Redes Neurais Profundas – Deep Learning

Aula 5 – Redes Neurais Convolucionais

Prof. Anderson Soares
www.inf.ufg.br/~anderson
www.deeplearningbrasil.com.br
Instituto de Informática
Universidade Federal de Goiás

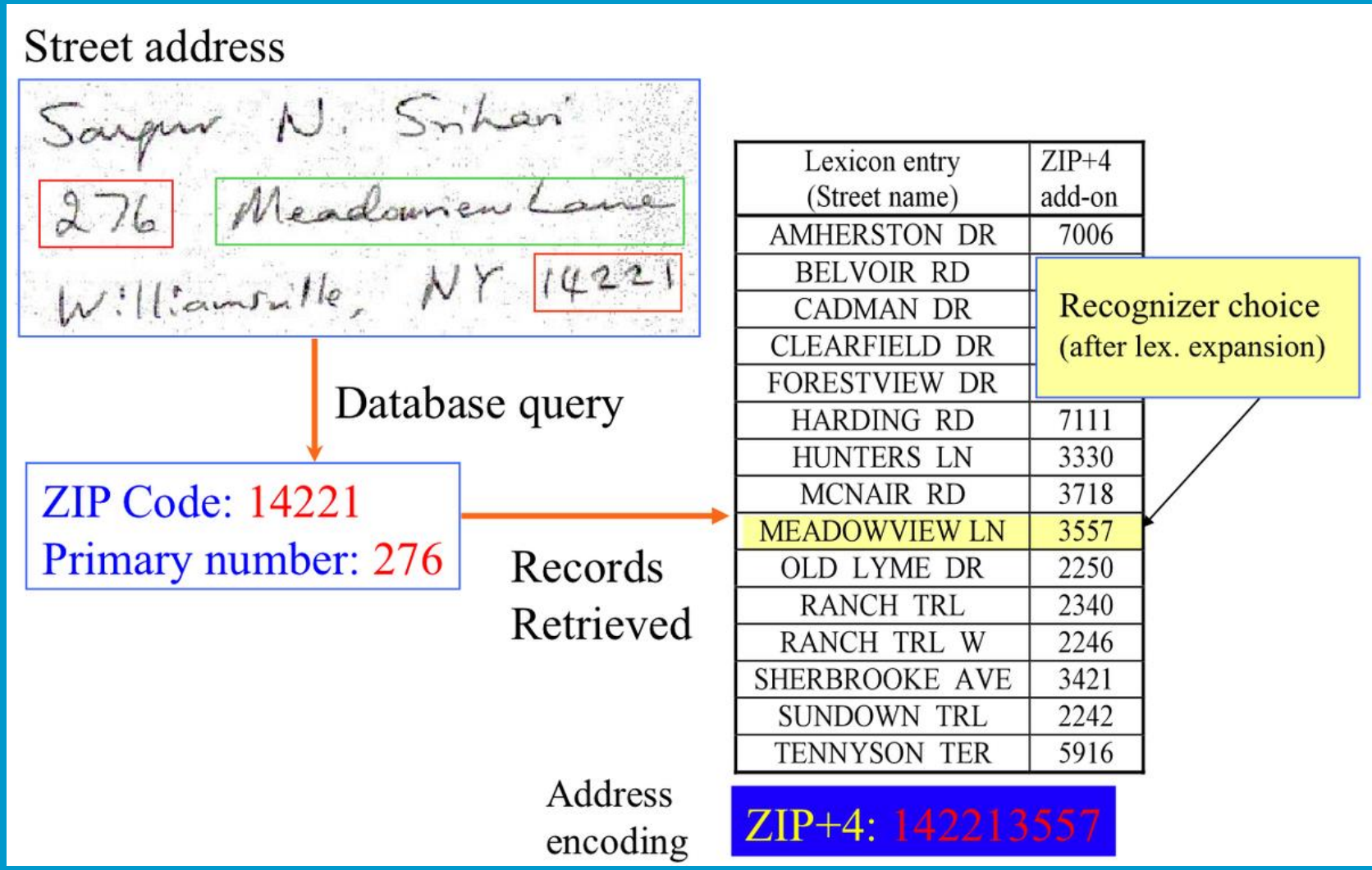
Aula 5:
Convolutional Neural Network

Agenda

- Contextualização: problema motivador
- Elementos de uma rede neural convolucional
- Codificação em tensorflow
- Codificação em Keras
- Problemas cuja técnica tem alto impacto
- Considerações finais

Problema

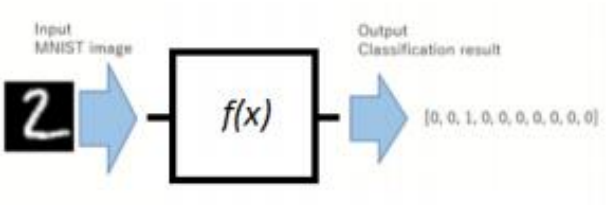
Problema

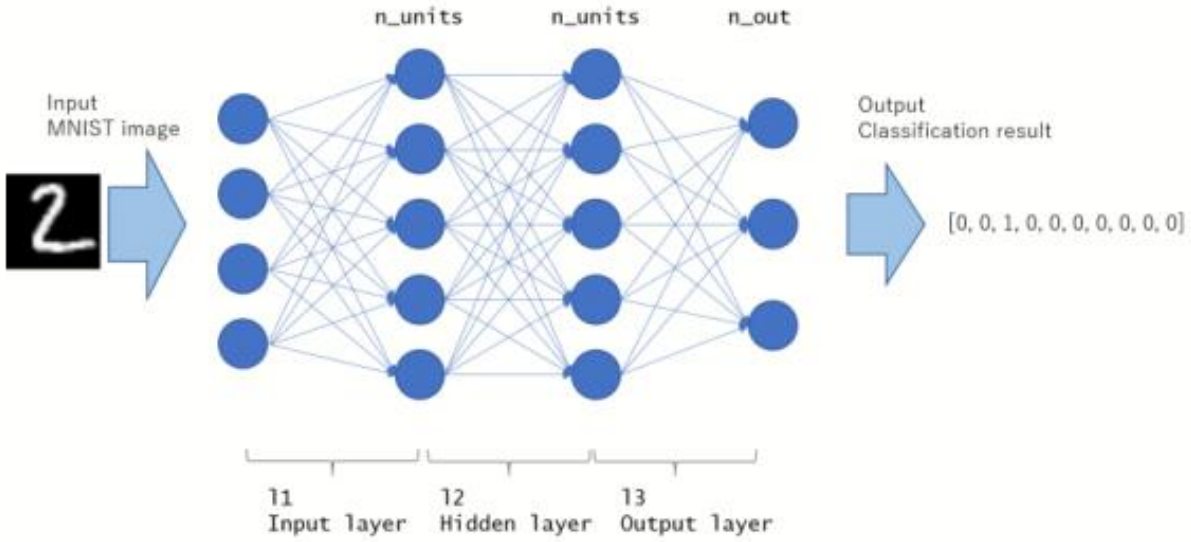


Lexicon entry (Street name)	ZIP+4 add-on
AMHERSTON DR	7006
BELVOIR RD	
CADMAN DR	
CLEARFIELD DR	
FORESTVIEW DR	
HARDING RD	7111
HUNTERS LN	3330
MCNAIR RD	3718
MEADOWVIEW LN	3557
OLD LYME DR	2250
RANCH TRL	2340
RANCH TRL W	2246
SHERBROOKE AVE	3421
SUNDOWN TRL	2242
TENNYSON TER	5916

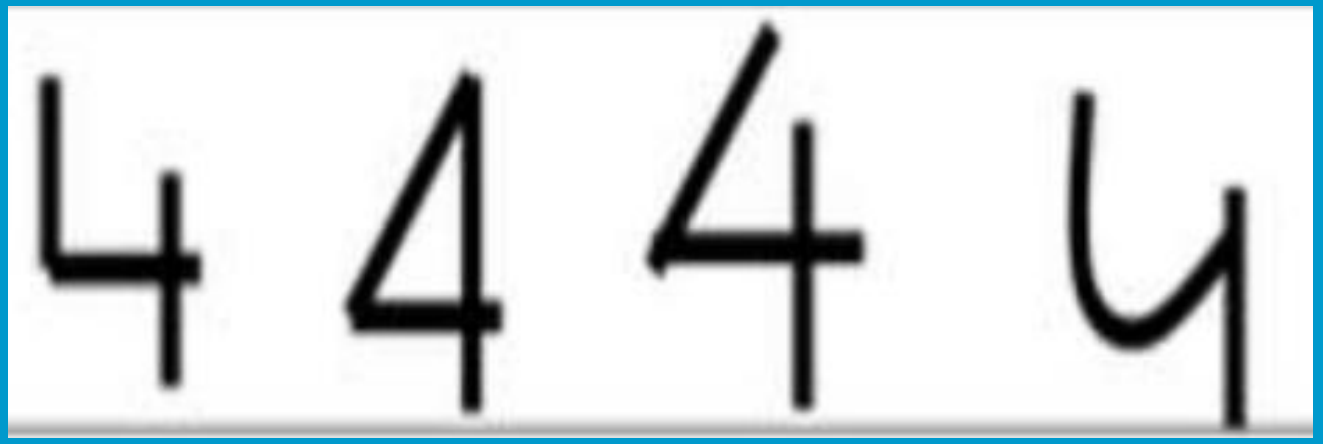
Recapitulando...

- MLP





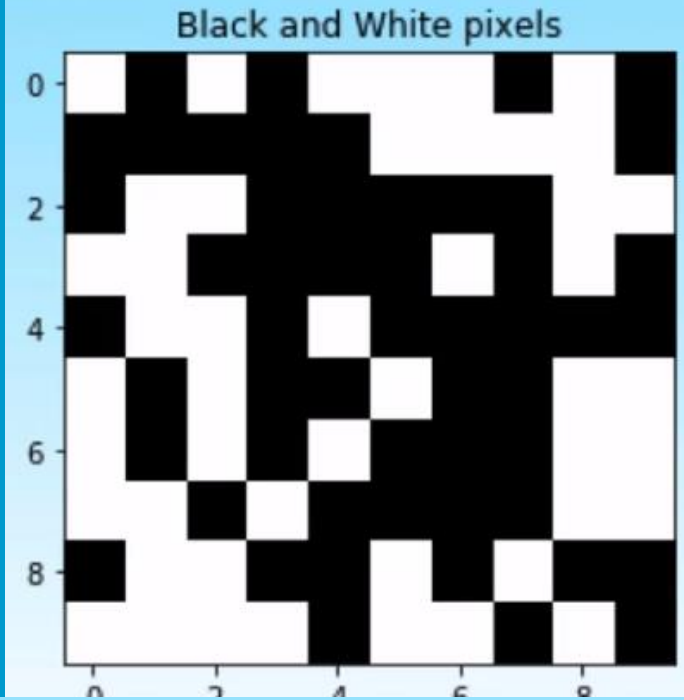
Problema...



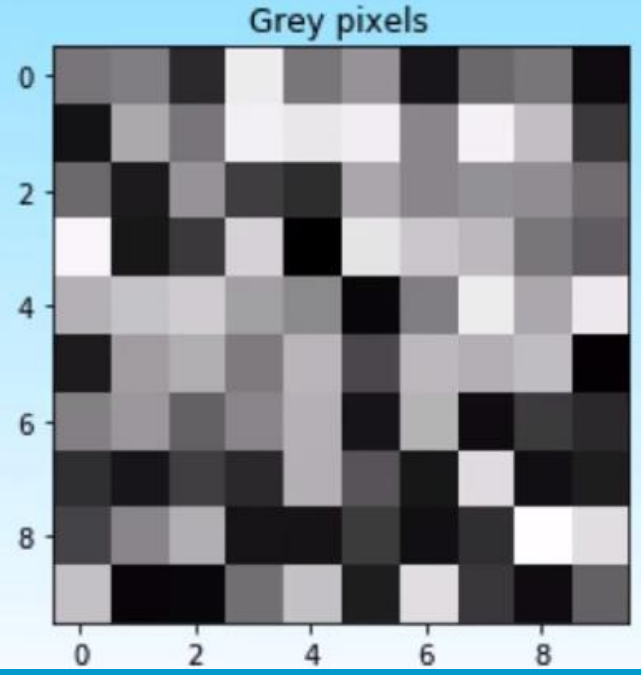
MNIST

Mixed National Institute of Standards and Technology (MNIST)

- Dataset para o problema de reconhecimento de dígitos escritos a mão
- 60,000 imagens de treino, 10,000 de teste, codificados como imagens 28×28 em escala de cinza
- Quantas formas temos para escrever?




```
array([[1, 0, 1, 0, 1, 1, 1, 0, 1, 0],
       [0, 0, 0, 0, 0, 1, 1, 1, 1, 0],
       [0, 1, 1, 0, 0, 0, 0, 0, 1, 1],
       [1, 1, 0, 0, 0, 0, 1, 0, 1, 0],
       [0, 1, 1, 0, 1, 0, 0, 0, 0, 0],
       [1, 0, 1, 0, 0, 1, 0, 0, 1, 1],
       [1, 0, 1, 0, 1, 0, 0, 0, 1, 1],
       [1, 1, 0, 1, 0, 0, 0, 0, 1, 1],
       [0, 1, 1, 0, 0, 1, 0, 1, 0, 0],
       [1, 1, 1, 1, 0, 1, 1, 0, 1, 0]])
```

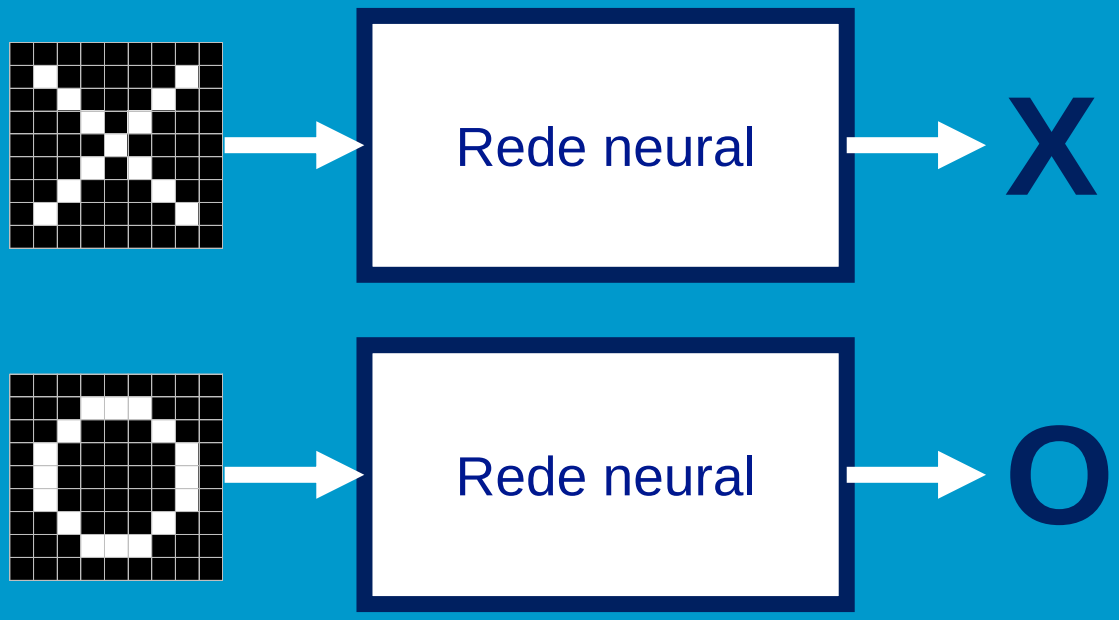



```
array([[127, 136,  48, 234, 128, 155,  24, 114, 128,  12],
       [ 18, 177, 127, 239, 230, 236, 145, 240, 195,  65],
       [116,  29, 155,  70,  51, 174, 144, 153, 149, 120],
       [243,  26,  66, 213,   1, 227, 203, 191, 128, 105],
       [183, 199, 207, 167, 146,   7, 136, 234, 175, 232],
       [ 31, 166, 180, 133, 187,  82, 192, 182, 194,   2],
       [139, 161, 108, 144, 183,  23, 185,  12,  67,  47],
       [ 53,  24,  72,  46, 182,  94,  25, 221,  16,  34],
       [ 76, 144, 181,  22,  21,  67,  16,  53, 250, 222],
       [197,   6,   7, 122, 198,  34, 222,  64,  12, 108]])
```

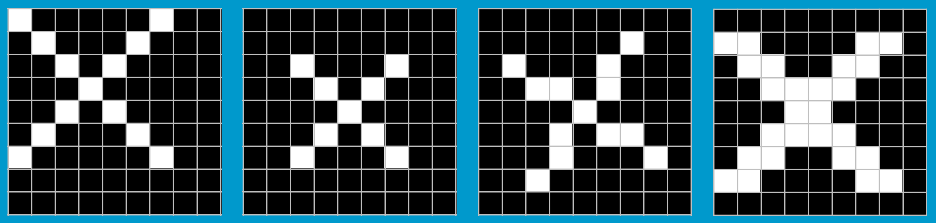
Decidir se uma figura contém X ou O

Matriz de pixeis

Por exemplo:

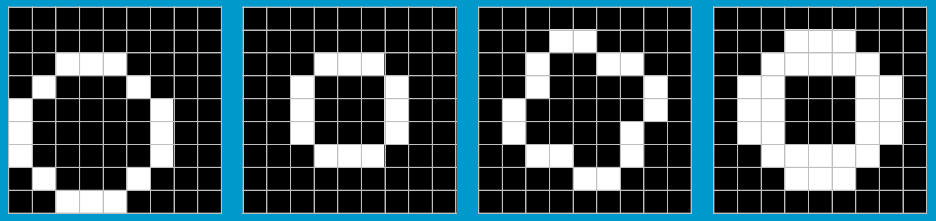


Casos mais complicados



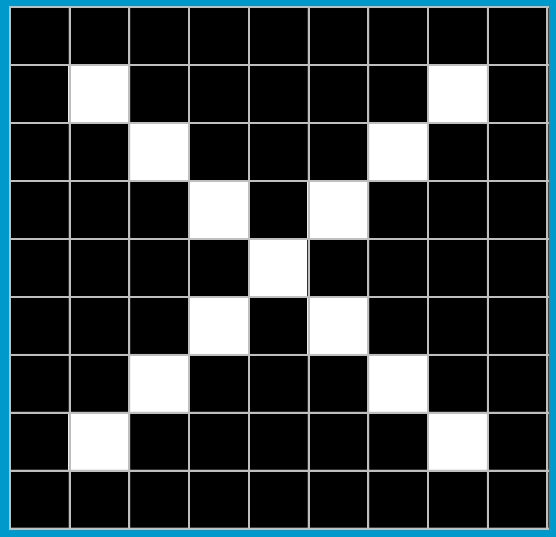
Translação Escala Rotação Peso

Rede neural → X



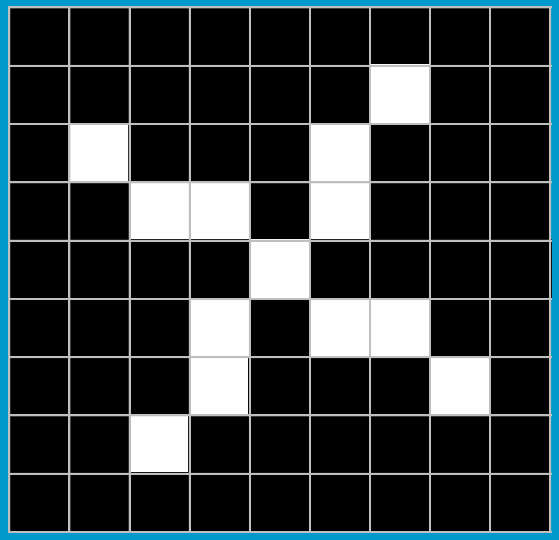
Rede neural → O

Decisão difícil



?

=

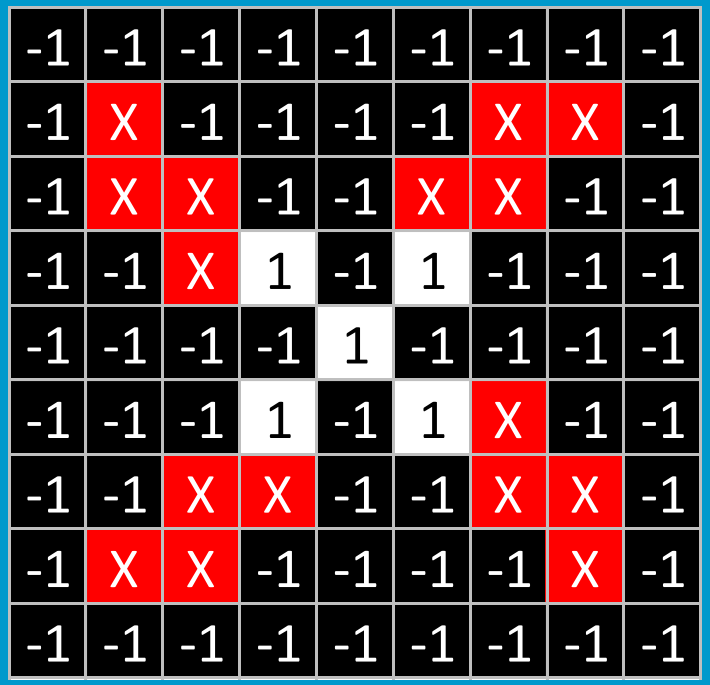


O que a rede “enxerga”?

-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	-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	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	-1	-1	-1	-1	-1	-1

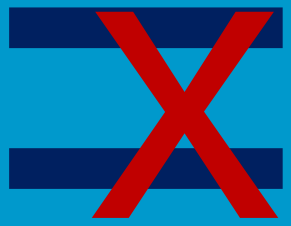
-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	1	-1	-1	-1
-1	-1	1	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	1	-1	-1
-1	-1	-1	1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

O que a rede “enxerga”?

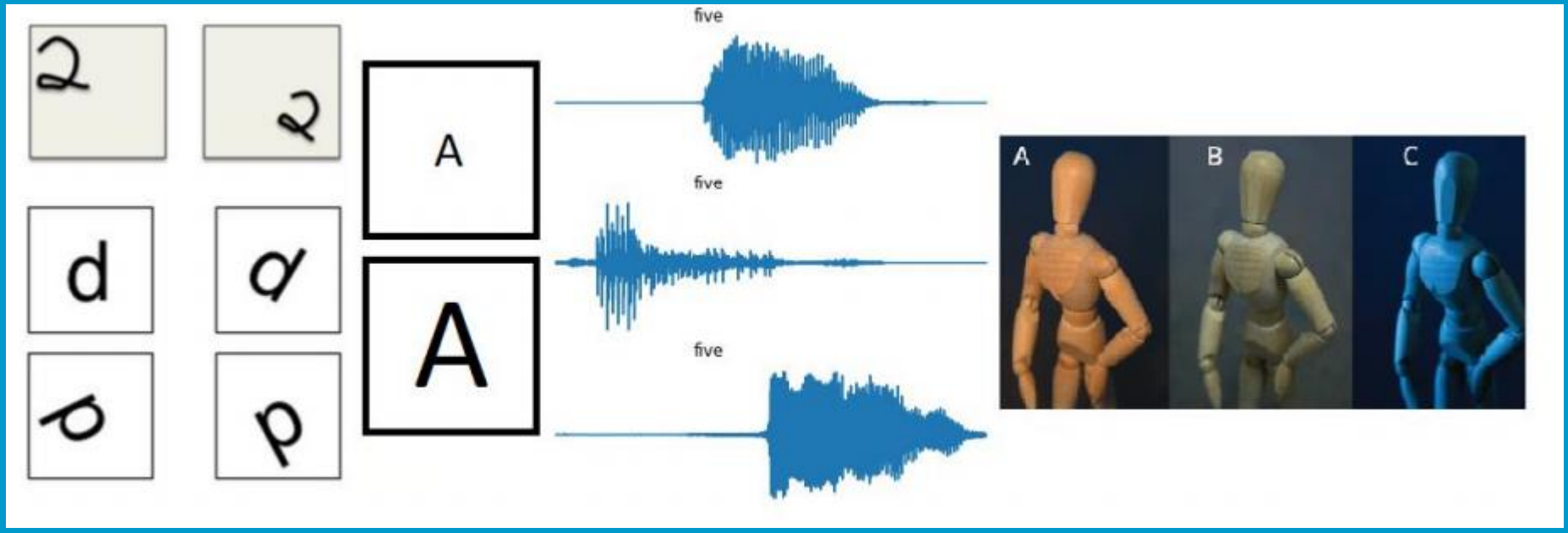


O que a rede “enxerga”?

