# II Redes neuronales convolucionales

Conceptos
Arquitectura
Implementación

Odin Eufracio

#### **Actividad 5**

Terminar el notebook 2.1\_FNN\_FashionMNIST.ipynb



Este ejercicio nos servirá para motivar la necesidad de las **redes convolucionales.** 

# Operador de convolución

## **Hubel and Wiesel experiment.**

La corteza visual (del gato) tiene unas pequeñas regiones de células que son sensibles a ciertas regiones del campo visual.

Además, las células de la corteza visual están conectadas usando una estructura por capas, las cuales *reconstruyen* el campo visual a diferentes niveles de abstracción, *hierarchical feature extraction*.



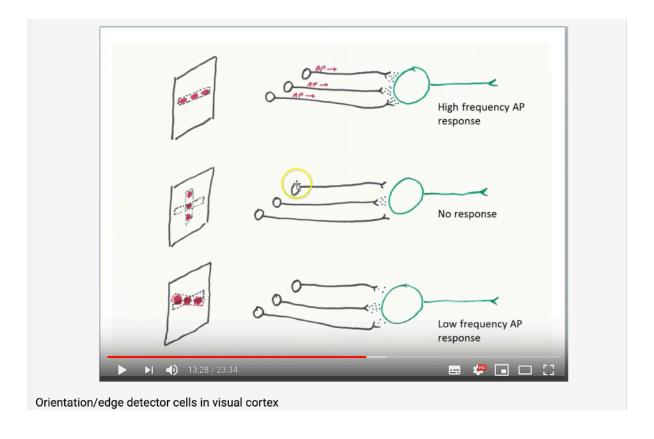
https://www.youtube.com/watch?v=y\_l4kQ5wjiw

https://www.youtube.com/watch?v=IOHayh06LJ4

https://www.youtube.com/watch?v=RSNofraG8ZE

# **Hubel and Wiesel experiment.**

#### Video interesante!



https://www.youtube.com/watch?v=v20-E\_2bT2c

# **Neocognitron (1980)**

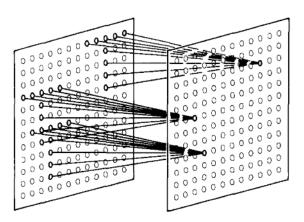


Fig. 3. Illustration showing the input interconnections to the cells within a single cell-plane

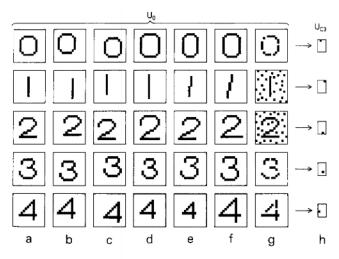


Fig. 6. Some examples of distorted stimulus patterns which the neocognitron has correctly recognized, and the response of the final layer of the network

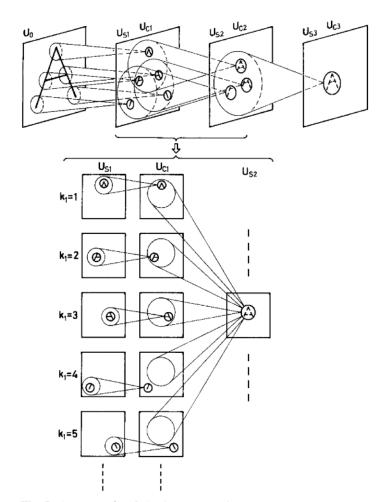


Fig. 5. An example of the interconnections between cells and the response of the cells after completion of self-organization

# LeNet-5 (1998)

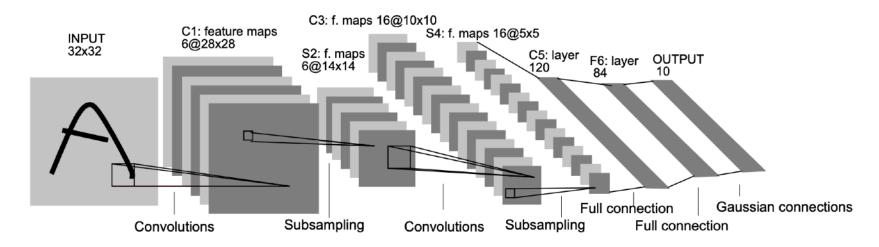


Fig. 2. Architecture of LeNet-5, a Convolutional Neural Network, here for digits recognition. Each plane is a feature map, i.e. a set of units whose weights are constrained to be identical.



