

# Transferencia de Aprendizaje

Julio Waissman

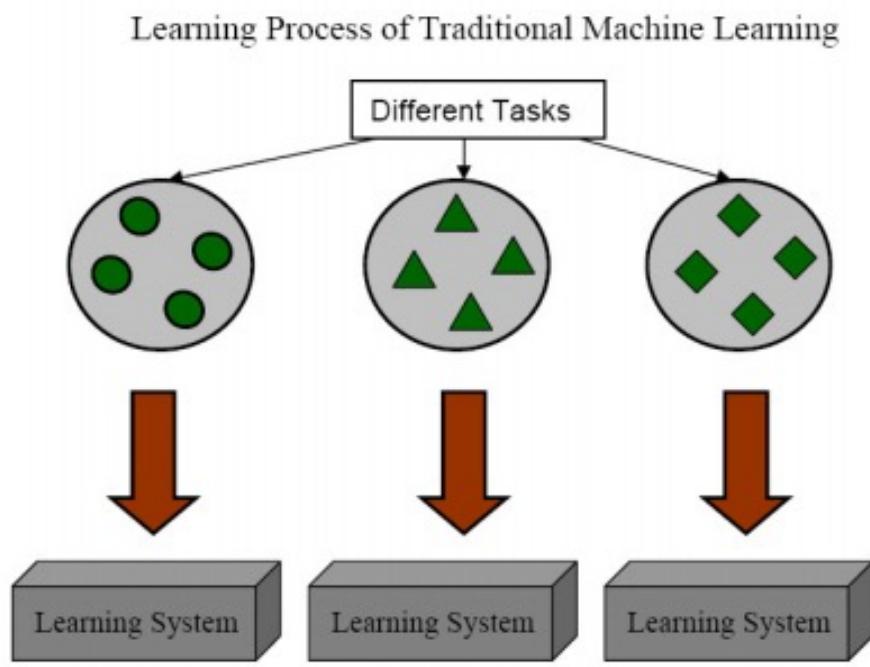
[julio.waissman@unison.mx](mailto:julio.waissman@unison.mx)

**Universidad de Sonora**

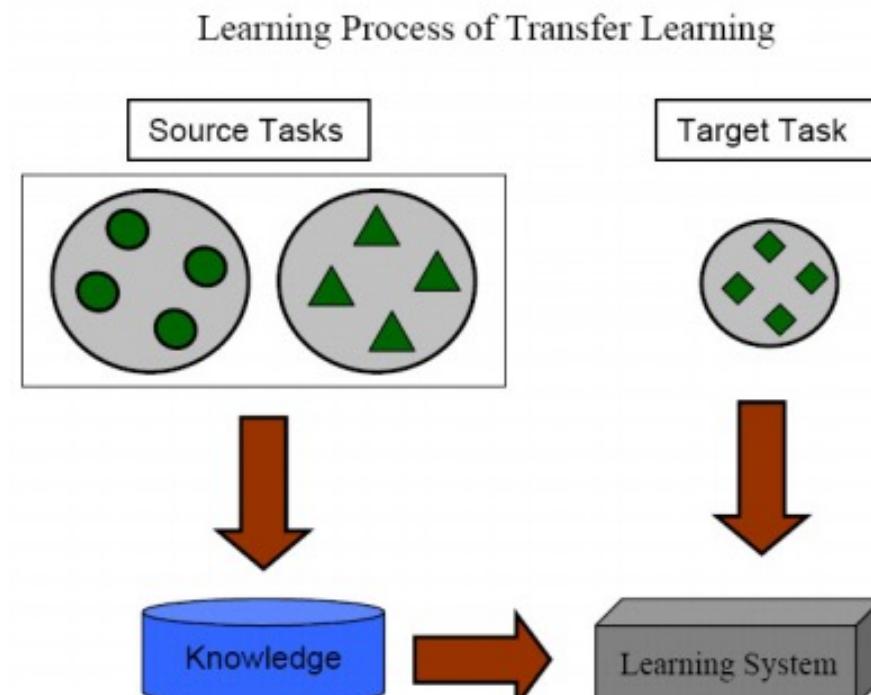


"El saber de mis hijos  
hará mi grandeza"

# Idea básica de transfer learning



(a) Traditional Machine Learning



(b) Transfer Learning

# Tipos de transfer learning

## Inductivo

- Adaptar modelo existente a nuevos datos etiquetados

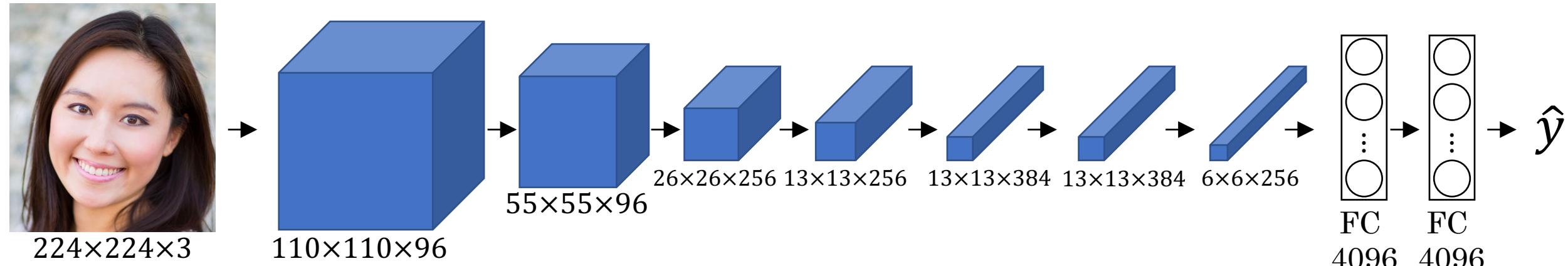
## Transductivo

- Adaptar modelo existente a nuevos datos no etiquetados

## No supervisado

- Adaptar modelo no supervisado existente a nuevos datos no etiquetados

# ¿Qué aprende una CNN?



- Tomamos 9 unidades por capa al azar
- Buscamos los 9 parches de muchas imágenes (en la imagen original) que maximice la activación