-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	-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	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	-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	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	-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	-1	-1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

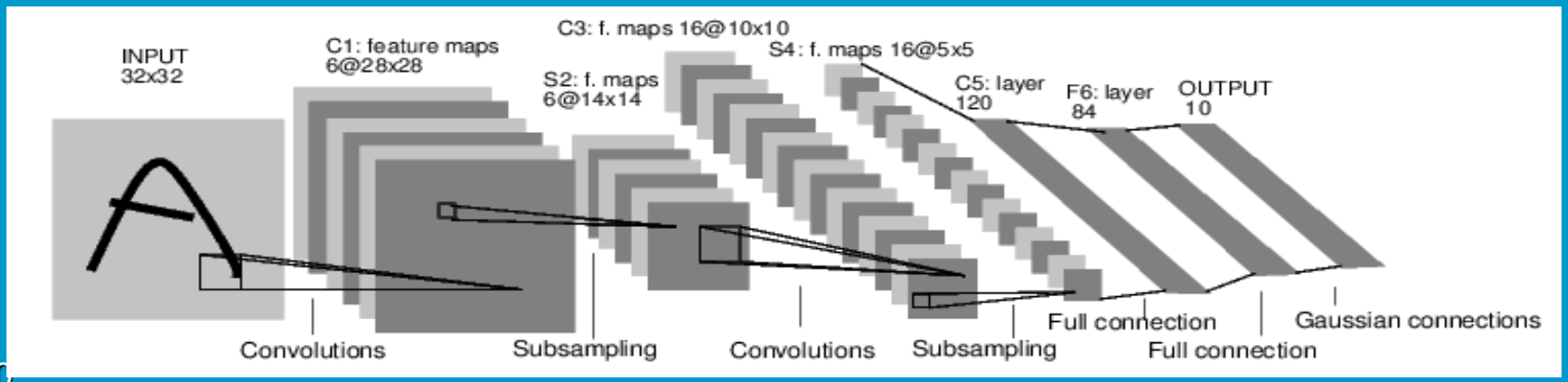

A
five
five
five
A
B
C

MNIST

Classifier	Test Error Rate (%)	References
Linear classifier (1-layer neural net)	12.0	LeCun et al. (1998)
K-nearest-neighbors, Euclidean (L2)	5.0	LeCun et al. (1998)
2-Layer neural net, 300 hidden units, mean square error	4.7	LeCun et al. (1998)
Support vector machine, Gaussian kernel	1.4	MNIST Website
Convolutional net, LeNet-5 (no distortions)	**0.95**	LeCun et al. (1998)
Methods using distortions		
Virtual support vector machine, deg-9 polynomial, (2-pixel jittered and deskewing)	0.56	DeCoste and Scholkopf (2002)
Convolutional neural net (elastic distortions)	0.4	Simard, Steinkraus, and Platt (2003)
6-Layer feedforward neural net (on GPU) (elastic distortions)	**0.35**	Ciresan, Meier, Gambardella, and Schmidhuber (2010)
Large/deep convolutional neural net (elastic distortions)	**0.35**	Ciresan, Meier, Masci, Maria Gambardella, and Schmidhuber (2011)
Committee of 35 convolutional networks (elastic distortions)	0.23	Ciresan, Meier, and Schmidhuber (2012)

Yann LeCun, Professor of Computer Science
The Courant Institute of Mathematical Sciences
New York University
Room 1220, 715 Broadway, New York, NY 10003, USA.
(212)998-3283 yann@cs.nyu.edu

Yann LeCun e Yoshua Bengio Introduziram o conceito de redes convolucionais (1995).



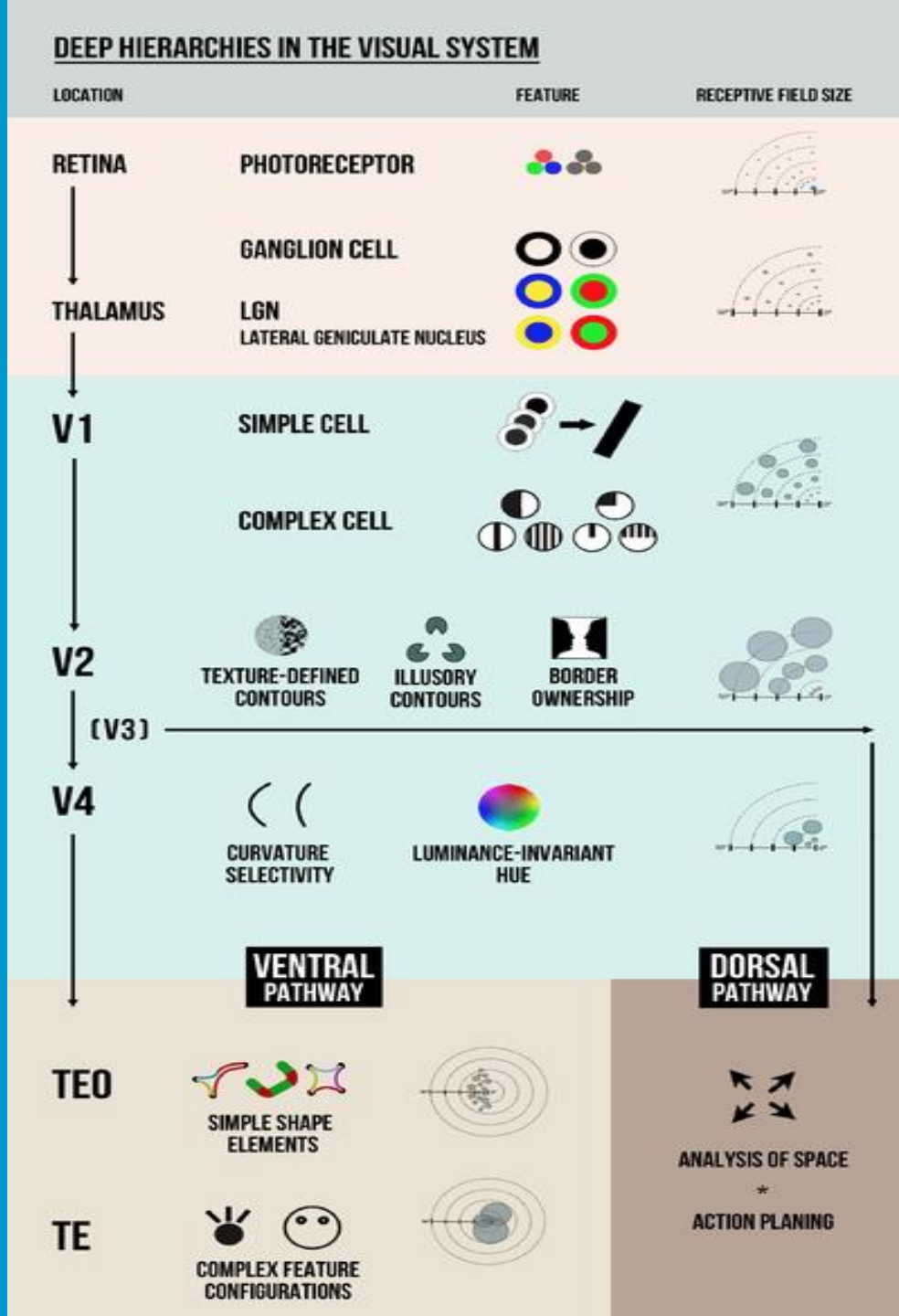
Rede Neural Convolucional

- CNN's foram inspiradas pela sensibilidade local e orientação seletiva do cérebo.

- Projetaram uma rede neural que implicitamente extraim características relevantes da entrada.

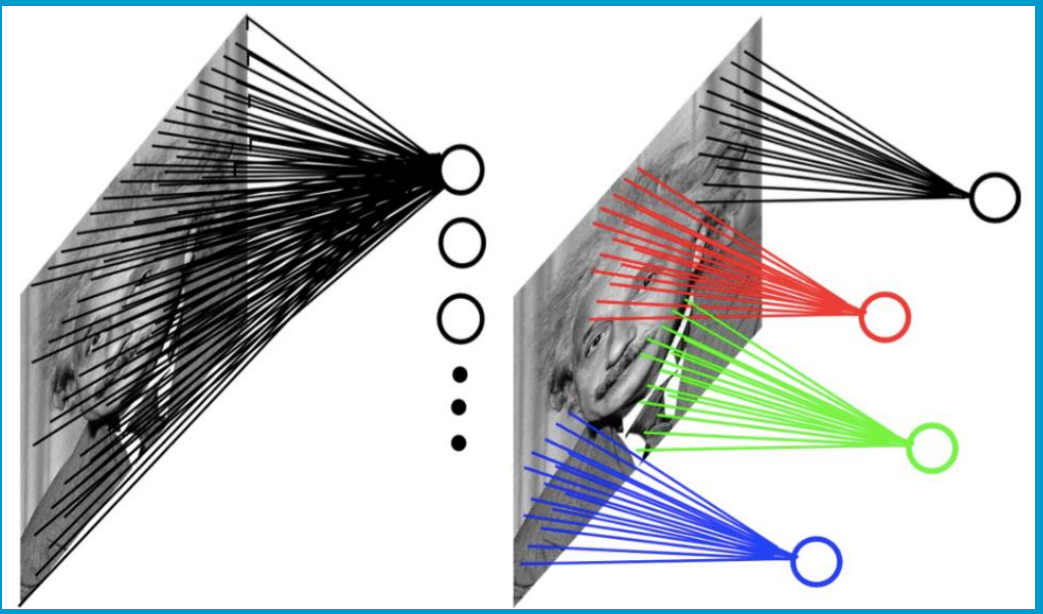
- Redes convolucionais são um tipo especial de multi-layer neural networks (MLP).

- Vision of the brain.
- Fotorreceptores
- Células ganglionares.
- Visão "central" e "periférica"



Rede Neural Convolucional

- Problema: Entrada pode ter uma dimensão muito alta. Multi-Layer Perceptron.
- Inspirado pelos experimentos de neurofisiologia [Hubel & Wiesel 1962], CNNs são um tipo especial de redes neurais que usam o conceito de campo receptivo local.



Exemplo: 200x200 imagem

a) MLP: 40,000 hidden units => 1.6 bilhões de parametros

b) CNN: 5x5 kernel, 100 campos receptivos => 2,500 parametros

Convolução

Convolução é uma operação matemática em duas funções (f e g) que produz uma terceira função, que normalmente é vista como uma versão modificada de uma das funções originais.

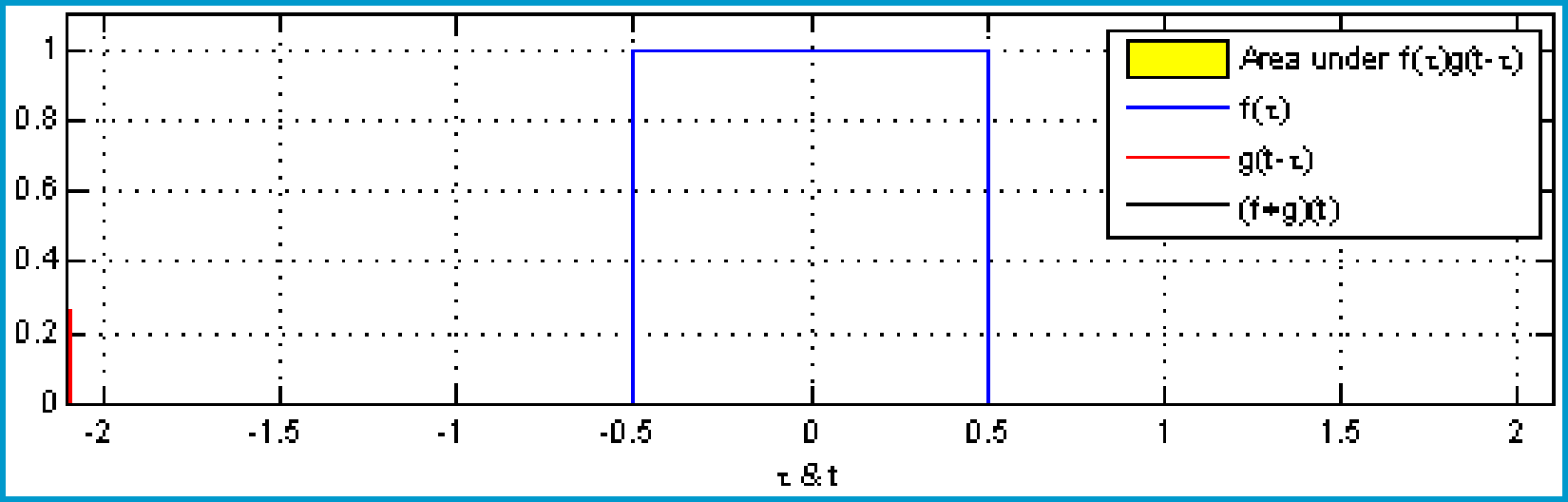
Comum no processamento de imagem:

- Altera as intensidades de um pixel para refletir as intensidades dos pixels circundantes.

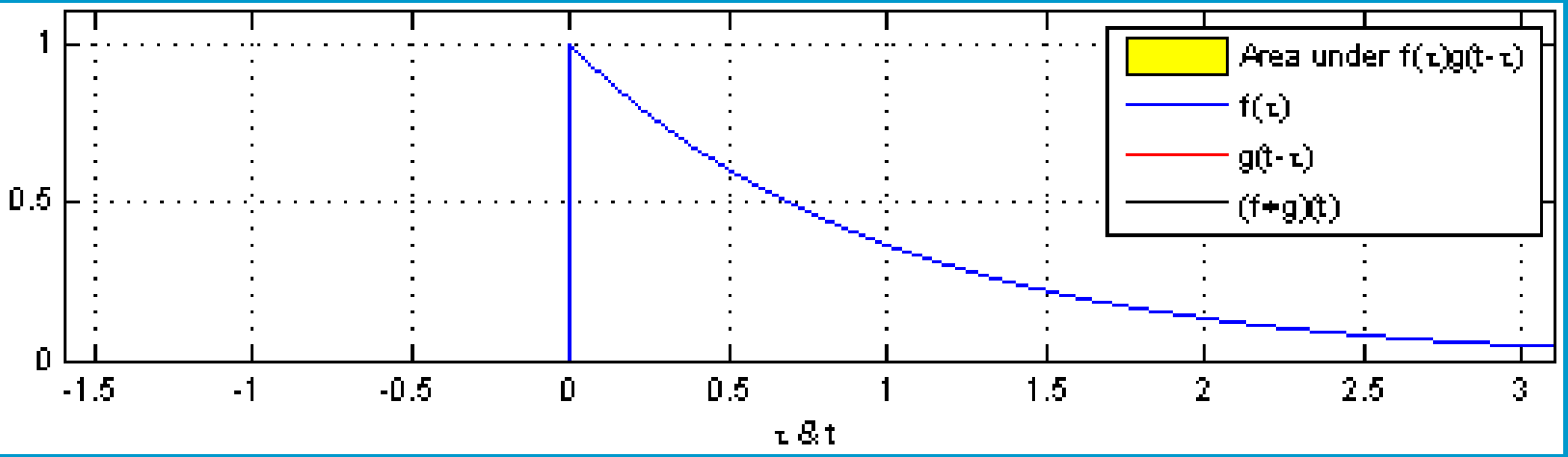
Convolução

- Não confundir com correlação cruzada:
- Ambas envolvem a integração de um produto entre duas funções.
  Convolução é usada para expressar a um sinal pela resposta característica de outro sinal.
- Correlação cruzada expressa o grau de correspondência entre os sinais.

Convolução



Convolução

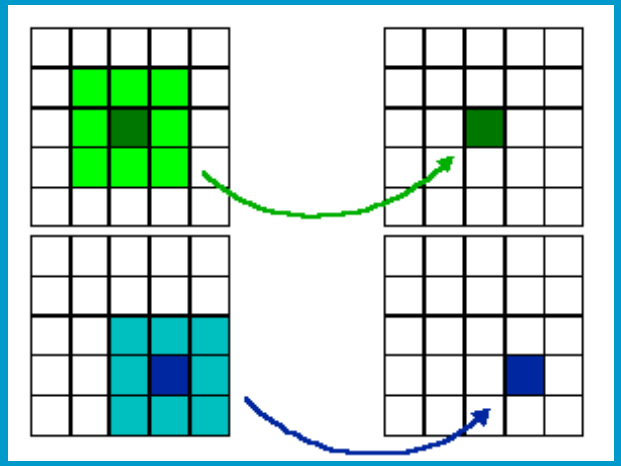


IMPORTANTE

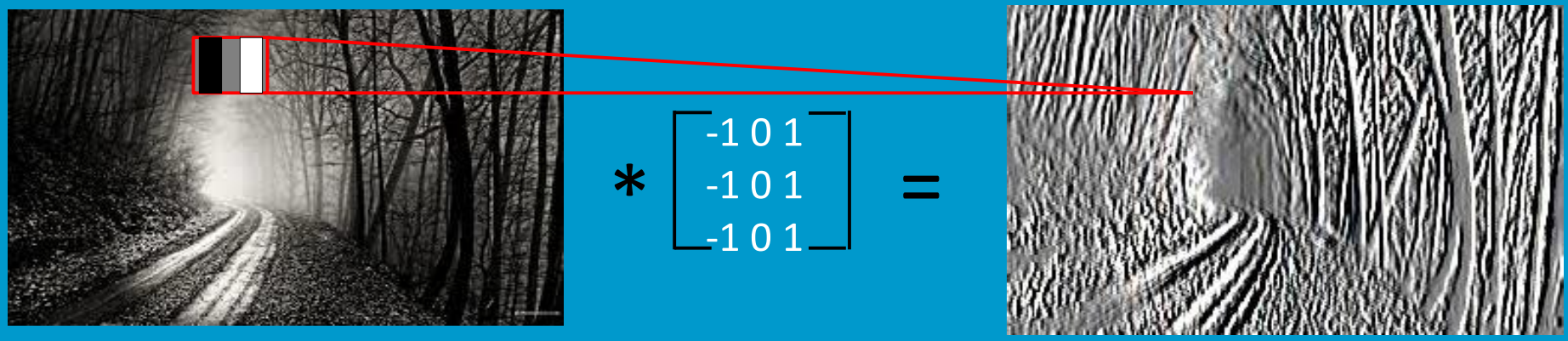
Convolução discreta

$$g(x) = f(x) \otimes h(x) = \sum_{\forall k} h(x-k) f(k)$$

$h(x)$: resposta de impulso (impulse response), *kernel*, máscara, filtro ou *template*.



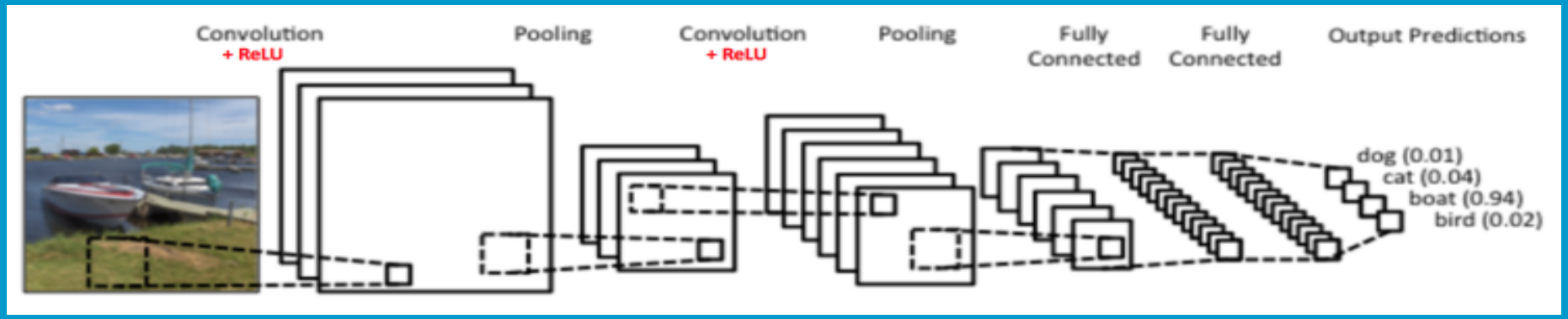
IMPORTANTE



$$f[x,y] * g[x,y] = \sum_{n_1=-\infty}^{\infty} \sum_{n_2=-\infty}^{\infty} f[n_1,n_2] \cdot g[x-n_1, y-n_2]$$

Multiplicação ponto-a-ponto e soma de um filtro com o sinal


CALMA, CALMA,
NÃO CRIEMOS PÂNICO
sbt
GERADORMEMES.COM



Entendendo a camada de convolução

Filtros: A matemática atrás da comparação

1. Multiplicar cada pixel da imagem pelo pixel correspondente do filtro.
2. Adicionar ao somatório.
3. Dividir pelo total de elementos.

