FILIPE ROLIM CORDEIRO (FILIPE.ROLIM@GMAIL.COM)

Dog vs Food


Verizon
4:20 PM
76%
Albums
chihuahua or muffin
Select
@teenybiscuit
karen zack @teenybiscuit · Mar 9
chihuahua or muffin ?

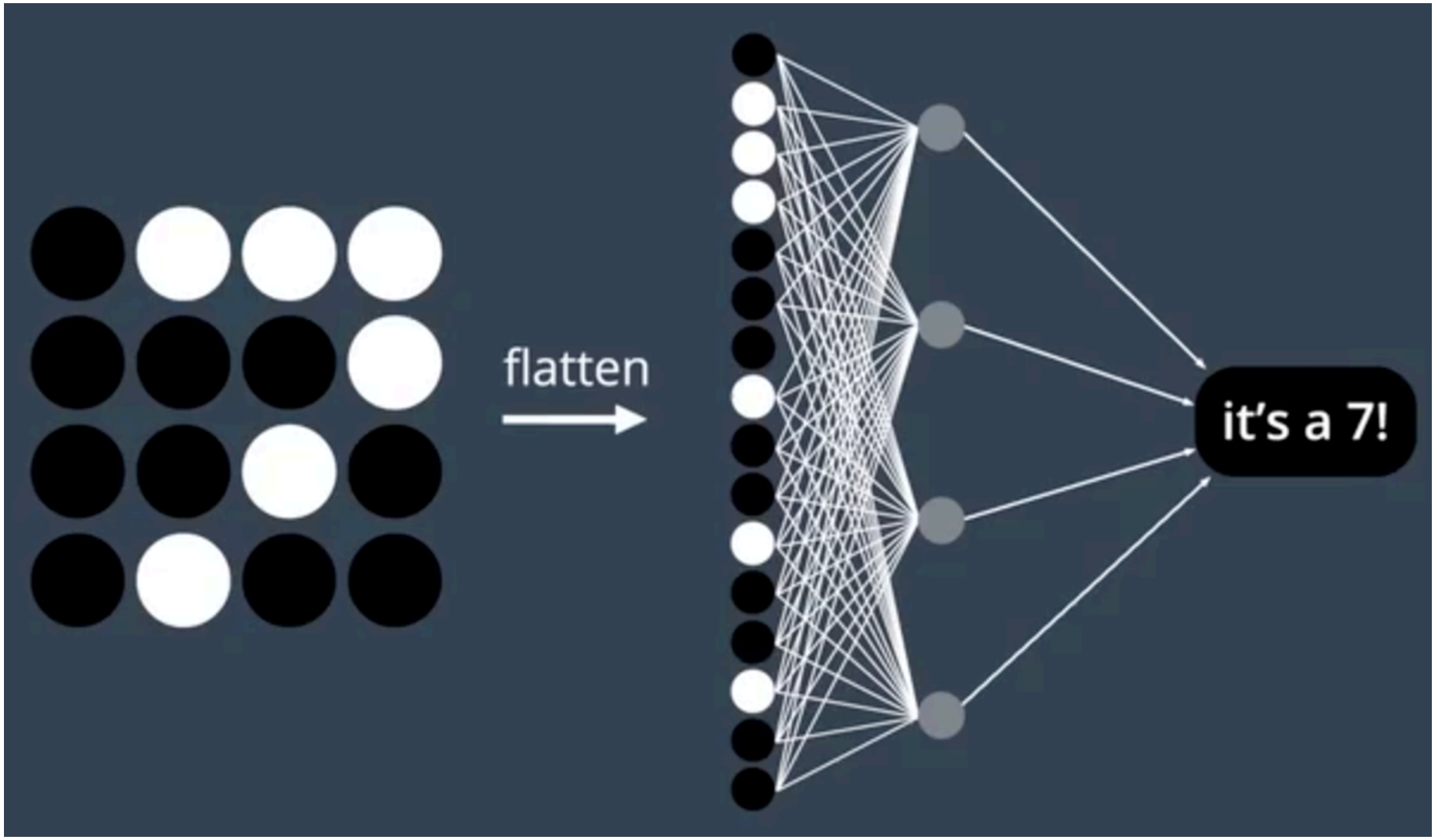

Verizon
4:20 PM
34%
Albums
puppy or bagel
Select
karen zack @teenybiscuit · Mar 7
puppy or bagel ?

Dog vs Food

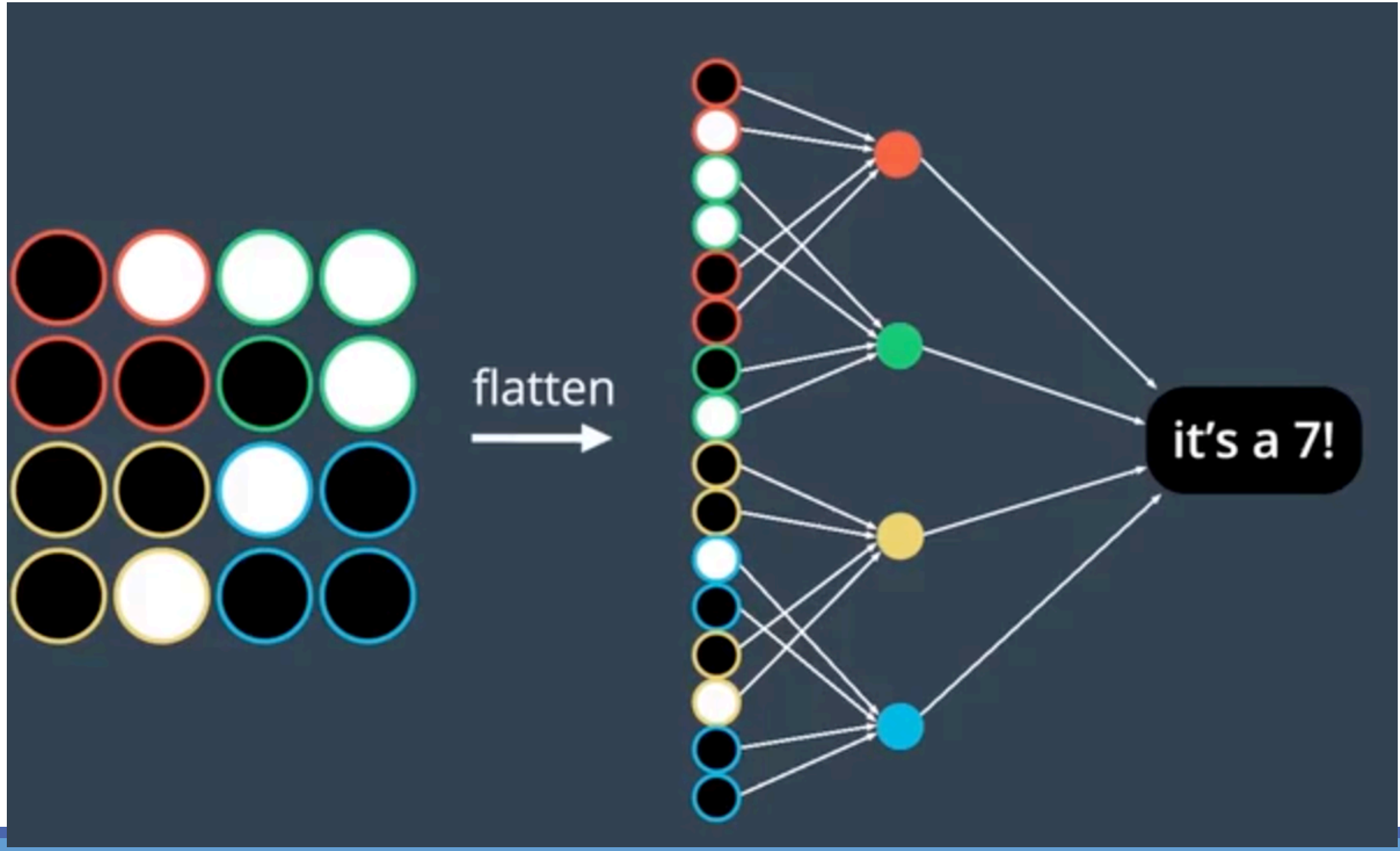

Verizon LTE 3:02 PM 42%
Albums
sheepdog or mop
Select
karen zack @teenybiscuit · Mar 9
sheepdog or mop ?

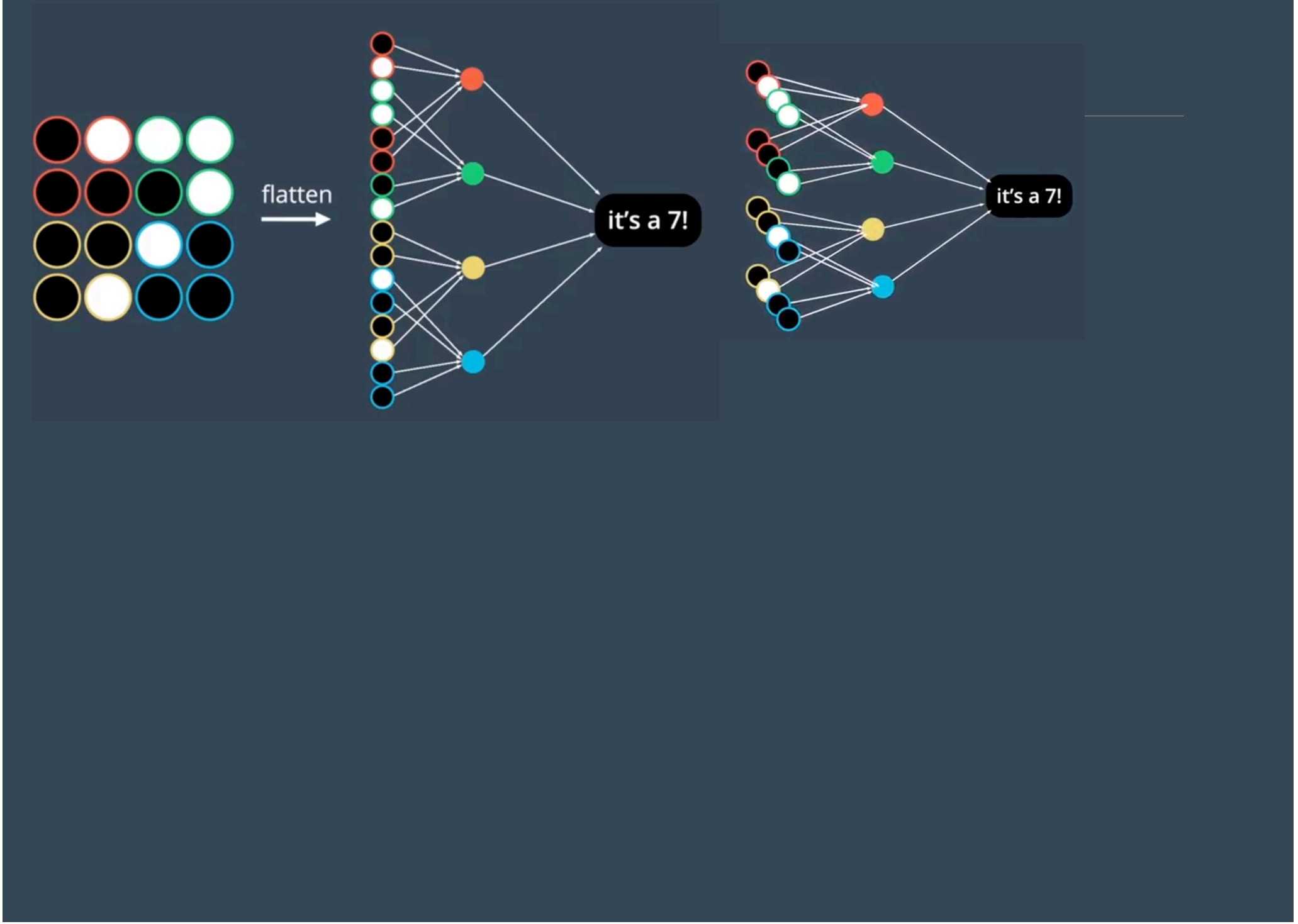

Verizon 4:20 PM 69%
Albums
kitten or ice cream
Select
@teenybiscuit
karen zack @teenybiscuit · Mar 14
kitten or ice cream ?

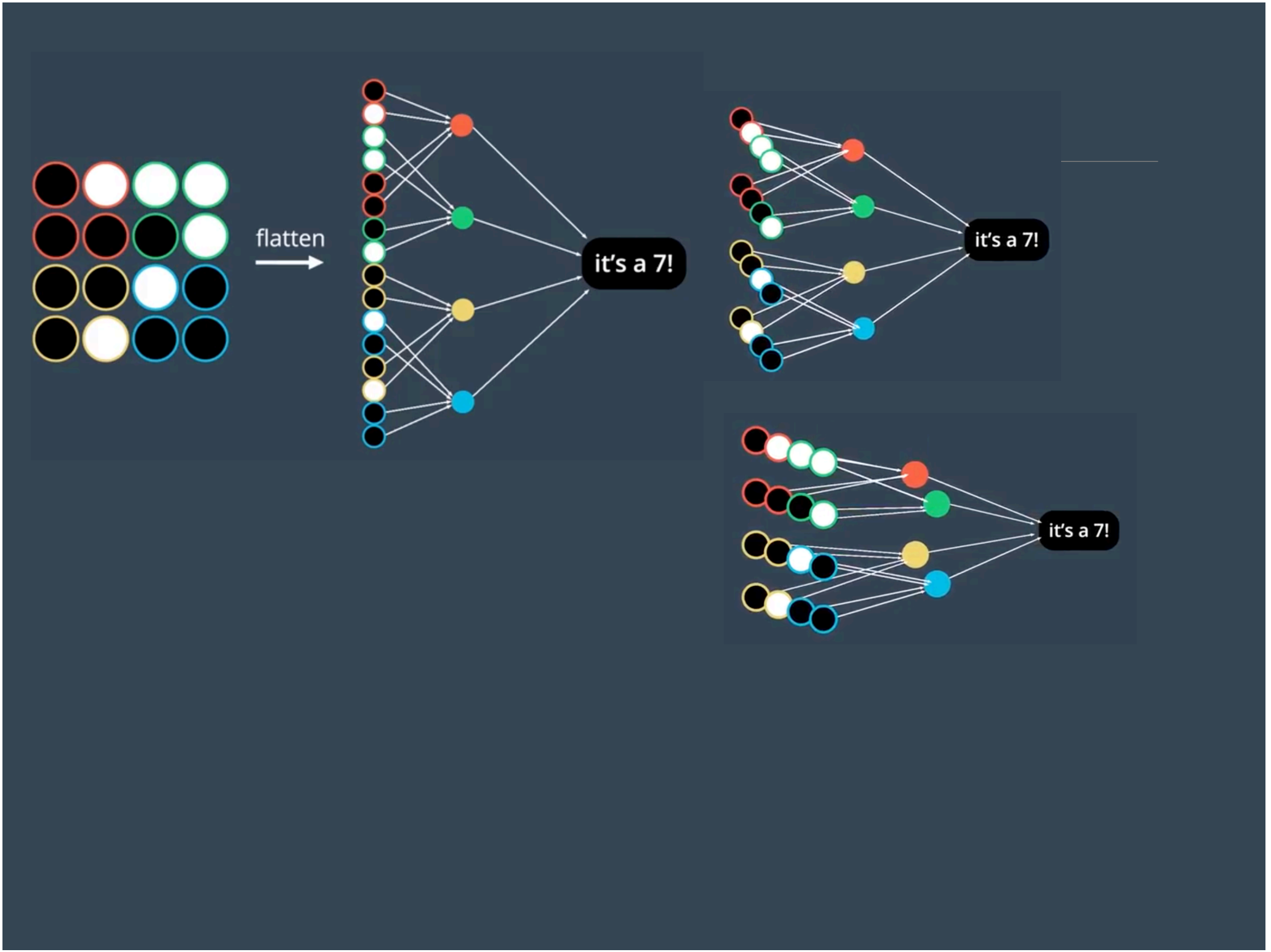
Classificação de Imagens com MLP

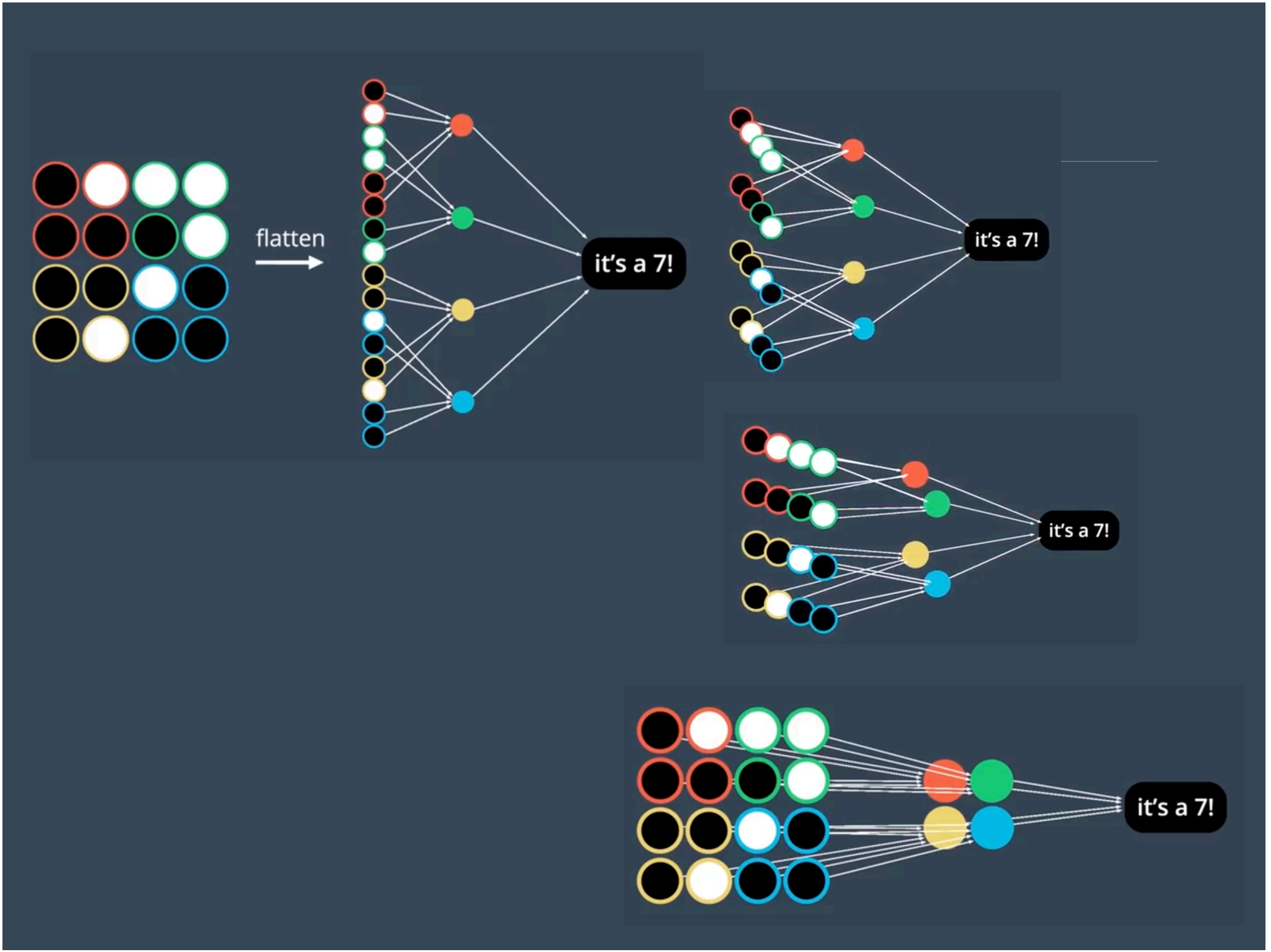


Classificação de Imagens com MLP

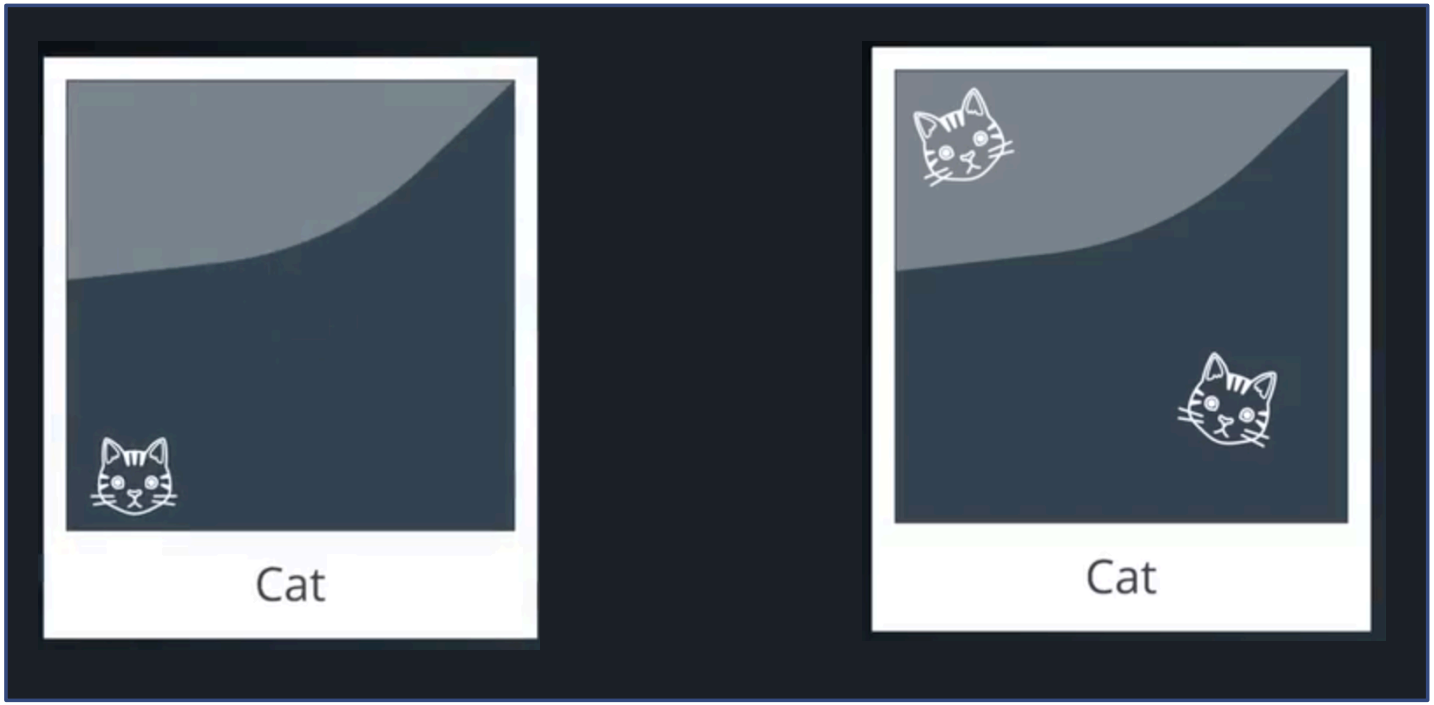



flatten
it's a 7!
it's a 7!


flatten
it's a 7!
it's a 7!
it's a 7!

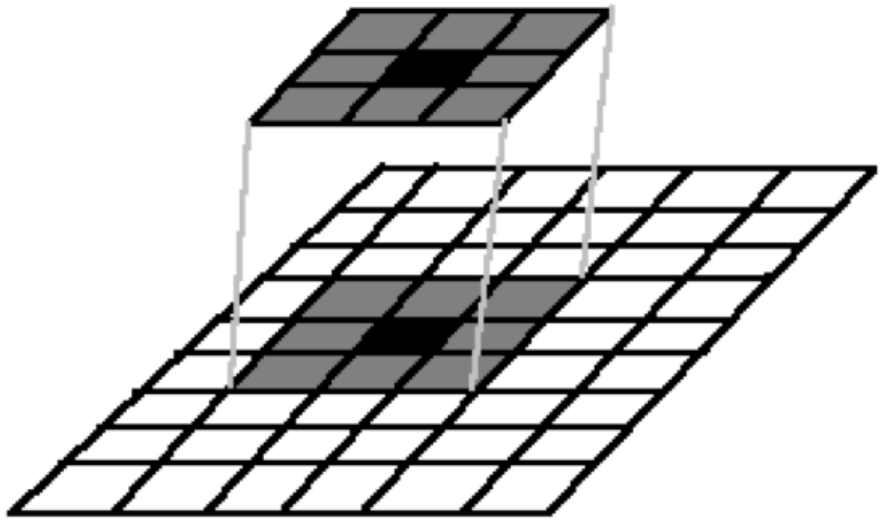

flatten
it's a 7!
it's a 7!
it's a 7!
it's a 7!

Conectividade Local



Convolução

- Definição de kernel/ máscara

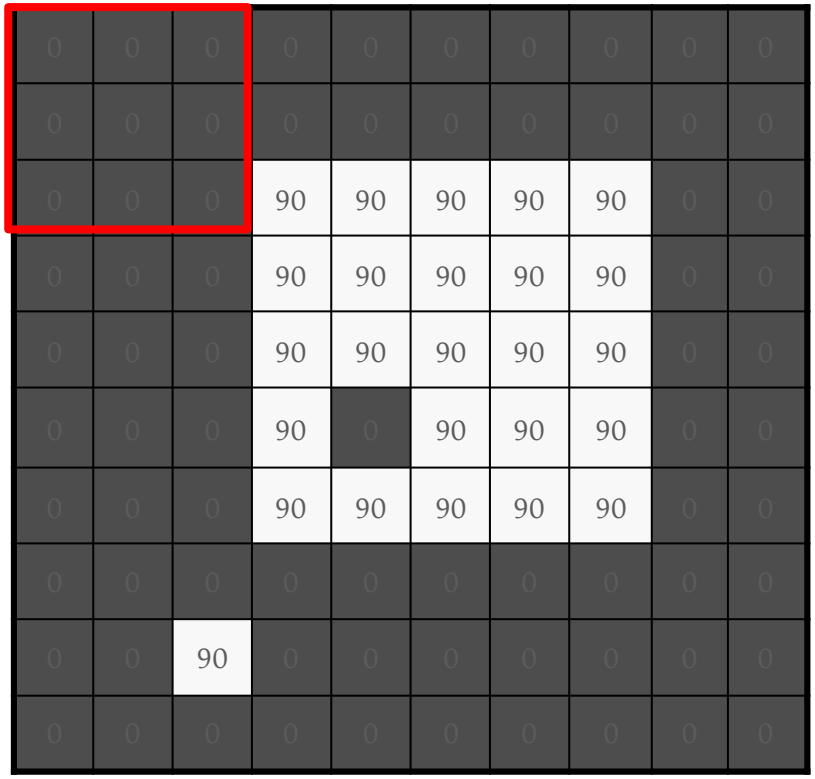


131	162	232	84	91	207
104	-1	0	+1	237	109
243	-2	0	+2	135	126
185	-1	0	+1	61	225
157	124	25	14	102	108
5	155	176	218	232	249

