Aprendizaje profundo

Redes convolucionales

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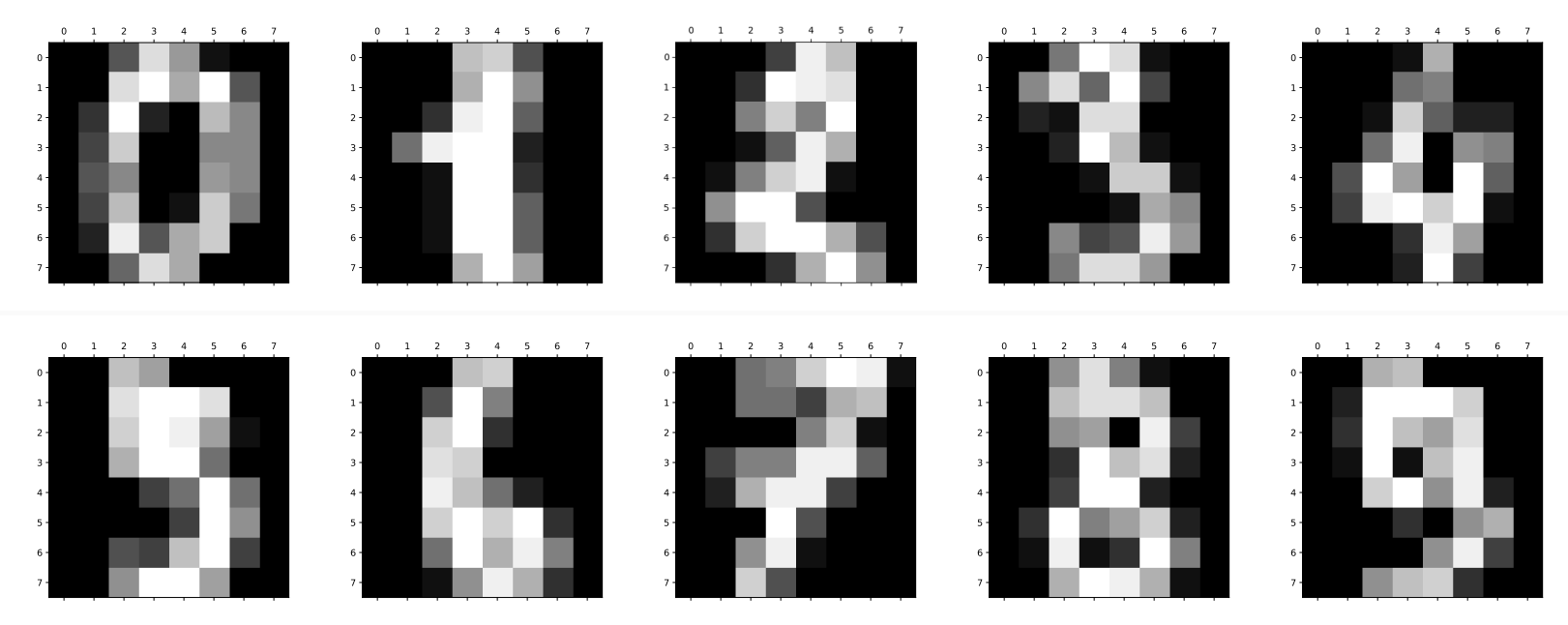
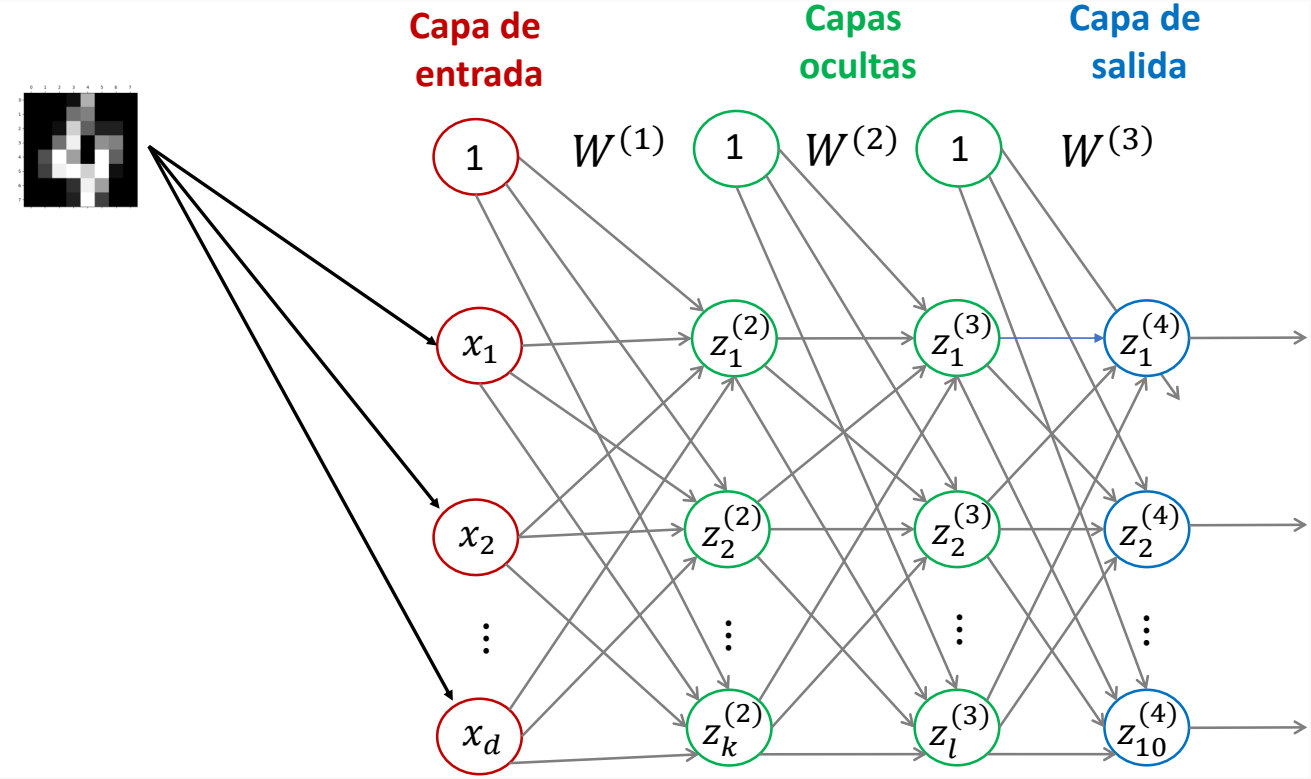
Clasificación de imágenes

- Por ejemplo, clasificar dígitos escritos a mano



Clasificación de imágenes con PMC

- Redes perceptrón multicapa tienen muchos parámetros
  - Por ej., si tenemos imágenes de 32×32 y 1 red con 1 sóla capa oculta con 10 neuronas tendríamos $(32 \times 32 \times 10) + 1$ pesos



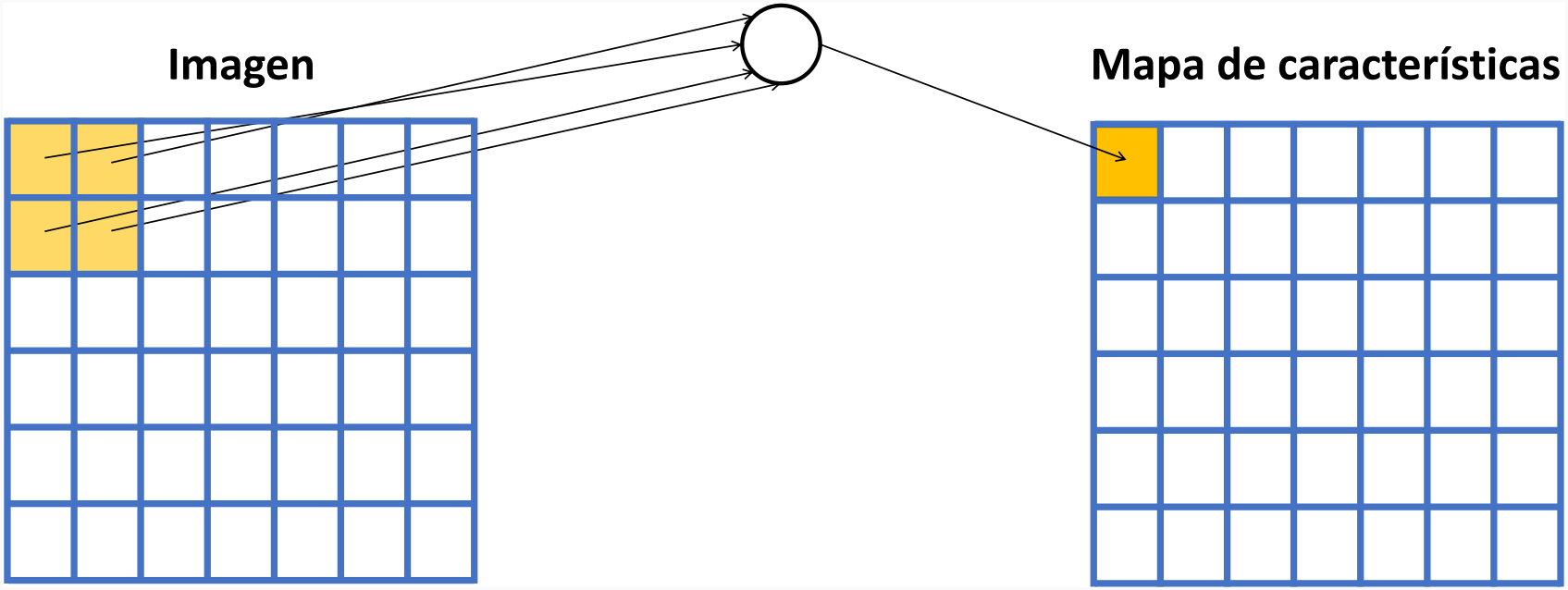
Capa convolucional

- Pueden verse como un caso especial de una capa densa con 2 variaciones
    1. Conectividad local (dispersa)
    2. Pesos compartidos

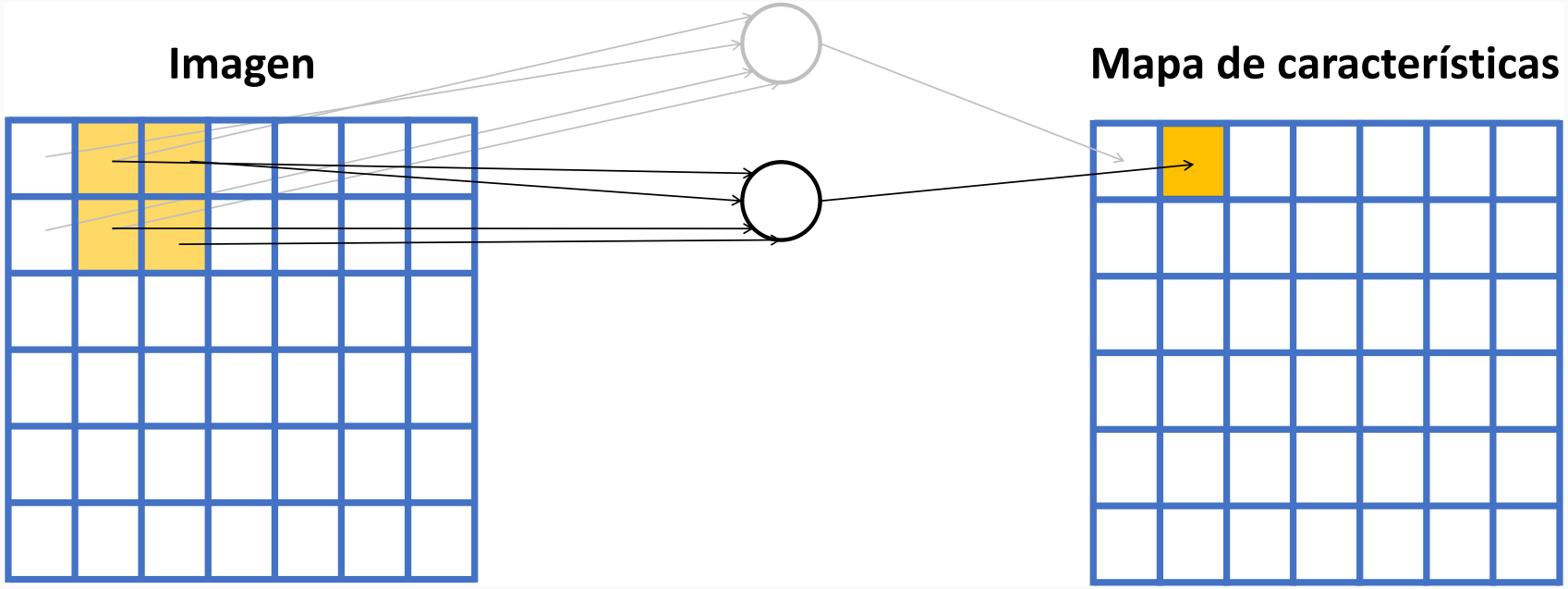
- Las representaciones obtenidas son más eficientes

- La operación es equivariante

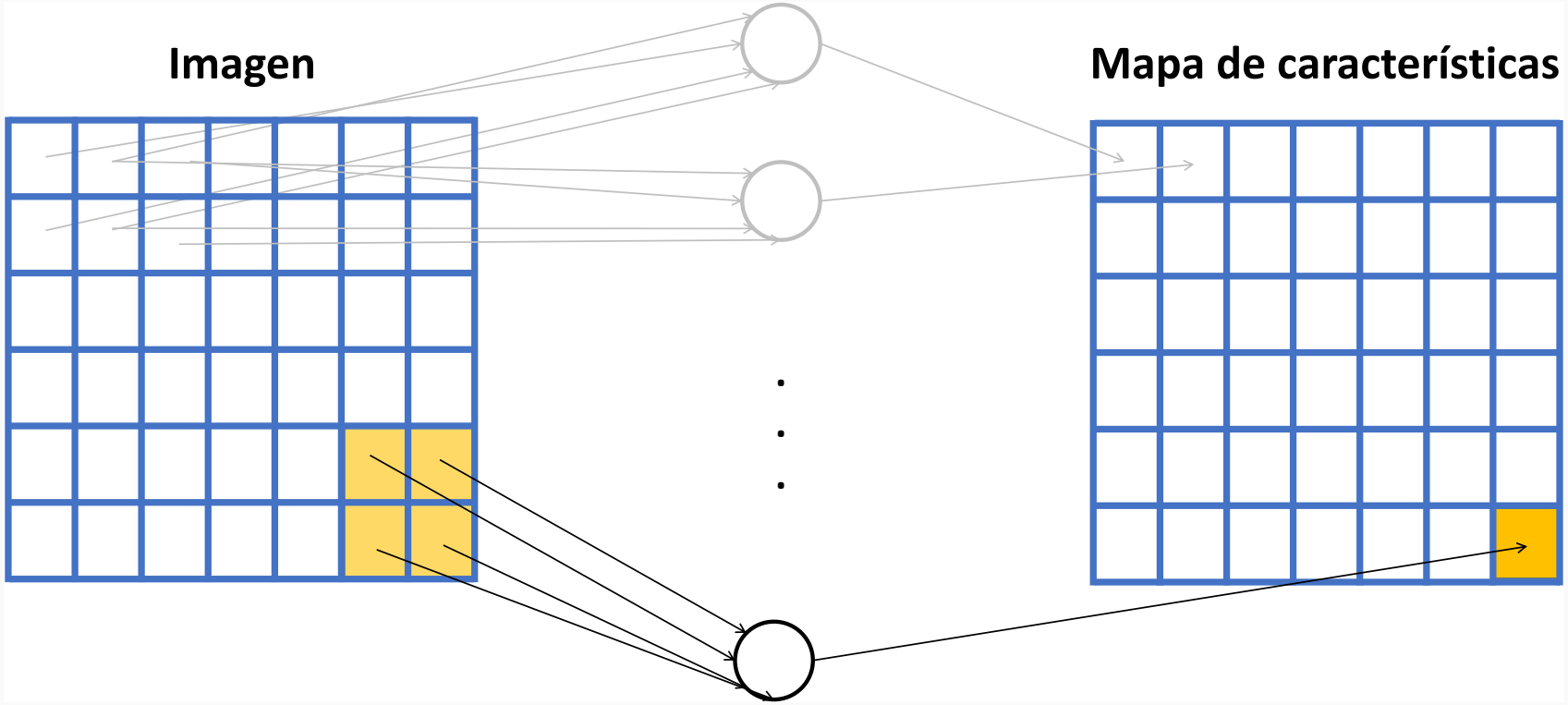
Conectividad local (1)



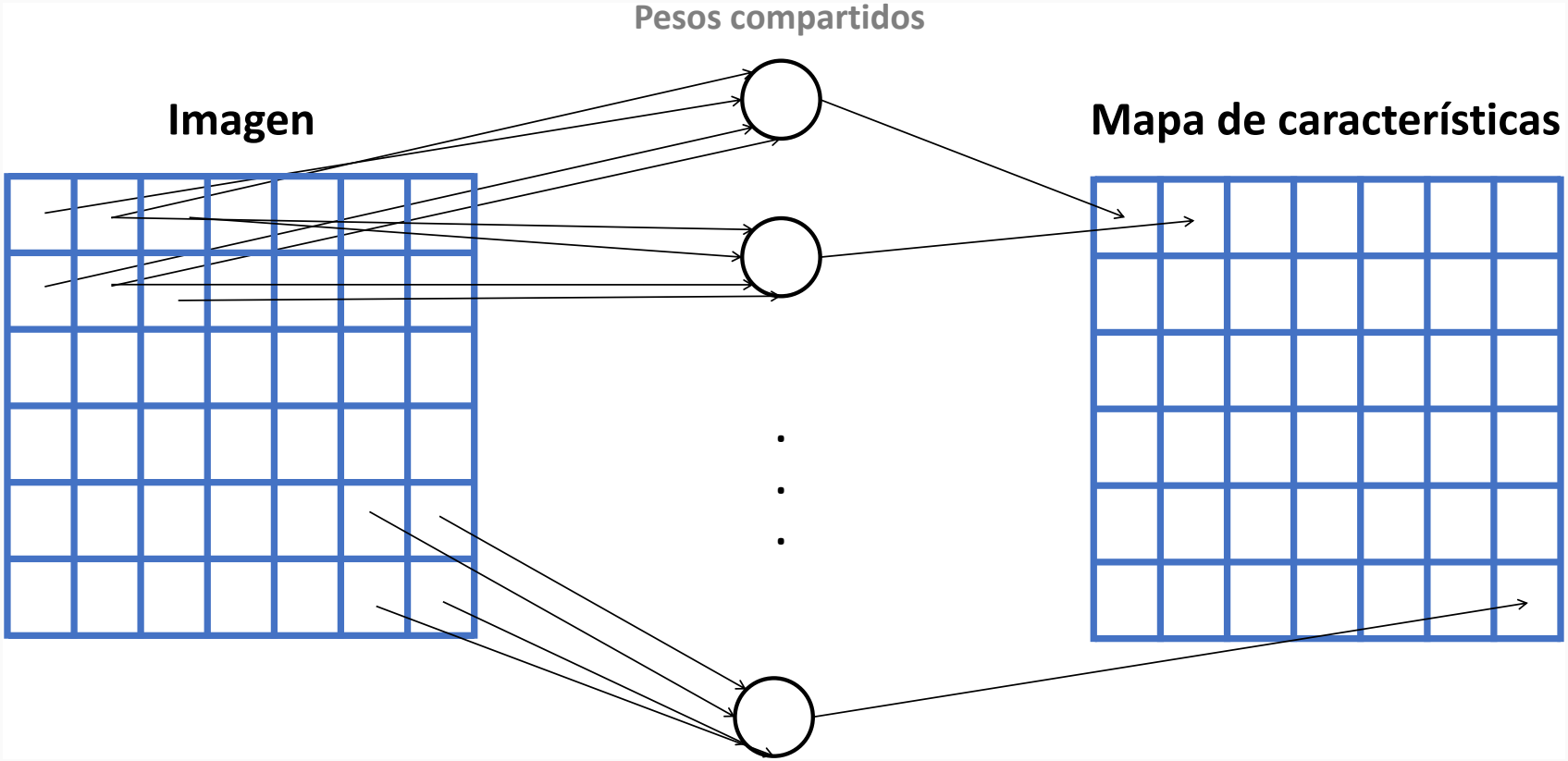
Conectividad local (2)