# Visualizing deep layers



Layer 1



Layer 2



Layer 3



Layer 4



Layer 5

# Visualizing deep layers: Layer 1



Layer 1



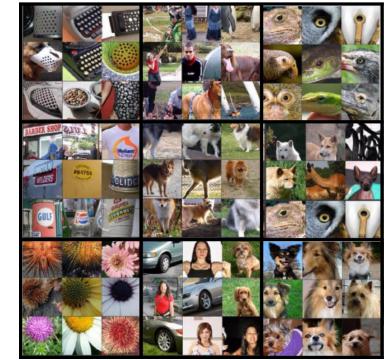
Layer 2



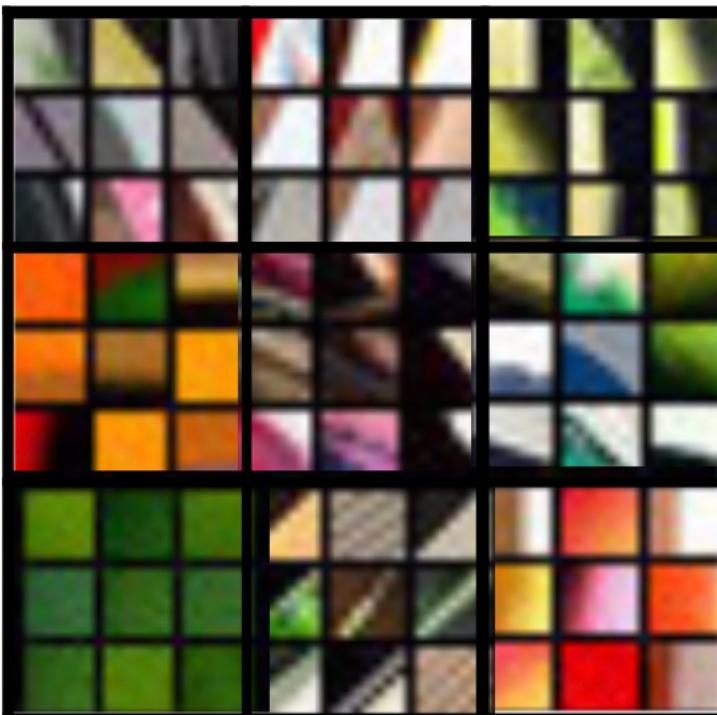
Layer 3



Layer 4



Layer 5



# Visualizing deep layers: Layer 2



Layer 1



Layer 2



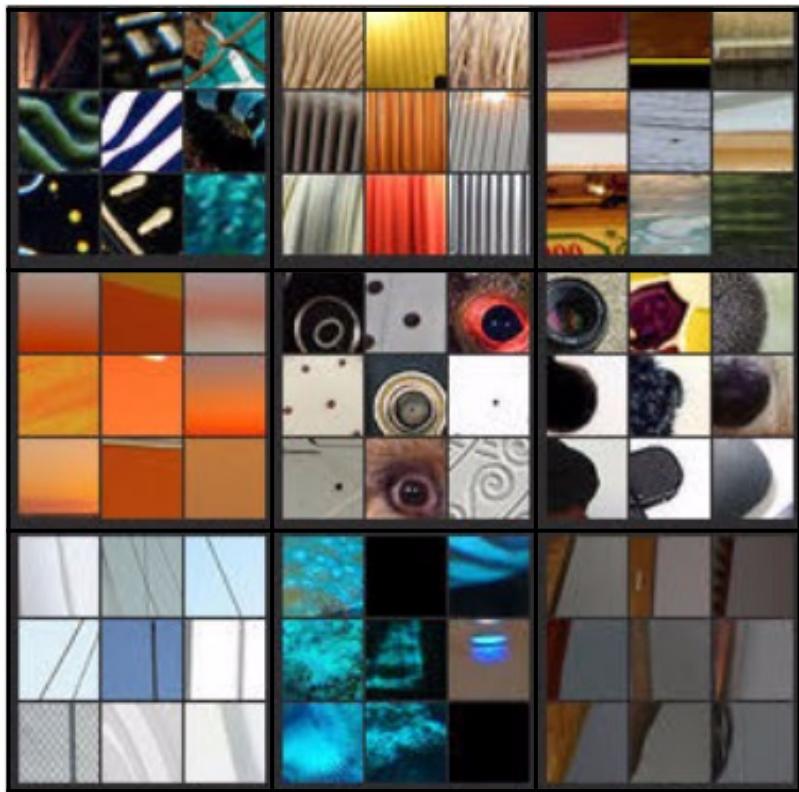
Layer 3



Layer 4



Layer 5



# Visualizing deep layers: Layer 3



Layer 1



Layer 2



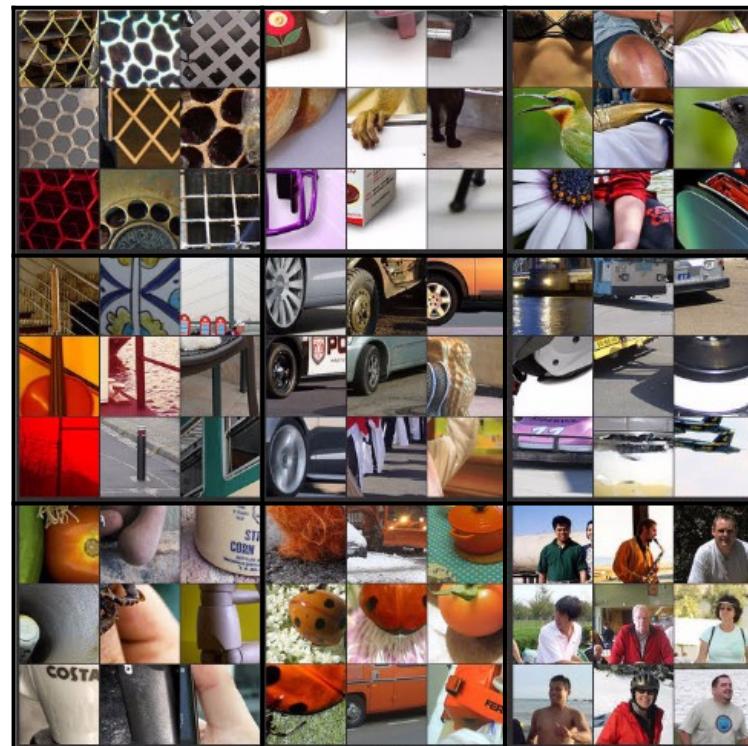
Layer 3



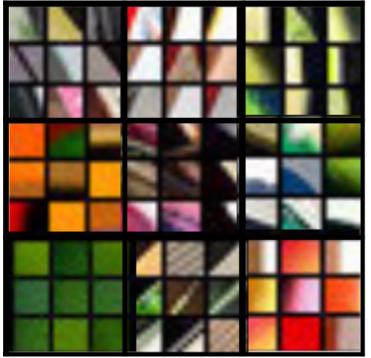
Layer 4



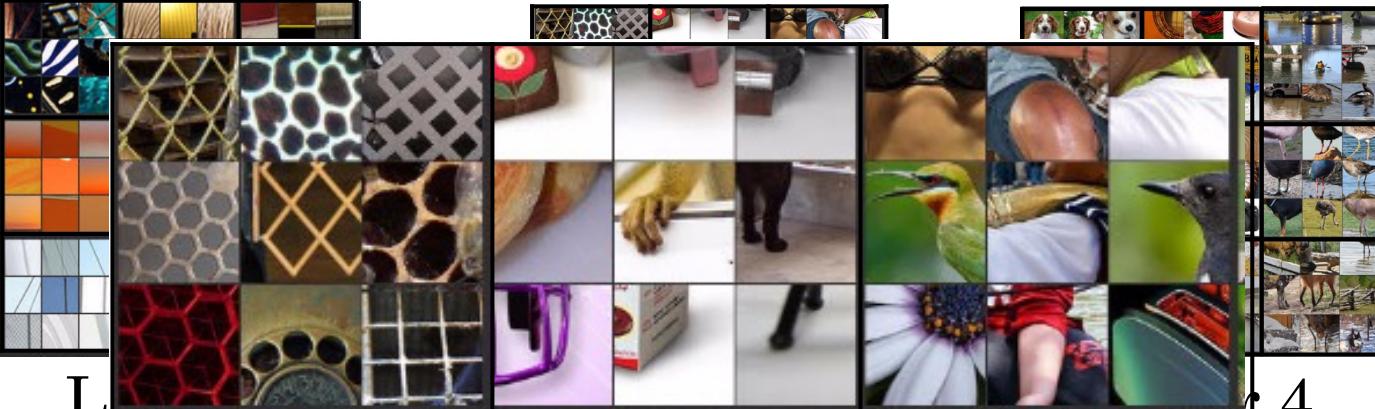
Layer 5



# Visualizing deep layers: Layer 3



Layer 1



L3

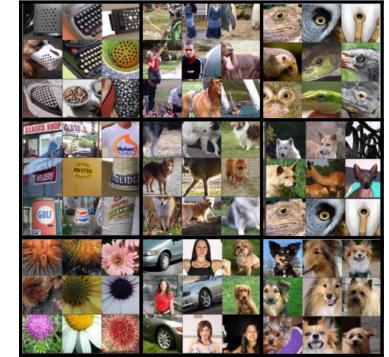
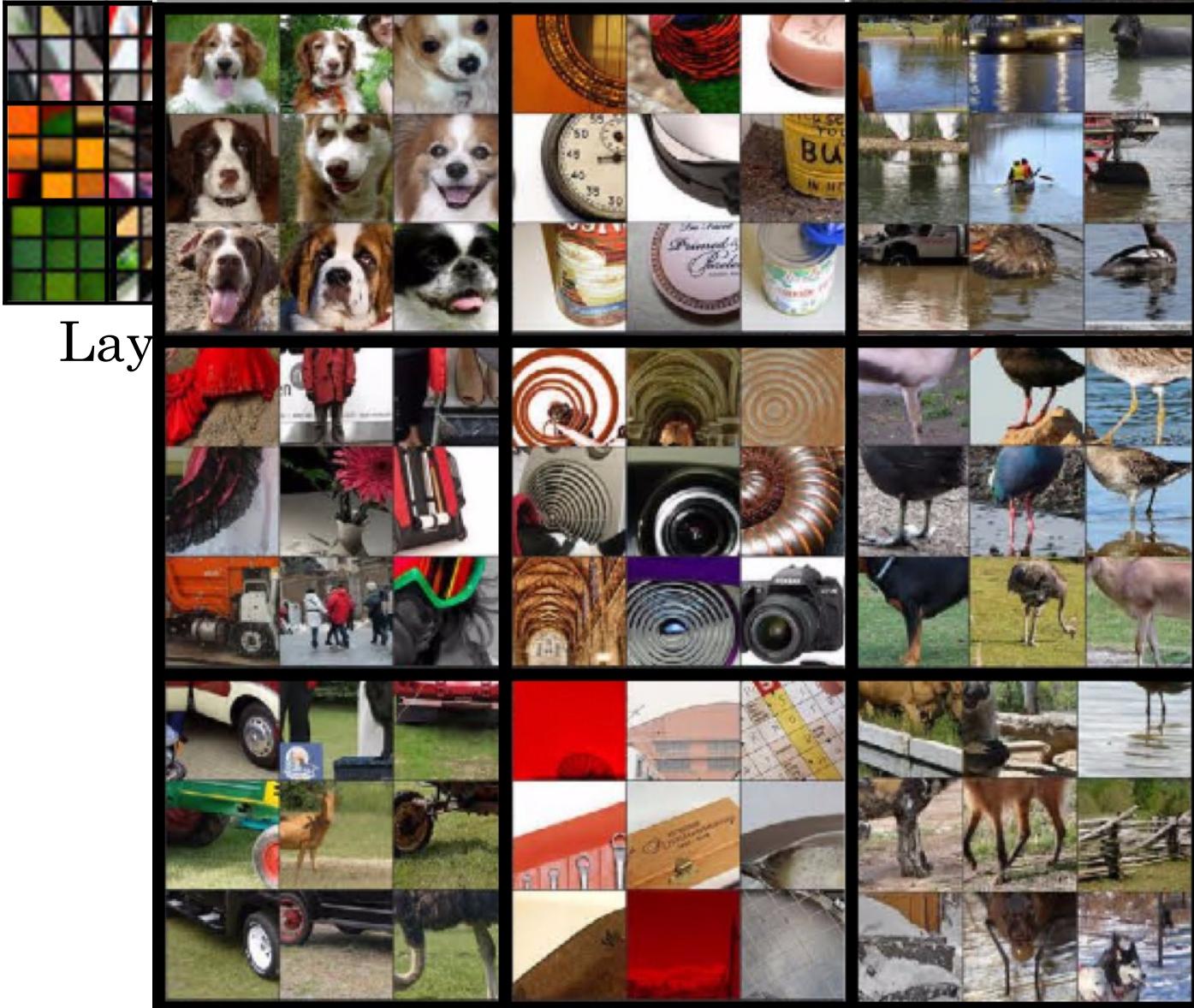