Filtros: A matemática atrás da comparação

H =

-1	1

G =

0	0	0	1	1	1	1	1

$G \otimes H = ?$

Filtros: A matemática atrás da comparação

H =

-1	1

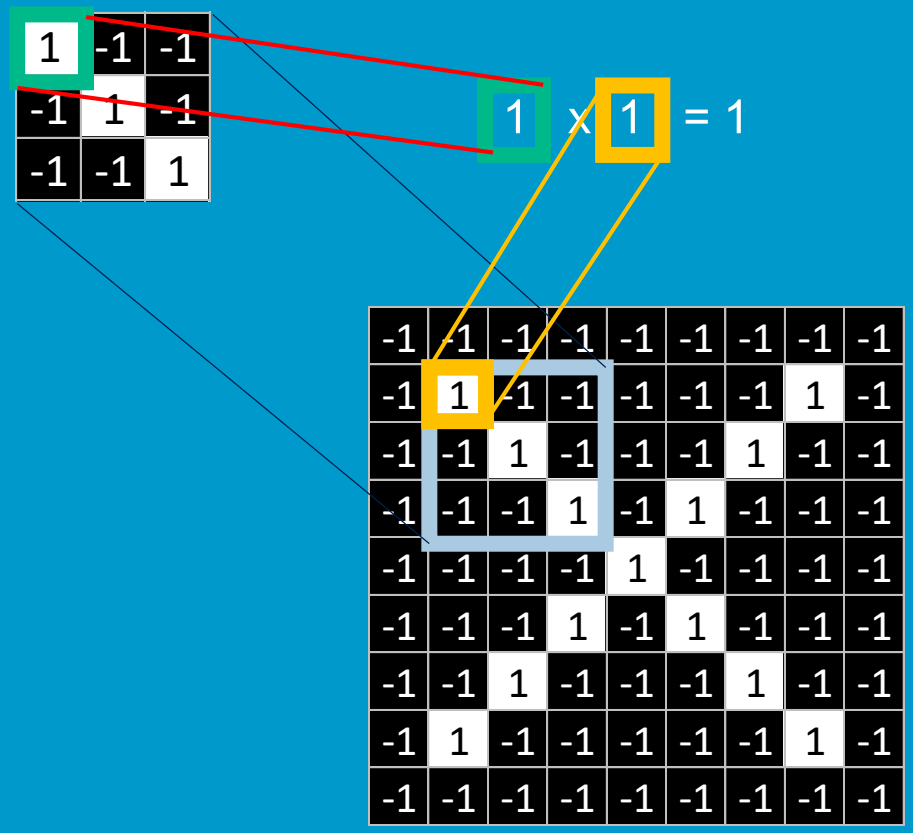
G =

0	0	0	1	1	1	1	1

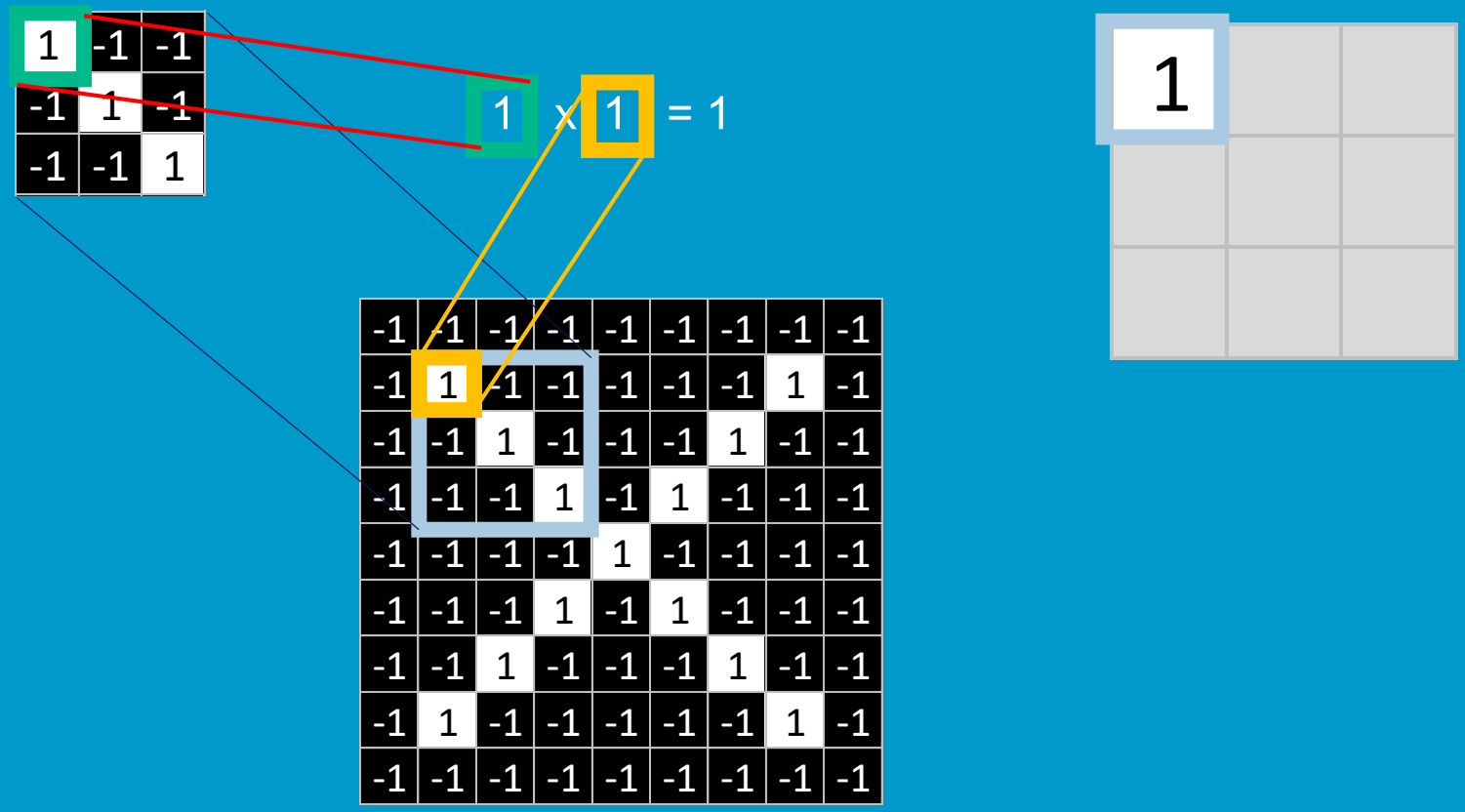
$G \otimes H =$

0	0	1	0	0	0	0	0

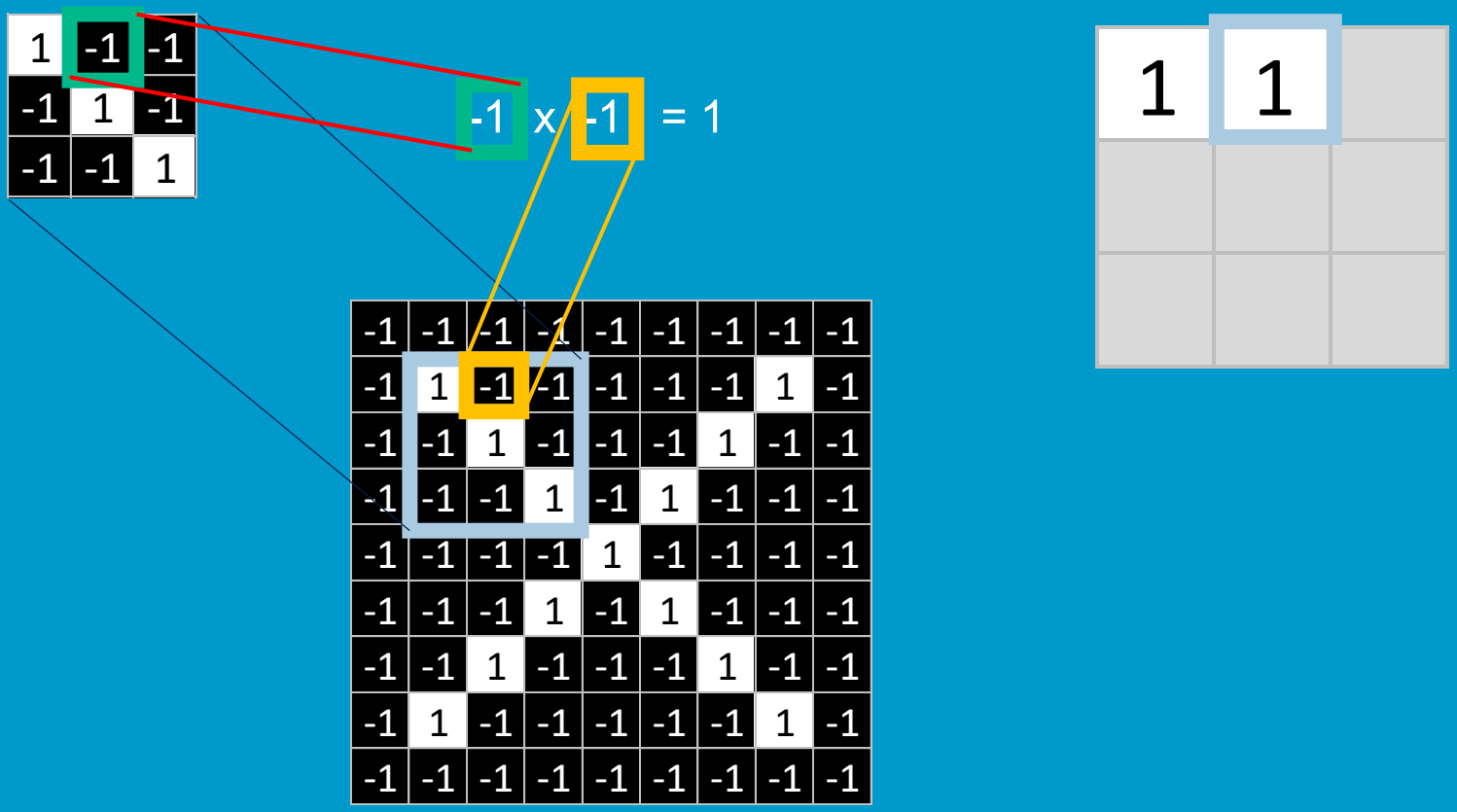
Filtros: A matemática atrás da comparação



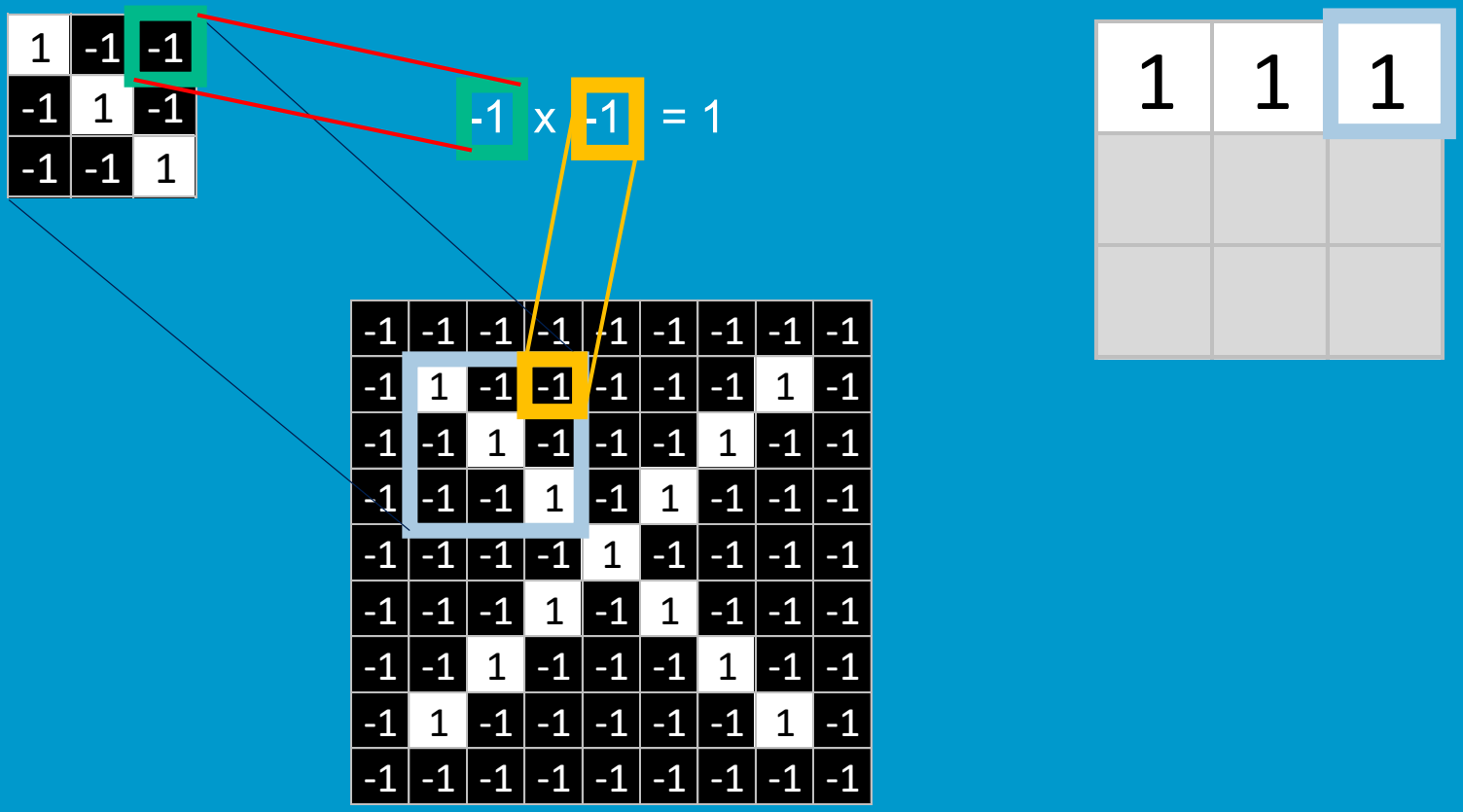
Filtros: A matemática atrás da comparação



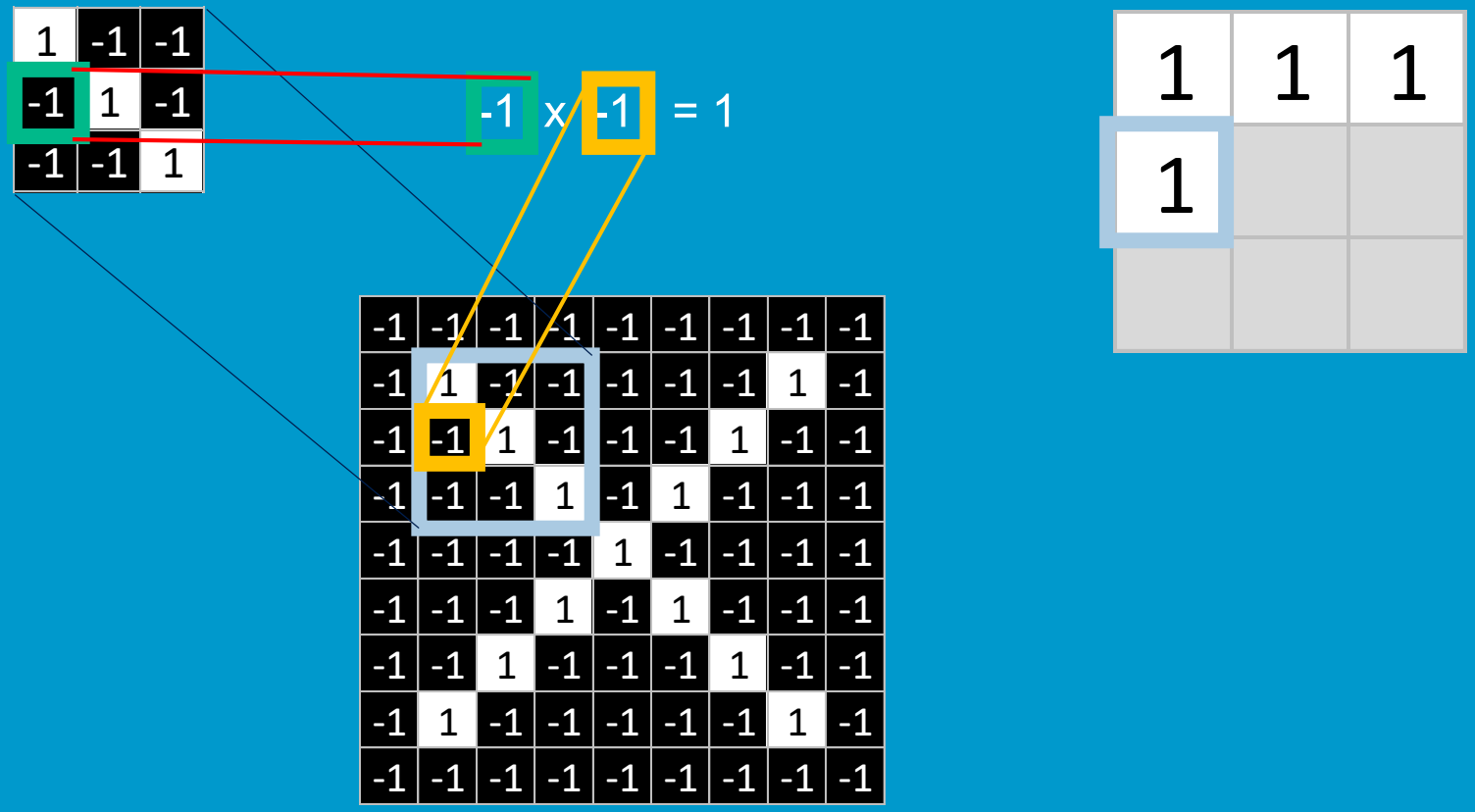
Filtros: A matemática atrás da comparação



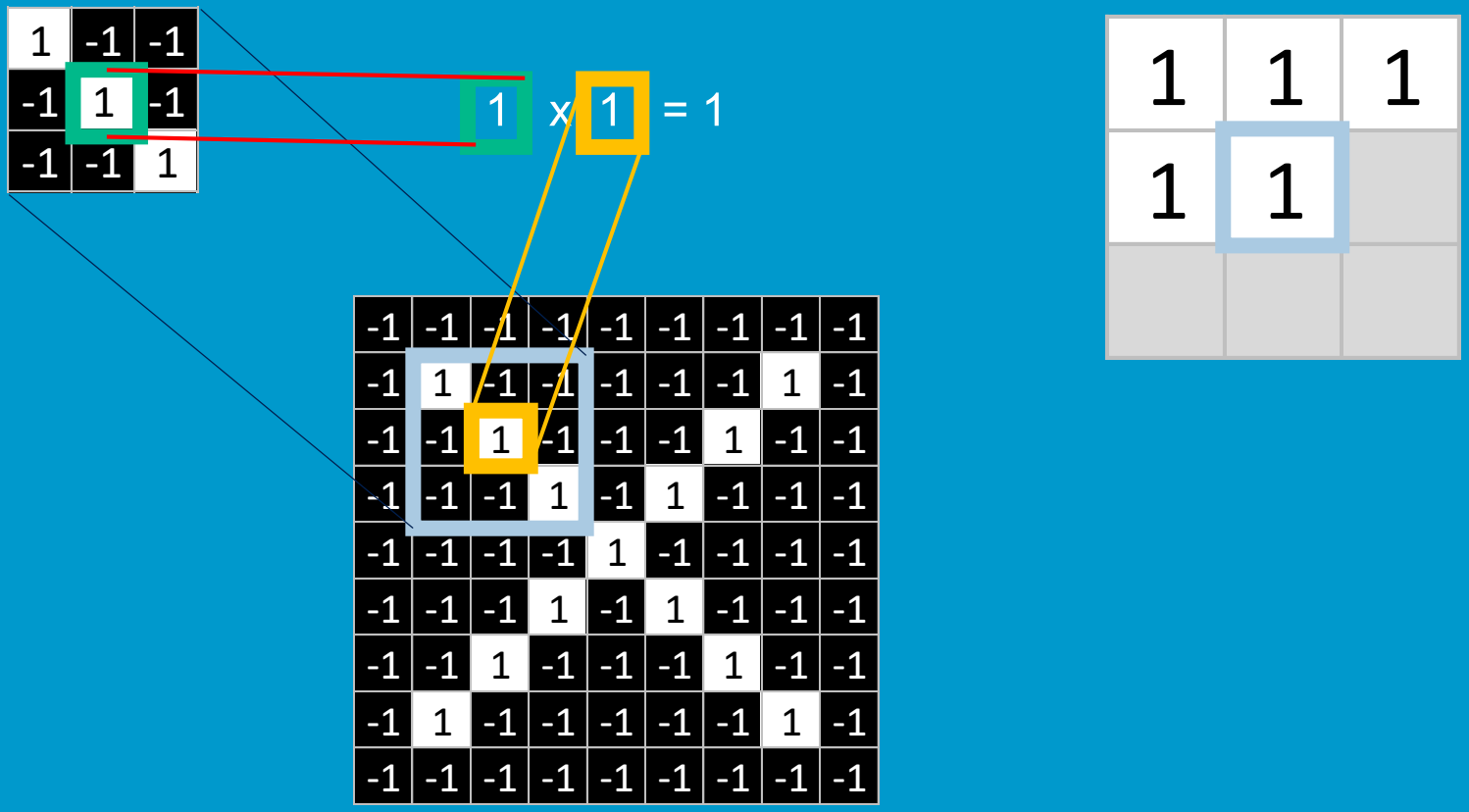
Filtros: A matemática atrás da comparação



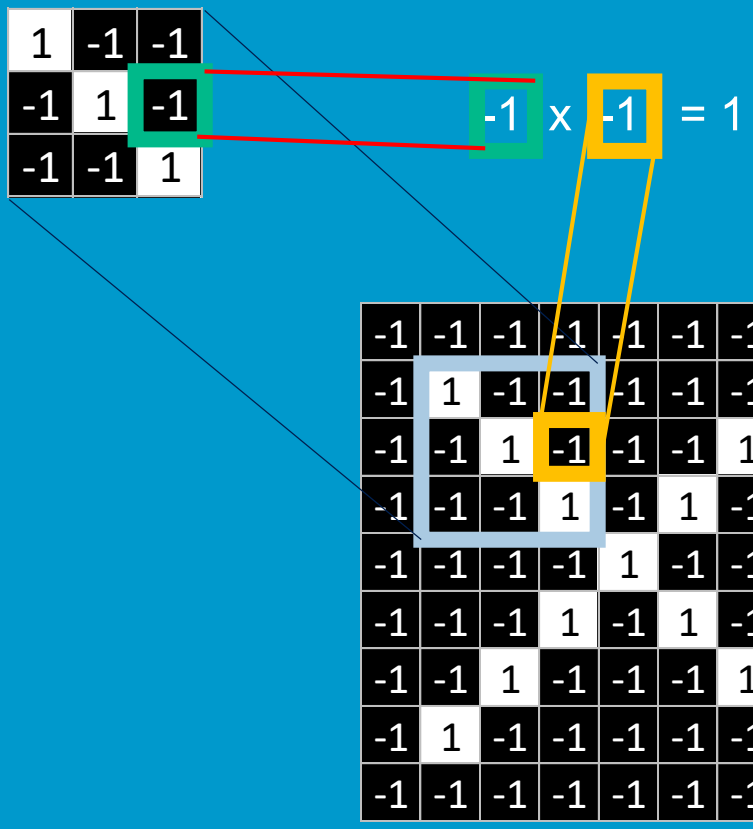
Filtros: A matemática atrás da comparação

