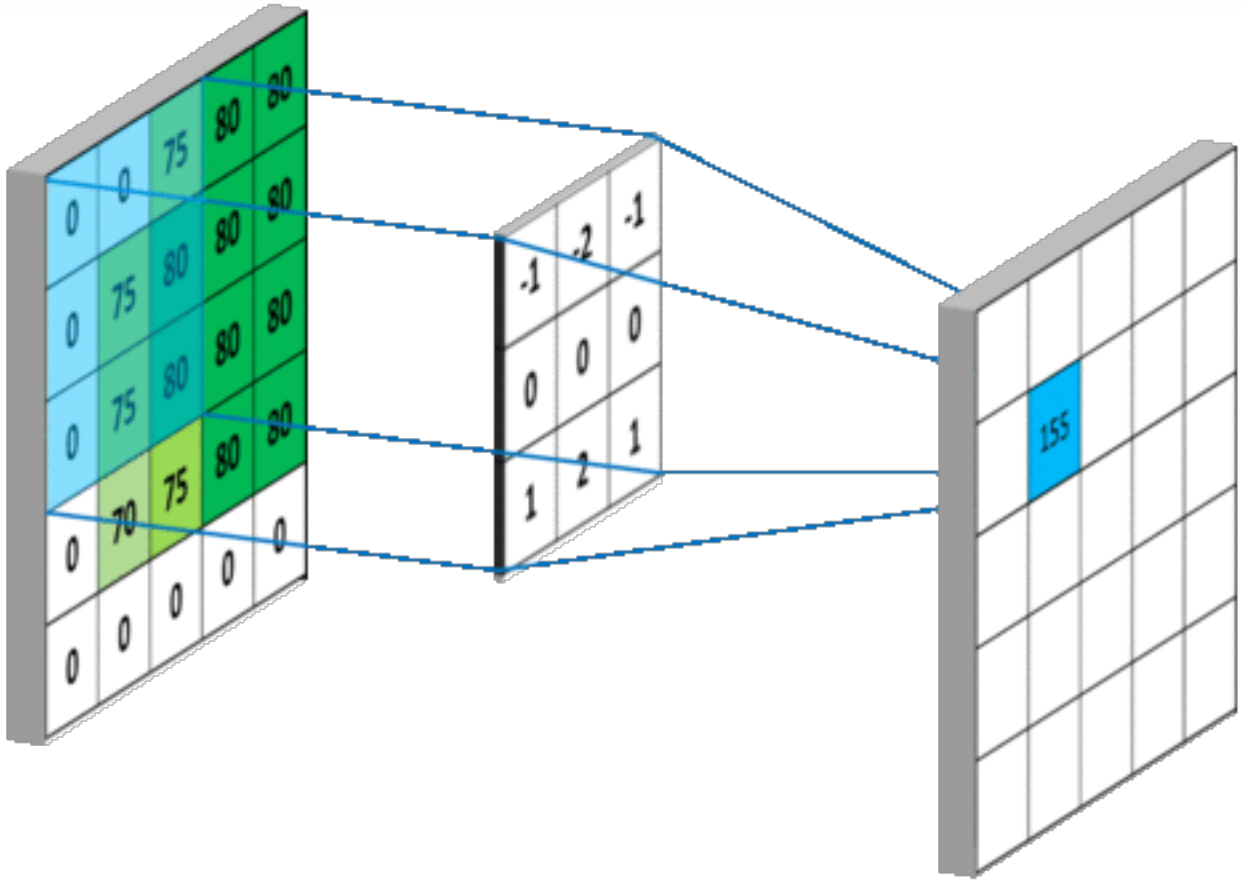
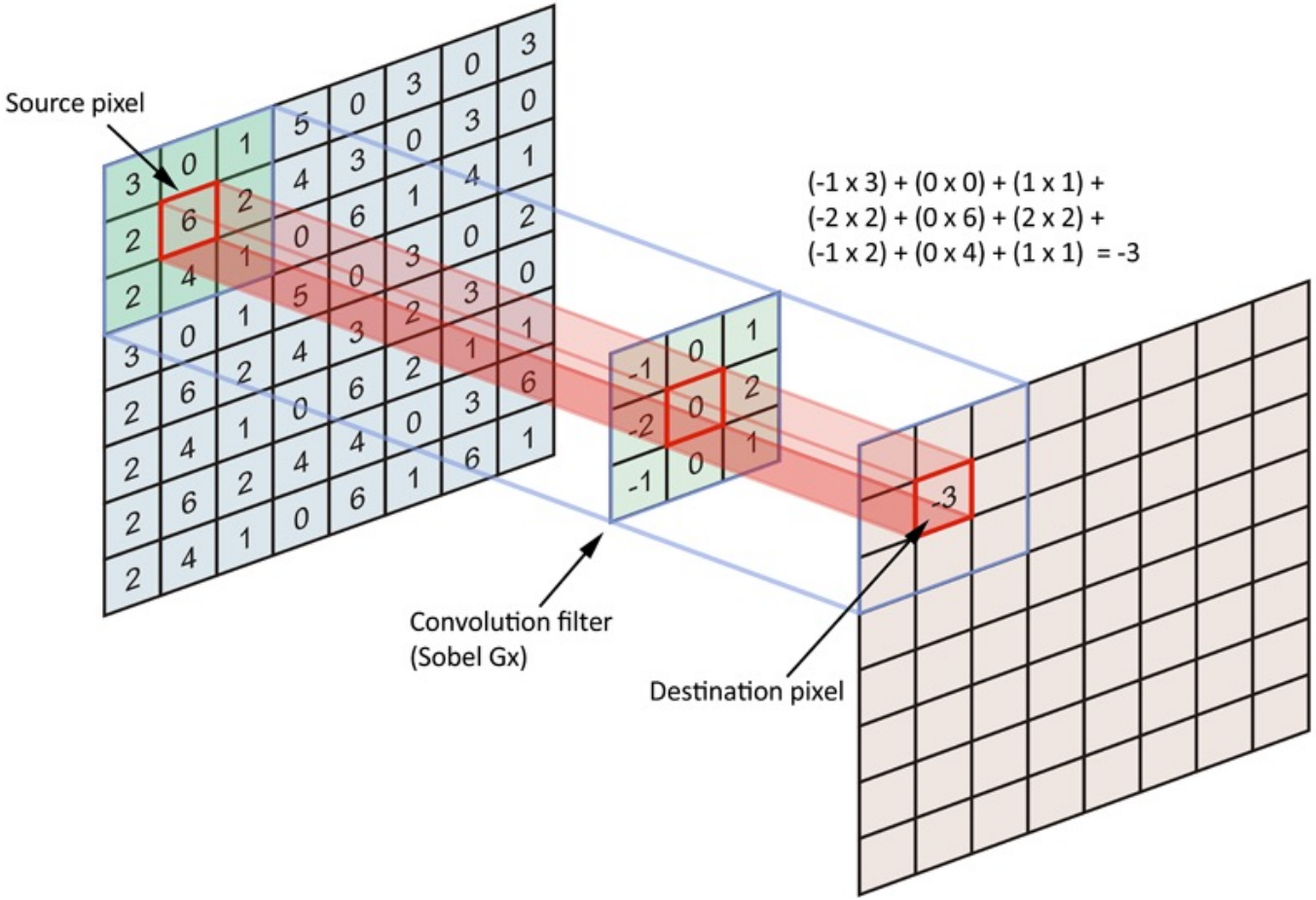


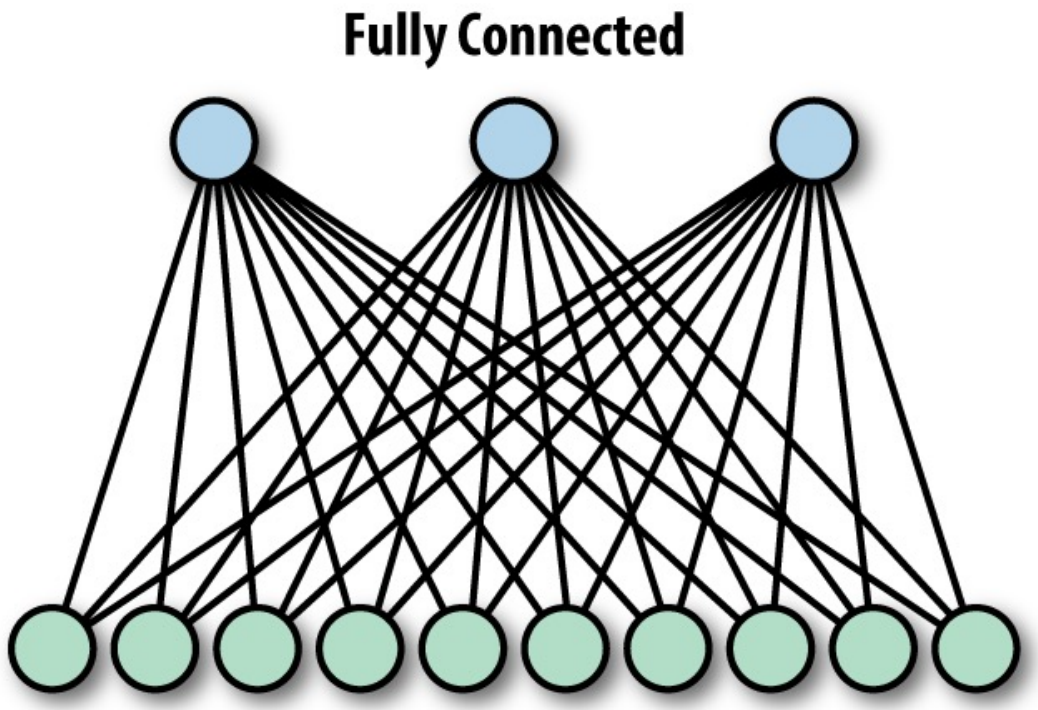

Image from: https://mlnotebook.github.io/post/CNN1/

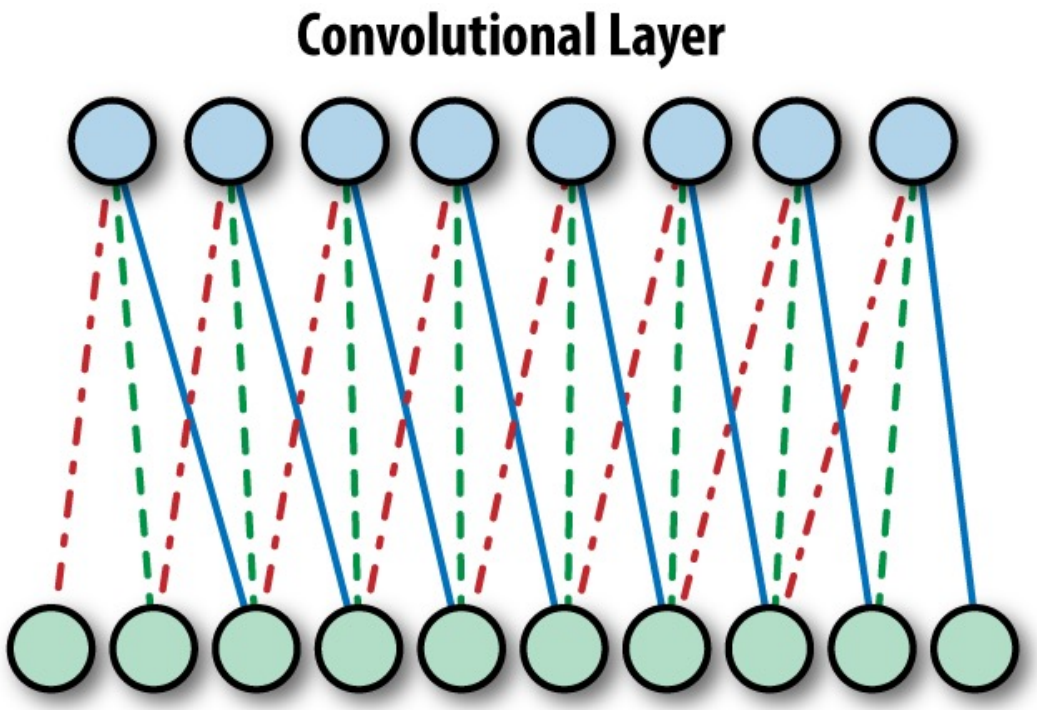
# Convolución 2D



# Redes Neuronales Convolucionales

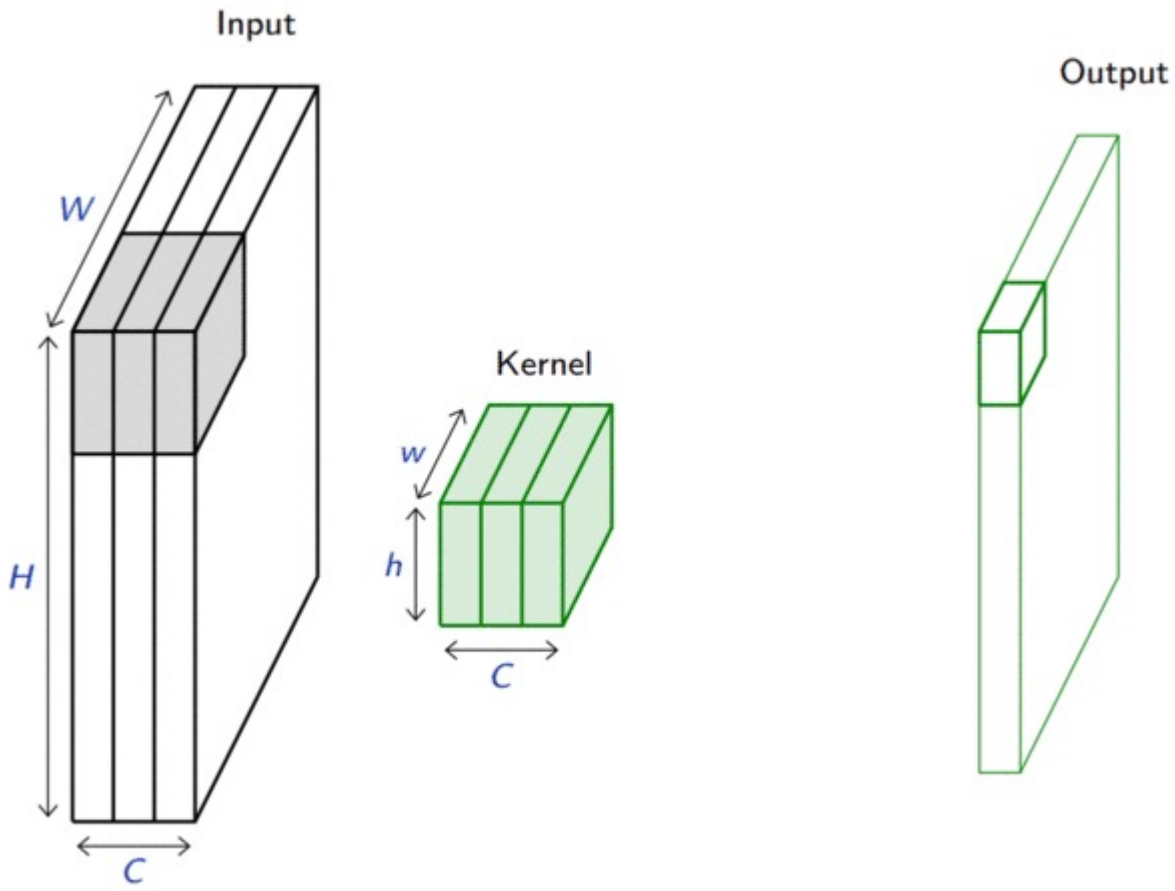
# Capas totalmente conectadas vs capas convolucionales