Conectividad local (3)



Pesos compartidos



Operación de convolución

- Convolución en 1 dimensión
  - Continua $s(t) = (x * k)(t) = \int_m x(m)k(t-m)dm$
  - Discreta $s[i] = (x * k)[i] = \sum_{m=-\infty}^{\infty} x[m]k[i-m]$
- Convolución en 2 dimensiones (discreta)
  - $S[i,j] = (I * K)[i,j] = \sum_m \sum_n I[m,n]K[i-m, j-n]$
  - $S[i,j] = (K * I)[i,j] = \sum_m \sum_n I[i-m, j-n]K[m,n]$
- Correlación cruzada (discreta)
  - $S(i,j) = (I * K)(i,j) = \sum_m \sum_n I(i+m, j+n)K(m,n)$

Operación de convolución

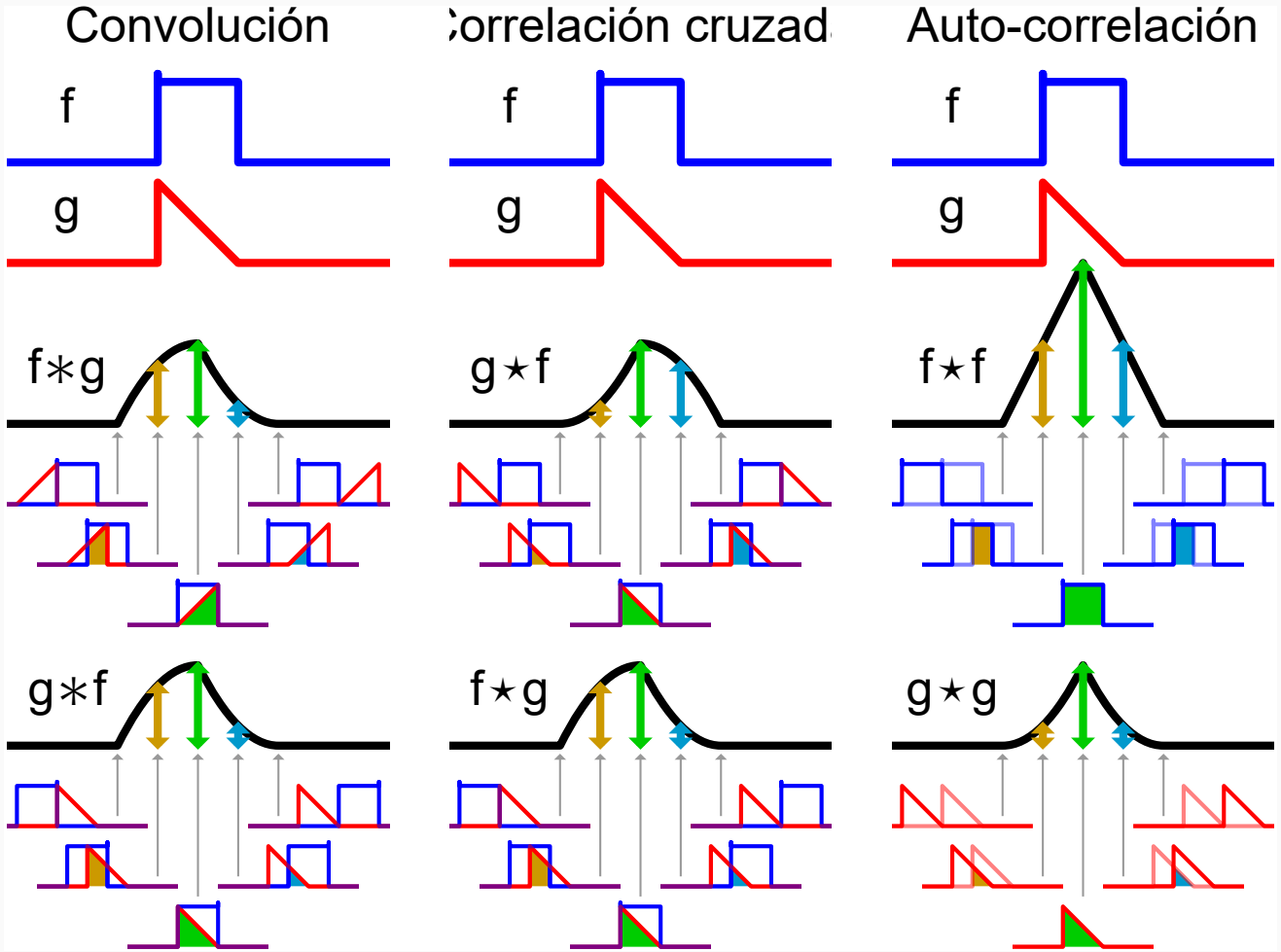
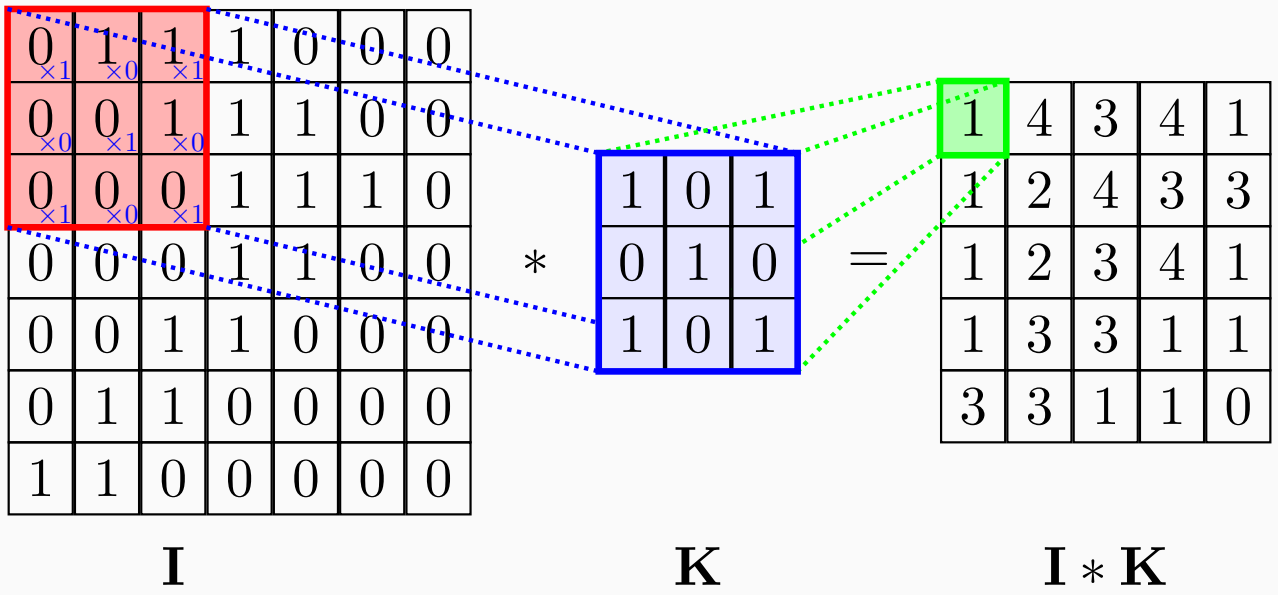
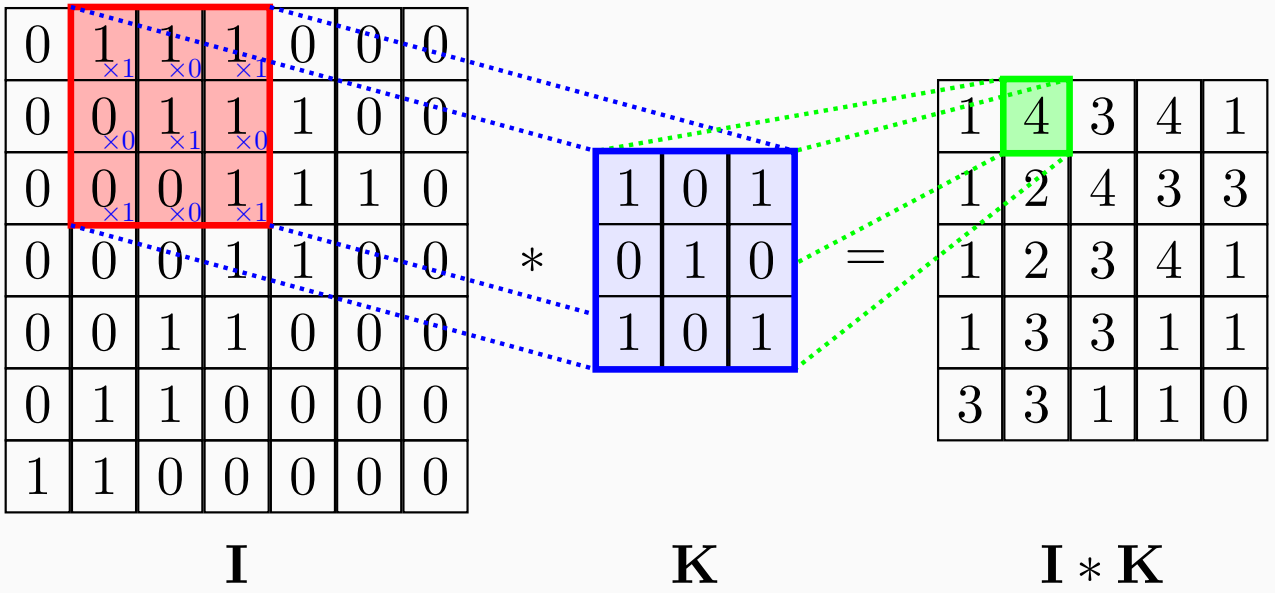


Imagen tomada de Wikipedia (Convolution)

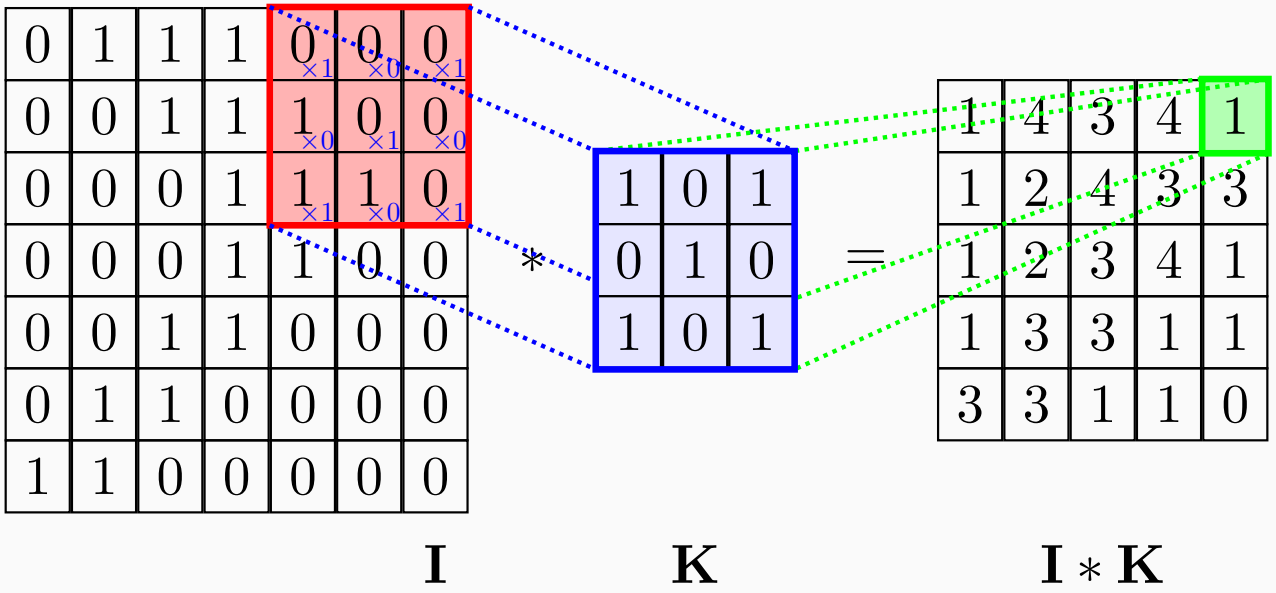
Convolución de una imagen con un filtro (1)



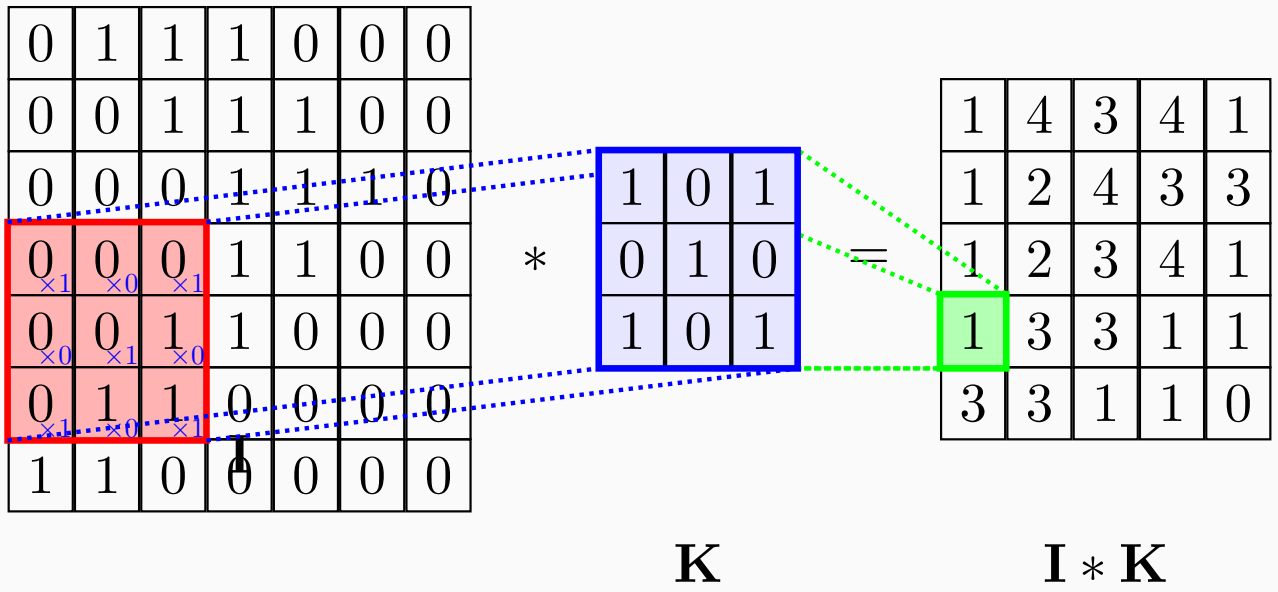
Convolución de una imagen con un filtro (2)



Convolución de una imagen con un filtro (3)



Convolución de una imagen con un filtro (4)



Capa convolucional

- Compuesta de filtros distintos
- La salida (mapas de activaciones) es un volumen

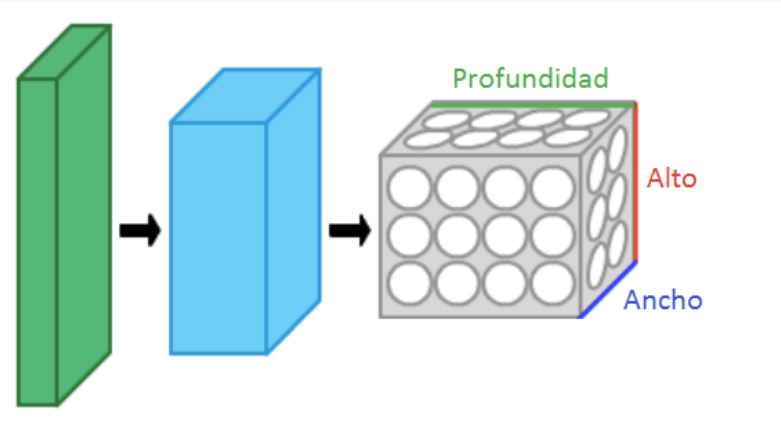
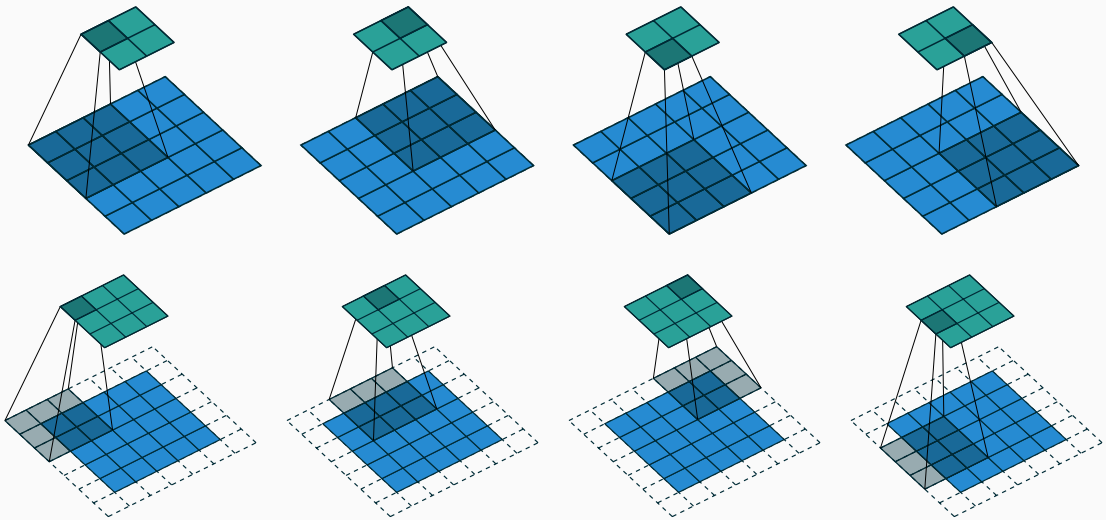


Imagen tomada de Wikipedia (Convolutional Neural Network)

Capa convolucional: hiperparámetros

- Número de filtros $N_{filtros}$, tamaño de cada filtro $F_H \times F_W$, desplazamiento S (*stride*) y relleno (*padding*)



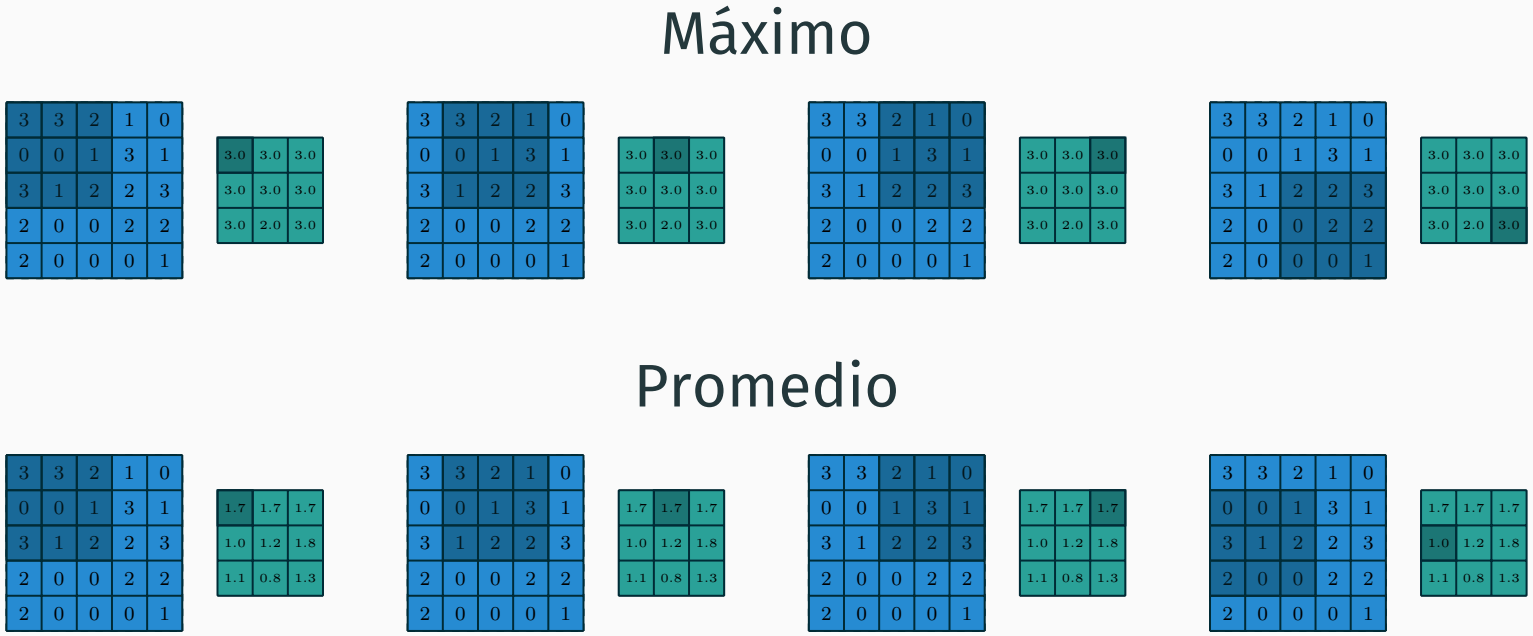
Imágenes creadas por Dumoulin and Visin. A guide to convolution arithmetic for deep learning, 2018.

$$H^{\{\ell\}} = \frac{H^{\{\ell-1\}} + 2P^{\{\ell-1\}} - F_H^{\{\ell\}}}{S^{\{\ell\}}} + 1$$

$$W^{\{\ell\}} = \frac{W^{\{\ell-1\}} + 2P^{\{\ell-1\}} - F_W^{\{\ell\}}}{S^{\{\ell\}}} + 1$$

Capa de submuestreo o decimación

- Capa para reducir dimensiones tomando el valor máximo (*max-pooling*) o el promedio (*average pooling*) de un grupo de activaciones usualmente contiguas



Imágenes creadas por Dumoulin and Visin. A guide to convolution arithmetic for deep learning, 2018.

