



# WALC 2024 Applied AI

## Introduction to Convolutions

Prof. Marcelo J. Rovai

[rovai@unifei.edu.br](mailto:rovai@unifei.edu.br)

UNIFEI - Federal University of Itajuba, Brazil

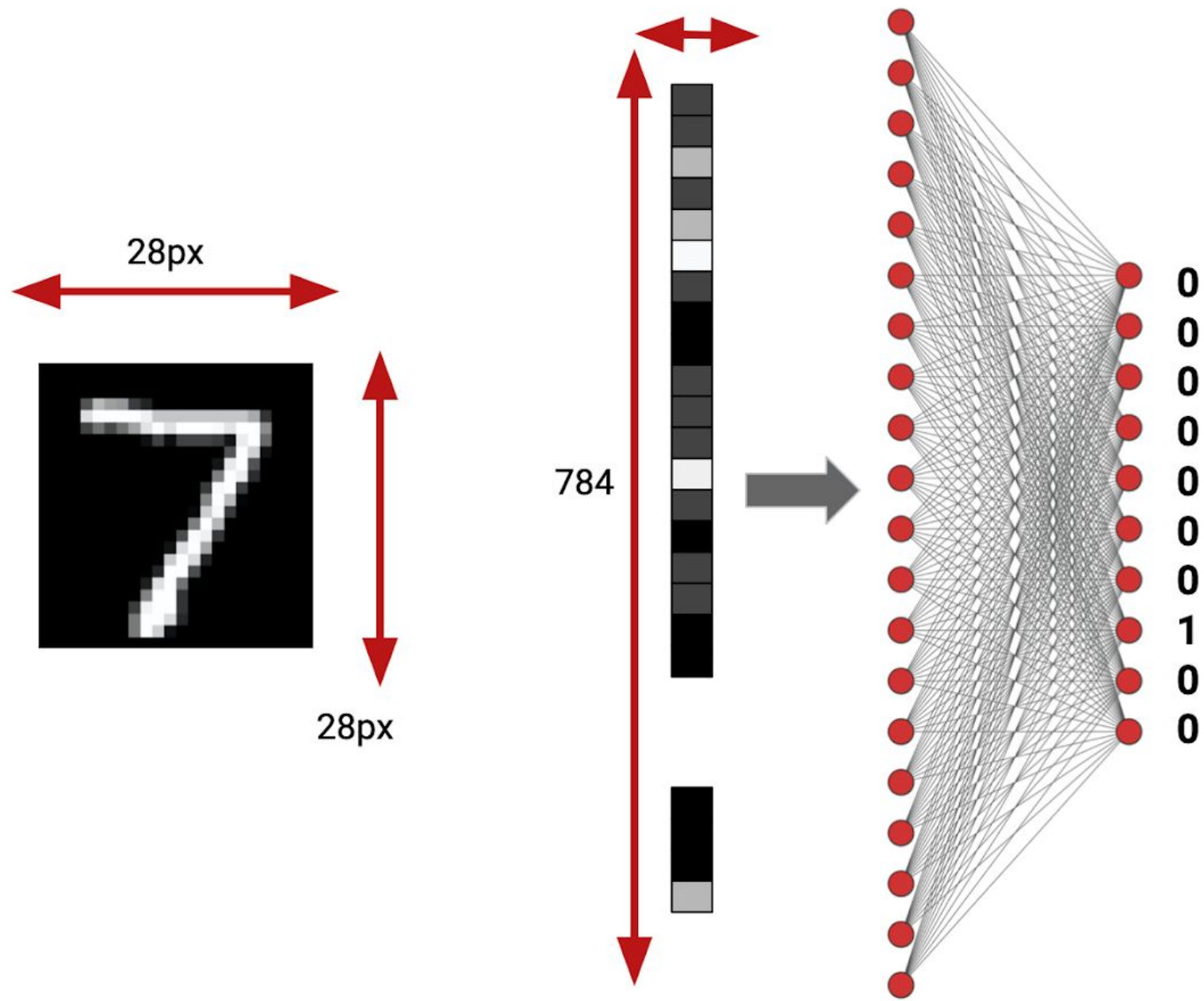
TinyML4D Academic Network Co-Chair



**TINYML4D**

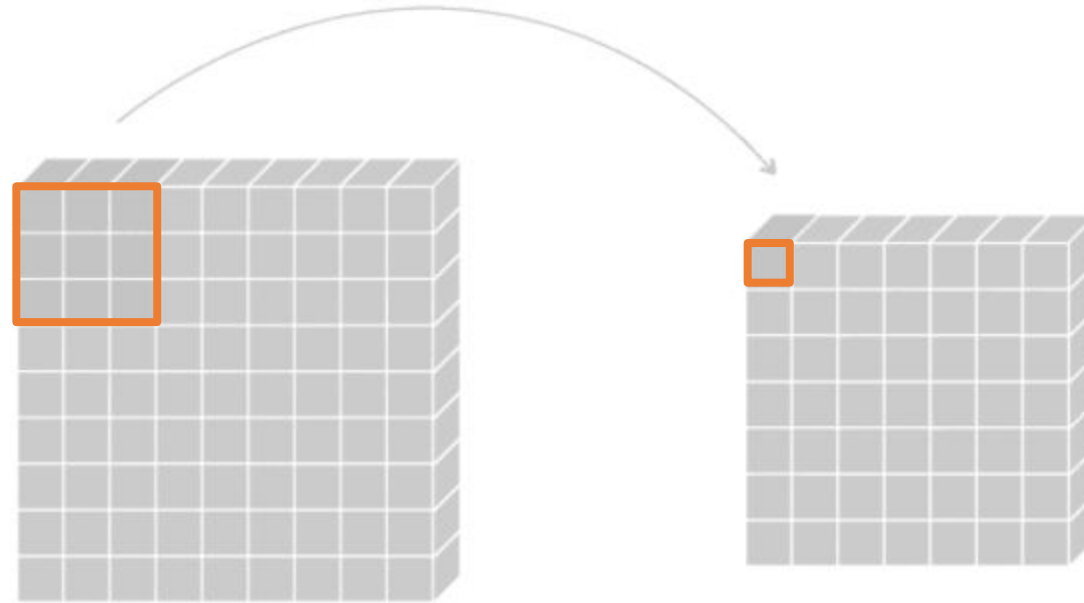
# Introducing Convolutions

Beyond weights and biases...

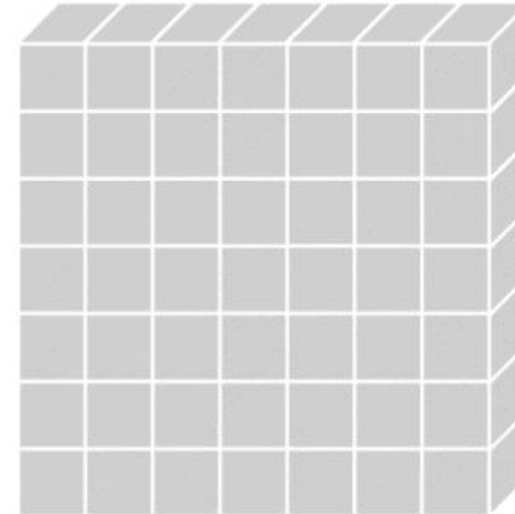
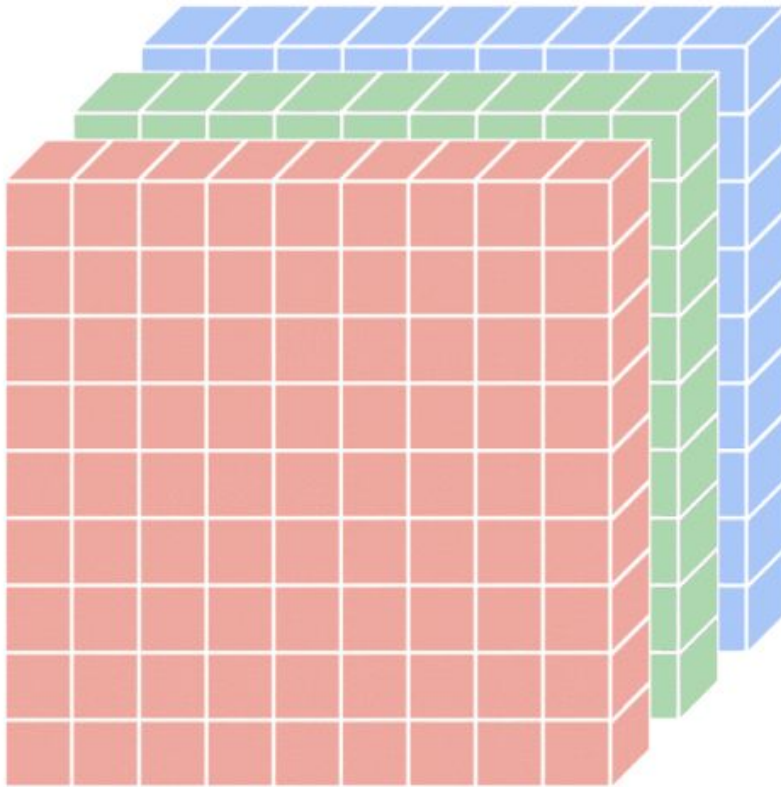