#### 'Godfathers of Al' honored with Turing Award, the Nobel Prize of computing

https://www.theverge.com/2019/3/27/18280665/ai-godfathers-turing-award-2018-yoshua-bengio-geoffrey-hinton-yann-lecun

# Componentes básicos de una CNN

Las CNN están basadas en una comprensión intuitiva de las *relaciones espaciales*.

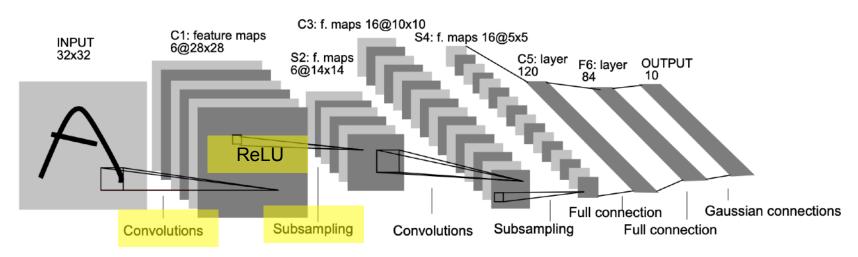


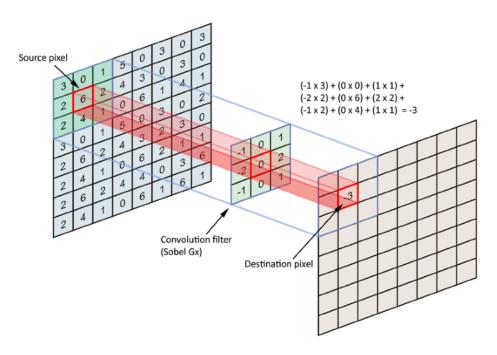
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Convolution + ReLU + Pooling + (Dense)

Estos *operadores* ayudan a *extraer / mantener* relaciones espaciales.

# Convolución (modificador de imágenes)

Las redes neuronales convolucionales CNN, son redes que usan el operador de convolución en al menos una capa (en realidad lo usan muchas veces!)



Jugar con kernel: http://setosa.io/ev/image-kernels/

Diferentes filtros (kernels), diferentes efectos + Padding + Stride

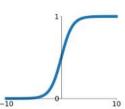
La convolución como una **multiplicación de matrices** h(W\*z+b)

# Función de activación ReLU: no-negatividad

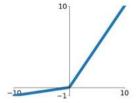
# **Activation Functions**

### **Sigmoid**

$$\sigma(x) = \frac{1}{1 + e^{-x}}$$

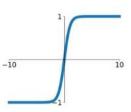


# Leaky ReLU max(0.1x, x)



#### tanh

tanh(x)