Capa de submuestreo: hiperparámetros

- Hiperparámetros: alto y ancho de la ventana que define el grupo (F_H, F_W), desplazamiento S, relleno (*padding*) P

- El alto $H^{\{\ell\}}$ y ancho $W^{\{\ell\}}$ de la salida de una capa de submuestreo está dado por

$$H^{\{\ell\}} = \frac{H^{\{\ell-1\}} + 2P - F_H}{S} + 1$$
$$W^{\{\ell\}} = \frac{W^{\{\ell-1\}} + 2P - F_W}{S} + 1$$

Submuestro global promedio

- Reduce las dimensiones de un volumen de características, tomando únicamente el promedio de cada mapa

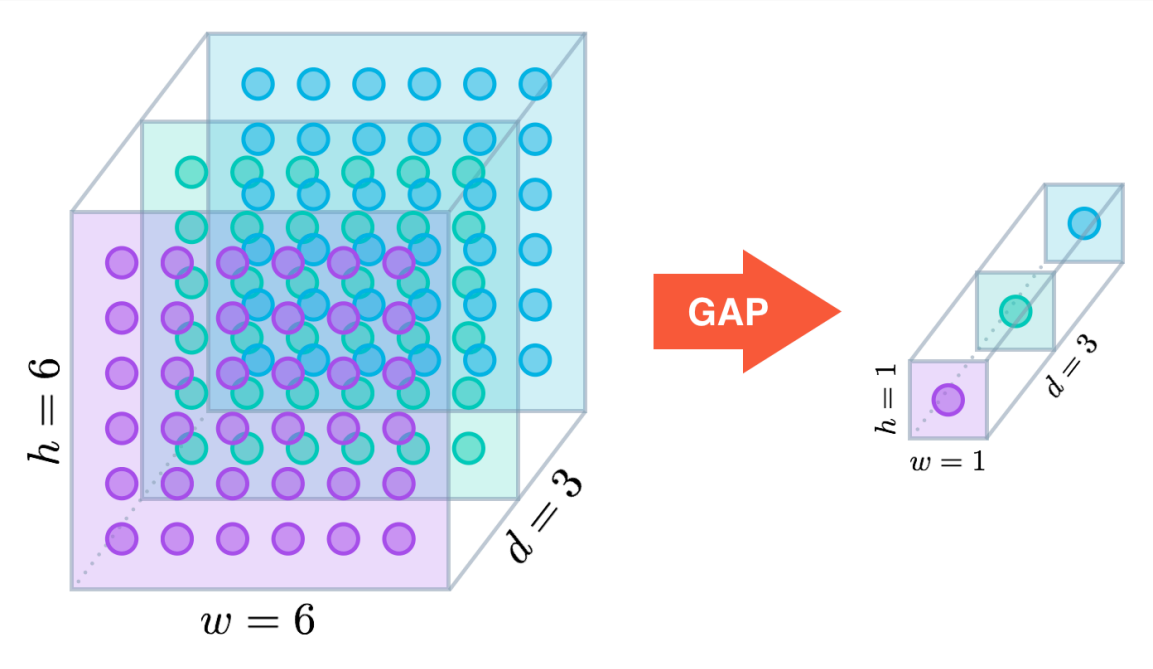


Imagen tomada de `https://alexisbcook.github.io/2017/global-average-pooling-layers-for-object-localization/`

Retro-propagación en capas convolucionales y de submuestreo

- Hacia adelante
  - Se aplican las operaciones de convolución con correspondiente activación y decimación
- Hacia atrás
  - En la convolución cada neurona actualiza los gradientes por separado y al final se suman para actualizar los pesos compartidos
  - En la decimación se actualiza sólo la neurona ganadora (*max-pooling*)

Convolución de 1×1

- Funciona como un tipo de decimación en profundidad

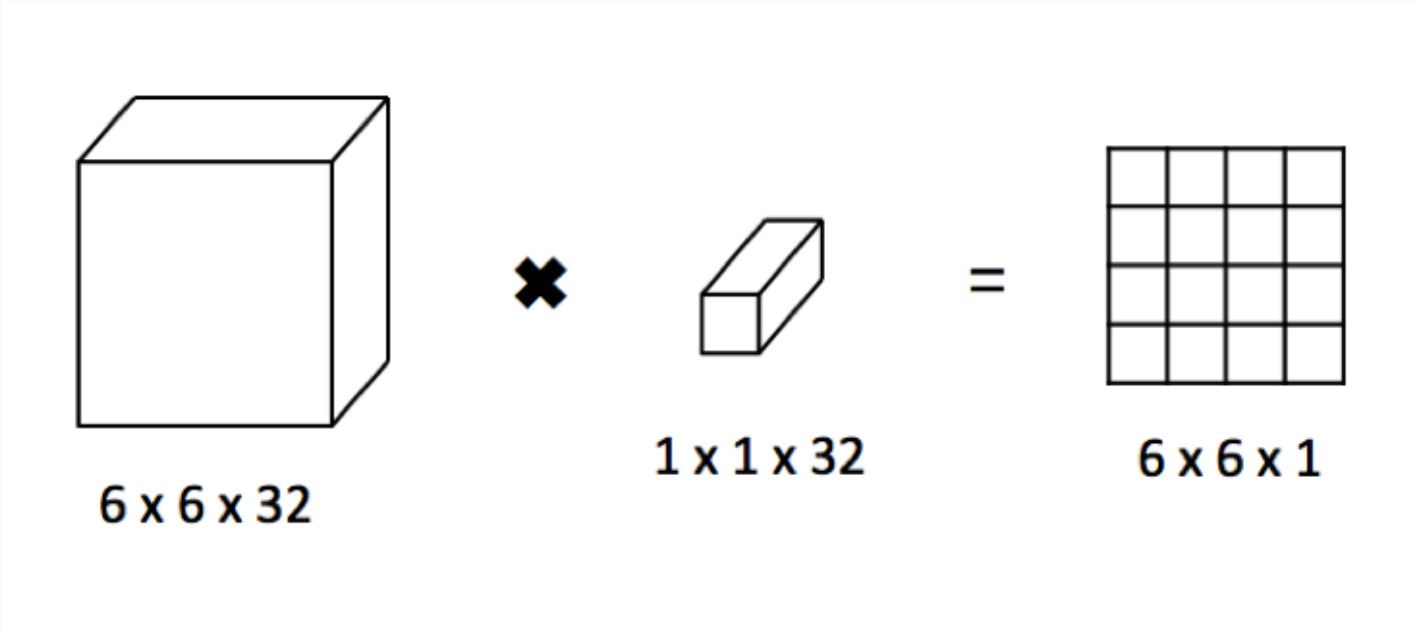
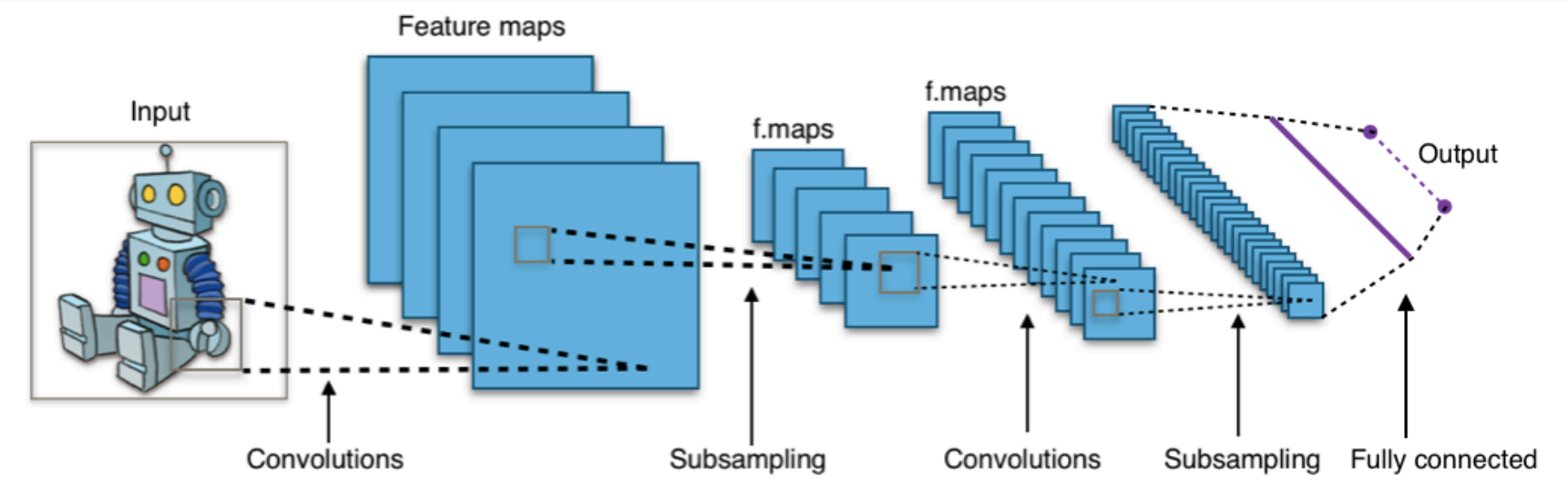


Imagen tomada de `https://medium.com/machine-learning-bites/deeplearning-series-convolutional-neural-networks-a9c2f2ee1524`

Red neuronal convolucional

- Compuesta de dos bloques principales
  1. *Extracción de características*: múltiples capas convolucionales y de submuestreo
  2. *Clasificación*: Una o más capas completamente conectadas (incluyendo la capa de salida)



Arquitecturas de redes convolucionales: LeNet

- Red poco profunda inspirada en la propuesta originalmente por LeCun et al. 1998

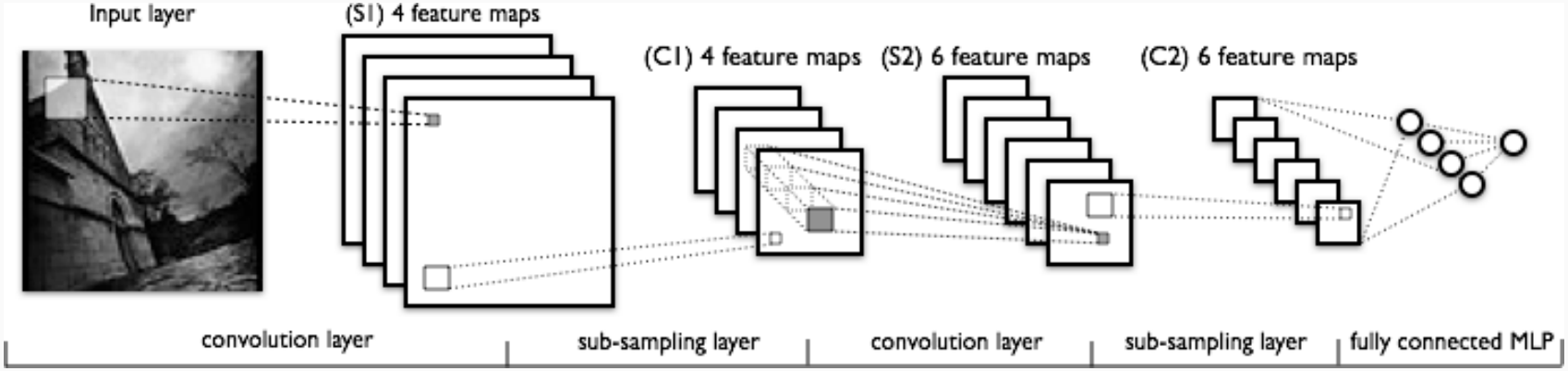


Imagen tomada de `http://deeplearning.net/tutorial/lenet.html`

Arquitecturas de redes convolucionales: AlexNet

- Usa función de activación ReLU
- Entrenamiento con version optimizada para 2 GPUs
- Normaliza respuestas
- Submuestreo con traslape

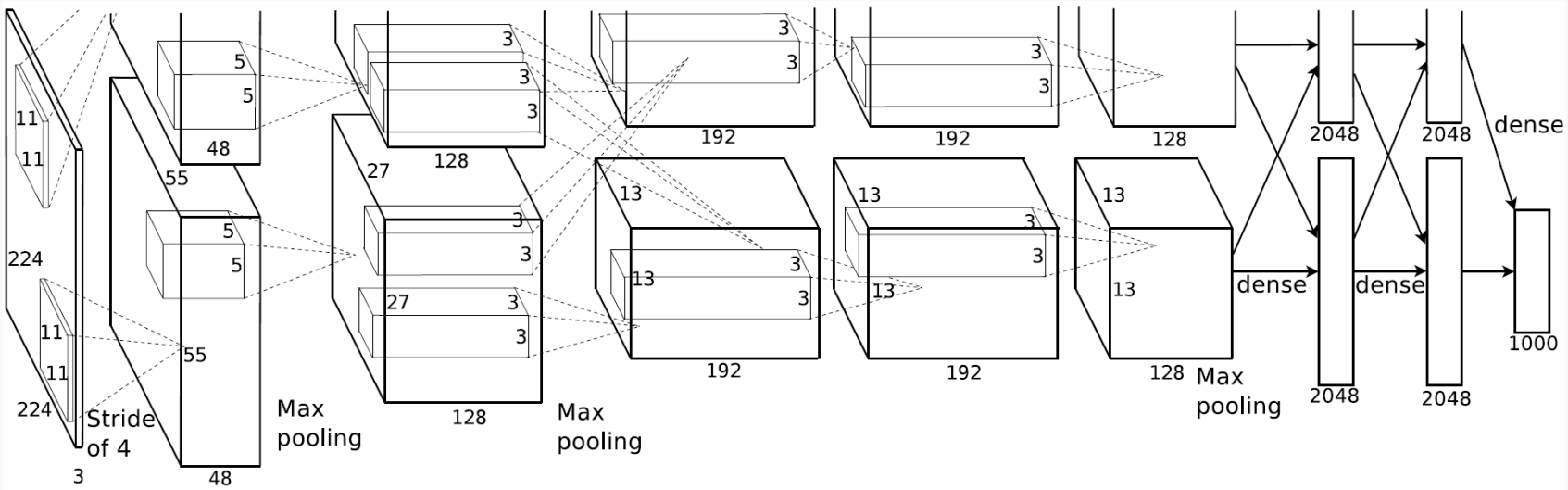


Imagen tomada de Krizhevsky et al. *ImageNet Classification with Deep Convolutional Neural Networks*, 2012

Arquitecturas de redes convolucionales: ZFNet

- Muy similar a AlexNet pero usa filtros más pequeños con menor desplazamiento

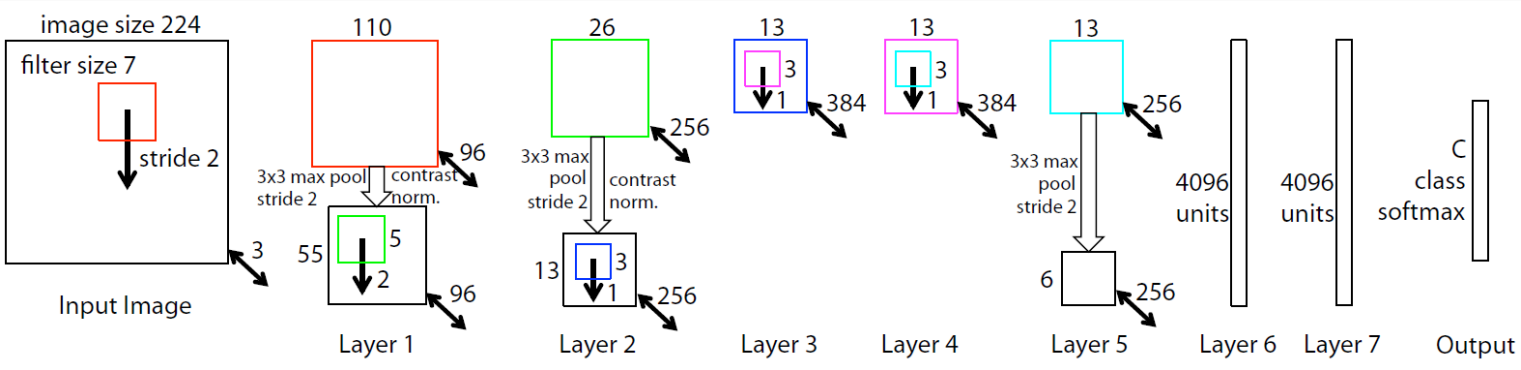


Imagen tomada de Zeiler and Fergus. *Visualizing and Understanding Convolutional Networks*, 2014

Arquitecturas de redes convolucionales: VGGNet

- 19 capas
- Filtros de 3×3 con desplazamientos de 1
- Max-pooling de 2×2 con desplazamientos de 2

Imagen tomada de diapositivas de Simonyan (ILSVRC Workshop 2014)

Arquitecturas de redes convolucionales: GoogleNet (1)

- 22 capas
- Utiliza bloque de capas convolucionales paralelas cuyas salidas se concatenan

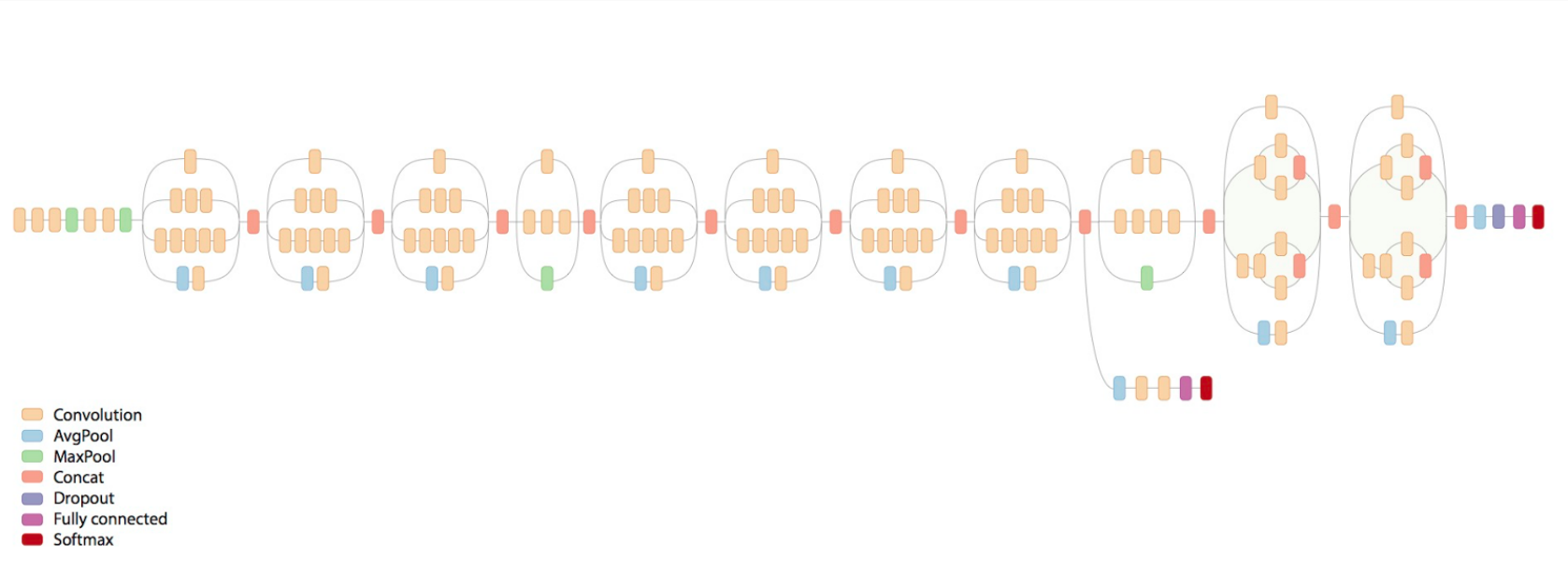


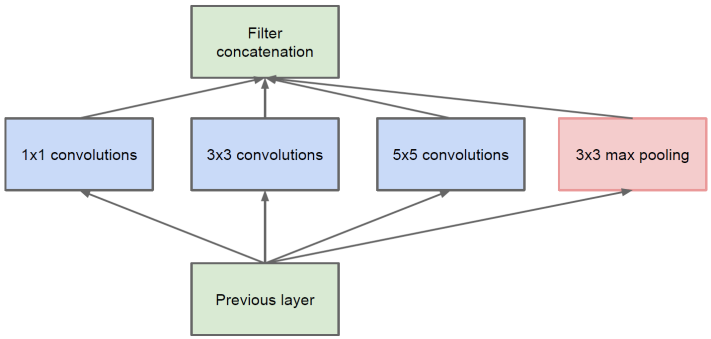
Imagen tomada de `https://research.googleblog.com/2016/03/train-your-own-image-classifier-with.html`