Layer 5



L4

# Visualizing deep layers: Layer 4



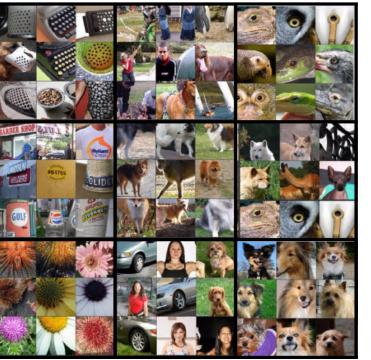
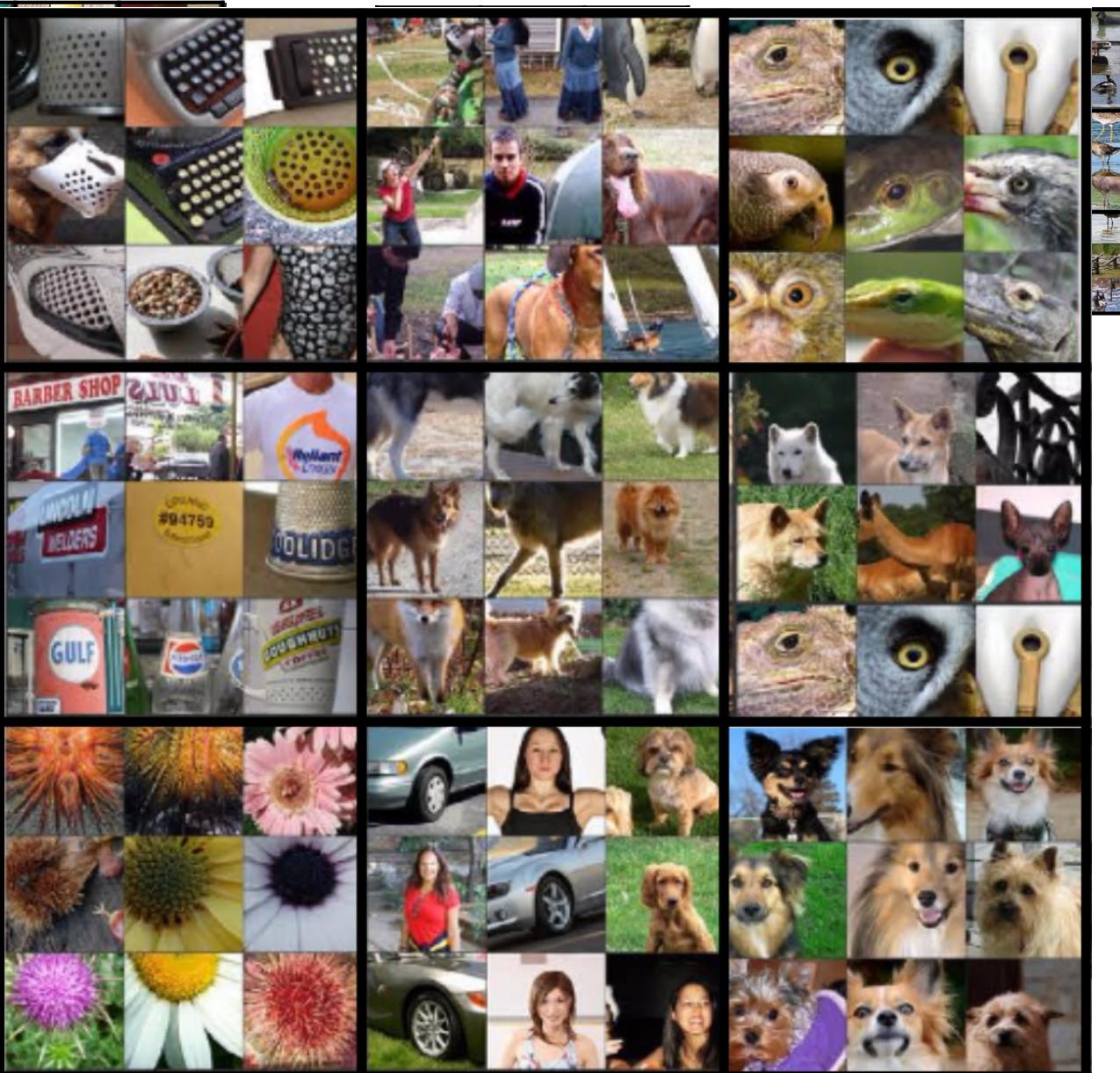
# Visualizing deep layers: Layer 5