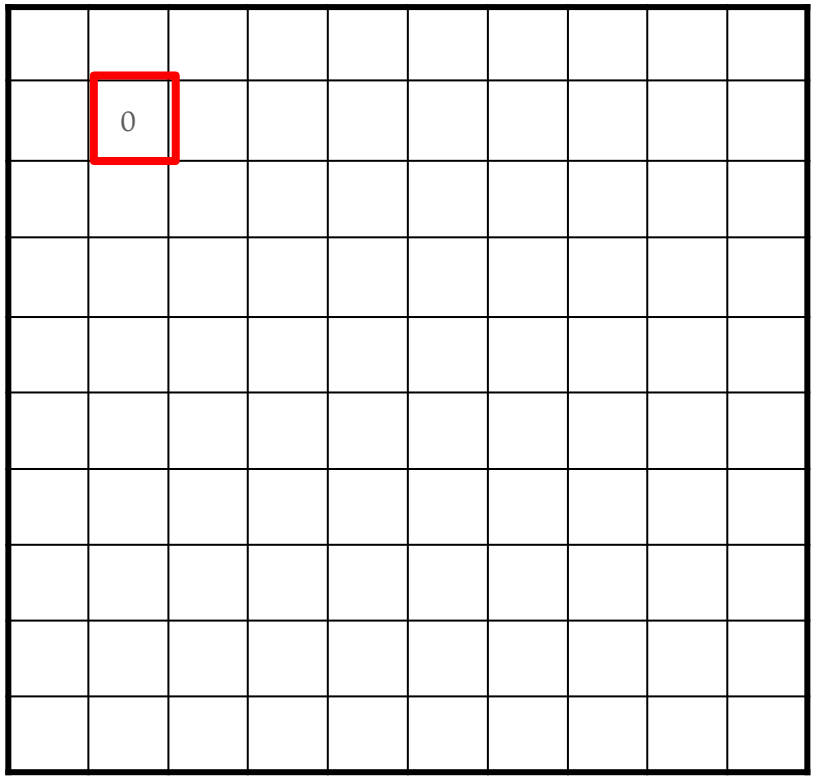
FILTRAGEM NO DOMÍNIO ESPACIAL

$$\frac{1}{9}\begin{bmatrix}1 & 1 & 1\\ 1 & 1 & 1\\ 1 & 1 & 1\end{bmatrix}$$

$F[x, y]$



$G[x, y]$

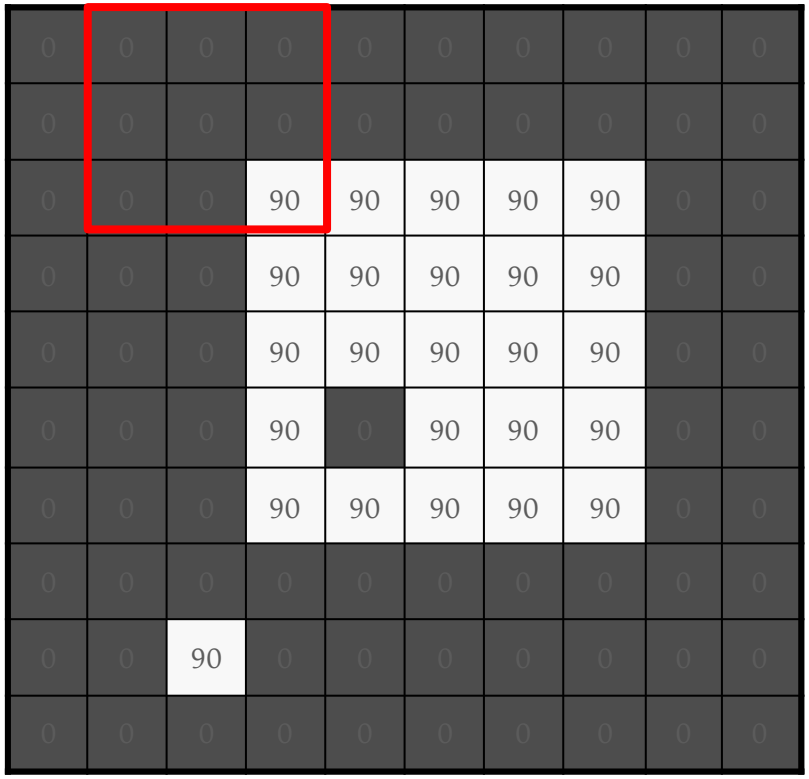


Source: S. Seitz

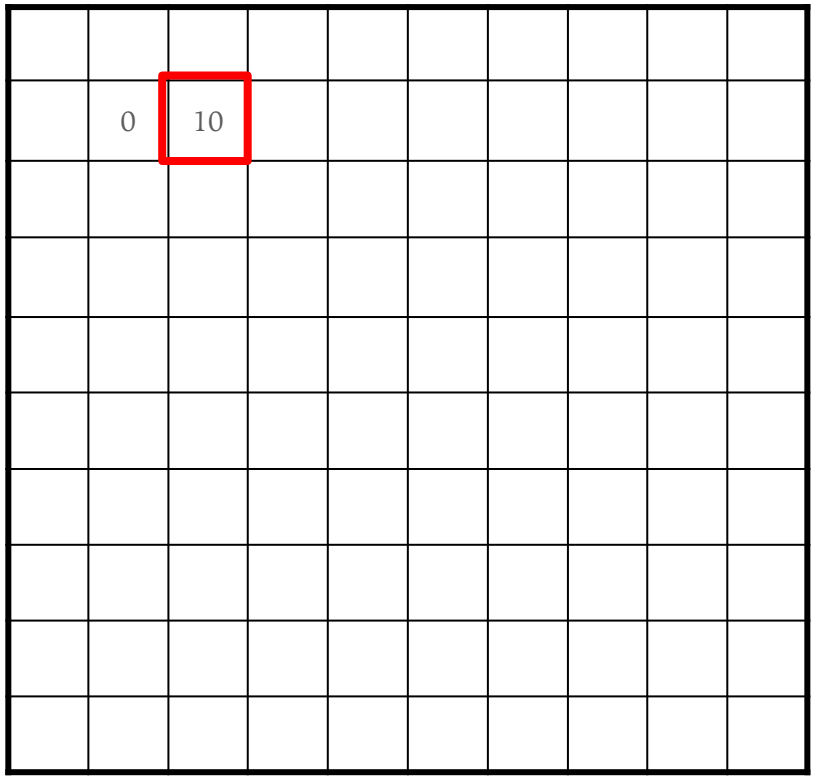
FILTRAGEM NO DOMÍNIO ESPACIAL

$$\frac{1}{9}\begin{bmatrix}1 & 1 & 1\\ 1 & 1 & 1\\ 1 & 1 & 1\end{bmatrix}$$

$F[x, y]$



$G[x, y]$

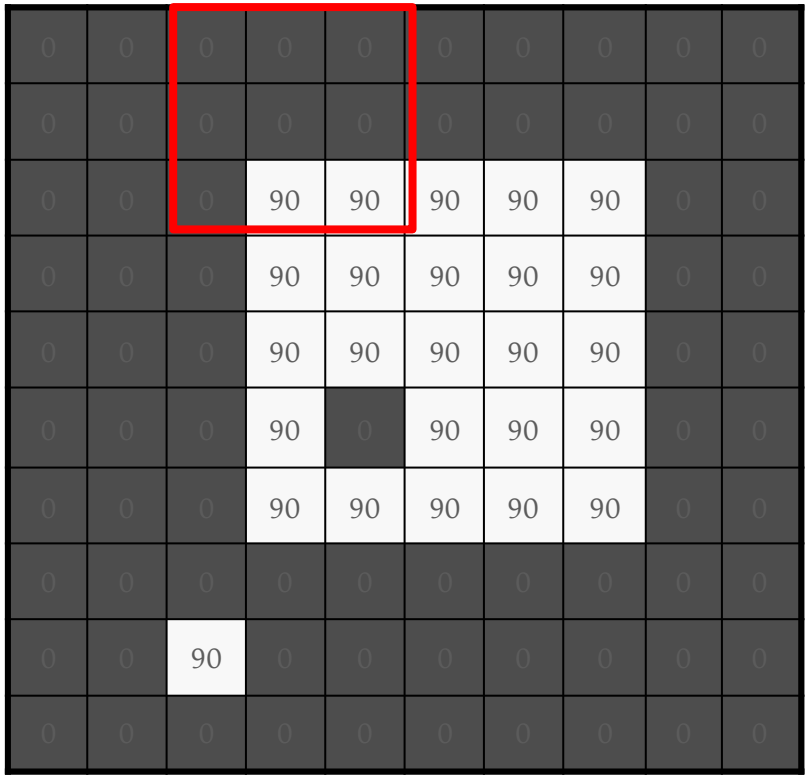


Source: S. Seitz

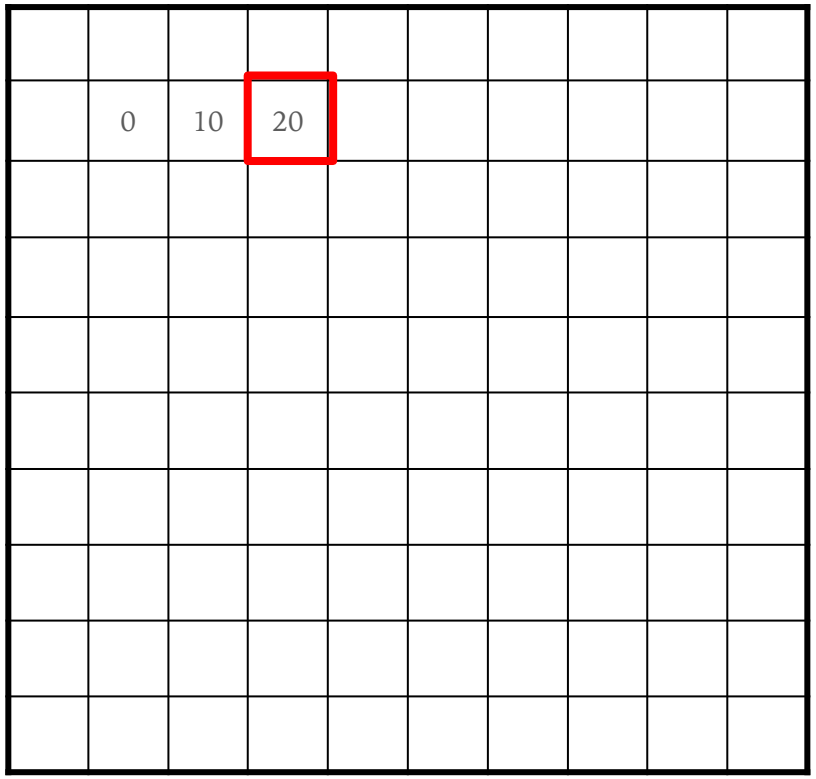
FILTRAGEM NO DOMÍNIO ESPACIAL

$$\frac{1}{9}\begin{bmatrix}1 & 1 & 1\\ 1 & 1 & 1\\ 1 & 1 & 1\end{bmatrix}$$

$F[x, y]$



$G[x, y]$

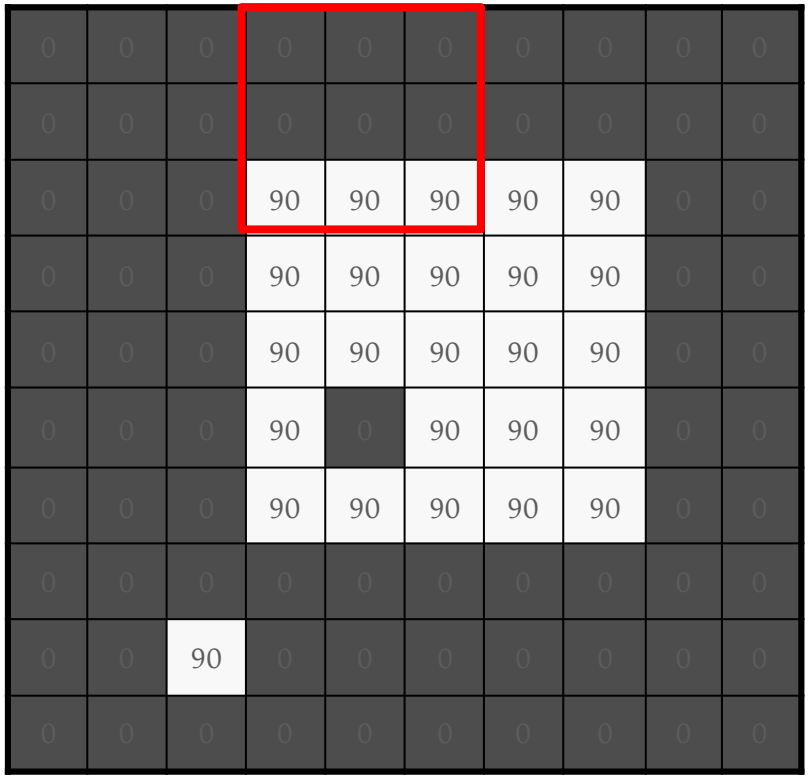


Source: S. Seitz

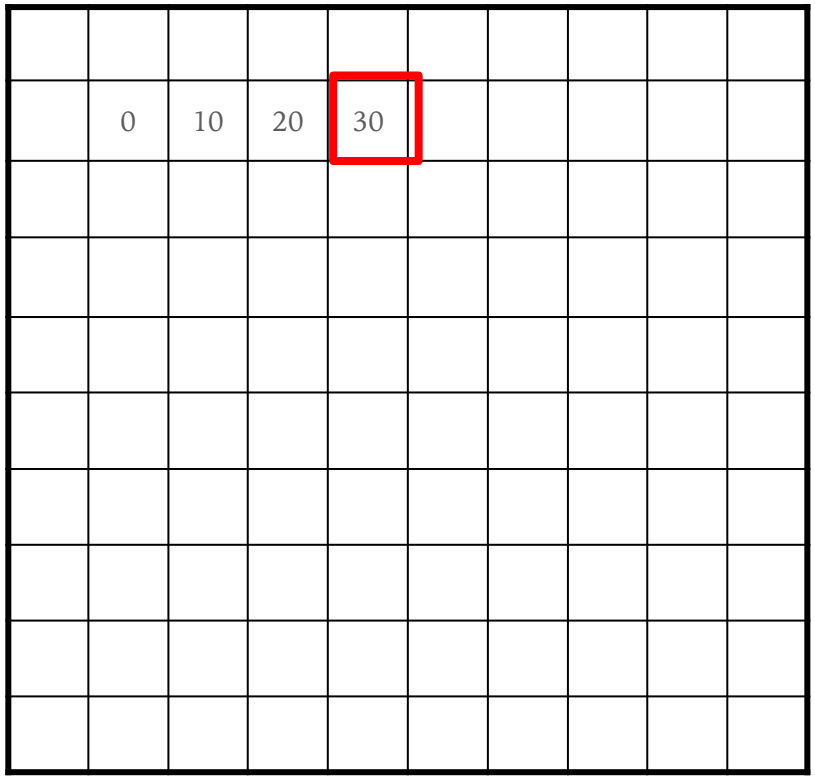
FILTRAGEM NO DOMÍNIO ESPACIAL

$$\frac{1}{9}\begin{bmatrix}1 & 1 & 1\\ 1 & 1 & 1\\ 1 & 1 & 1\end{bmatrix}$$

$F[x, y]$



$G[x, y]$

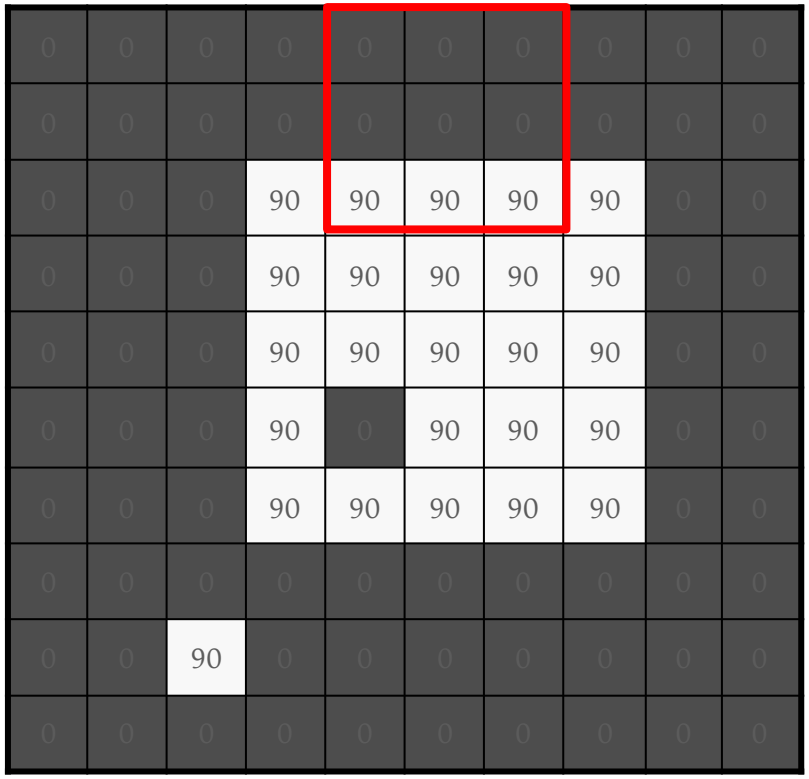


Source: S. Seitz

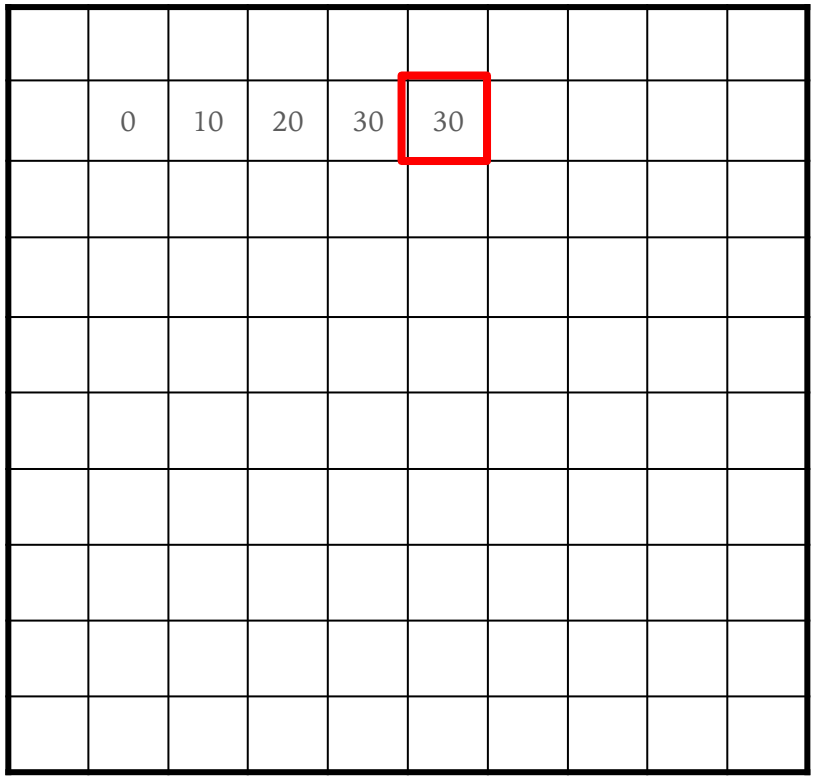
FILTRAGEM NO DOMÍNIO ESPACIAL

$$\frac{1}{9}\begin{bmatrix}1 & 1 & 1\\ 1 & 1 & 1\\ 1 & 1 & 1\end{bmatrix}$$

$F[x, y]$



$G[x, y]$

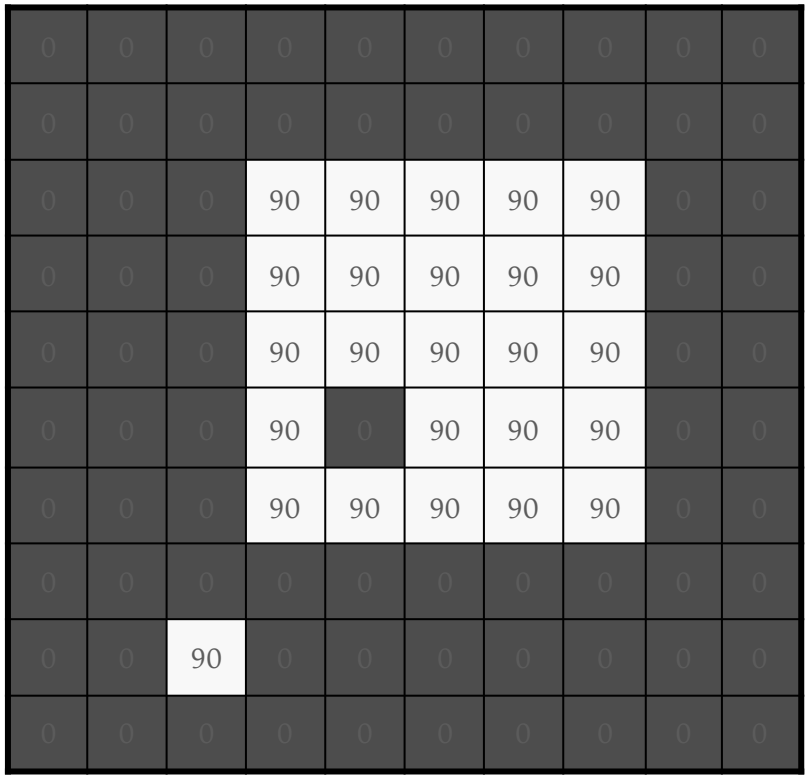


Source: S. Seitz

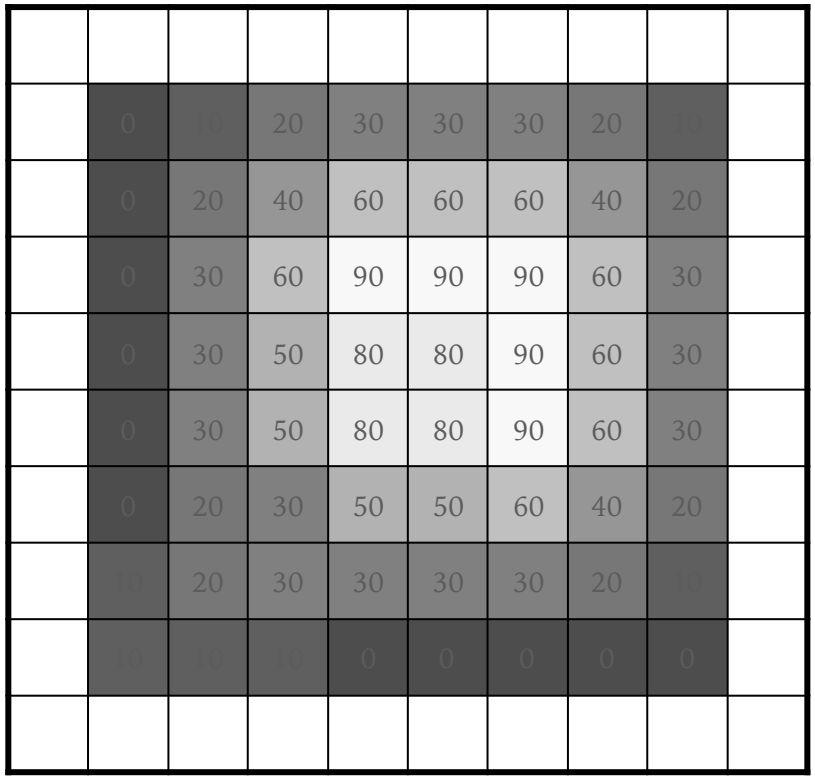
FILTRAGEM NO DOMÍNIO ESPACIAL

$$\frac{1}{9}\begin{bmatrix}1 & 1 & 1\\ 1 & 1 & 1\\ 1 & 1 & 1\end{bmatrix}$$

$F[x, y]$

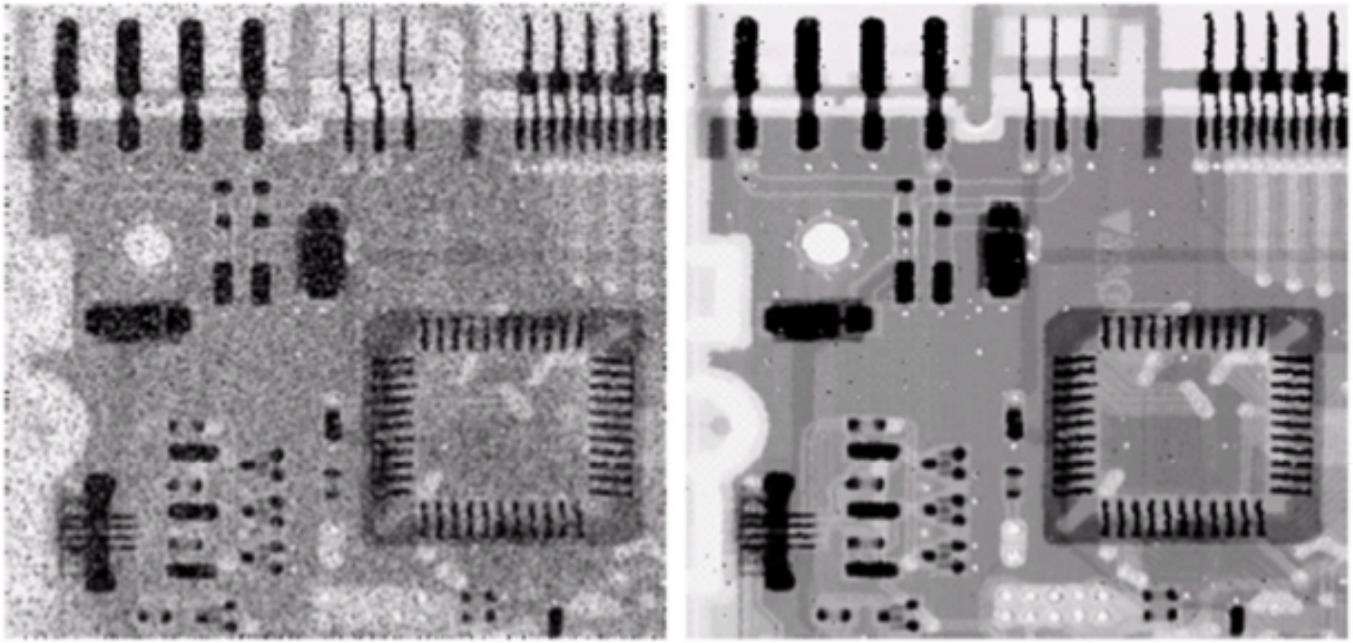


$G[x, y]$



Source: S. Seitz

Filtros Lineares – Suavização



Filtragem Linear

- Filtro de Média
  - Suavização

$$R = \frac{\sum z_i}{n}, i \in [1, n]$$

Exemplo: máscara 3 x 3

$$\frac{1}{9} \times \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

Borramento proporcional ao tamanho da máscara

Filtragem Linear

- Filtro Gaussiano
  - Suavização

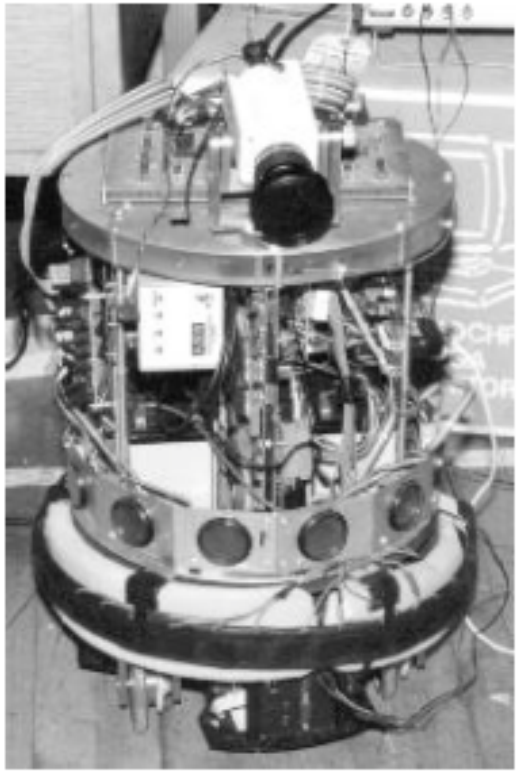
Filtro de média ponderada

Mais importância para pixels mais próximos do centro da máscara

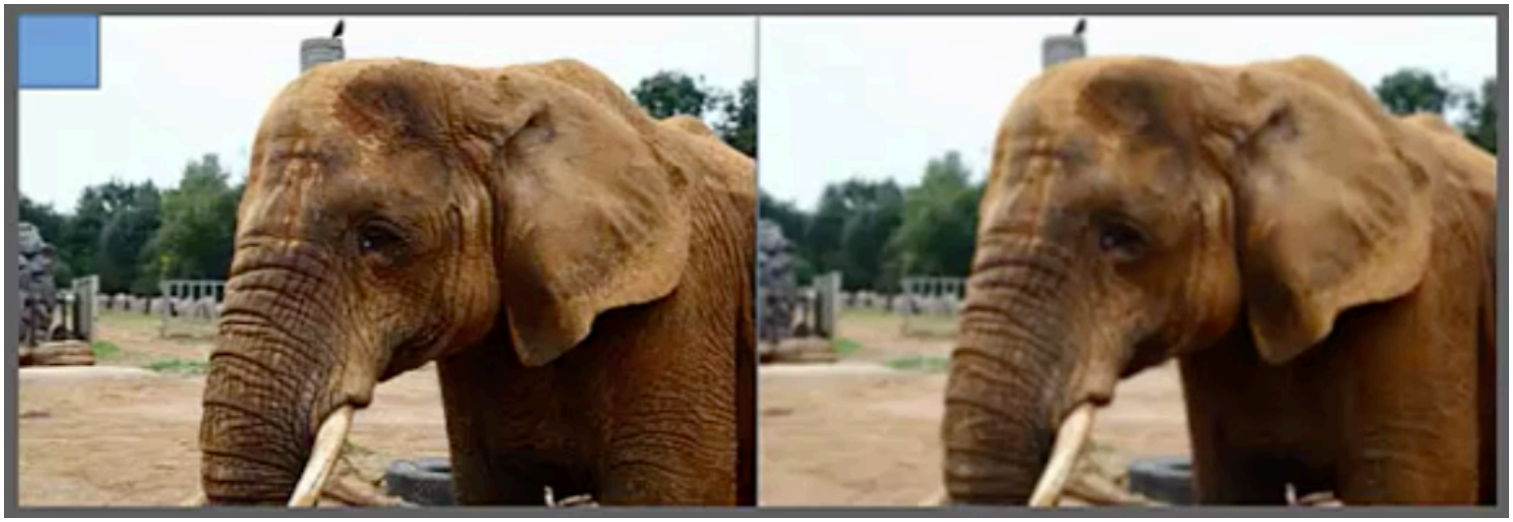
- Menos borramento

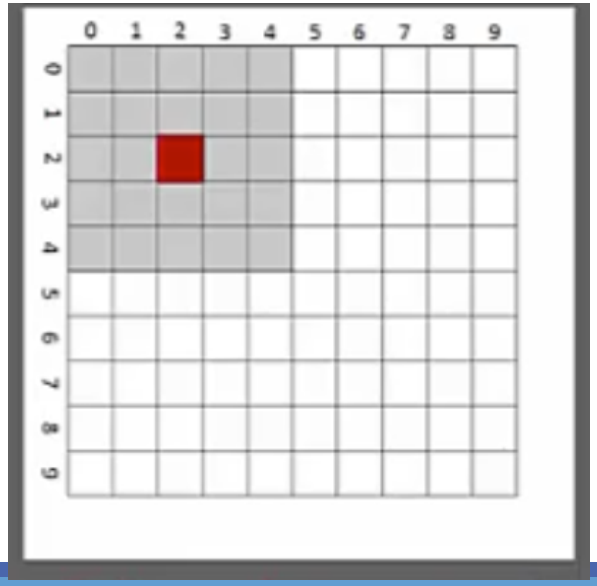
Exemplo: máscara 3 x 3

$$\frac{1}{100} \times \begin{array}{|c|c|c|} \hline 8 & 12 & 8 \\ \hline 12 & 20 & 12 \\ \hline 8 & 12 & 8 \\ \hline \end{array}$$



Suavização





$$Kernel\_ = \frac{1}{25}\begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix}$$

Filtro de Aguçamento

- O Contrário de suavização

Filtragem no OpenCV

- Filtros específicos
  - Média

```
#media
blur = cv2.blur(image,(3,3))
cv2.imshow('Averaging', blur)
```

  - Gaussiano

```
#Kernel Gaussiano
Gaussian = cv2.GaussianBlur(image,(7,7),0)
cv2.imshow("Gaussian Blurring", Gaussian)
```

  - Mediana

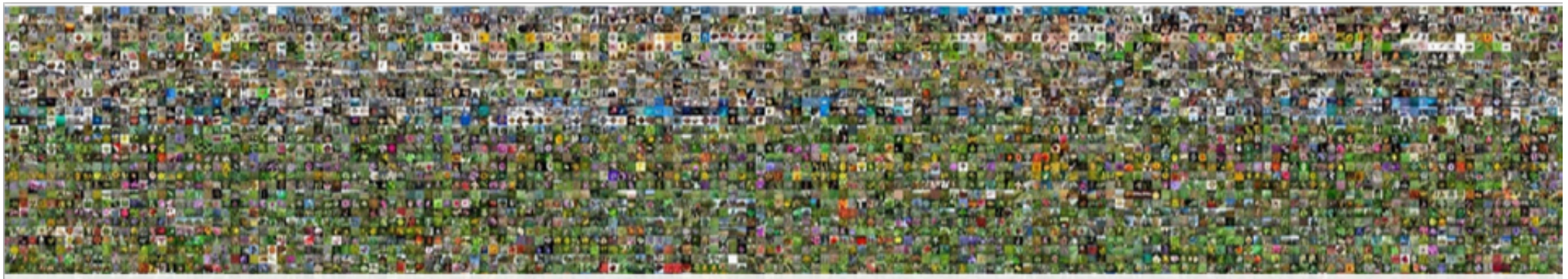
```
#Mediana
median = cv2.medianBlur(image,5)
cv2.imshow("Median Blurring", median)
```

  - bilateral

```
#Bilateral - remove ruido e mantem contraste
bilateral = cv2.bilateralFilter(image,9,75,75)
cv2.imshow('Bilateral', bilateral)
```

Exercício Filtro

- Implementar um filtro de média (kernel 5x5)
  - filtro_media.ipynb

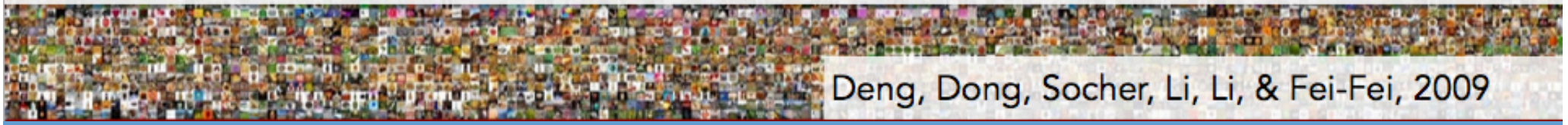


IMAGENET

www.image-net.org

22K categories and 14M images

- Animals
  - Bird
  - Fish
  - Mammal
  - Invertebrate
- Plants
  - Tree
  - Flower
- Food
- Materials
- Structures
- Artifact
  - Tools
  - Appliances
  - Structures
- Person
- Scenes
  - Indoor
  - Geological Formations
- Sport Activities



Deng, Dong, Socher, Li, Li, & Fei-Fei, 2009

IMAGENET Large Scale Visual Recognition Challenge

Steel drum

The Image Classification Challenge:

1,000 object classes

1,431,167 images

Output:
Scale
T-shirt
Steel drum
Drumstick
Mud turtle

✔

Output:
Scale
T-shirt
Giant panda
Drumstick
Mud turtle

✗

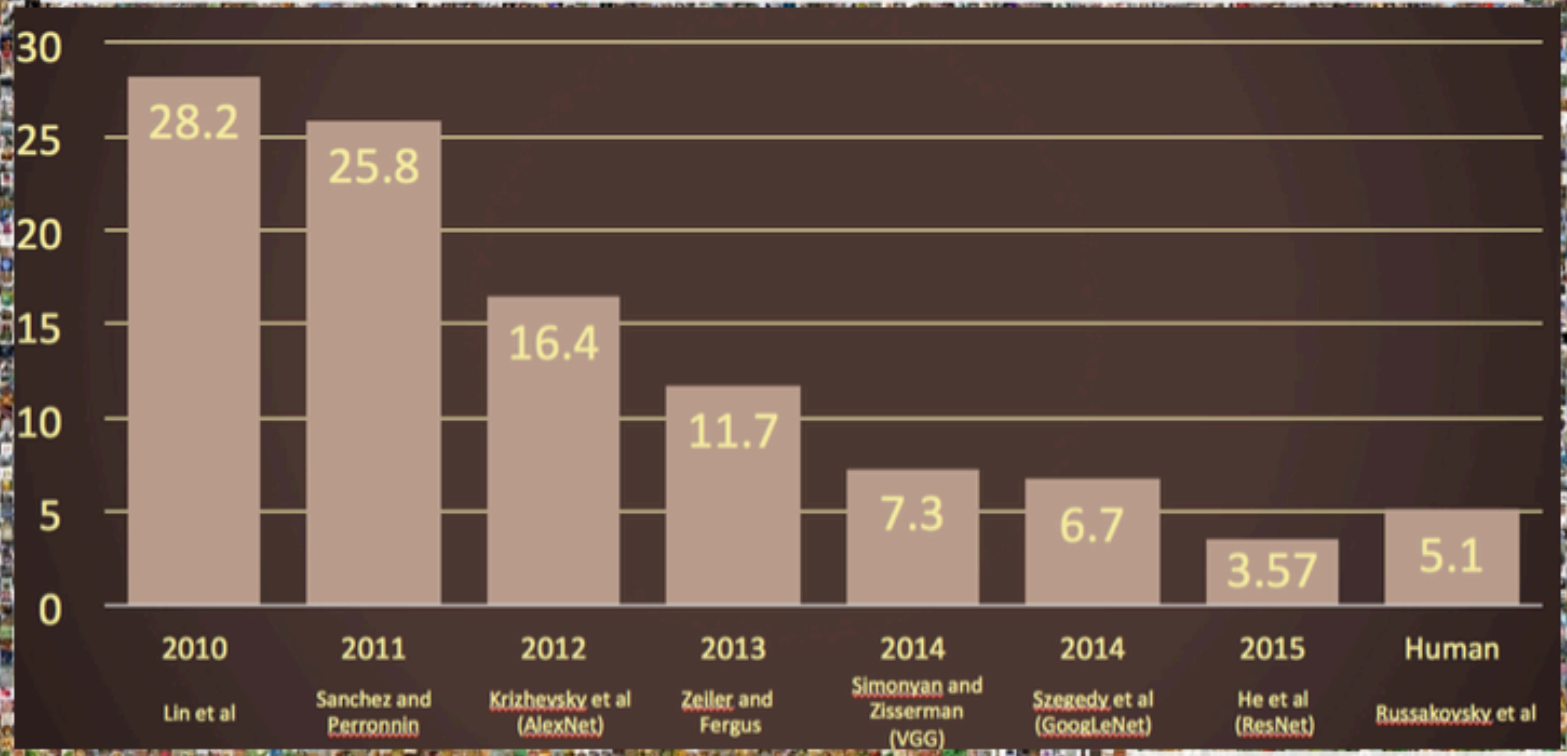
Russakovsky et al. arXiv, 2014

IMAGENET Large Scale Visual Recognition Challenge

The Image Classification Challenge:

1,000 object classes

1,431,167 images



Russakovsky et al. arXiv, 2014

IMAGENET Large Scale Visual Recognition Challenge

Year 2010

NEC-UIUC

Dense descriptor grid: HOG, LBP

Coding: local coordinate, super-vector

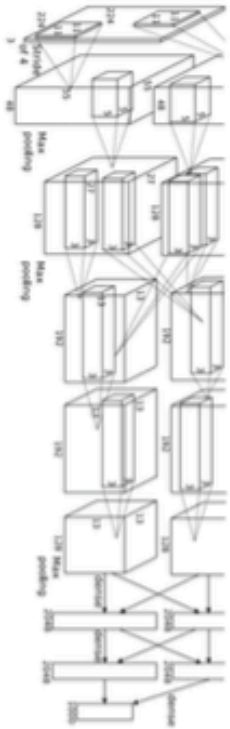
Pooling, SPM

Linear SVM

[Lin CVPR 2011]

Year 2012

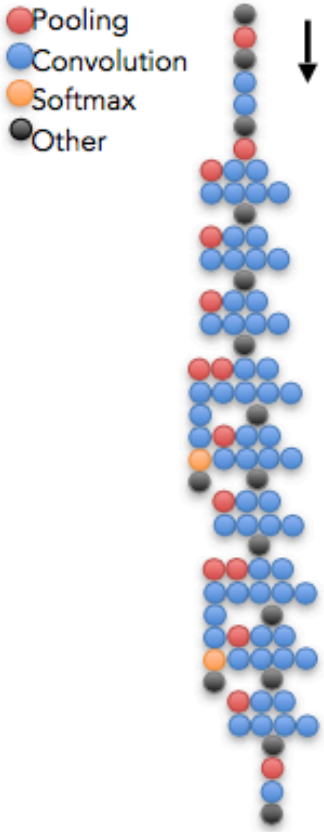
SuperVision



[Krizhevsky NIPS 2012]

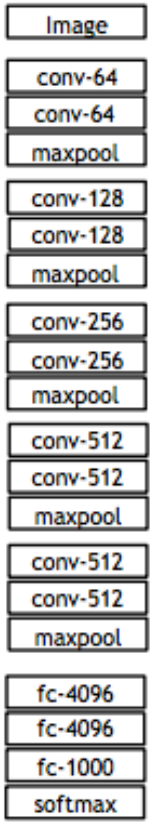
Year 2014

GoogLeNet



[Szegedy arxiv 2014]

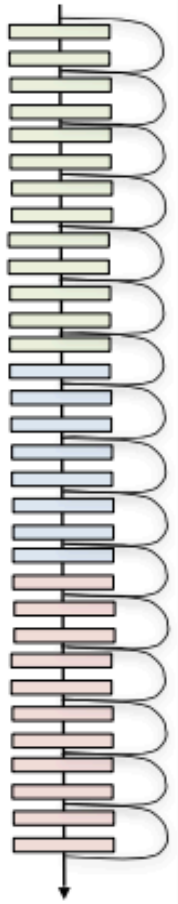
VGG



[Simonyan arxiv 2014]