Fuente: https://www.oreilly.com/library/view/learning-tensorflow/9781491978504/ch04.html

# Convolución 2D




**La conectividad es local en el espacio y total en profundidad**

**Weight-sharing** el número de parámetros e introduce invarianza a la traslación

**Las funciones de activación no lineal** (ej. ReLU) son aplicadas a cada elemento individualmente

Extracted from: https://documents.epfl.ch/users/f/fl/fleuret/www/dlc/dlc-slides-4a-dag-autograd-conv.pdf

# Convolución 2D

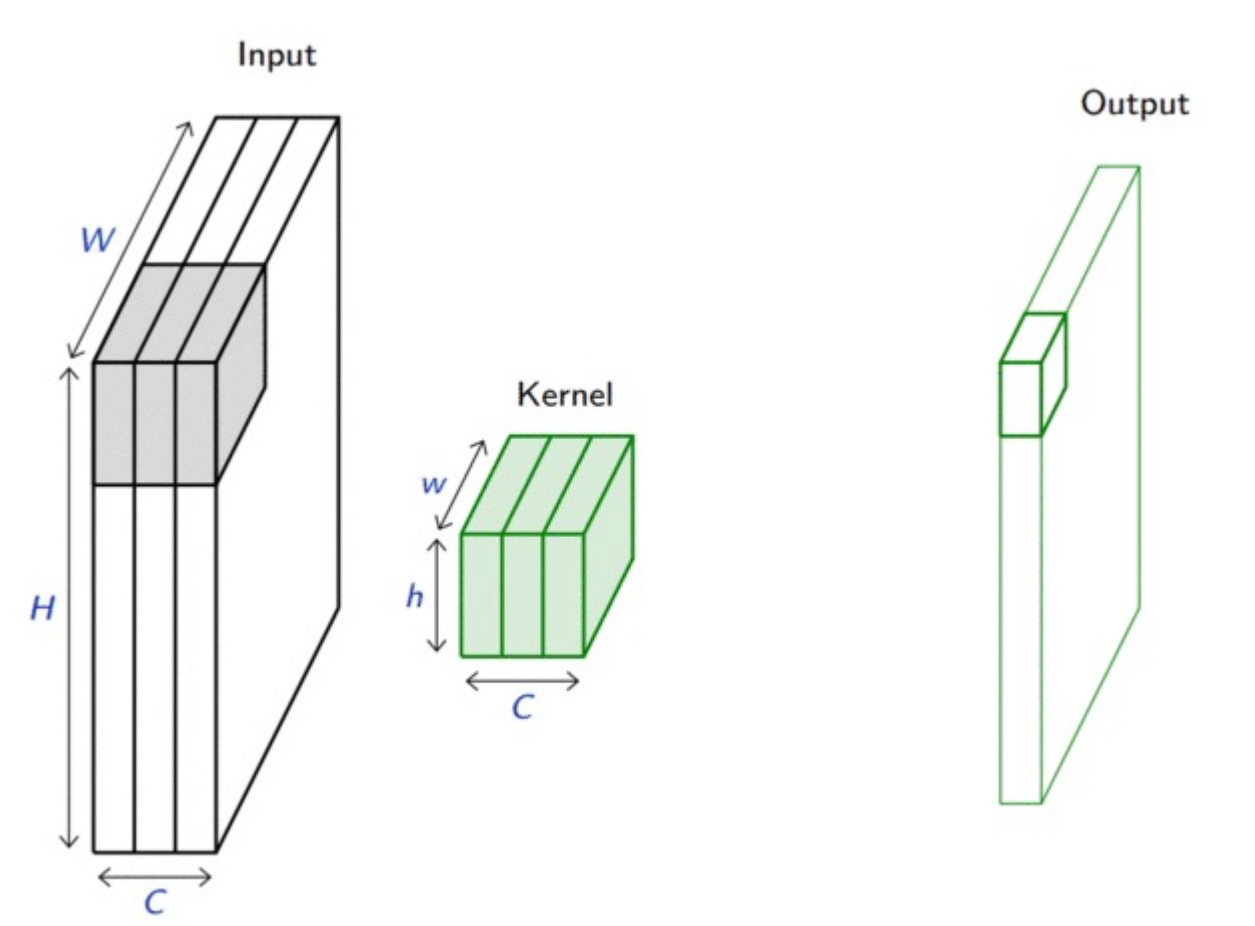
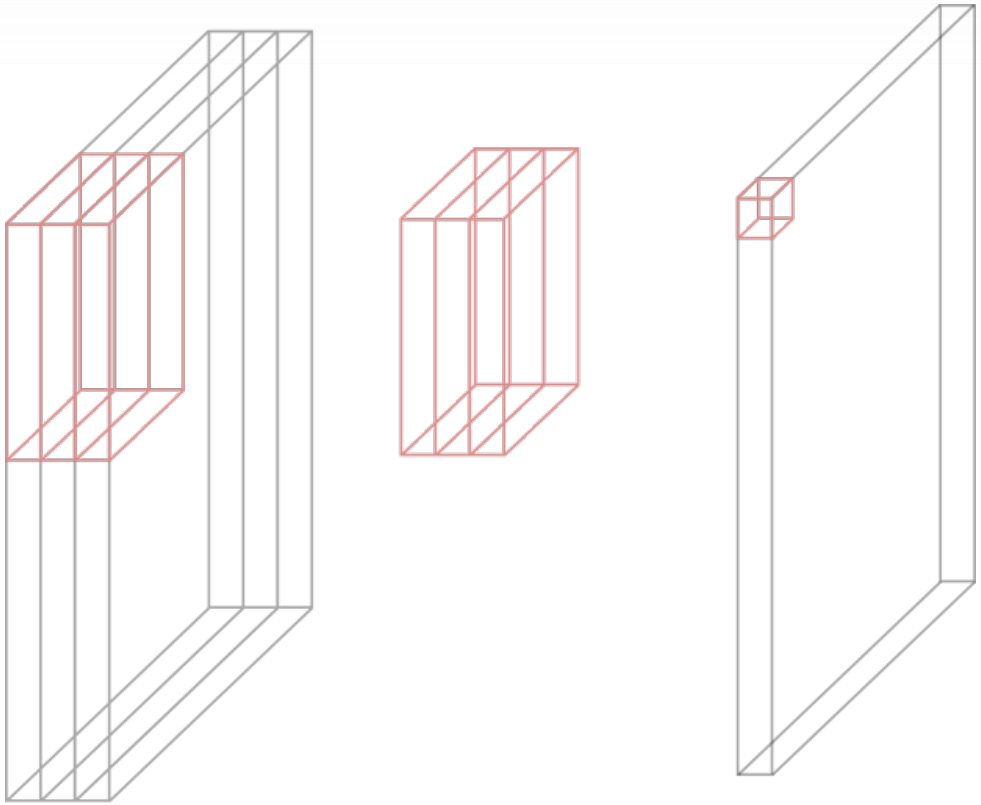


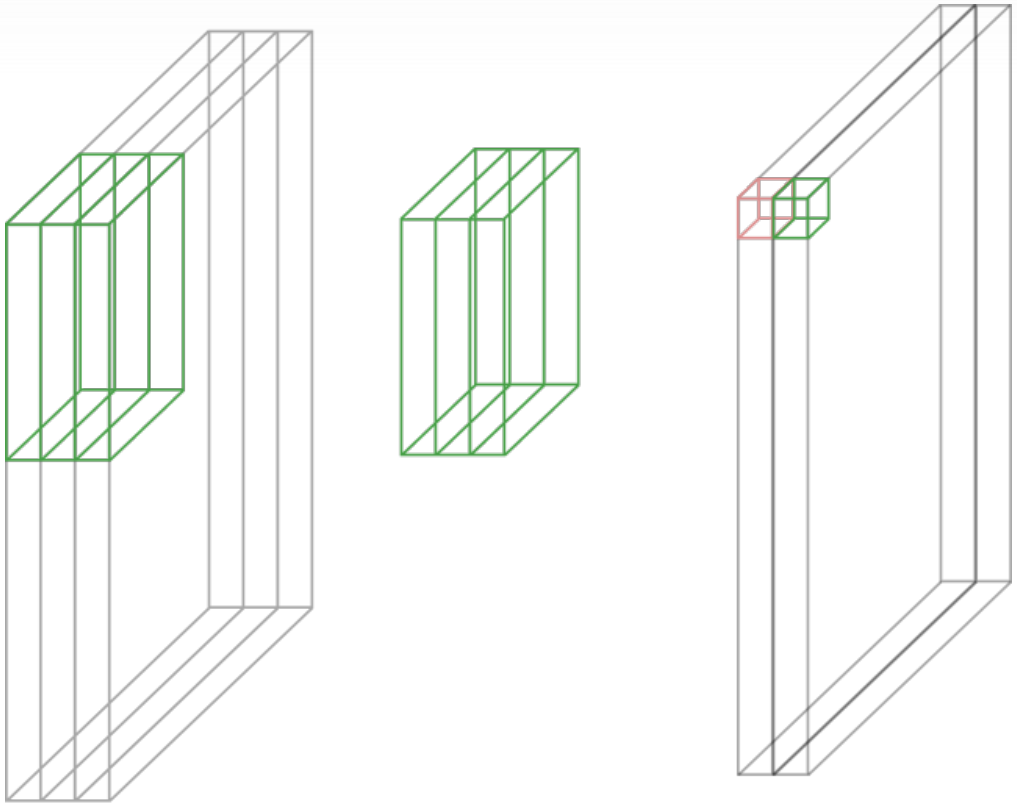

Imagen extraída de: https://documents.epfl.ch/users/f/fl/fleuret/www/dlc/dlc-slides-4a-dag-autograd-conv.pdf