Layer 1

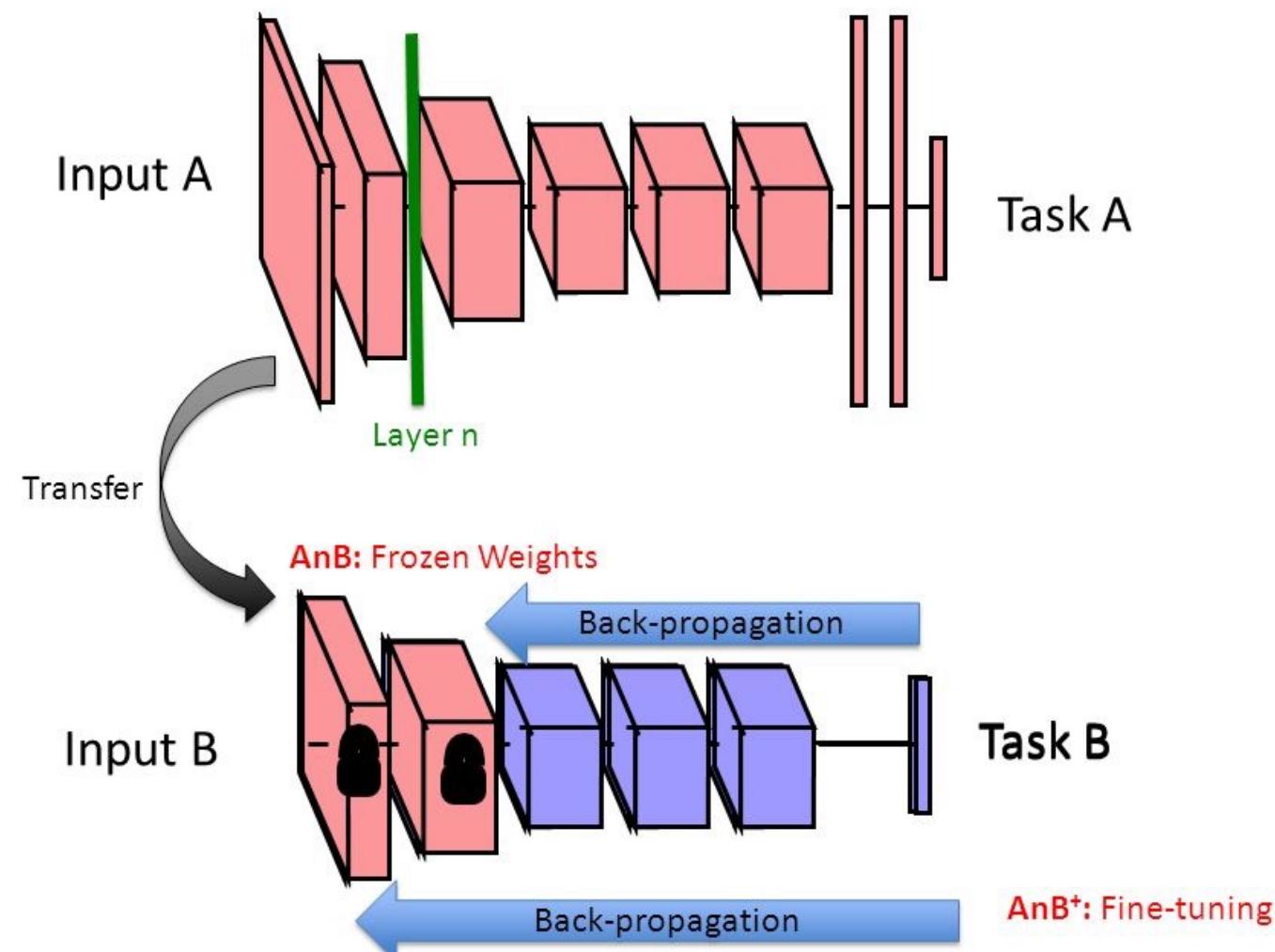


Layer 1

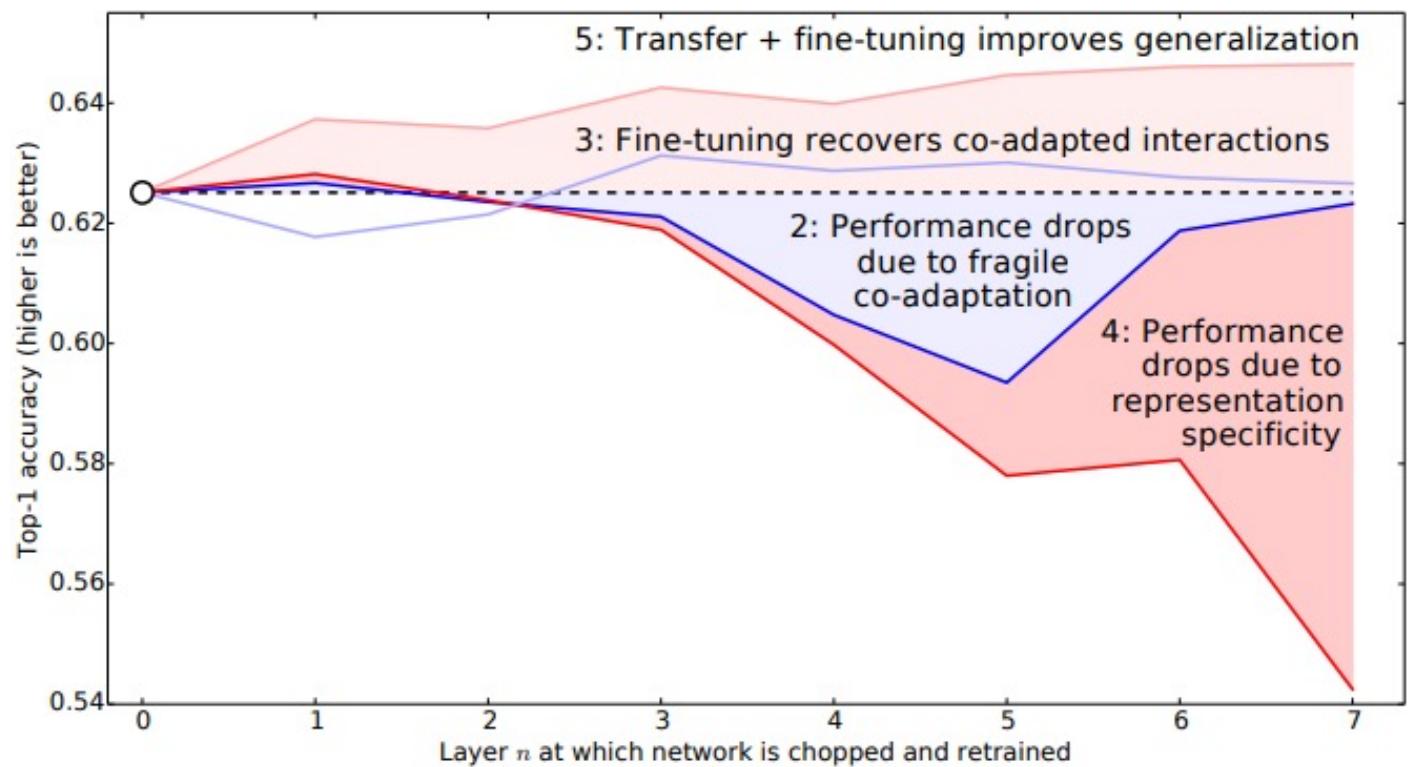
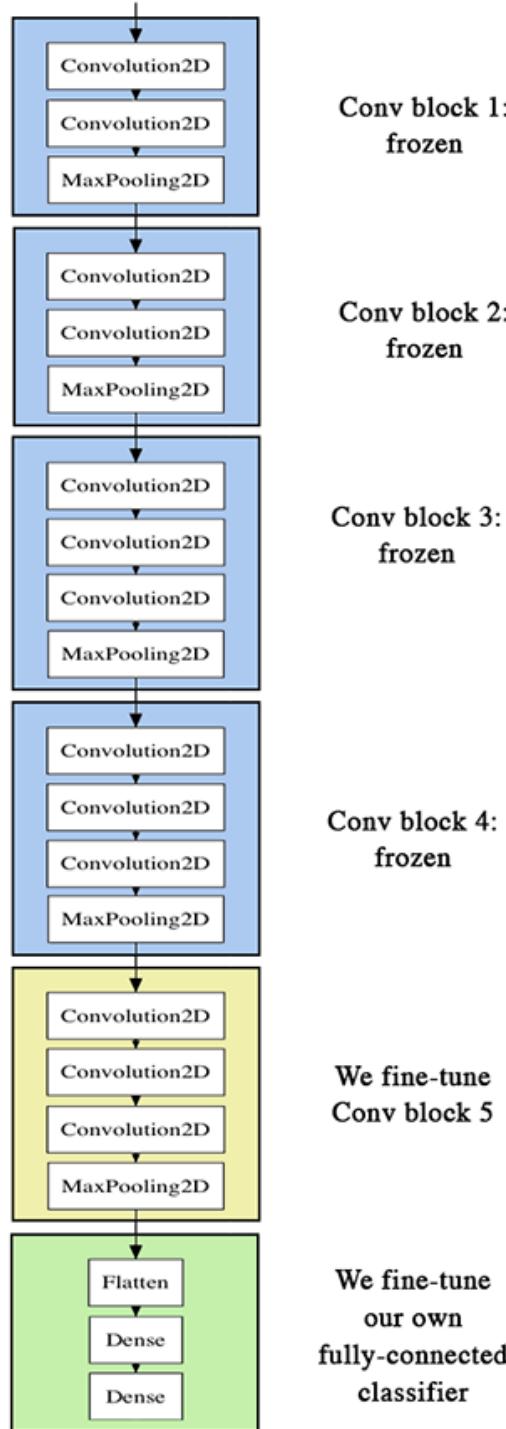