Arquitecturas de redes convolucionales: GoogleNet (2)

type	patch size/ stride	output size	depth	#1×1	#3×3 reduce	#3×3	#5×5 reduce	#5×5	pool proj	params	ops
convolution	7×7/2	112×112×64	1							2.7K	34M
max pool	3×3/2	56×56×64	0								
convolution	3×3/1	56×56×192	2		64	192				112K	360M
max pool	3×3/2	28×28×192	0								
inception (3a)		28×28×256	2	64	96	128	16	32	32	159K	128M
inception (3b)		28×28×480	2	128	128	192	32	96	64	380K	304M
max pool	3×3/2	14×14×480	0								
inception (4a)		14×14×512	2	192	96	208	16	48	64	364K	73M
inception (4b)		14×14×512	2	160	112	224	24	64	64	437K	88M
inception (4c)		14×14×512	2	128	128	256	24	64	64	463K	100M
inception (4d)		14×14×528	2	112	144	288	32	64	64	580K	119M
inception (4e)		14×14×832	2	256	160	320	32	128	128	840K	170M
max pool	3×3/2	7×7×832	0								
inception (5a)		7×7×832	2	256	160	320	32	128	128	1072K	54M
inception (5b)		7×7×1024	2	384	192	384	48	128	128	1388K	71M
avg pool	7×7/1	1×1×1024	0								
dropout (40%)		1×1×1024	0								
linear		1×1×1000	1							1000K	1M
softmax		1×1×1000	0								

Tabla tomada de Szegedy et al. Going deeper with convolutions, 2014

Bloques Inception



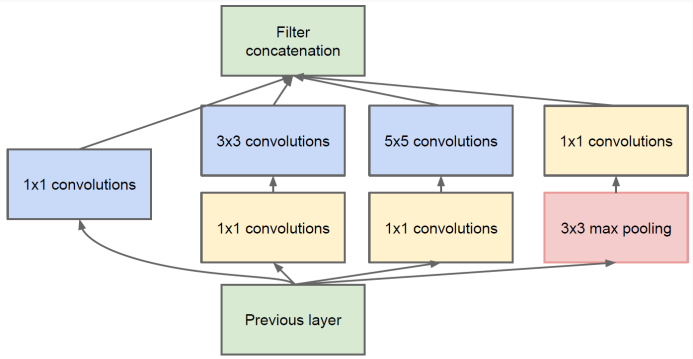


Imagen tomada de Szegedy et al. Going deeper with convolutions, 2014

Sobre profundidad en redes convolucionales (1)

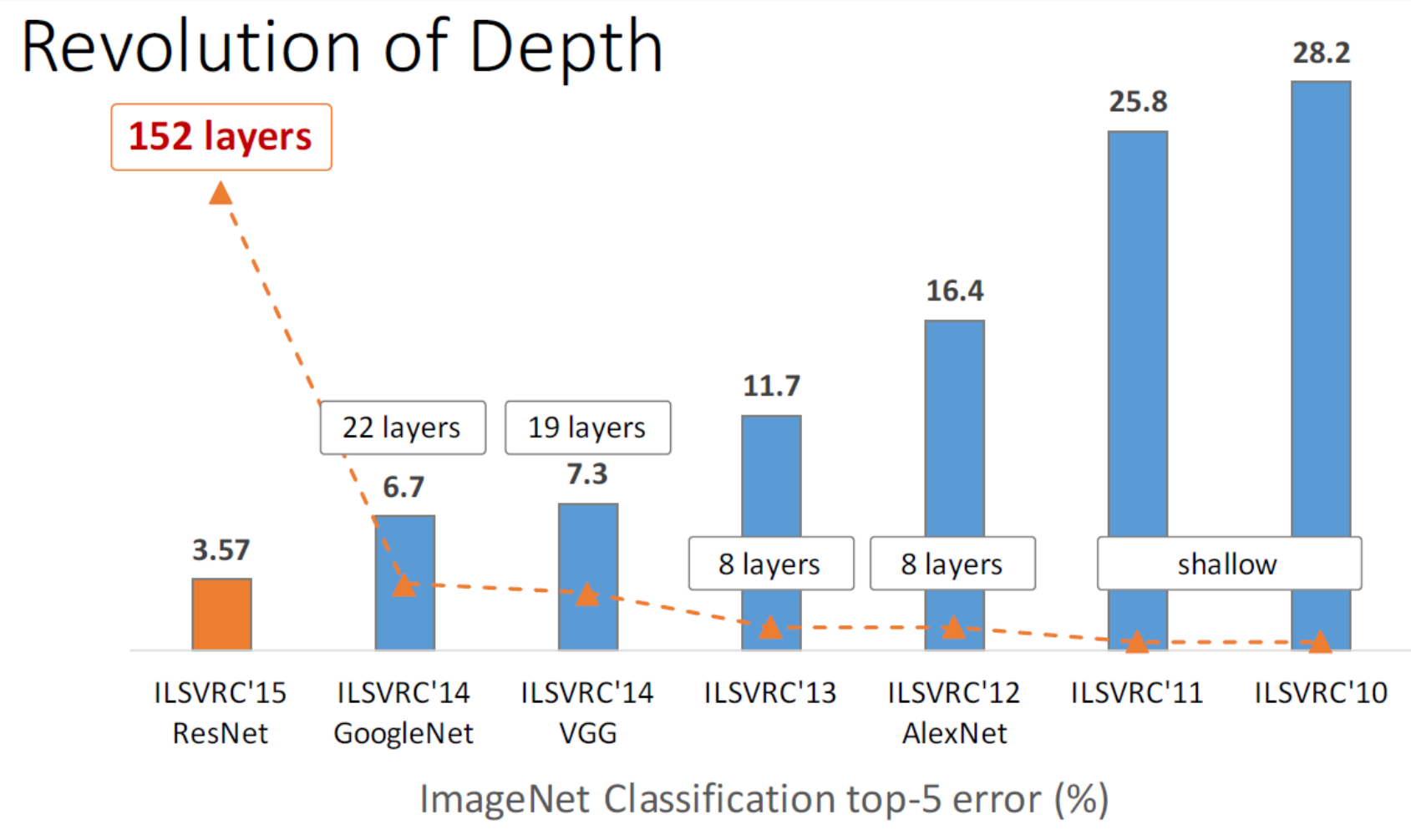


Imagen tomada de diapositivas de Kaiming He (ICML 2016)

Sobre profundidad en redes convolucionales (2)

- Problemas con el desvanecimiento y explosión de respuestas (hacia adelante) y gradientes (hacia atrás)

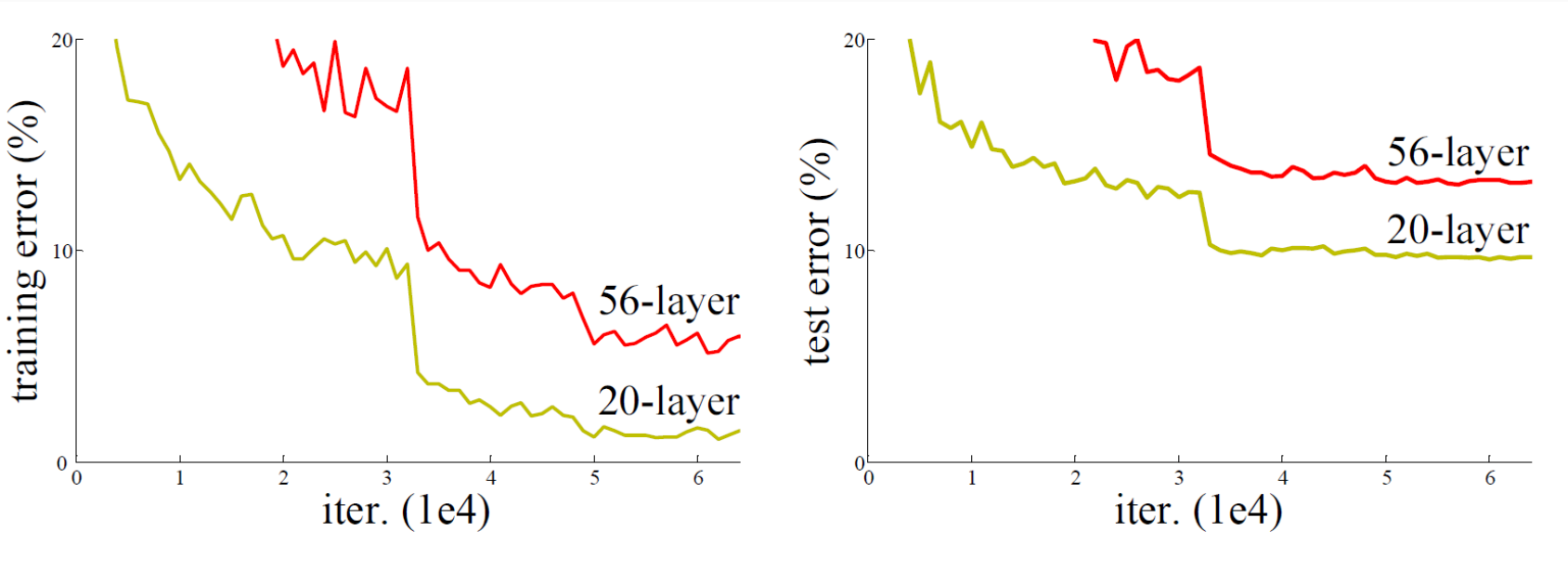


Imagen tomada de He et al. *Deep Residual Learning for Image Recognition*, 2015

Entrenando redes más profundas: ResNet (1)

- Reformula los mapeos que se desean aprender a residuales
- Más fácil de optimizar los residuales que el mapeo original[1]

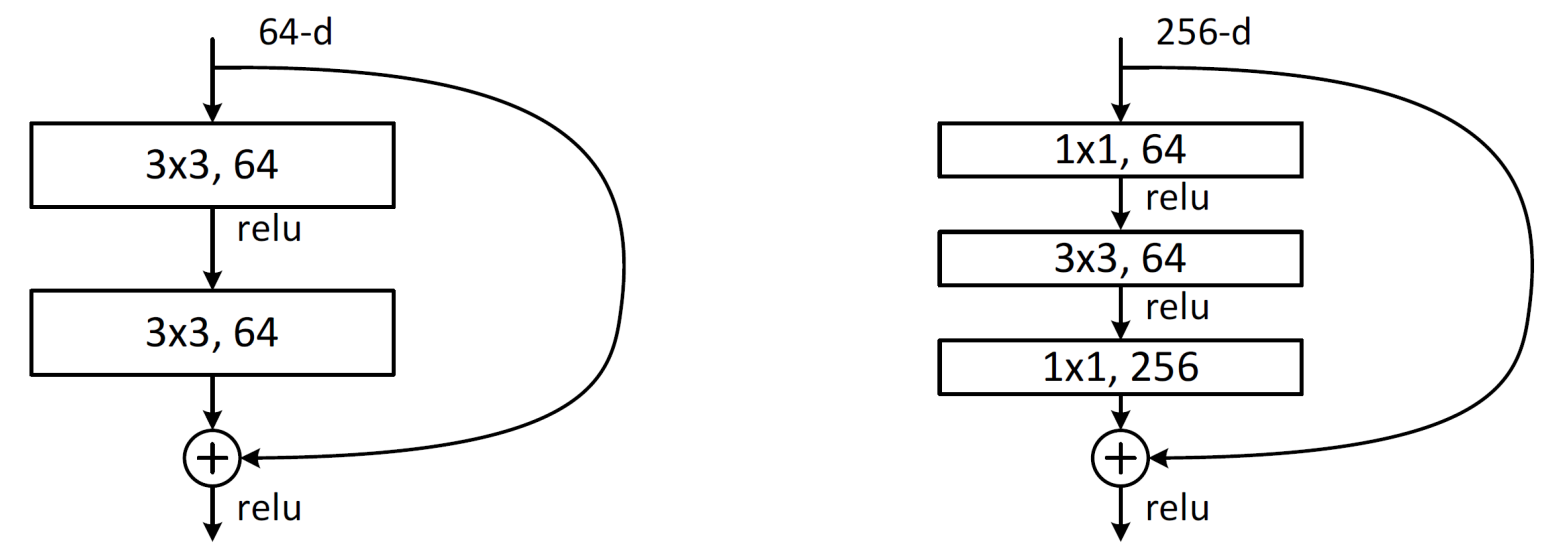


Imagen tomada de He et al. Deep Residual Learning for Image Recognition, 2015

[1]Se ha mostrado que son aproximadores universales: Lin y Jegelka. ResNet with one-neuron hidden layers is a Universal Approximator, 2018.

Entrenando redes más profundas: ResNet (2)

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times23$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

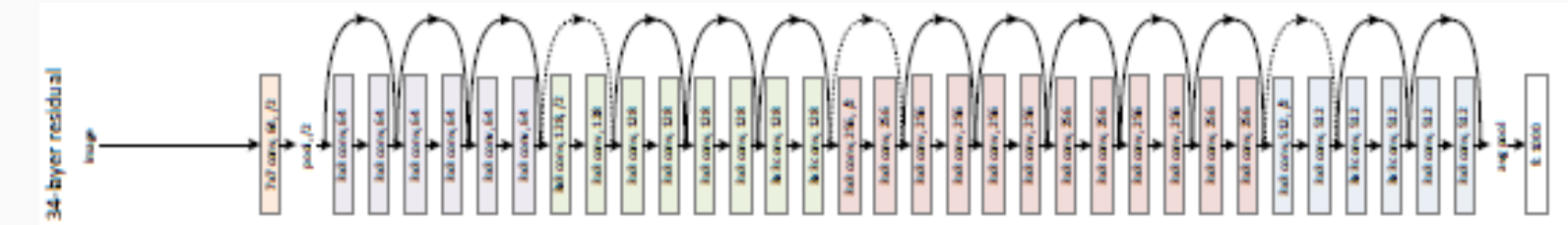


Imagen y tabla tomadas de He et al. *Deep Residual Learning for Image Recognition*, 2015

Entrenando redes más profundas: ResNet (3)

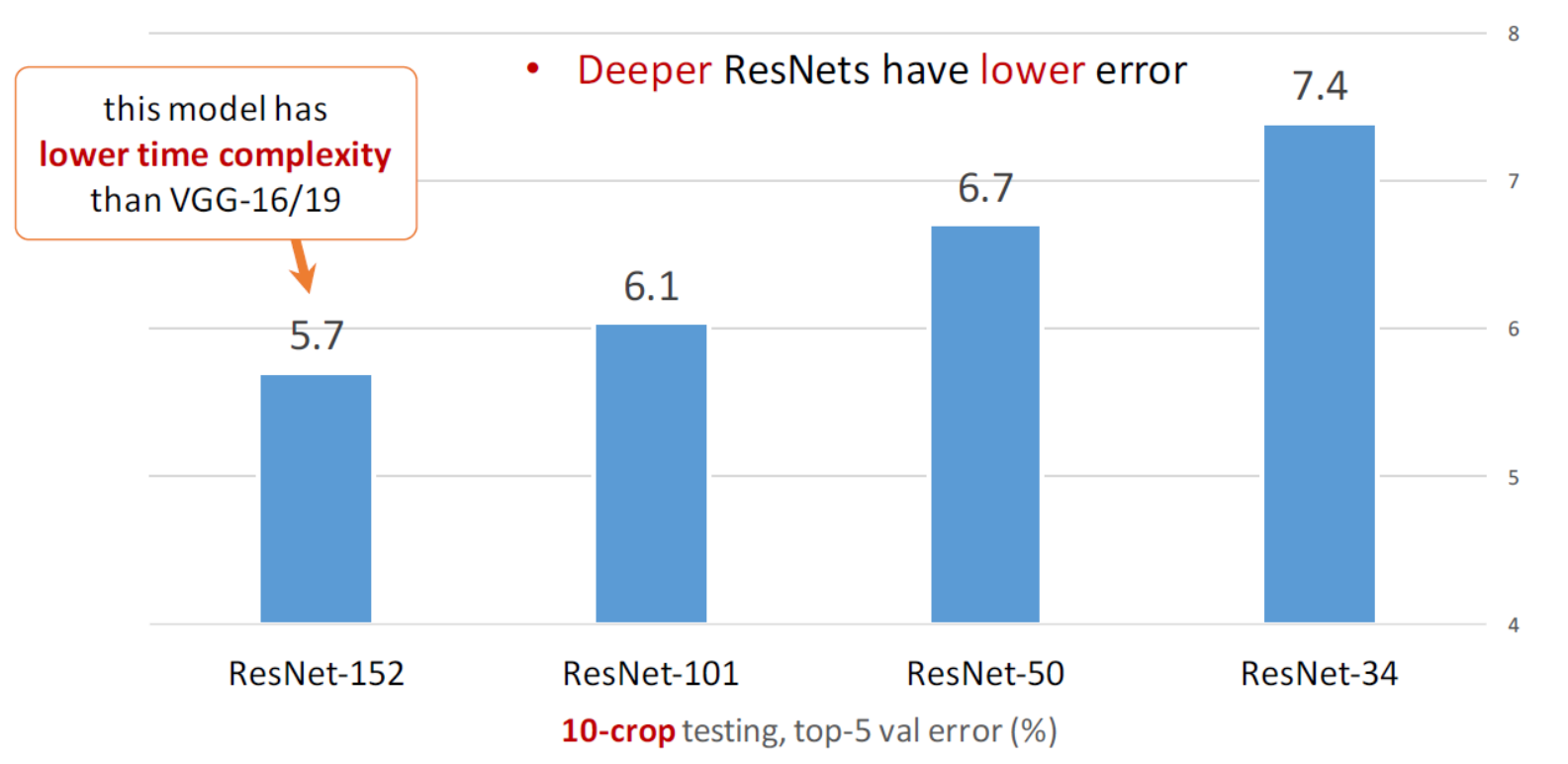


Imagen tomada de diapositivas de Kaiming He (ICML 2016)

Entrenando redes más profundas: DenseNet (1)

- Utiliza bloques que conectan la salida de cada capa con las entradas de capas subsecuentes.