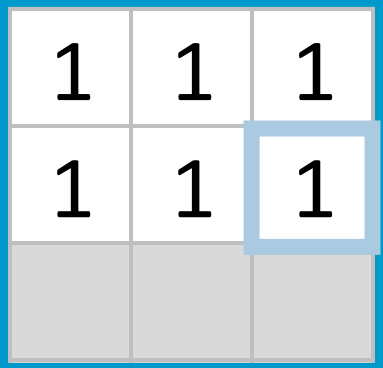


Filtros: A matemática atrás da comparação

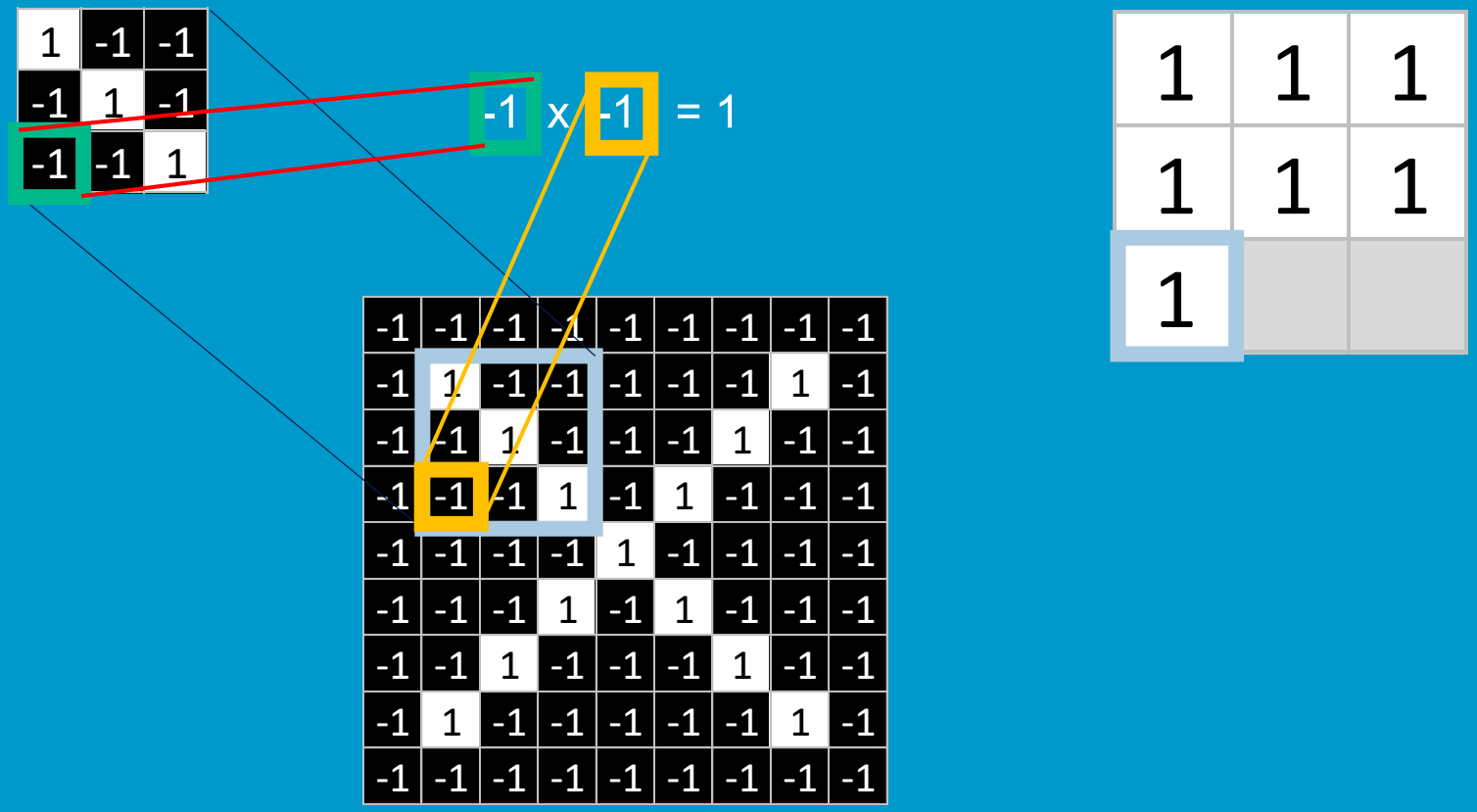


Filtros: A matemática atrás da comparação

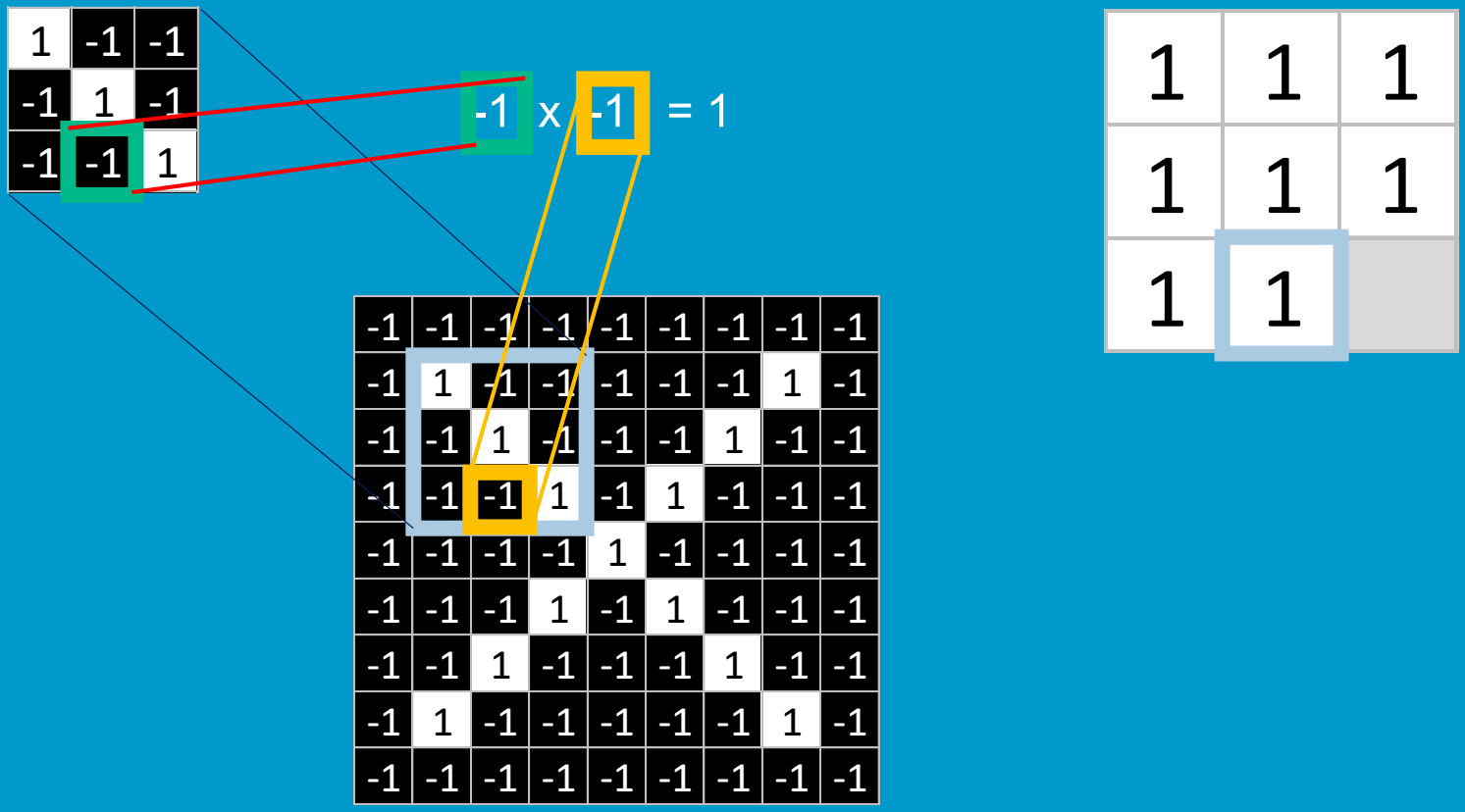




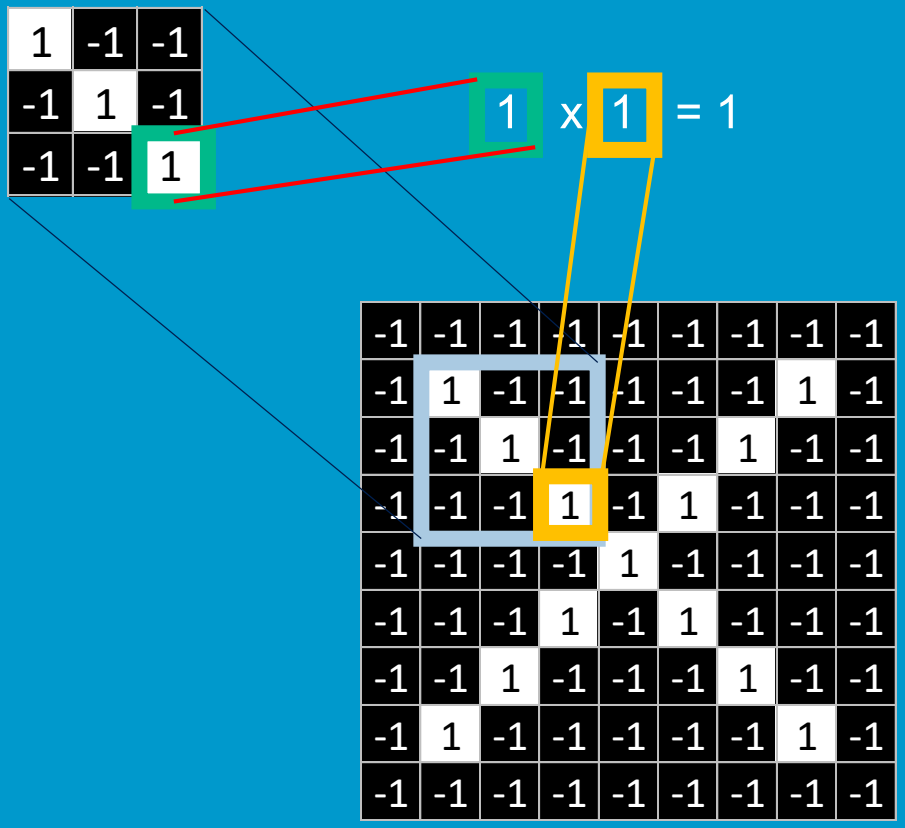
Filtros: A matemática atrás da comparação



Filtros: A matemática atrás da comparação

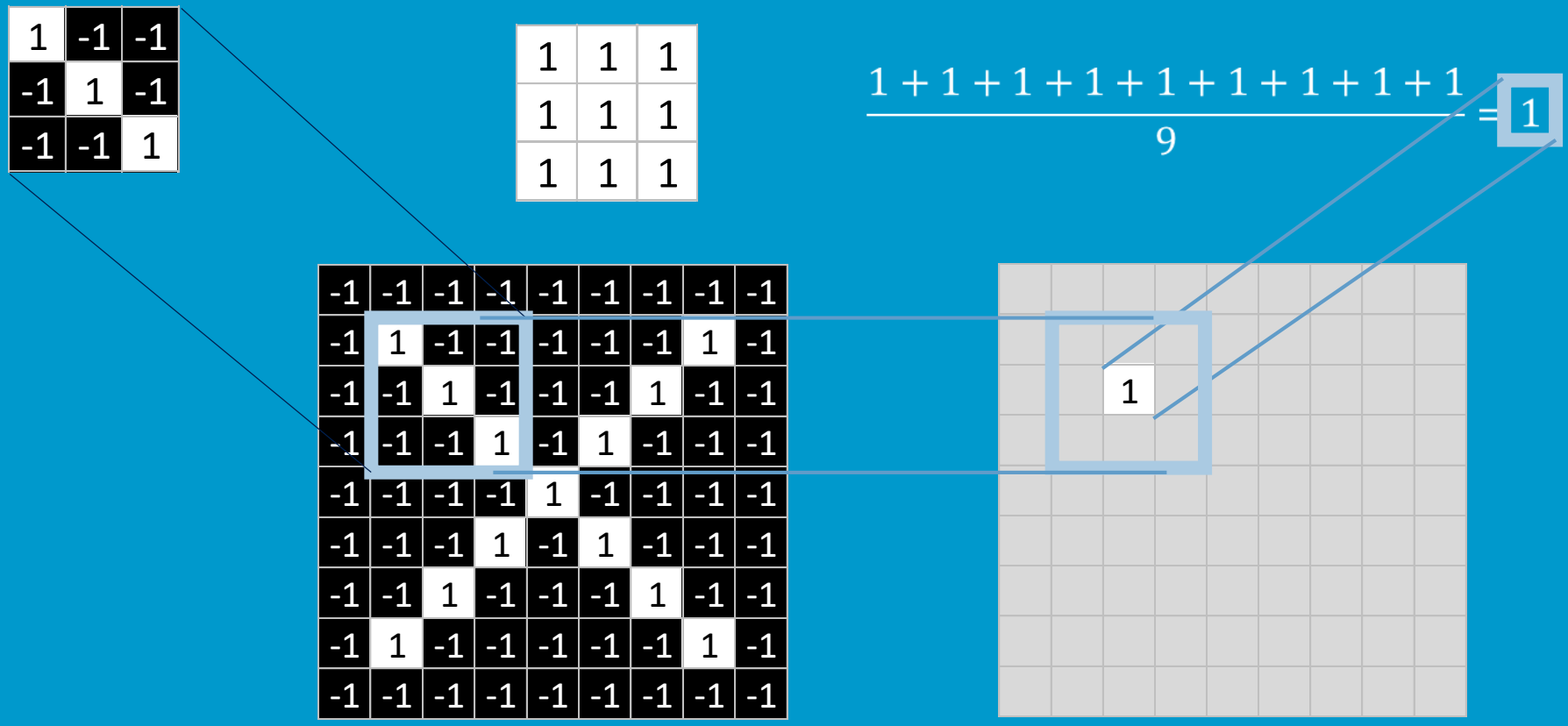


Filtros: A matemática atrás da comparação

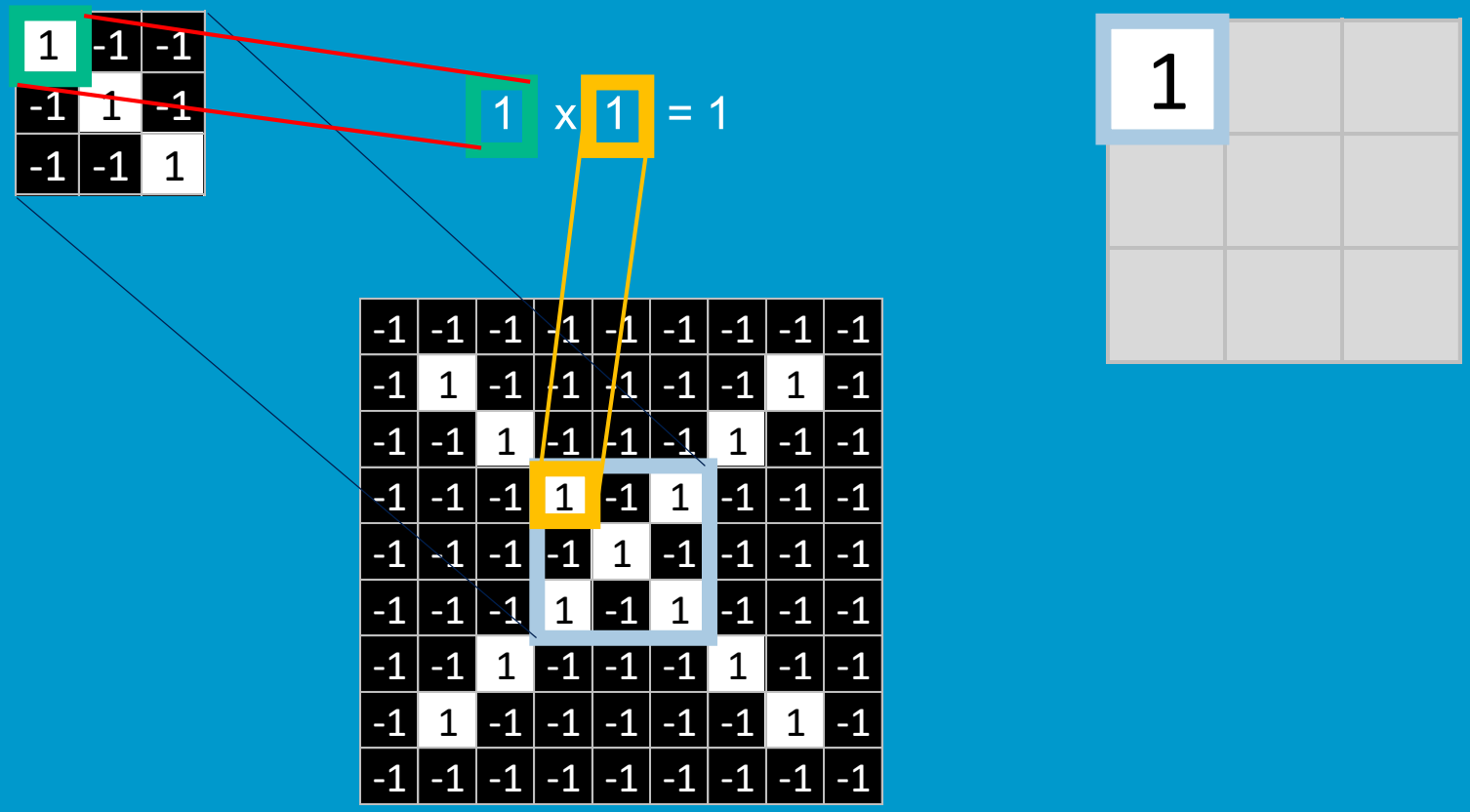


1	1	1
1	1	1
1	1	1

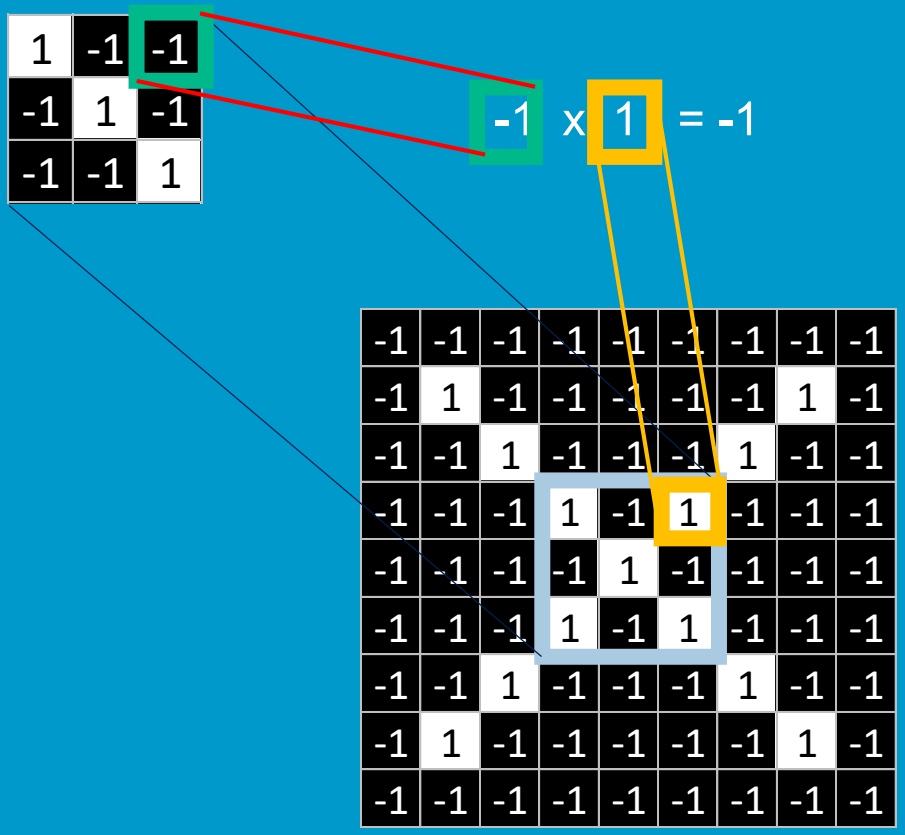
Filtros: A matemática atrás da comparação



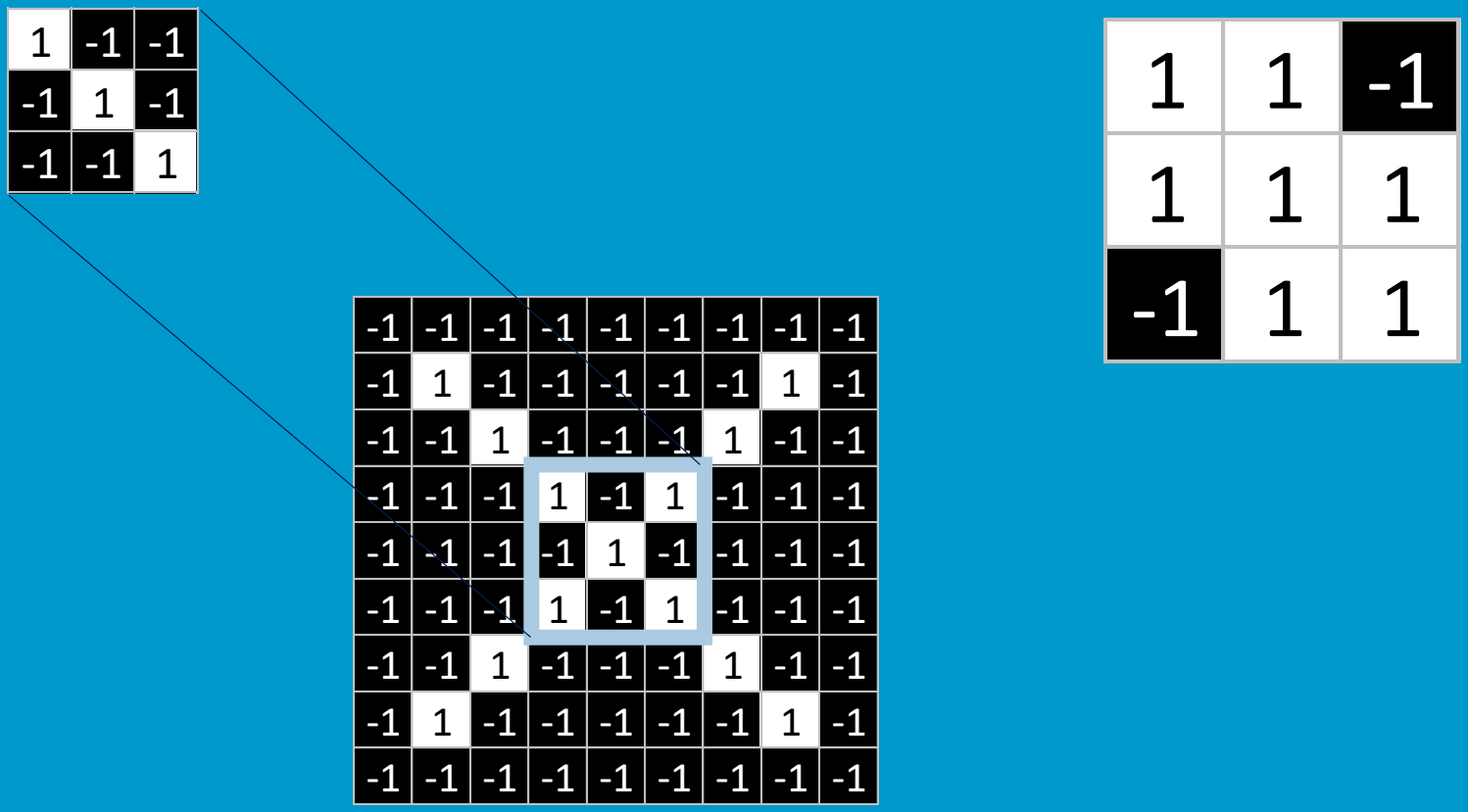
Filtros: A matemática atrás da comparação



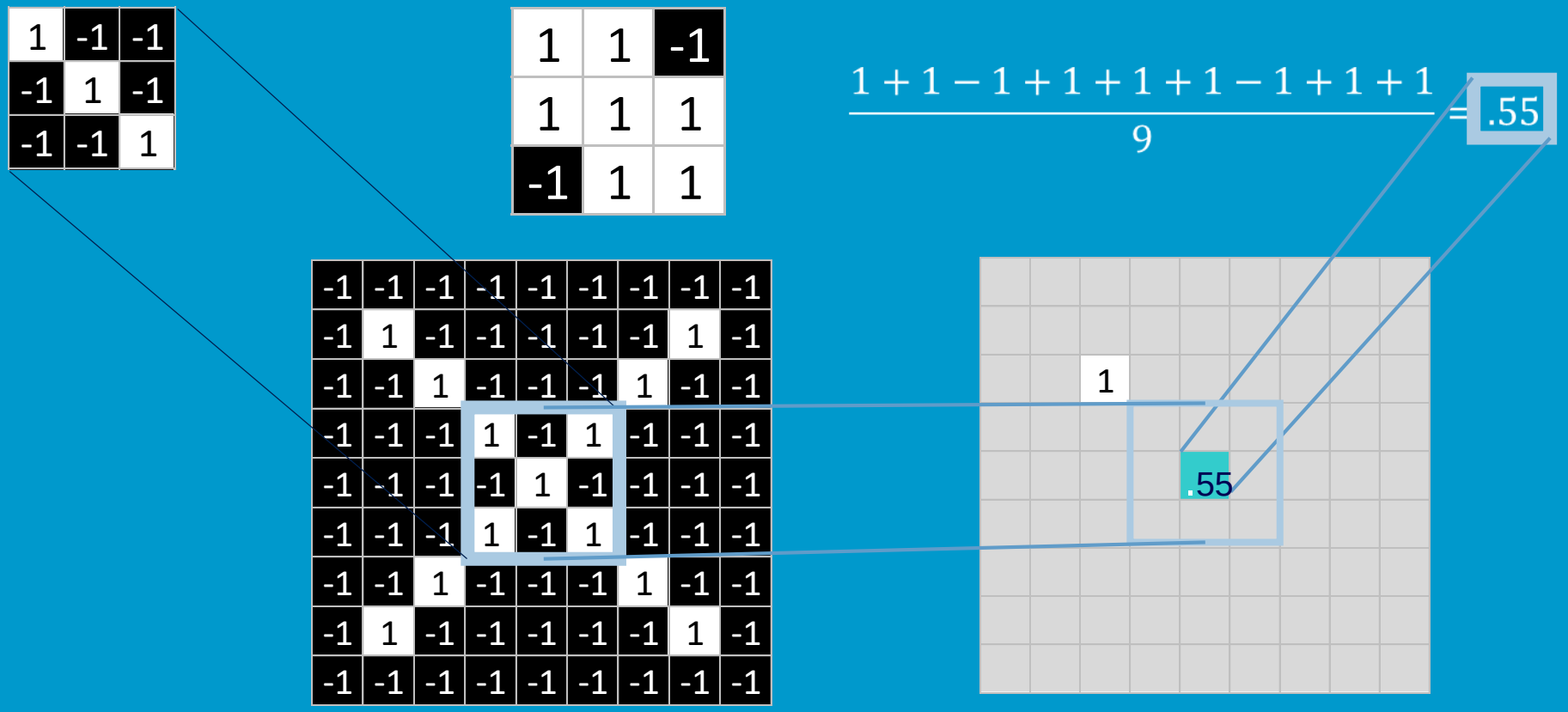
Filtros: A matemática atrás da comparação