# Standard Convolution (1 Channel)

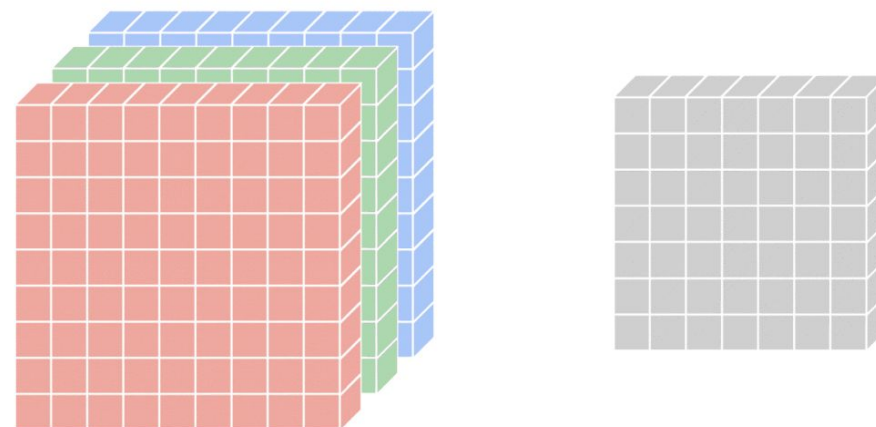


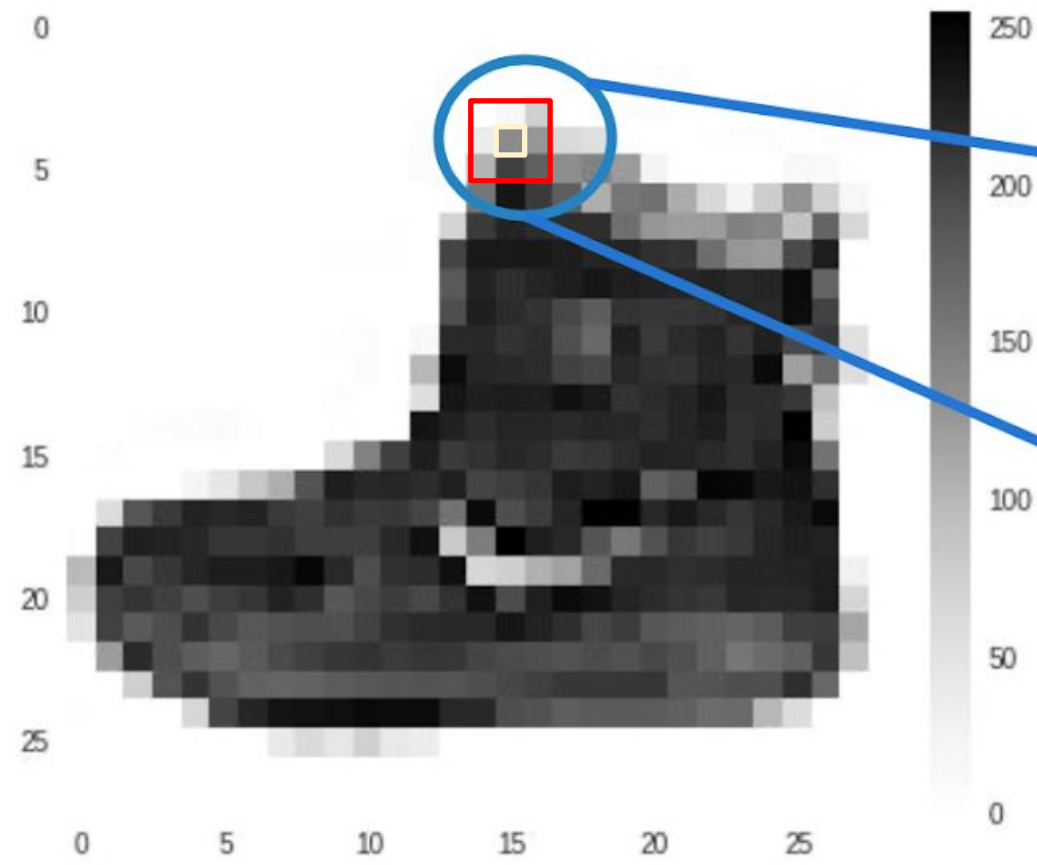
# Standard Convolution (**3 Channel**—e.g., *RGB*)



# Standard Convolution (**3 Channel**—e.g., *RGB*)

- Input Feature Map
  - $8 \times 8 \times 3$
  - Width  $\times$  Height  $\times$  Channels
- Kernel (*1 Filter*)
  - $3 \times 3 \times 3$