# Salida de una capa convolucional

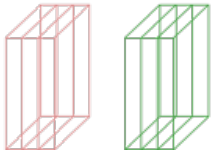


Parámetros a aprender en la capa

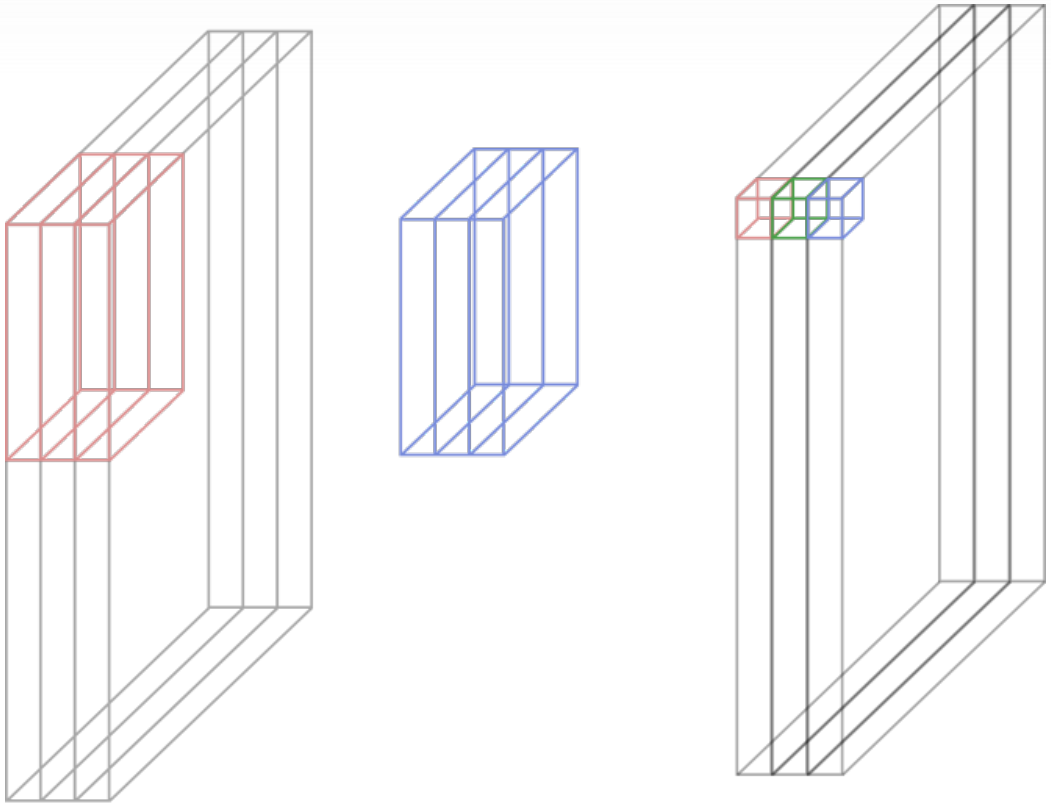
# Salida de una capa convolucional



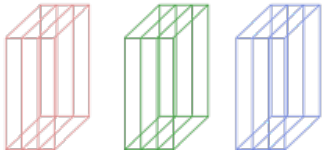
Parámetros a aprender en la capa



# Salida de una capa convolucional



Parámetros a aprender en la capa



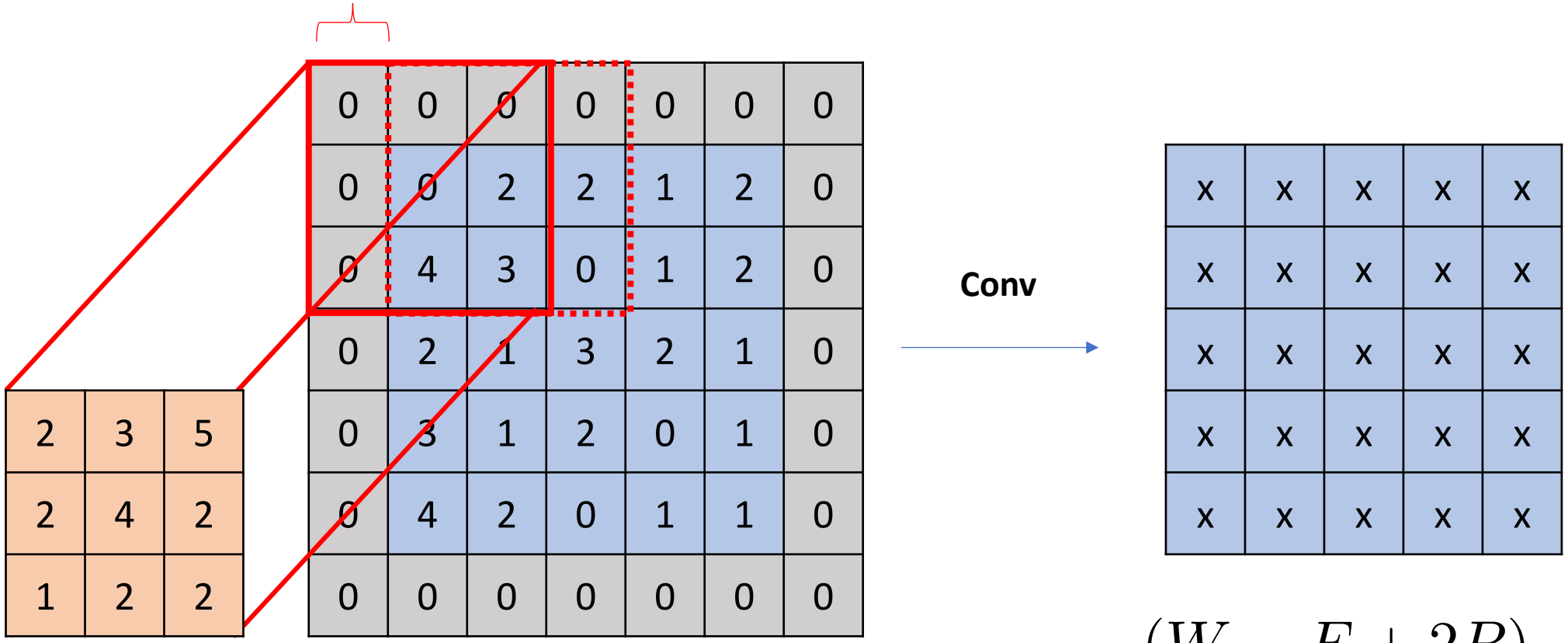
# Hiperparámetros de una capa convolucional

Relación entrada/salida

**Stride: S = 1**

**Entrada: W = 5x5**

**Salida: O = 5x5**



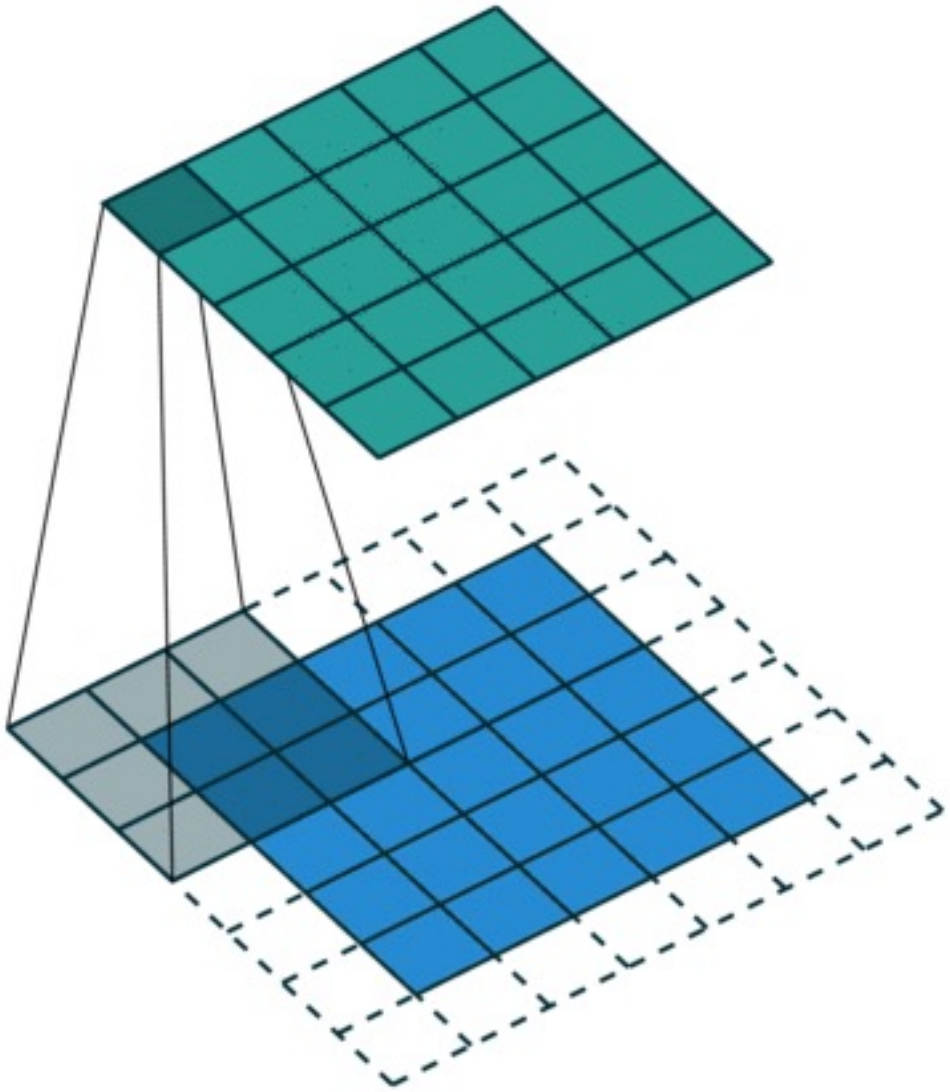

**Kernel F=3**

**Padding P = 1**

$$O = \frac{(W - F + 2P)}{S} + 1$$

# Convolución con P=1, S=1 y F=3

**Mantiene  las dimensiones**



Animación extraída de
http://deeplearning.net/software/theano/tutorial/conv_arithmetic.html

# Hiperparámetros de una capa convolucional

Relación entrada/salida

**Stride: S = 1**

**Entrada: W = 5x5**

| | | | | |
|---|---|---|---|---|
| 0 | 2 | 2 | 1 | 2 |
| 4 | 3 | 0 | 1 | 2 |
| 2 | 1 | 3 | 2 | 1 |
| 3 | 1 | 2 | 0 | 1 |
| 4 | 2 | 0 | 1 | 1 |

**Kernel F=3**

| | | |
|---|---|---|
| 2 | 3 | 5 |
| 2 | 4 | 2 |
| 1 | 2 | 2 |

**Padding P = 0**

**Conv**

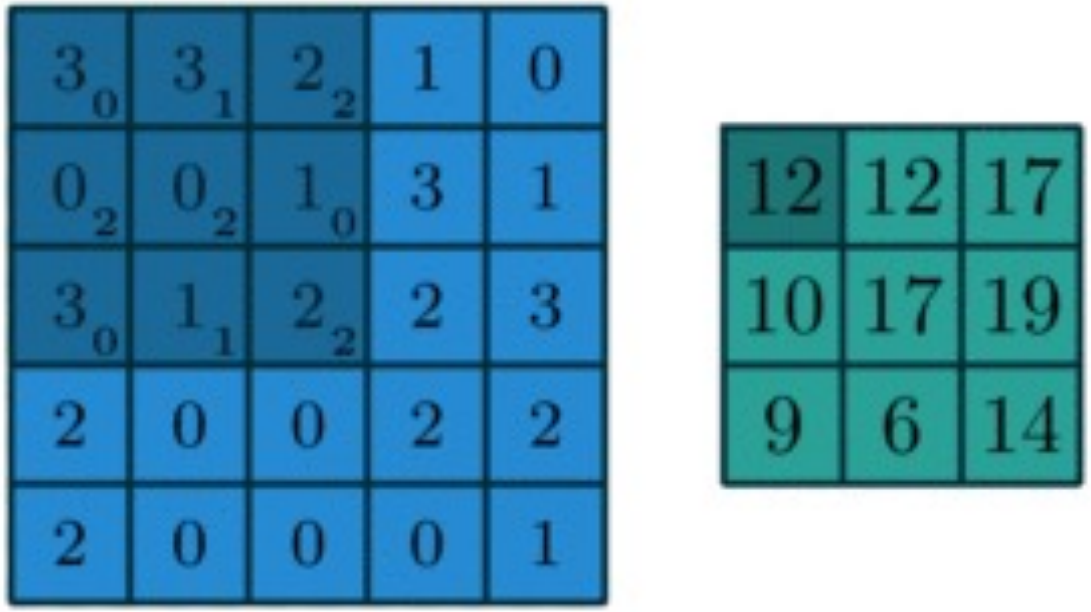
**Salida: O = 3x3**

| | | |
|---|---|---|
| x | x | x |
| x | x | x |
| x | x | x |

$$O = \frac{(W - F + 2P)}{S} + 1$$

# Convolución con P=0, S=1, F=3, w=5

**El tamaño de salida O se reduce a 3**




Animación extraída de
http://deeplearning.net/software/theano/tutorial/conv_arithmetic.html

# Hiperparámetros de una capa convolucional

Relación entrada/salida

**Stride: S = 2**

**Entrada: W = 5x5**

| | | | | |
|---|---|---|---|---|
| 0 | 2 | 2 | 1 | 2 |
| 4 | 3 | 0 | 1 | 2 |
| 2 | 1 | 3 | 2 | 1 |
| 3 | 1 | 2 | 0 | 1 |
| 4 | 2 | 0 | 1 | 1 |