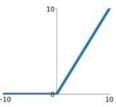


# Maxout

$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

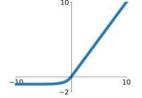
#### ReLU

 $\max(0, x)$ 



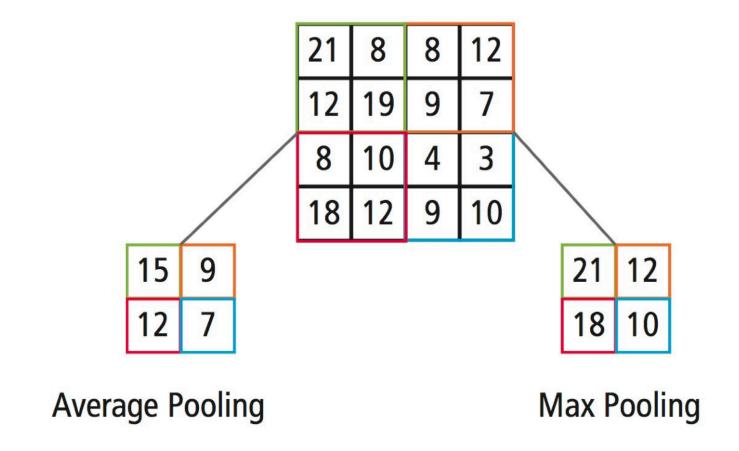
#### **ELU**

$$\begin{cases} x & x \ge 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



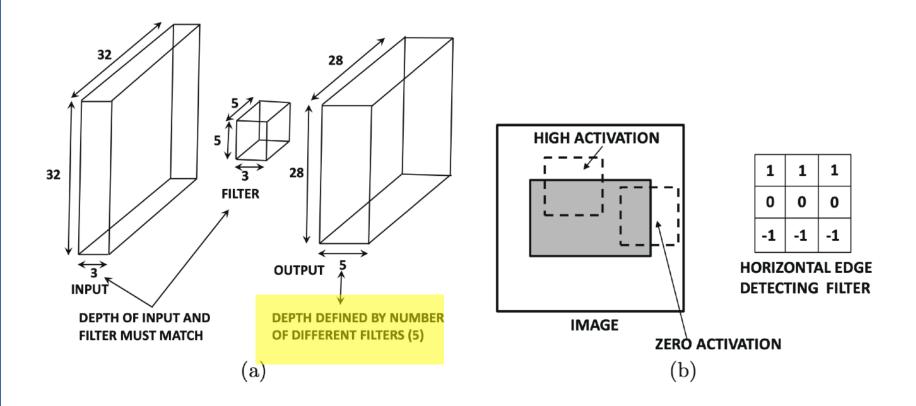
Efecto de no-negatividad? Es lo natural? Solo combinaciones aditivas?

# Pooling: submuestreo

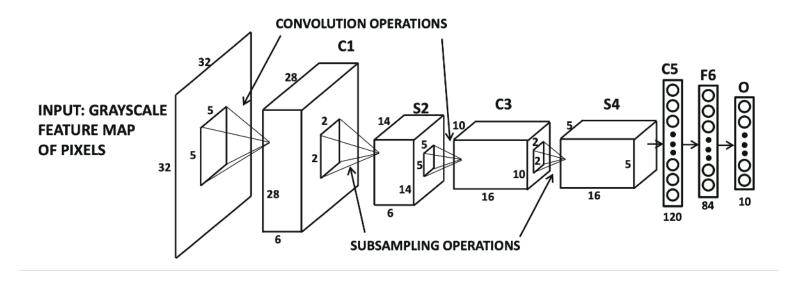


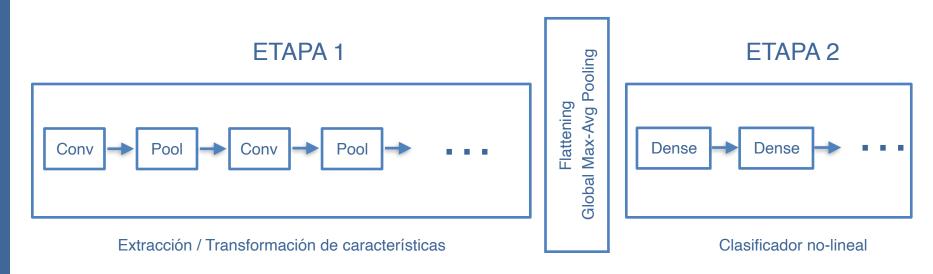
Downsampling: Conveniente (velocidad) +. Translation Invariance