0	64	128
48	192	144
142	226	168

Current Pixel Value is 192  
Consider neighbor Values

-1	0	-2
.5	4.5	-1.5
1.5	2	-3

Filter Definition

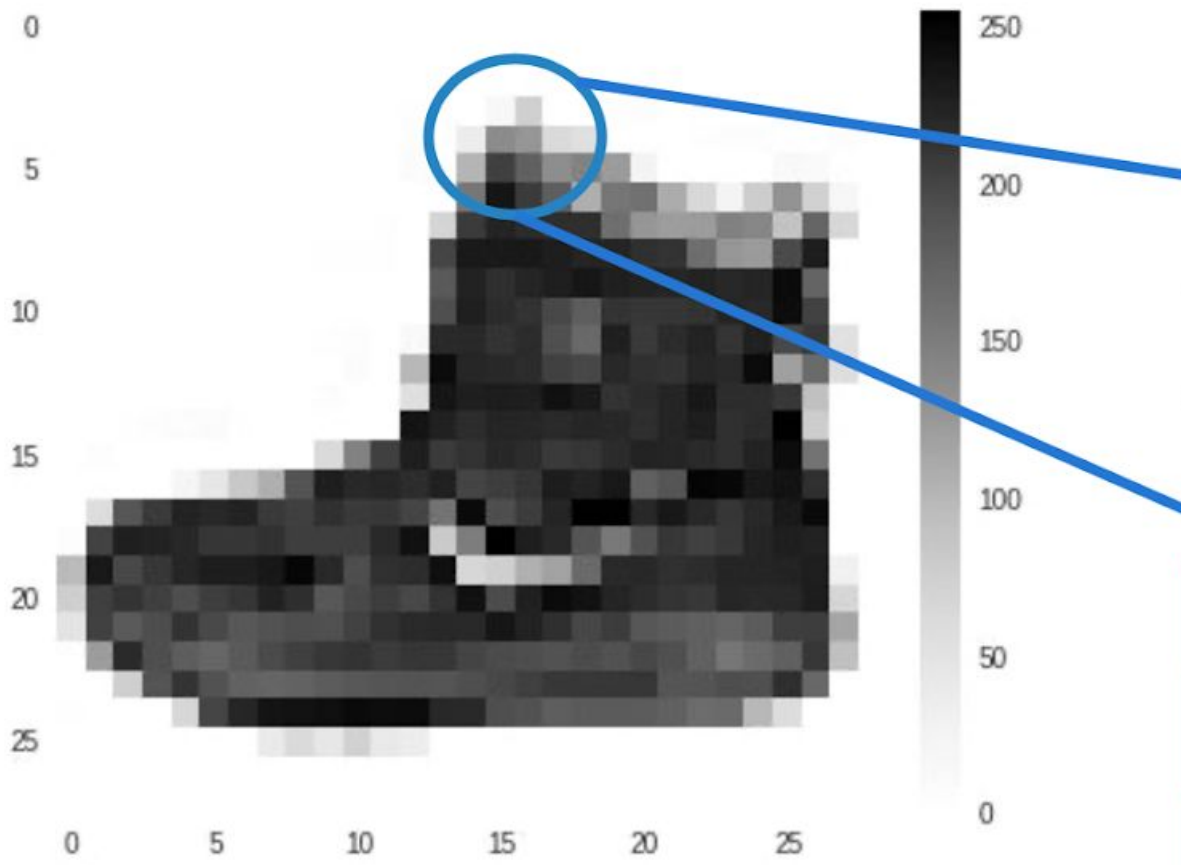
CURRENT\_PIXEL\_VALUE = 192

$$\begin{aligned} \text{NEW\_PIXEL\_VALUE} = & (-1 * 0) + (0 * 64) + (-2 * 128) + \\ & (.5 * 48) + (4.5 * 192) + (-1.5 * 144) + \\ & (1.5 * 42) + (2 * 226) + (-3 * 168) \end{aligned}$$