**Kernel =3**

| | | |
|---|---|---|
| 2 | 3 | 5 |
| 2 | 4 | 2 |
| 1 | 2 | 2 |

**Padding P = 0**

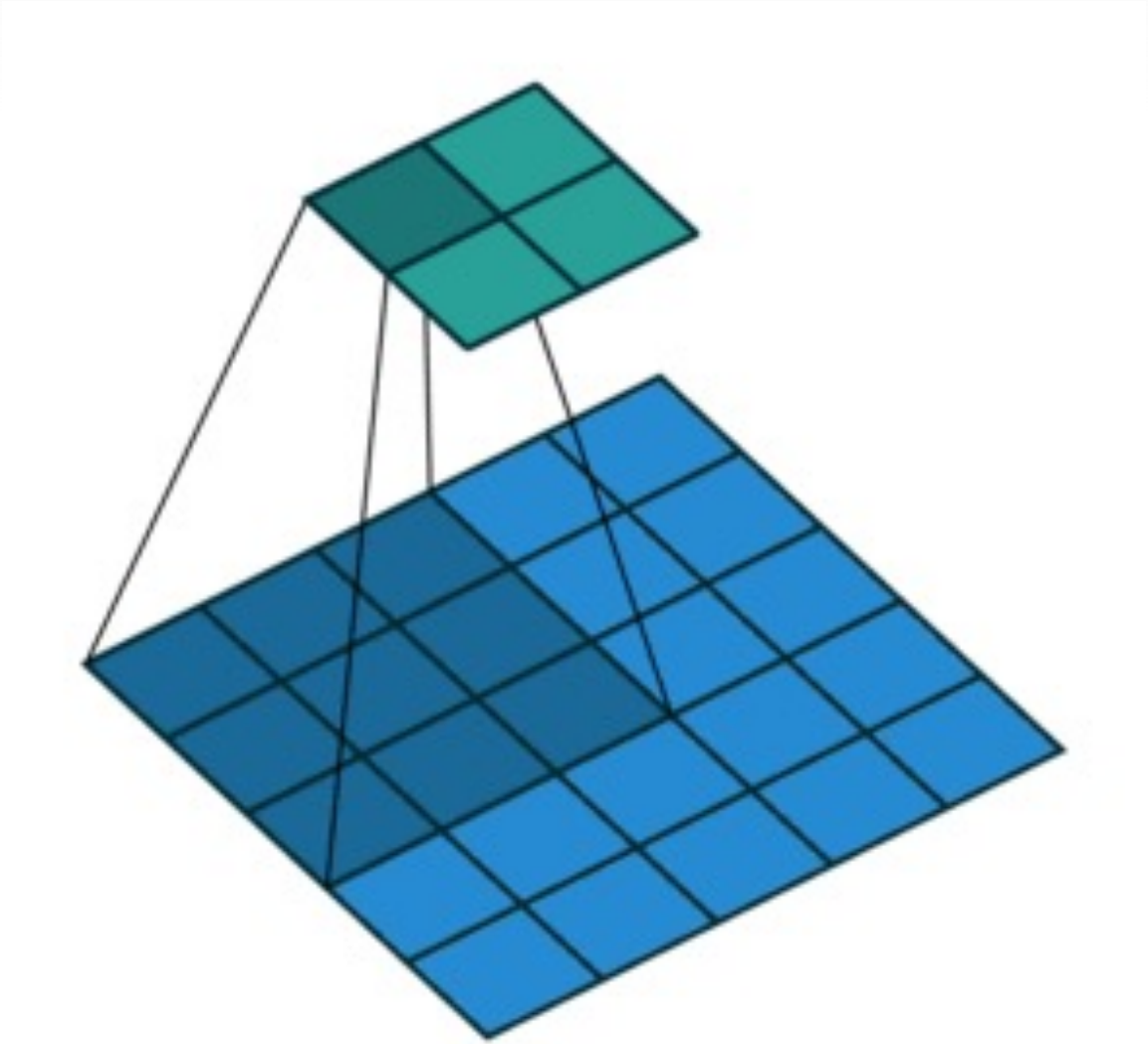
**Conv**

**Salida: O = 3x3**

| | |
|---|---|
| x | x |
| x | x |

$$O = \frac{(W - F + 2P)}{S} + 1$$

# Convolución con P=0, S=2, F=3,w=5



**El tamaño de salida O se reduce a 2**

Animación extraída de
http://deeplearning.net/software/theano/tutorial/conv_arithmetic.html

# Capa de Max-Pooling

| | | | |
|---|---|---|---|
| 0 | 2 | 2 | 1 |
| 4 | 3 | 0 | 1 |
| 2 | 1 | 3 | 2 |
| 3 | 1 | 2 | 0 |

**2x2 Max Pooling** →

| | |
|---|---|
| 4 | 2 |
| 3 | 3 |

- Reduce la dimensión de los feature maps
- Contribuye a la invarianza respecto a pequeñas traslaciones en las imágenes de entrada

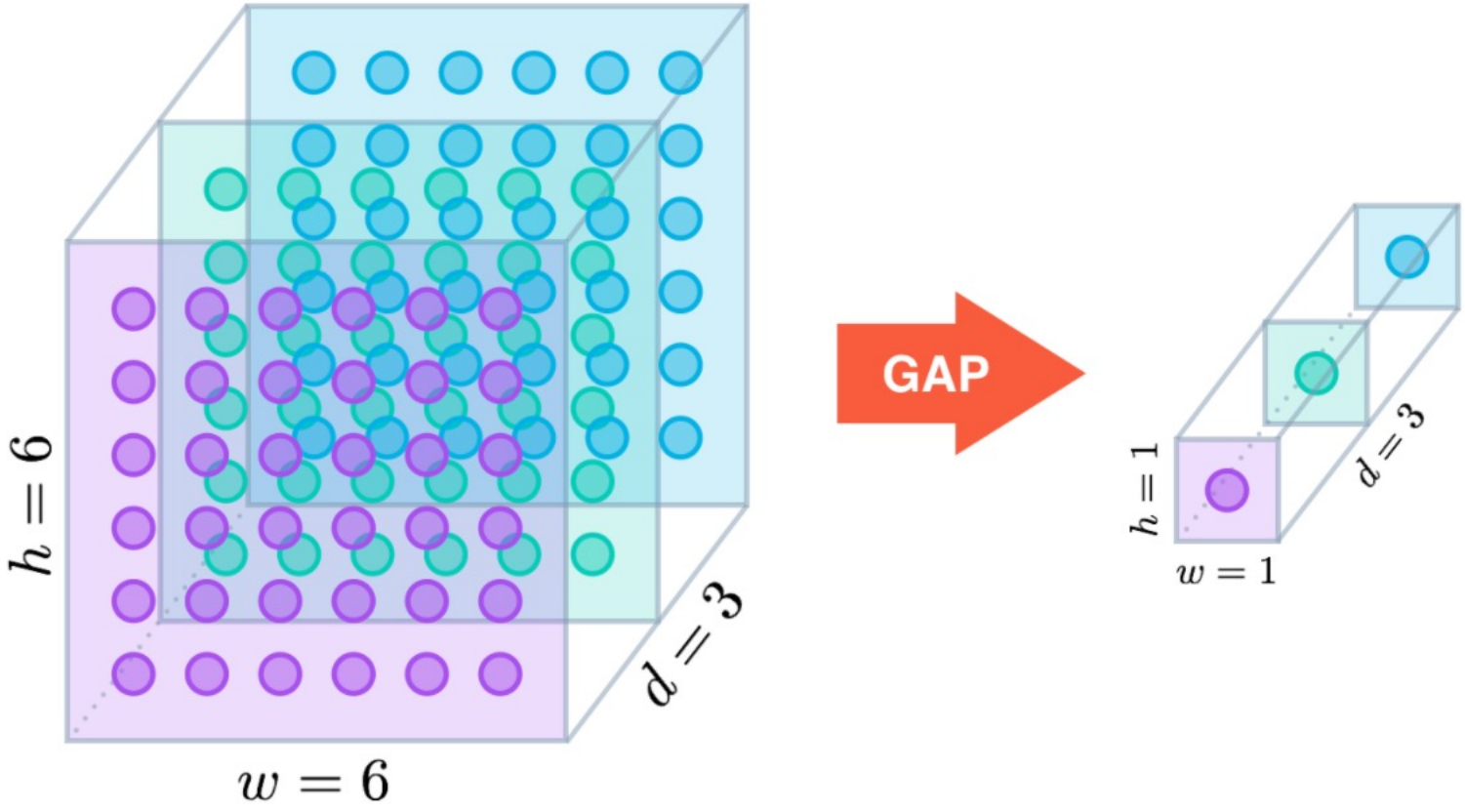
# Capa de Avg-Pooling

| | | | |
|---|---|---|---|
| 0 | 2 | 2 | 1 |
| 4 | 3 | 0 | 1 |
| 2 | 1 | 3 | 2 |
| 3 | 1 | 2 | 0 |

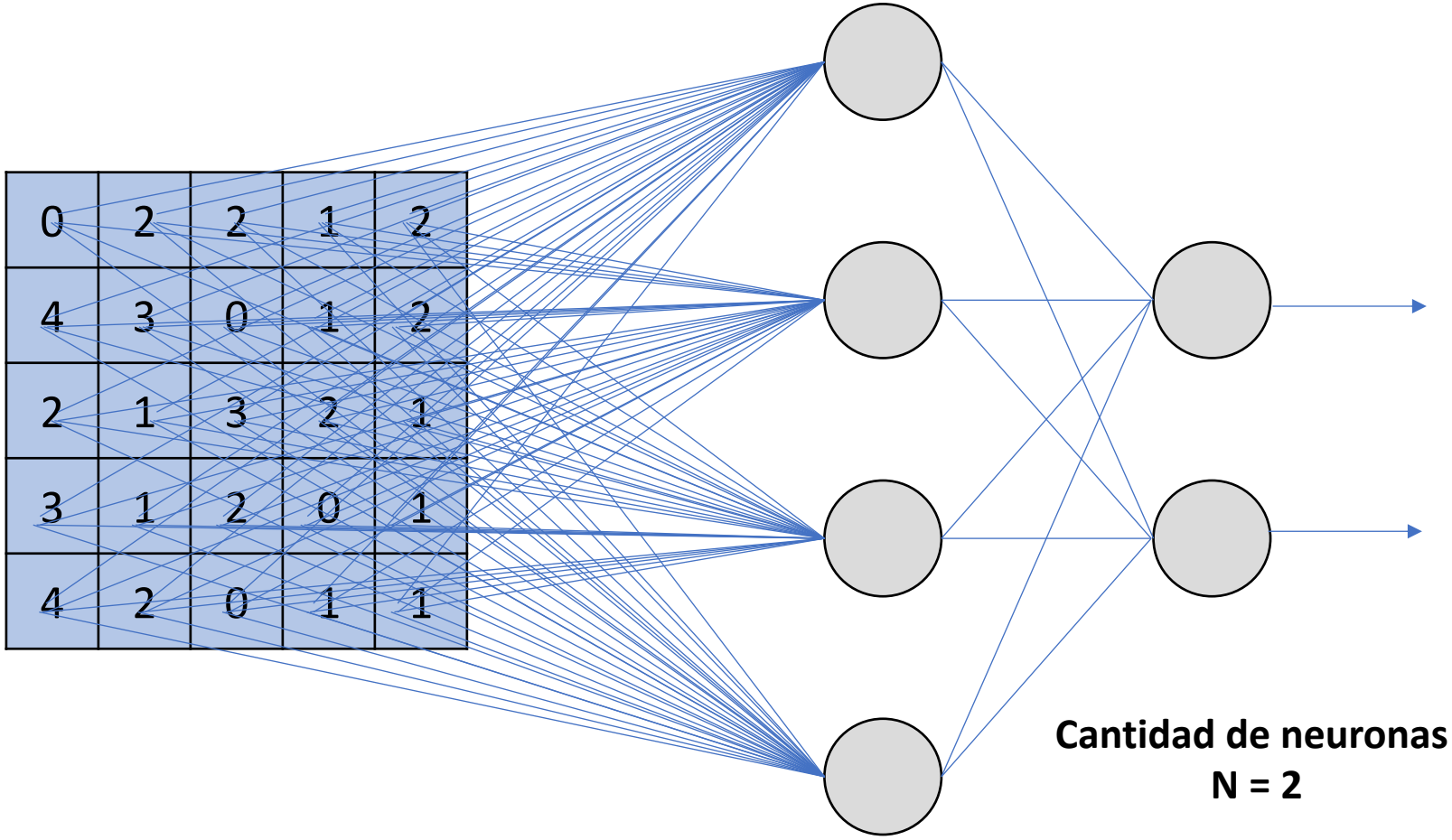
**2x2 Avg Pooling**

| | |
|---|---|
| 9/4 | 4/4 |
| 7/4 | 7/4 |

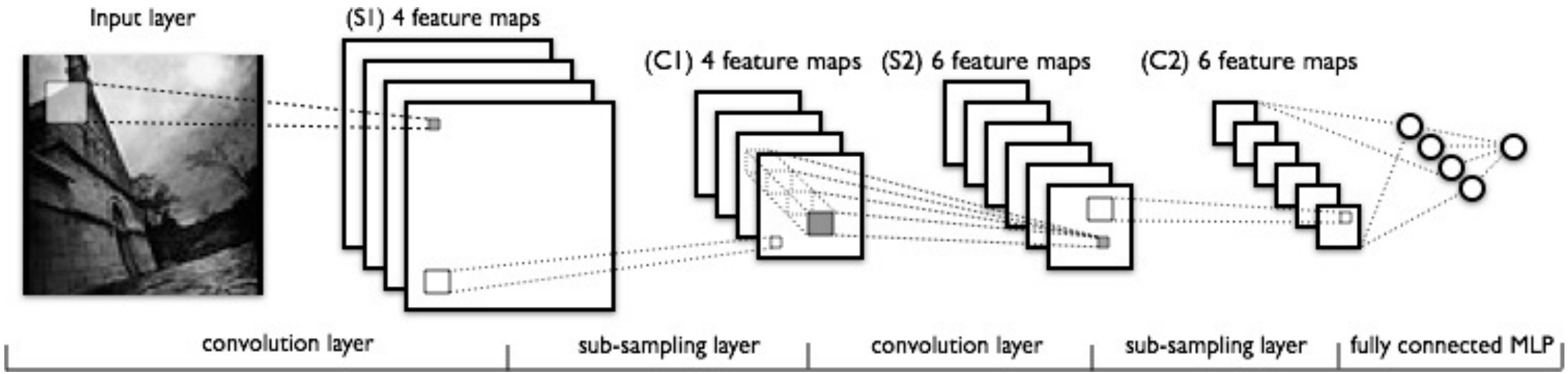
# Global Average Pooling



# Capa Fully Connected (Totalmente Conectada)



# Redes Neuronales Convolucionales




- Las convoluciones tienen soporte local

- Implementan ’weight sharing’ reduciendo el número de parámetros e introduciendo invarianza espacial