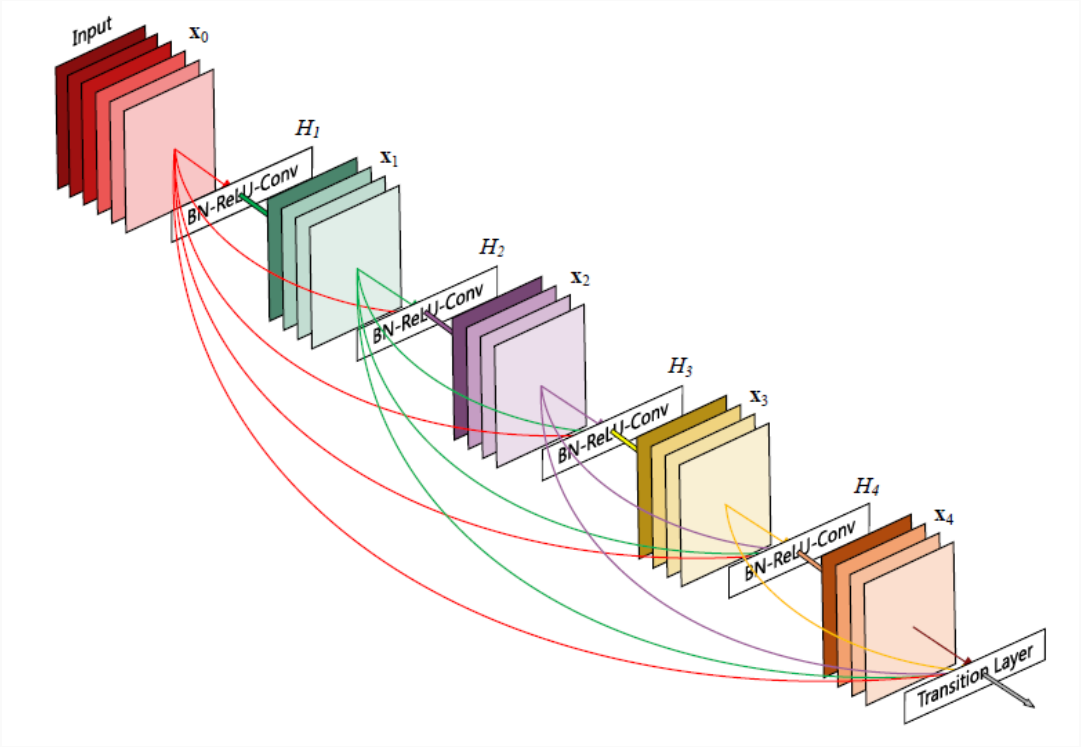


Imagen tomada de Huang et al. Densely Connected Convolutional Networks, 2018

Entrenando redes más profundas: DenseNet (2)

Layers	Output Size	DenseNet-121($k = 32$)	DenseNet-169($k = 32$)	DenseNet-201($k = 32$)	DenseNet-161($k = 48$)
Convolution	112×112	7×7 conv, stride 2			
Pooling	56×56	3×3 max pool, stride 2			
Dense Block (1)	56×56	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$
Transition Layer (1)	56×56	1×1 conv			
	28×28	2×2 average pool, stride 2			
Dense Block (2)	28×28	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$
Transition Layer (2)	28×28	1×1 conv			
	14×14	2×2 average pool, stride 2			
Dense Block (3)	14×14	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 24$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 32$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 48$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 36$
Transition Layer (3)	14×14	1×1 conv			
	7×7	2×2 average pool, stride 2			
Dense Block (4)	7×7	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 16$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 32$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 32$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 24$
Classification Layer	1×1	7×7 global average pool			
		1000D fully-connected, softmax			

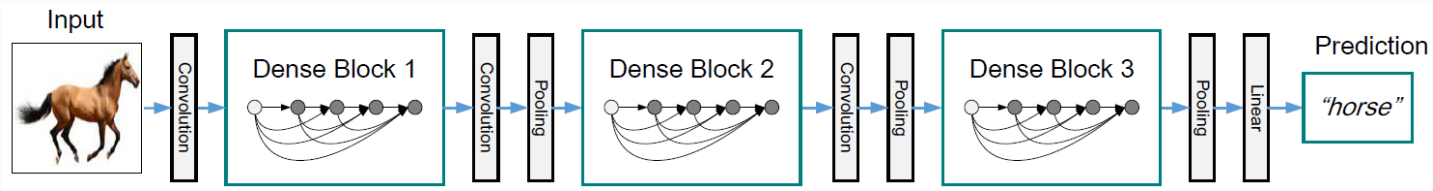


Imagen y tabla tomadas de Huang et al. Densely Connected Convolutional Networks, 2018

Filtros separables

- Filtros que pueden descomponerse como el producto de 2 más simples. Por ej., un filtro 2D puede separarse en 2 filtros 1D.

$$\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} \times \begin{bmatrix} -1 & 0 & 1 \end{bmatrix}$$

Convolución espacial separable

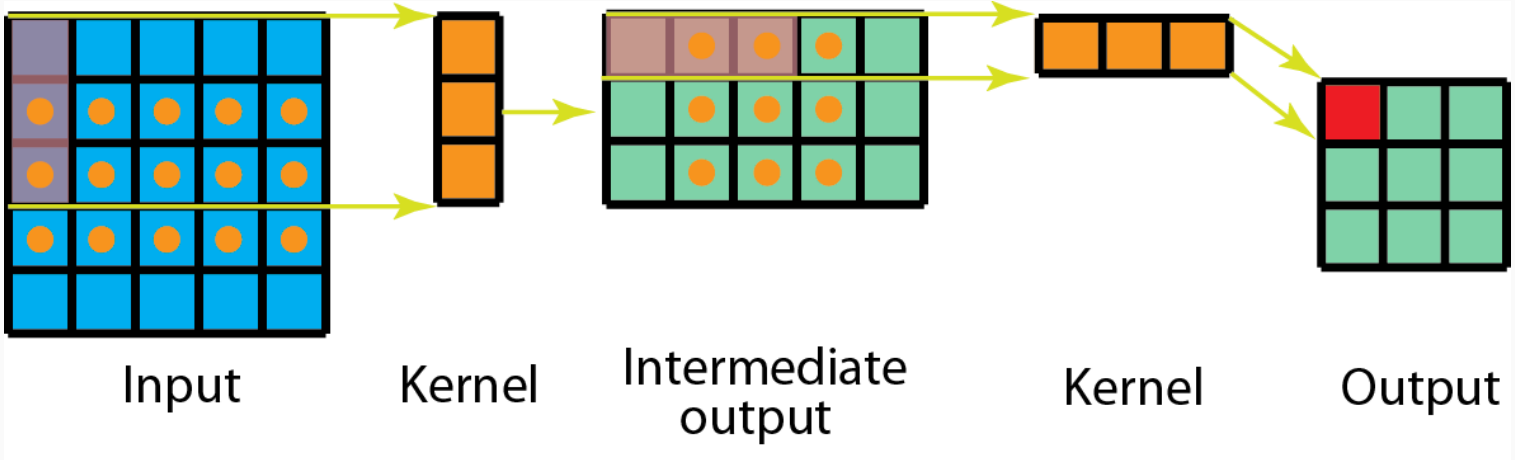


Imagen tomada de Kunlun Bai. A Comprehensive Introduction to Different Types of Convolutions in Deep Learning, 2019.

Convolución en profundidad

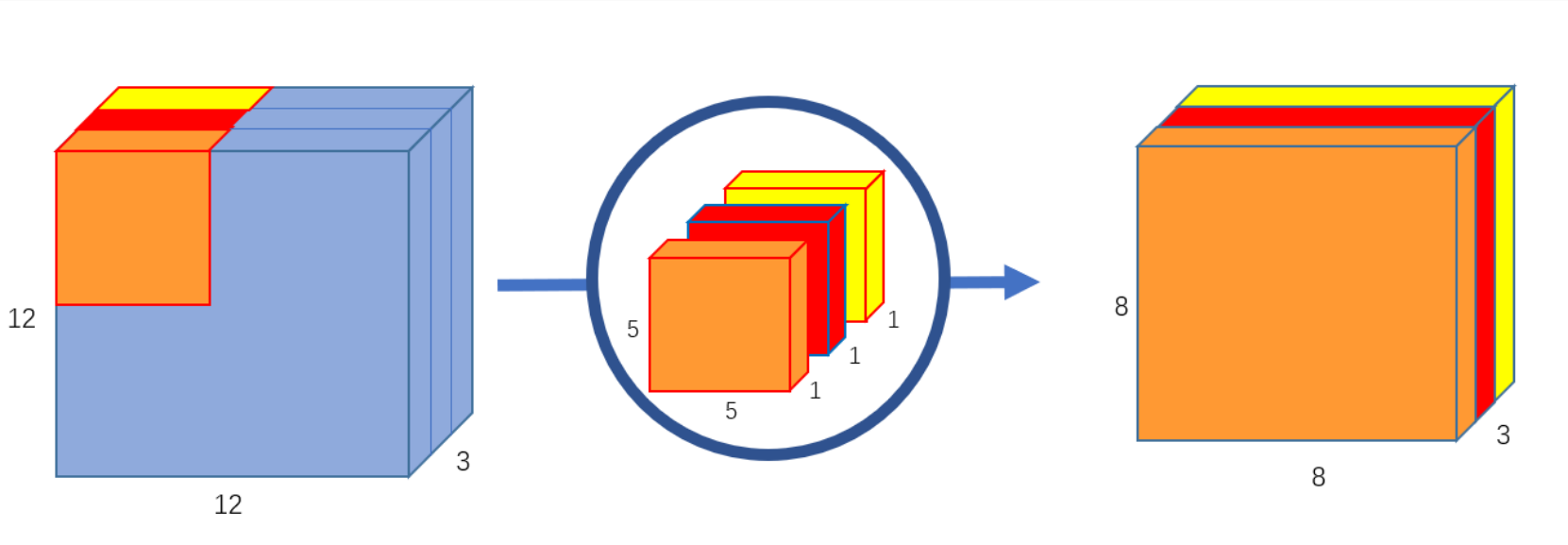


Imagen tomada de Chi-Feng Wang. A Basic Introduction to Separable Convolutions, 2018.

Convolución puntual (de 1×1)

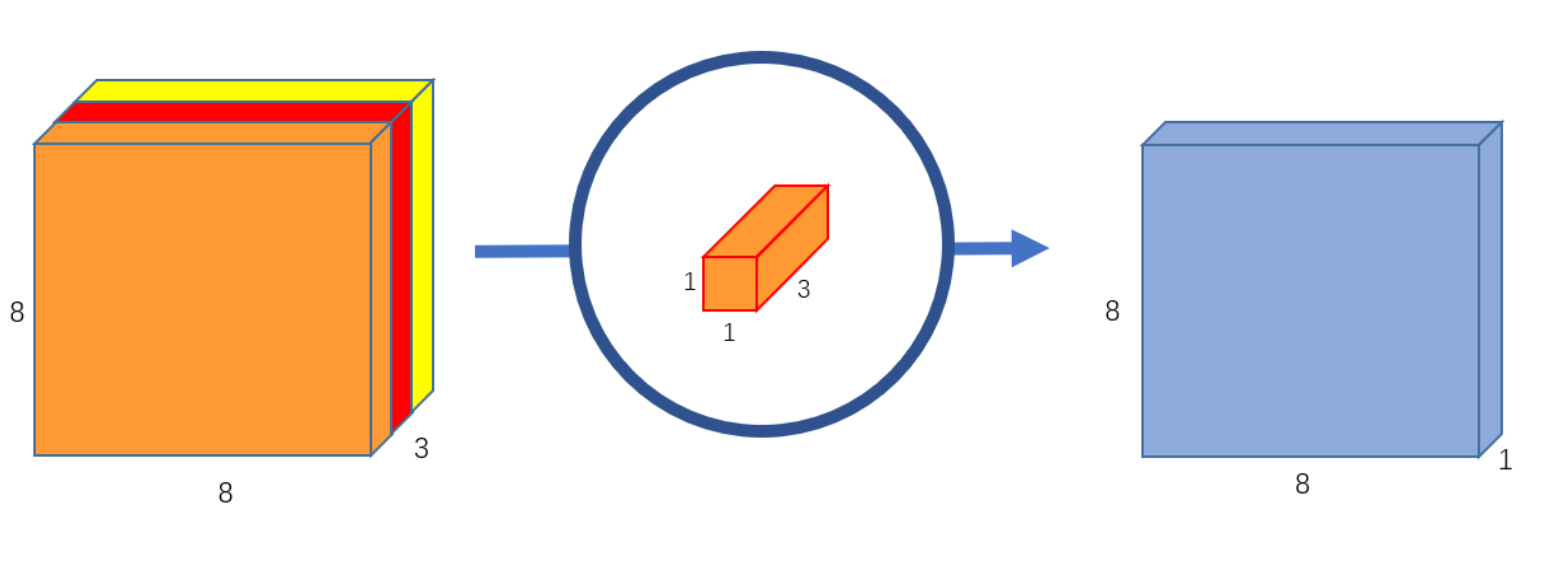


Imagen tomada de Chi-Feng Wang. A Basic Introduction to Separable Convolutions, 2018.

Convolución puntual (de 1×1)

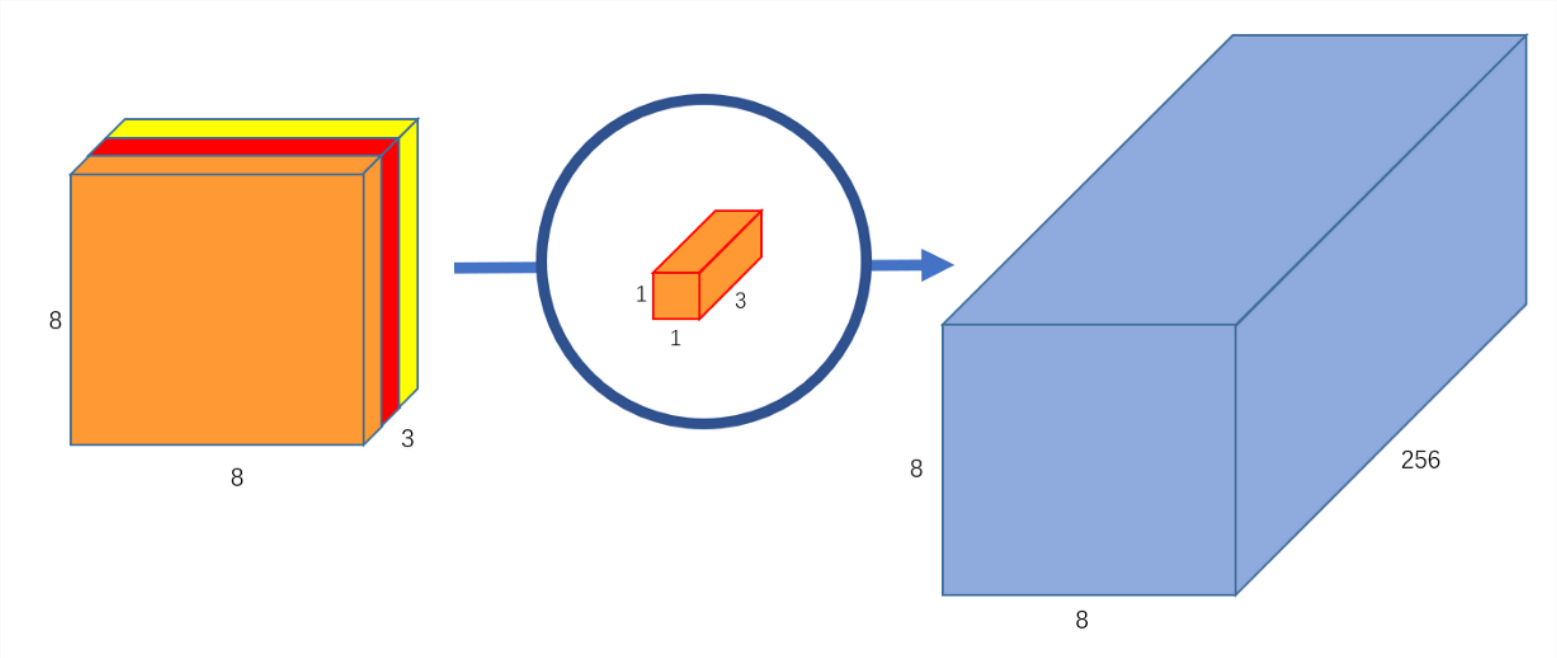


Imagen tomada de Chi-Feng Wang. A Basic Introduction to Separable Convolutions, 2018.

Convolución separable en profundidad

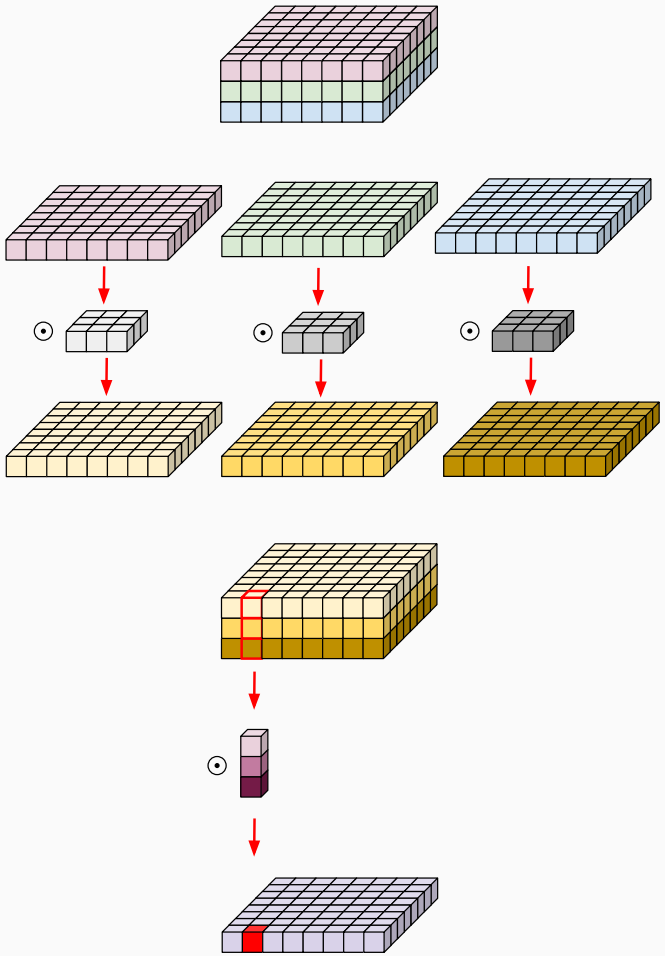


Imagen tomada de Eli Bendersky. Depthwise separable convolutions for machine learning, 2018.

Bloques Inception y convoluciones separables

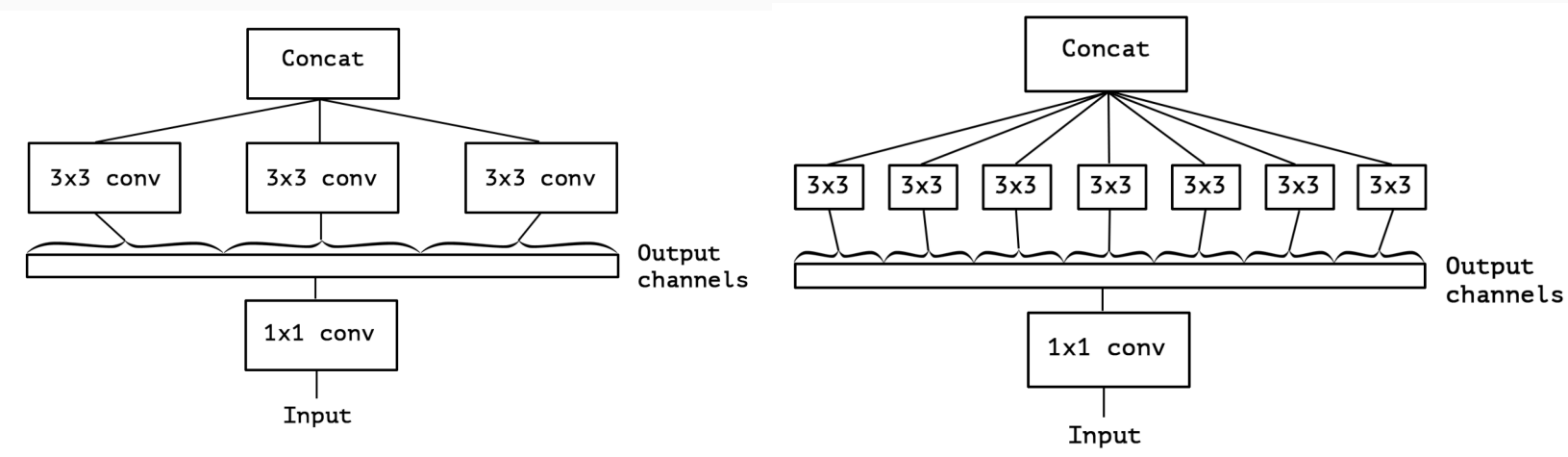


Imagen tomada de F. Chollet. Xception: Deep Learning with Depthwise Separable Convolutions, 2017.