-256  
672  
11

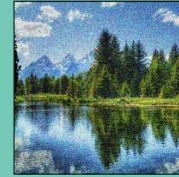
427 ← New Pixel Value





**Kernels = Filters**

# Different Filters



Noise



Gaussian Blur



Sharpen More



Fragment



Facet



Pointillize



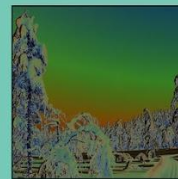
Mosaic



Tiles



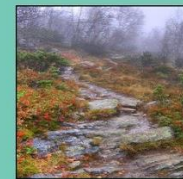
Mezzotint



Solarize



Trace Contour



Wind



Clouds



Find Edges



Shape Blur



Fibers

# Image Kernels

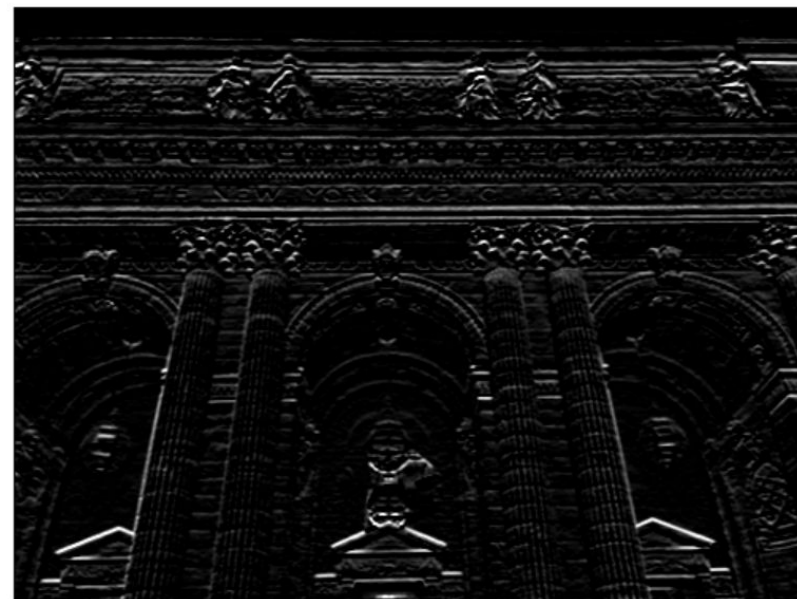


-1	0	1
-2	0	2
-1	0	1

custom

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

custom



<https://setosa.io/ev/image-kernels/>

0	64	128	128
48	192	144	144
142	226	168	0
255	0	0	64

0	64
48	192

192

128	128
144	144

144

142	226
255	0

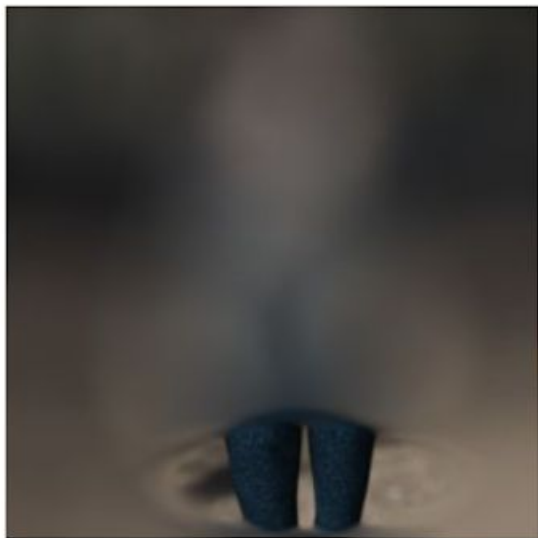
255

168	0
0	64

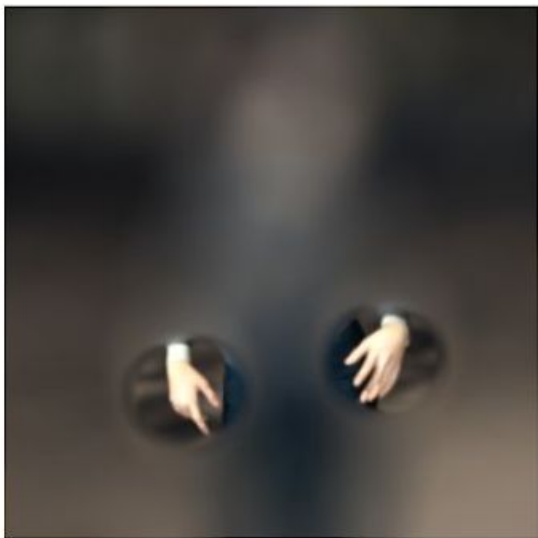
168

192	144