Layer 5

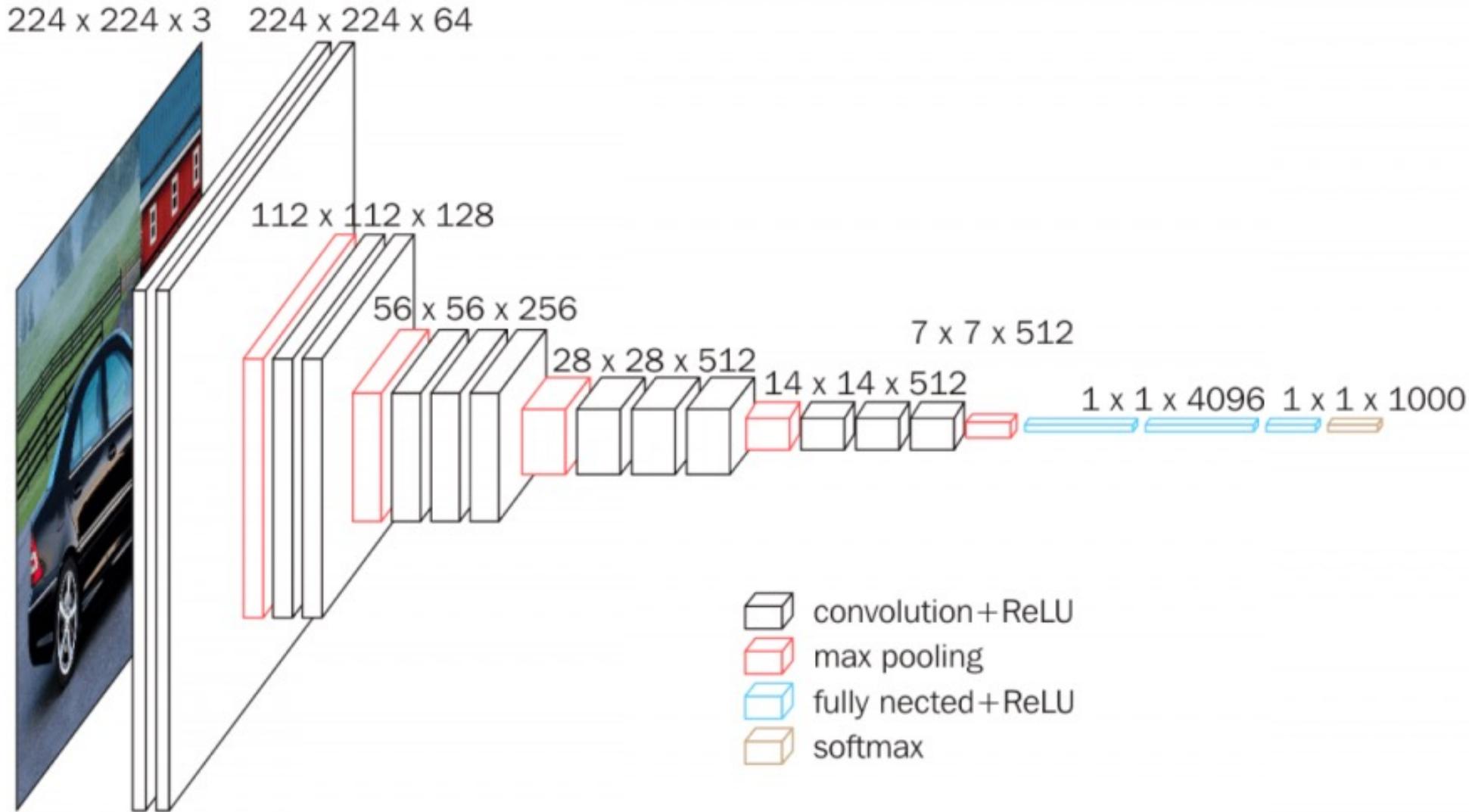
# Transfer Learning Overview



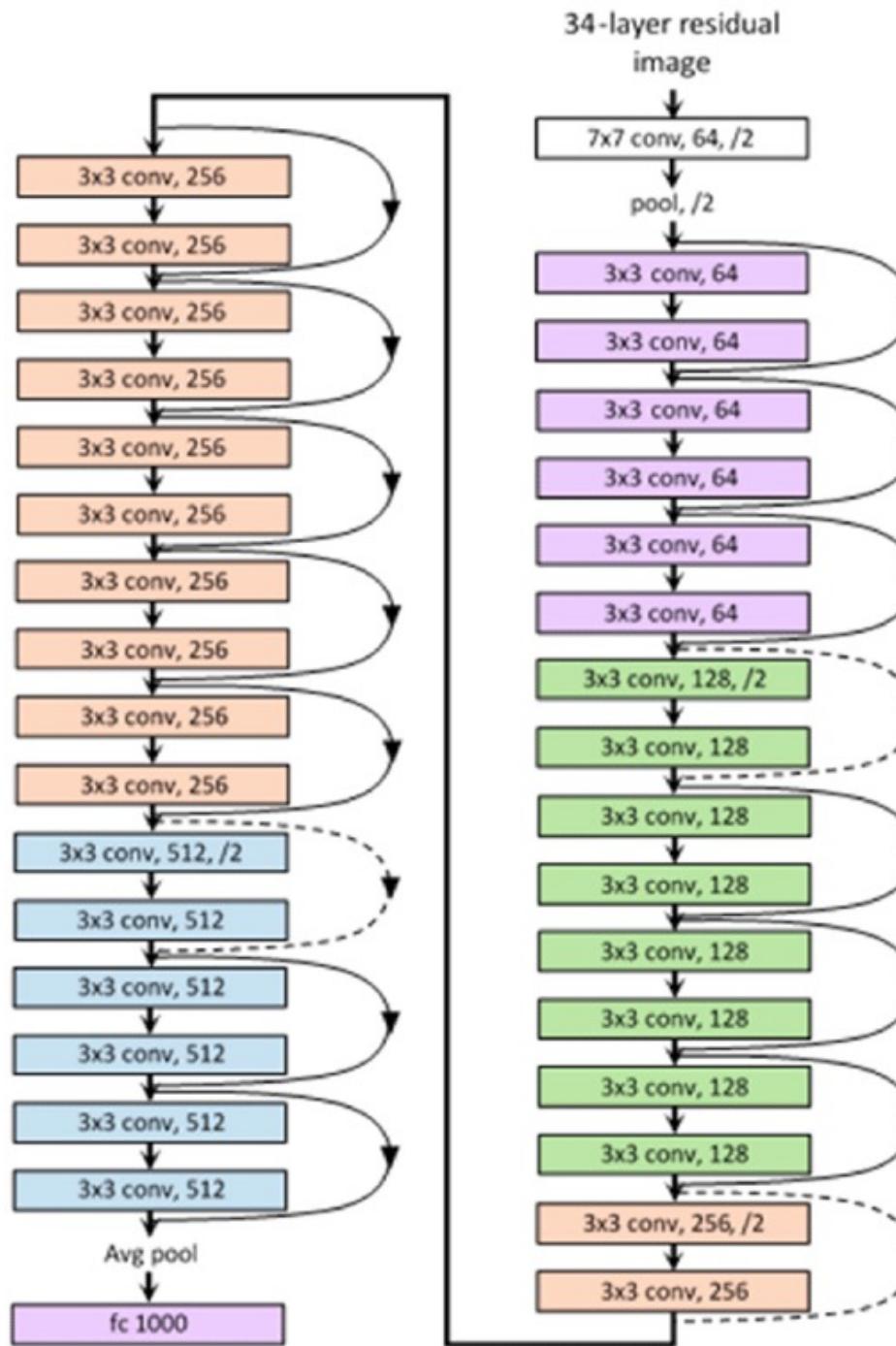
# ¿Cómo hacer el transfer learning?