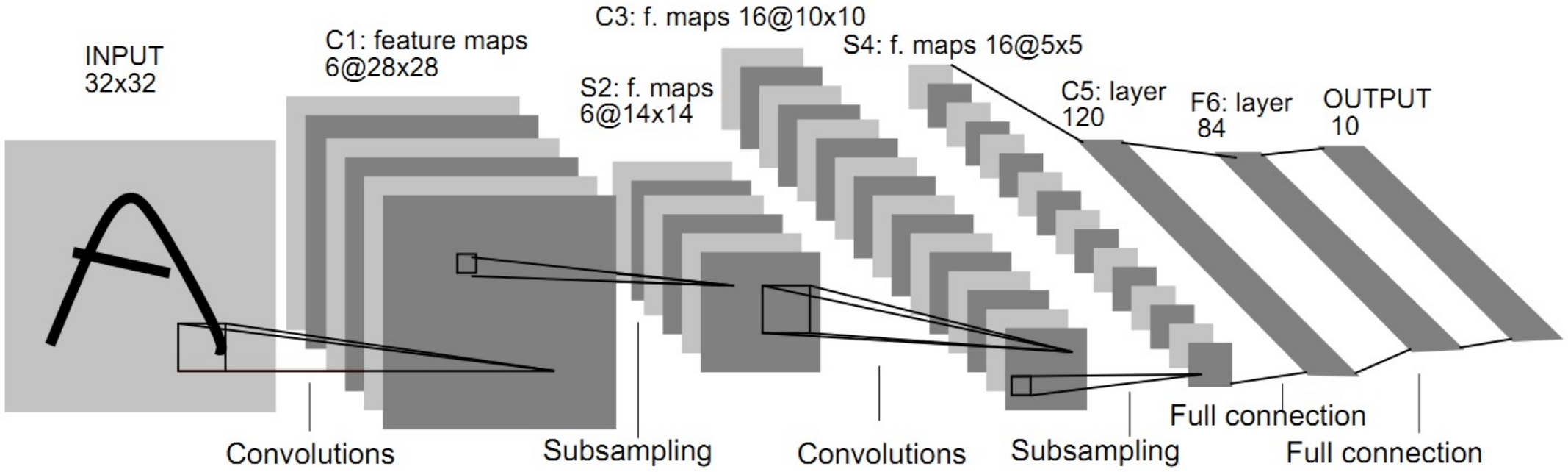
# ConvNets para el análisis de imágenes: Ventajas

- Naturalmente adaptadas a la **estructura regular** de las imágenes (por medio de la operación de convolución)
- Invariantes respecto a traslaciones
- Aprendizaje **end-to-end**
- Bajos requerimientos de memoria: **weight sharing**
- **Eficientes** en test-time
- Buen grado de **generalización** si se entrenan con suficientes datos

# Algunas arquitecturas clásicas para clasificación

LeNet-5 (1998, Clasificación de dígitos MNIST)

$$O = \frac{(W - F + 2P)}{S} + 1$$



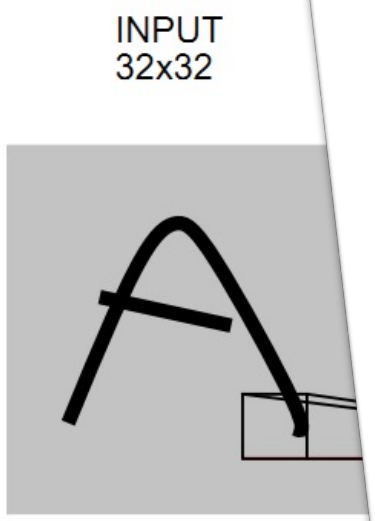

| Convolutions | Subsampling | Convolutions | Subsampling |
|---|---|---|---|
| F=5x5 | Avg Pooling | F=5x5 | Avg Pooling |
| S=1 | F=2x2 | S=1 | F=2x2 |
| | S=2 | | S=2 |

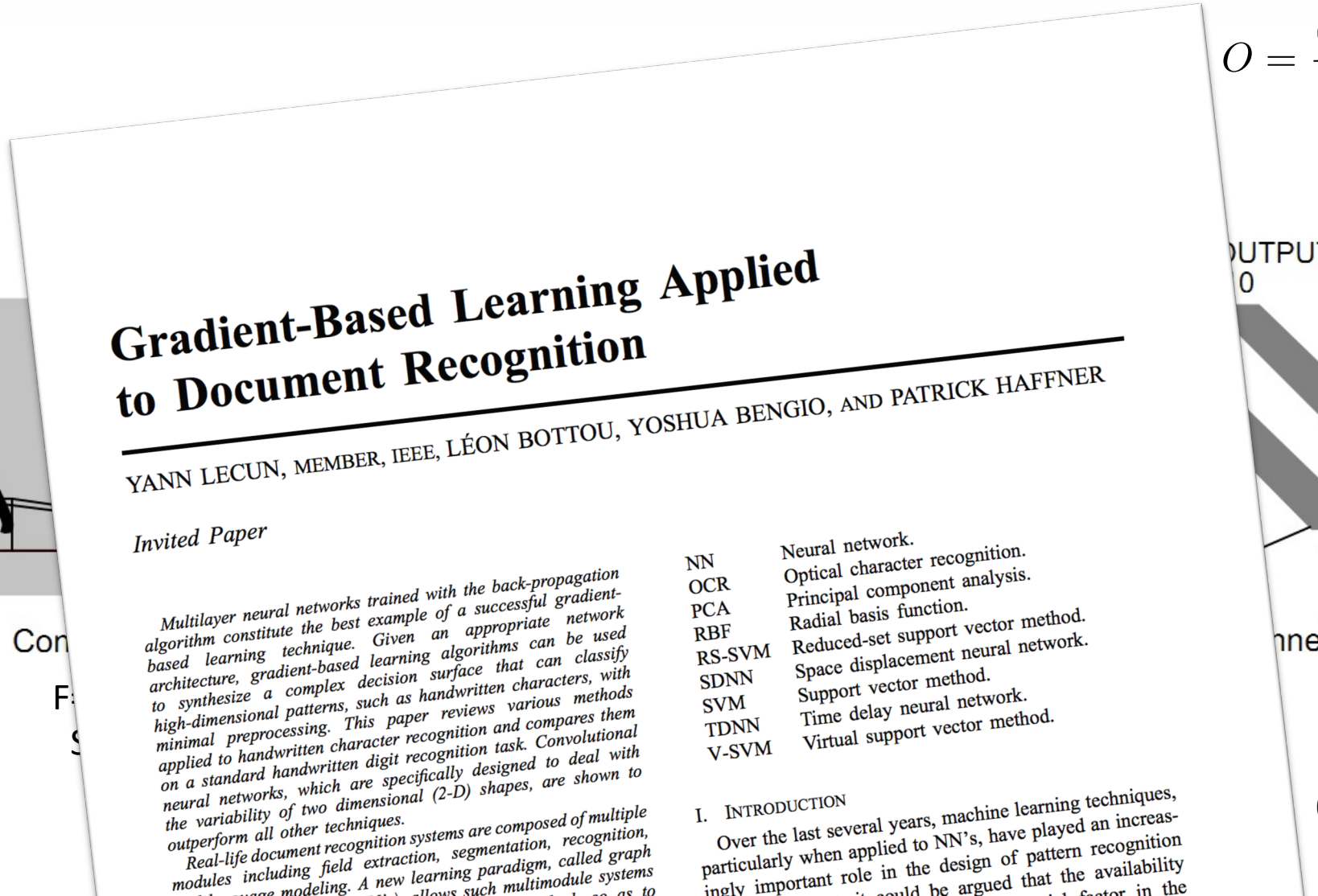
**60.000 parámetros**

# Algunas arquitecturas clásicas para clasificación

LeNet-5 (1998, Clasificación de dígitos MNIST)

$$O = \frac{(W - F + 2P)}{S} + 1$$



# Gradient-Based Learning Applied to Document Recognition

YANN LECUN, MEMBER, IEEE, LÉON BOTTOU, YOSHUA BENGIO, AND PATRICK HAFFNER

*Invited Paper*

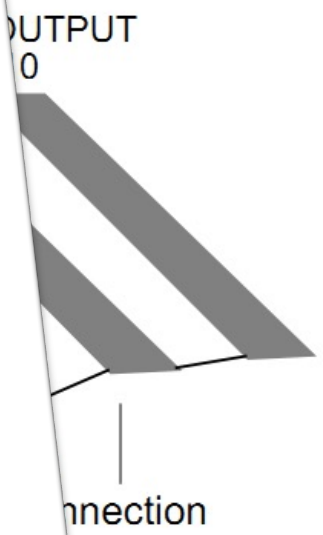
*Multilayer neural networks trained with the back-propagation algorithm constitute the best example of a successful gradient-based learning technique. Given an appropriate network architecture, gradient-based learning algorithms can be used to synthesize a complex decision surface that can classify high-dimensional patterns, such as handwritten characters, with minimal preprocessing. This paper reviews various methods applied to handwritten character recognition and compares them on a standard handwritten digit recognition task. Convolutional neural networks, which are specifically designed to deal with the variability of two dimensional (2-D) shapes, are shown to outperform all other techniques.*

*Real-life document recognition systems are composed of multiple modules including field extraction, segmentation, recognition,*

| | |
|---|---|
| NN | Neural network. |
| OCR | Optical character recognition. |
| PCA | Principal component analysis. |
| RBF | Radial basis function. |
| RS-SVM | Reduced-set support vector method. |
| SDNN | Space displacement neural network. |
| SVM | Support vector method. |
| TDNN | Time delay neural network. |
| V-SVM | Virtual support vector method. |

I. INTRODUCTION

Over the last several years, machine learning techniques, particularly when applied to NN's, have played an increas-

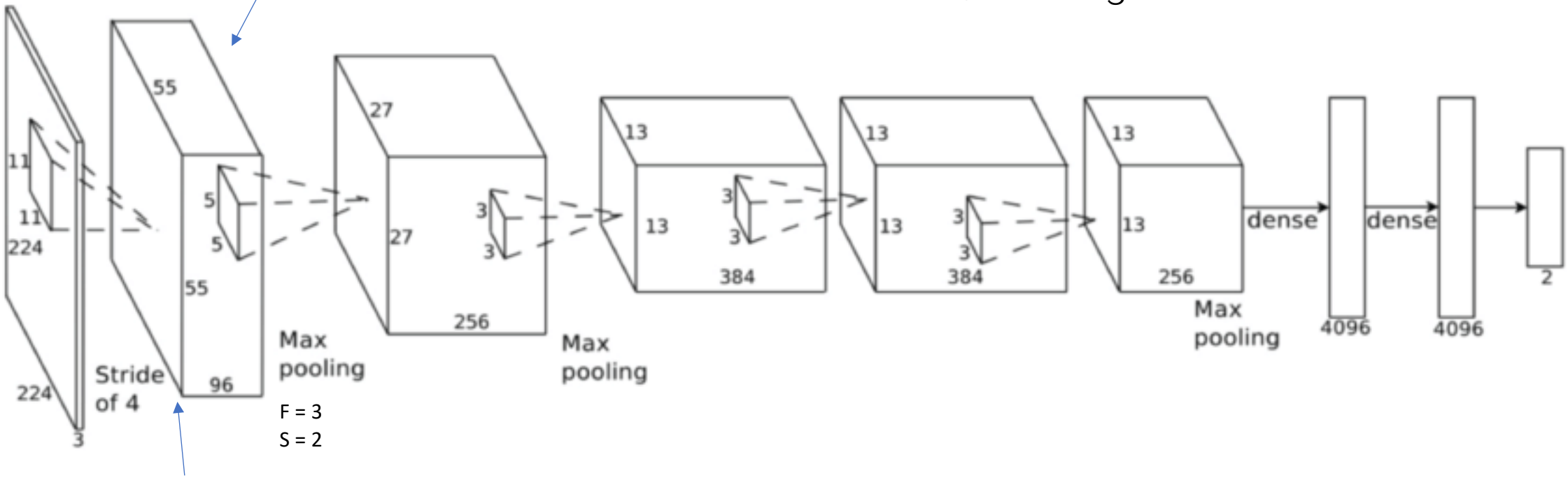



**60.000 parámetros**

# Algunas arquitecturas clásicas para clasificación

## AlexNet (2012)

Cuántos parámetros tiene la capa de pooling → Ninguno!




Cuántos parámetros tiene la primera capa convolucional? → 11 x 11 x 3 x 96 = 35.000

**Para crear c/ nuevo feature map, uso TODOS los canales del viejo feature map**

- Cada capa tiene muchos más feature maps que LeNet. Total de parámetros: 60 millones.