Year 2015

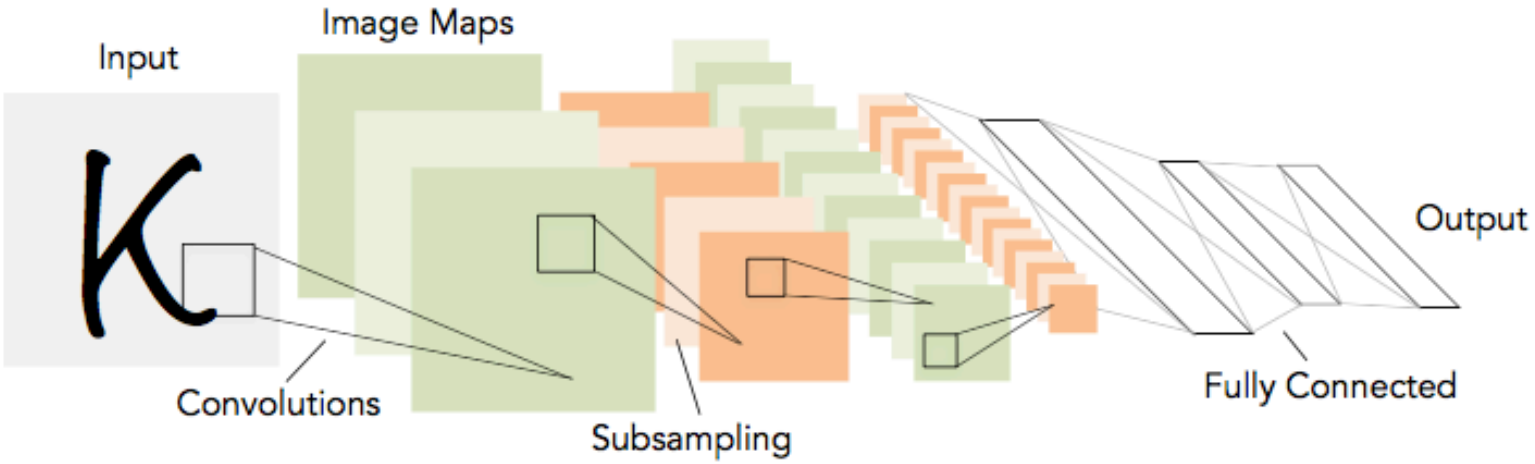
MSRA



[He ICCV 2015]

Redes Neurais Convolutivas (CNN) não foram inventadas do dia para a noite

1998
LeCun et al.



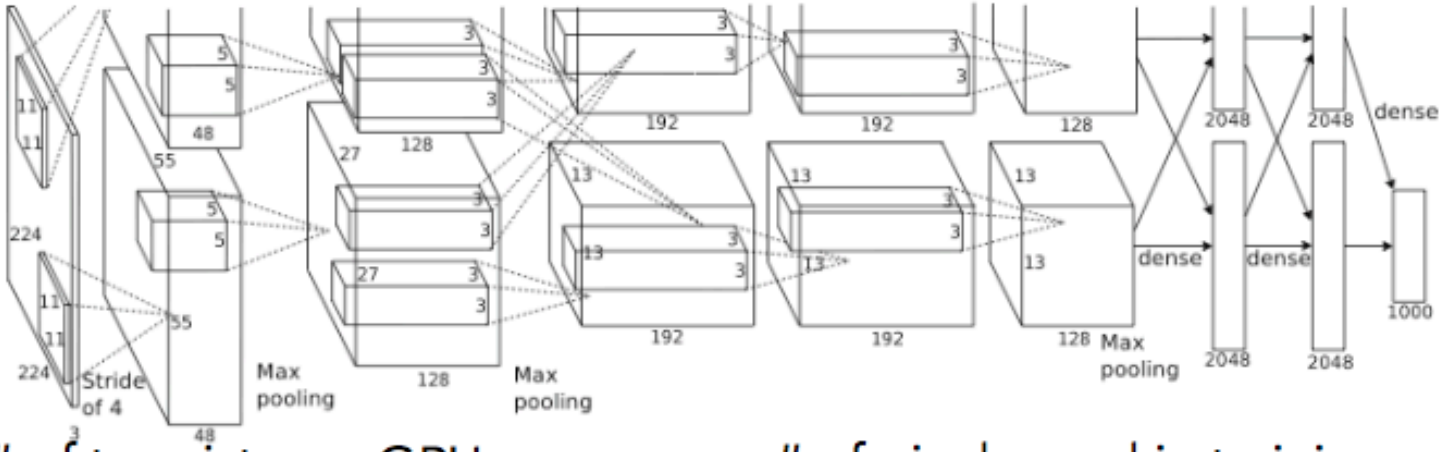
# of transistors

10^6

# of pixels used in training

10^7 NIST

2012
Krizhevsky et al.



# of transistors

10^9

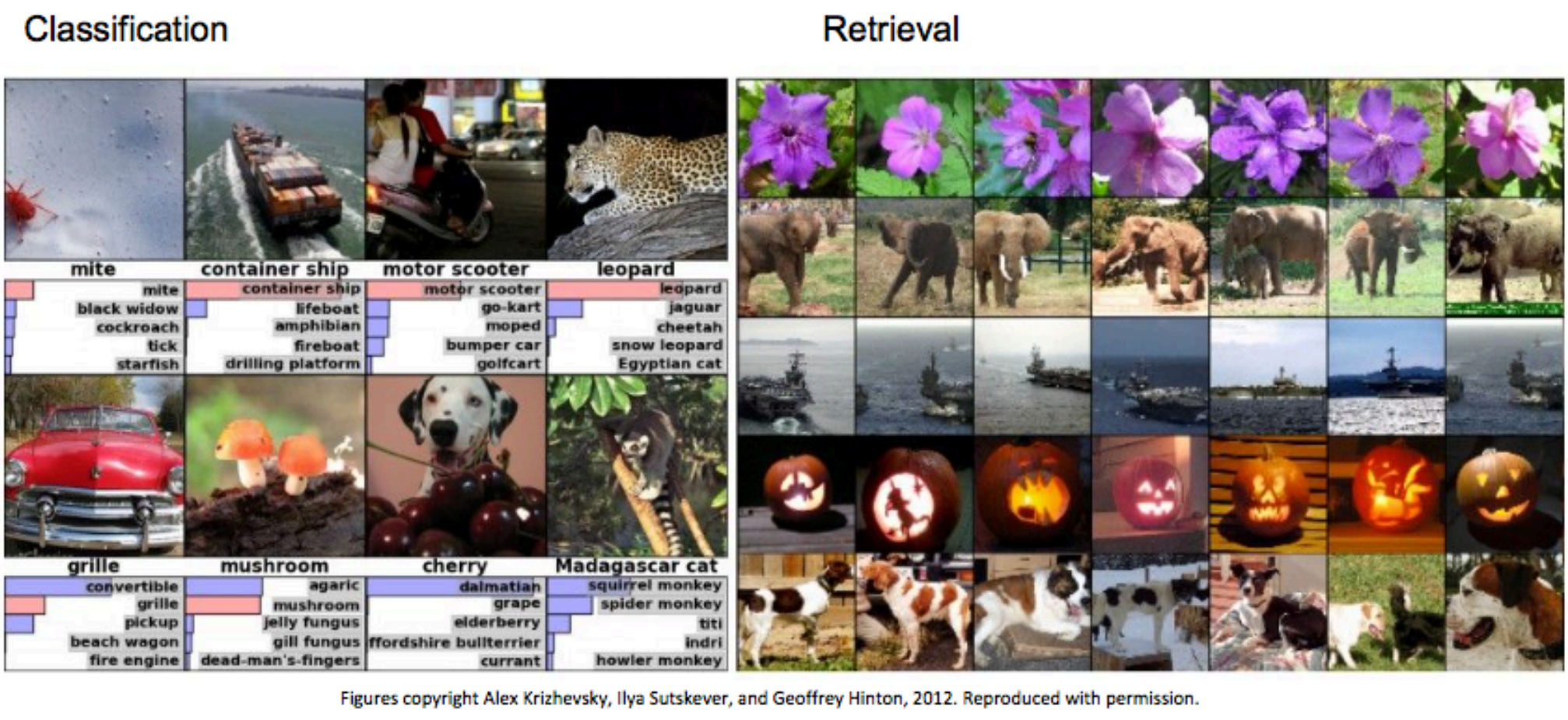
GPUs

# of pixels used in training

10^{14} IMAGENET

Figure copyright Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, 2012. Reproduced with permission.

ConvNets estão em todo lugar



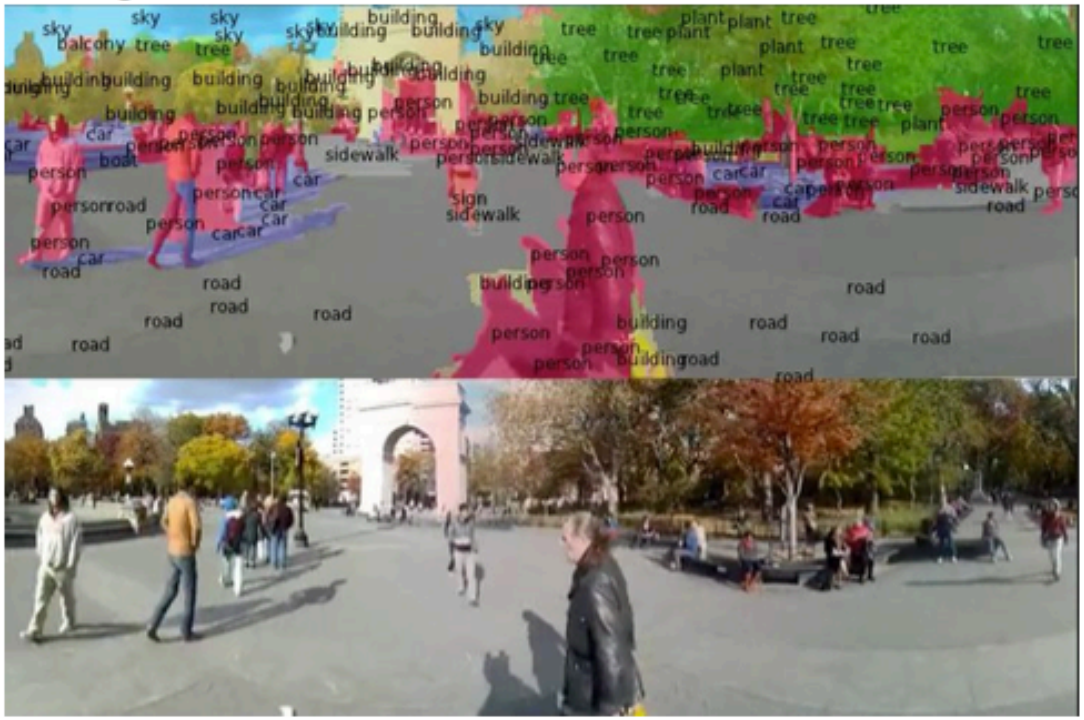
ConvNets estão em todo lugar

Detection

Figures copyright Shaoqing Ren, Kaiming He, Ross Girschick, Jian Sun, 2015. Reproduced with permission.

[Faster R-CNN: Ren, He, Girshick, Sun 2015]

Segmentation



Figures copyright Clement Farabet, 2012. Reproduced with permission.

[Farabet et al., 2012]

ConvNets estão em todo lugar

Photo by Lane McIntosh. Copyright CS231n 2017.

self-driving cars

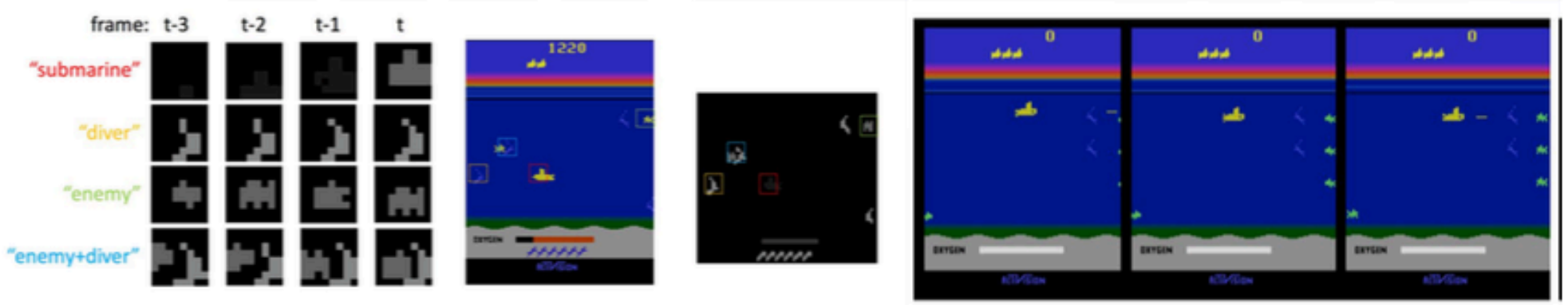
NVIDIA Tesla line
(these are the GPUs on rye01.stanford.edu)

Note that for embedded systems a typical setup would involve NVIDIA Tegras, with integrated GPU and ARM-based CPU cores.

ConvNets estão em todo lugar

Images are examples of pose estimation, not actually from Toshev & Szegedy 2014. Copyright Lane McIntosh.

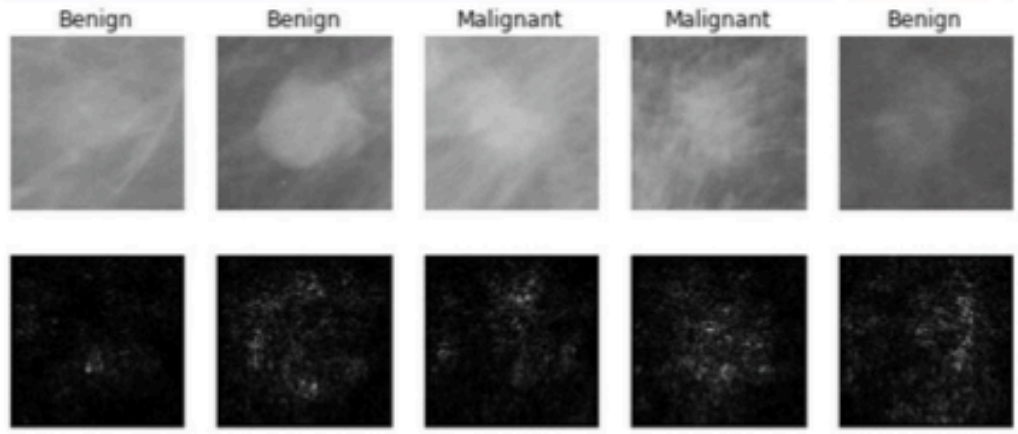
[Toshev, Szegedy 2014]



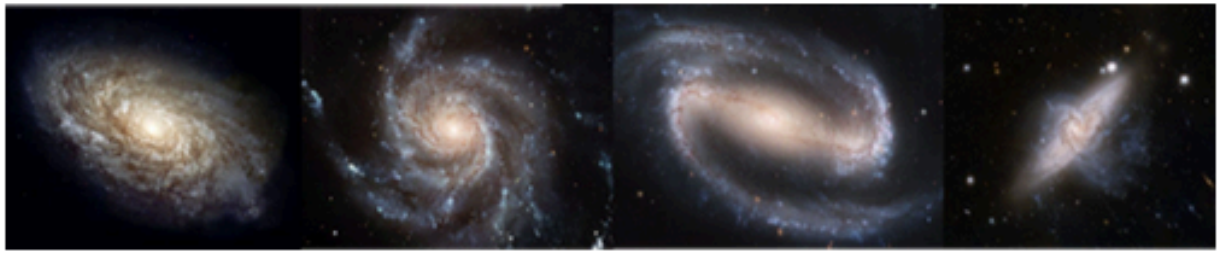
[Guo et al. 2014]

Figures copyright Xiaoxiao Guo, Satinder Singh, Honglak Lee, Richard Lewis, and Xiaoshi Wang, 2014. Reproduced with permission.

ConvNets estão em todo lugar



[Levy et al. 2016]



[Dieleman et al. 2014]

[Sermanet et al. 2011]
[Ciresan et al.]

Descrição de Imagens

No errors

A white teddy bear sitting in the grass

A man riding a wave on top of a surfboard

Minor errors

A man in a baseball uniform throwing a ball

A cat sitting on a suitcase on the floor

Somewhat related

A woman is holding a cat in her hand

A woman standing on a beach holding a surfboard

Image Captioning

[Vinyals et al., 2015]
[Karpathy and Fei-Fei, 2015]

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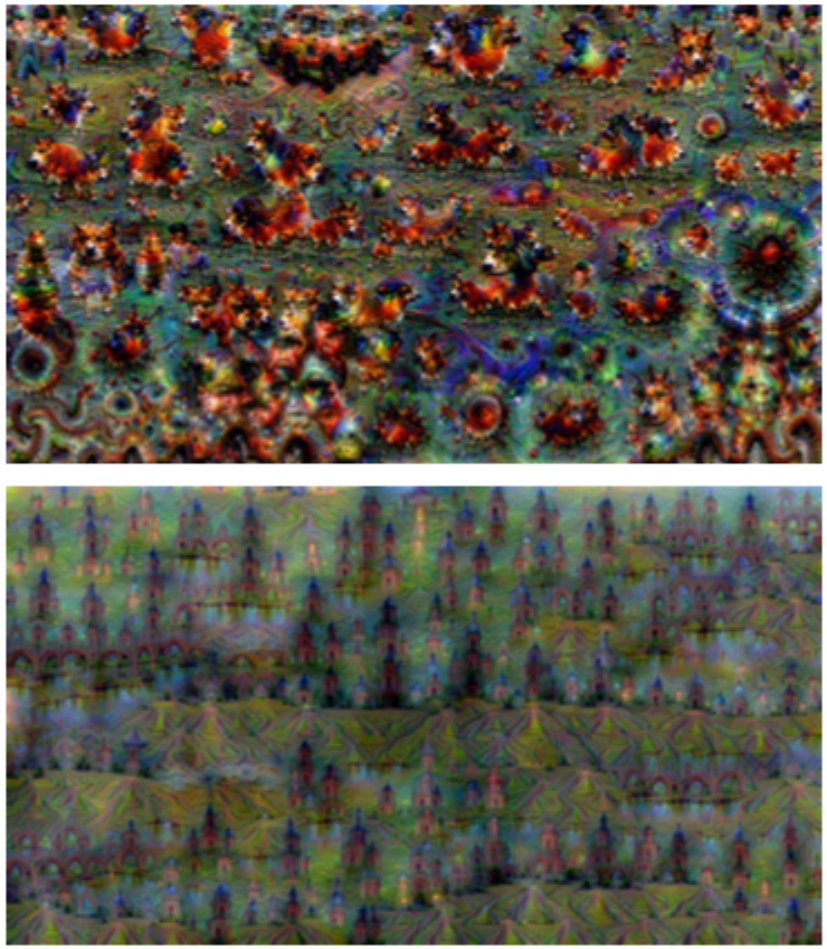
https://pixabay.com/en/luggage-antique-cat-1643010/
https://pixabay.com/en/teddy-plush-bears-cute-teddy-bear-1623436/
https://pixabay.com/en/surf-wave-summer-sport-litoral-1668716/
https://pixabay.com/en/woman-female-model-portrait-adult-983967/
https://pixabay.com/en/handstand-lake-meditation-496008/
https://pixabay.com/en/baseball-player-shortstop-infield-1045263/

Captions generated by Justin Johnson using Neuraltalk2

Transferência de Estilo



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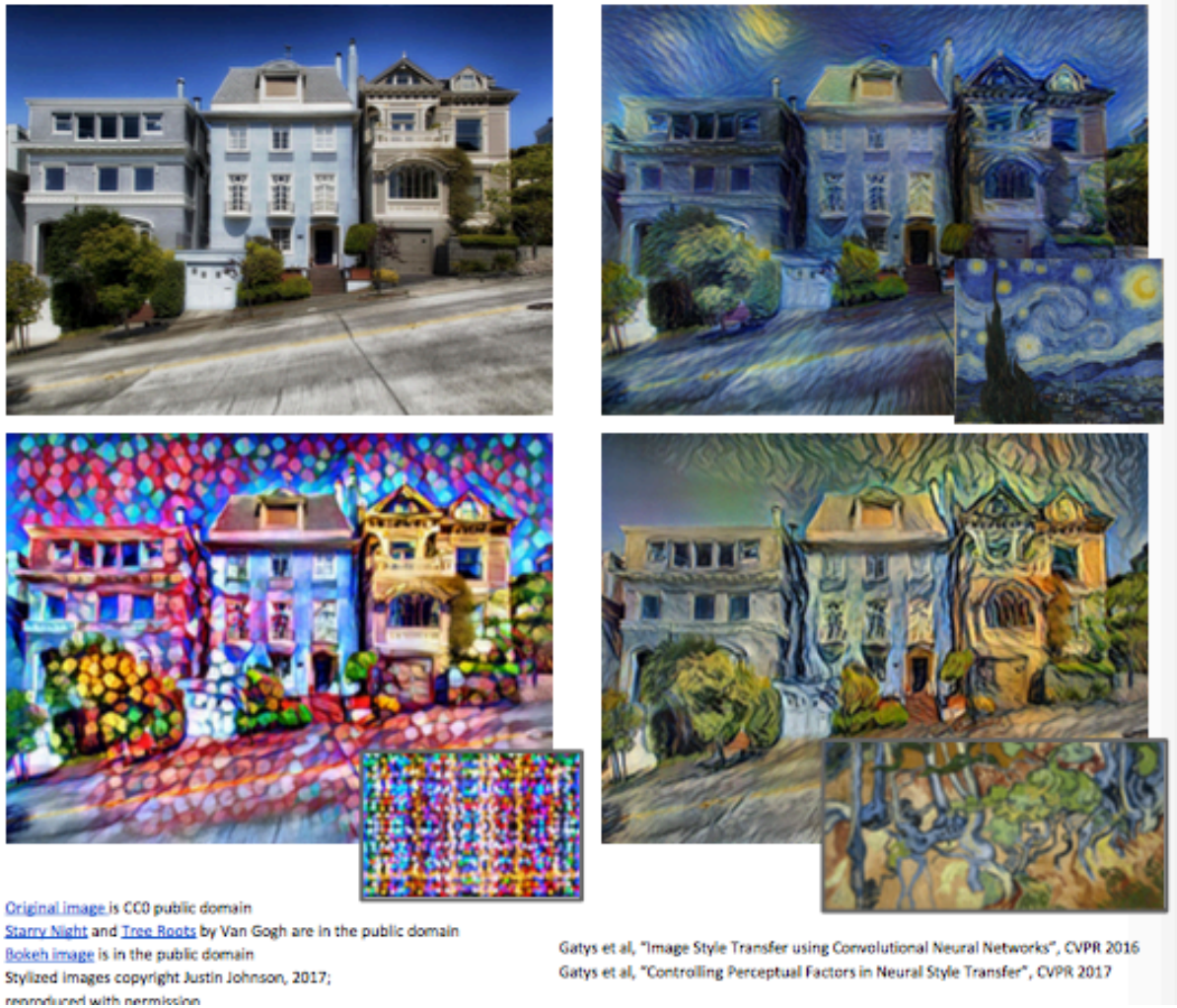
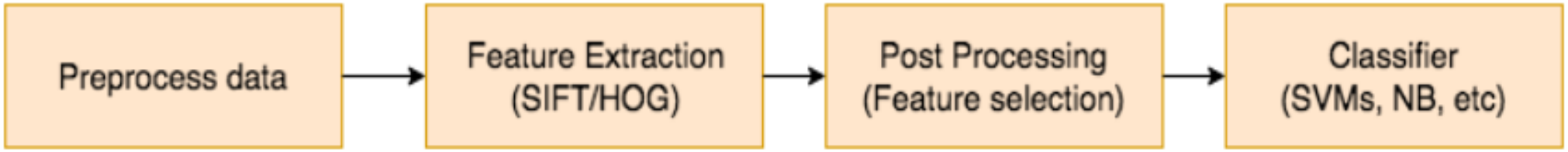


Original image is CC0 public domain
Starry Night and Tree Roots by Van Gogh are in the public domain
Bokeh image is in the public domain
Stylized images copyright Justin Johnson, 2017;
reproduced with permission

Gatys et al, "Image Style Transfer using Convolutional Neural Networks", CVPR 2016
Gatys et al, "Controlling Perceptual Factors in Neural Style Transfer", CVPR 2017

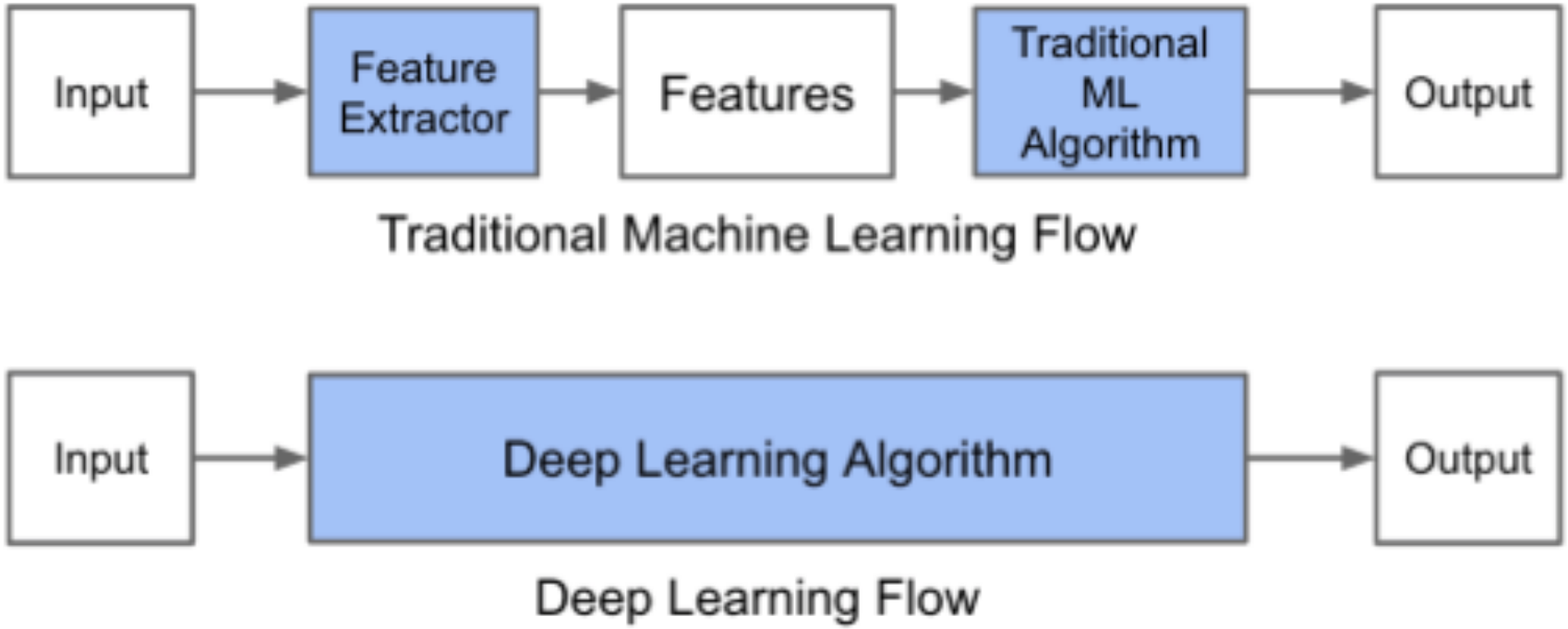
Era Pré Deep Learning



- Cons:
  - Características Manuais difíceis de se construir
  - Processo que demanda tempo
  - Quais conjuntos de características maximizam acurácia?
  - Tende a causar overfitting.

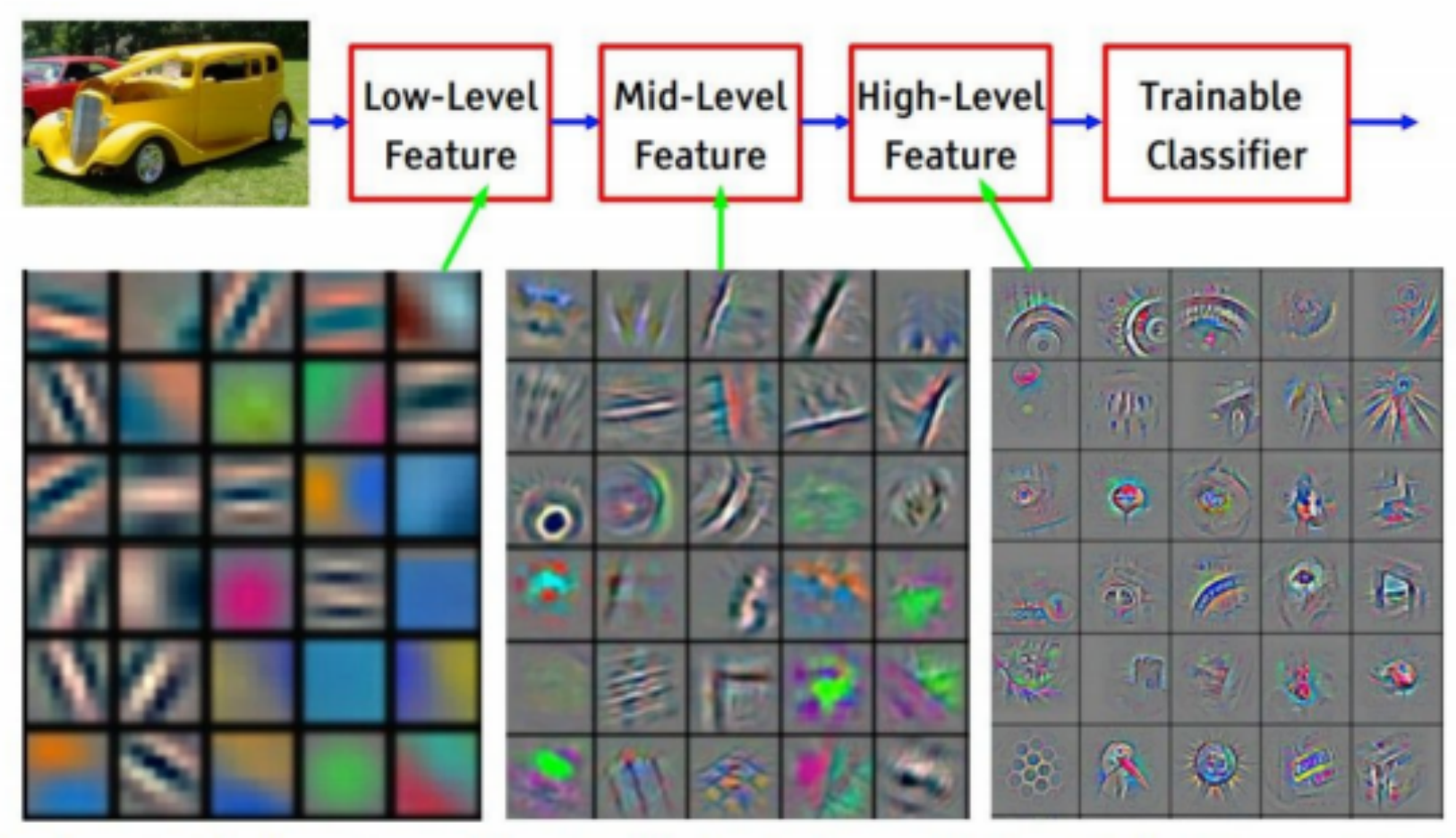
Redes Neurais Convolutivas

Fluxograma Deep Learning



O que é Deep Learning

- Composição de transformações não lineares dos dados



Um pouco de história..