Xception

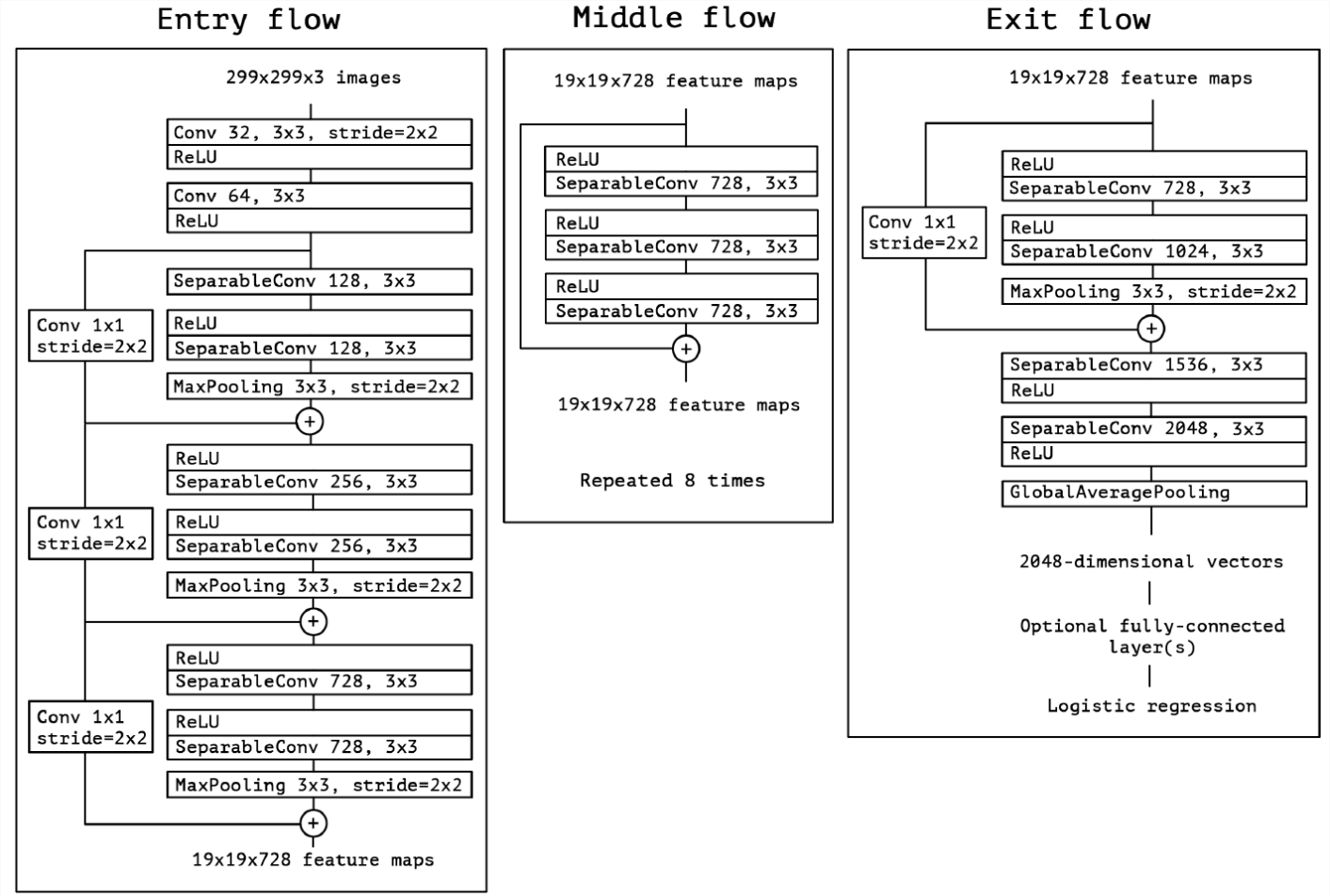


Imagen tomada de F. Chollet. Xception: Deep Learning with Depthwise Separable Convolutions, 2017.

Convolución dilatada

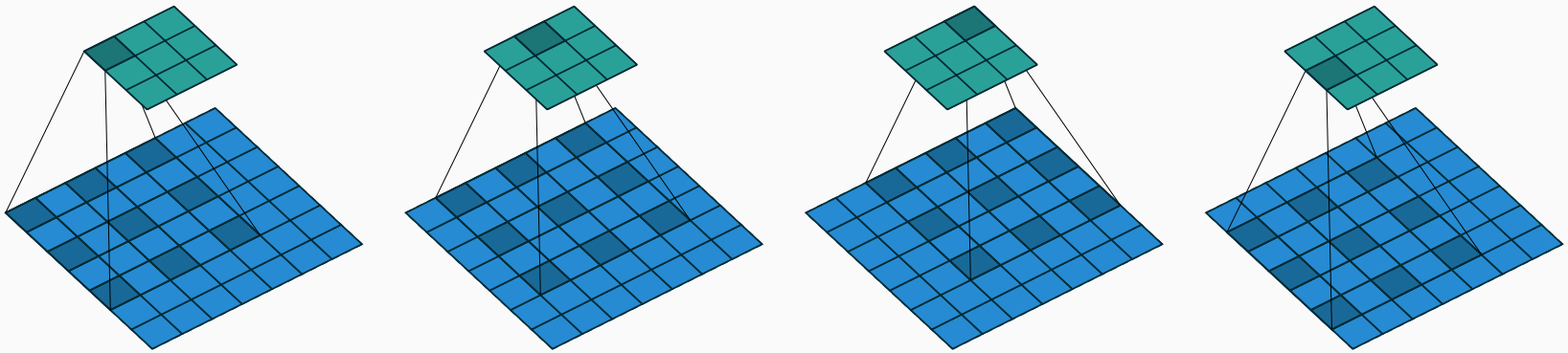


Imagen tomada de Dumoulin and Visin. *A guide to convolution arithmetic for deep learning*, 2018.

Visualizando respuestas

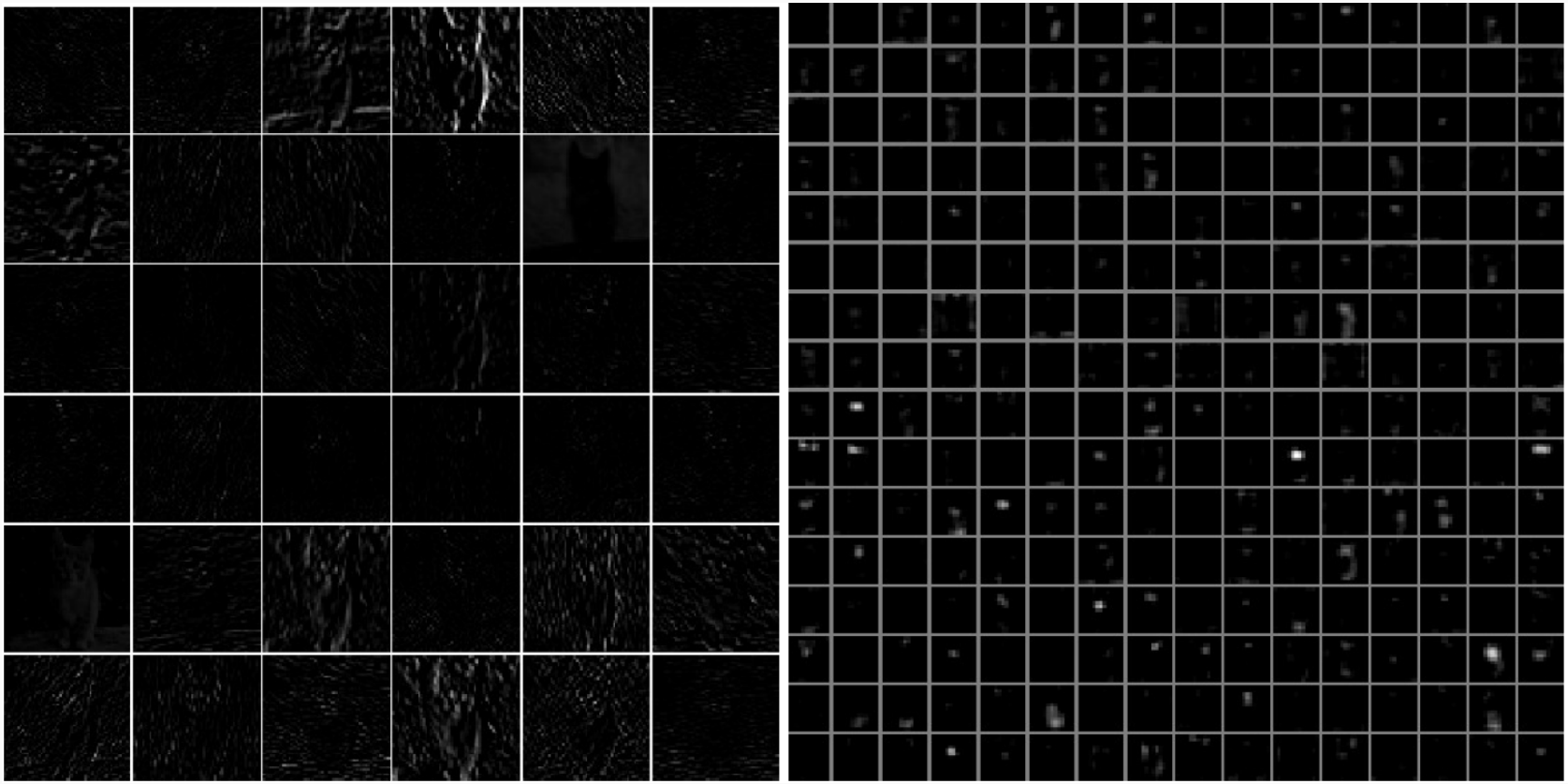


Imagen tomada de `http://cs231n.github.io/understanding-cnn/`

Visualizando pesos

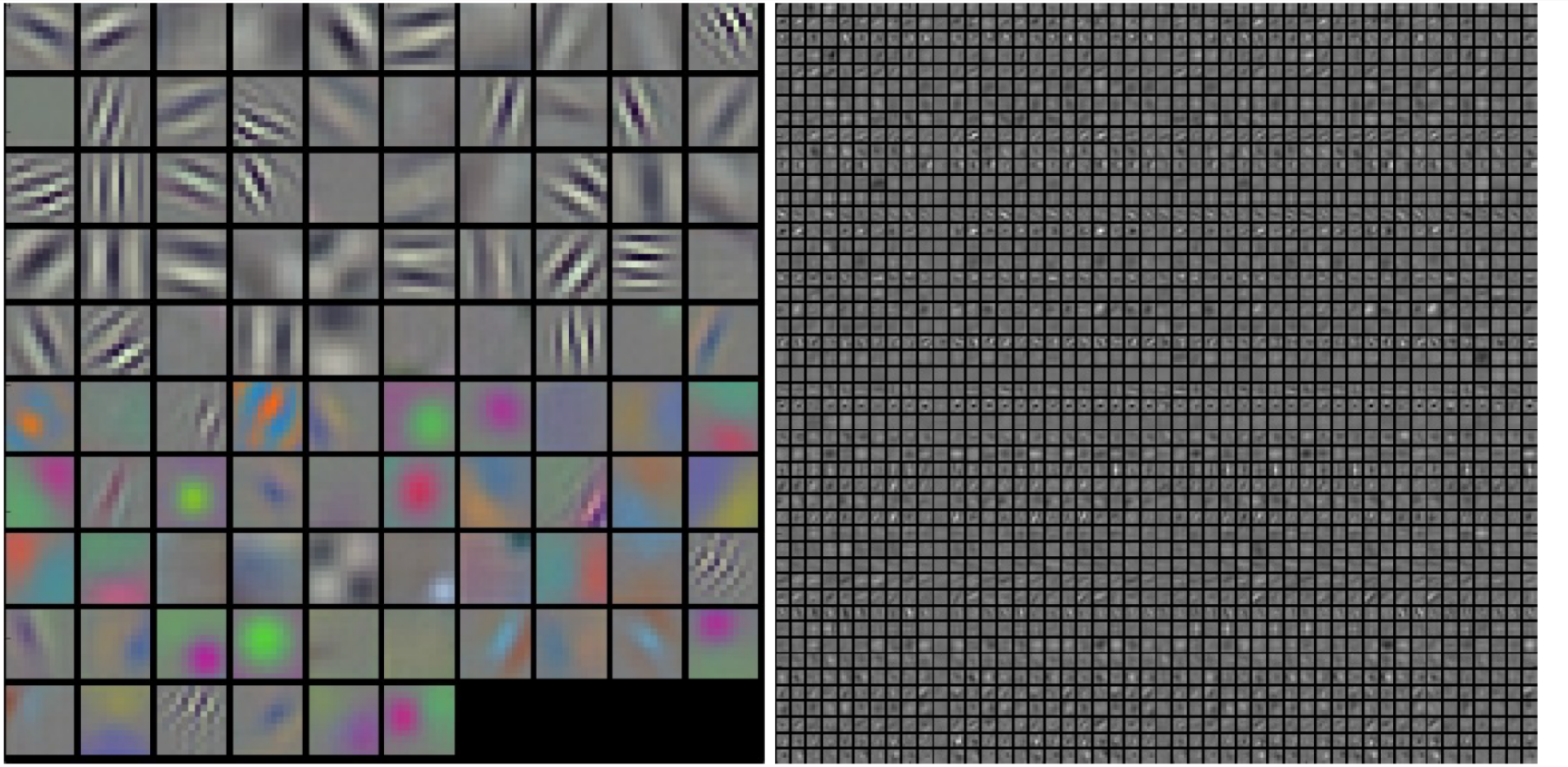


Imagen tomada de `http://cs231n.github.io/understanding-cnn/`

Visualizando imágenes con respuestas máximas

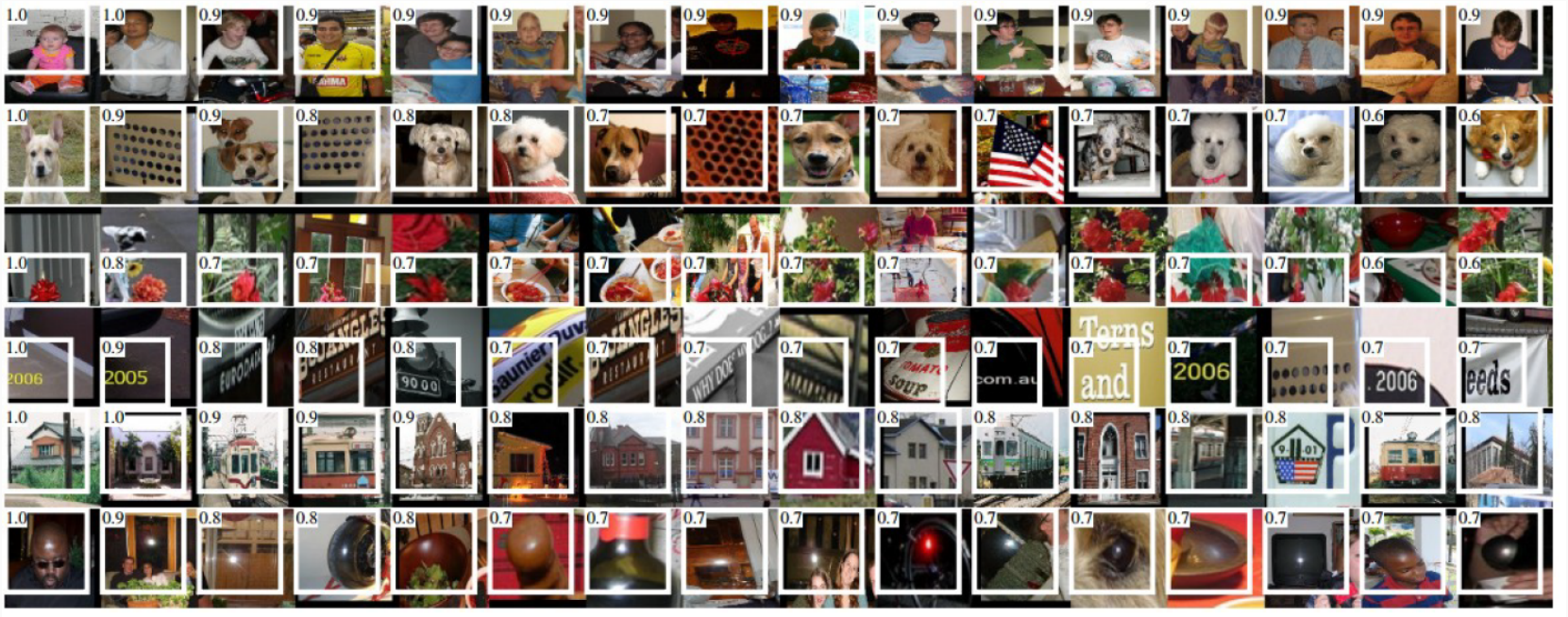


Imagen tomada de `http://cs231n.github.io/understanding-cnn/`

Visualizando obstrucciones

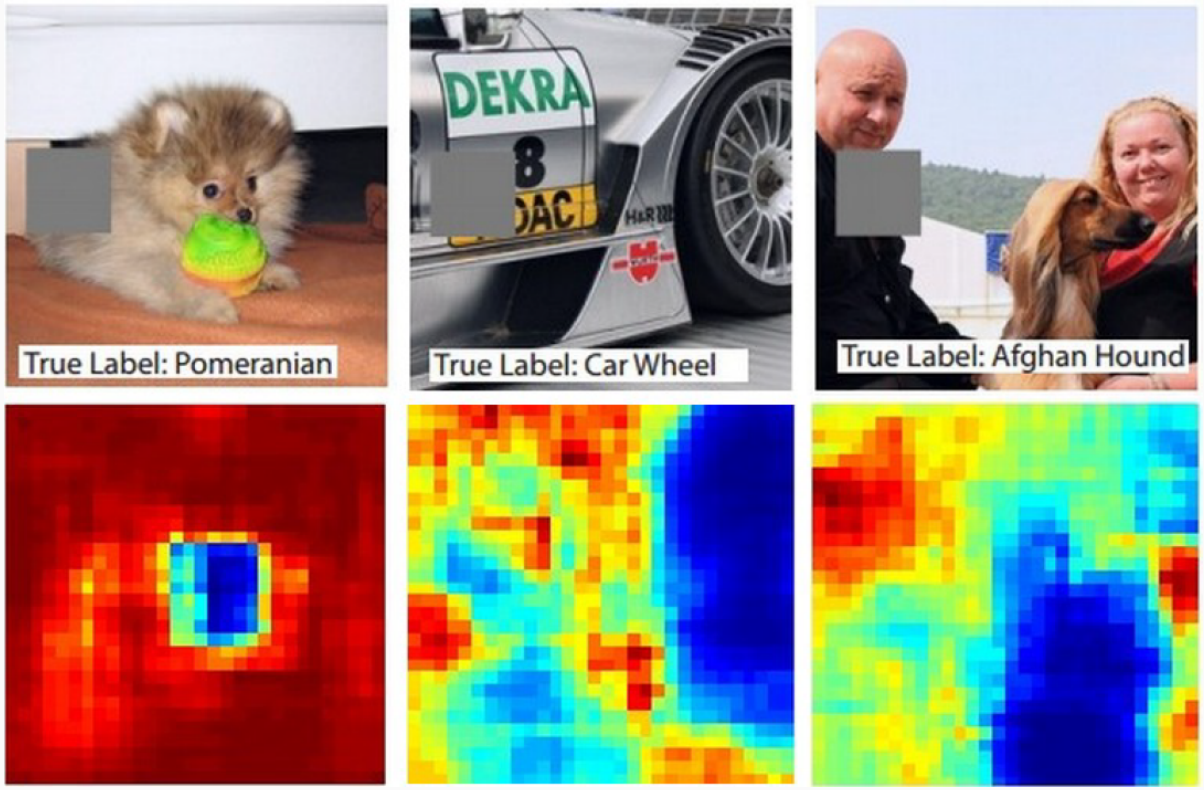


Imagen tomada de `http://cs231n.github.io/understanding-cnn/`

Red de-convolucional

- Se puede poner una red de-convolucional en cada capa de una red convolucional para visualizar sus respuestas