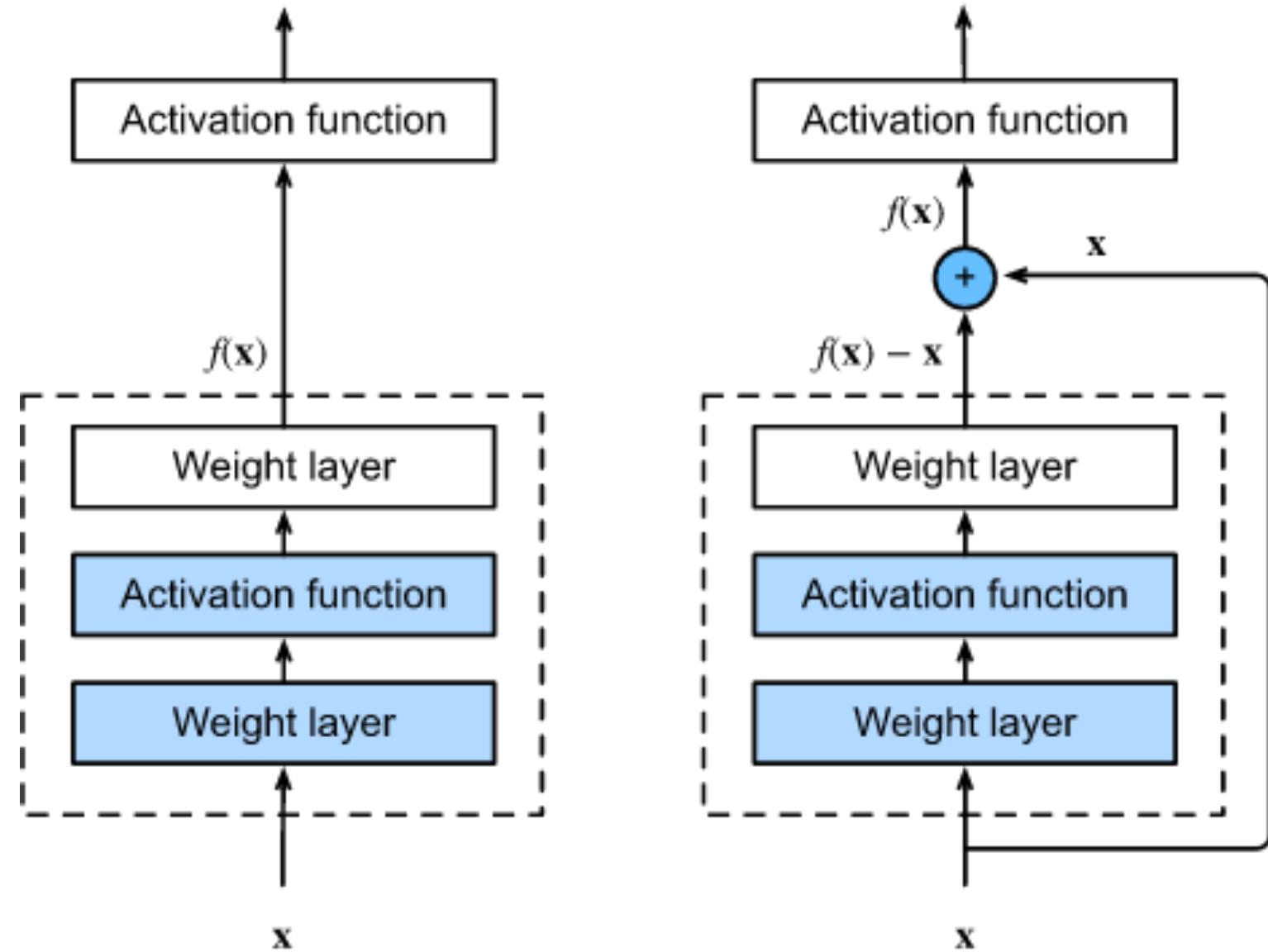
# Algunos modelos conocidos: VGG-16

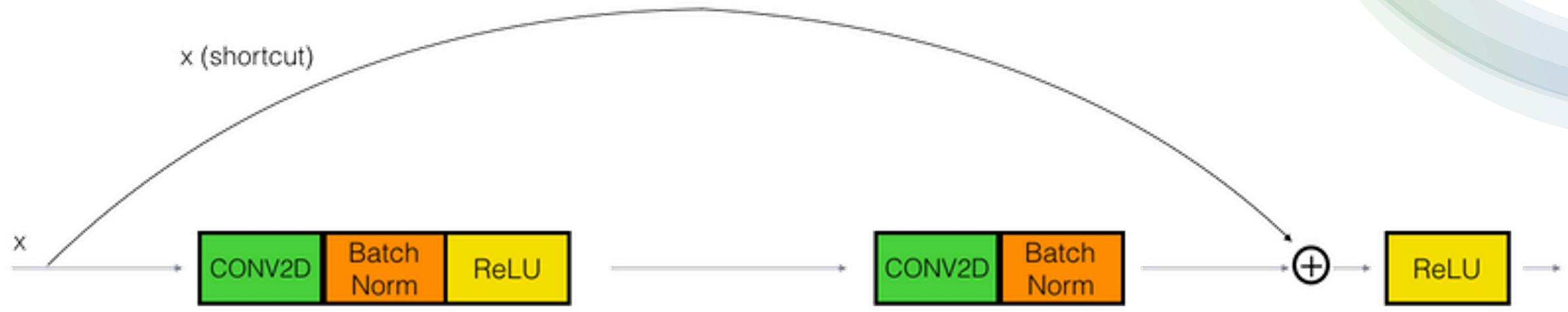


# Algunos modelos conocidos: ResNet



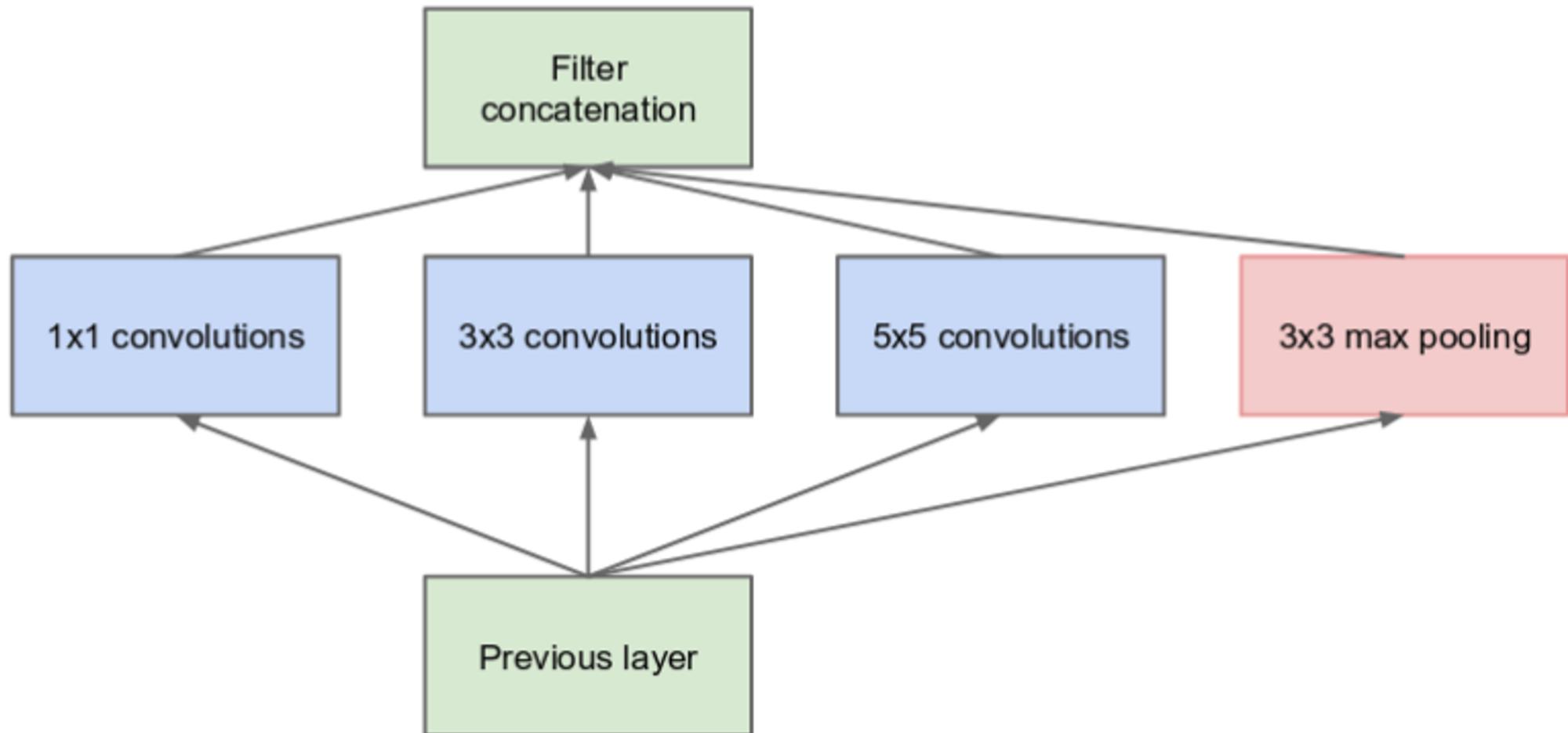
# Algunos Modelos: ResNet





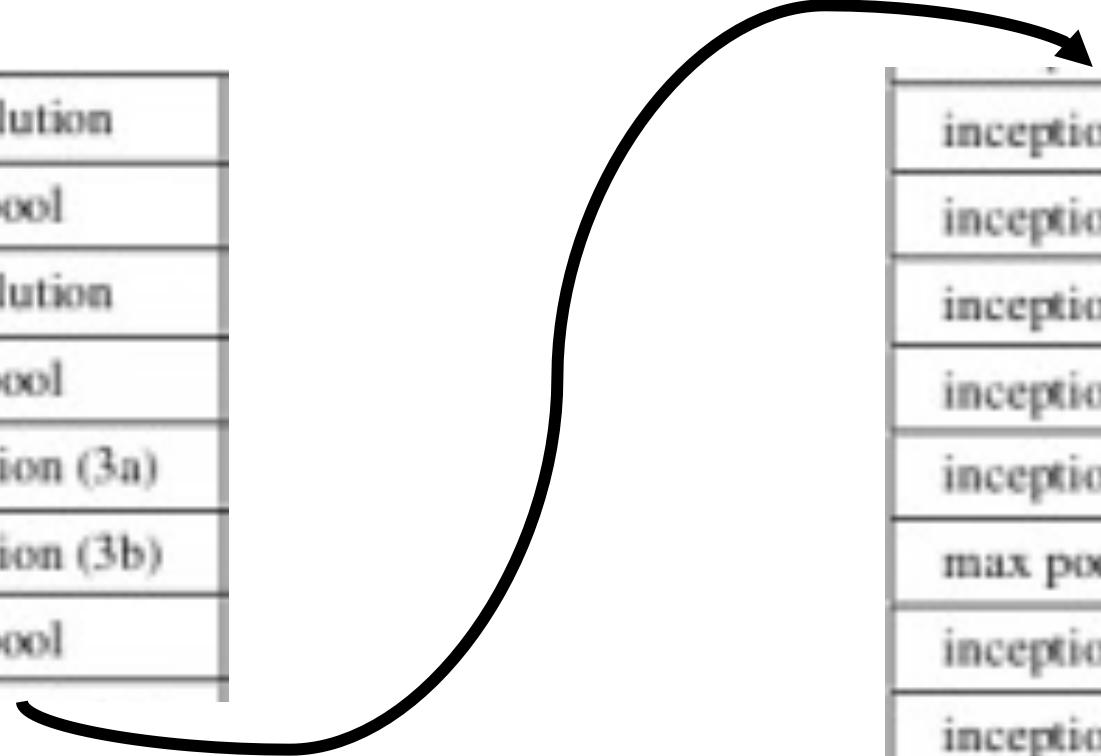
## Algunos Modelos: ResNet

# Algunos modelos: Inception



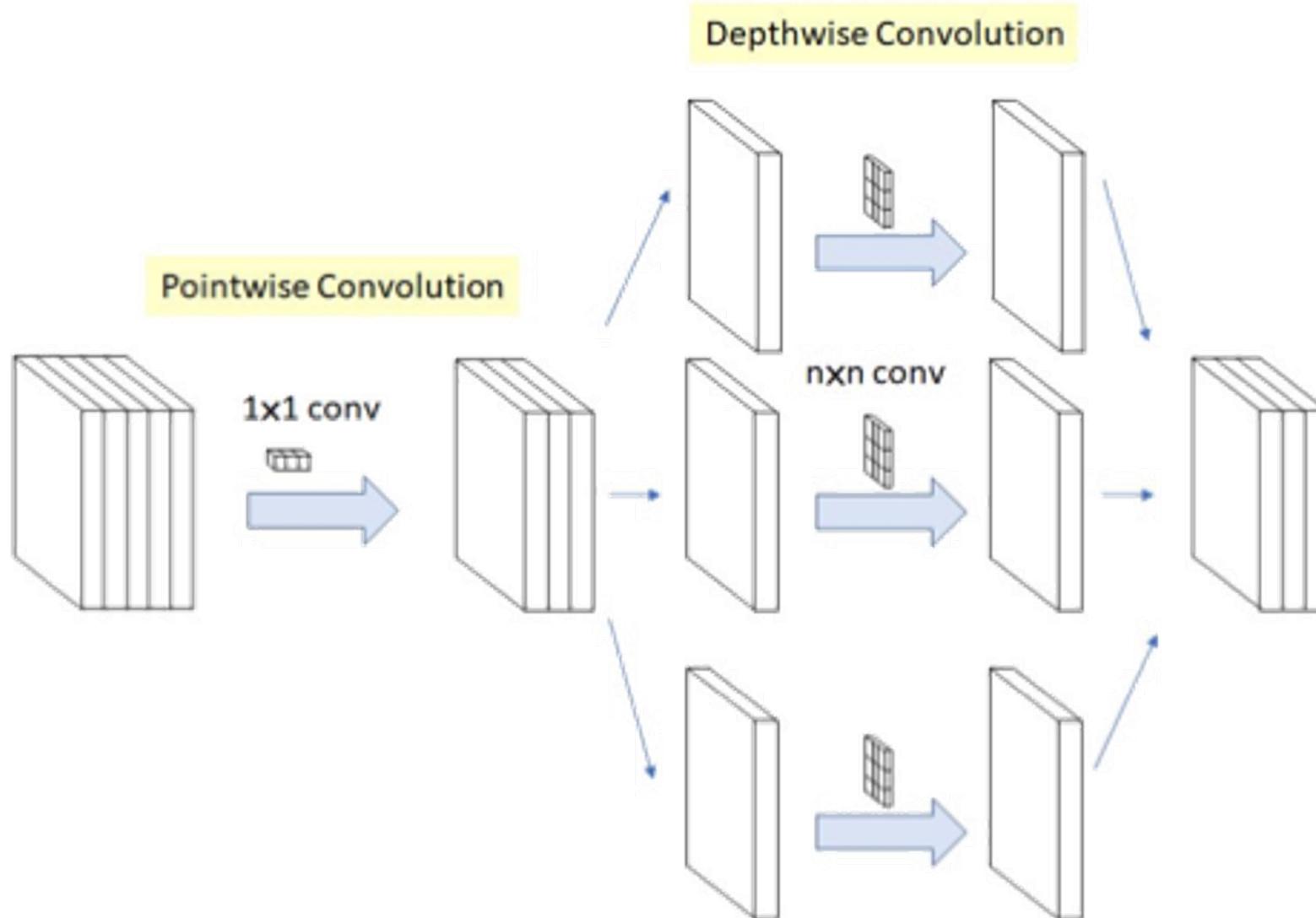
# Algunos modelos: Inception

convolution
max pool
convolution
max pool
inception (3a)
inception (3b)
max pool

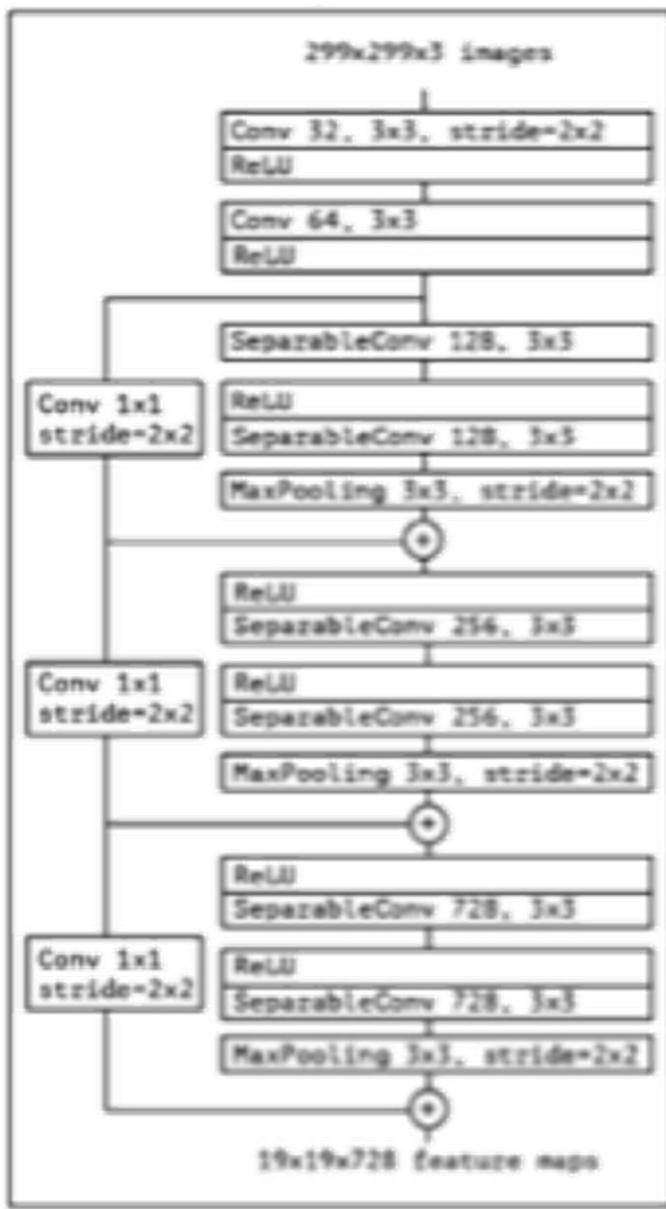


inception (4a)
inception (4b)
inception (4c)
inception (4d)
inception (4e)
max pool
inception (5a)
inception (5b)
avg pool
dropout (40%)
linear
softmax

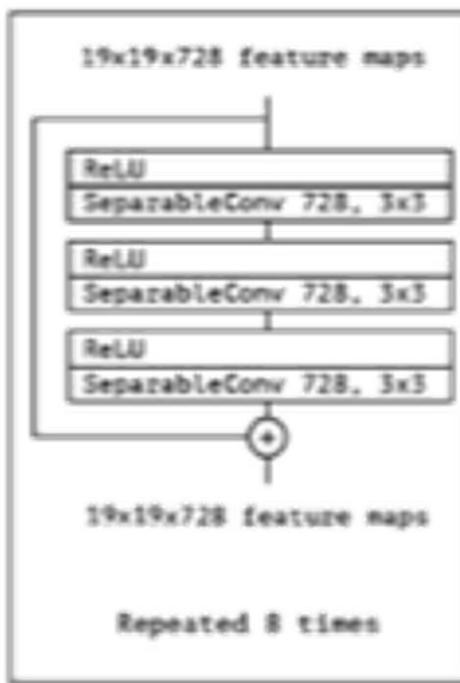
# Algunos modelos: Xception



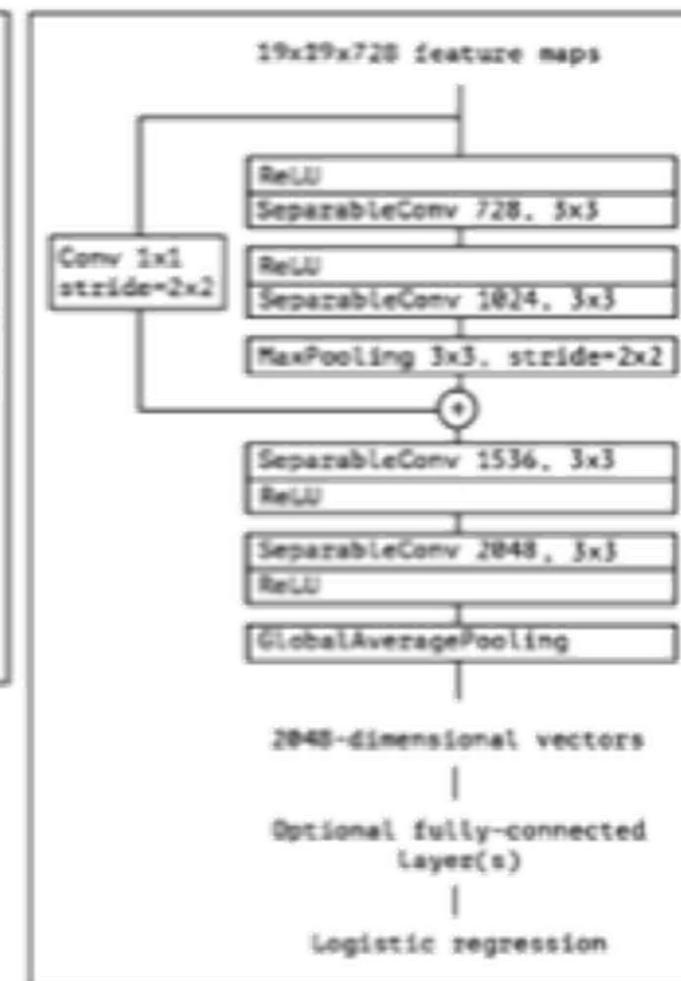
### Entry flow



## Middle flow



### Exit flow



# ¿Dónde consultar modelos existentes?

- Papers with code: <https://paperswithcode.com>
- Tensorflow Hub: <https://www.tensorflow.org/resources/models-datasets>
- Model Zoo: <https://modelzoo.co>
- Hugging face: <https://huggingface.co/models>



deeplearning.ai

# Neural Style Transfer

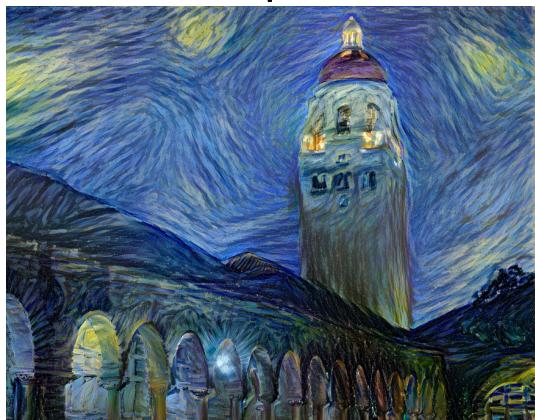
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# Neural style transfer