Hubel & Wiesel,

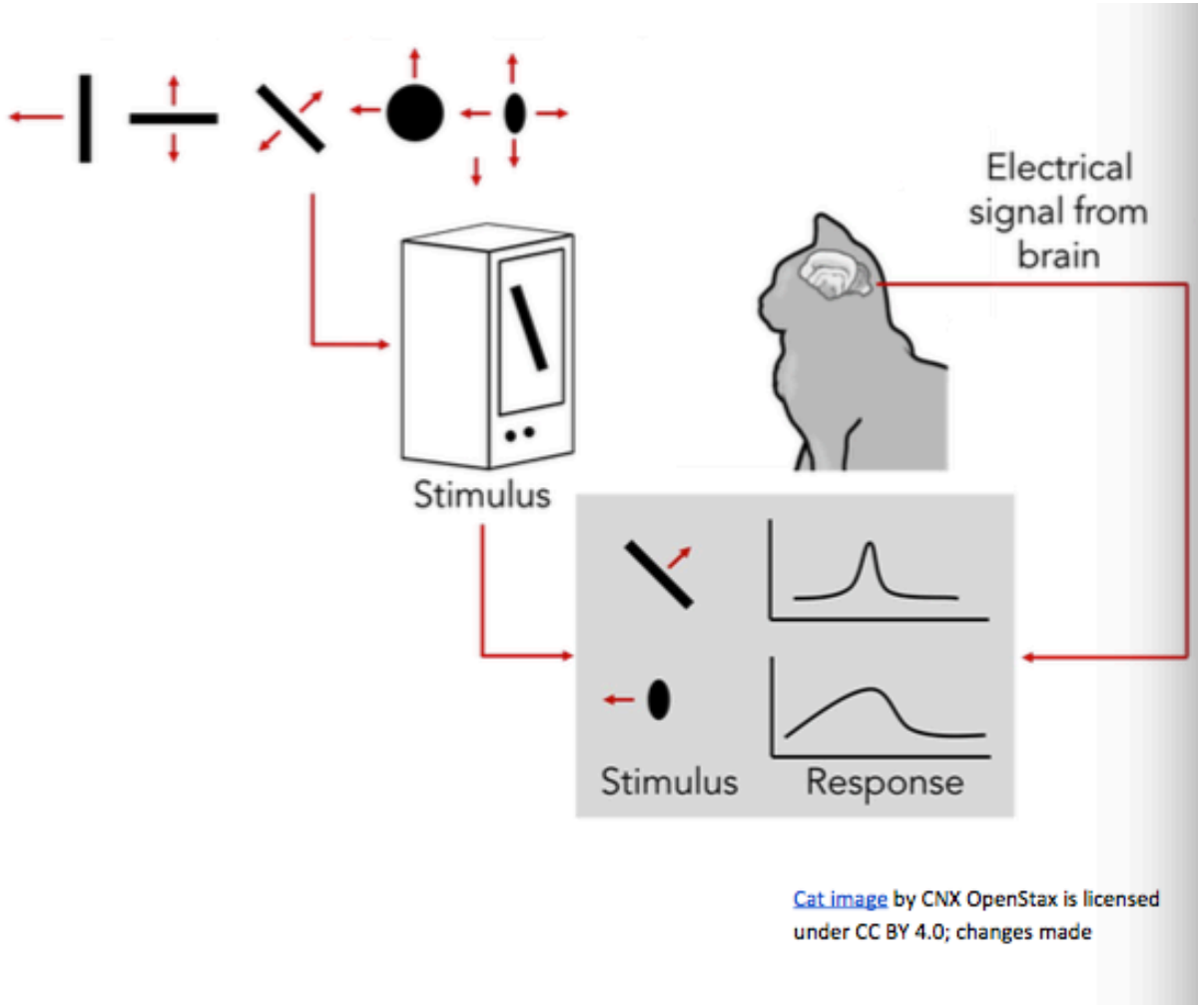
1959

RECEPTIVE FIELDS OF SINGLE NEURONES IN
THE CAT'S STRIATE CORTEX

1962

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

1968…



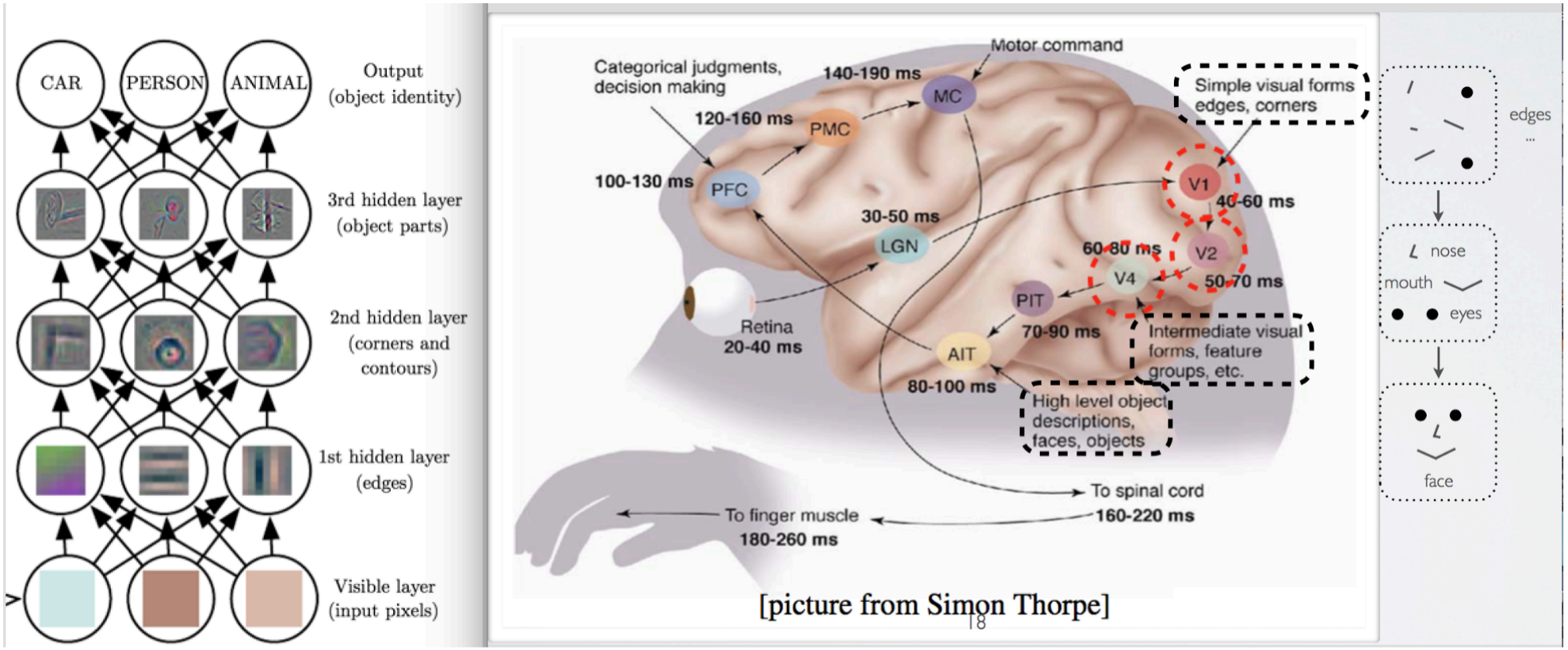
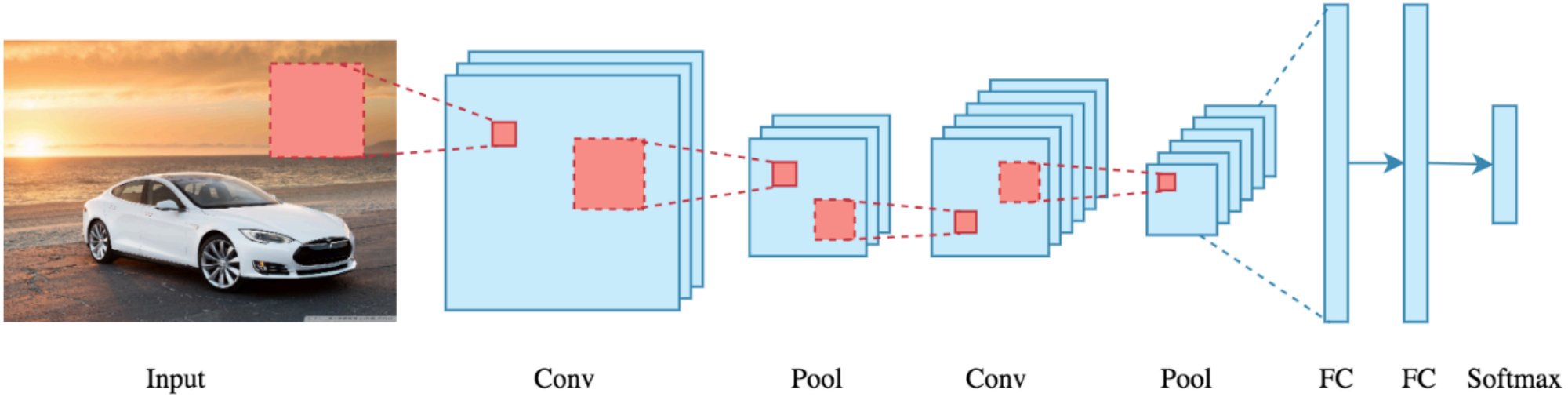


Fig 1. Image Courtesy: Hugo Larochelle Slides.

CNN

- Modelos CNN possuem arquitetura similar



Tipos de Camadas

- Convolutiva (CONV)
- Pooling (POOL)
- Fully-conected (FC)
- Batch Normalization (BN)
- Dropout(DO)
- Softmax

Neural Network

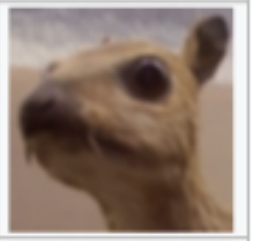
Linear classifiers

Camada Convolutiva

Convoluções

Operation	Kernel	Image result
Identity	$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$	
Edge detection	$\begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix}$	
	$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$	
	$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$	

Convoluções

Sharpen	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	
Box blur (normalized)	$\frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$	
Gaussian blur 3 × 3 (approximation)	$\frac{1}{16}\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$	
Gaussian blur 5 × 5 (approximation)	$\frac{1}{256}\begin{bmatrix} 1 & 4 & 6 & 4 & 1 \\ 4 & 16 & 24 & 16 & 4 \\ 6 & 24 & 36 & 24 & 6 \\ 4 & 16 & 24 & 16 & 4 \\ 1 & 4 & 6 & 4 & 1 \end{bmatrix}$	
Unsharp masking 5 × 5 Based on Gaussian blur with amount as 1 and threshold as 0 (with no image mask)	$\frac{-1}{256}\begin{bmatrix} 1 & 4 & 6 & 4 & 1 \\ 4 & 16 & 24 & 16 & 4 \\ 6 & 24 & -476 & 24 & 6 \\ 4 & 16 & 24 & 16 & 4 \\ 1 & 4 & 6 & 4 & 1 \end{bmatrix}$	

Convolução

1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

Input

1	0	1
0	1	0
1	0	1

Filter / Kernel

Convolução

1x1	1x0	1x1	0	0
0x0	1x1	1x0	1	0
0x1	0x0	1x1	1	1
0	0	1	1	0
0	1	1	0	0

Input x Filter

4		

Feature Map

Convolução

1	1x1	1x0	0x1	0
0	1x0	1x1	1x0	0
0	0x1	1x0	1x1	1
0	0	1	1	0
0	1	1	0	0

Input x Filter

4	3	

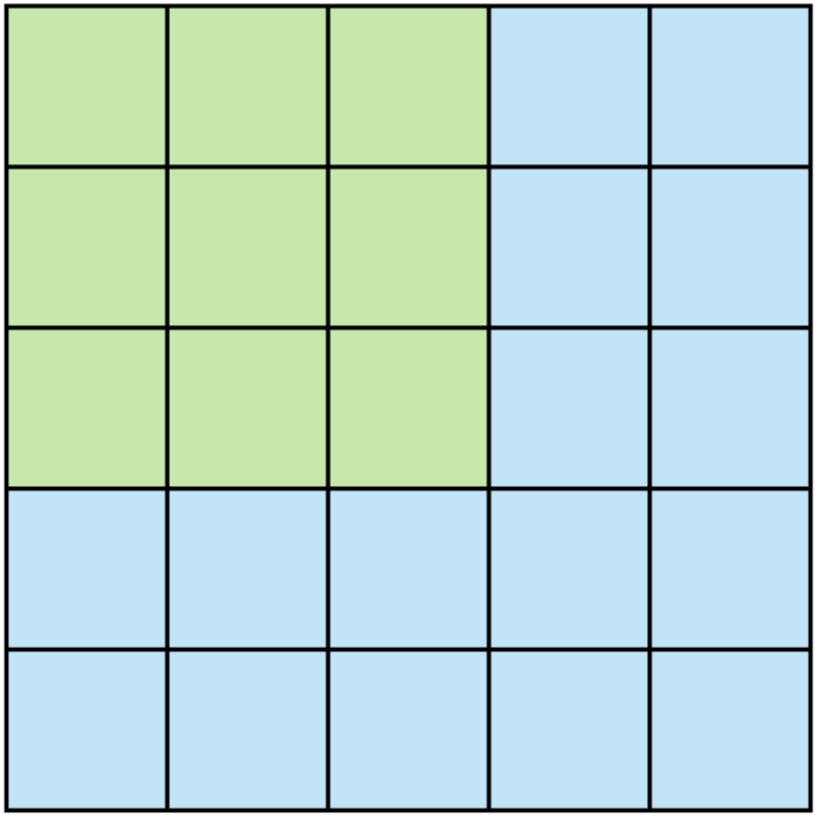
Feature Map

Convolução

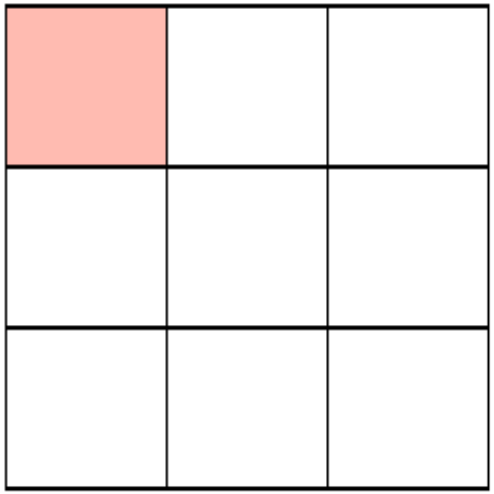
1x1	1x0	1x1	0	0
0x0	1x1	1x0	1	0
0x1	0x0	1x1	1	1
0	0	1	1	0
0	1	1	0	0

4		

Stride

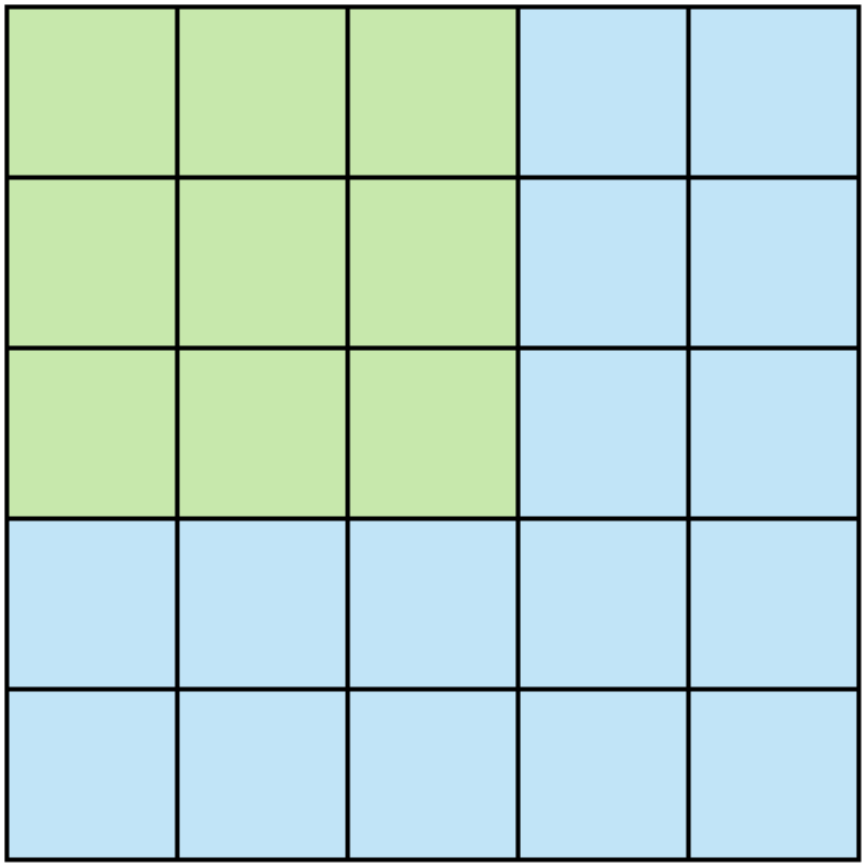


Stride 1

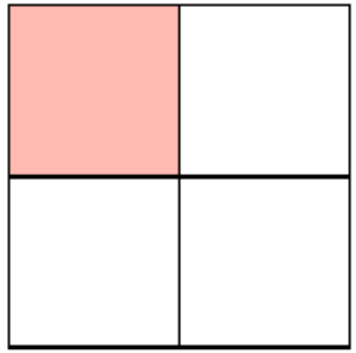


Feature Map

Stride

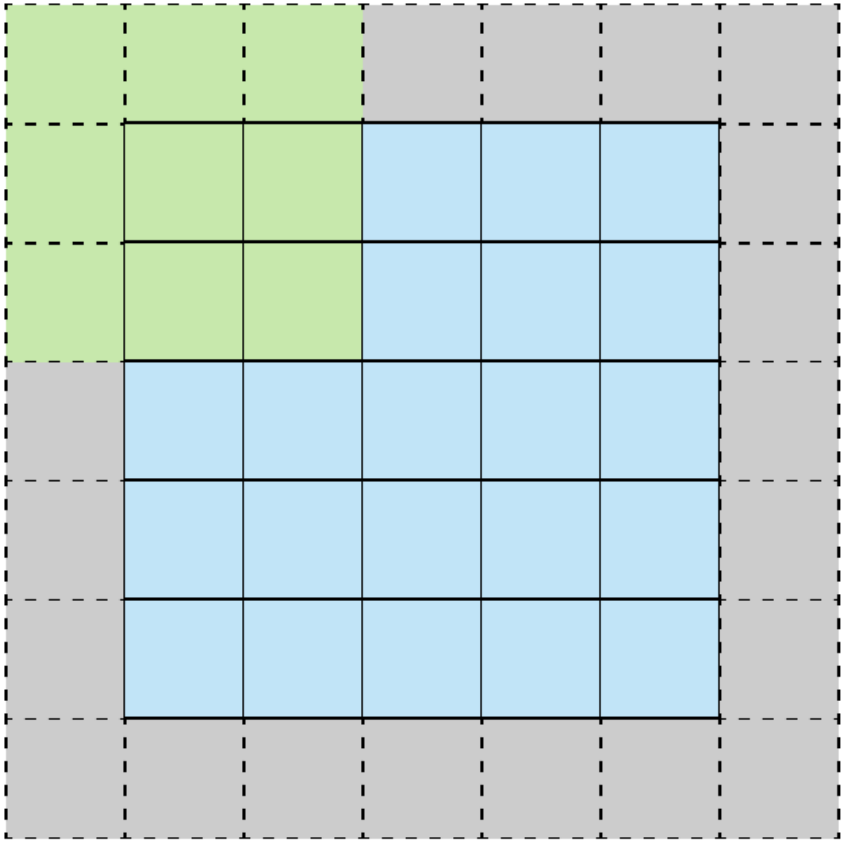


Stride 2

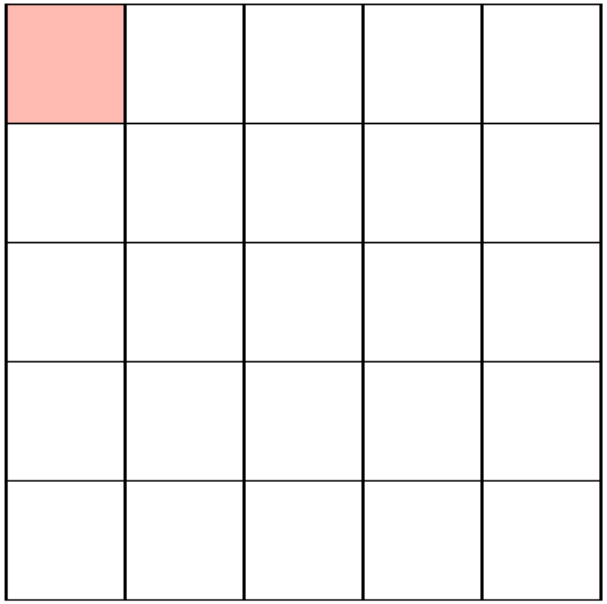


Feature Map

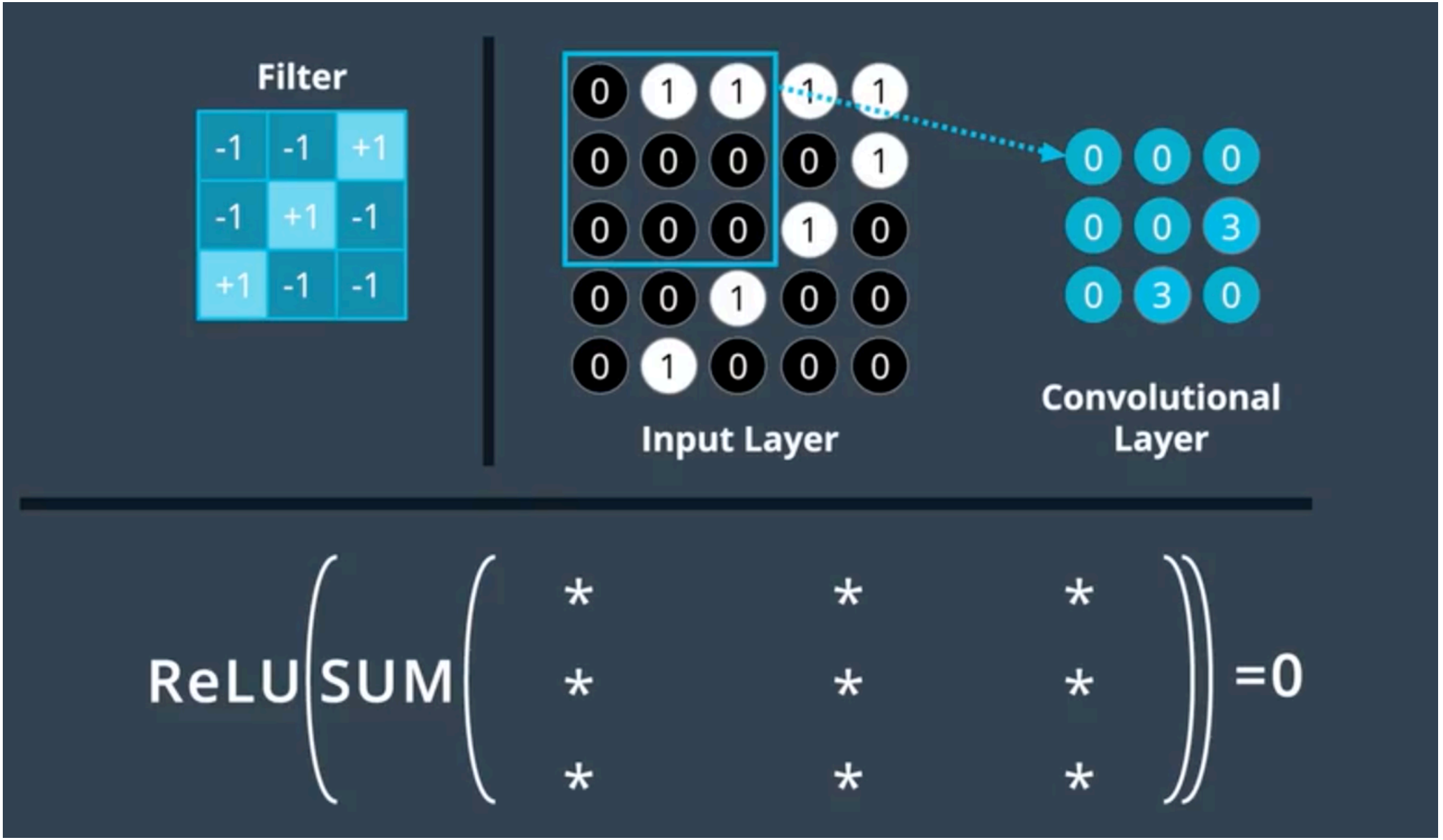
Padding

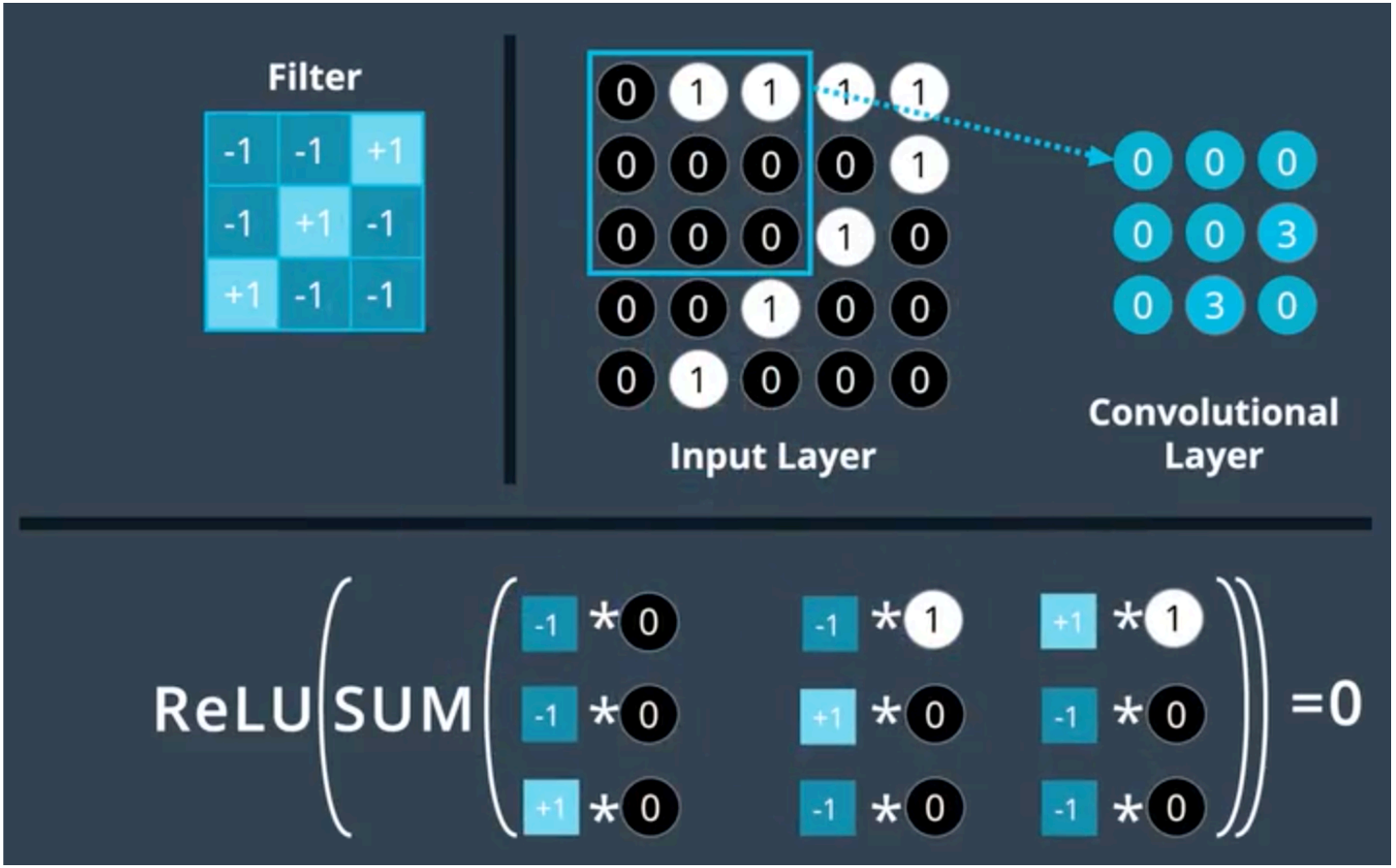


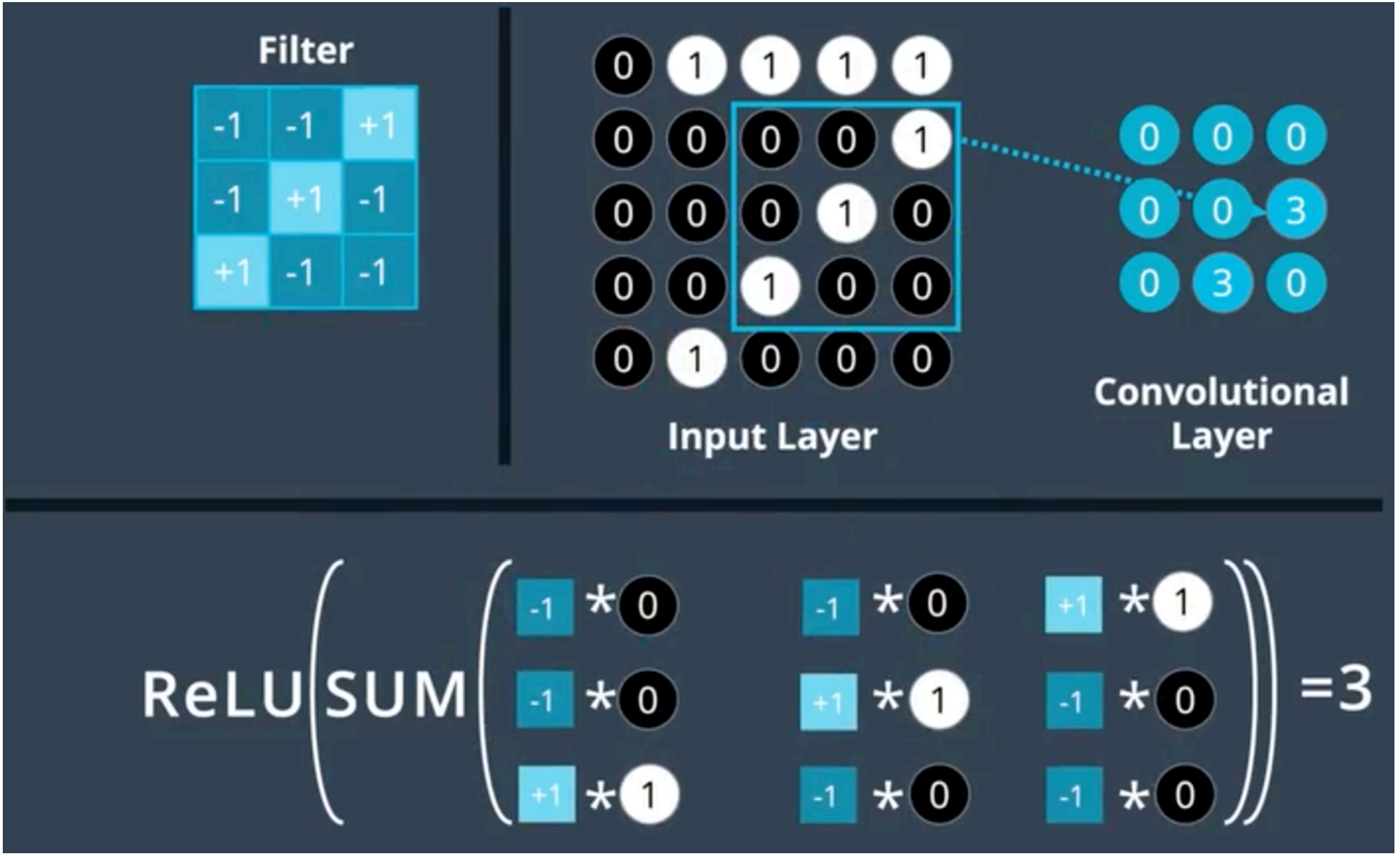
Stride 1 with Padding

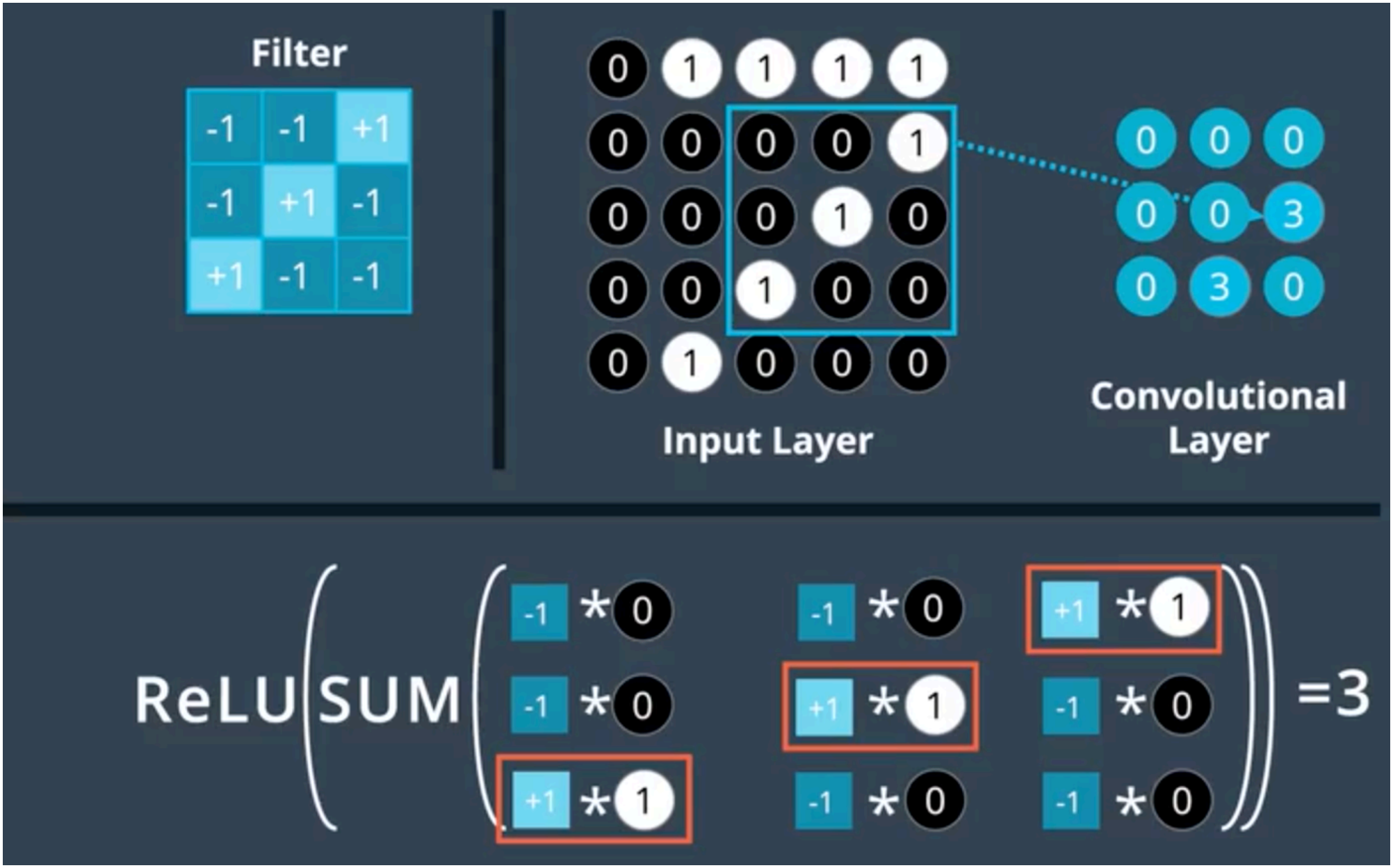


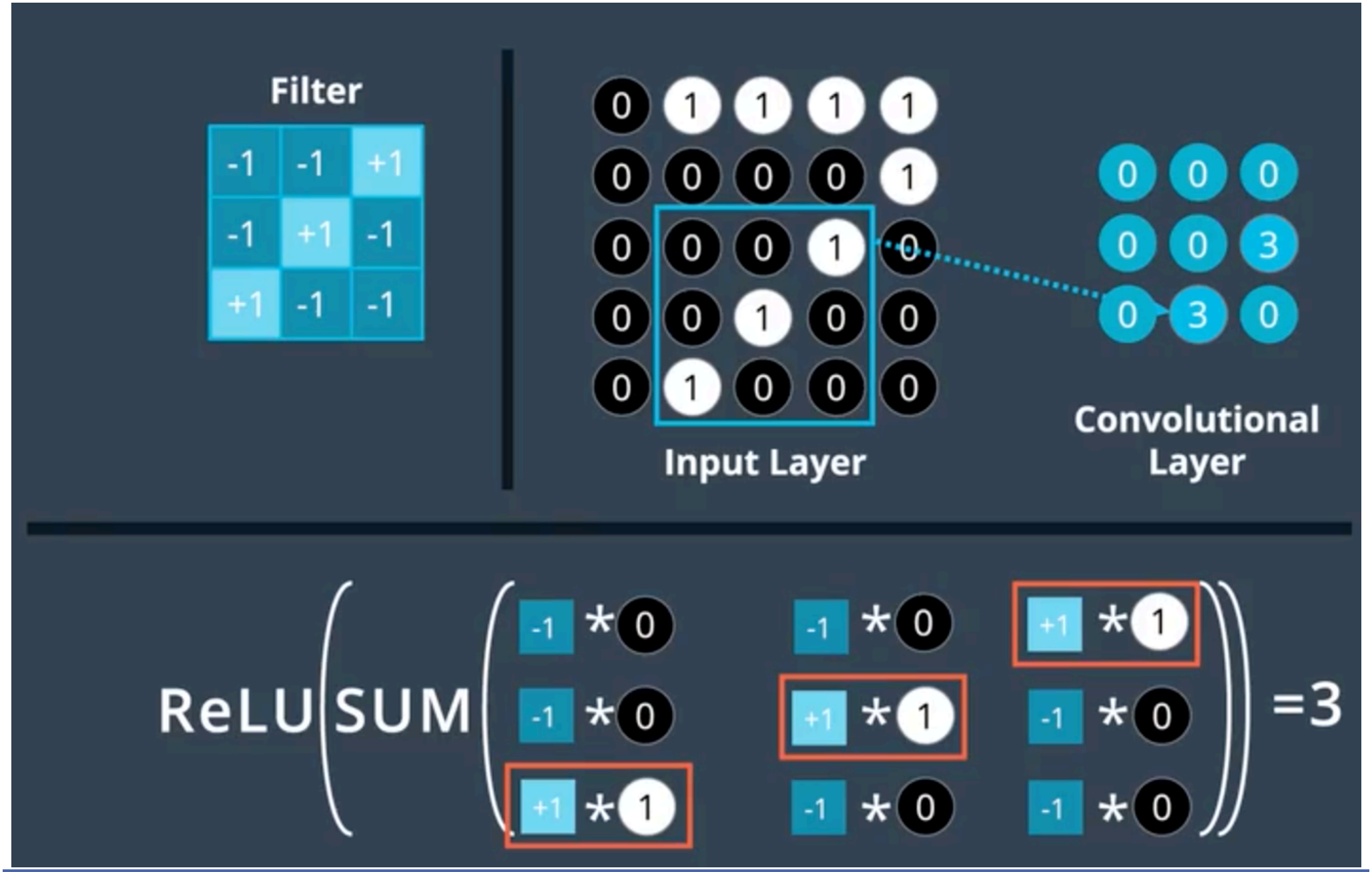
Feature Map

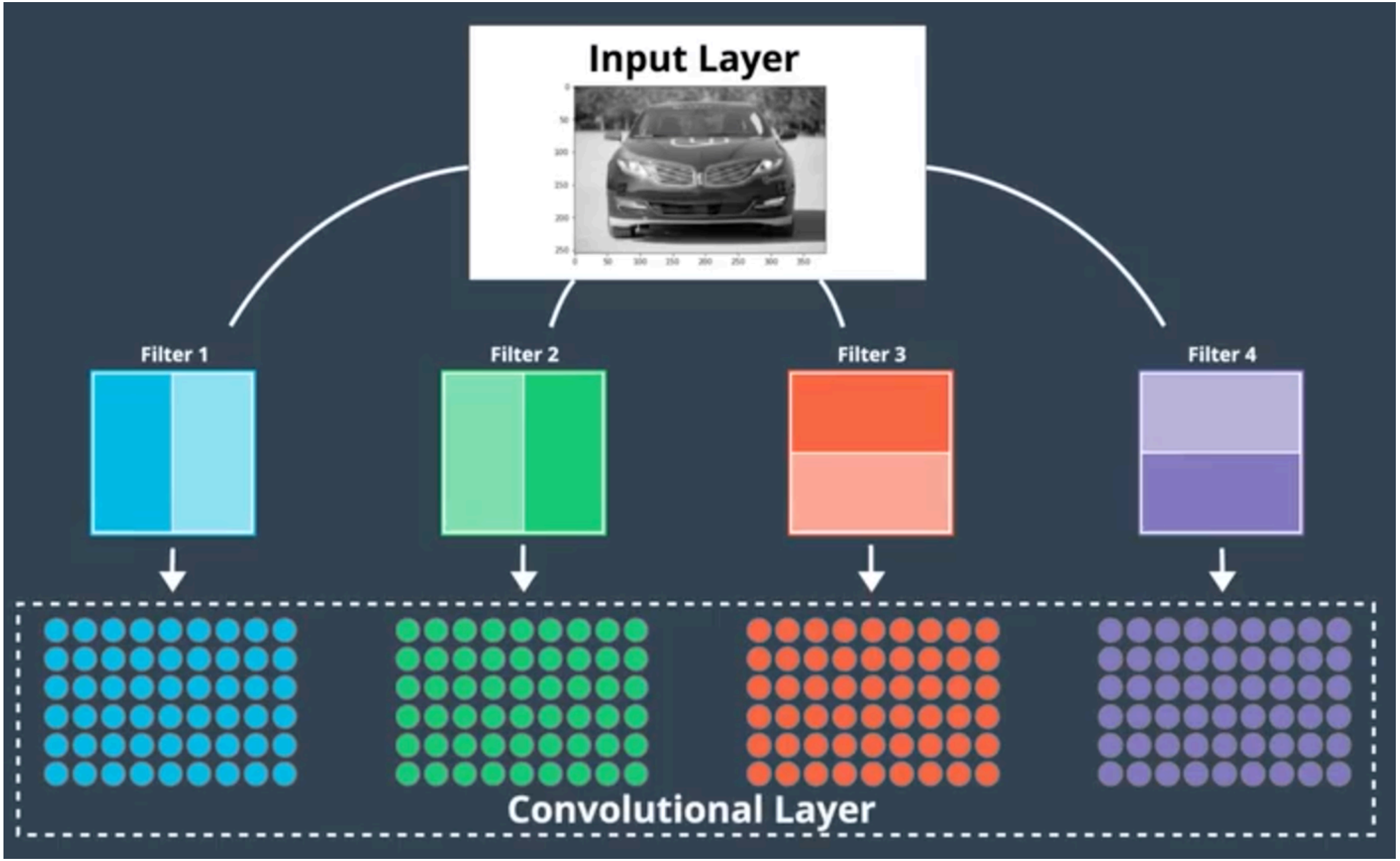

Filter
-1 -1 +1
-1 +1 -1
+1 -1 -1
0 1 1 1 1
0 0 0 0 1
0 0 0 1 0
0 0 1 0 0
0 1 0 0 0
Input Layer
0 0 0
0 0 3
0 3 0
Convolutional Layer
ReLU(SUM(* * * * * * * * *))=0