# **Pooling: submuestreo**

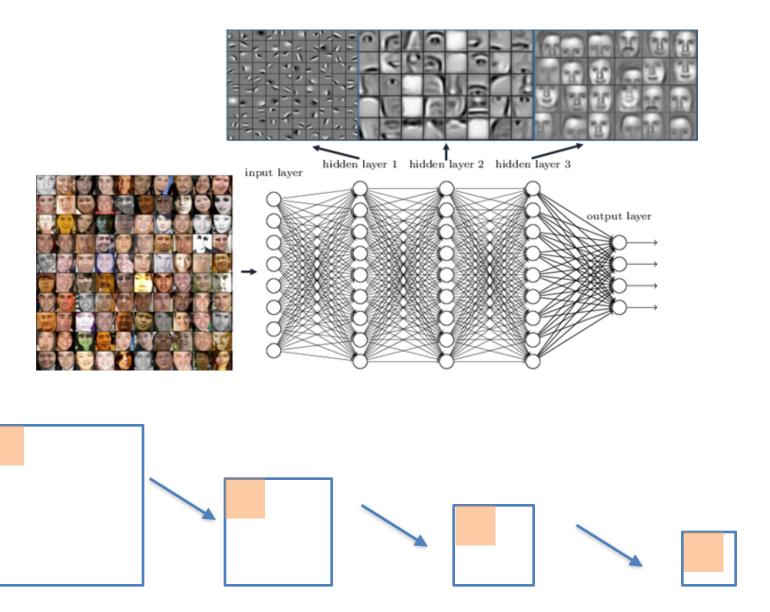


# **Arquitectura CNN**





# Arquitectura CNN: hierarchical feature extraction



# Arquitectura CNN: guías generales

Filtros pequeños: 3x3, 5x5, 7x7

Repetir: Conv + Pool + Conv + Pool + Conv + Pool + ...

#### Incrementar el numero de *feature maps*

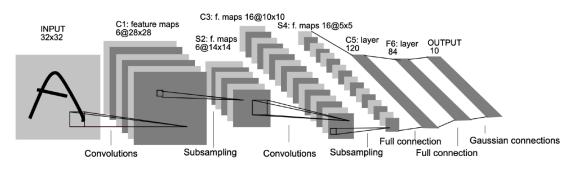


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En las ultimas capas totalmente conectadas, **disminuir** poco a poco.

# Nota: reducción de dimensiones durante las capas

Como afectan las dimensiones al aplicar el operar de convolución

$$h(W*z+b)$$
 ->  $Img_{out} = Img_{in}*w$ 

$$\begin{aligned} dim(\operatorname{Img}_{in}) &= w \times h \times c \\ dim(w) &= k \times k \times c \times f \\ dim(\operatorname{Img}_{out}) &= w^{'} \times h^{'} \times f \end{aligned}$$

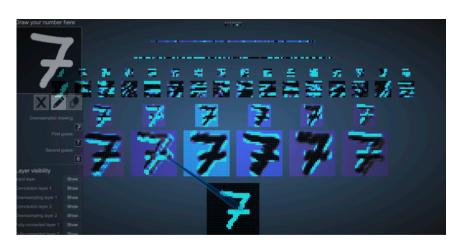
Como afectan las dimensiones al aplicar *convolution(f)* & *padding(p)* & *stride(s)* (solo una dimensión)

$$dim(Img_{in}) = w \times h \times c$$

$$w' = (w - f + 2p)/s + 1$$

#### **Actividad 6**

"Jugar" con <a href="http://scs.ryerson.ca/~aharley/vis/conv/flat.html">http://scs.ryerson.ca/~aharley/vis/conv/flat.html</a>



Terminar el notebook 2.2\_CNN\_FashionMNIST.ipynb



Terminar el notebook 2.3\_CNN\_CIFAR.ipynb

Retroalimentación.

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