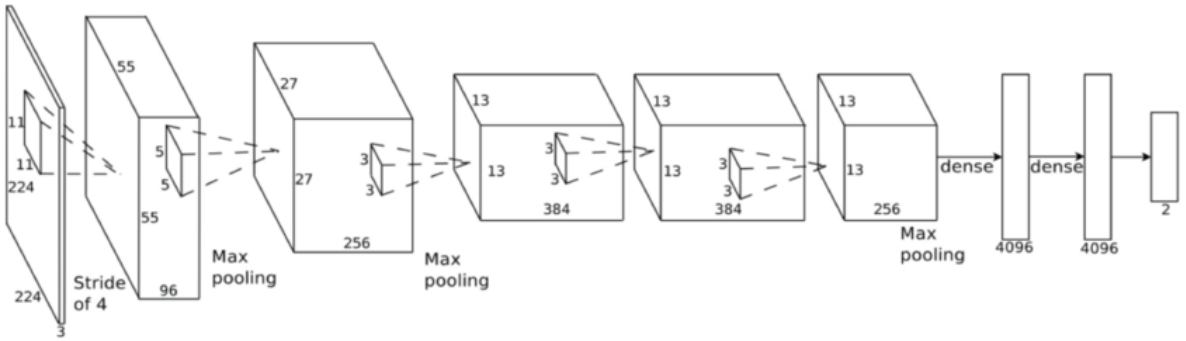
$$O = \frac{(W - F + 2P)}{S} + 1$$

**Text**

# Algunas arquitecturas clásicas para clasificación

## AlexNet (2012)

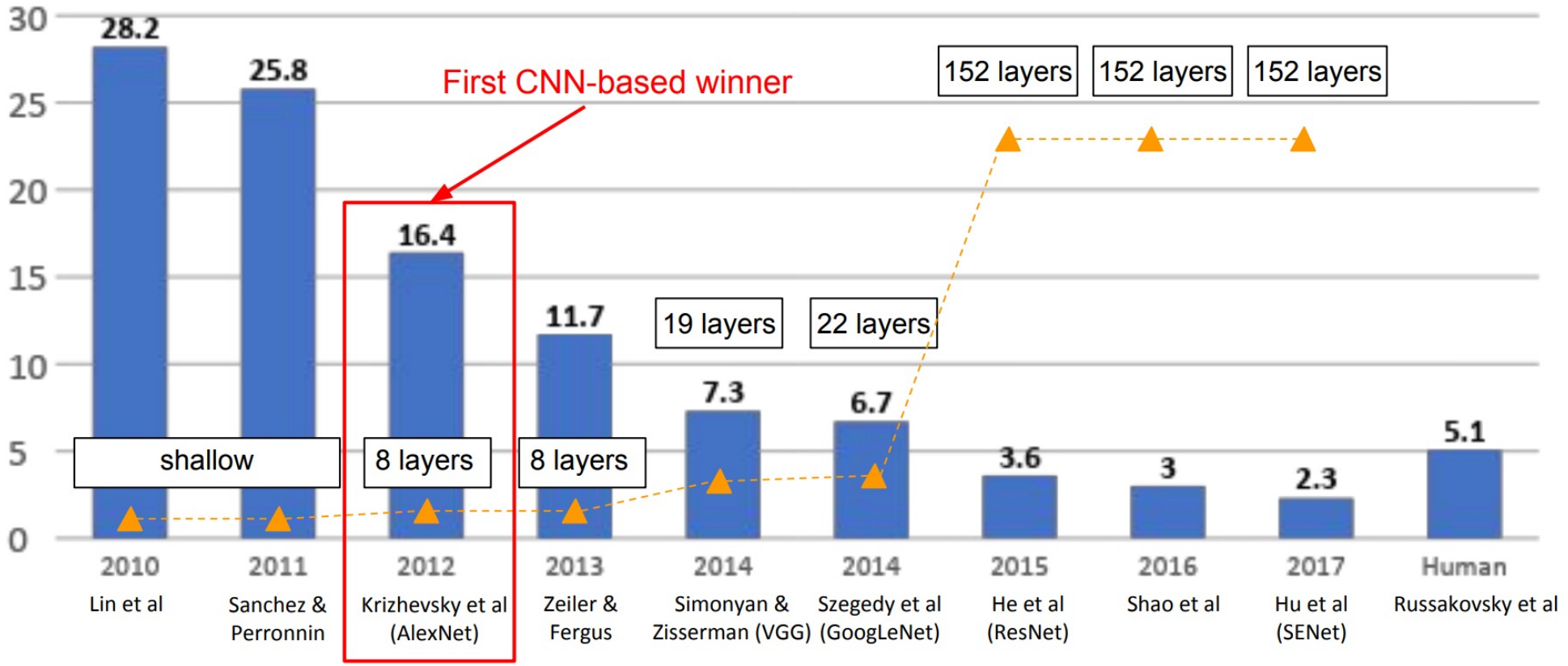
| Layer | Units (Perceptrones) | Weights (Parametros) |
|---|---|---|
| $L_1$ (Conv) | 290,400 | 34,848 |
| $L_2$ (Conv) | 186,624 | 307,200 |
| $L_3$ (Conv) | 64,896 | 884,736 |
| $L_4$ (Conv) | 64,869 | 663,552 |
| $L_5$ (Conv) | 43,264 | 442,368 |
| $L_6$ (Dense) | 4096 | 37,748,736 |
| $L_7$ (Dense) | 4096 | 16,777,216 |
| $L_8$ (Dense) | 1000 | 4,096,000 |
| Conv Subtotal | 650,080 | 2,332,704 |
| Dense Subtotal | 9192 | 58,621,952 |
| Total | 659,272 | 60,954,656 |




De los 60 Millones de parámetros,
58 Millones corresponden a las últimas capas densas!

# Algunas arquitecturas clásicas para clasificación

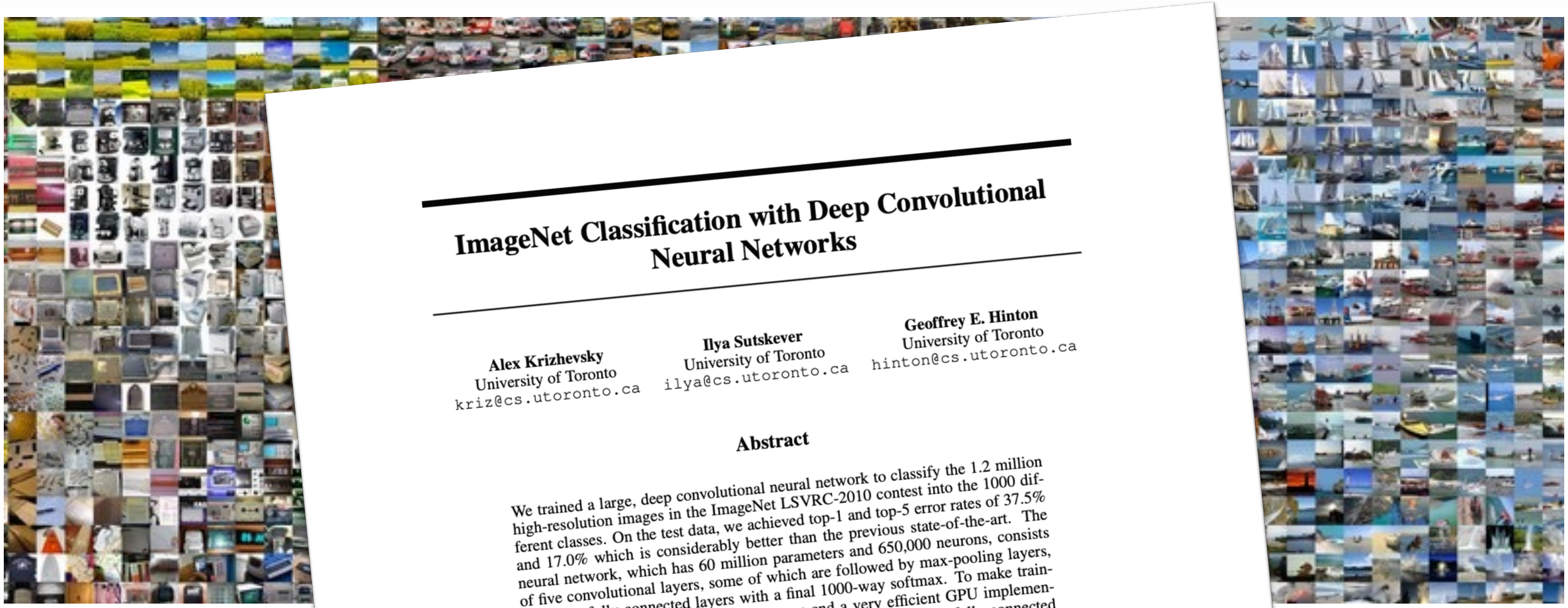
## AlexNet (2012)




Fuente: Slides del curso Stanford CS231

# Algunas arquitecturas clásicas para clasificación

AlexNet (2012)



## ImageNet Classification with Deep Convolutional Neural Networks


**Alex Krizhevsky**
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**Geoffrey E. Hinton**
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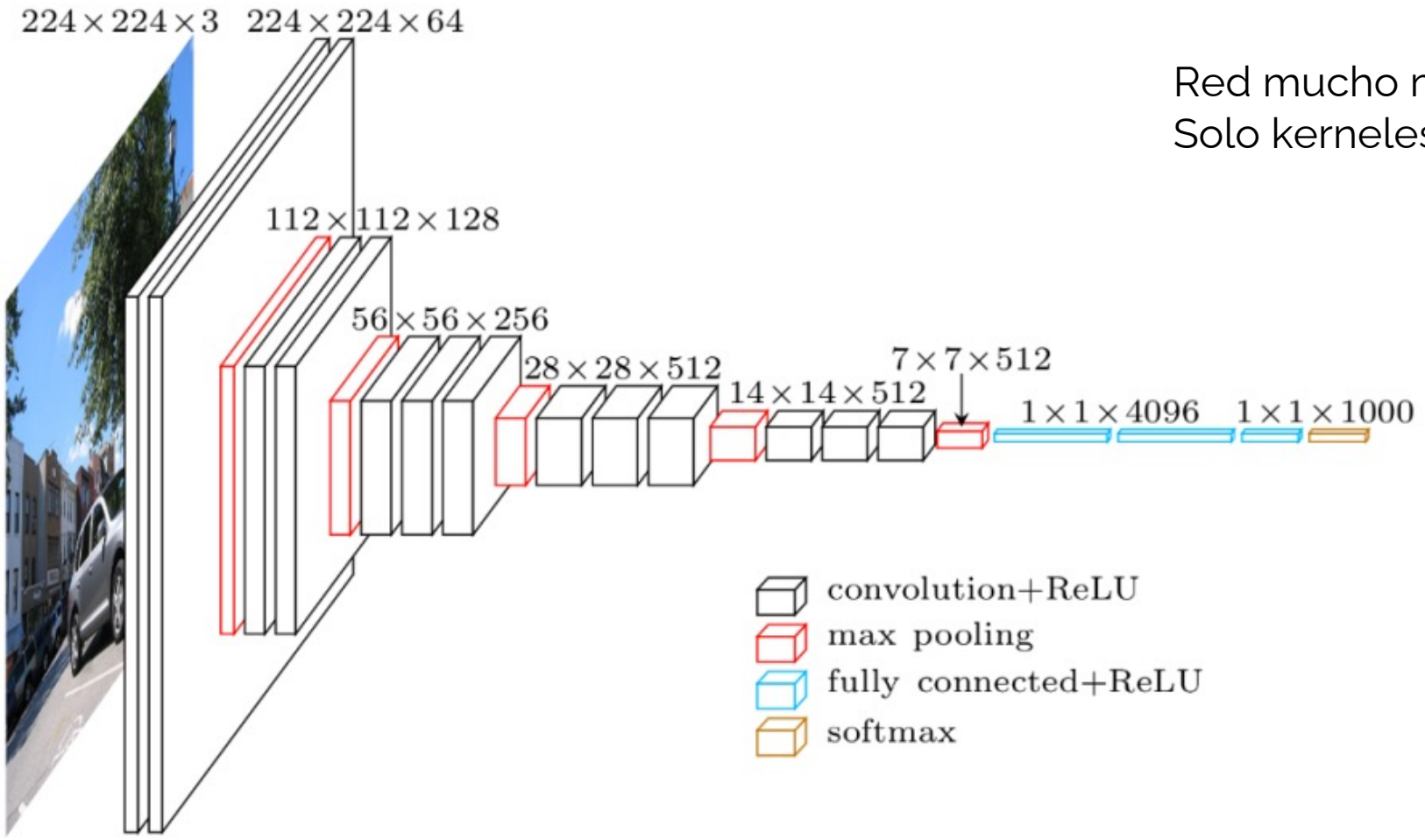
### Abstract


We trained a large, deep convolutional neural network to classify the 1.2 million high-resolution images in the ImageNet LSVRC-2010 contest into the 1000 different classes. On the test data, we achieved top-1 and top-5 error rates of 37.5% and 17.0% which is considerably better than the previous state-of-the-art. The neural network, which has 60 million parameters and 650,000 neurons, consists of five convolutional layers, some of which are followed by max-pooling layers, and three fully-connected layers with a final 1000-way softmax. To make training faster, we used non-saturating neurons and a very efficient GPU implementation of the convolution operation. To reduce overfitting in the fully-connected layers we employed a recently-developed regularization method called "dropout" that proved to be very effective. We also entered a variant of this model in the ILSVRC-2012 competition and achieved a winning top-5 test error rate of 15.3%,

# Algunas arquitecturas clásicas para clasificación

VGGNet (2014)