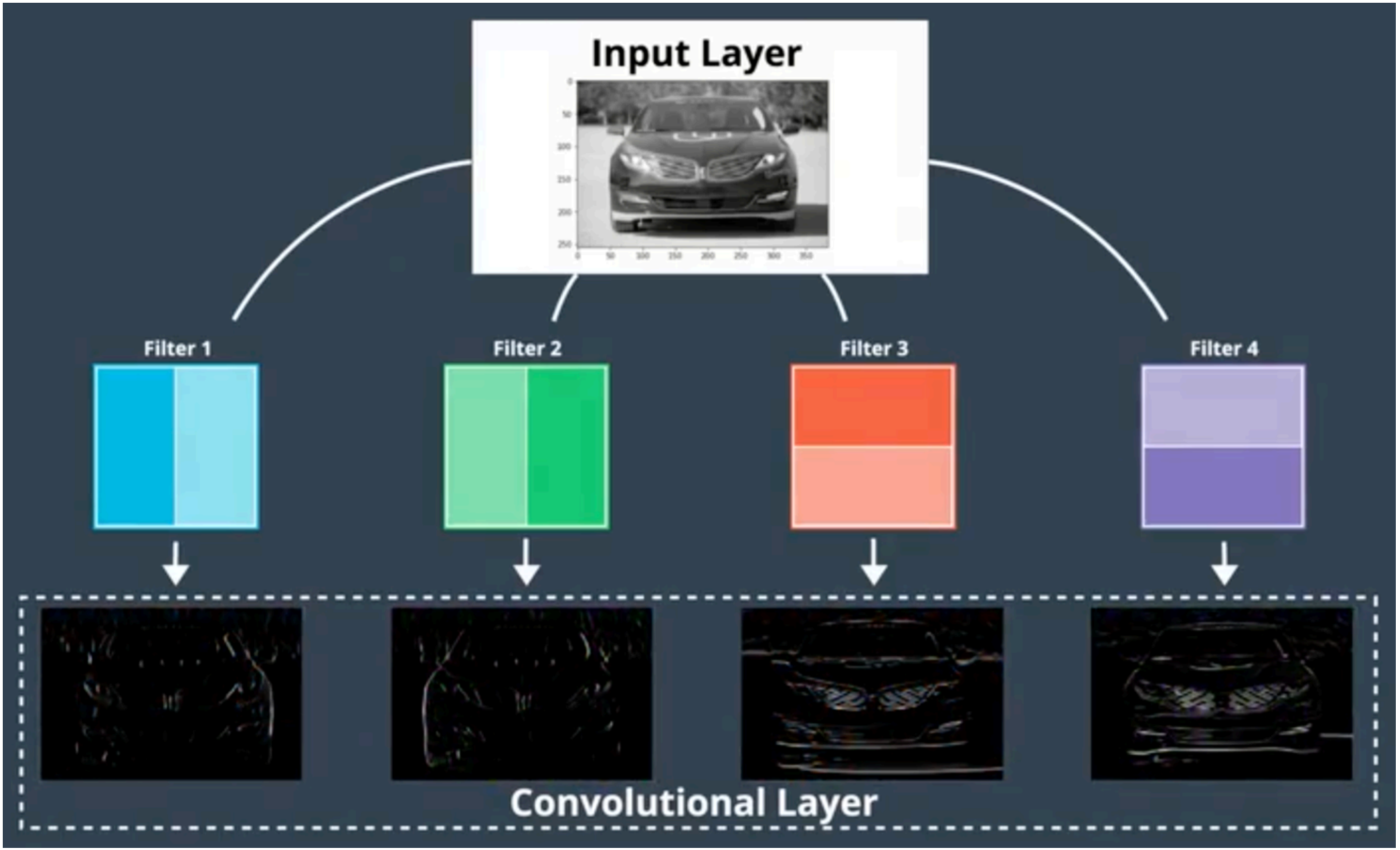

Filter
-1 -1 +1
-1 +1 -1
+1 -1 -1
0 1 1 1 1
0 0 0 0 1
0 0 0 1 0
0 0 1 0 0
0 1 0 0 0
Input Layer
0 0 0
0 0 3
0 3 0
Convolutional Layer
ReLU SUM
-1 * 0
-1 * 1
+1 * 1
-1 * 0
+1 * 0
-1 * 0
+1 * 0
-1 * 0
-1 * 0
=0

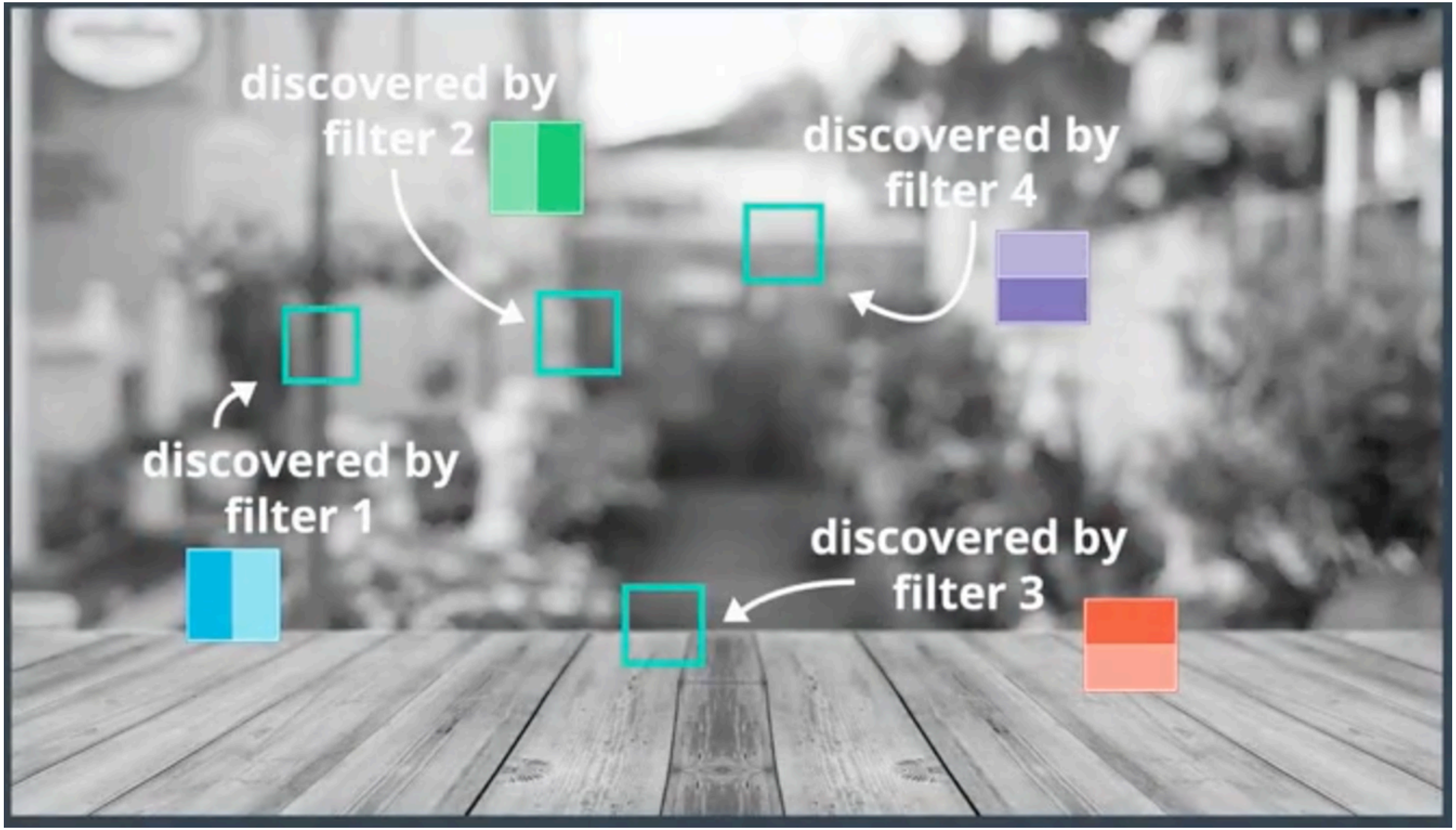

Filter
-1 -1 +1
-1 +1 -1
+1 -1 -1
0 1 1 1 1
0 0 0 0 1
0 0 0 1 0
0 0 1 0 0
0 1 0 0 0
Input Layer
0 0 0
0 0 3
0 3 0
Convolutional Layer
ReLU SUM
-1 * 0
-1 * 0
+1 * 1
-1 * 0
+1 * 1
-1 * 0
+1 * 1
-1 * 0
-1 * 0
=3


Filter
-1 -1 +1
-1 +1 -1
+1 -1 -1
0 1 1 1 1
0 0 0 0 1
0 0 0 1 0
0 0 1 0 0
0 1 0 0 0
Input Layer
0 0 0
0 0 3
0 3 0
Convolutional Layer
ReLU SUM
-1 * 0
-1 * 0
+1 * 1
-1 * 0
+1 * 1
-1 * 0
+1 * 1
-1 * 0
-1 * 0
=3

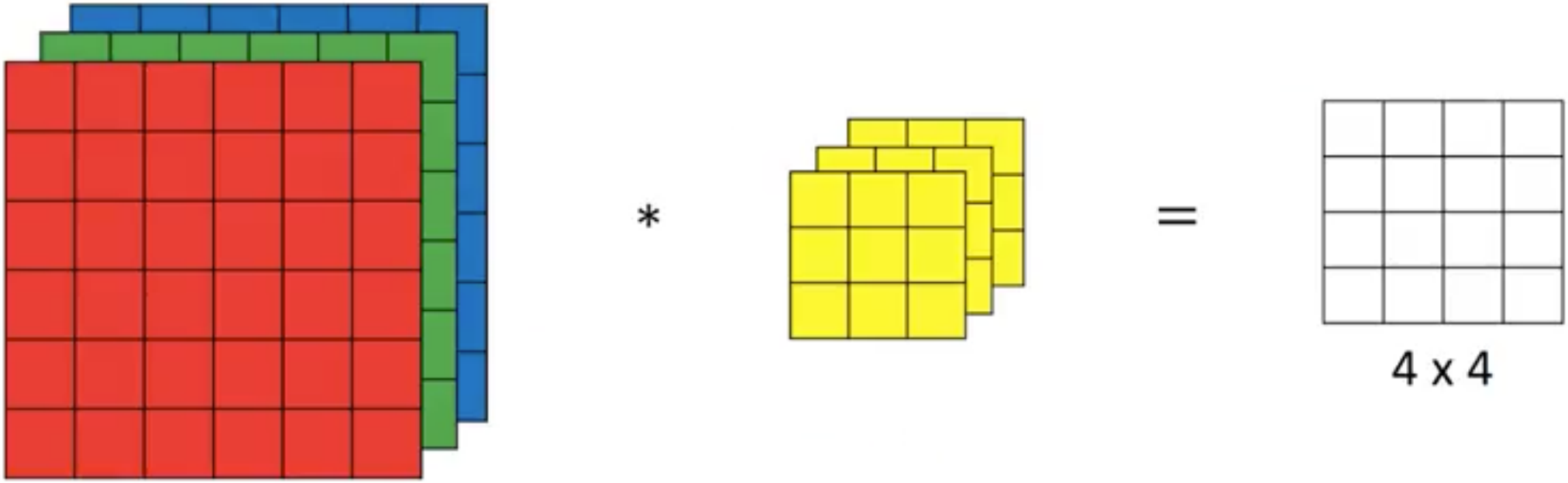

Filter
-1 -1 +1
-1 +1 -1
+1 -1 -1
0 1 1 1 1
0 0 0 0 1
0 0 0 1 0
0 0 1 0 0
0 1 0 0 0
Input Layer
0 0 0
0 0 3
0 3 0
Convolutional Layer
ReLU SUM
-1 * 0
-1 * 0
+1 * 1
-1 * 0
+1 * 1
-1 * 0
-1 * 0
-1 * 0
+1 * 1
=3


Input Layer
Filter 1
Filter 2
Filter 3
Filter 4
Convolutional Layer

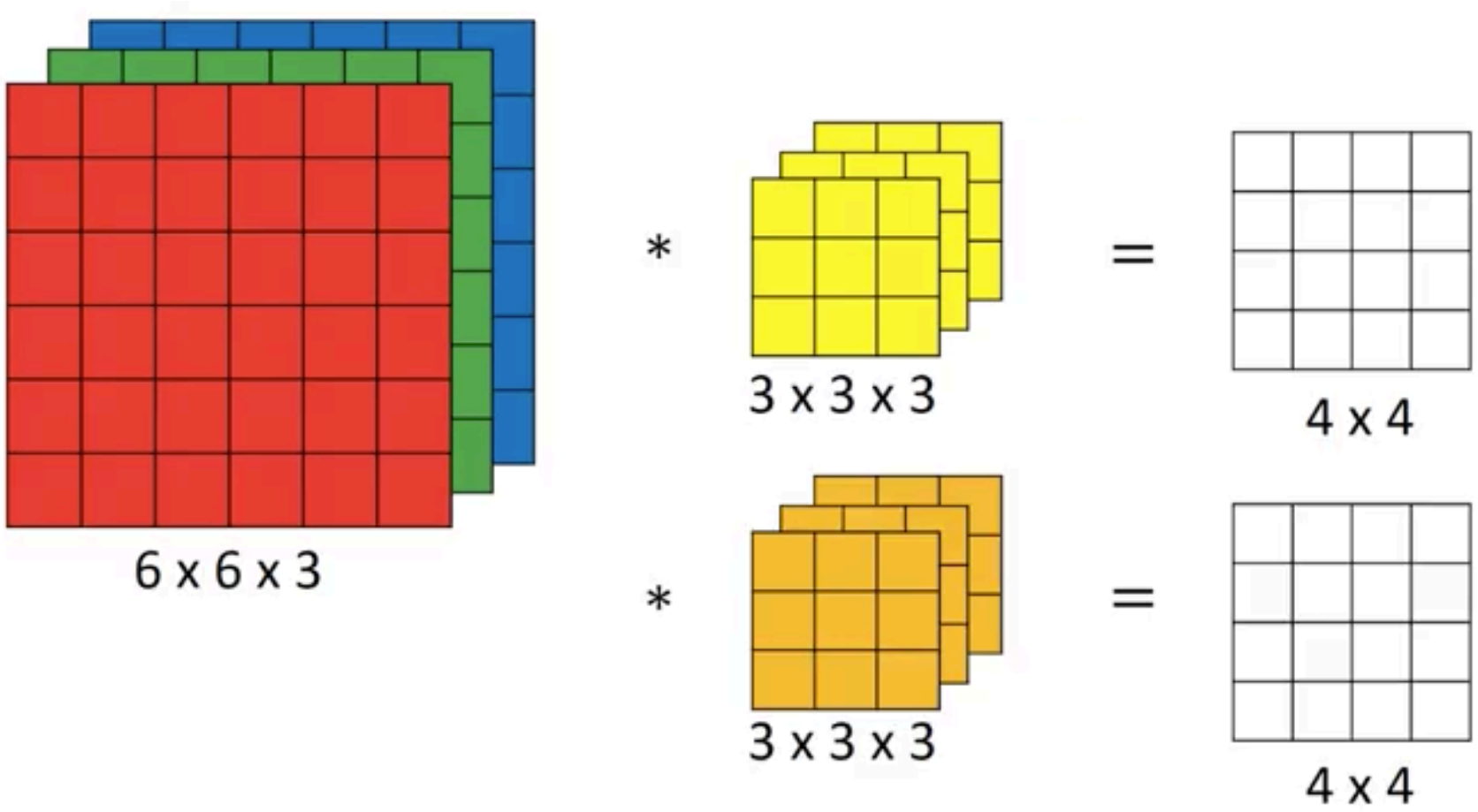

Input Layer
Filter 1
Filter 2
Filter 3
Filter 4
Convolutional Layer


discovered by
filter 2
discovered by
filter 4
discovered by
filter 1
discovered by
filter 3

Convolução em Imagem RGB

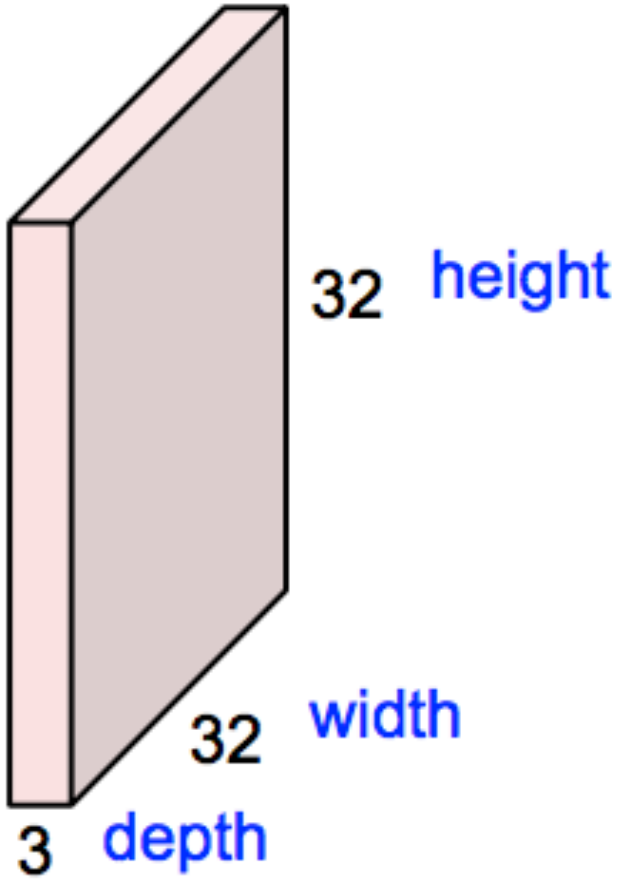


Múltiplos Filtros

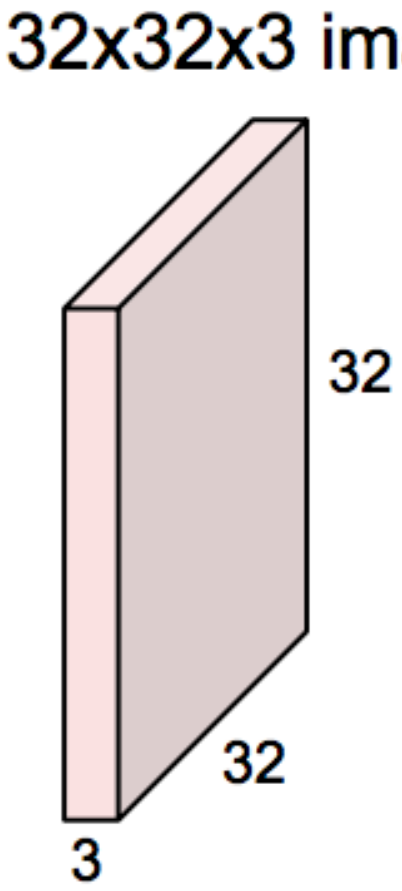


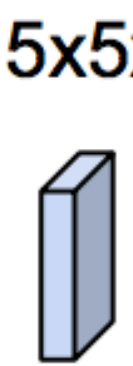
Camada Convolutiva

- Imagem 32x32x3



Camada Convolutiva

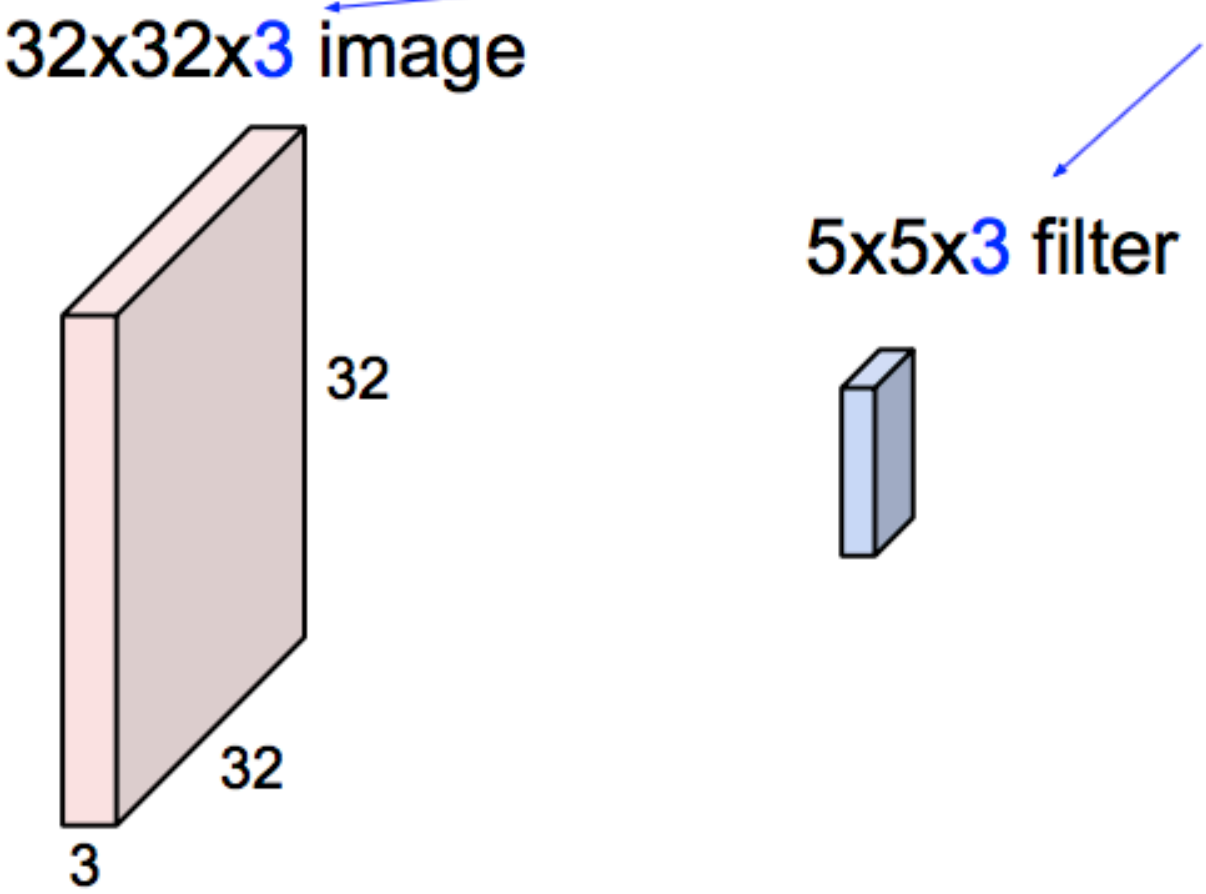




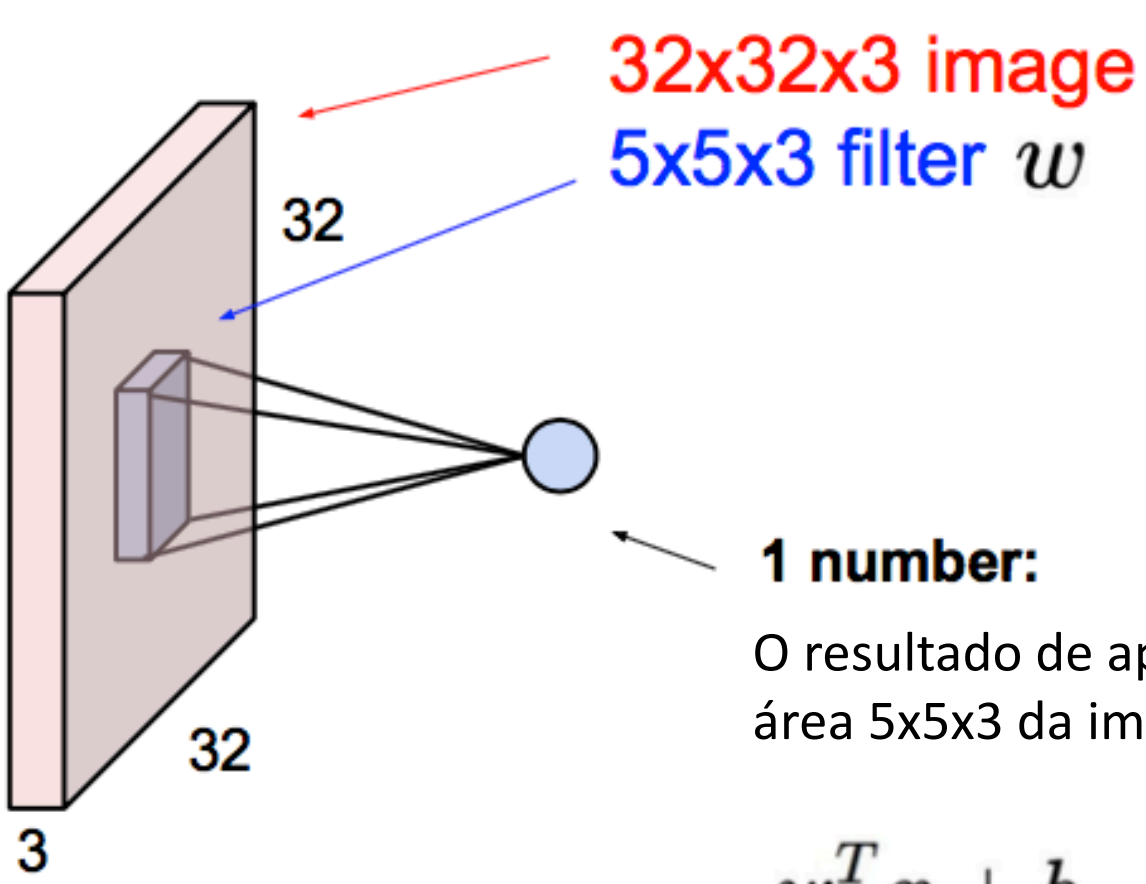
Convolve o filtro com a imagem

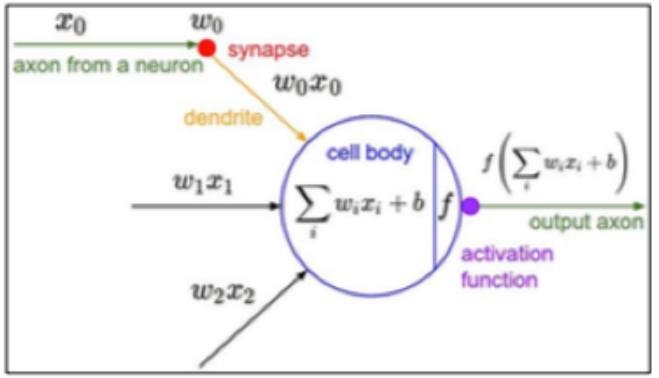
Camada Convolutiva

Filtro possui a profundidade
do volume de entrada



Camada Convolutiva





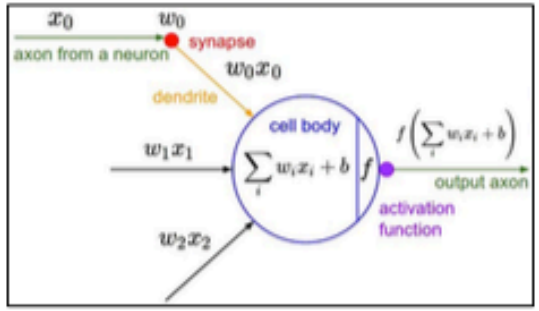
Neurônio com conectividade local

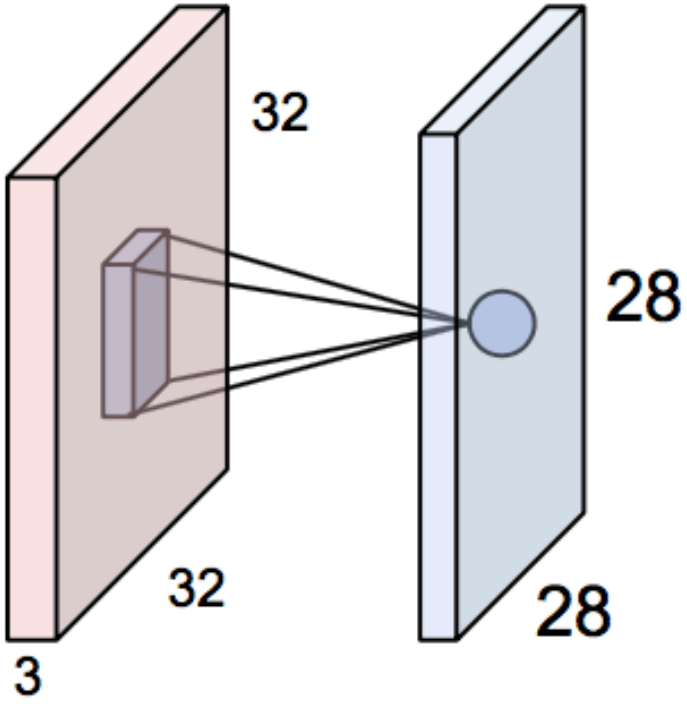
1 number:

O resultado de aplicar o produto entre o filtro e a área 5x5x3 da imagem (5*5*3=75 produtos + bias)

$$w^T x + b$$

Camada Convolutiva



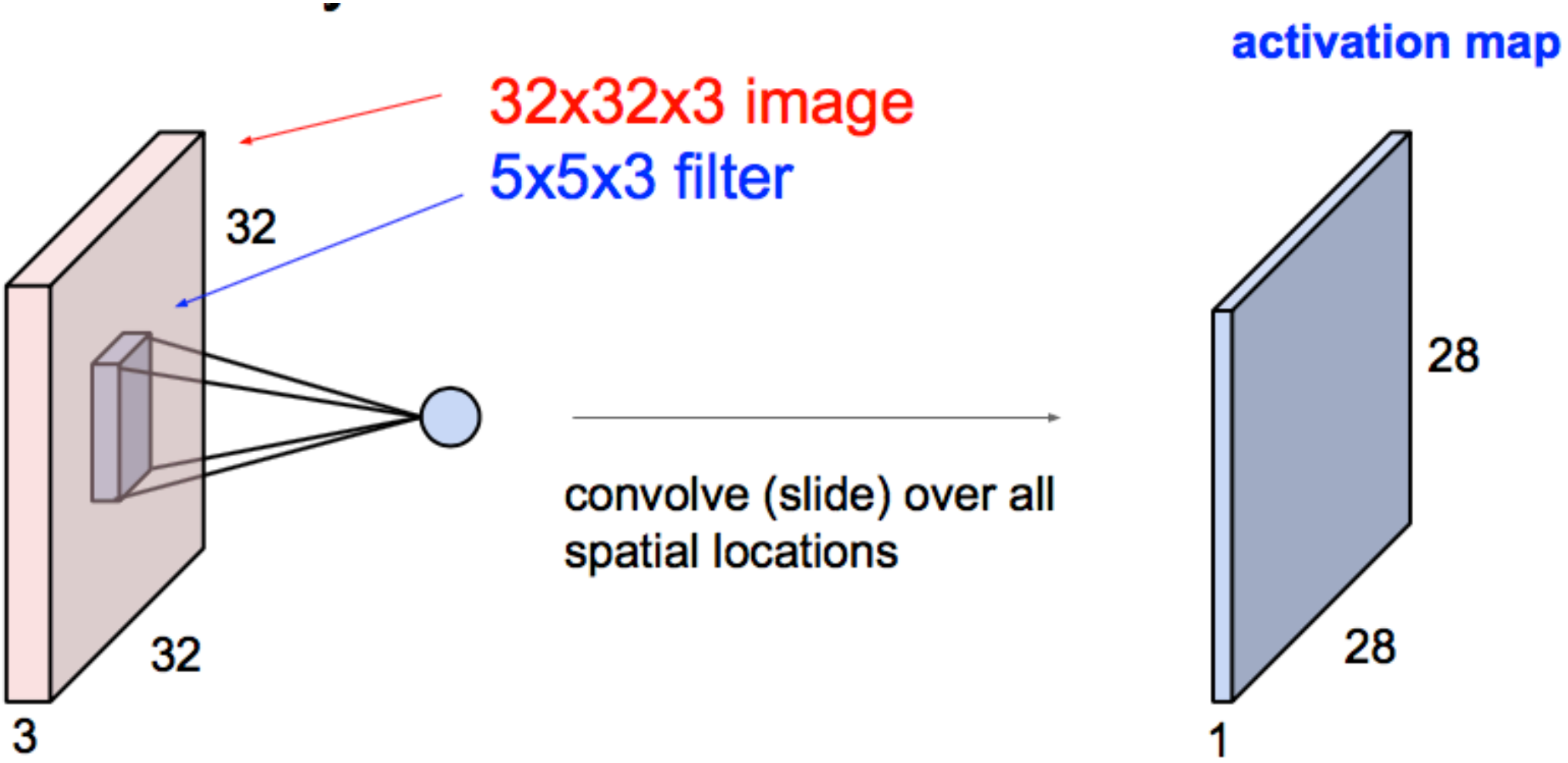


Um mapa de ativação é uma camada 28x28 de saídas de neurônios:

1. Cada uma está conectada a uma pequena região da imagem
2. Todos compartilham os parâmetros

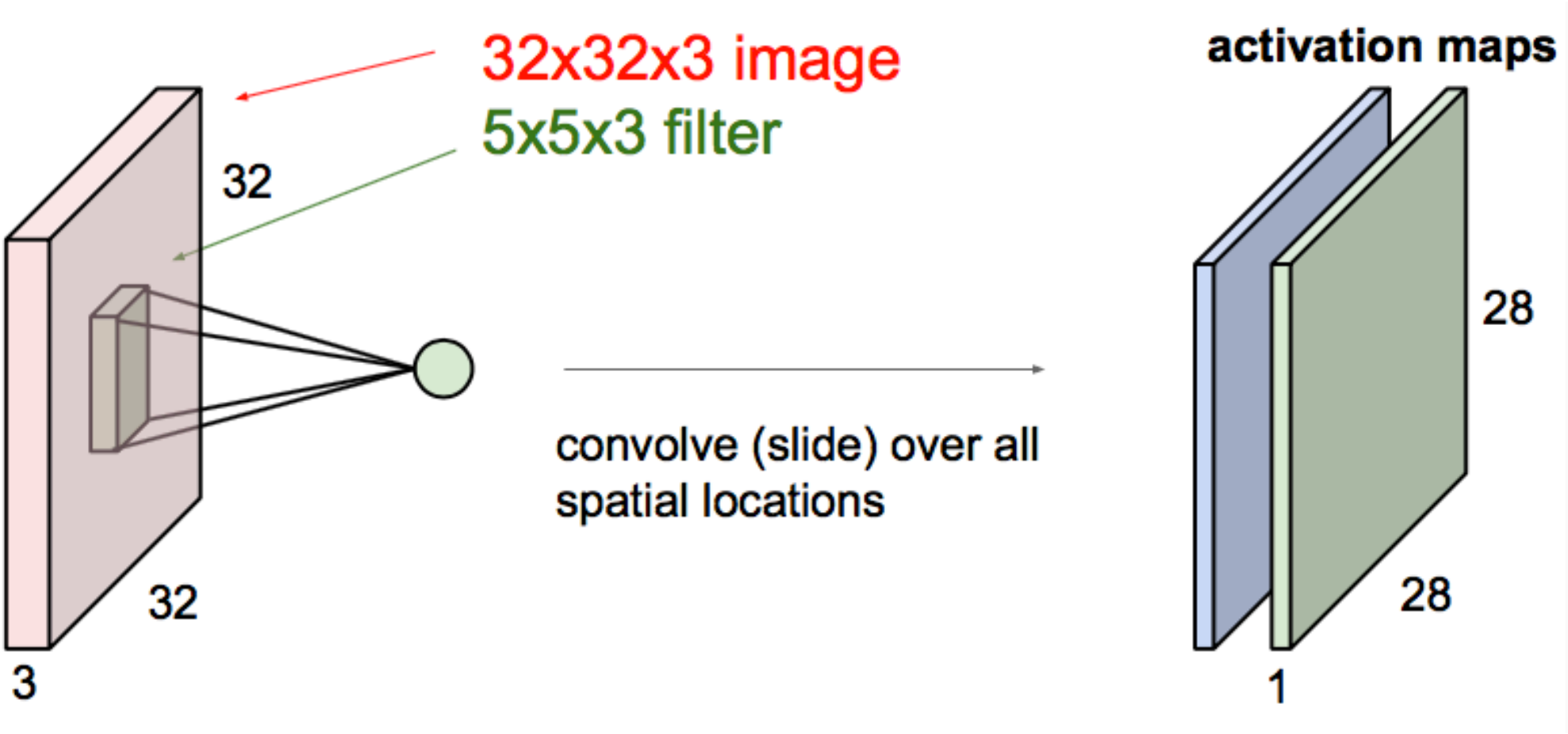
Filtro 5x5 -> campo receptivo 5x5 para cada neurônio

Camada Convolutiva



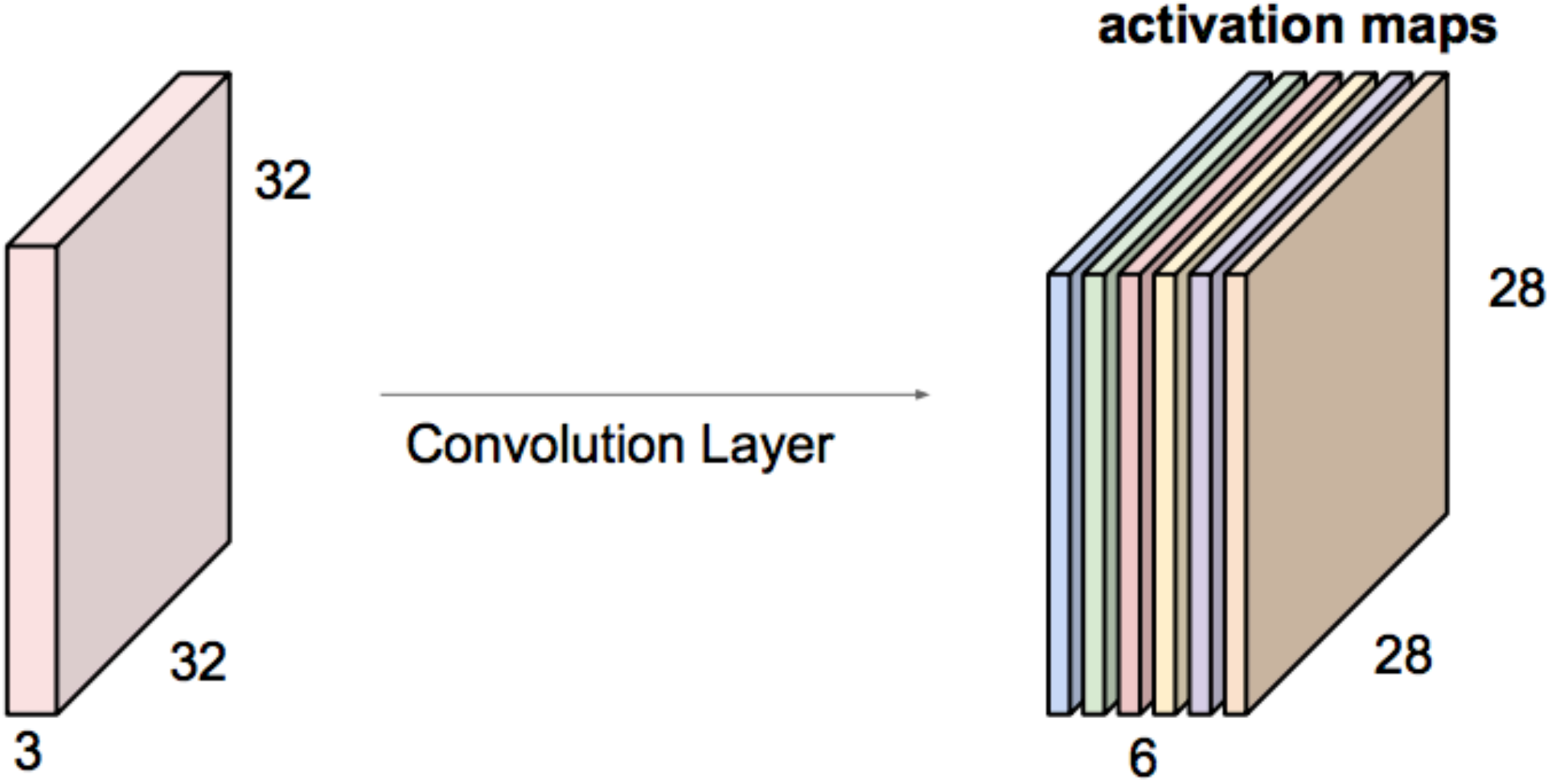
Camada Convolutiva

- Considere um segundo filtro **verde**



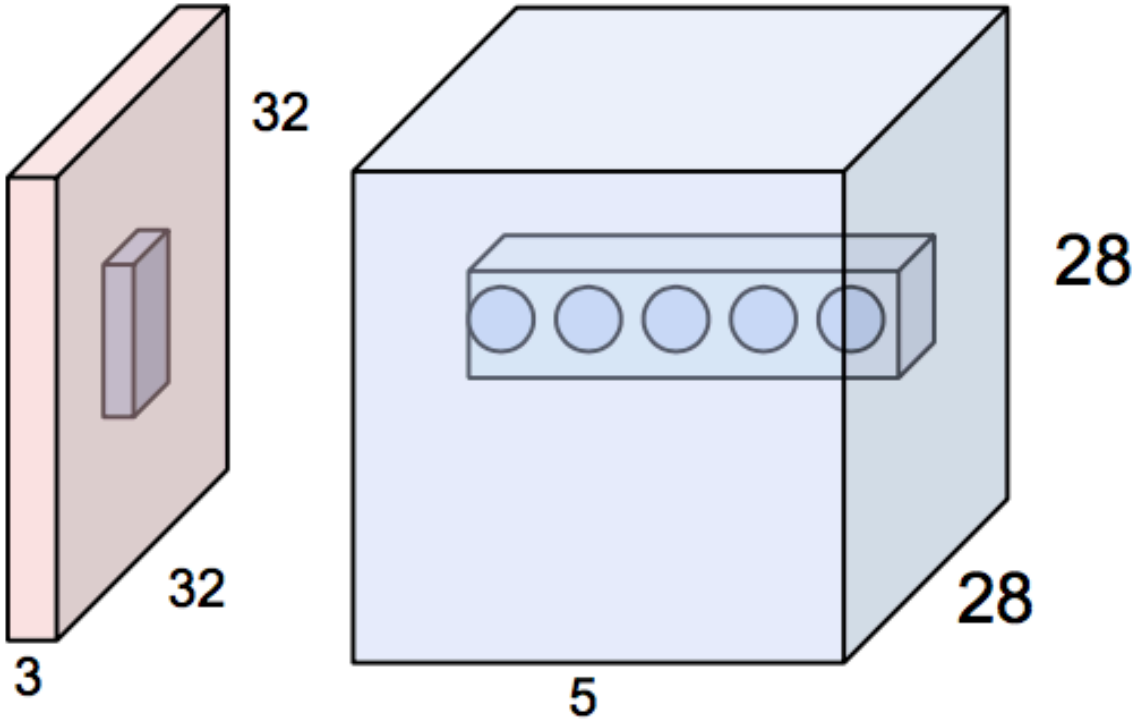
Camada Convolutiva

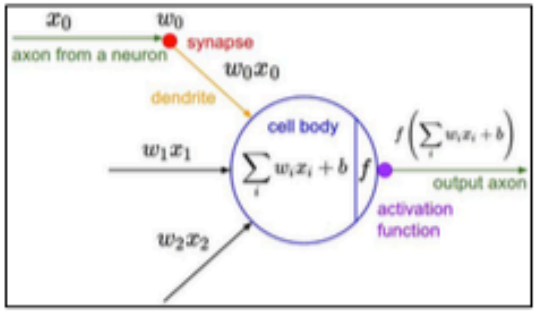
- Se tivéssemos 6 filtros 5x5, teríamos 6 mapas de ativação



Juntamos tudo para obter uma ”nova imagem” de tamanho 28x28x6!

Camada Convolutiva



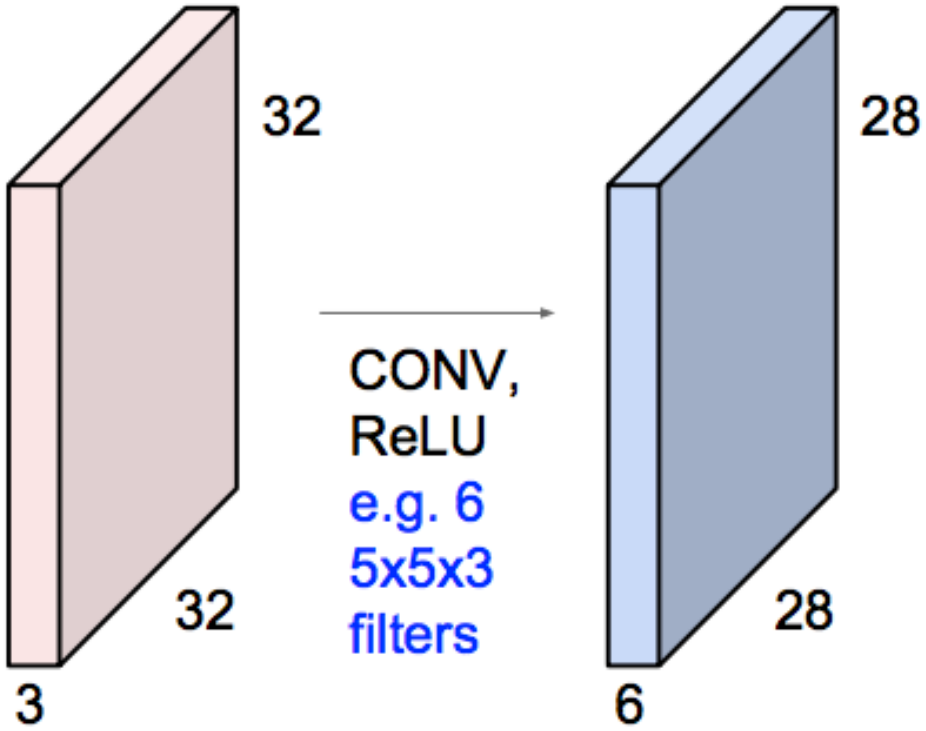


Ex: com 5 filtros, a camada CONV consiste de neurônios agrupados em um grid 3D (28x28x5)

Vão existir 5 diferentes neurônios observando a mesma região do volume de entrada

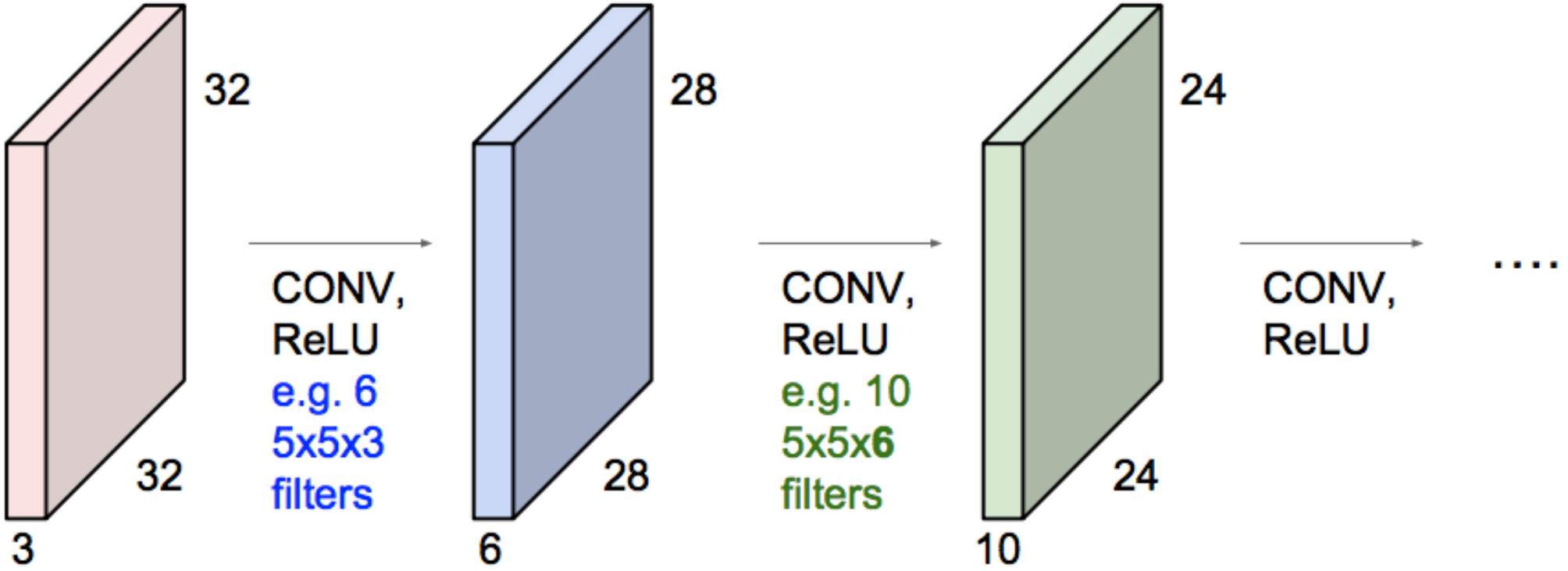
Camadas Convolutivas

- ConvNet é uma sequencia de Camadas Convolutivas, intercaladas com funções de ativação

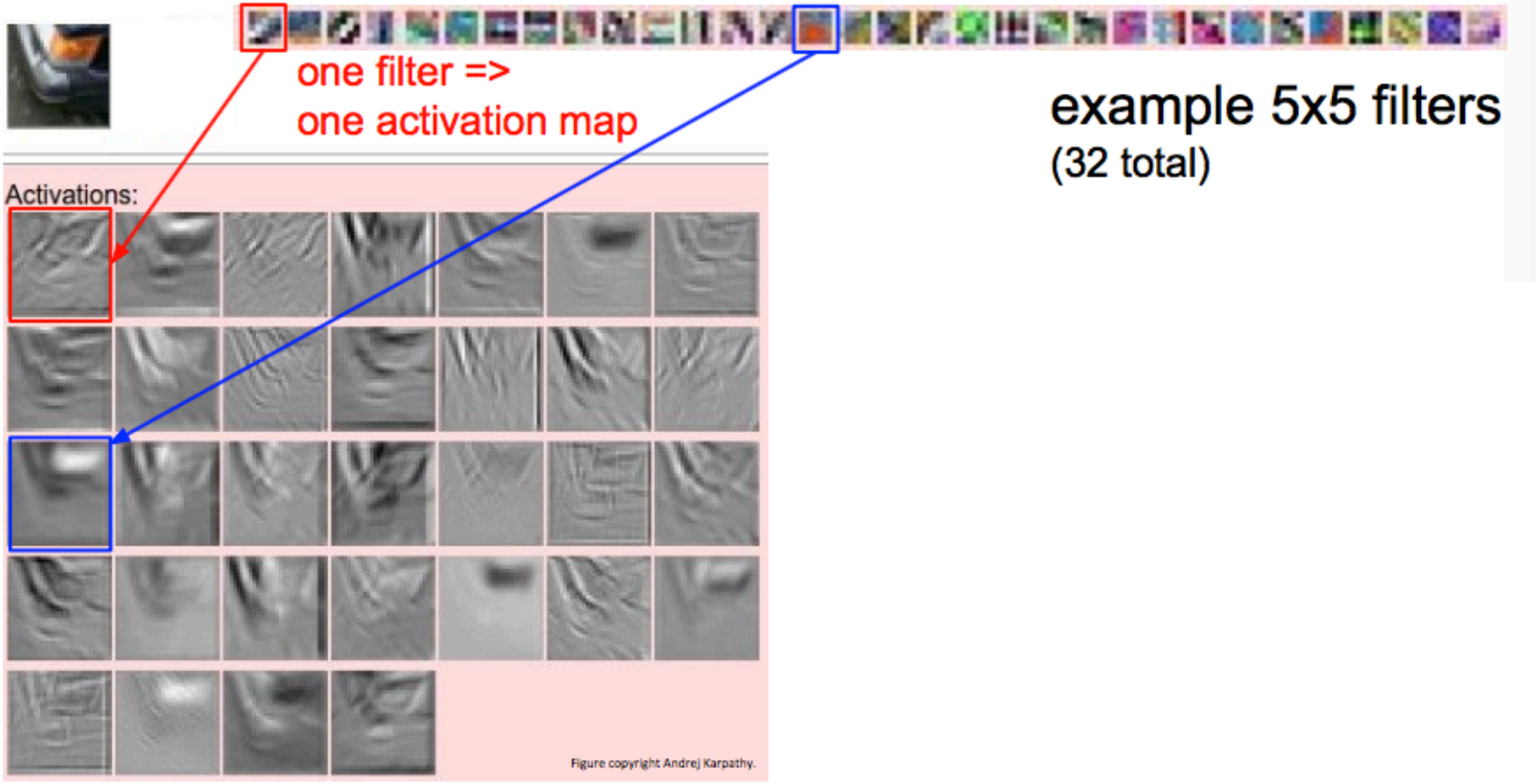


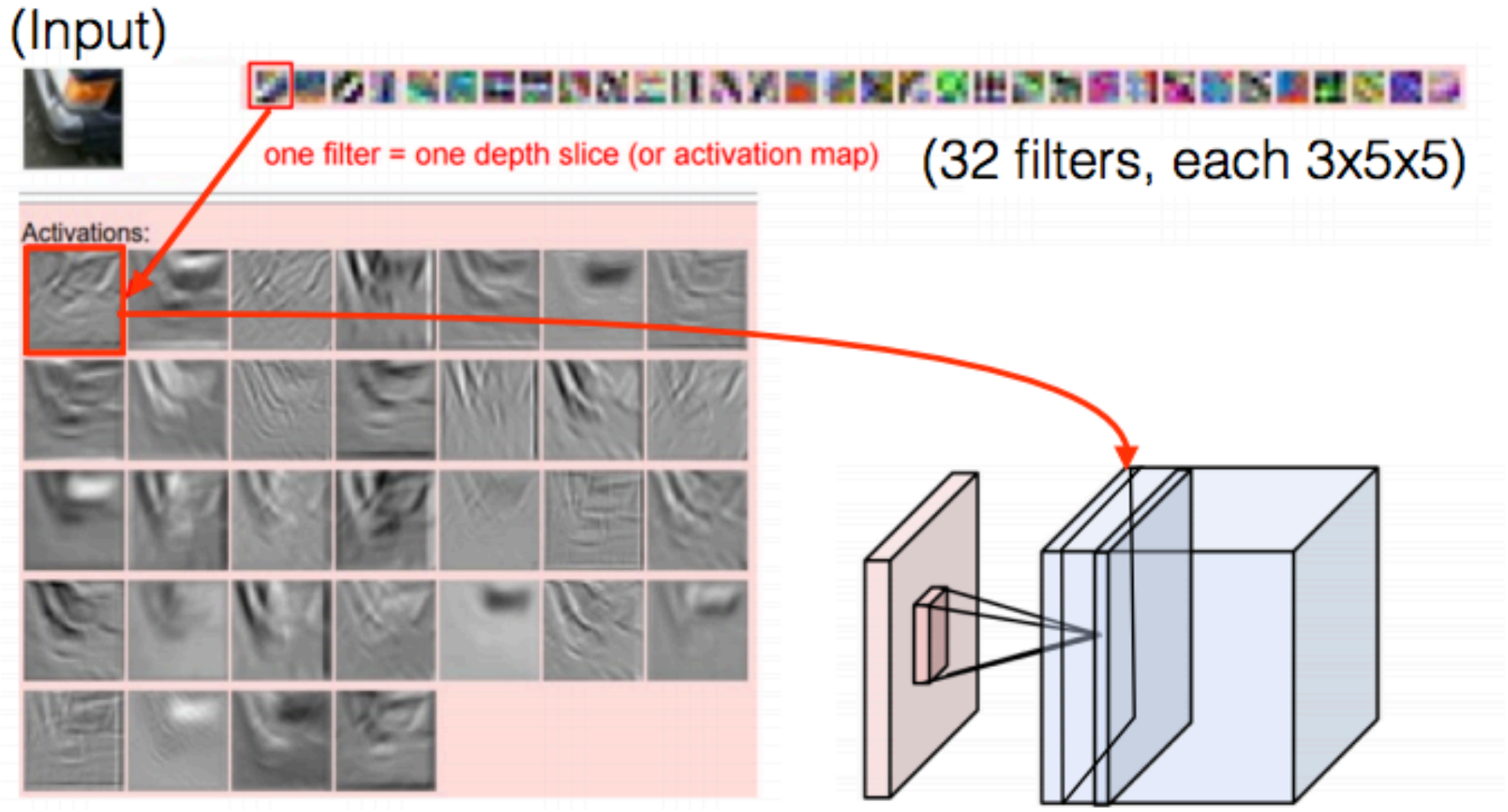
Camadas Convolutivas

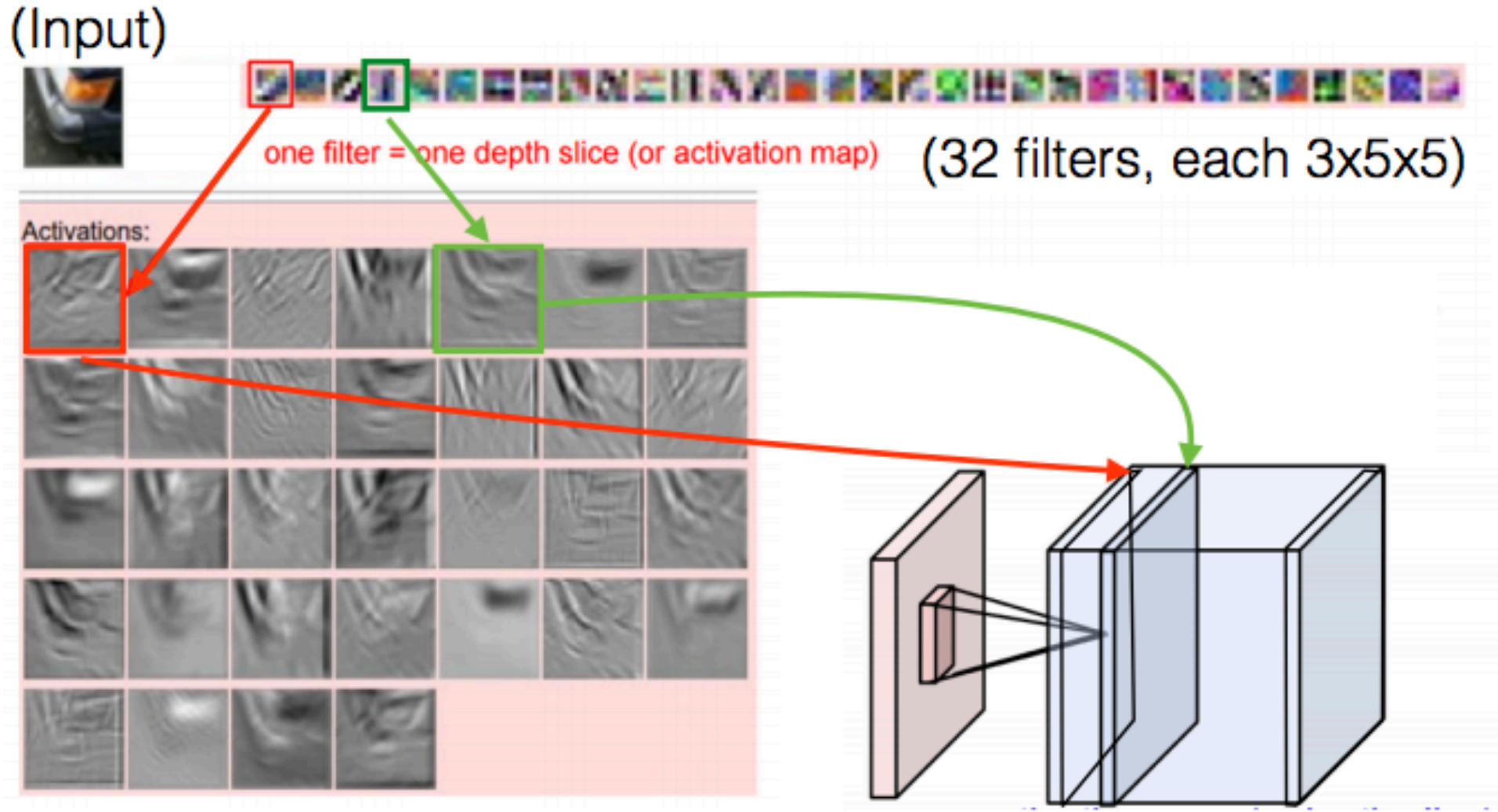
- ConvNet é uma sequencia de Camadas Convolutivas, intercaladas com funções de ativação



Exemplo ConvNet


one filter =>
one activation map
example 5x5 filters
(32 total)
Activations:
Figure copyright Andrej Karpathy.


(Input)
one filter = one depth slice (or activation map)
(32 filters, each 3x5x5)
Activations:


(Input)
one filter = one depth slice (or activation map)
(32 filters, each 3x5x5)
Activations:

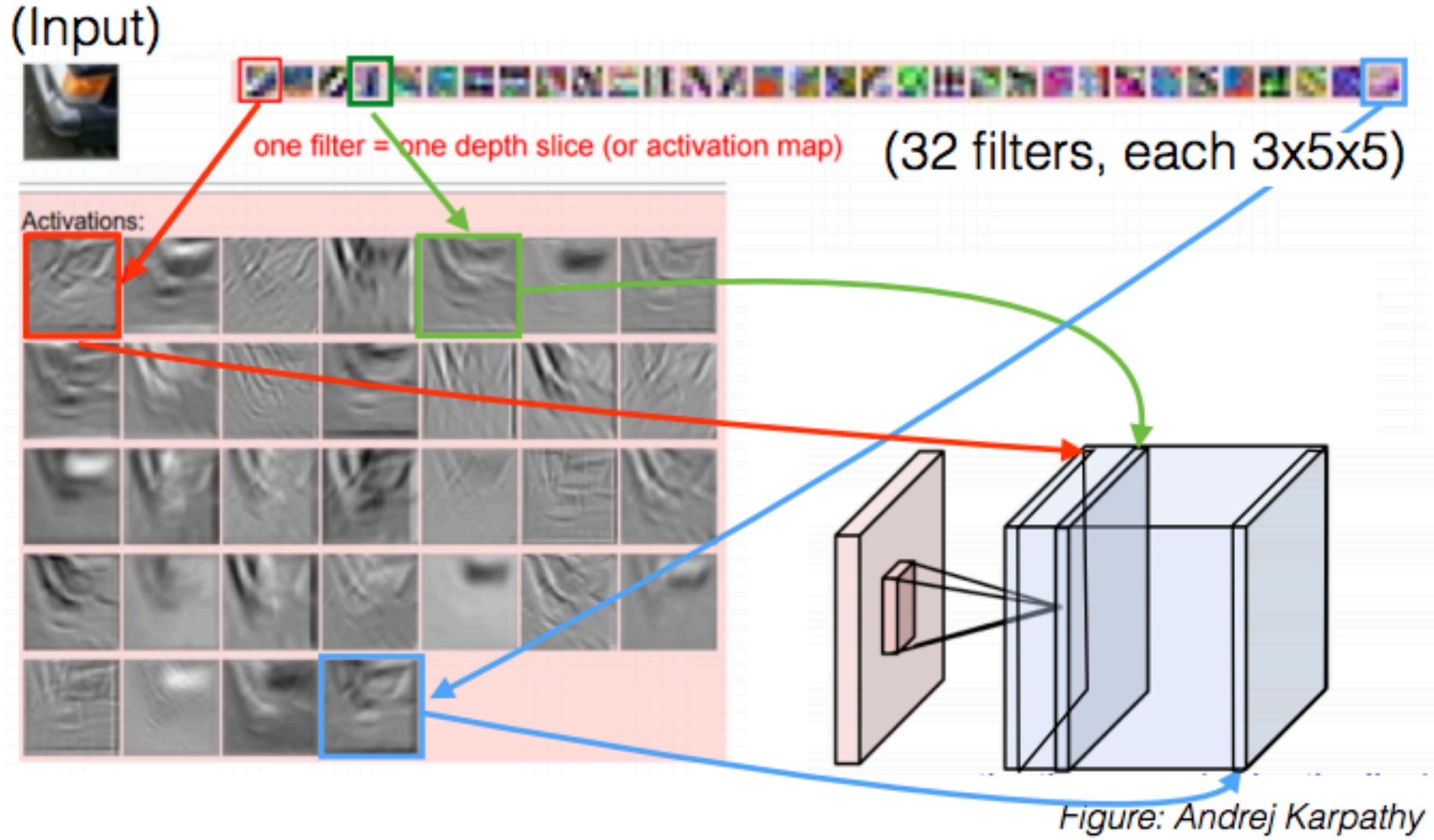


Figure: Andrej Karpathy

Resumo: Camada Convolutiva

- Aceita volume do tamanho $\boldsymbol{W_1 \times H_1 \times D_1}$
- Requer 4 hiperparâmetros:
  - Número de filtros **K**,
  - Tamanho do Filtro **F**,
  - Stride **S**,
  - Quantidade de zero padding **P**.
- Produz um volume $\boldsymbol{W_2 \times H_2 \times D_2}$ onde:
  - $\boldsymbol{W_2 = \frac{W_1 - F + 2P}{S} + 1}$
  - $\boldsymbol{H_2 = \frac{H_1 - F + 2P}{S} + 1}$
  - $\boldsymbol{D_2 = K}$
- $\boldsymbol{F \cdot F \cdot D_1}$ pesos por filtro. Total de $(\boldsymbol{F \cdot F \cdot D_1})$ pesos e **K** biases;

Resumo: Camada Convolutiva

- Aceita volume do tamanho $W_1 \times H_1 \times D_1$
- Requer 4 hiperparâmetros:
  - Número de filtros **K**,
  - Tamanho do Filtro **F**,
  - Stride **S**,
  - Quantidade de zero padding **P**.