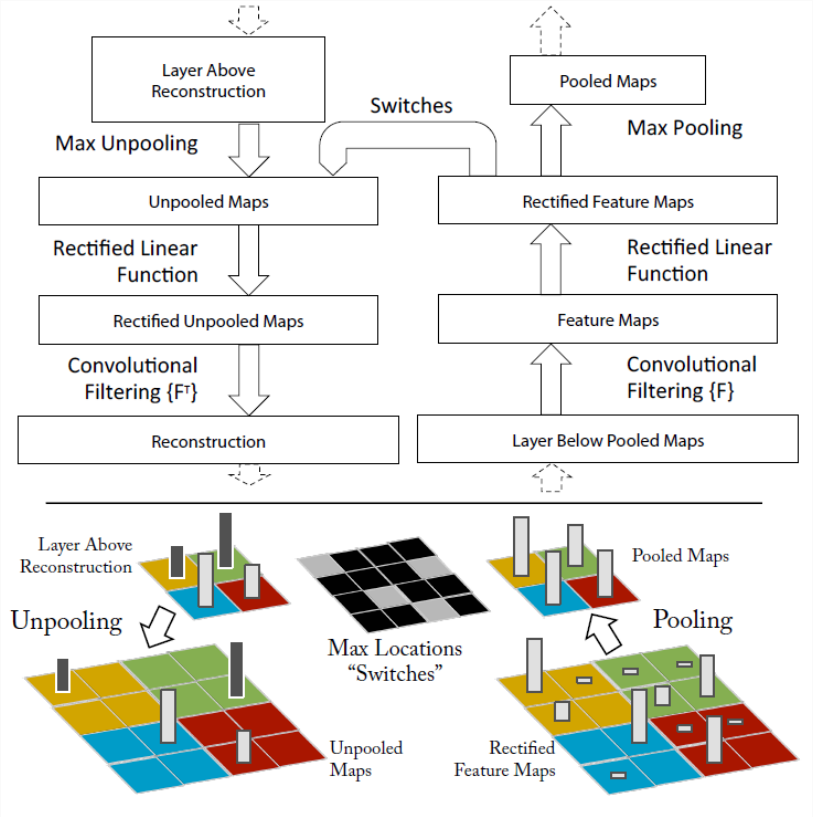


Imagen tomada de Zeiler and Fergus. *Visualizing and Understanding Convolutional Networks*, 2014

DeepDream de Google: diferentes clases

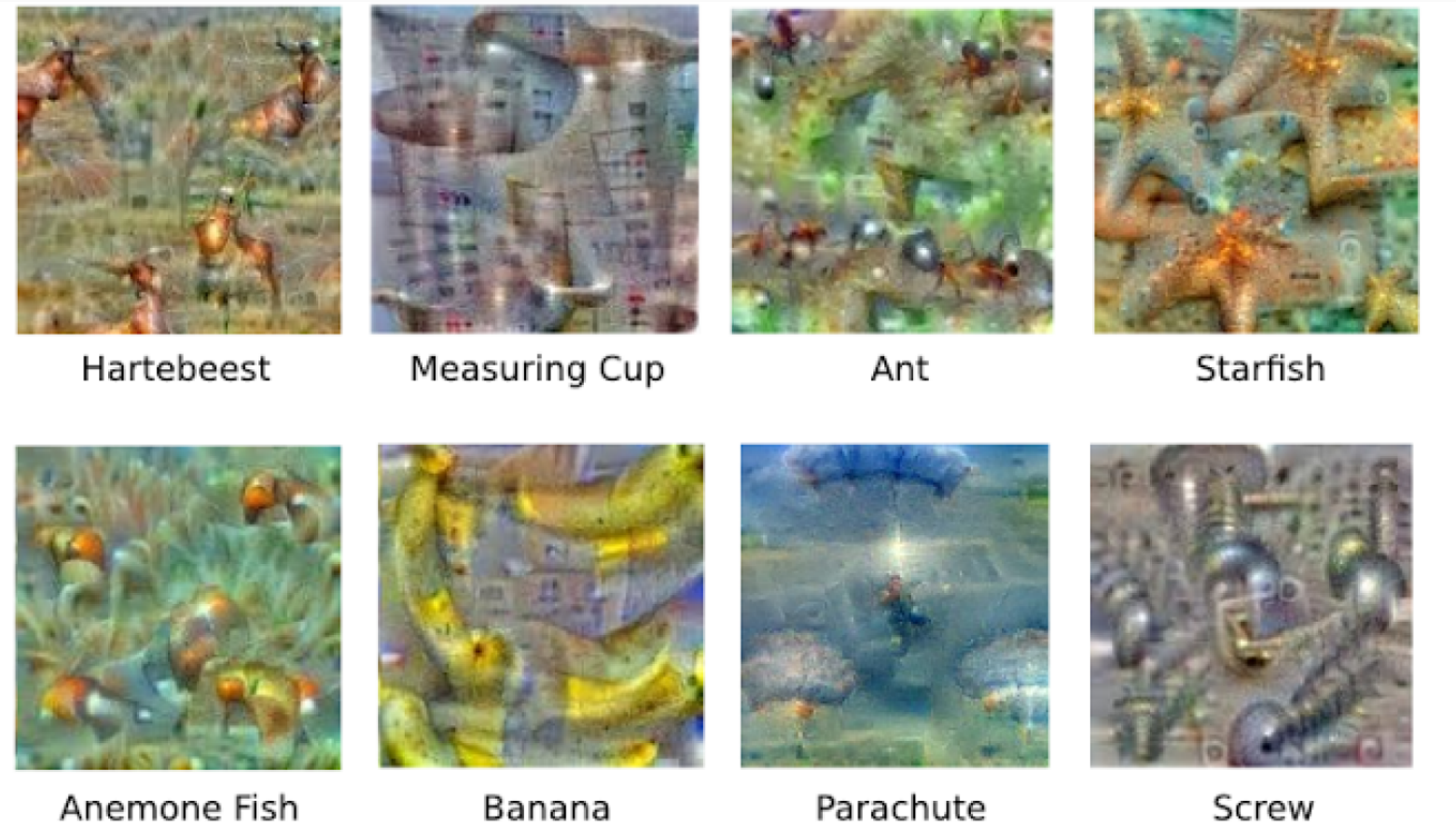


Imagen tomada de `https://research.googleblog.com/2015/06/inceptionism-going-deeper-into-neural.html`

DeepDream de Google: características de bajo nivel

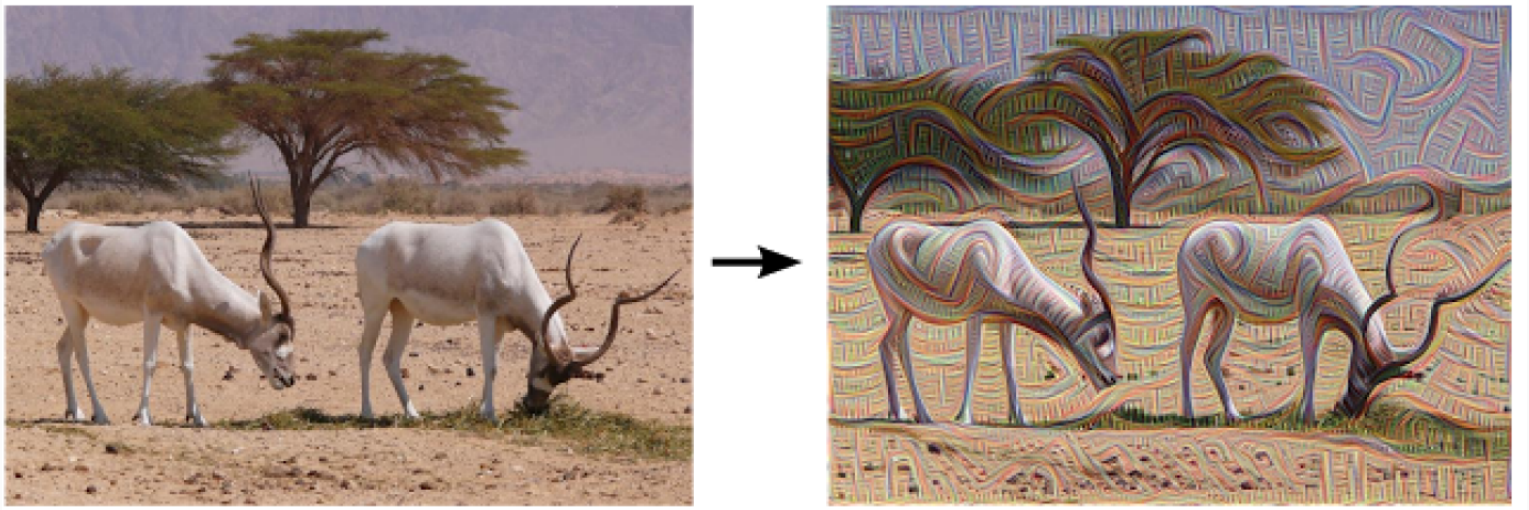


Imagen tomada de `https://research.googleblog.com/2015/06/inceptionism-going-deeper-into-neural.html`

DeepDream de Google: características de alto nivel

Imagen tomada de `https://research.googleblog.com/2015/06/inceptionism-going-deeper-into-neural.html`

DeepDream de Google: influencia de imagen original

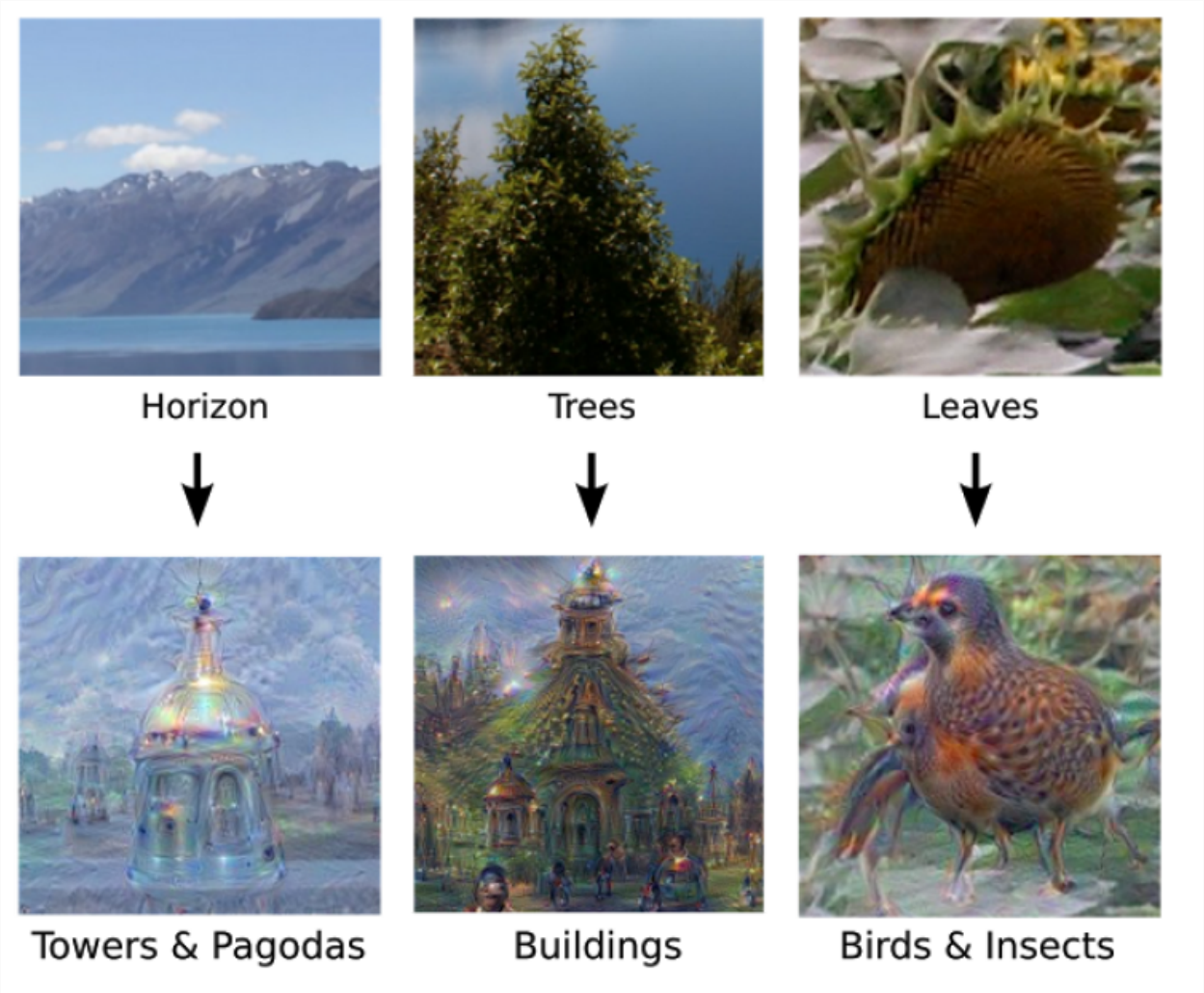


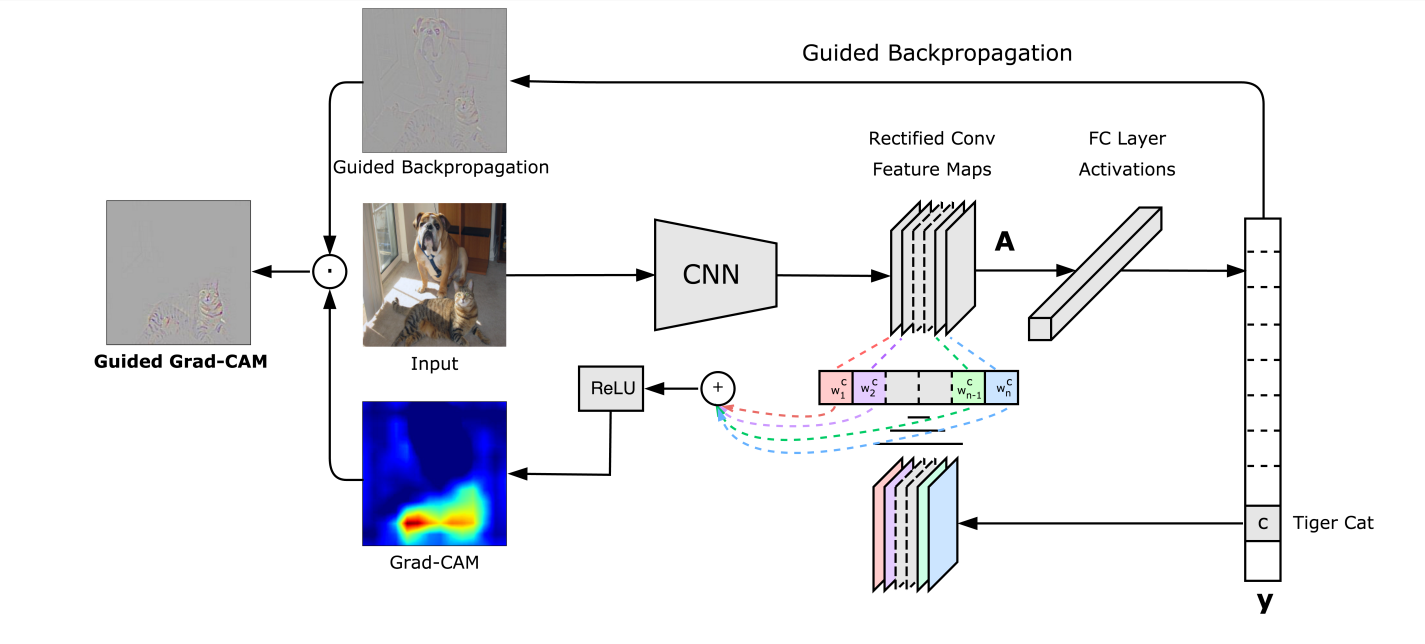
Imagen tomada de `https://research.googleblog.com/2015/06/inceptionism-going-deeper-into-neural.html`

DeepDream de Google: de forma aleatoria e iterativa

Imagen tomada de `https://research.googleblog.com/2015/06/inceptionism-going-deeper-into-neural.html`

Gradient-weighted Class Activation Mapping (Grad-CAM)

- Método para visualizar las regiones de la imagen que el modelo considera más importantes para una predicción
- Emplea información de los gradientes específicos a la clase para producir un mapa de calor de importancia



Redes convolucionales 1D

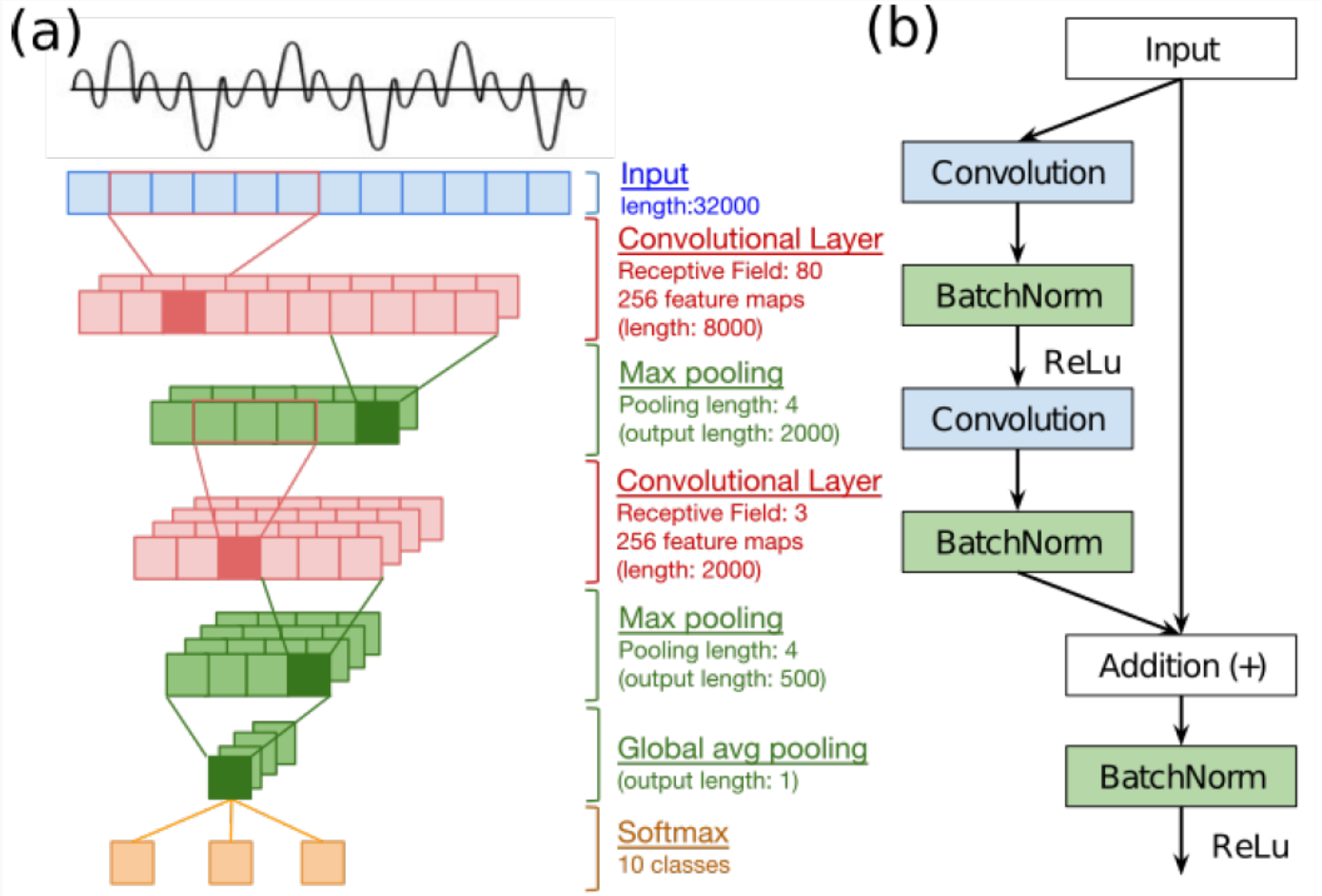


Imagen tomada de Dai et al. *Very Deep Convolutional Neural Networks for Raw Waveforms*, 2016

Redes convolucionales 3D (1)