255	168

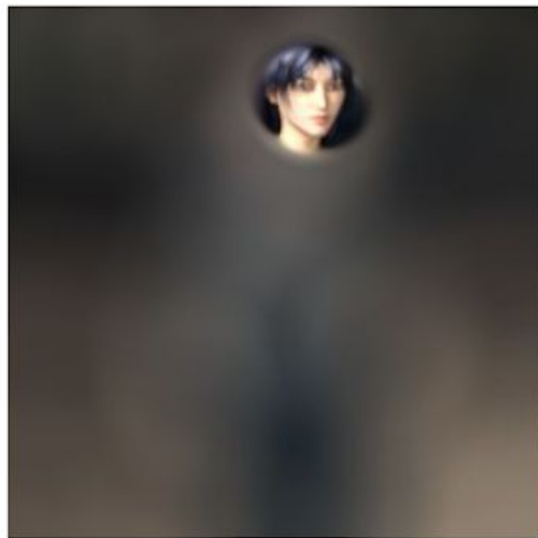
Max Pooling



+

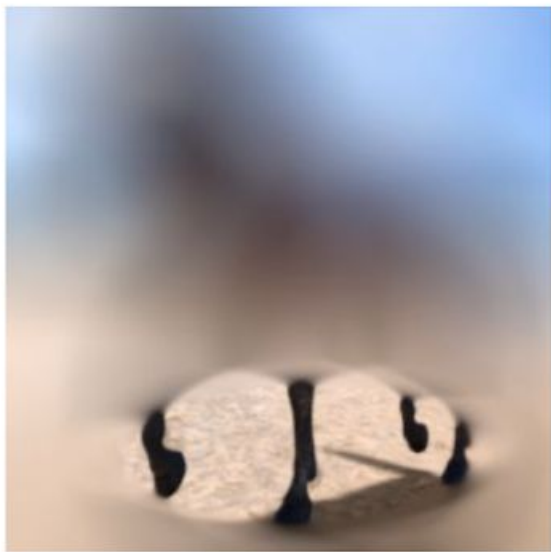


+

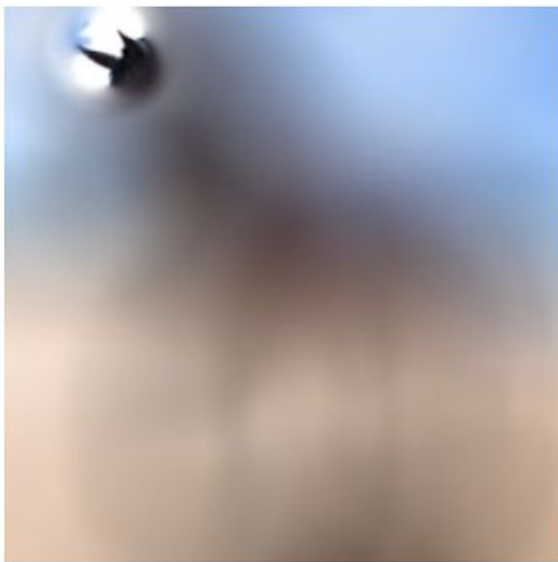


=

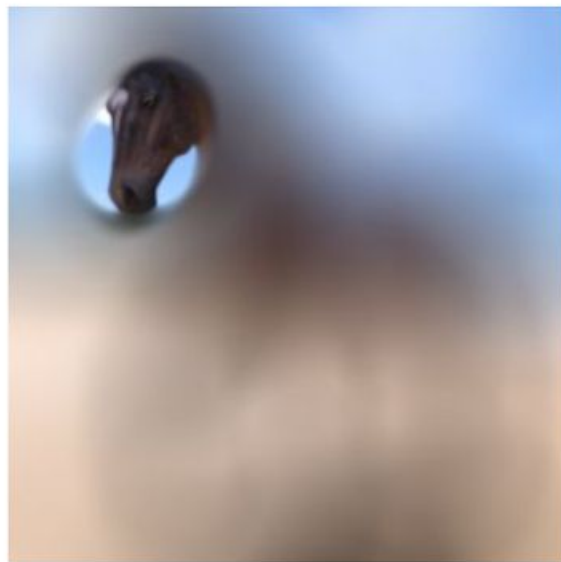
**HUMAN**



+



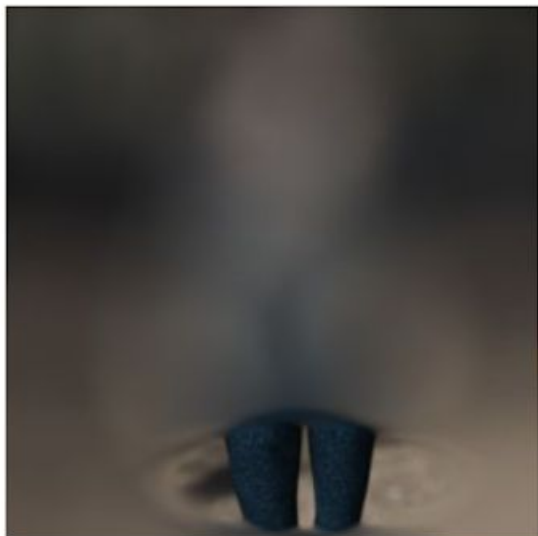
+



=

**HORSE**

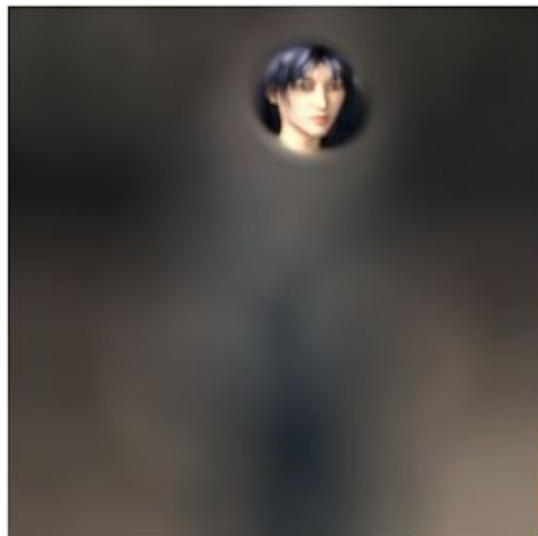




+

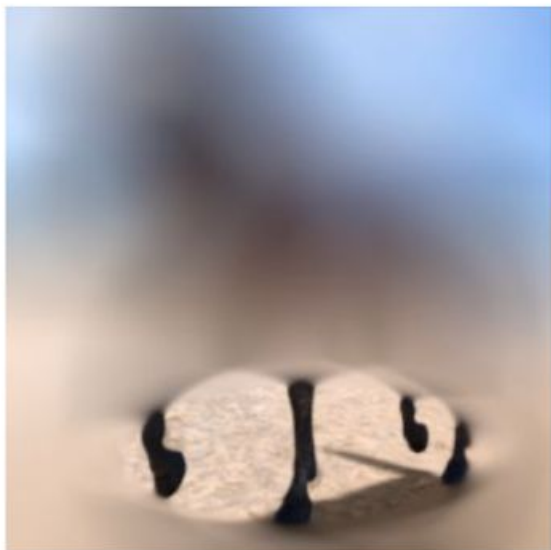


+



=

**HUMAN**

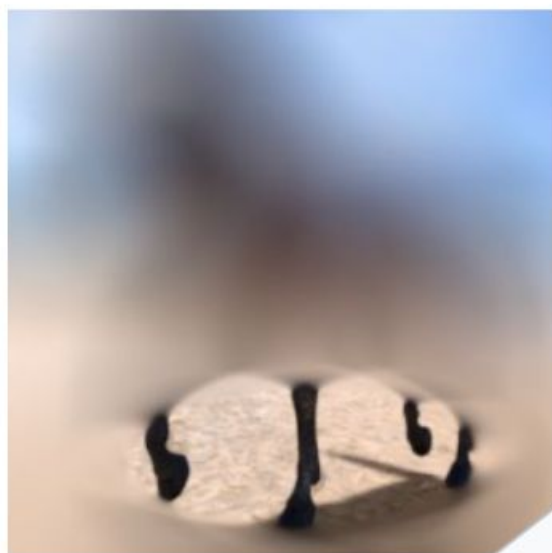


+

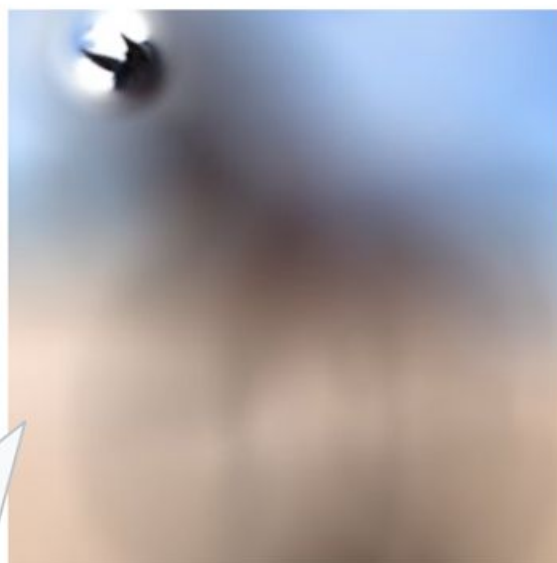


=

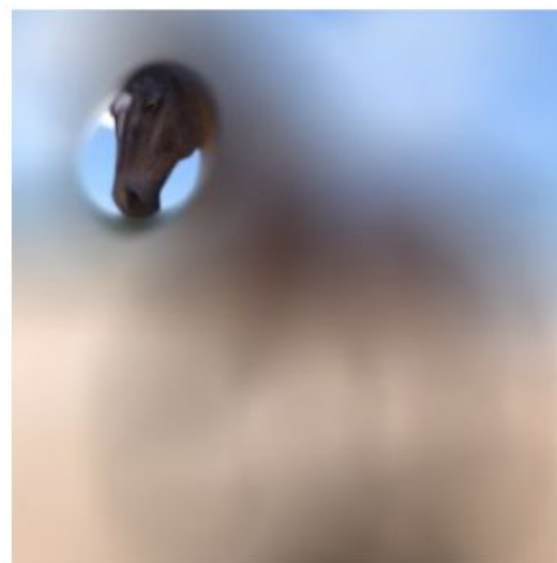
**HORSE**



+



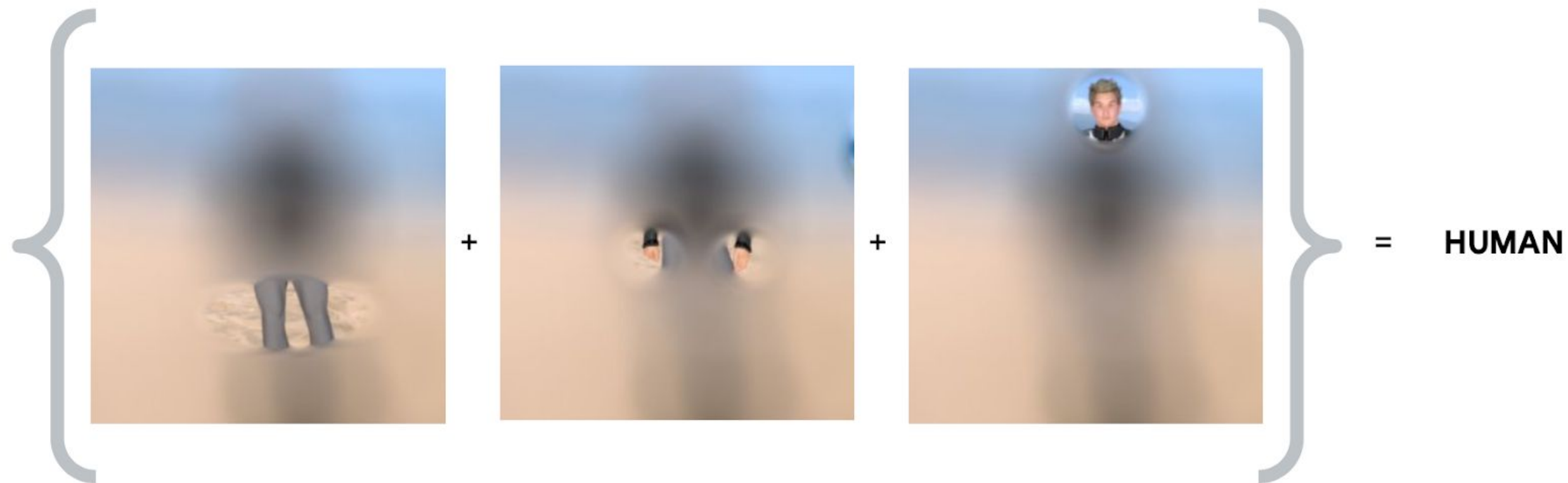
+

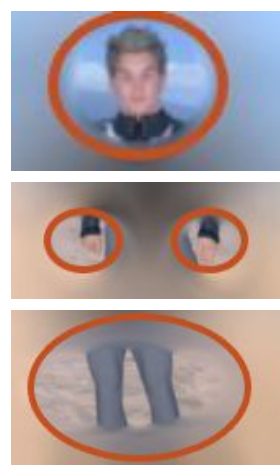
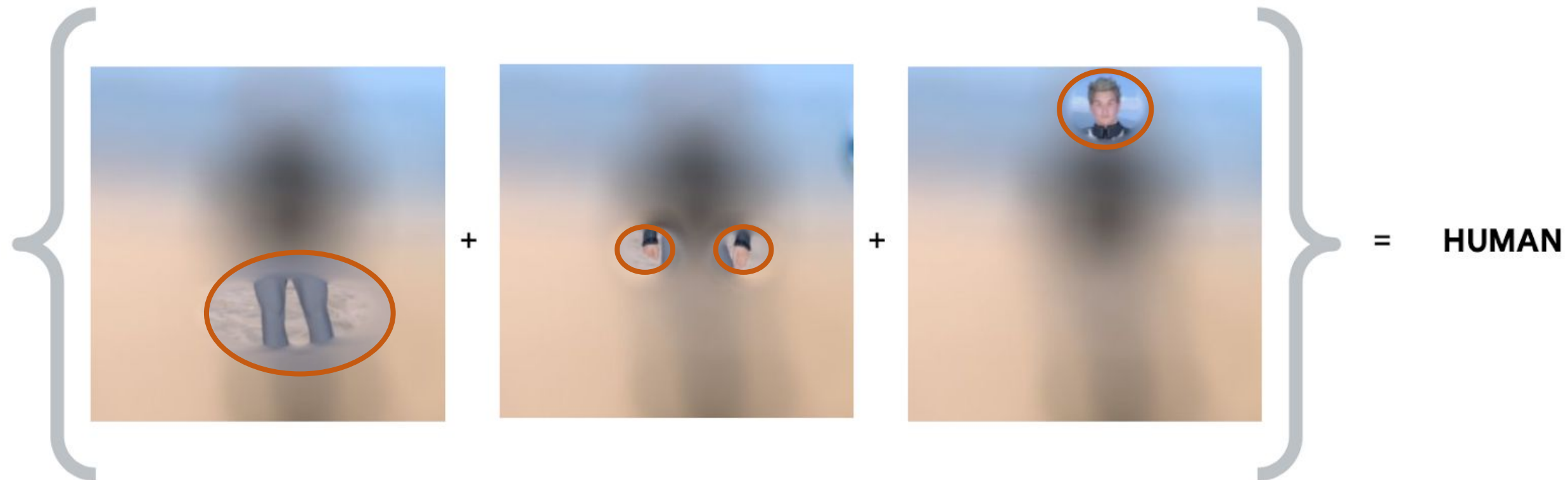


=

HORSE

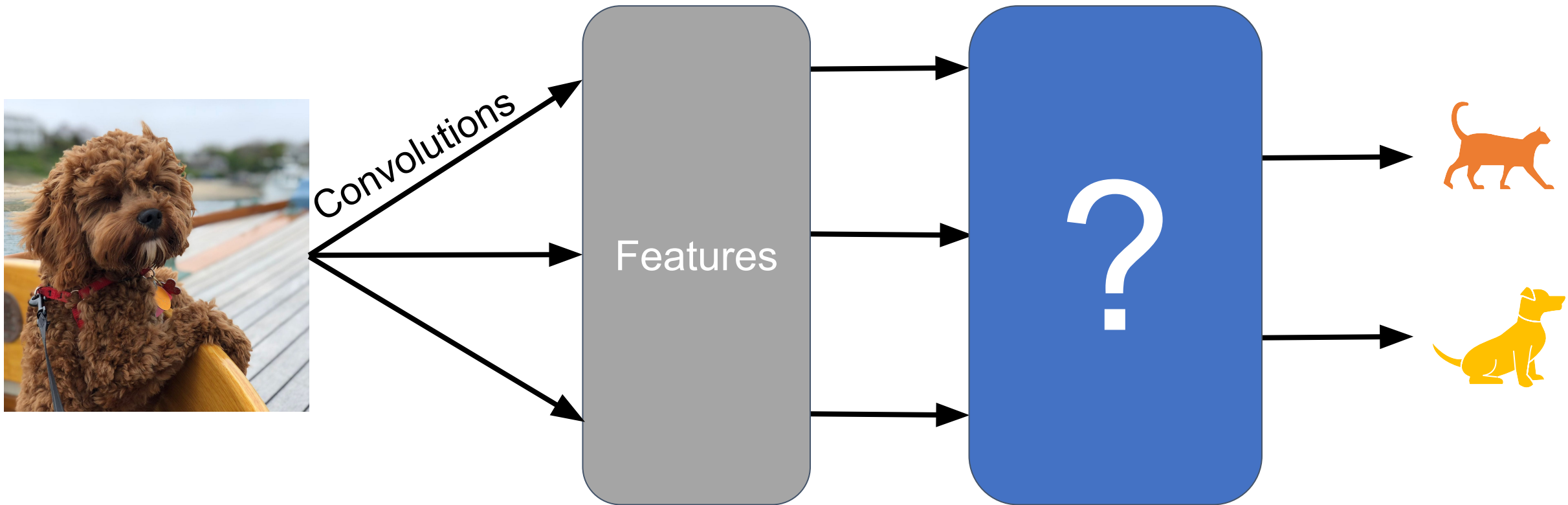
**Filters** can then be combined with **labels** to make a **prediction** of the image contents...