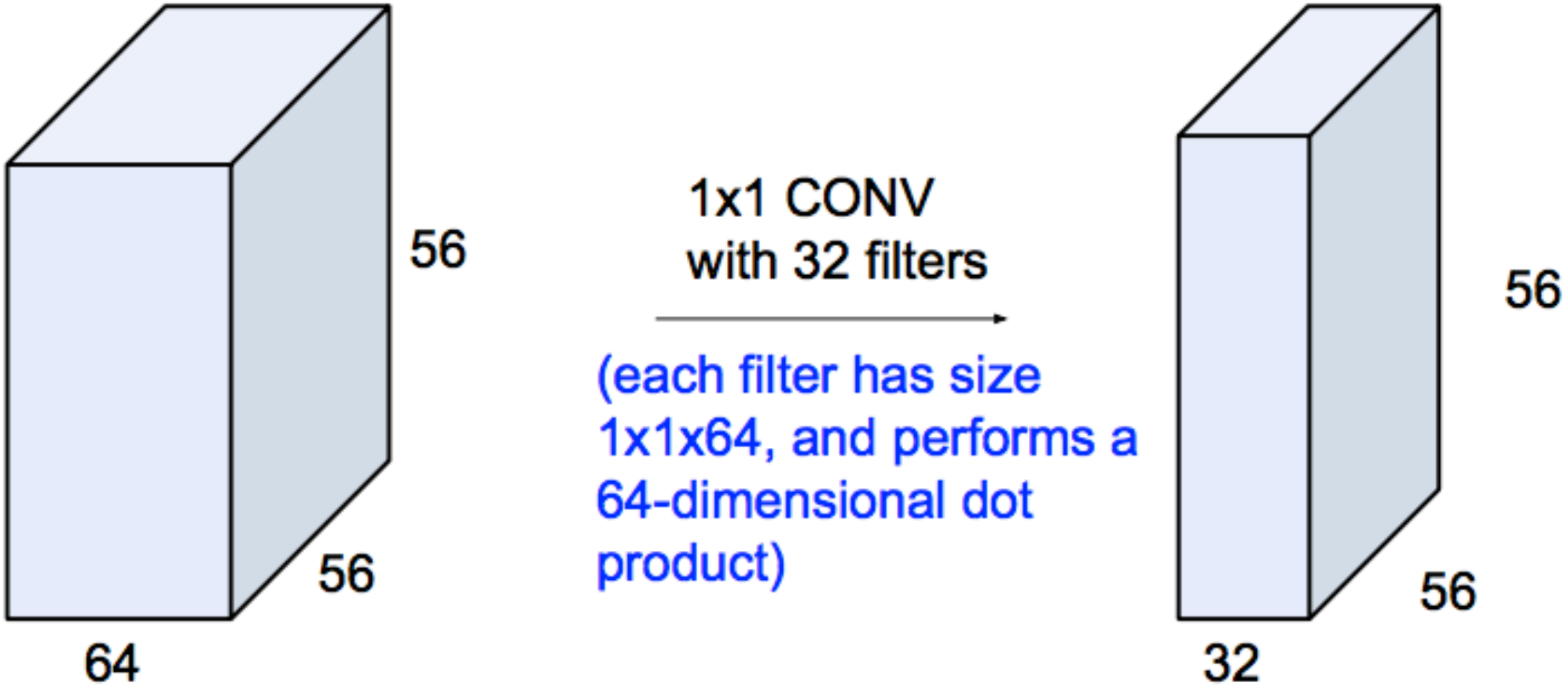
Configurações comuns:

K= (potência de 2. Ex: 32,64,128,512)
- F=3, S=1, P=1
- F =5,S=1, P=2
- F=1, S=1, P=0

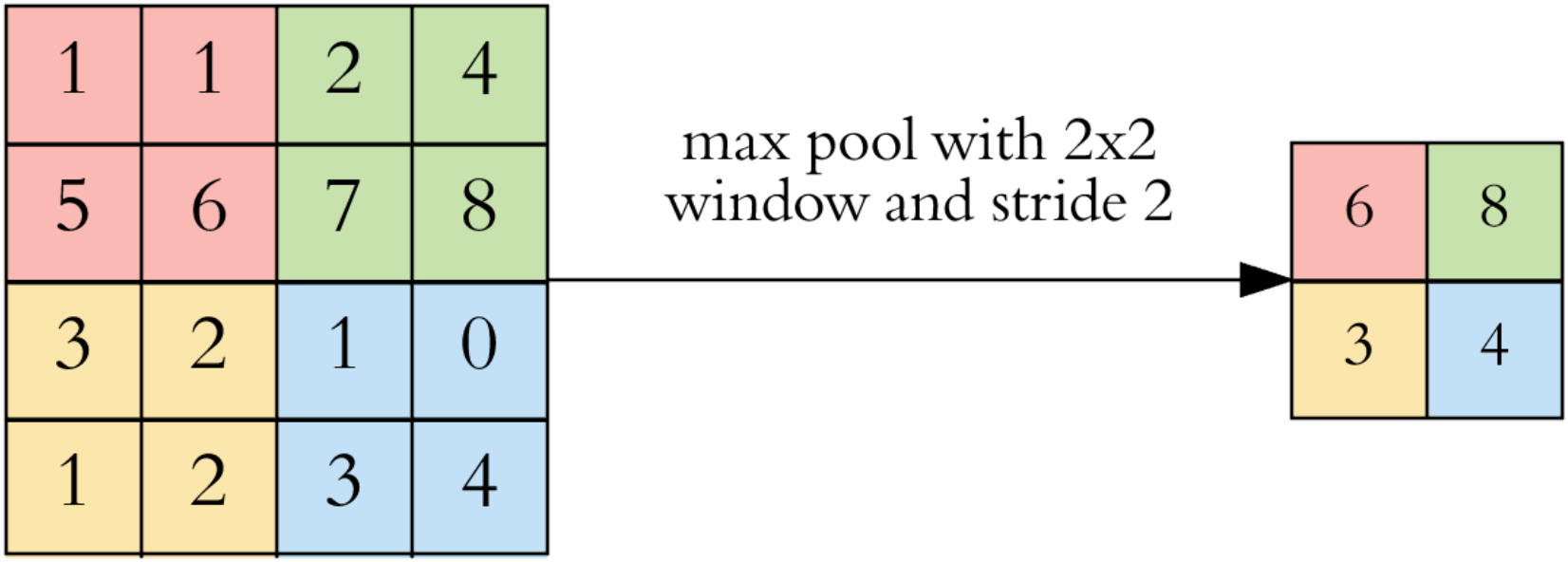
- Produz um volume $W_2 \times H_2 \times D_2$ onde:
  - $W_2 = \frac{W_1 - F + 2P}{S} + 1$
  - $H_2 = \frac{H_1 - F + 2P}{S} + 1$
  - $D_2 = K$
- $F \cdot F \cdot D_1$ pesos por filtro. Total de $(F \cdot F \cdot D_1)$ pesos e **K** biases;

Camada convolutiva

- Camada 1x1 também faz sentido

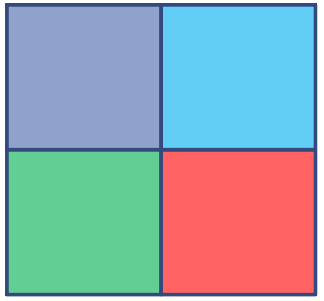


Pooling

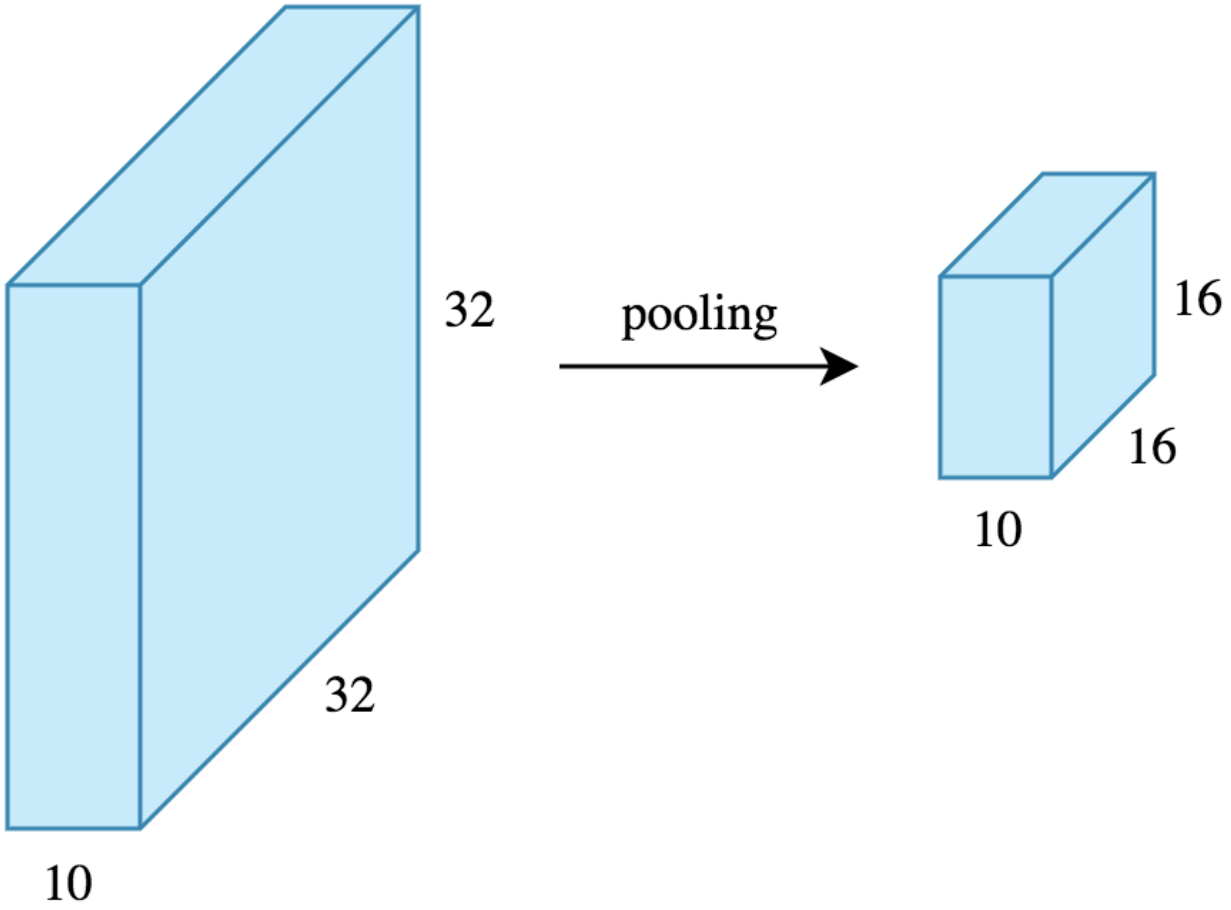

1 1 2 4
5 6 7 8
3 2 1 0
1 2 3 4
max pool with 2x2
window and stride 2
6 8
3 4

Camada de Pooling: Max Pooling

1	3	2	1
2	9	1	1
1	3	2	3
5	6	1	2

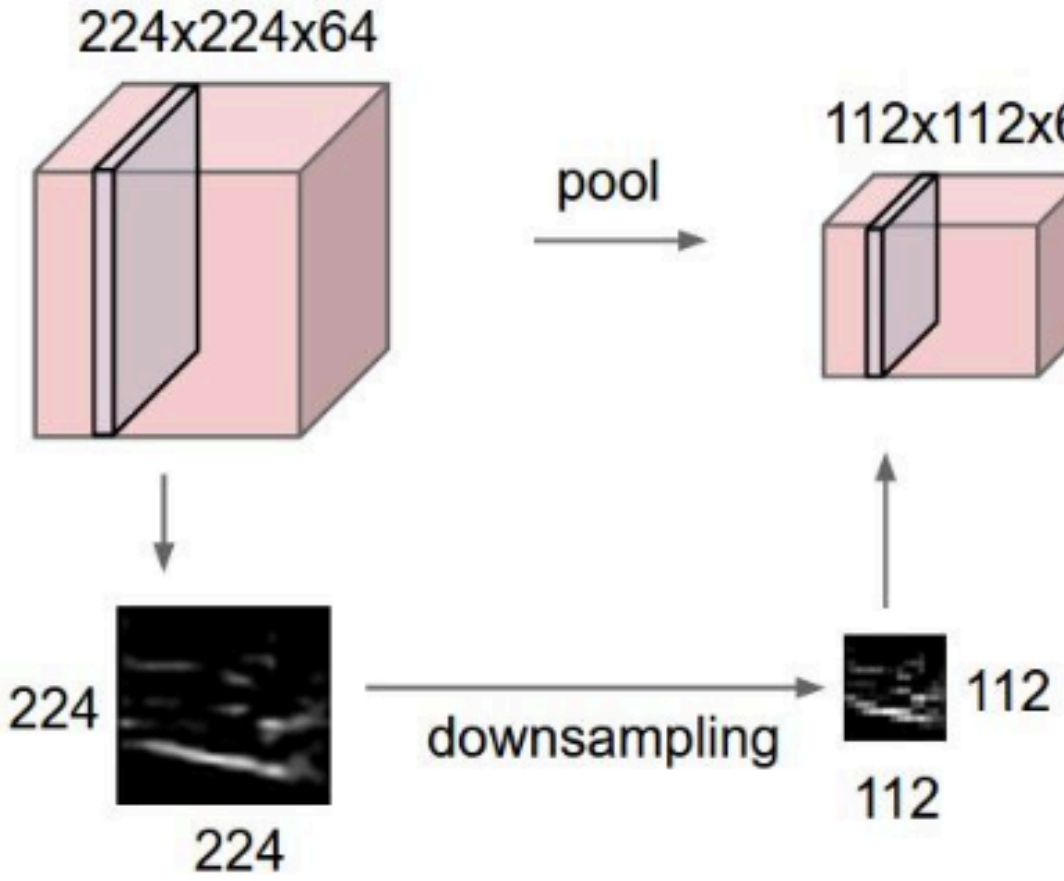


Pooling



Camada de Pooling

- Torna a representação menor
- Opera sobre cada mapa de ativação independentemente.



Resumo de Pooling

- Aceita um volume de tamanho $\boldsymbol{W_1 \times H_1 \times D_1}$
- Requer dois hiperparâmetros:
  - Tamanho da janela **F**,
  - Stride **S**
- Produz um volume de tamanho $\boldsymbol{W_2 \times H_2 \times D_2}$, onde:
  - $\boldsymbol{W_2 = \frac{W_1 - F}{S} + 1}$
  - $\boldsymbol{H_2 = \frac{H_1 - F}{S} + 1}$
  - $\boldsymbol{D_2 = D_1}$
- Introduz zero parâmetros
- Não é comum usar zero-padding para camadas de pooling.

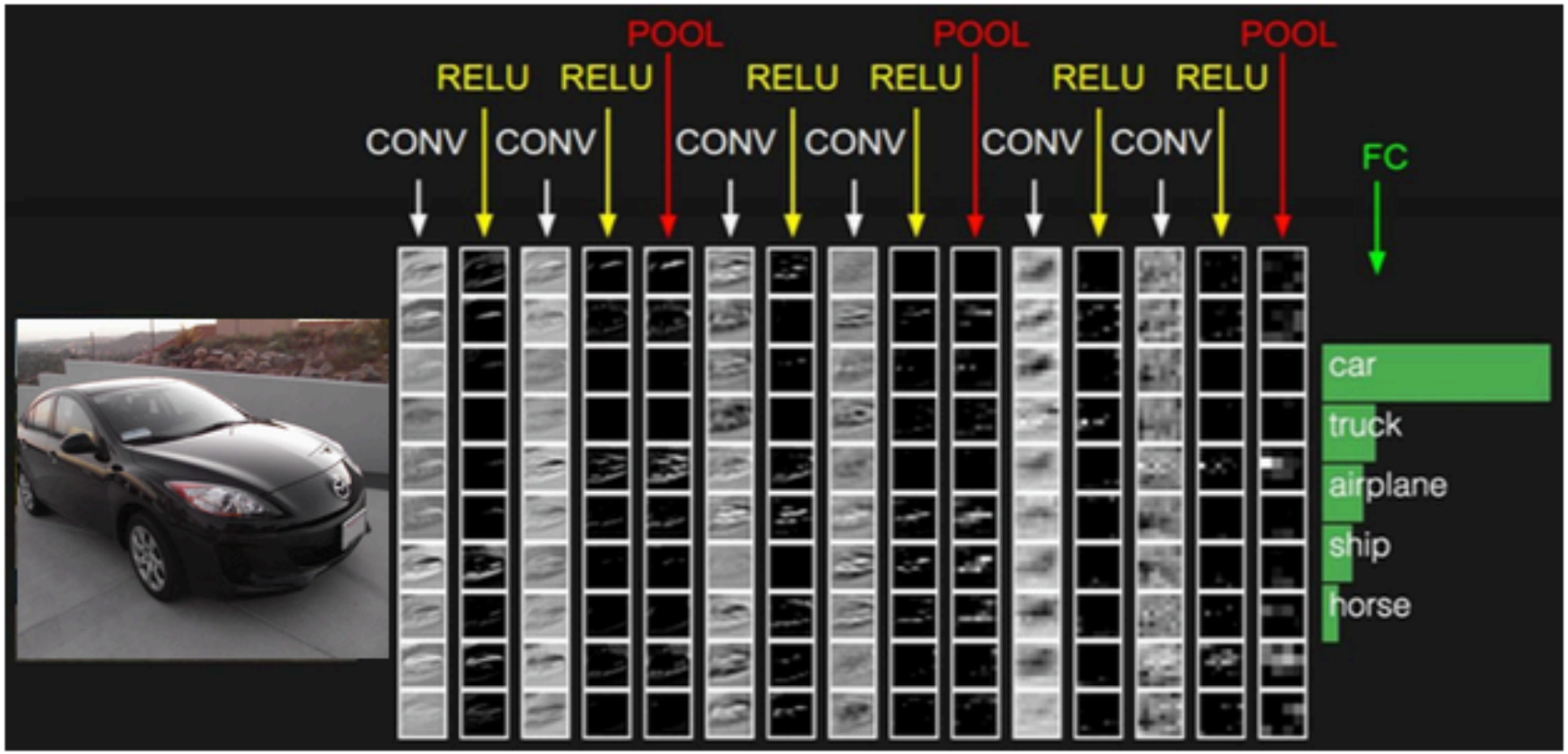
Resumo de Pooling

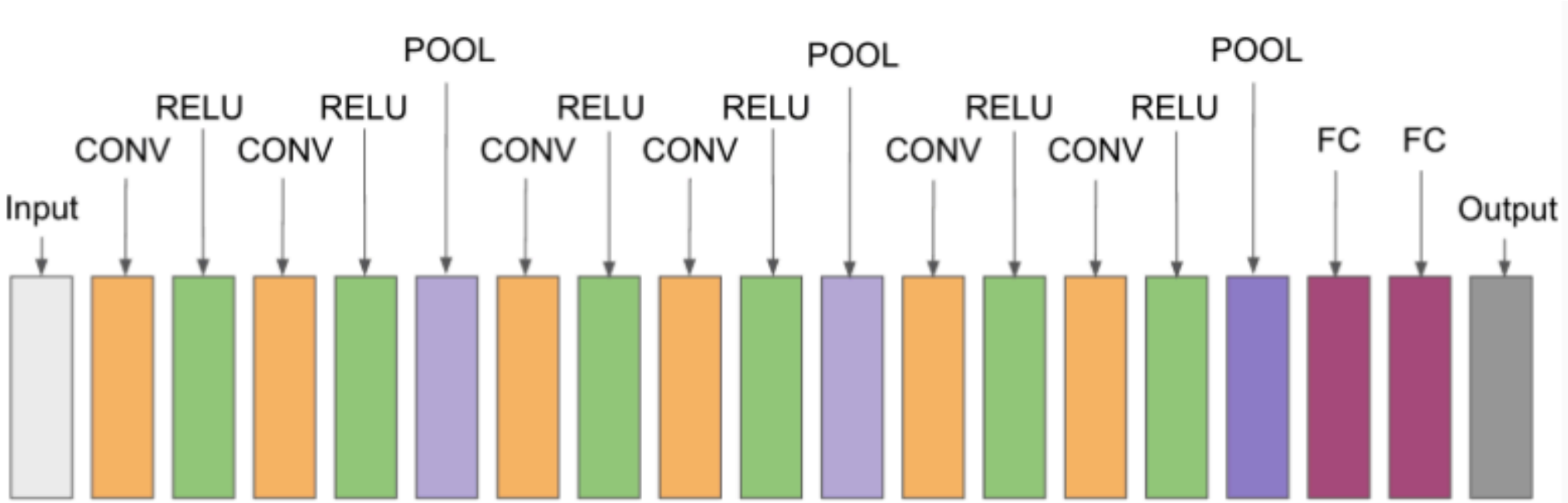
- Aceita um volume de tamanho $W_1 \times H_1 \times D_1$
- Requer três hiperparâmetros:
  - Tamanho da janela **F**,
  - Stride **S**
- Produz um volume de tamanho $W_2 \times H_2 \times D_2$, onde:
  - $W_2 = \frac{W_1 - F}{S} + 1$
  - $H_2 = \frac{H_1 - F}{S} + 1$
  - $D_2 = D_1$
- Introduz zero parâmetros
- Não é comum usar zero-padding para camadas de pooling.

Configurações comuns:
F=2, S=2
F=3, S=2

Fully Conected Layer (FC layer)

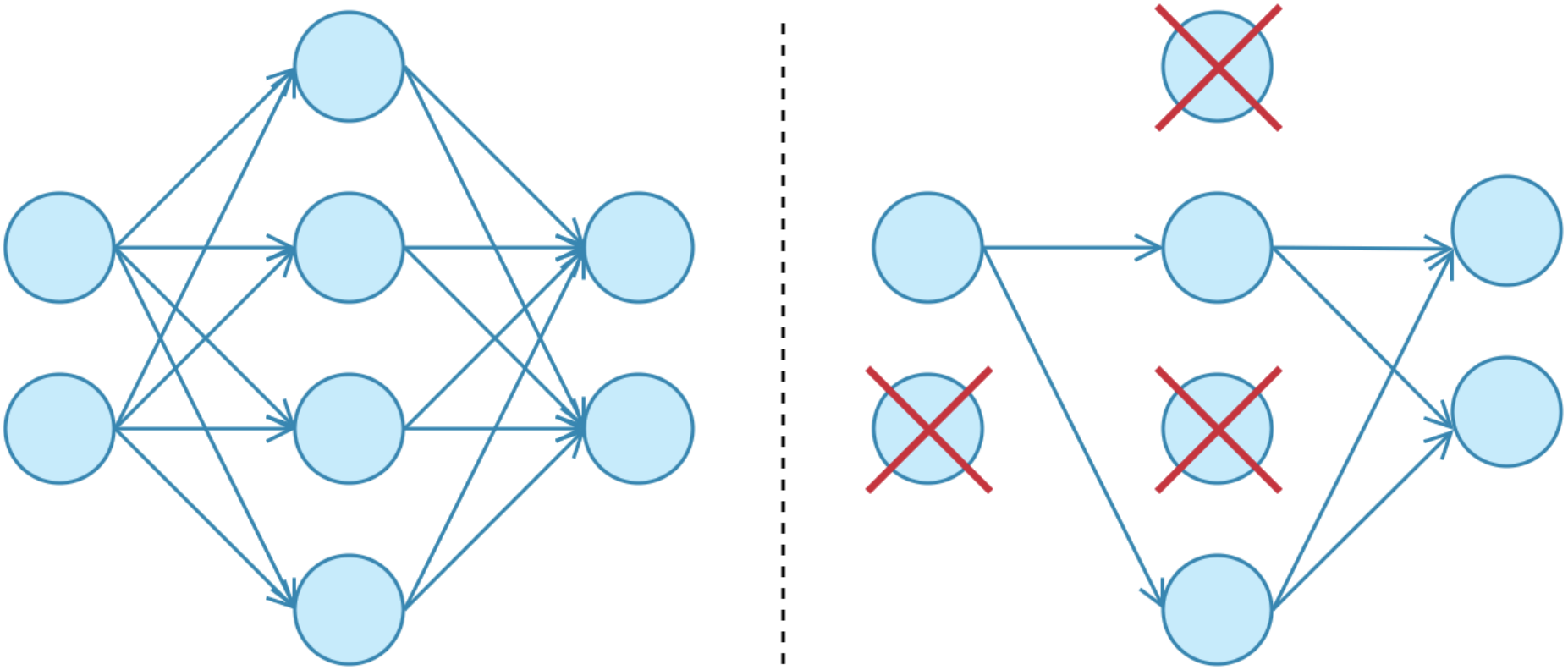
- Contem neurônios que conectam todo o volume de entrada, como em redes neurais tradicionais.





Example of a CNN Architecture

Dropout



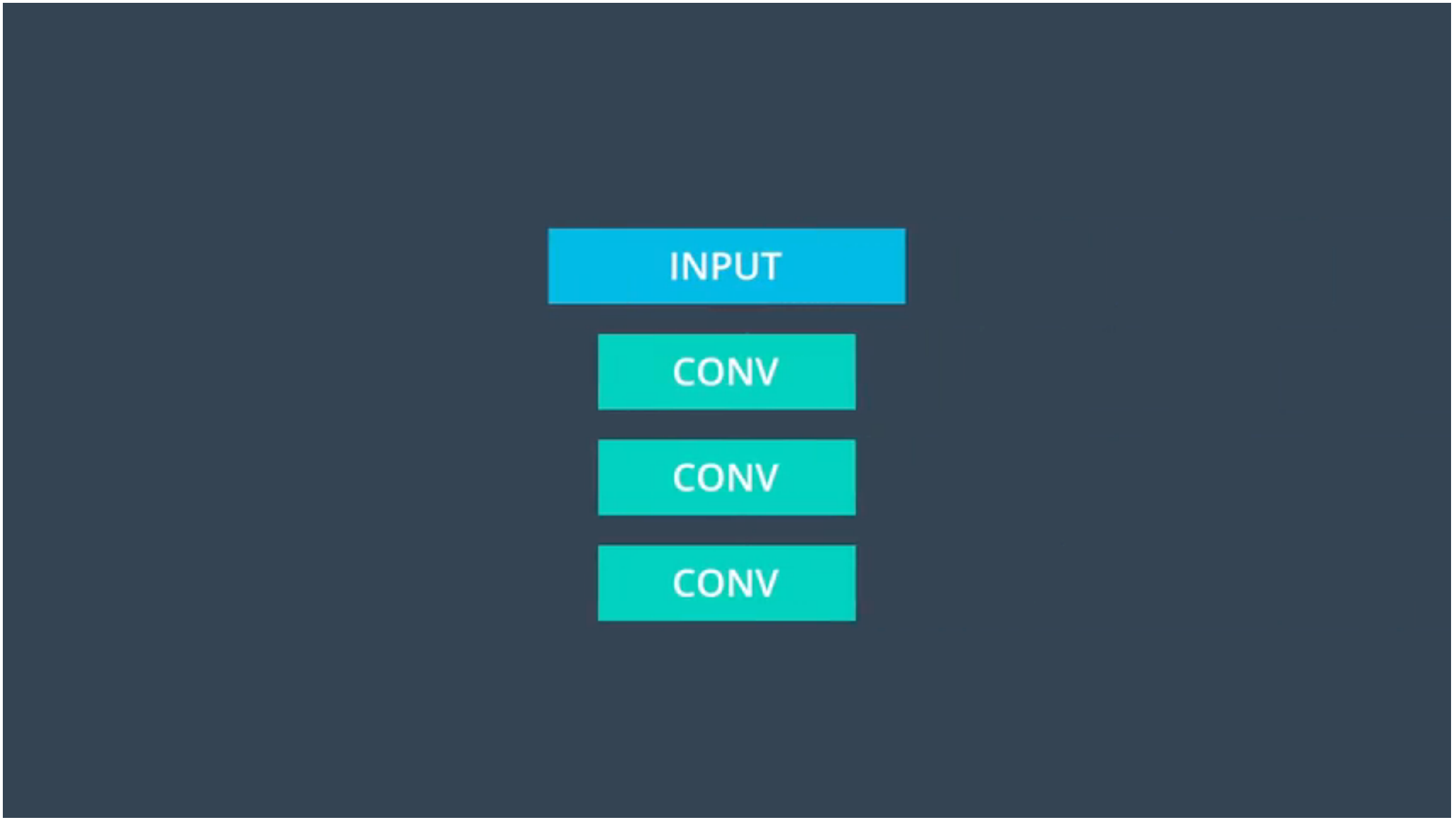
Sem Dropout

Com Dropout

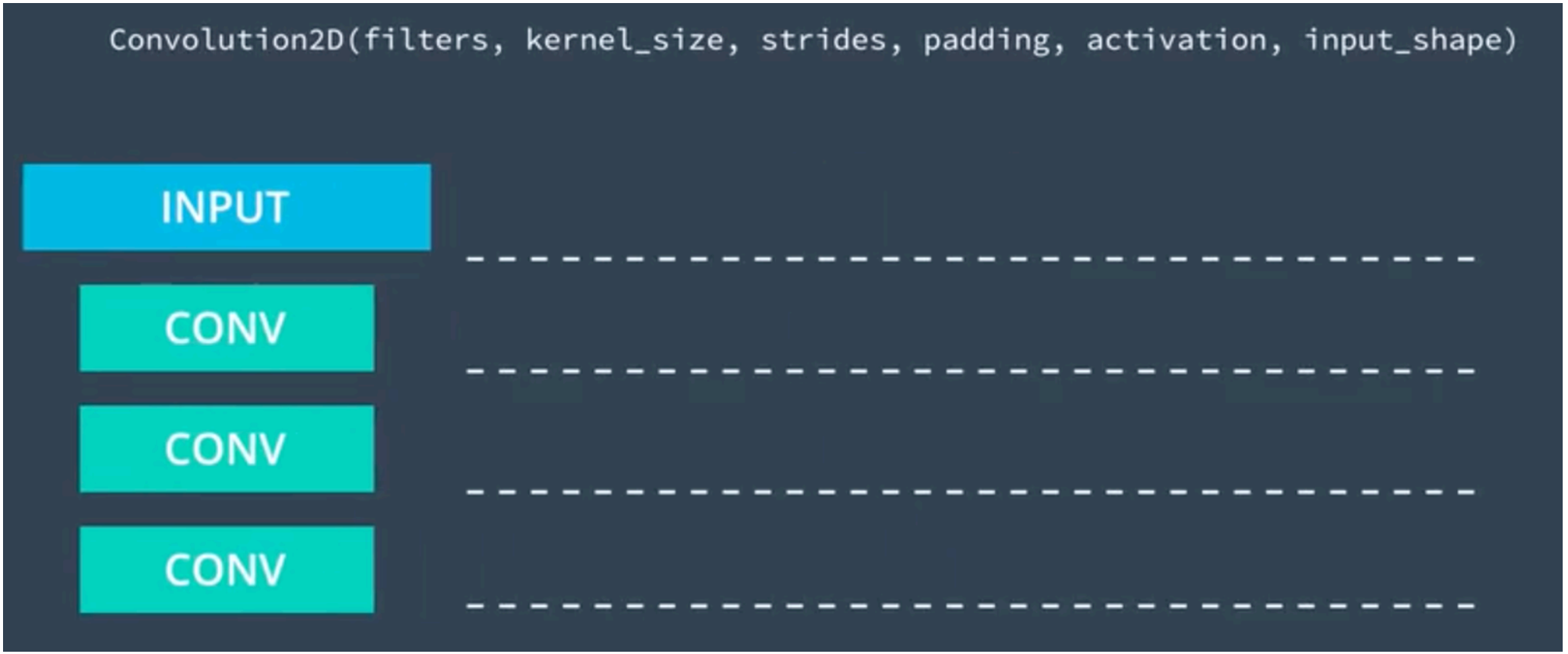
Resumo

- ConvNets enfileiram camadas CONV, POOL, FC;
- Tendência em direção à filtros menores e arquiteturas mais profundas;
- Arquiteturas tradicionais se parecem com:
  - **[(CONV-RELU)*N-POOL?]*M-(FC-RELU)*K, SOFTMAX**
  - Onde N é até aprox. 5, M é alto, 0<=K <=2
  - Arquiteturas como ResNet/GoogLeNet desafiam esse paradigma.