Content

Style



Generated image



Content

Style



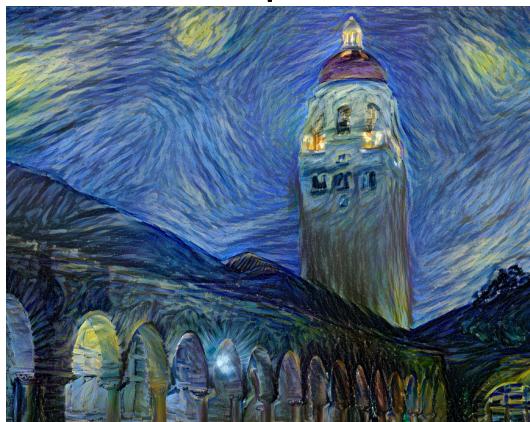
Generated image

# Neural style transfer cost function



Content C

Style S



Generated image G

$$J(G) = \alpha J_{\text{Content}}(C, G) + \beta J_{\text{Style}}(S, G)$$

# Find the generated image $G$

1. Initiate  $G$  randomly

$G: 100 \times 100 \times 3$



2. Use gradient descent to minimize  $J(G)$



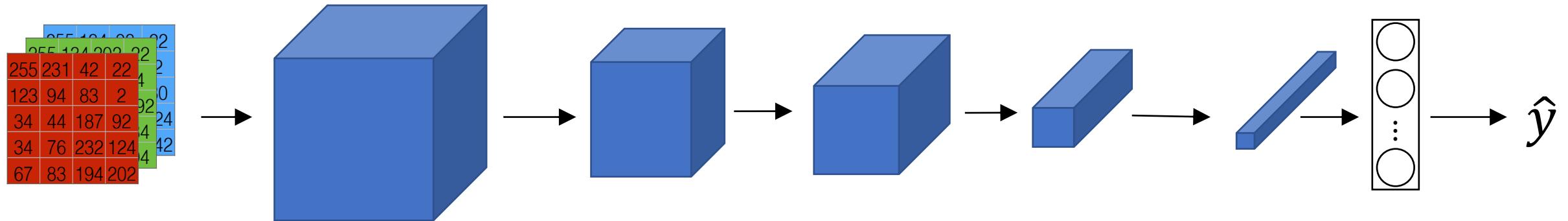
# Content cost function

$$J(G) = \alpha J_{content}(C, G) + \beta J_{style}(S, G)$$

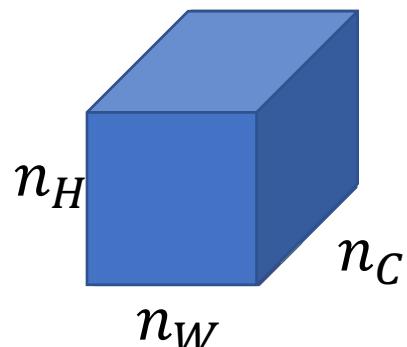
- Say you use hidden layer  $l$  to compute content cost.
- Use pre-trained ConvNet. (E.g., [VGG network](#))
- Let  $a^{[l]}(C)$  and  $a^{[l]}(G)$  be the activation of layer  $l$  on the images
- If  $a^{[l]}(C)$  and  $a^{[l]}(G)$  are similar, both images have similar content

$$J_{content}(C, G) = \frac{1}{2} \| \underbrace{a^{[l]}(C)}_{\text{activation}} - \underbrace{a^{[l]}(G)}_{\text{activation}} \|_2^2$$

# Meaning of the “style” of an image



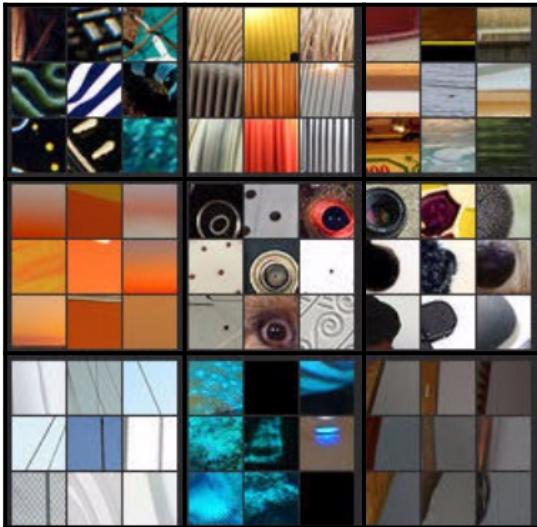
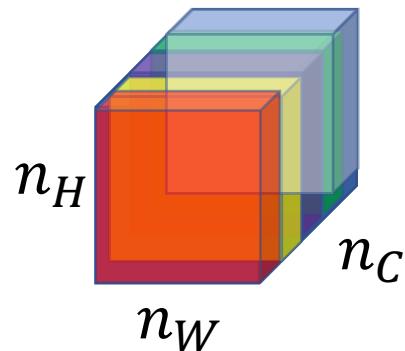
Say you are using layer  $l$ 's activation to measure “style.”  
Define style as correlation between activations across channels.