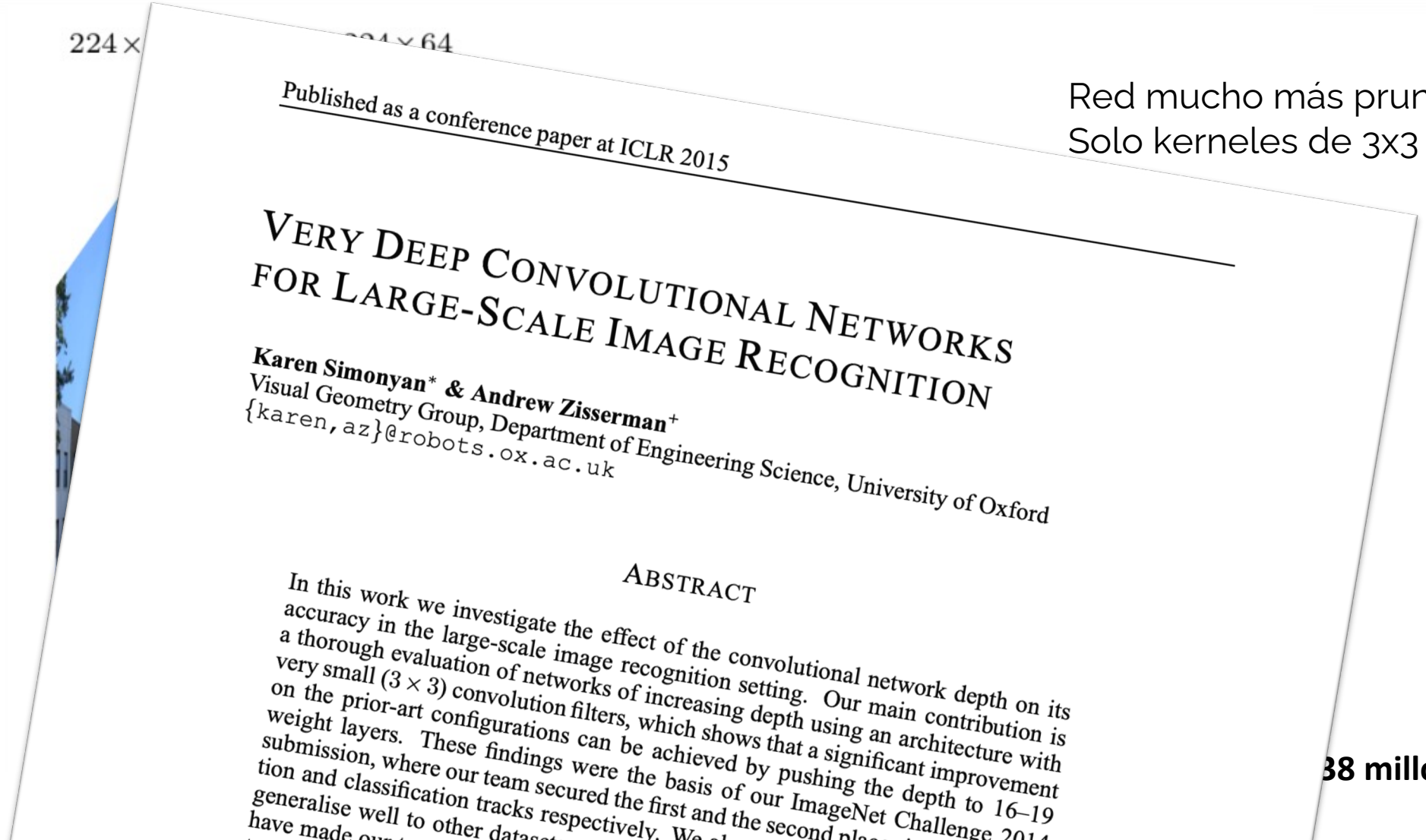



Red mucho más prunda, que utiliza
Solo kerneles de 3x3 y pooling de 2x2

**138 millones de parámetros**

# Algunas arquitecturas clásicas para clasificación

VGGNet (2014)



224 ×

Published as a conference paper at ICLR 2015

VERY DEEP CONVOLUTIONAL NETWORKS FOR LARGE-SCALE IMAGE RECOGNITION

**Karen Simonyan*** **& Andrew Zisserman+**
Visual Geometry Group, Department of Engineering Science, University of Oxford
{karen,az}@robots.ox.ac.uk

ABSTRACT

In this work we investigate the effect of the convolutional network depth on its accuracy in the large-scale image recognition setting. Our main contribution is a thorough evaluation of networks of increasing depth using an architecture with very small ($3 \times 3$) convolution filters, which shows that a significant improvement on the prior-art configurations can be achieved by pushing the depth to 16–19 weight layers. These findings were the basis of our ImageNet Challenge 2014 submission, where our team secured the first and the second pla
tion and classification tracks respectively. We
generalise well to other datas
have made our

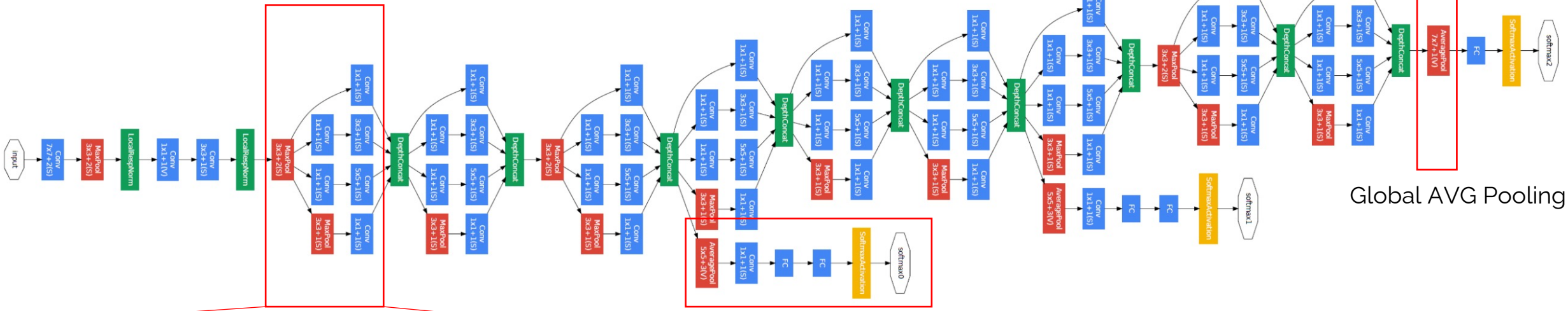
Red mucho más prunda, que utiliza
Solo kerneles de 3x3 y pooling de 2x2

**38 millones de parámetros**

# Algunas arquitecturas clásicas para clasificación

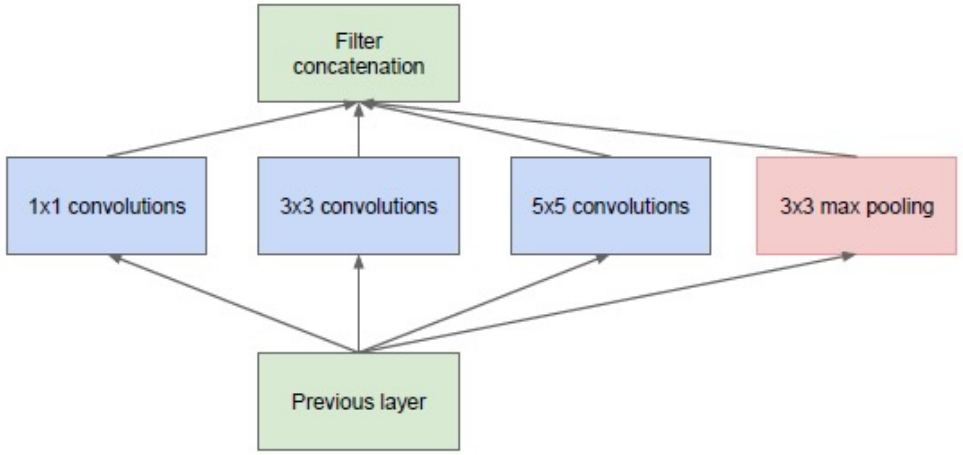
## GoogLeNet (2014, InceptionV1)

Inception Modules




Clasificadores auxiliares

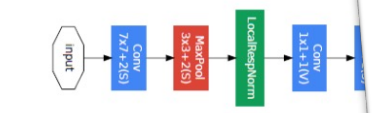
Global AVG Pooling

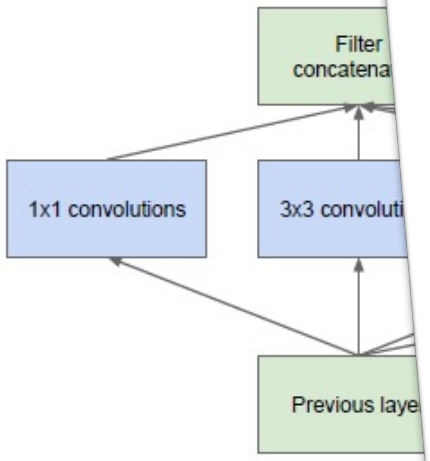



(a) Inception module, naïve version

**4 Millones de parámetros**

# Algunas arquitecturas clásicas para clasificación




(a) Inception

## Going deeper with convolutions


**Christian Szegedy**
Google Inc.

**Wei Liu**
University of North Carolina, Chapel Hill

**Yangqing Jia**
Google Inc.

**Pierre Sermanet**
Google Inc.

**Scott Reed**
University of Michigan

**Dragomir Anguelov**
Google Inc.

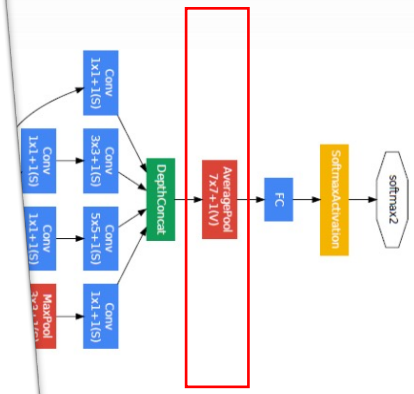
**Dumitru Erhan**
Google Inc.

**Vincent Vanhoucke**
Google Inc.

**Andrew Rabinovich**
Google Inc.


### Abstract

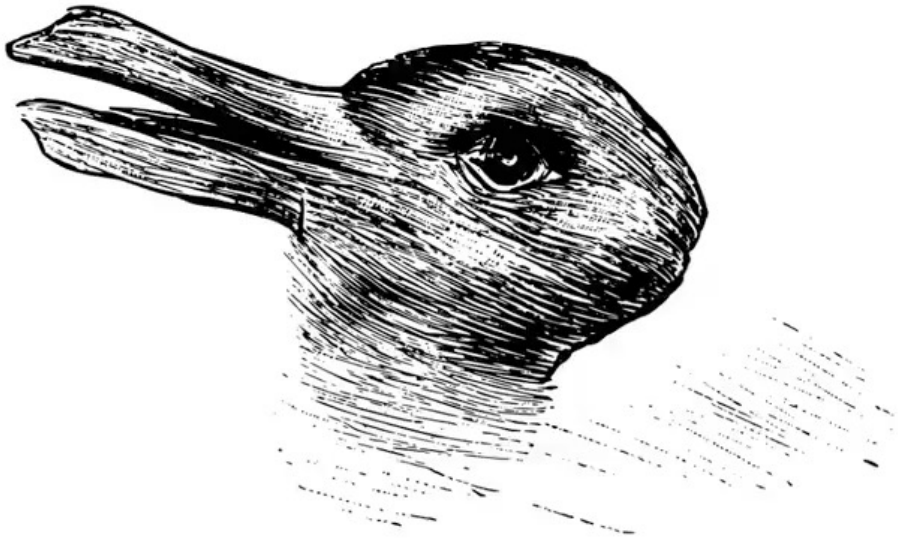

We propose a deep convolutional neural network architecture codenamed Incep-
tion, which was responsible for setting the new state of the art for classification
and detection in the ImageNet Large-Scale Visual Recognition Challenge 2014
The main hallmark of this architecture is the improved utilization
This was achieved by a carefully

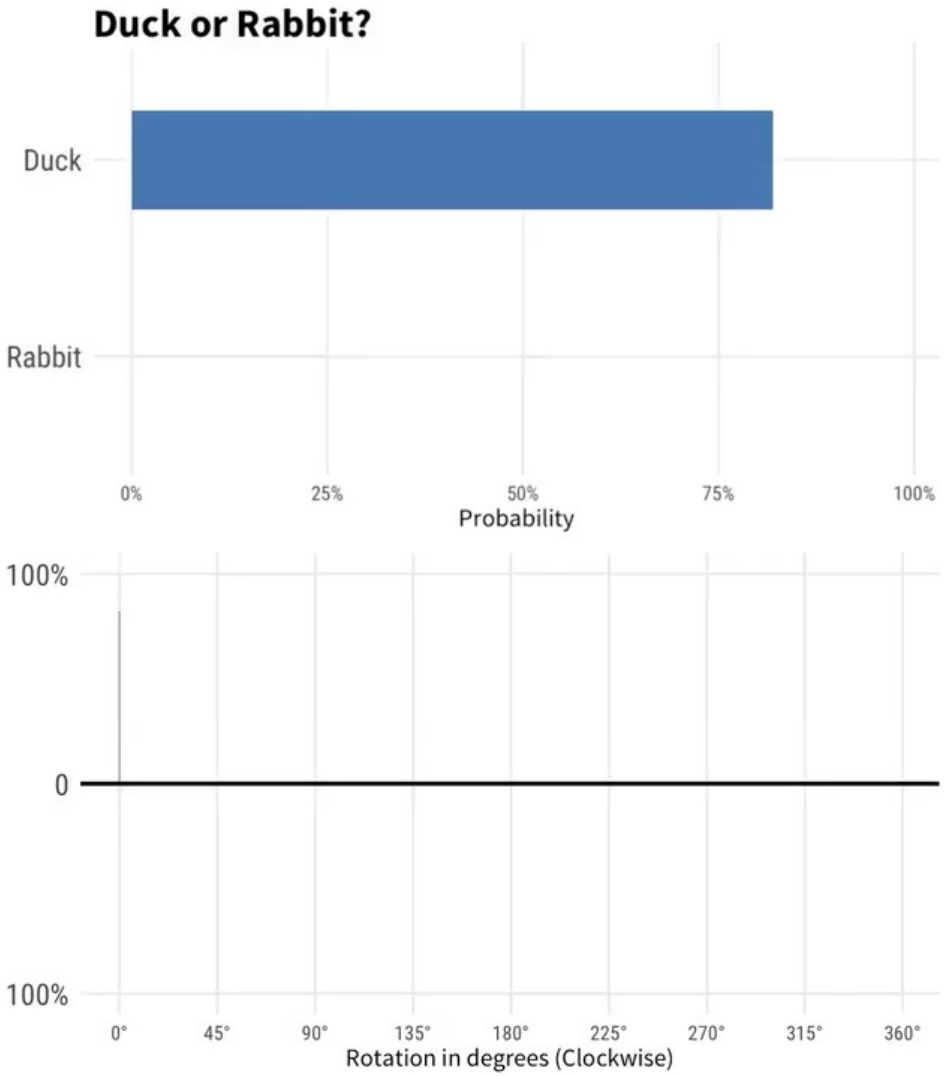




Global AVG Pooling

de parámetros

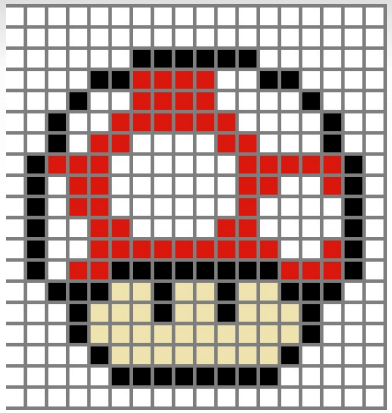
# Salidas de una CNN para clasificación de imágenes