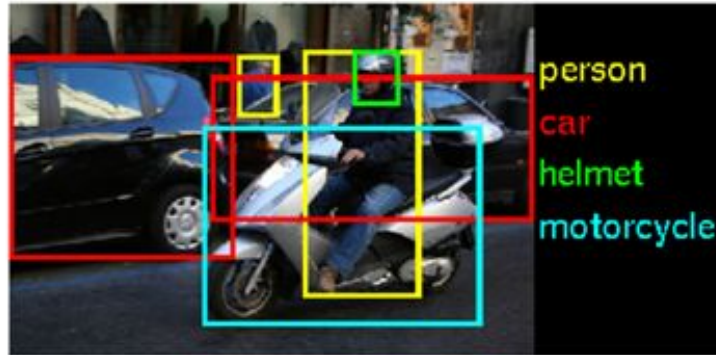
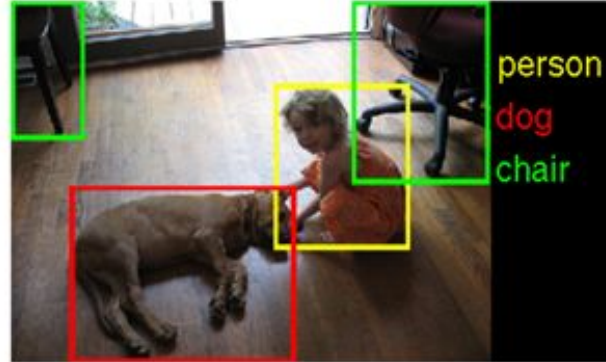
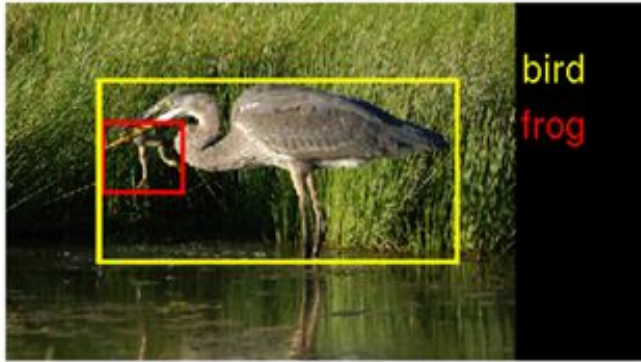




# How might we combine these features to **classify an object**?

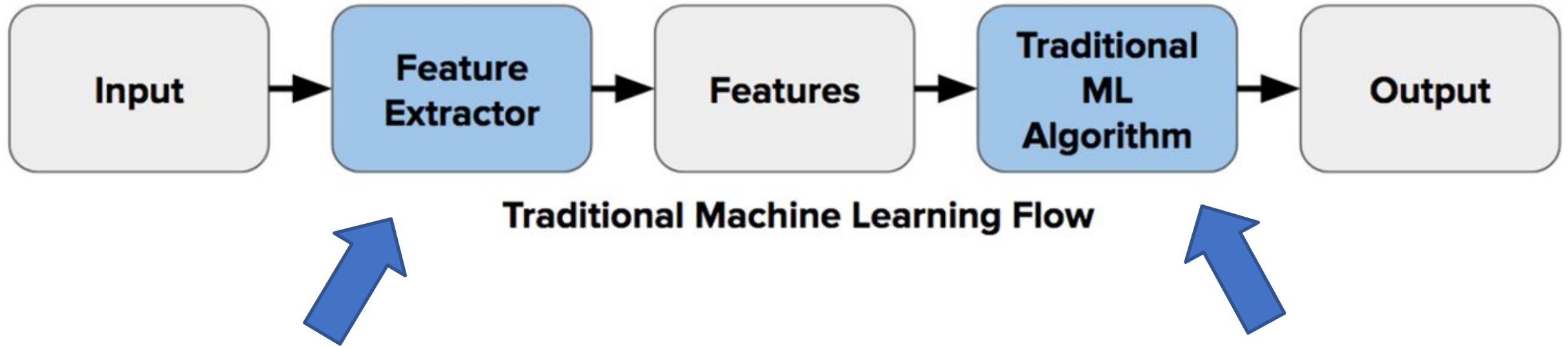


# The ImageNet Challenge and the Birth of CNNs



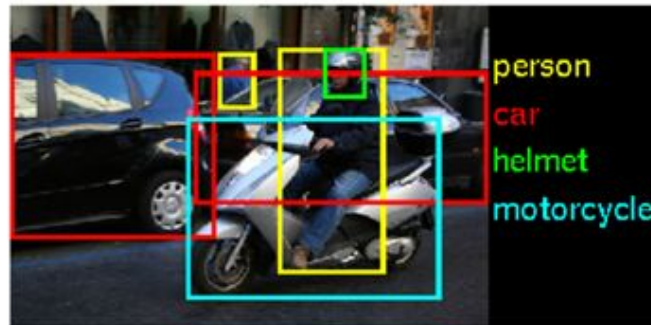
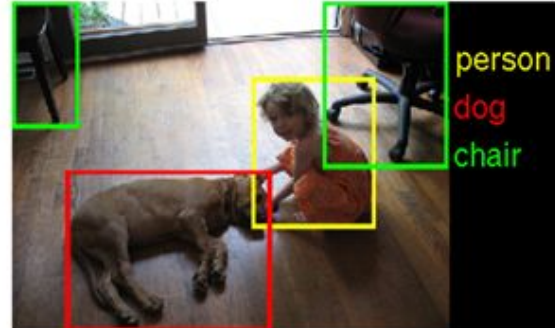
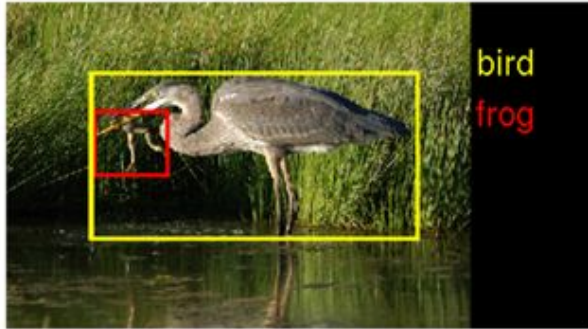
The ImageNet Challenge provided 1.2 million examples of 1,000 **labeled** items and challenged algorithms to learn from the data and then was tested on another 100,000 images

# The ImageNet Challenge and the Birth of CNNs



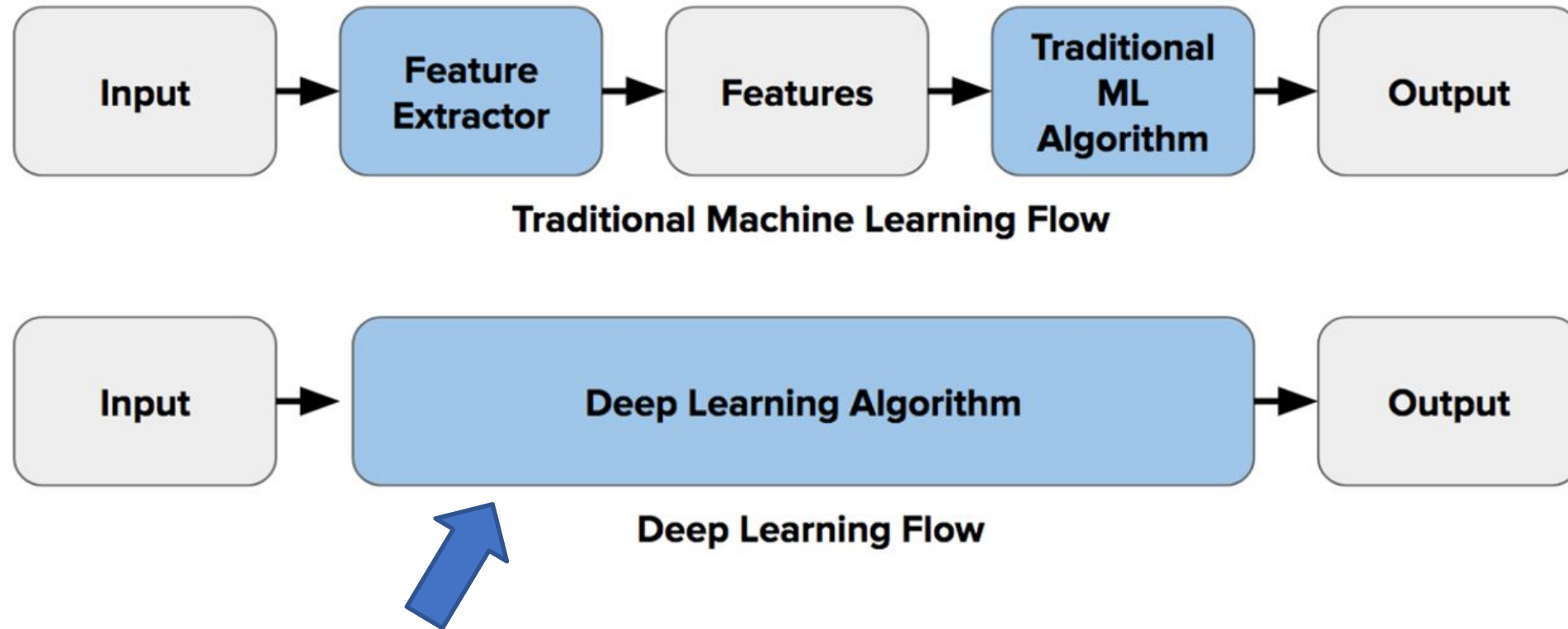
**Vertical Lines, Horizontal Lines, Changes in Color, Changes in Focus, etc.**      **Regression, Clustering, etc.**