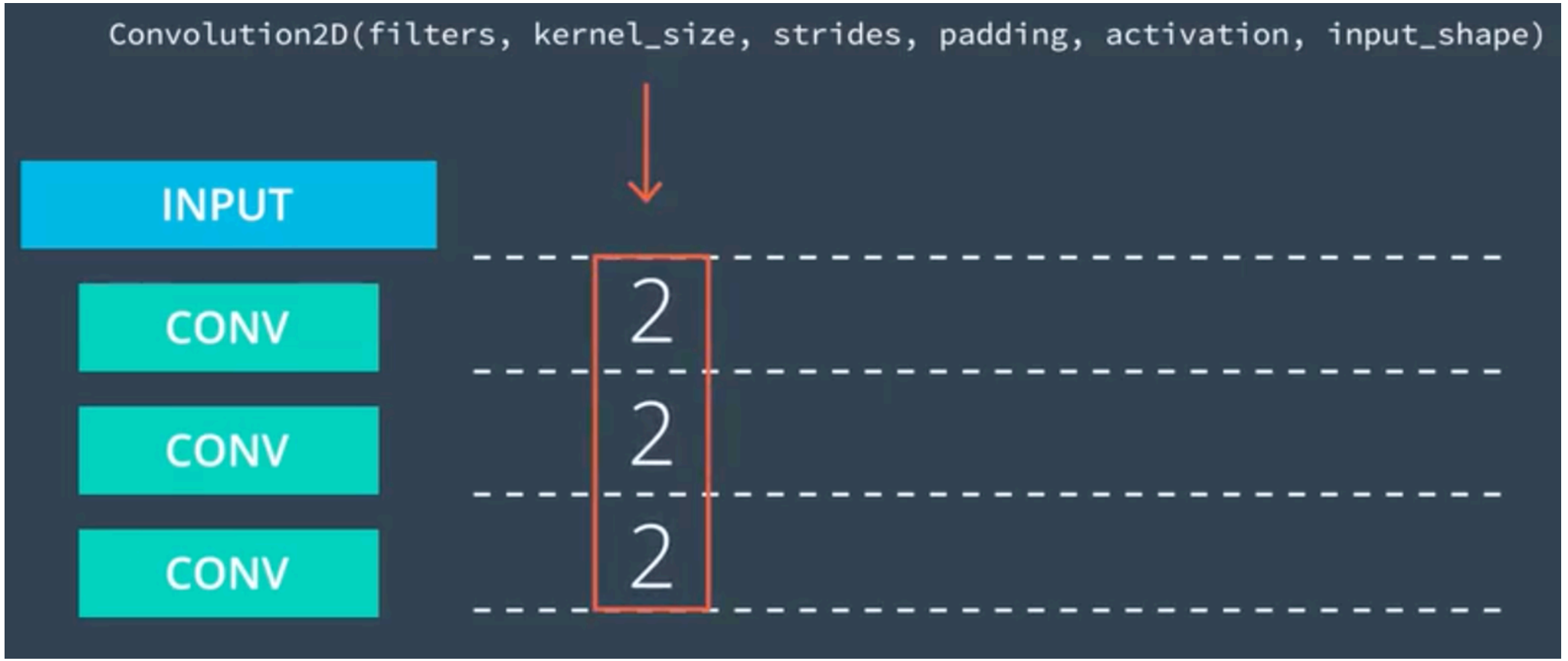
CNN com Keras


INPUT
CONV
CONV
CONV

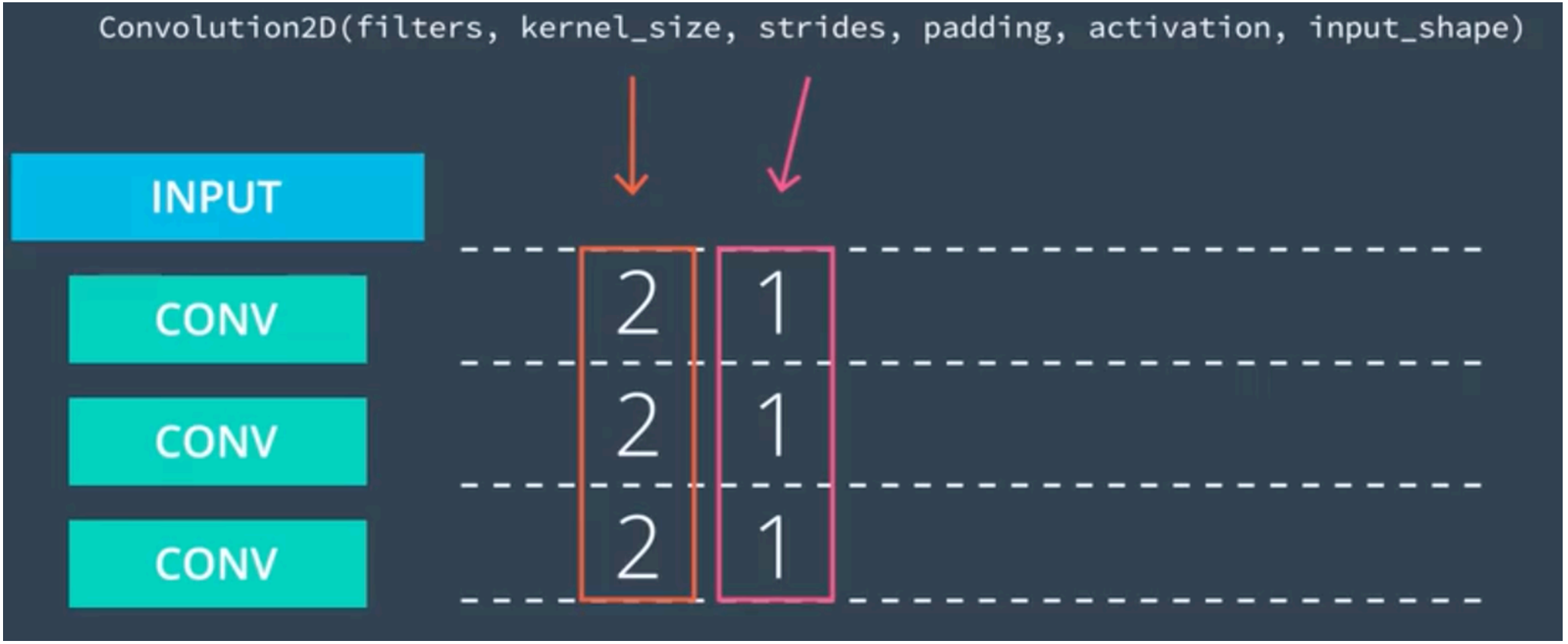
Camada convolutiva no keras



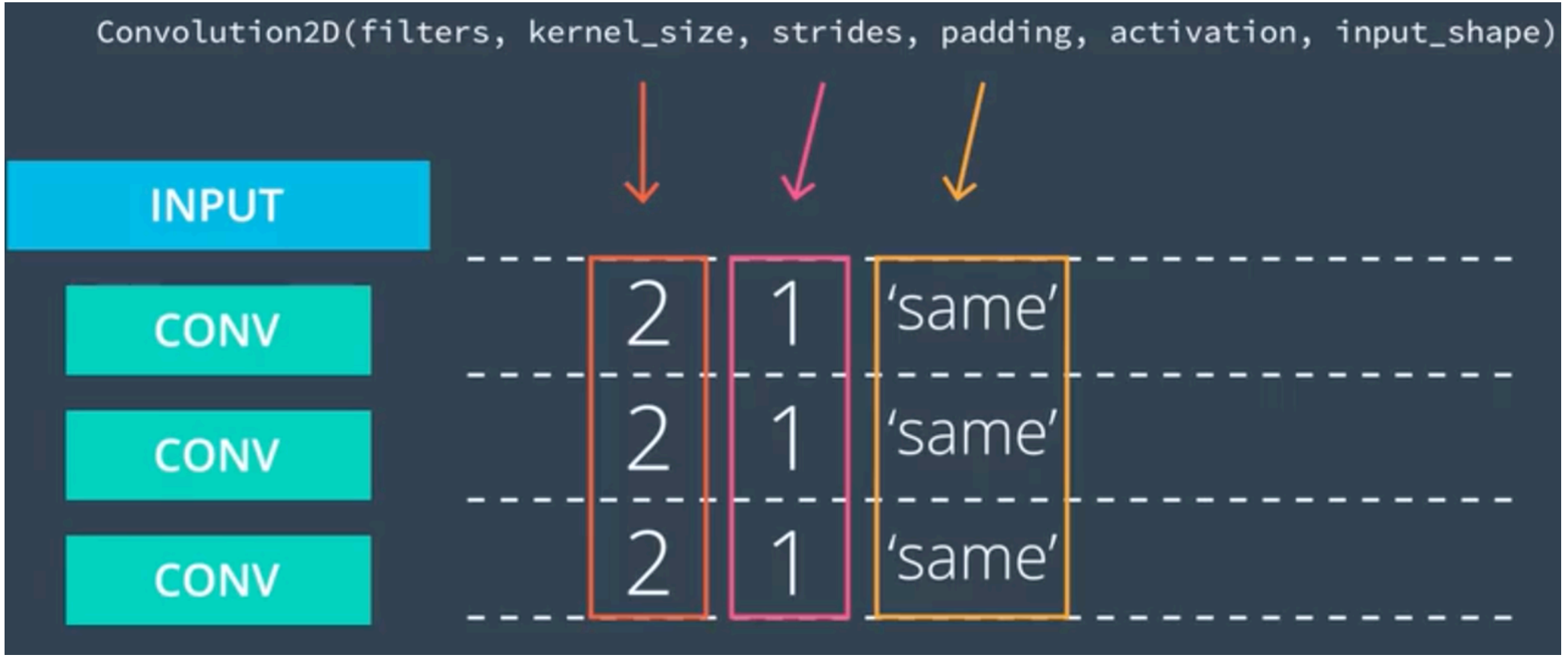
Camada convolutiva no keras



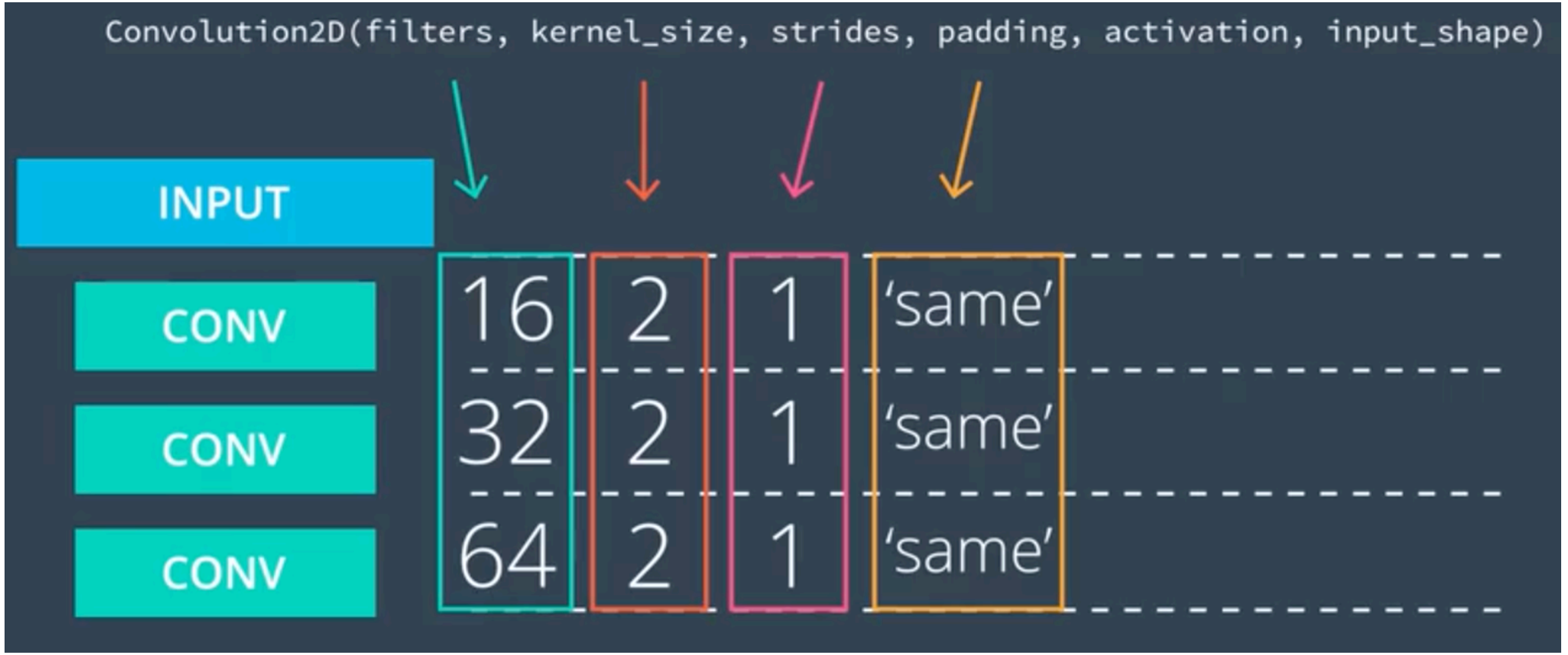
Camada convolutiva no keras



Camada convolutiva no keras

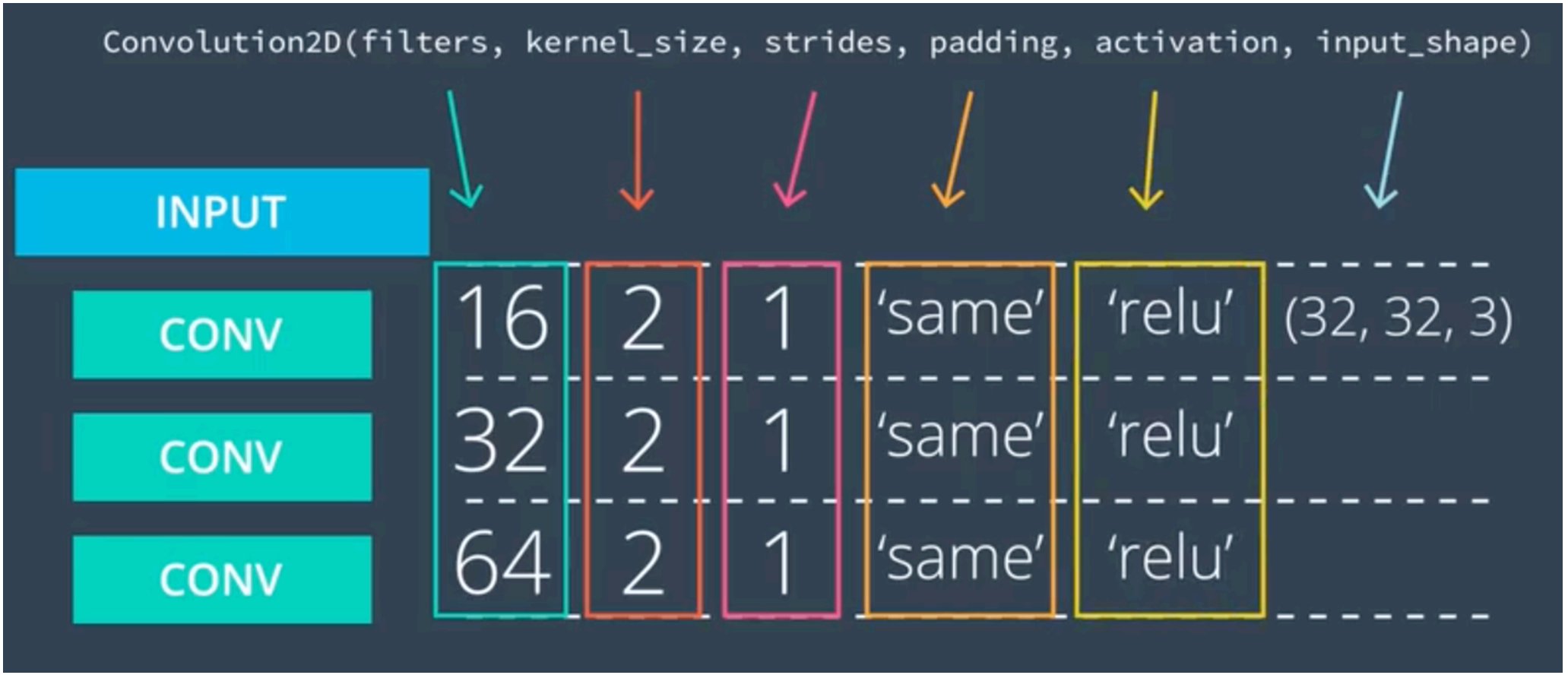


Camada convolutiva no keras



Camada convolutiva no keras

Camada convolutiva no keras

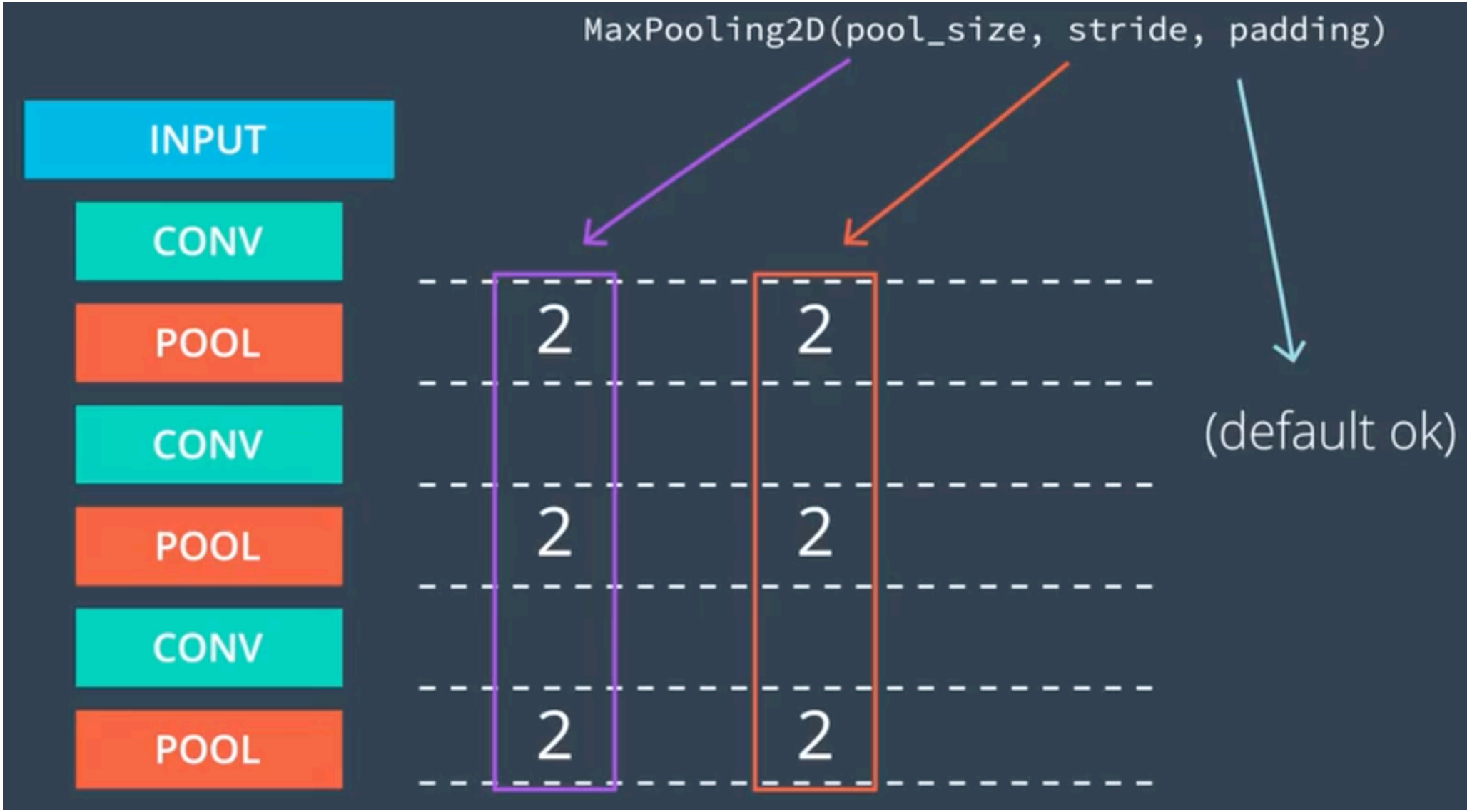


```python
from keras.models import Sequential
from keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout

model = Sequential()
model.add(Conv2D(filters=16, kernel_size=2, padding='same', activation='relu',
                 input_shape=(32, 32, 3)))
model.add(Conv2D(filters=32, kernel_size=2, padding='same', activation='relu'))
model.add(Conv2D(filters=64, kernel_size=2, padding='same', activation='relu'))

model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_4 (Conv2D)            (None, 32, 32, 16)        208
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 32, 32, 32)        2080
_________________________________________________________________
conv2d_6 (Conv2D)            (None, 32, 32, 64)        8256
=================================================================
Total params: 10,544
Trainable params: 10,544
Non-trainable params: 0
_________________________________________________________________
```

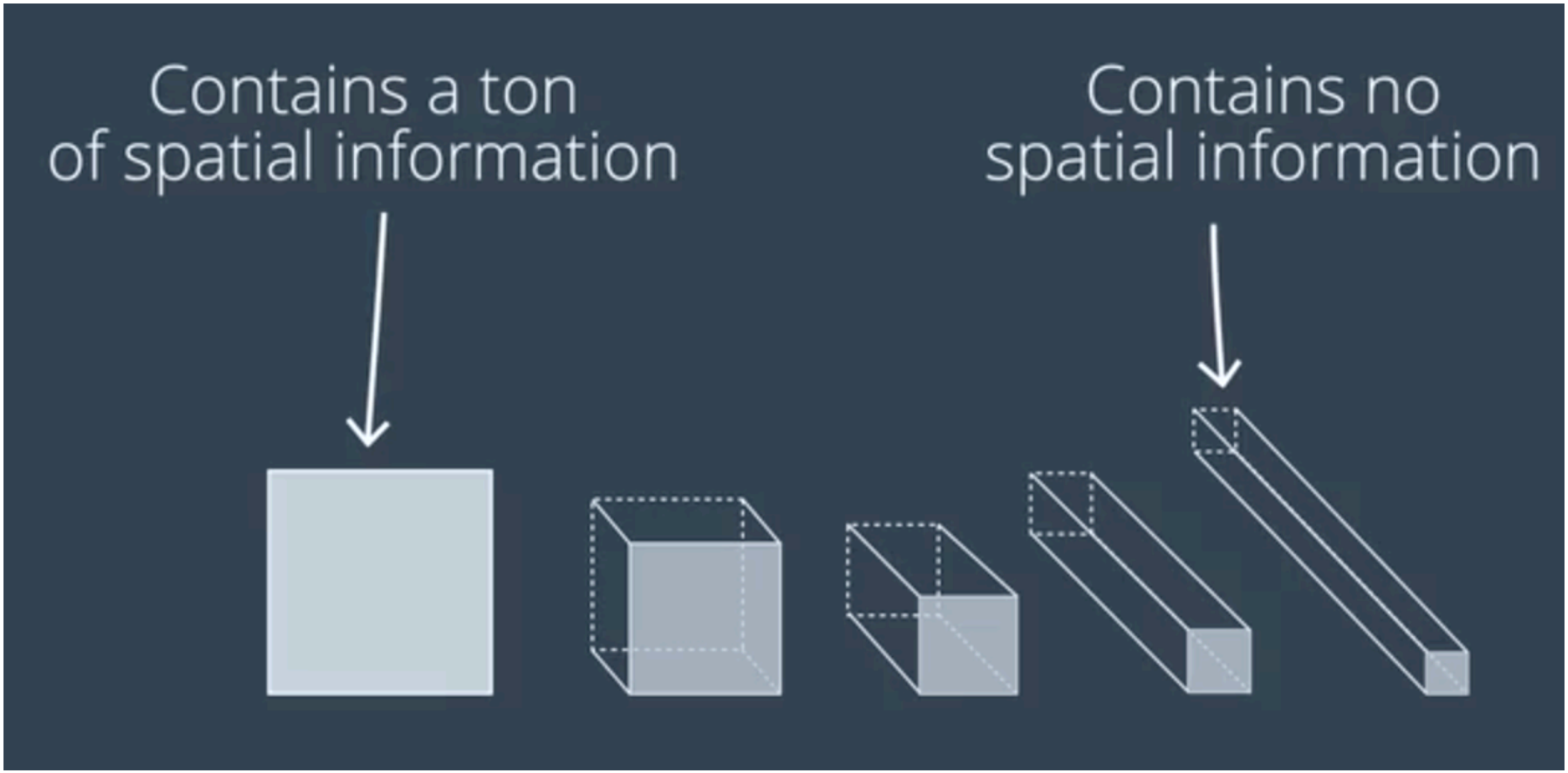
Código

- Cifar10_cnn_full.ipynb


MaxPooling2D(pool_size, stride, padding)
INPUT
CONV
POOL
CONV
POOL
CONV
POOL
2
2
2
2
2
2
(default ok)

```python
from keras.models import Sequential
from keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout

model = Sequential()
model.add(Conv2D(filters=16, kernel_size=2, padding='same', activation='relu',
                 input_shape=(32, 32, 3)))
model.add(MaxPooling2D(pool_size=2))
model.add(Conv2D(filters=32, kernel_size=2, padding='same', activation='relu'))
model.add(MaxPooling2D(pool_size=2))
model.add(Conv2D(filters=64, kernel_size=2, padding='same', activation='relu'))
model.add(MaxPooling2D(pool_size=2))

model.summary()
```

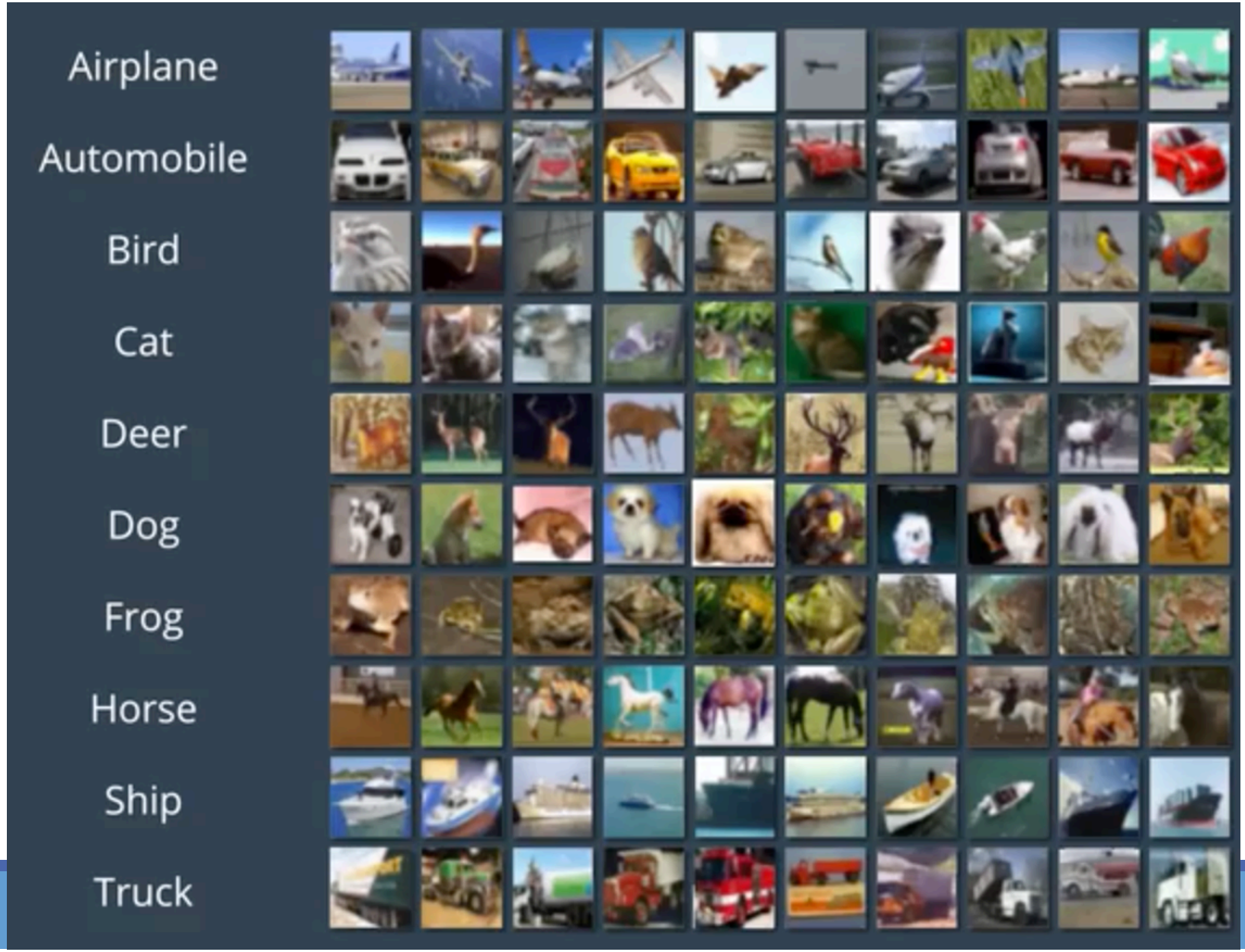
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 32, 32, 16)        208
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 16, 16, 16)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 16, 16, 32)        2080
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 8, 8, 32)          0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 8, 8, 64)          8256
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 4, 4, 64)          0
=================================================================
Total params: 10,544
Trainable params: 10,544
Non-trainable params: 0
_________________________________________________________________
```


Contains a ton
of spatial information
Contains no
spatial information

```python
from keras.models import Sequential
from keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout

model = Sequential()
model.add(Conv2D(filters=16, kernel_size=2, padding='same', activation='relu',
                 input_shape=(32, 32, 3)))
model.add(MaxPooling2D(pool_size=2))
model.add(Conv2D(filters=32, kernel_size=2, padding='same', activation='relu'))
model.add(MaxPooling2D(pool_size=2))
model.add(Conv2D(filters=64, kernel_size=2, padding='same', activation='relu'))
model.add(MaxPooling2D(pool_size=2))
model.add(Flatten())
model.add(Dense(500, activation='relu'))
model.add(Dense(10, activation='softmax'))

model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 32, 32, 16)        208
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 16, 16, 16)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 16, 16, 32)        2080
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 8, 8, 32)          0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 8, 8, 64)          8256
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 4, 4, 64)          0
_________________________________________________________________
dropout_1 (Dropout)          (None, 4, 4, 64)          0
_________________________________________________________________
flatten_1 (Flatten)          (None, 1024)              0
_________________________________________________________________
dense_1 (Dense)              (None, 500)               512500
_________________________________________________________________
dropout_2 (Dropout)          (None, 500)               0
_________________________________________________________________
dense_2 (Dense)              (None, 10)                5010
=================================================================
Total params: 528,054
Trainable params: 528,054
Non-trainable params: 0
```

Tarefa


Airplane
Automobile
Bird
Cat
Deer
Dog
Frog
Horse
Ship
Truck

- Comparar desempenho MLP vs CNN

1. Load CIFAR -10 Database

```
1 import keras
2 from keras.datasets import cifar10
3
4 # load the pre-shuffled train and test data
5 (x_train, y_train), (x_test, y_test) = cifar10.load_data()
```

2. Visualize the first 24 training images

```
1 import numpy as np
2 import matplotlib.pyplot as plt
3 %matplotlib inline
4
5 fig = plt.figure(figsize=(20,5))
6 for i in range(36):
7     ax = fig.add_subplot(3, 12, i + 1, xticks=[], yticks=[])
8     ax.imshow(np.squeeze(x_train[i]))
```

3. Rescale the images by dividing every pixel in every image by 255

```
# rescale [0,255] --> [0,1]
x_train = x_train.astype('float32')/255
x_test = x_test.astype('float32')/255
```

4. Break dataset into Training, Testing, and Validation sets

```
from keras.utils import np_utils

# one-hot encode the labels
num_classes = len(np.unique(y_train))
y_train = keras.utils.to_categorical(y_train, num_classes)
y_test = keras.utils.to_categorical(y_test, num_classes)

# break training set into training and validation sets
(x_train, x_valid) = x_train[5000:], x_train[:5000]
(y_train, y_valid) = y_train[5000:], y_train[:5000]

# print shape of training set
print('x_train shape:', x_train.shape)

# print number of training, validation, and test images
print(x_train.shape[0], 'train samples')
print(x_test.shape[0], 'test samples')
print(x_valid.shape[0], 'validation samples')
```

```
x_train shape: (45000, 32, 32, 3)
45000 train samples
10000 test samples
```

MLP

5. Define the model architecture

```
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten

# define the model
model = Sequential()
model.add(Flatten(input_shape = x_train.shape[1:]))
model.add(Dense(1000, activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(512, activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(num_classes, activation='softmax'))
model.summary()
```

Layer (type)	Output Shape	Param #
flatten_1 (Flatten)	(None, 3072)	0
dense_1 (Dense)	(None, 1000)	3073000
dropout_1 (Dropout)	(None, 1000)	0
dense_2 (Dense)	(None, 512)	512512
dropout_2 (Dropout)	(None, 512)	0
dense_3 (Dense)	(None, 10)	5130

Total params: 3,590,642.0
Trainable params: 3,590,642.0
Non-trainable params: 0.0

6. Compile the model

```
# compile the model
model.compile(loss='categorical_crossentropy', optimizer='rmsprop',
                    metrics=['accuracy'])
```

7. Train the model

```
from keras.callbacks import ModelCheckpoint

# train the model
checkpointer = ModelCheckpoint(filepath='model.weights.best.hdf5', verbose=1,
                               save_best_only=True)
hist = model.fit(x_train, y_train, batch_size=32, epochs=5,
          validation_data=(x_valid, y_valid), callbacks=[checkpointer],
          verbose=2, shuffle=True)
```

8. Load the model with the best classification accuracy on the validation set

```
# load the weights that yielded the best validation accuracy
model.load_weights('model.weights.best.hdf5')
```

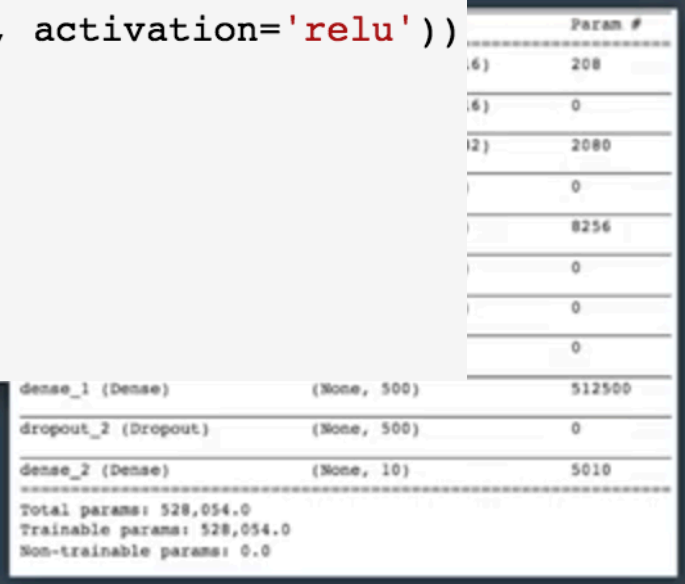
9. Calculate classification accuracy on test set

```
# evaluate and print test accuracy
score = model.evaluate(x_test, y_test, verbose=0)
print('\n', 'Test accuracy:', score[1])
```

CNN

5. Define the model architecture

```
from keras.models import Sequential
from keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout

model = Sequential()
model.add(Conv2D(filters=16, kernel_size=2, padding='same', activation='relu',
                 input_shape=(32, 32, 3)))
model.add(MaxPooling2D(pool_size=2))
model.add(Conv2D(filters=32, kernel_size=2, padding='same', activation='relu'))
model.add(MaxPooling2D(pool_size=2))
model.add(Conv2D(filters=64, kernel_size=2, padding='same', activation='relu'))
model.add(MaxPooling2D(pool_size=2))
model.add(Dropout(0.3))
model.add(Flatten())
model.add(Dense(500, activation='relu'))
model.add(Dropout(0.4))
model.add(Dense(10, activation='softmax'))

model.summary()
```



		Param #
		208
		0
		2080
		0
		8256
		0
		0
		0
dense_1 (Dense)	(None, 500)	512500
dropout_2 (Dropout)	(None, 500)	0
dense_2 (Dense)	(None, 10)	5010

Total params: 528,054.0
Trainable params: 528,054.0
Non-trainable params: 0.0

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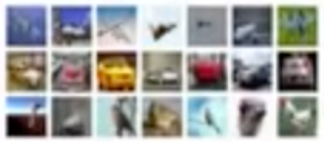

CIFAR-10 - Object Recognition in Images

Identify the subject of 60,000 labeled images

231 teams · 2 years ago

Overview Data Discussion Leaderboard More Submit Predictions

Overview

Description Evaluation

CIFAR-10 is an established computer-vision dataset used for object recognition. It is a subset of the 80 million tiny images dataset and consists of 60,000 32x32 color images containing one of 10 object classes, with 6000 images per class. It was collected by Alex Krizhevsky, Vinod Nair, and Geoffrey Hinton.

Kaggle is hosting a CIFAR-10 leaderboard for the machine learning community to use for fun and practice. You can see how your approach compares to the latest research methods on Rodrigo Benenson's classification results page.