- Respuesta en redes convolucionales 2D en una imagen

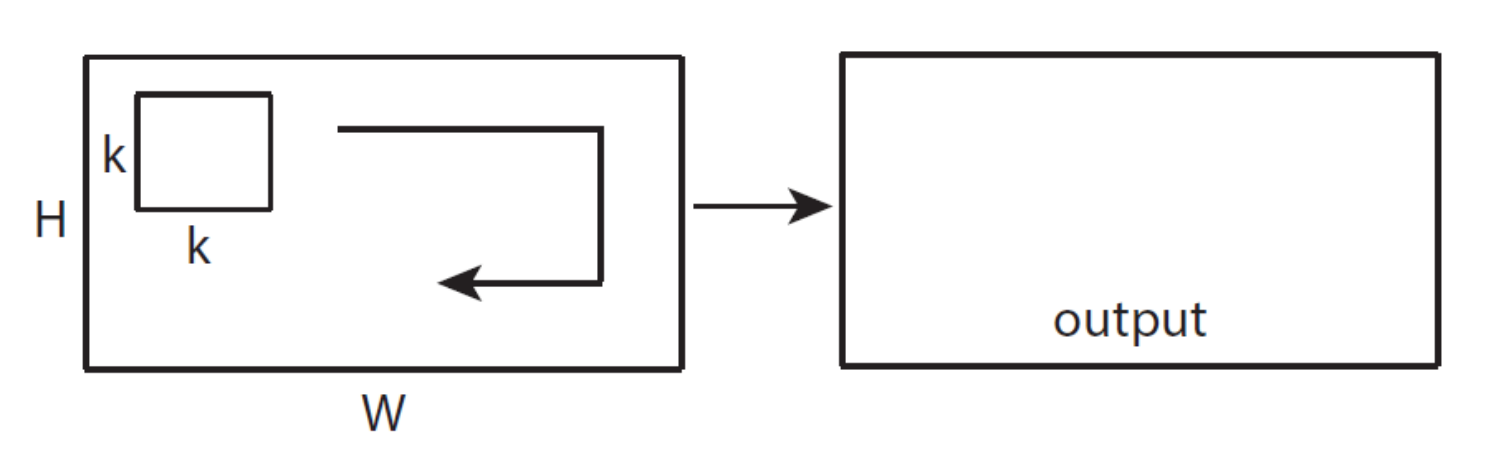


Imagen tomada de Tran et al. *Learning Spatiotemporal Features with 3D Convolutional Networks*, 2015

Redes convolucionales 3D (2)

- Respuesta en redes convolucionales 2D en varias imágenes

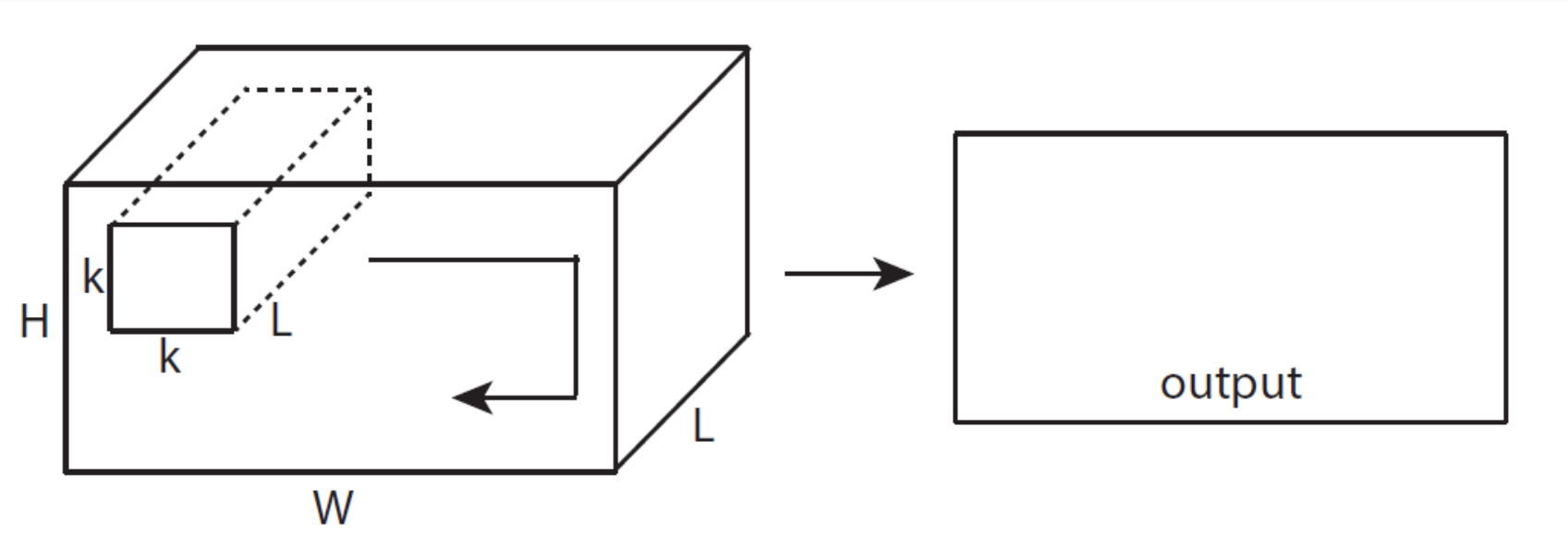


Imagen tomada de Tran et al. *Learning Spatiotemporal Features with 3D Convolutional Networks*, 2015

Redes convolucionales 3D (3)

- Respuesta en redes convolucionales 3D

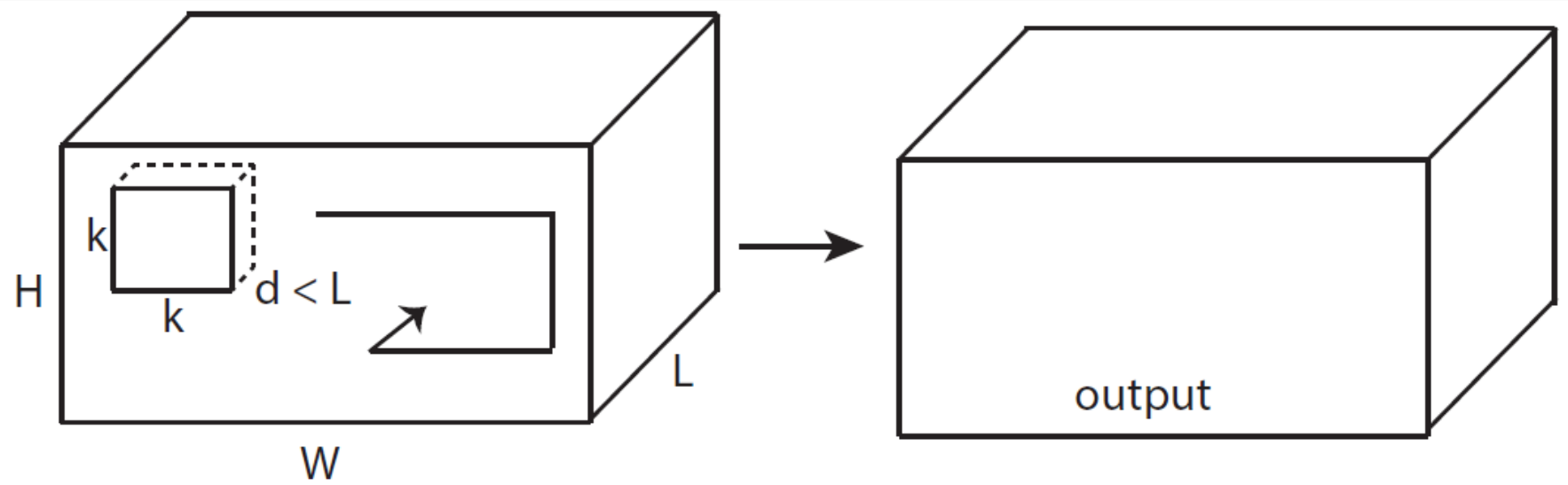


Imagen tomada de Tran et al. *Learning Spatiotemporal Features with 3D Convolutional Networks*, 2015

Aprendizaje por transferencia

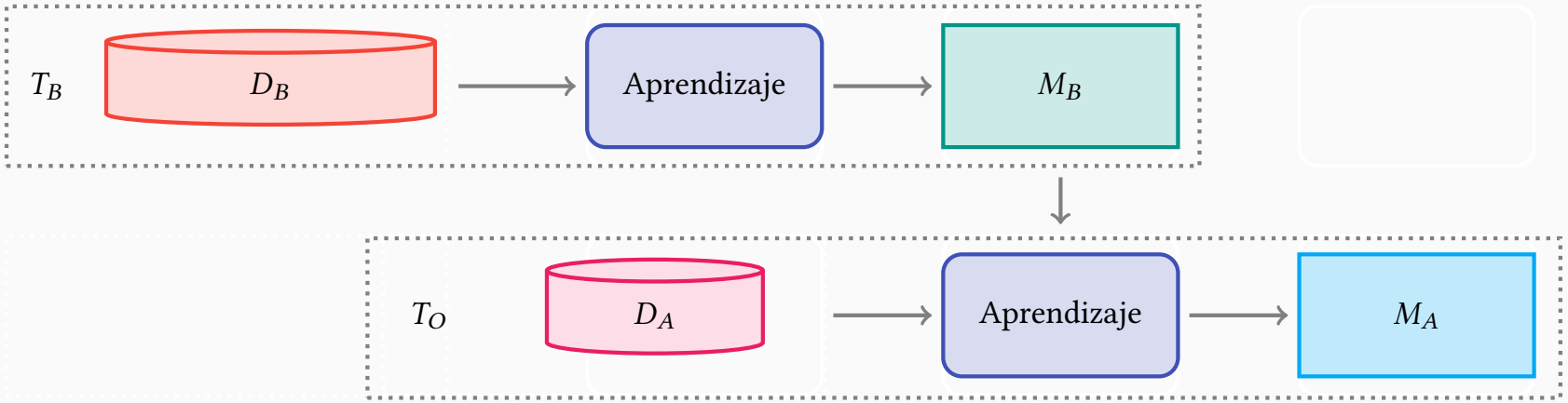


Imagen cortesía de Berenice Montalvo

Desempeño en distintas tareas

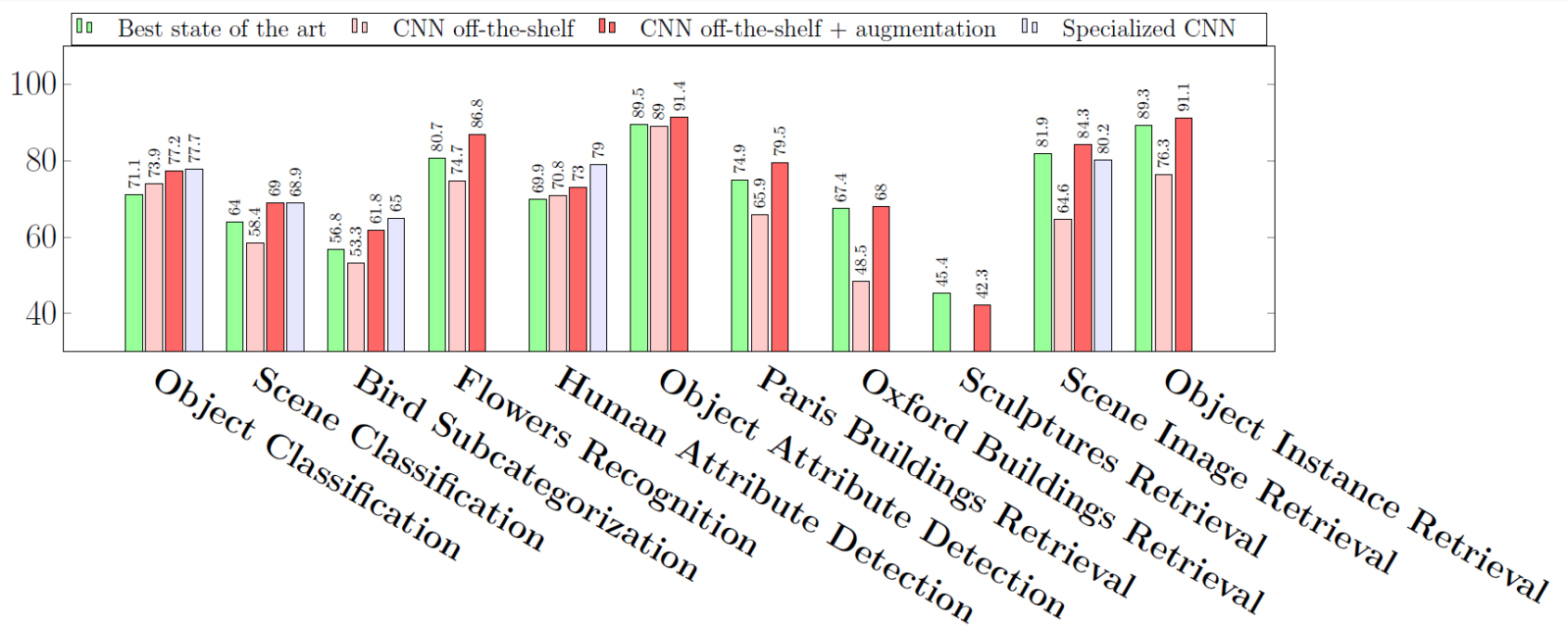


Imagen tomada de Razavian et al. CNN Features off-the-shelf: an Astounding Baseline for Recognition, 2014

Desempeño en tareas con distintas características (1)

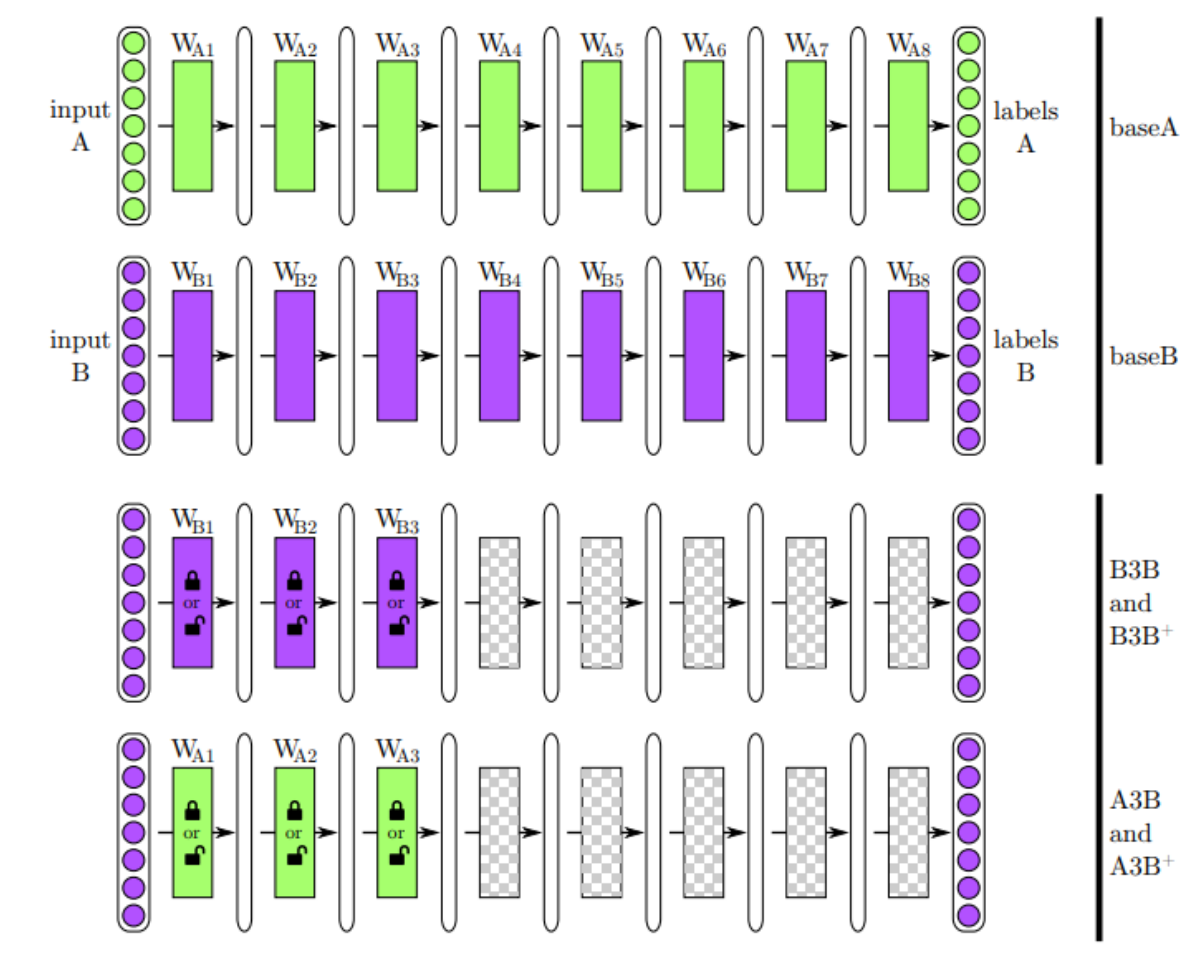
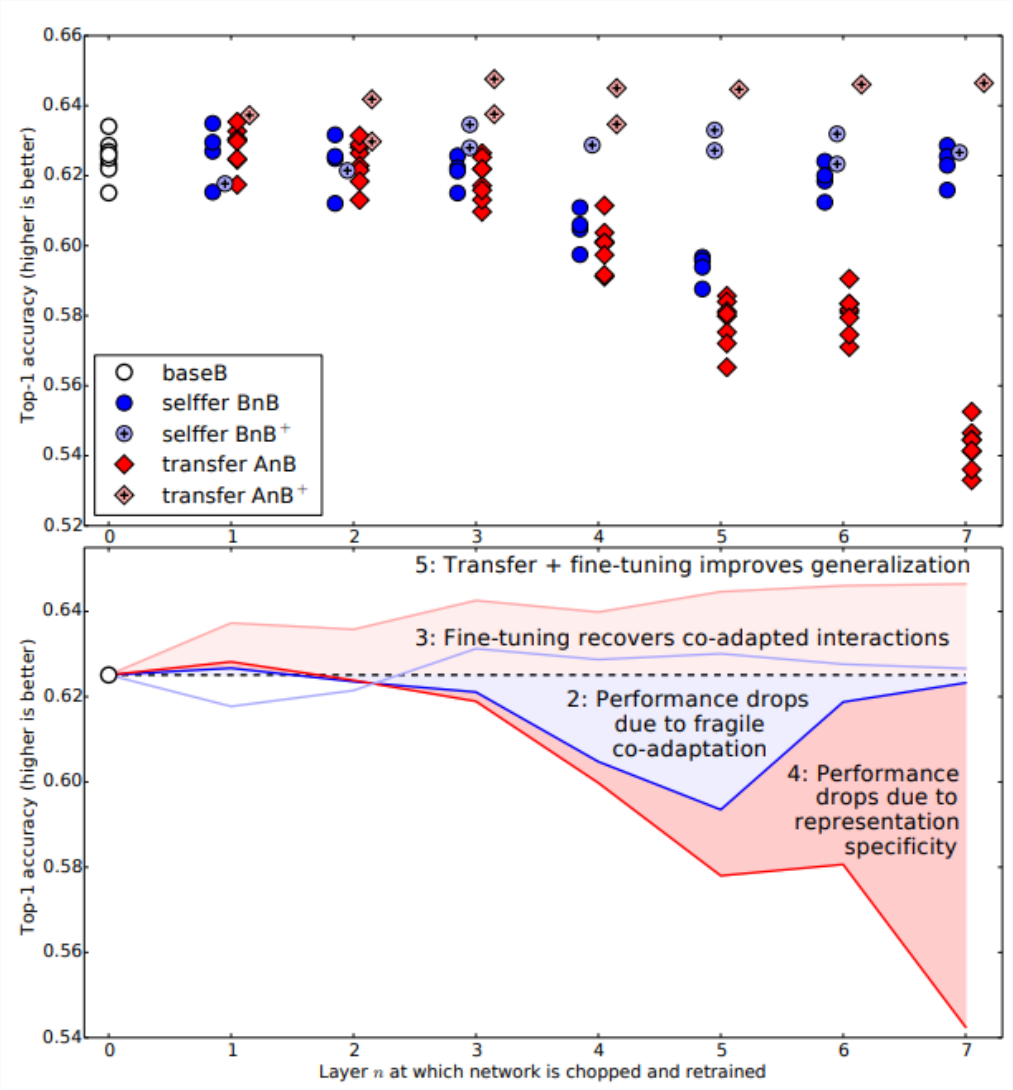


Imagen tomada de Yosinski et al. How transferable are features in deep neural networks?, 2014

Desempeño en tareas con distintas características (2)



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