Filtros: A matemática atrás da comparação



Filtros: A matemática atrás da comparação



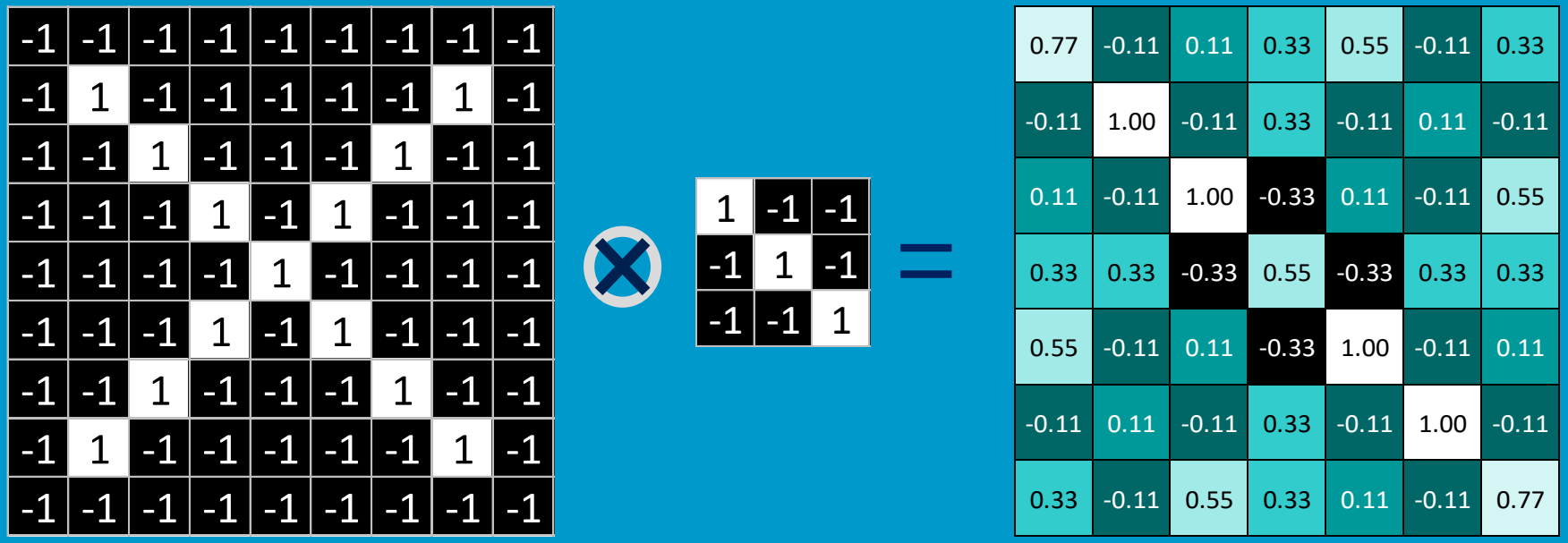
Filtros: A matemática atrás da comparação

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	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	-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	-1	-1	-1	-1	1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77

Filtros: A matemática atrás da comparação



Filtros: A matemática atrás da comparação

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

Matriz numérica do filtro convolucional

Table 3.2: Visualização do filtro convolucional

Visualization of the filter on the image

0	0	0	0	0	0	0
0	40	0	0	0	0	0
40	0	40	0	0	0	0
40	20	0	0	0	0	0
0	50	0	0	0	0	0
0	0	50	0	0	0	0
25	25	0	50	0	0	0

Pixel representation of receptive field

*

0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0

Pixel representation of filter

Multiplication and Summation = 0

Figure 3.2: Imagem de entrada para aplicação do filtro de convolução

0	0	0	0	0	0	30
0	0	0	0	50	50	50
0	0	0	20	50	0	0
0	0	0	50	50	0	0
0	0	0	50	50	0	0
0	0	0	50	50	0	0
0	0	0	50	50	0	0

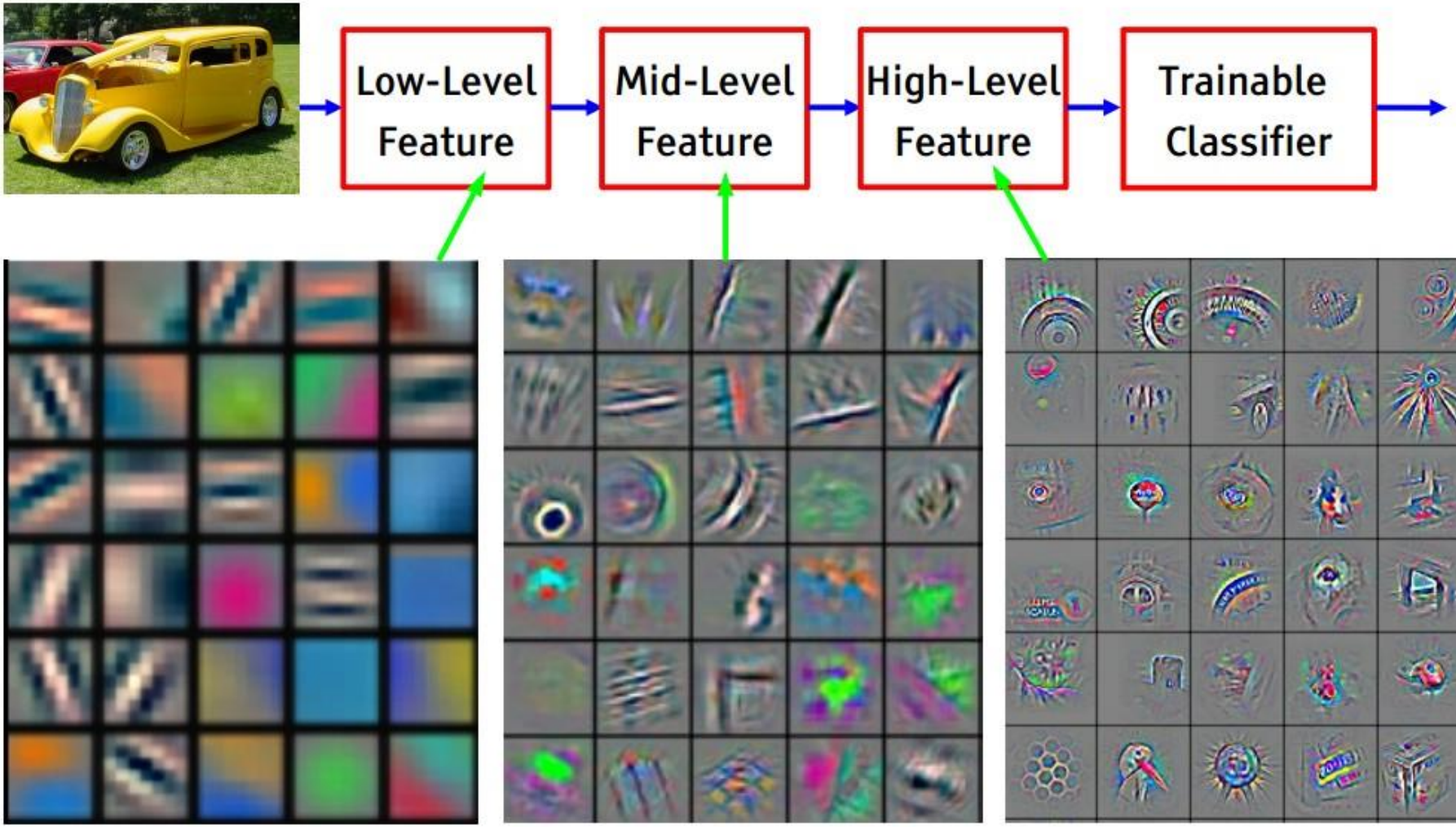
Imagem de entrada considerando a região do amarelo no canto superior esquerdo

0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0

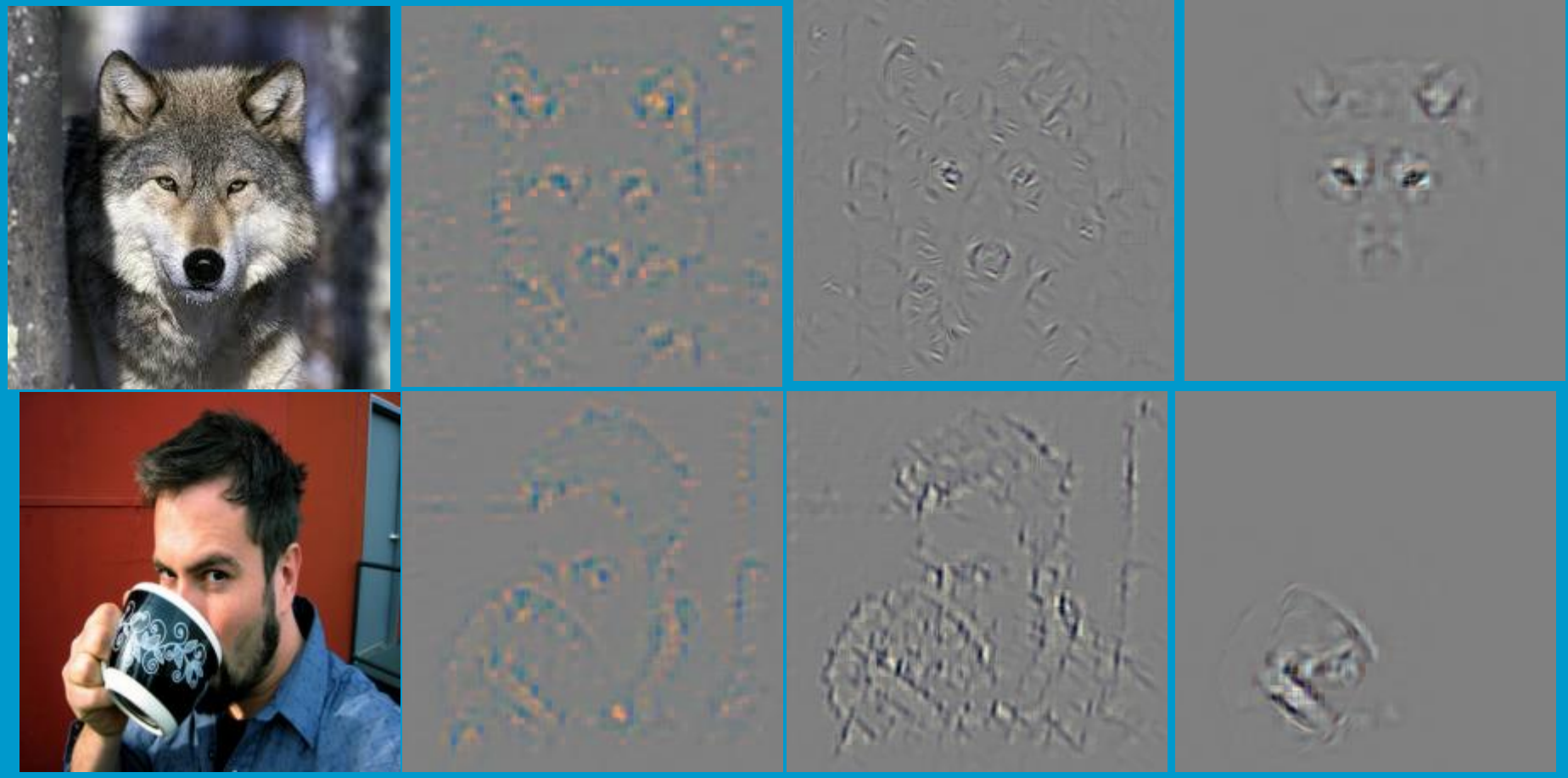
Table 3.4: Filtro convolucional

O resultado, omitindo-se a multiplicação dos valores zerados será dado por (50*30)+(50*30)+(50*30)+(20*30)+(50*30)=6600.
O valor 6600 quantifica a presença da característica descrita pelo filtro convolucional na imagem.

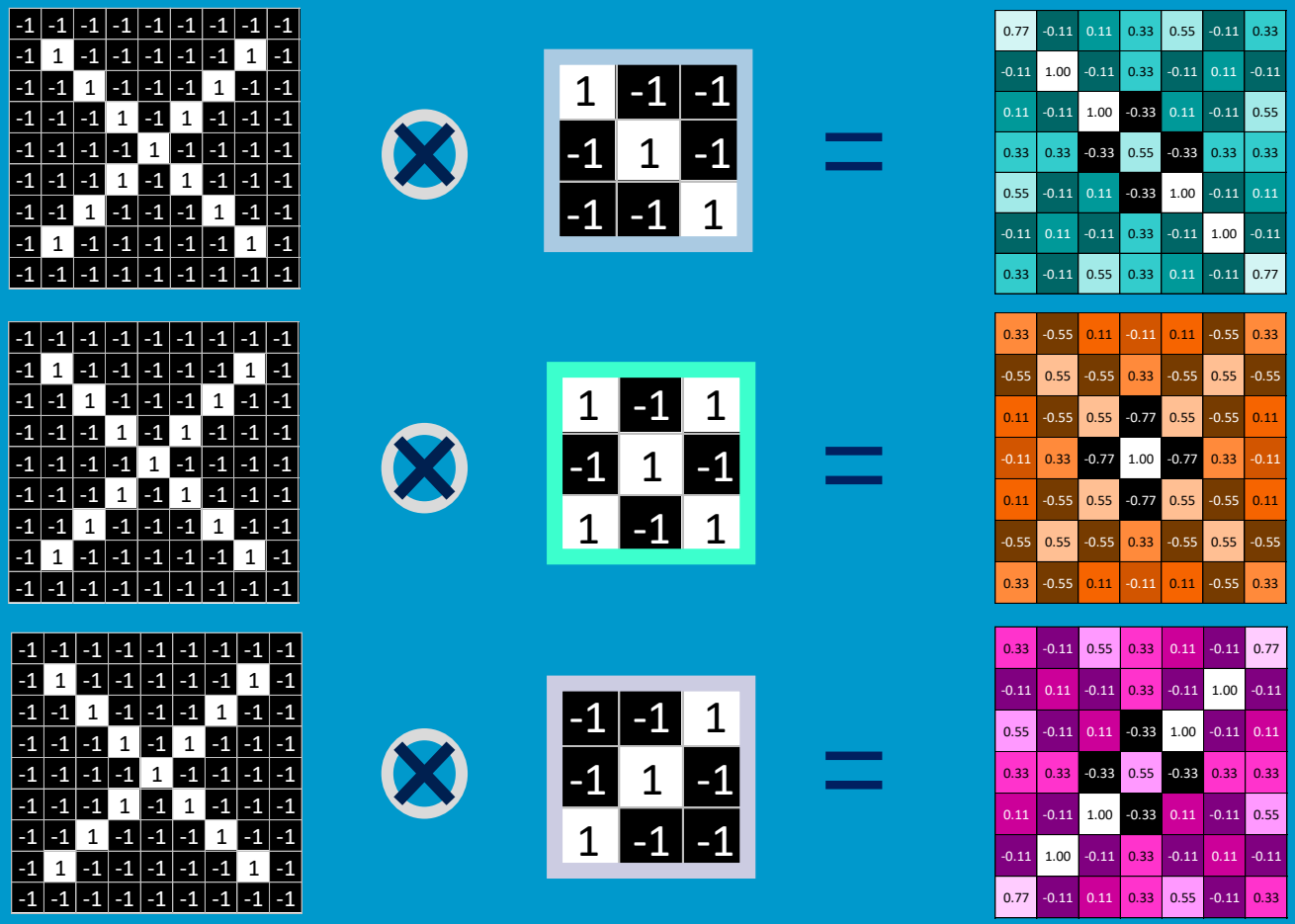
[From recent Yann LeCun slides]



Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

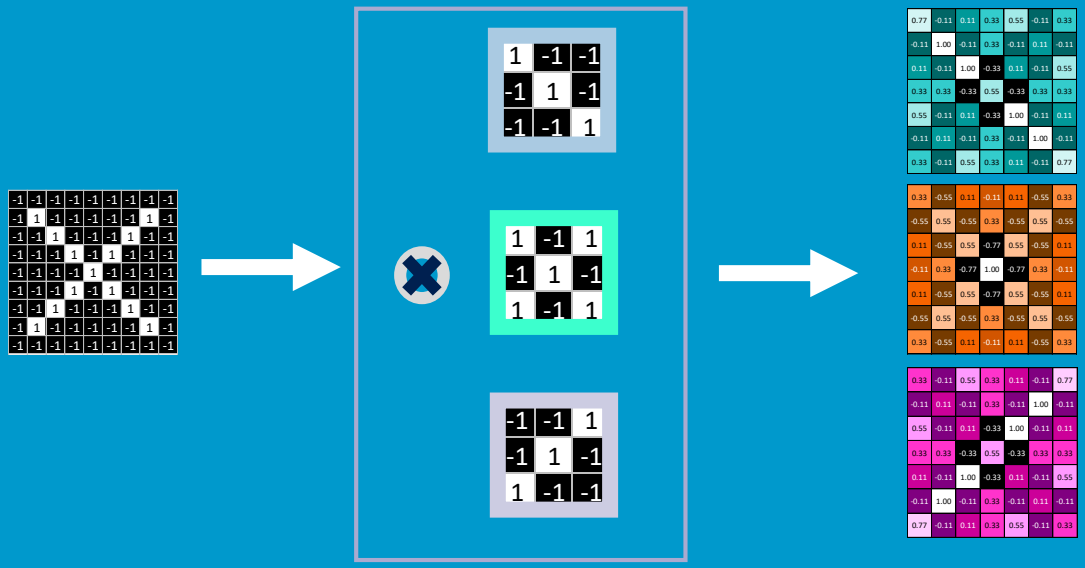


Obtido de: https://github.com/InFoCusp/tf_cnnvis
Ver o vídeo de http://yosinski.com/deepvis


-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 -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 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 -1 -1 -1 -1 -1 -1
1 -1 -1
-1 1 -1
-1 -1 1
0.77 -0.11 0.11 0.33 0.55 -0.11 0.33
-0.11 1.00 -0.11 0.33 -0.11 0.11 -0.11
0.11 -0.11 1.00 -0.33 0.11 -0.11 0.55
0.33 0.33 -0.33 0.55 -0.33 0.33 0.33
0.55 -0.11 0.11 -0.33 1.00 -0.11 0.11
-0.11 0.11 -0.11 0.33 -0.11 1.00 -0.11
0.33 -0.11 0.55 0.33 0.11 -0.11 0.77
1 -1 1
-1 1 -1
1 -1 1
0.33 -0.55 0.11 -0.11 0.11 -0.55 0.33
-0.55 0.55 -0.55 0.33 -0.55 0.55 -0.55
0.11 -0.55 0.55 -0.77 0.55 -0.55 0.11
-0.11 0.33 -0.77 1.00 -0.77 0.33 -0.11
0.11 -0.55 0.55 -0.77 0.55 -0.55 0.11
-0.55 0.55 -0.55 0.33 -0.55 0.55 -0.55
0.33 -0.55 0.11 -0.11 0.11 -0.55 0.33
-1 -1 1
-1 1 -1
1 -1 -1
0.33 -0.11 0.55 0.33 0.11 -0.11 0.77
-0.11 0.11 -0.11 0.33 -0.11 1.00 -0.11
0.55 -0.11 0.11 -0.33 1.00 -0.11 0.11
0.33 0.33 -0.33 0.55 -0.33 0.33 0.33
0.11 -0.11 1.00 -0.33 0.11 -0.11 0.55
-0.11 1.00 -0.11 0.33 -0.11 0.11 -0.11
0.77 -0.11 0.11 0.33 0.55 -0.11 0.33

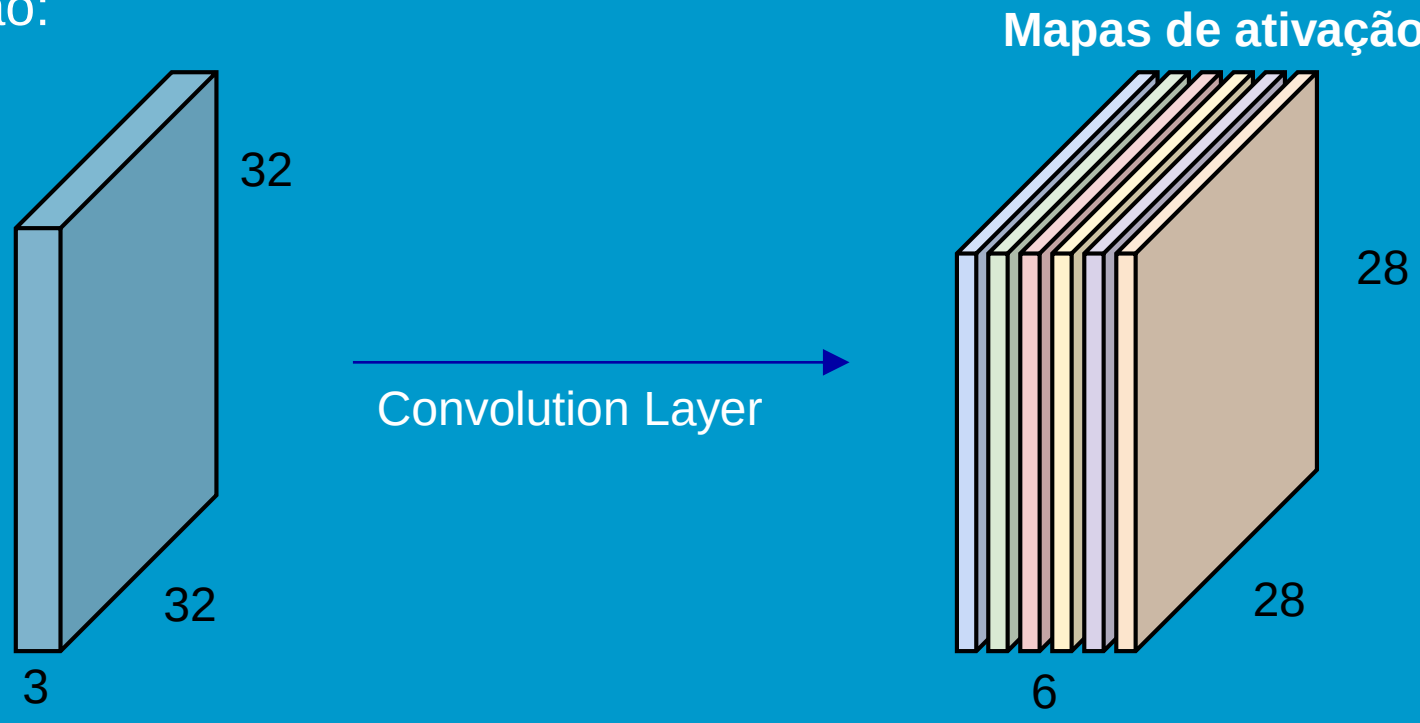
Camada de convolução

Uma imagem gera um conjunto de imagens



Camada de convolução

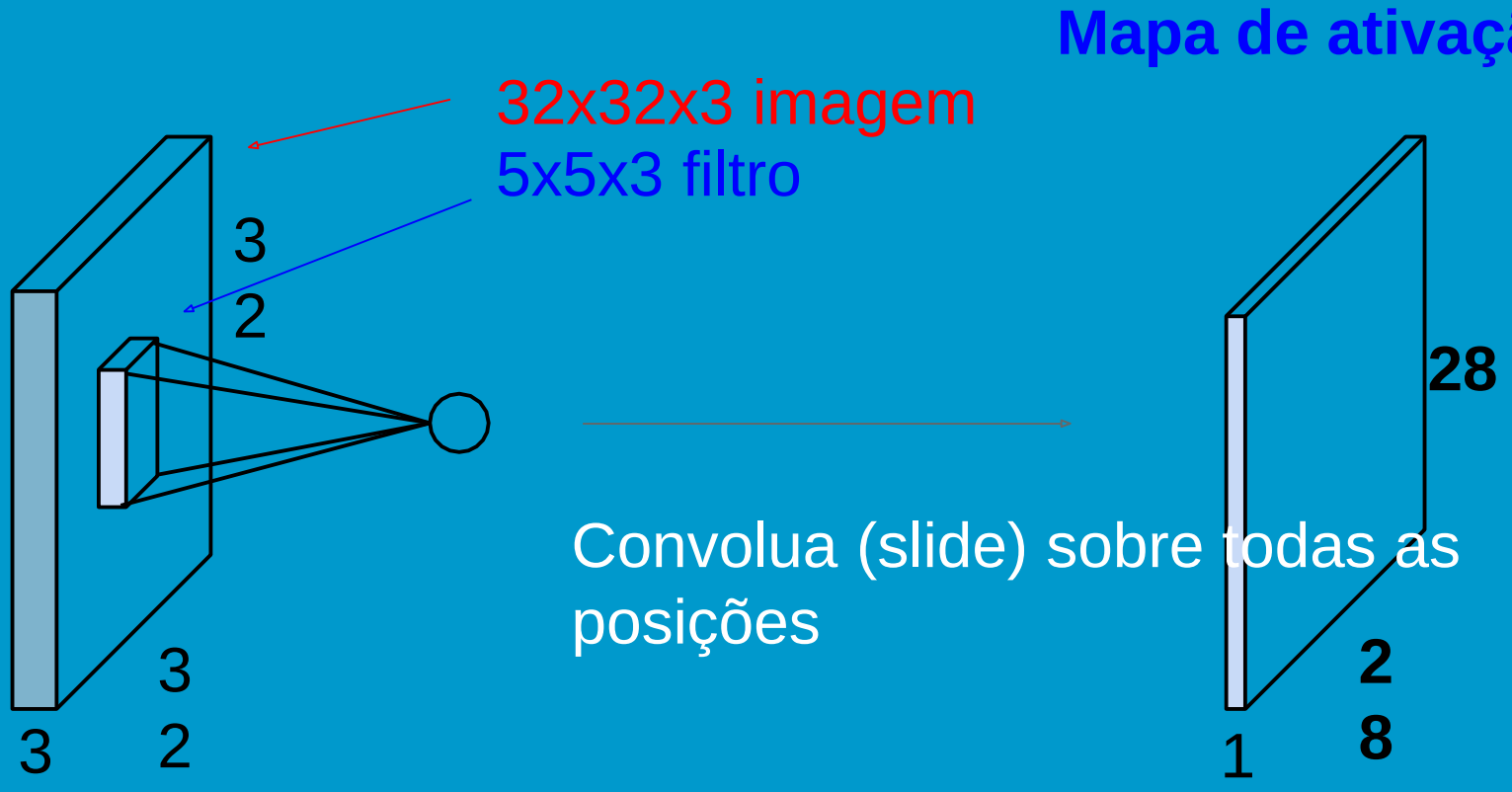
Por exemplo, se nós temos 6 filtros 5x5, nós iremos obter 6 mapas de ativação:



Nós empilhamos estas novamos imagens 28x28x6!