# The ImageNet Challenge and the Birth of CNNs



- In 2010, teams had a 75-50% error
- In 2011, teams had 75-25% error
- In 2012 still, no team had less than 25% error barrier, except **AlexNet** at 15% (Top-5)

# The ImageNet Challenge and the Birth of CNNs

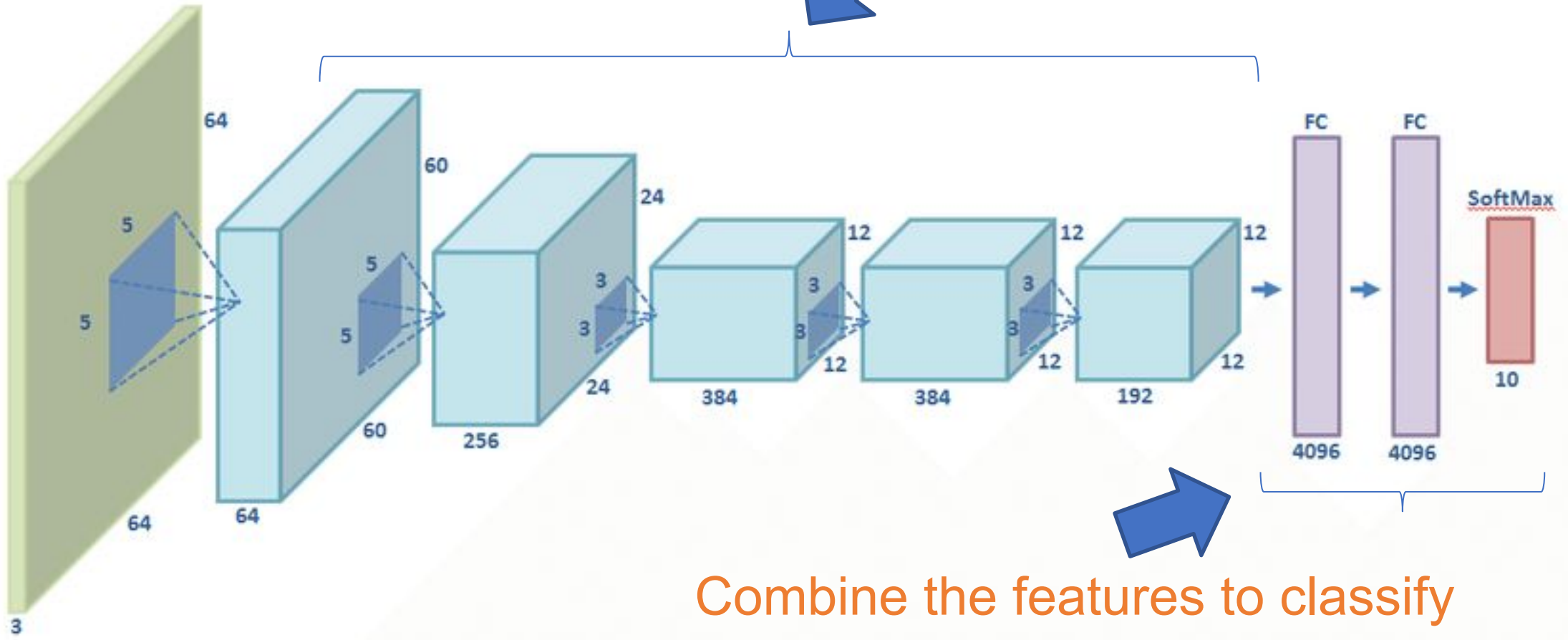


Let the computer figure out its features and how to combine them!