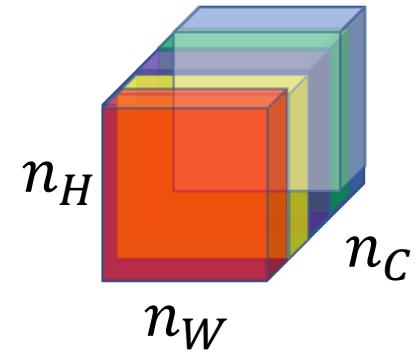
How correlated are the activations  
across different channels?

# Intuition about style of an image

Style image



Generated Image



[Gatys et al., 2015. A neural algorithm of artistic style]

# Style matrix

Let  $a_{i,j,k}^{[l]}$  = activation at  $(i, j, k)$ .  $G^{[l]}$  is  $n_c^{[l]} \times n_c^{[l]}$

$$\rightarrow G_{kk'}^{[l](s)} = \sum_{i=1}^{n_h^{[l]}} \sum_{j=1}^{n_w^{[l]}} a_{ijk}^{[l](s)} a_{ijk'}^{[l](s)}$$

$$\rightarrow G_{kk'}^{[l](w)} = \sum_{i=1}^{n_h^{[l]}} \sum_{j=1}^{n_w^{[l]}} a_{ijk}^{[l](w)} a_{ijk'}^{[l](w)}$$

H W C  
↓ ↓ ↓

$n_c$

$$G_{kk'}^{[l]} \quad \forall k, k' \in \{1, \dots, n_c\}$$

"Gram matrix"

$$\begin{aligned} J_{style}^{[l]}(S, G) &= \frac{1}{(\dots)} \| G_{kk'}^{[l](s)} - G_{kk'}^{[l](w)} \|_F^2 \\ &= \frac{1}{(2n_h^{[l]} n_w^{[l]})^2} \sum_k \sum_{k'} (G_{kk'}^{[l](s)} - G_{kk'}^{[l](w)})^2 \end{aligned}$$

# Style cost function

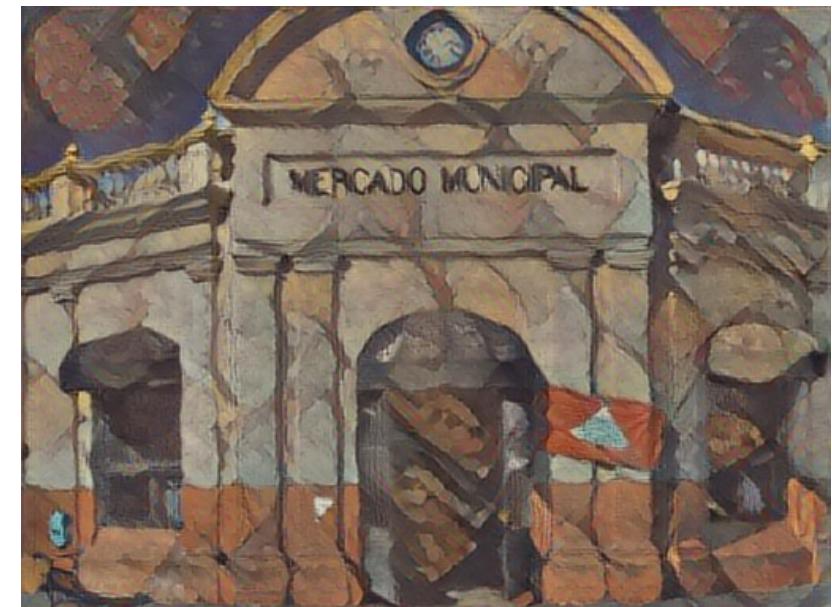
$$\left\| G^{[l](s)} - G^{[l](G)} \right\|_F^2$$

$$J_{style}^{[l]}(S, G) = \frac{1}{\left(2n_H^{[l]} n_W^{[l]} n_C^{[l]}\right)^2} \sum_k \sum_{k'} (G_{kk'}^{[l](s)} - G_{kk'}^{[l](G)})$$

$$J_{style}(S, G) = \sum_l \lambda^{[l]} J_{style}^{[l]}(S, G)$$

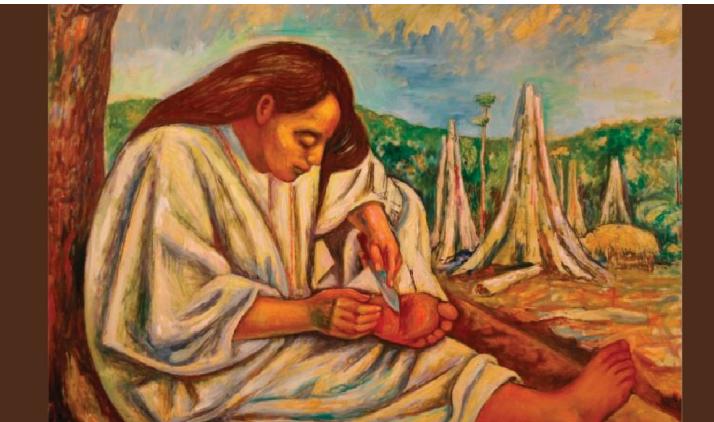
$$\underbrace{J(G)}_G = \alpha J_{content}(S, G) + \beta J_{style}(S, G)$$

# Ejemplos



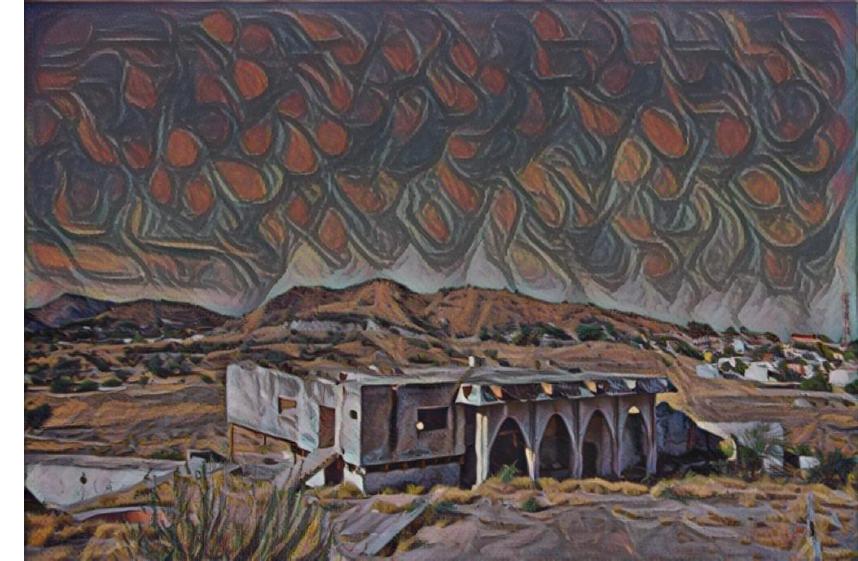
Jose Luis Aguilera Luzanía

# Ejemplos



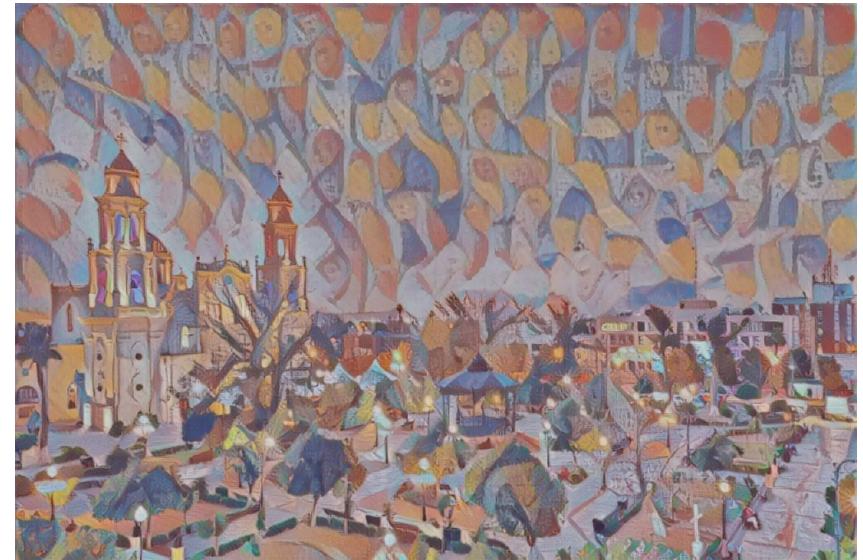
Christopher Arce Díaz

# Ejemplos



Raúl Murcia Yocupicio

# Ejemplos



Ximena Sandoval