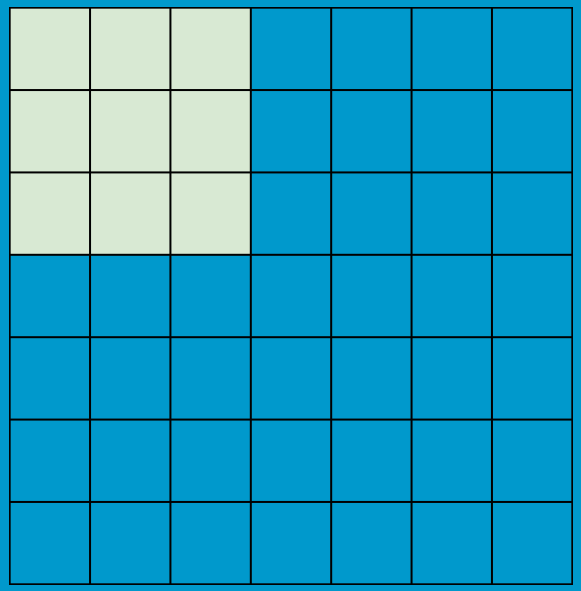
Camada de convolução: detalhes

Olhando mais de perto as dimensões:



Camada de convolução: detalhes

Olhando mais de perto as dimensões:

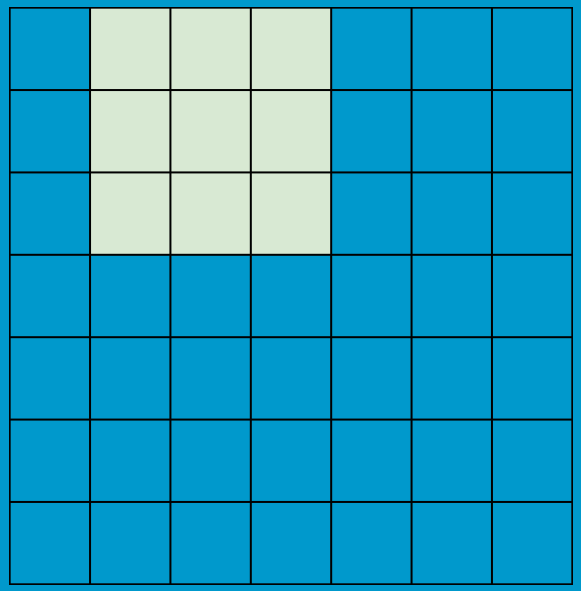


Entrada 7x7

Filtro 3x3

Camada de convolução: detalhes

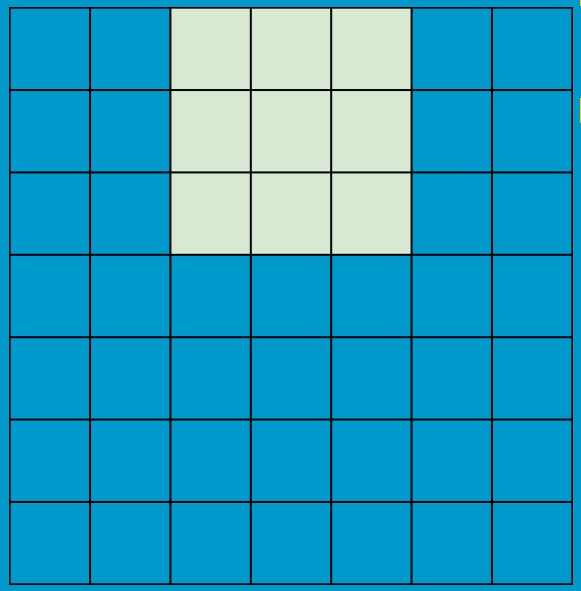
Olhando mais de perto as dimensões:



- Entrada 7x7
- Filtro 3x3

Camada de convolução: detalhes

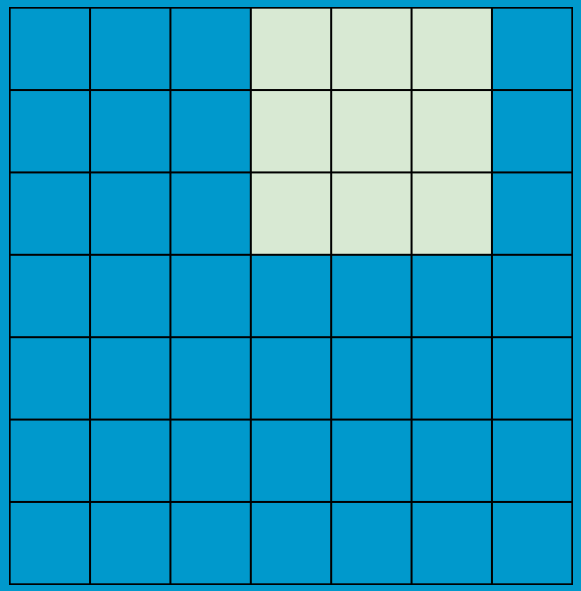
Olhando mais de perto as dimensões:



- Entrada 7x7
- Filtro 3x3

Camada de convolução: detalhes

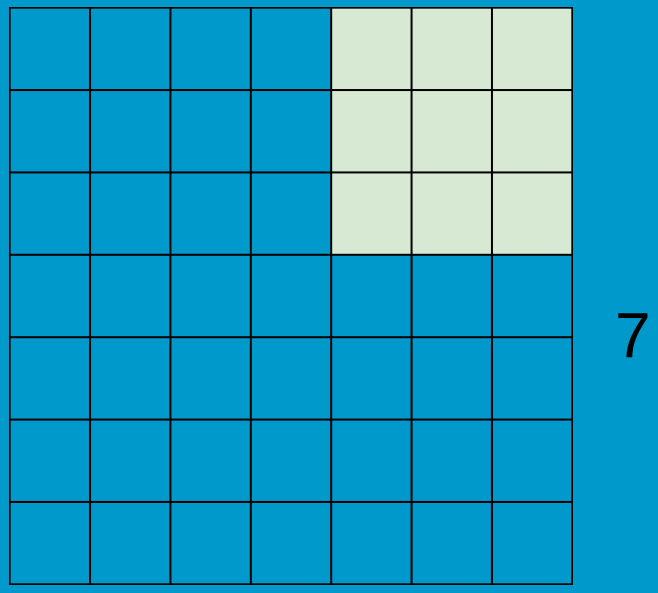
Olhando mais de perto as dimensões:



- Entrada 7x7
- Filtro 3x3

Camada de convolução: detalhes

Olhando mais de perto as dimensões:

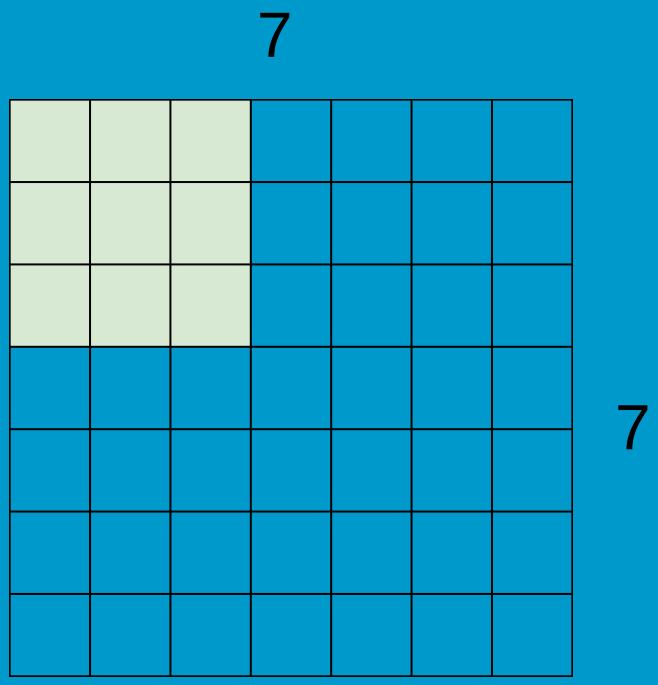


- Entrada 7x7
- Filtro 3x3

=> 5x5 output

Camada de convolução: detalhes

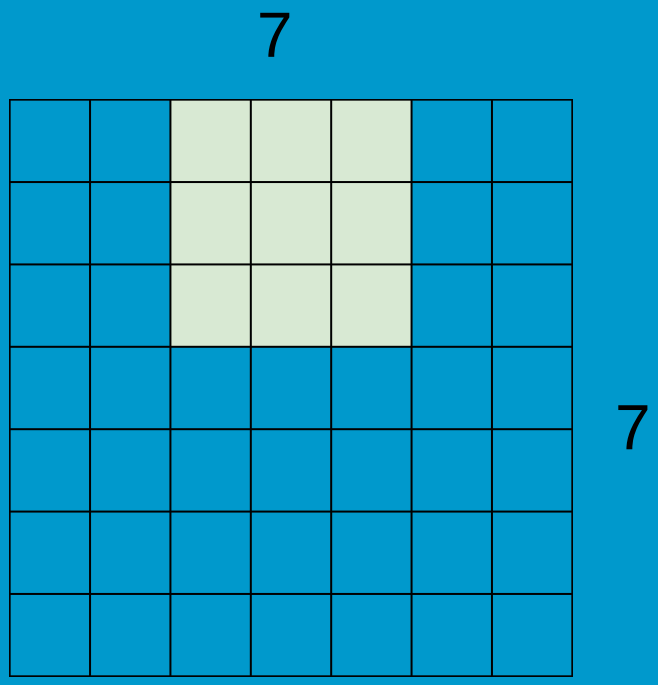
Olhando mais de perto as dimensões:



Entrada 7x7
Filtro 3x3 filter
com stride 2

Camada de convolução: detalhes

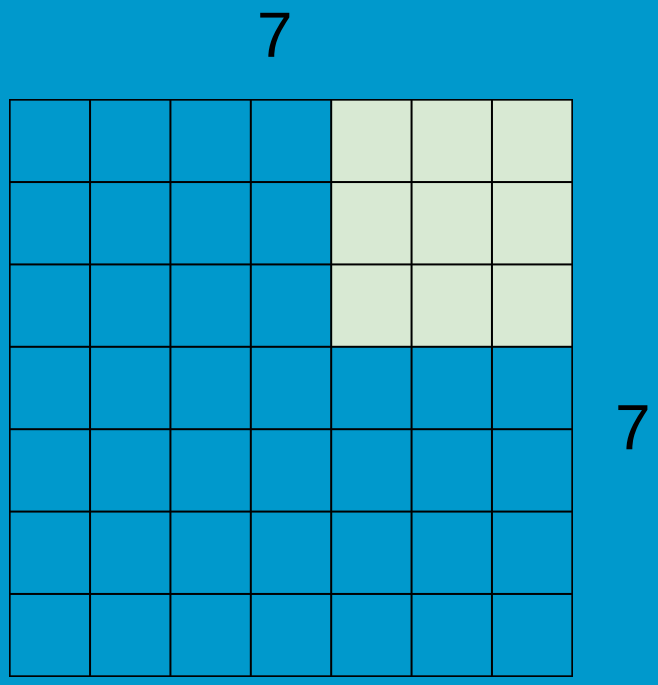
Olhando mais de perto as dimensões:



Entrada 7x7
Filtro 3x3 filter
com stride 2

Camada de convolução: detalhes

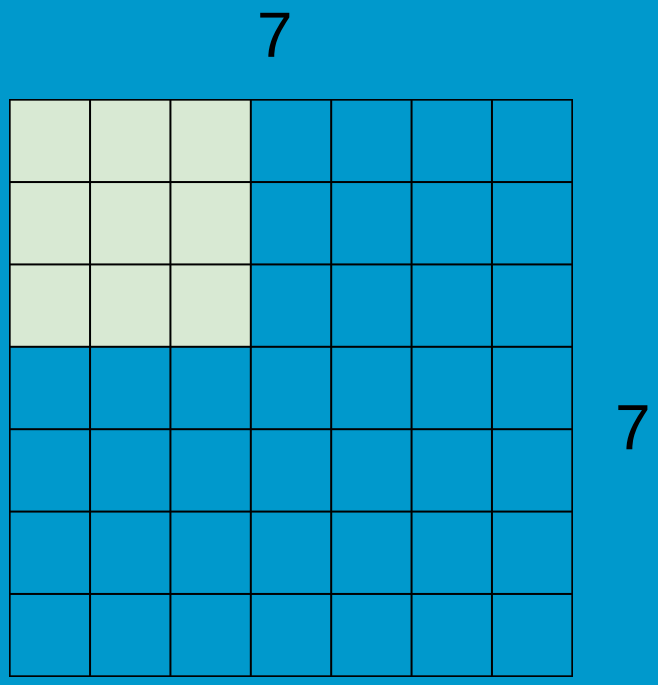
Olhando mais de perto as dimensões:



Entrada 7x7
Filtro 3x3 filter
com stride 2
=> Saída 3x3

Camada de convolução: detalhes

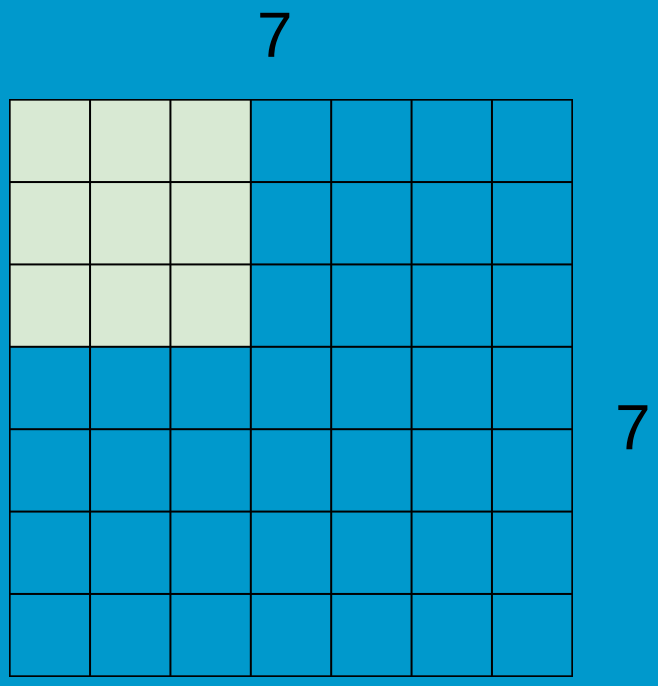
Olhando mais de perto as dimensões:



Entrada 7x7
Filtro 3x3 filter
com stride 3

Camada de convolução: detalhes

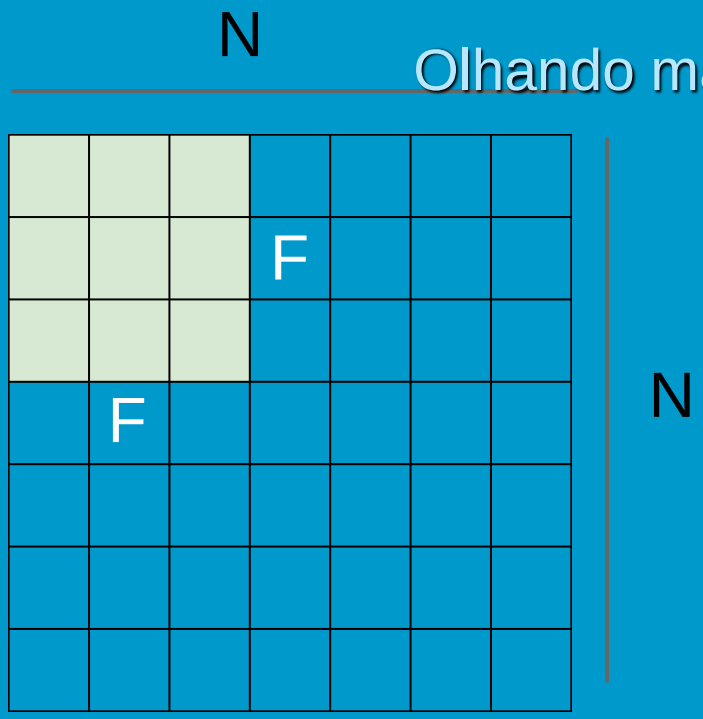
Olhando mais de perto as dimensões:



Entrada 7x7
Filtro 3x3 filter
com stride 3

doesn’t fit!
Você não consegue usar um filtro 3x3 em uma imagem 7x7 com stride 3.

Camada de convolução: detalhes



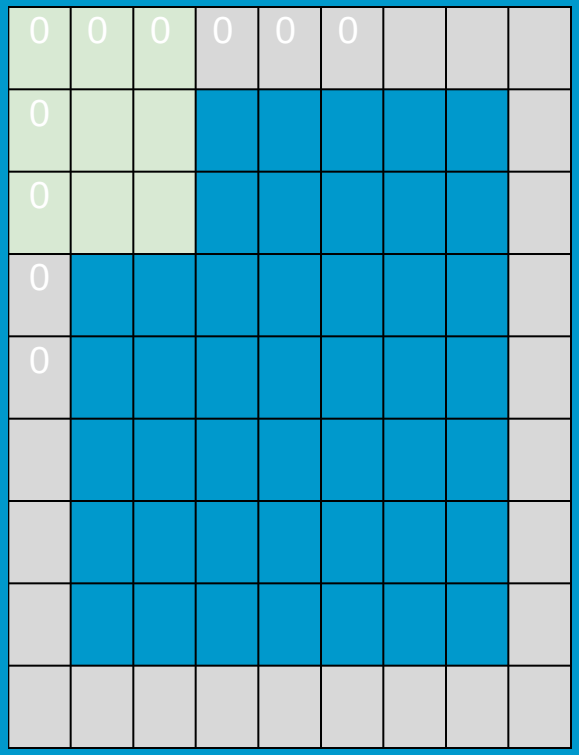
Olhando mais de perto as dimensões:

Calculando a saída:
(N - F) / stride + 1

e.g. N = 7, F = 3:
stride 1 => (7 - 3)/1 + 1 = 5
stride 2 => (7 - 3)/2 + 1 = 3
stride 3 => (7 - 3)/3 + 1 = 2.33 :\

Camada de convolução: detalhes

Na prática, costuma-se usar zero na borda

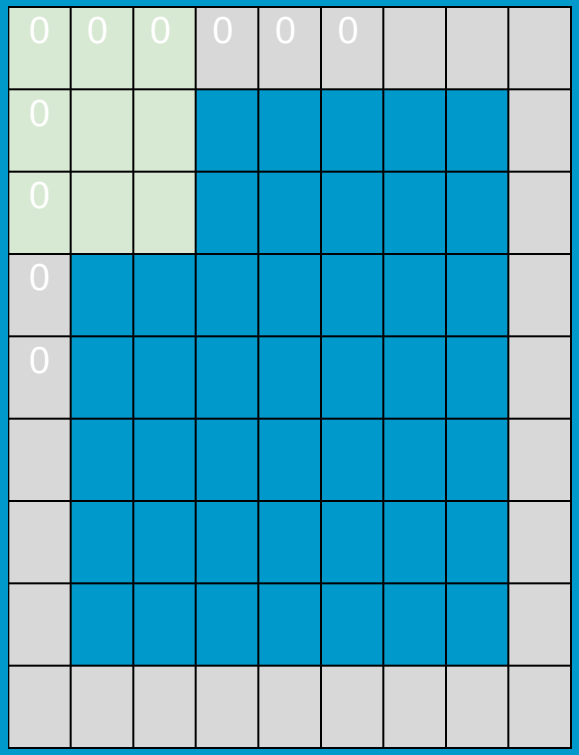


e.g. Entrada 7x7
Filtro 3x3 com **stride 1**
pad com 1 pixel de borda
=> Qual é a saída?

(recall:)
(N - F) / stride + 1

Camada de convolução: detalhes

Na prática, costuma-se usar zero na borda

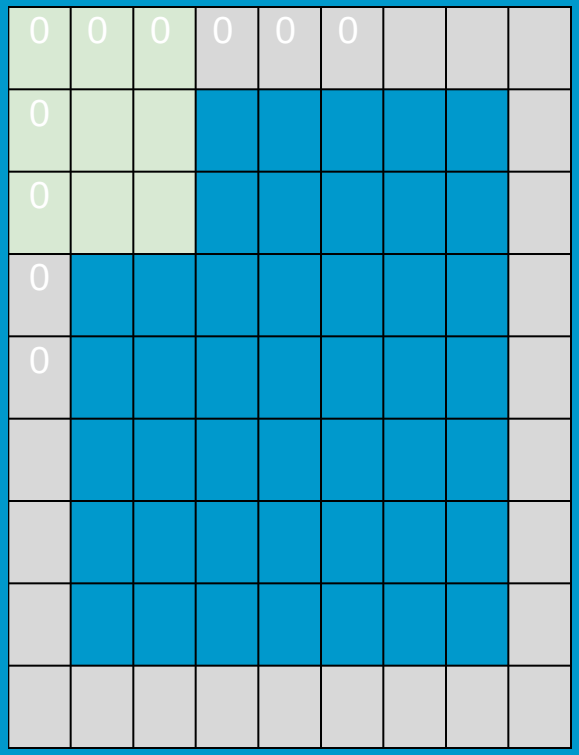


e.g. Entrada 7x7
Filtro 3x3 com **stride 1**
pad com 1 pixel de borda
=> Qual é a saída?

7x7 output!