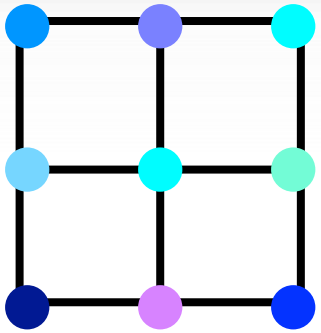


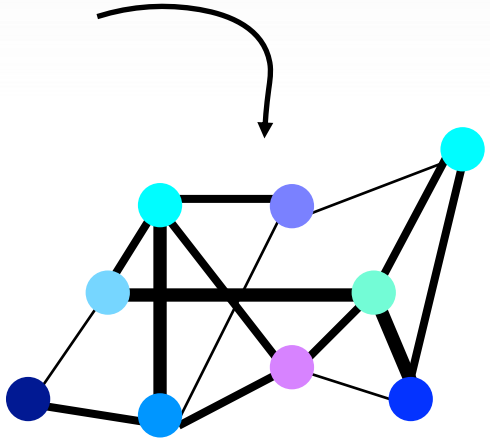



Predictions provided by the Google Cloud Vision API
Animation by Max Woolf (@minimaxir)

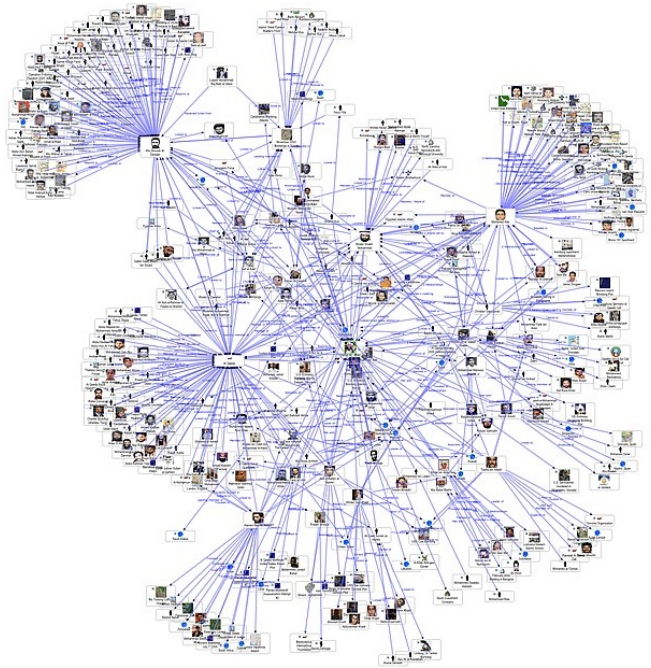
# Redes Neuronales Convolucionales en grafos



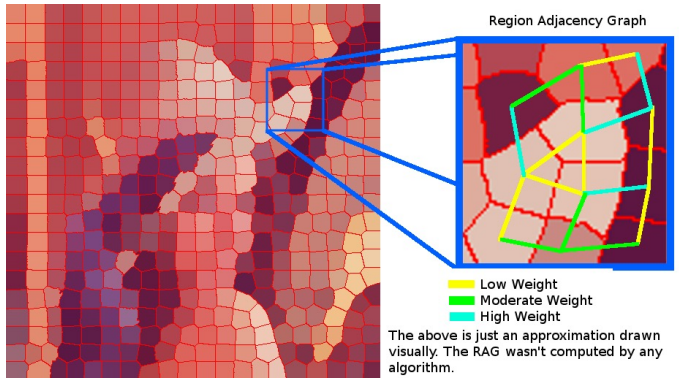




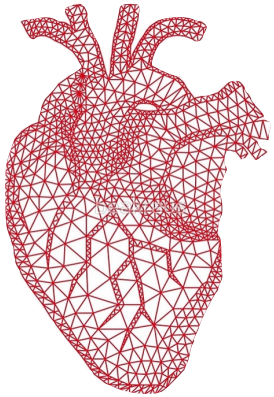
Redes sociales



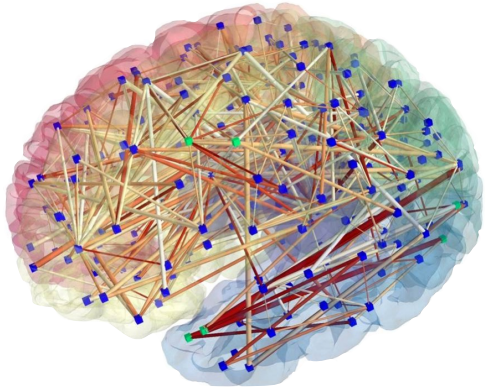
Superpixels




Meshes

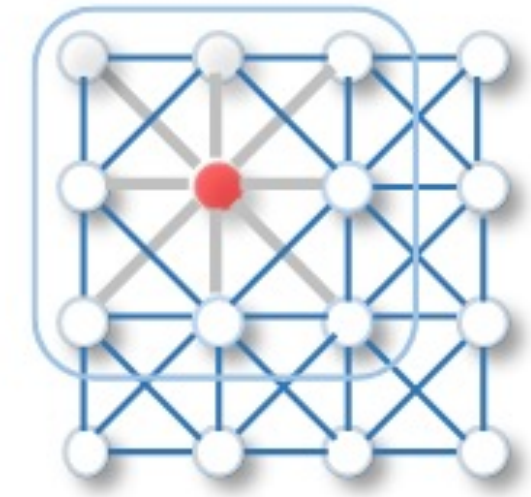


Brain Networks

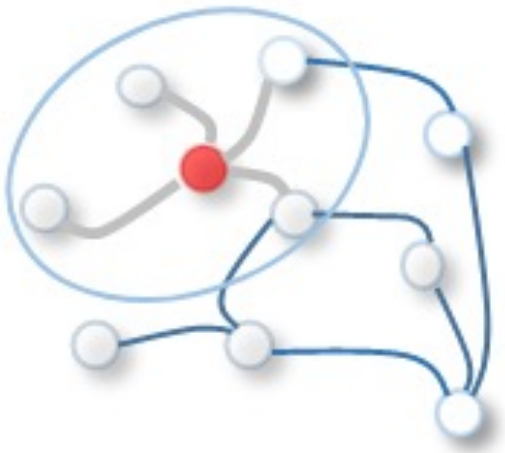


# ConvNets en grafos y dominios irregulares

**Convolución 2D clásica**

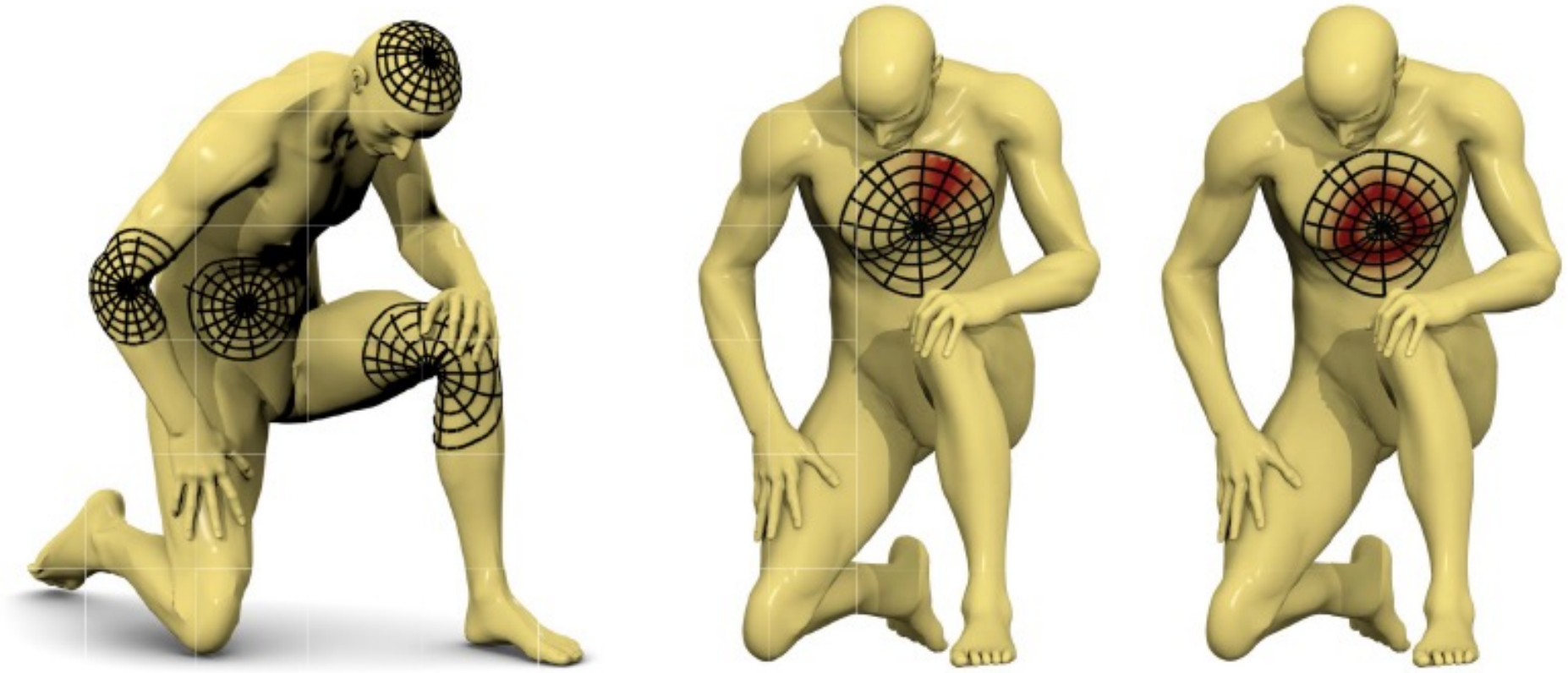


**Convolución en grafos**

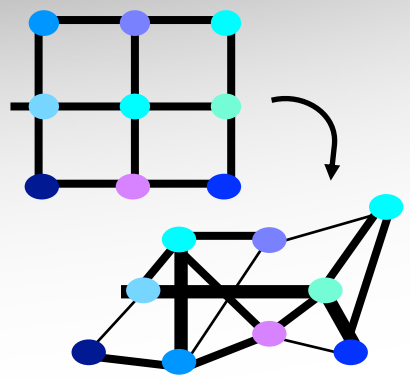


”A Comprehensive Survey on Graph Neural Networks” Wu et al, 2019

# ConvNets en grafos y dominios irregulares



# ConvNets en grafos



Geometric deep learning:
going beyond Euclidean data

Michael M. Bronstein, Joan Bruna, Yann LeCun, Arthur Szlam, Pierre Vandergheynst

- **Filtrado espacial** : La convolución se define directamente en el dominio original del grafo

  ✓ Interpretación intuitiva y analogía simple con convoluciones en dominios estructurados

  - Requiere definir un sistema de vecindad y un orden para los nodos

- **Filtrado espectral**: Convoluciones en el dominio espacial corresponden a multiplicaciones en el dominio de Fourier

  ✓ No se requiere la noción de orden entre vecinos

  ✓ Definición precisa del concepto de convolución por medio del análisis espectral de grafos

  ✓ Se pueden modelar filtros estrictamente localizados en el grafo

  - Los filtros que se aprenden en una estrcutura de grafo dada no pueden ser transferidos a otras

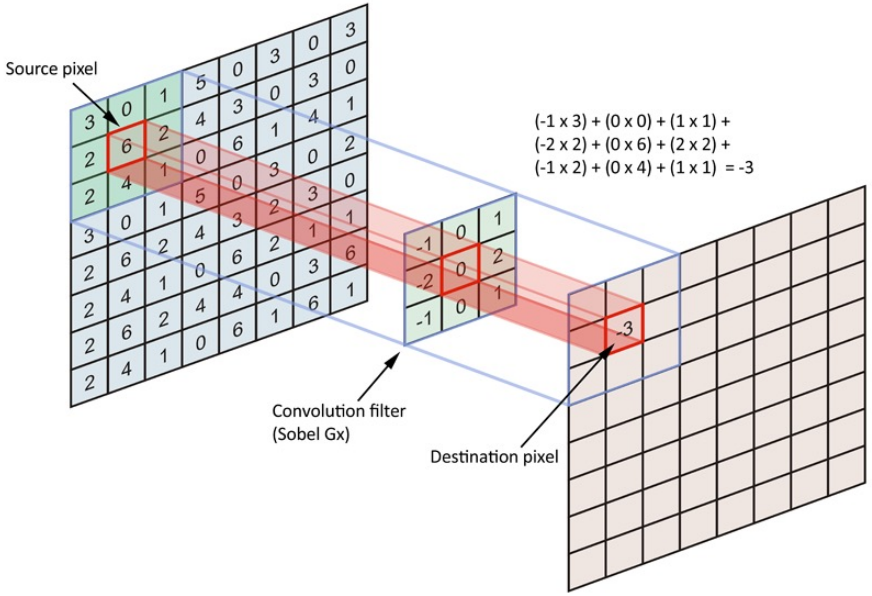
## Clase 4

# Redes Neuronales Convolucionales


Enzo Ferrante

eferrante@sinc.unl.edu.ar

@enzoferrante



Universidad de SanAndrés

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