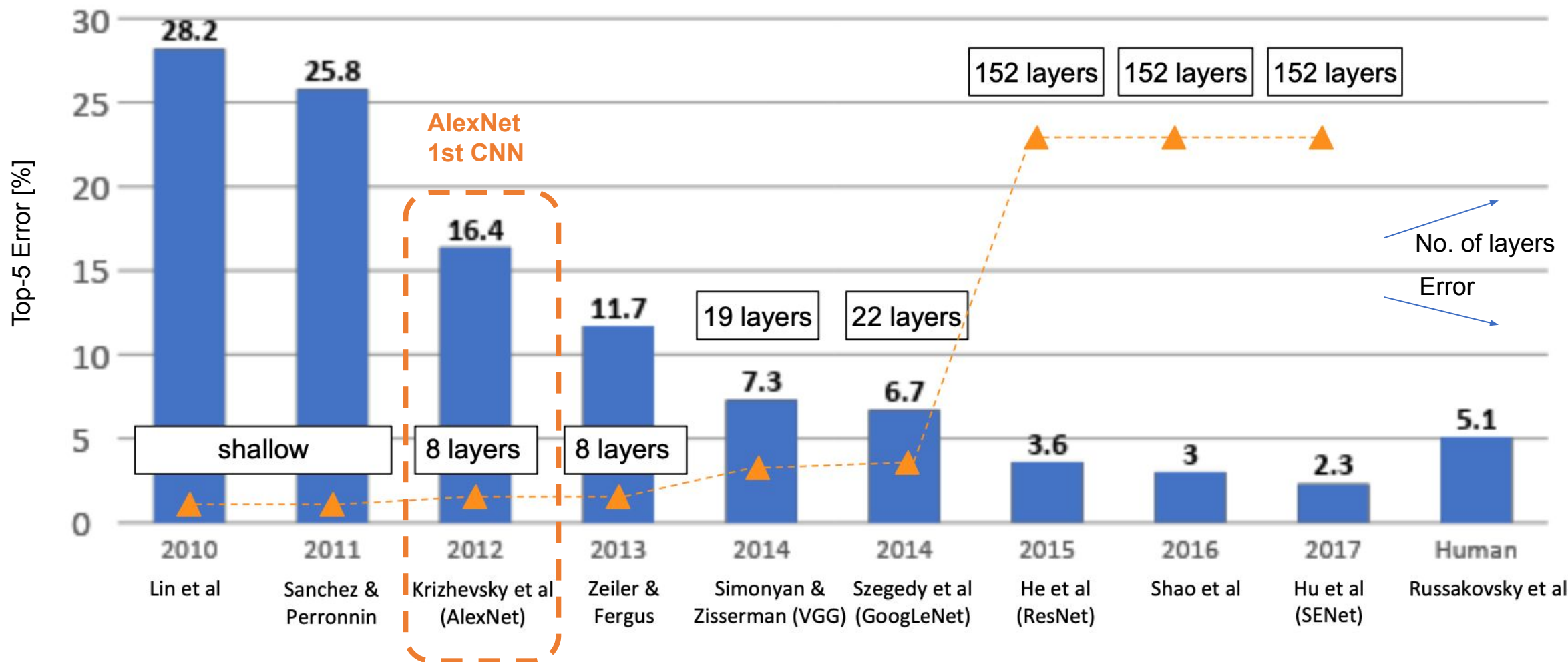
# AlexNet

Use convolutions to find features and summarize them into higher-level features



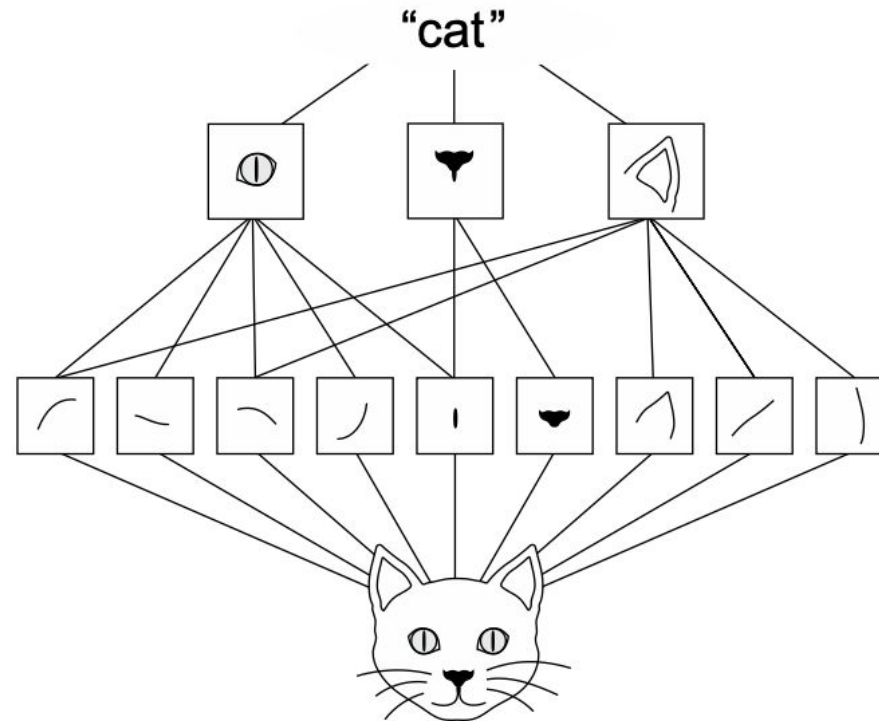
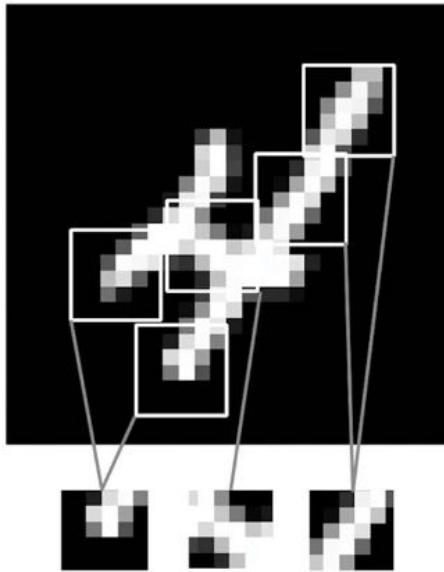
Combine the features to classify the various objects in the dataset.

# ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



# The convolution operation

The fundamental difference between a densely connected layer and a convolution layer is this: **Dense layers learn global patterns** in their input feature space (for example, for an MNIST digit, patterns involving all pixels), whereas **convolution layers learn local patterns**—in the case of images, patterns found in small 2D windows of the inputs. In the previous example, these windows were all  $3 \times 3$ .



*They can learn spatial hierarchies of patterns. A first convolution layer will learn small local patterns such as edges, a second convolution layer will learn larger patterns made of the features of the first layers, and so on.*



# Image Classification with CNN

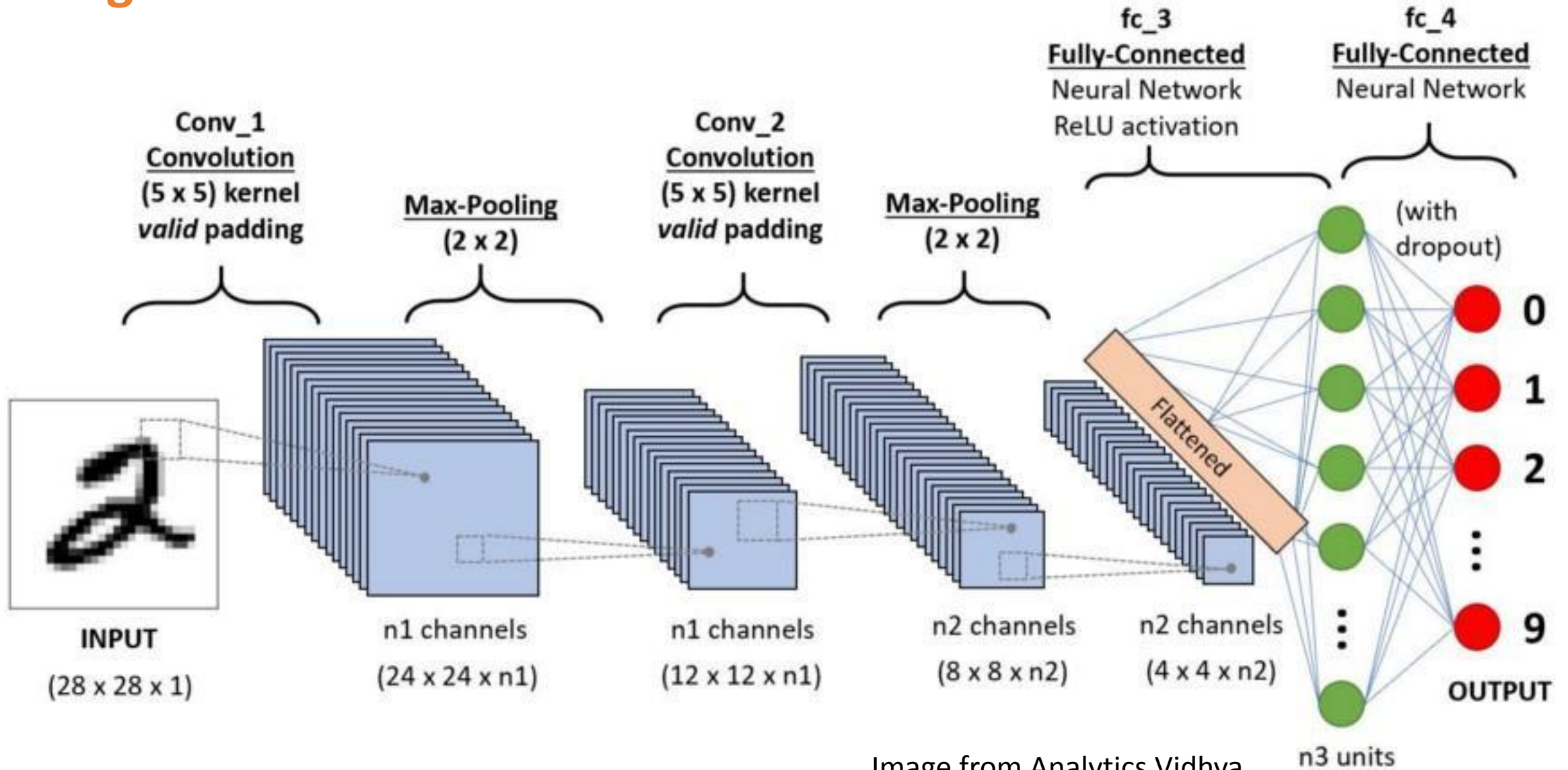


Image from Analytics Vidhya

# Exploring CNN

ConvNetJS MNIST demo

<https://cs.stanford.edu/people/karpathy/convnetjs/demo/mnist.html>

ConvNetJS CIFAR-10 demo

<https://cs.stanford.edu/people/karpathy/convnetjs/demo/cifar10.html>

CNN Explainer

<https://poloclub.github.io/cnn-explainer/>

# Questions?



27°

Taller sobre  
Tecnologías de Redes Internet  
para América Latina y el Caribe

Organización General