Camada de convolução: detalhes

Na prática, costuma-se usar zero na borda



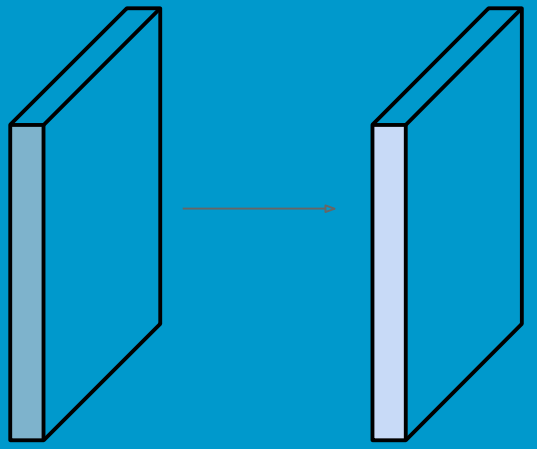
e.g. Entrada 7x7
Filtro 3x3 com **stride 1**
pad com 1 pixel de borda
=> Qual é a saída?

7x7 output!
Geralmente o mais comum é camada com stride 1, filtros de tamanho FxF e zero-padding (F-1)/2. (preserva a dimensão)
e.g. F = 3 => zero pad with 1 F = 5 => zero pad with 2 F = 7 => zero pad with 3

(N + 2*padding - F) / stride + 1

Camada de convolução: detalhes

Exemplos:

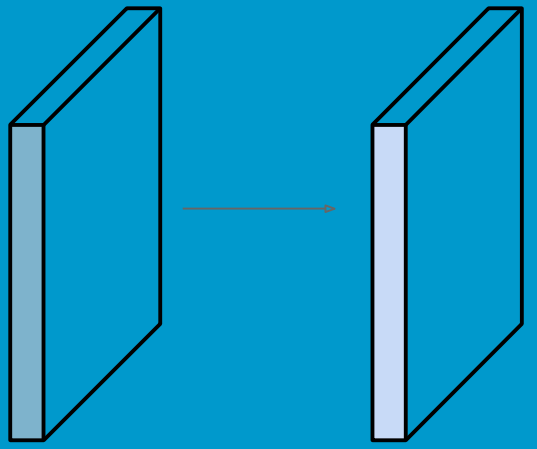


Entrada: **32x32x3**
10 filtros 5x5 com stride 1, pad 2

Dimensão da saída: ?

Camada de convolução: detalhes

Exemplos:

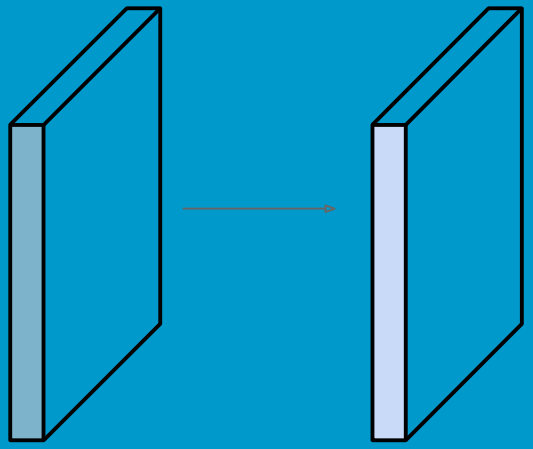


Entrada: **32x32x3**
10 filtros 5x5 com stride 1, pad 2

Dimensão da saída:
(32+2*2-5)/1+1 = 32

Logo: **32x32x10**

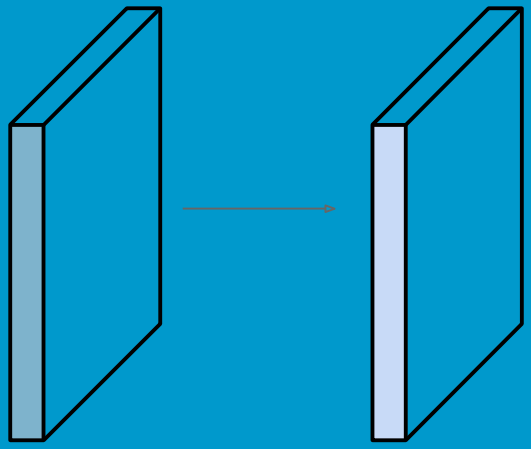
Camada de convolução: detalhes



Entrada: **32x32x3**
10 filtros 5x5 com stride 1, pad 2

Número de parâmetros na camada?

Camada de convolução: detalhes



Entrada: **32x32x3**
10 filtros 5x5 com stride 1, pad 2

Número de parâmetros na camada?
Cada filtro possui 5*5*3 + 1 = 76 parâmetros
=> 76*10 = **760**

(+1 for bias)

Camada de convolução: detalhes

Summary. To summarize, the Conv Layer:

- Accepts a volume of size $W_1 \times H_1 \times D_1$
- Requires four hyperparameters:
  - Number of filters K,
  - their spatial extent F,
  - the stride S,
  - the amount of zero padding P.
- Produces a volume of size $W_2 \times H_2 \times D_2$ where:
  - $W_2 = (W_1 - F + 2P)/S + 1$
  - $H_2 = (H_1 - F + 2P)/S + 1$ (i.e. width and height are computed equally by symmetry)
  - $D_2 = K$
- With parameter sharing, it introduces $F \cdot F \cdot D_1$ weights per filter, for a total of $(F \cdot F \cdot D_1) \cdot K$ weights and K biases.
- In the output volume, the d-th depth slice (of size $W_2 \times H_2$) is the result of performing a valid convolution of the d-th filter over the input volume with a stride of S, and then offset by d-th bias.

Camada de convolução: implementação

```
# Camada de convolução com 32 filtros e kernel de tamanho 5
conv1 = tf.layers.conv2d(x, 32, 5, activation=tf.nn.relu)

# Camada de convolução com 64 filtros e kernel de tamanho 3
conv2 = tf.layers.conv2d(conv1, 64, 3, activation=tf.nn.relu)
```

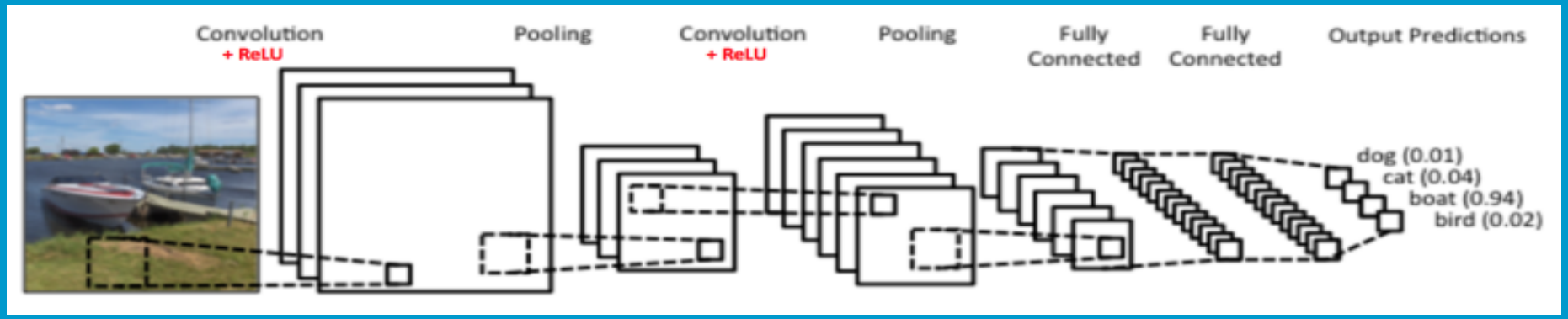
Camada de convolução: demonstrações

Animações dos parâmetros de deslocamento dos filtros convolucionais

https://github.com/vdumoulin/conv_arithmetic

Animações de convolução:

http://setosa.io/ev/image-kernels/

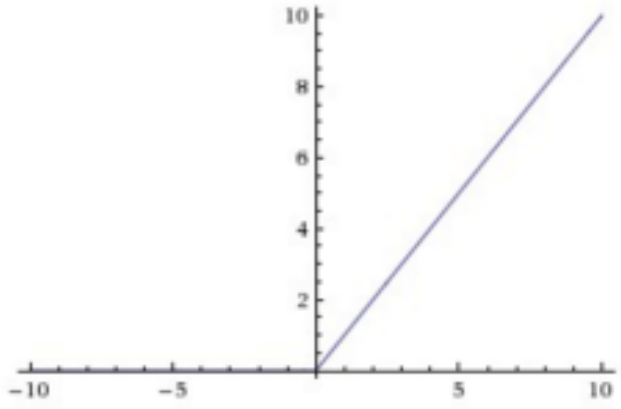


Entendendo a camada ReLU

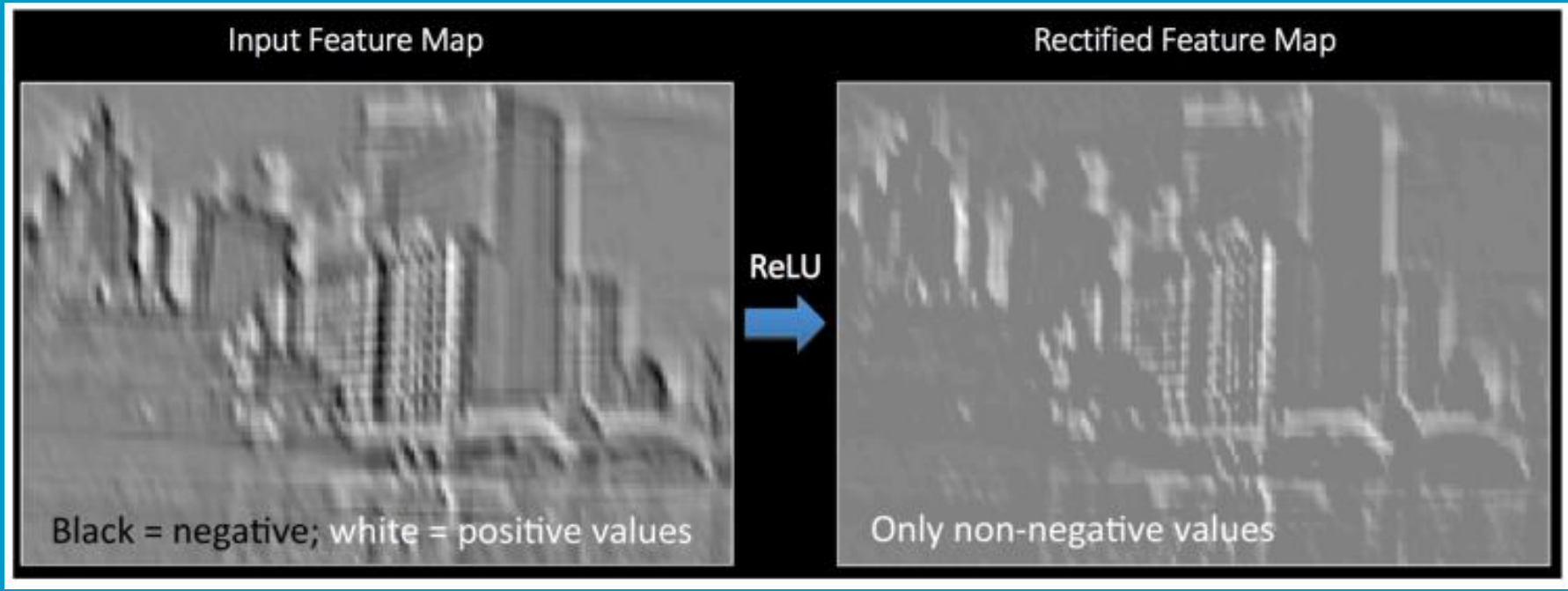
Entendendo a camada ReLU

- Rectified Linear Units
- Função de ativação das deep learnings
  - Veremos outras no curso

Output = Max(zero, Input)

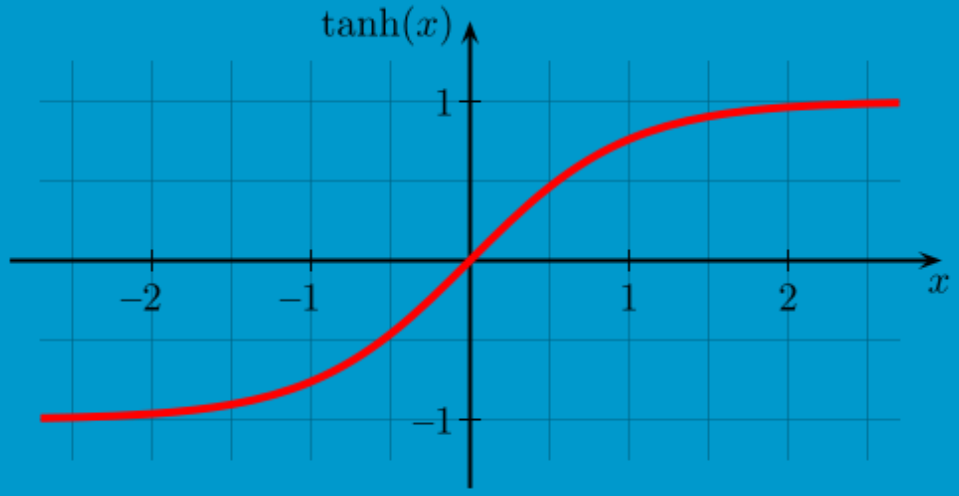


Entendendo a camada ReLU



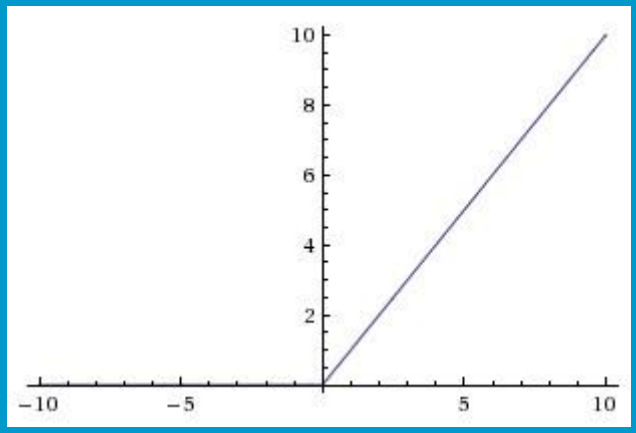
Entendendo a camada ReLU

Tanh(x)



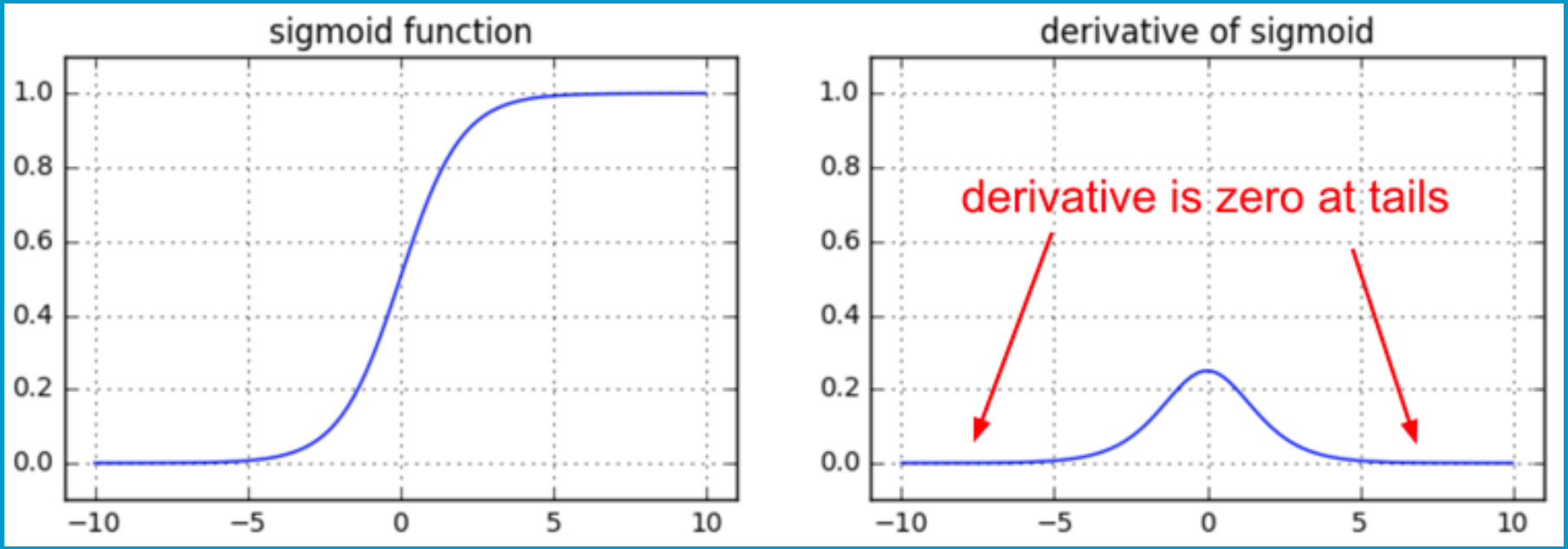
$$\tanh(x) = \frac{e^x -}{}$$

ReLU

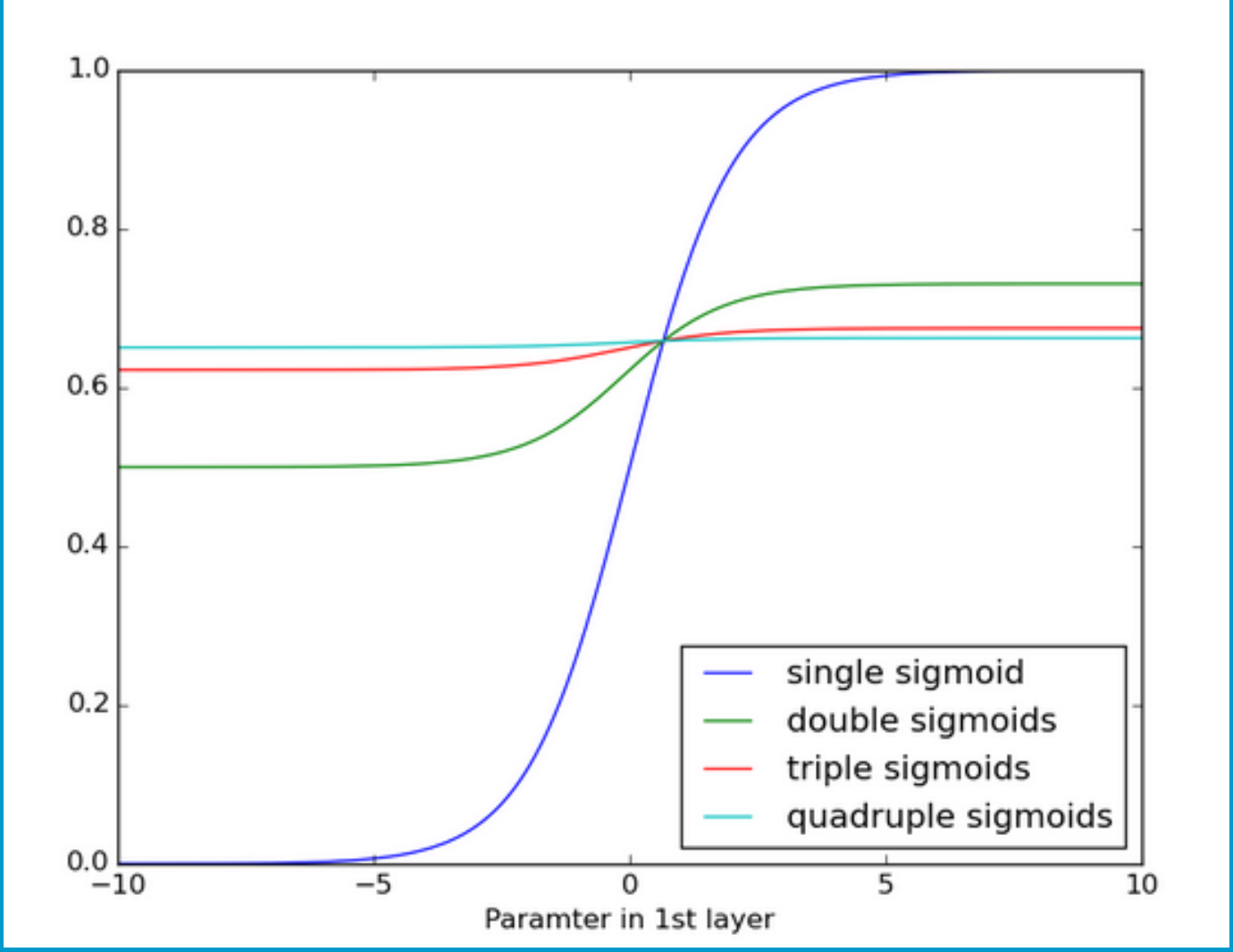


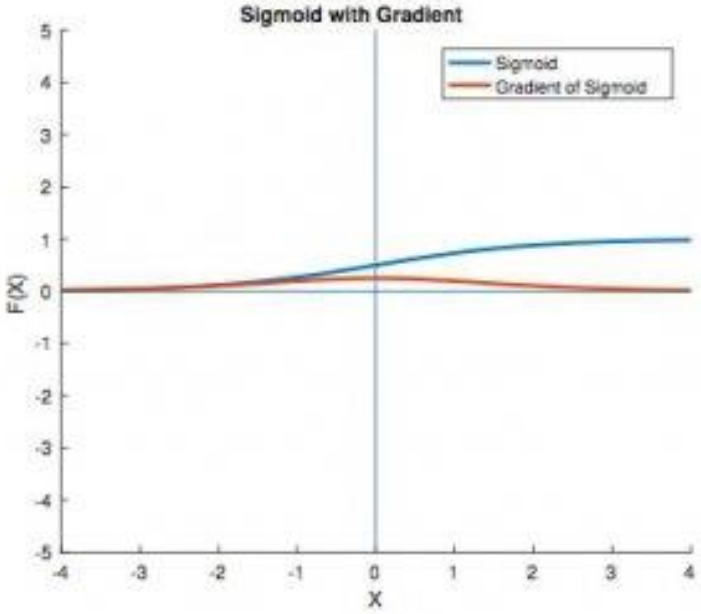
$$f(x) = \max(($$

Entendendo a camada ReLU

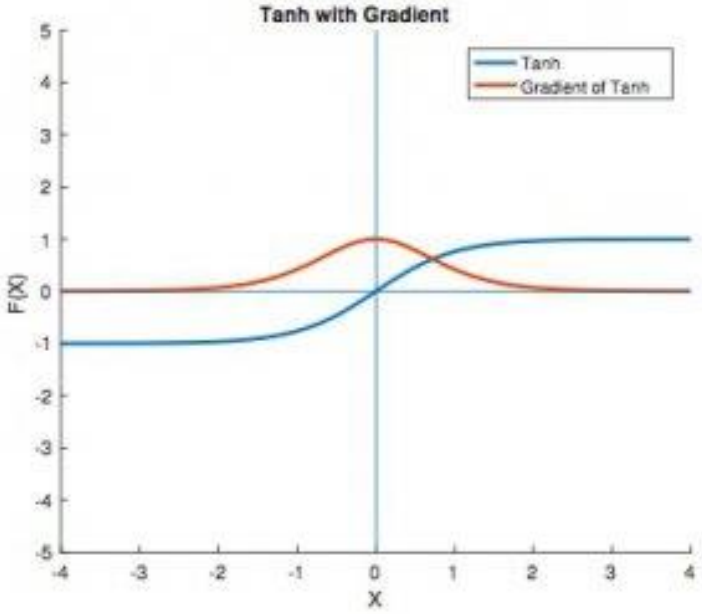


Entendendo a camada ReLU

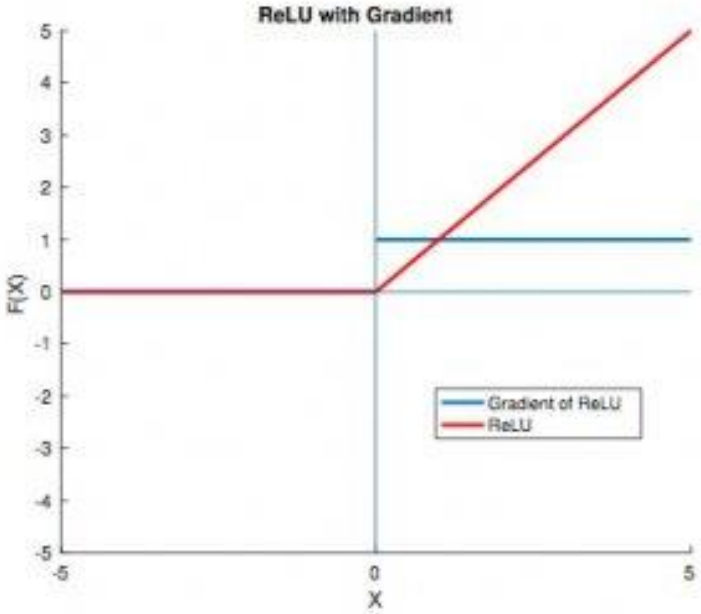




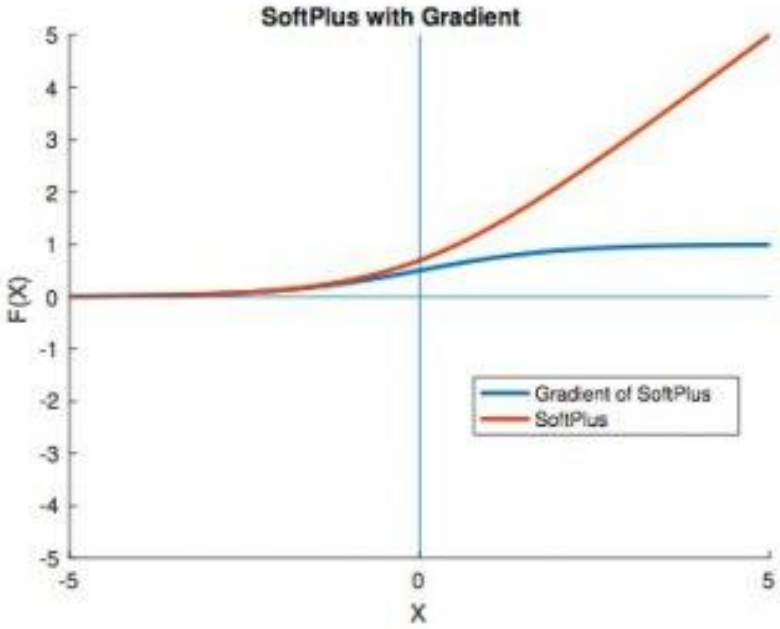
(a) Sigmoid



(b) Tanh

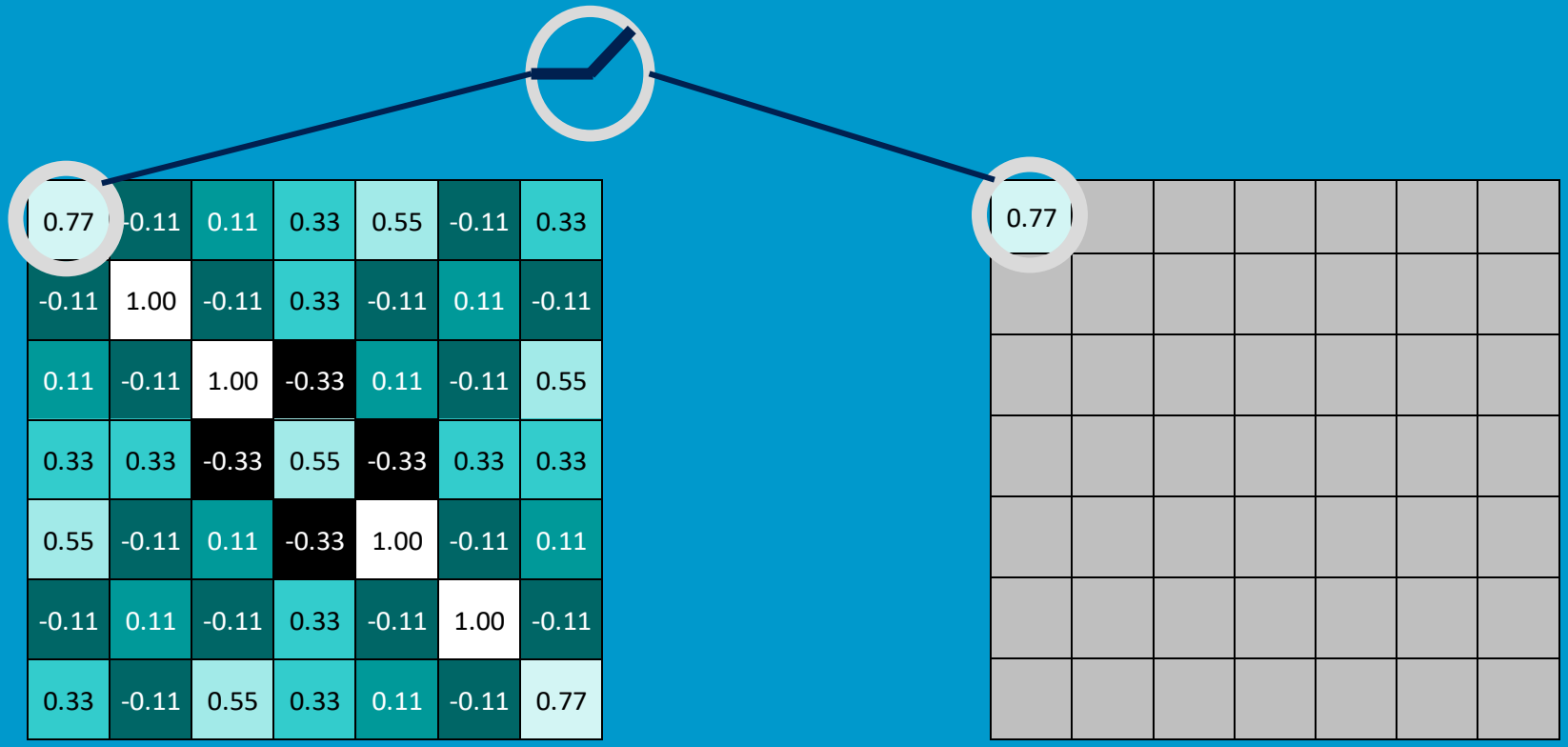


(c) ReLU

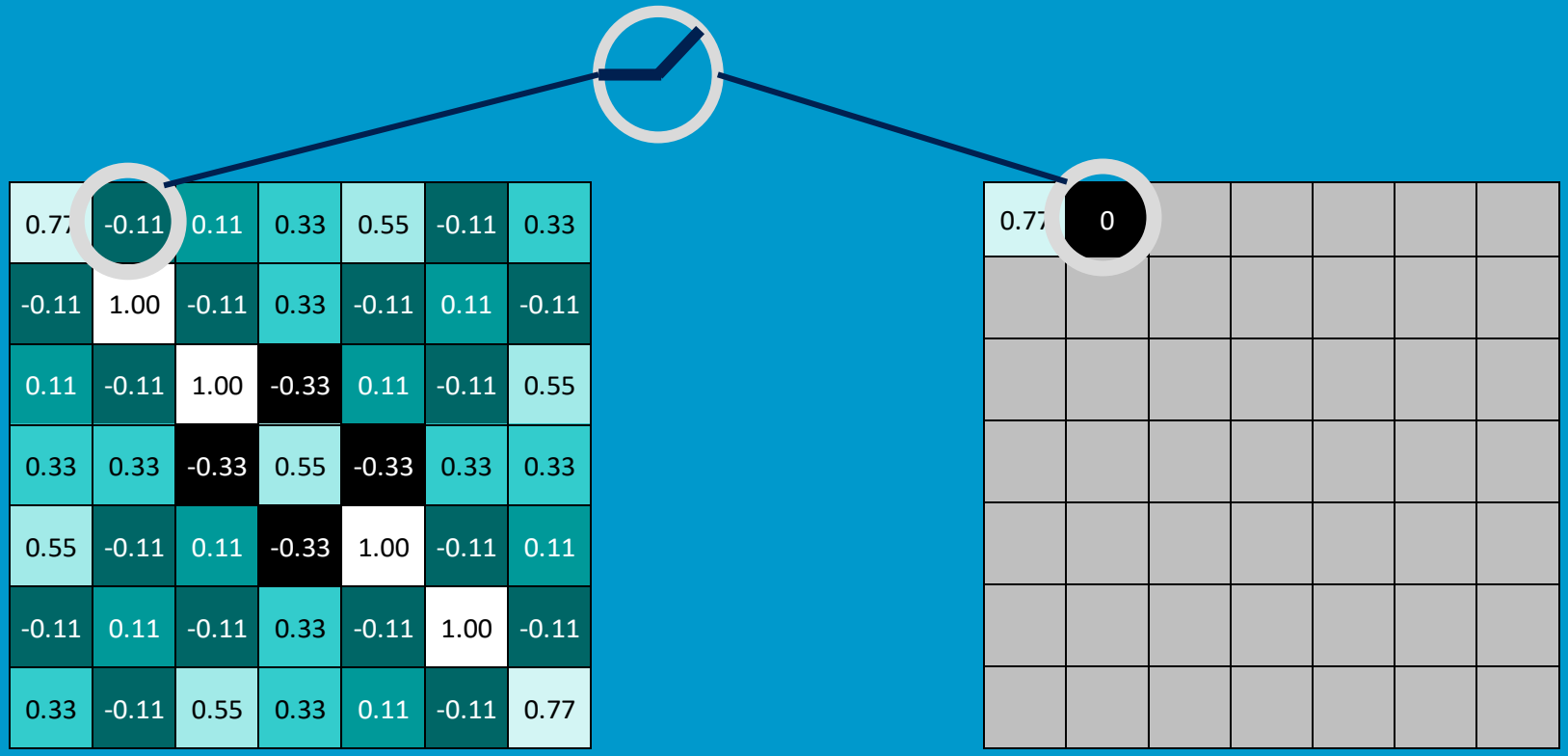


(d) Softplus

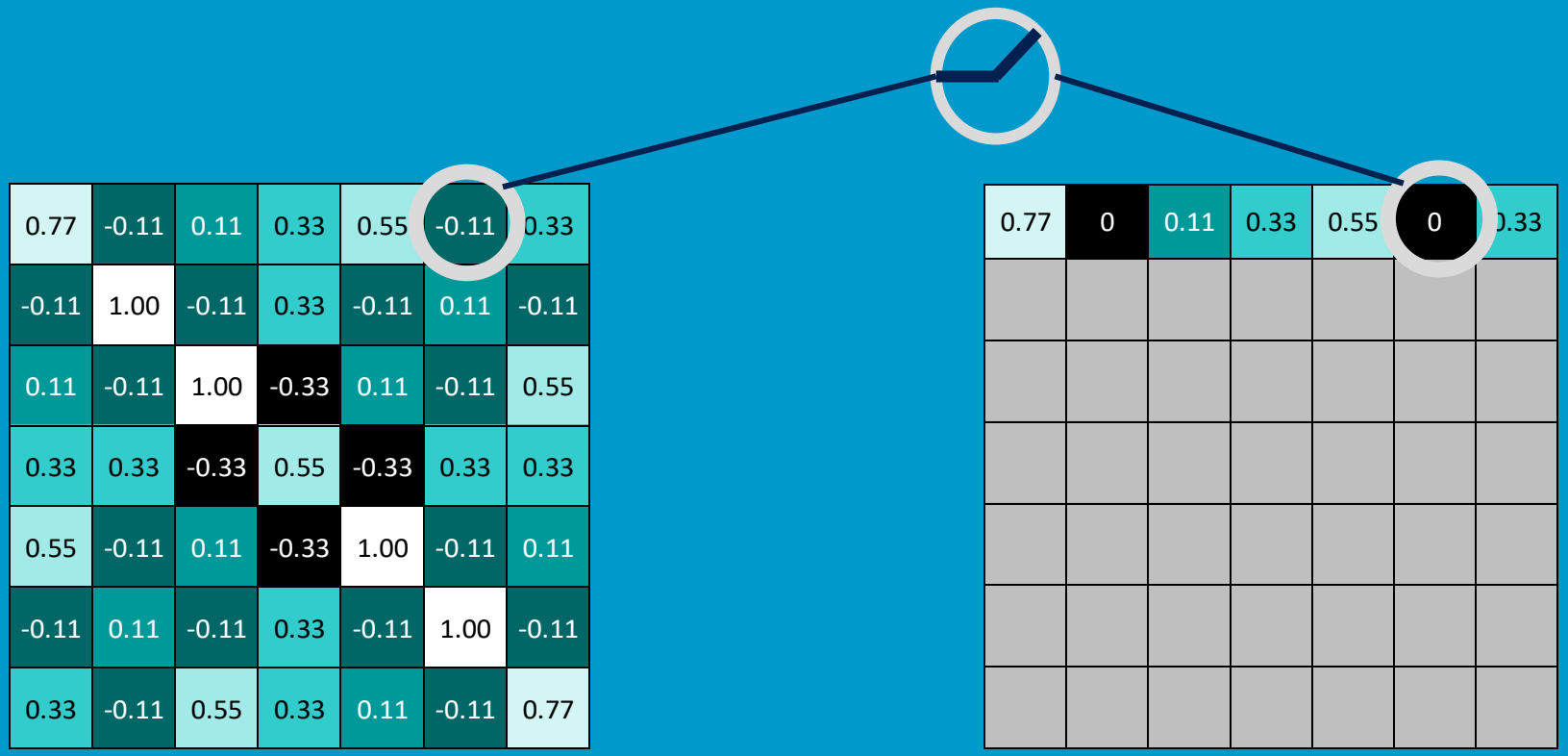
Entendendo a camada ReLU



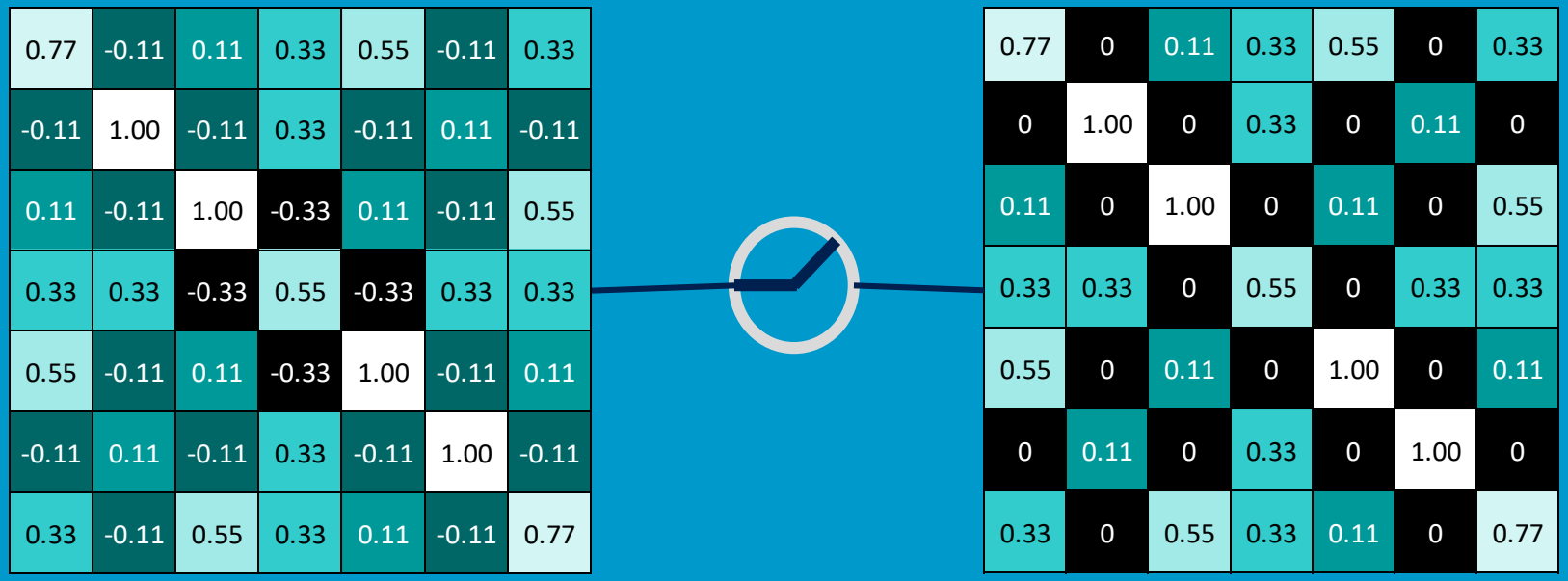
Entendendo a camada ReLU

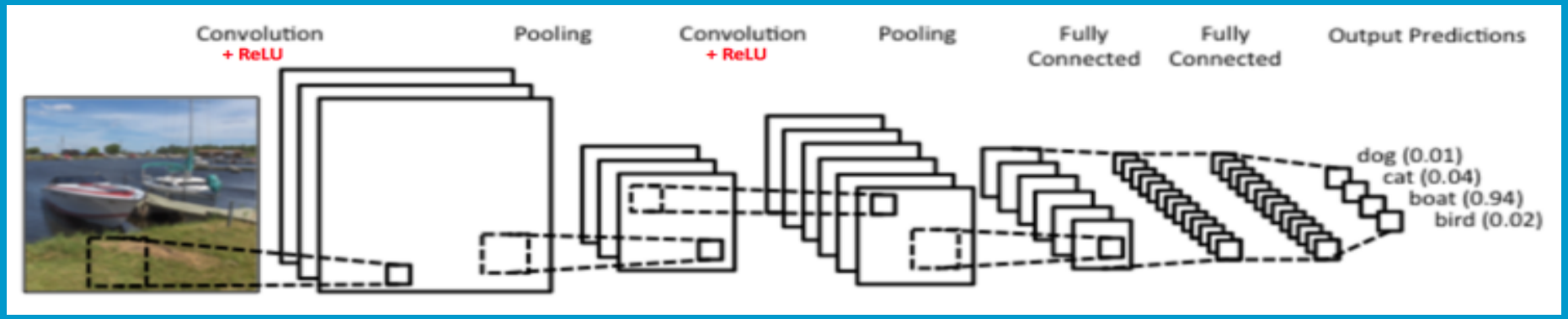


Entendendo a camada ReLU



Entendendo a camada ReLU





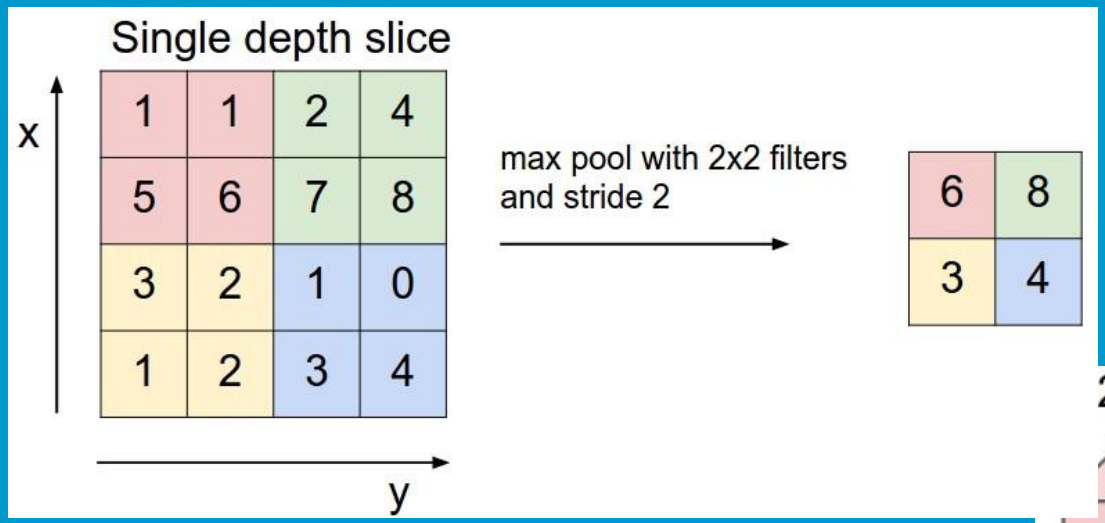
Entendendo a camada Pooling

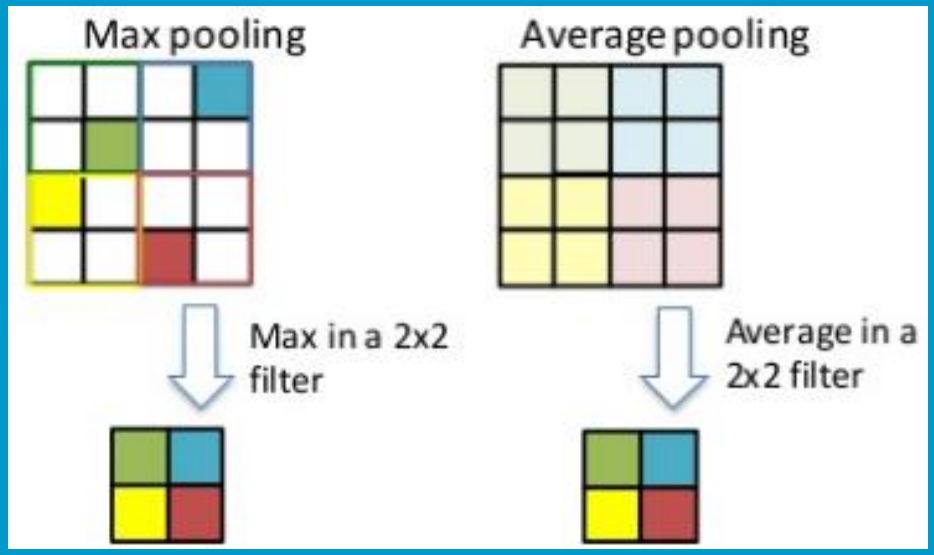
Entendendo a camada de Pooling

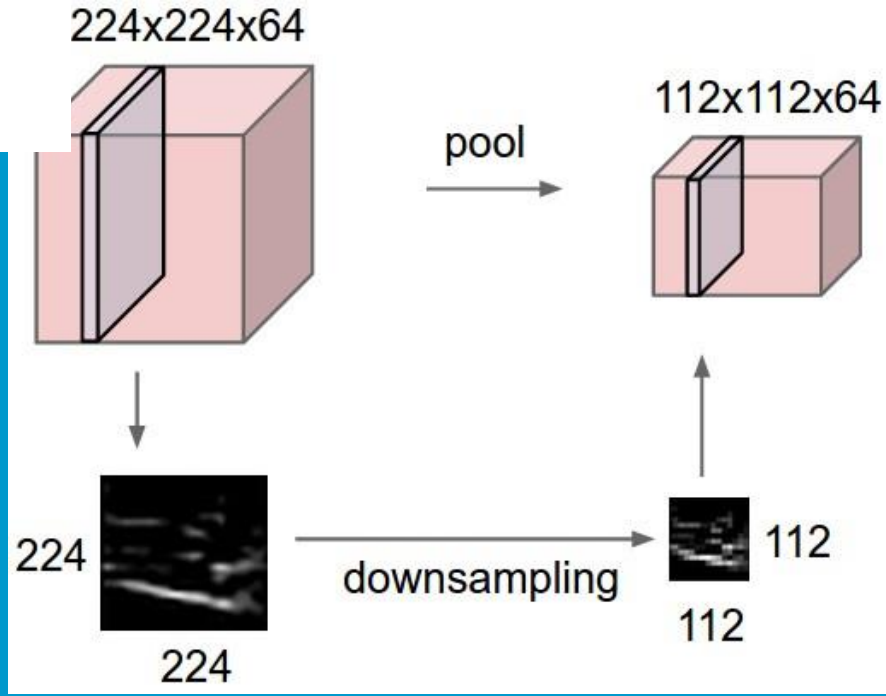
- A camada pooling torna a convolução invariante a translação, rotação e shifting (janelamento).
- Também chamada de “downsample”
- Opções: Min, Max, Média.
- Opção mais usada: max-pooling.

Entendendo a camada de Pooling

- Toma-se a maior ativação para propagar na região de interesse do campo receptivo.
- Mesmo imagens pouco deslocadas, uma vez que estamos à procura de maior ativação, somos capazes de capturar semelhanças entre as imagens.


Single depth slice
x
y
1 1 2 4
5 6 7 8
3 2 1 0
1 2 3 4
max pool with 2x2 filters
and stride 2
6 8
3 4

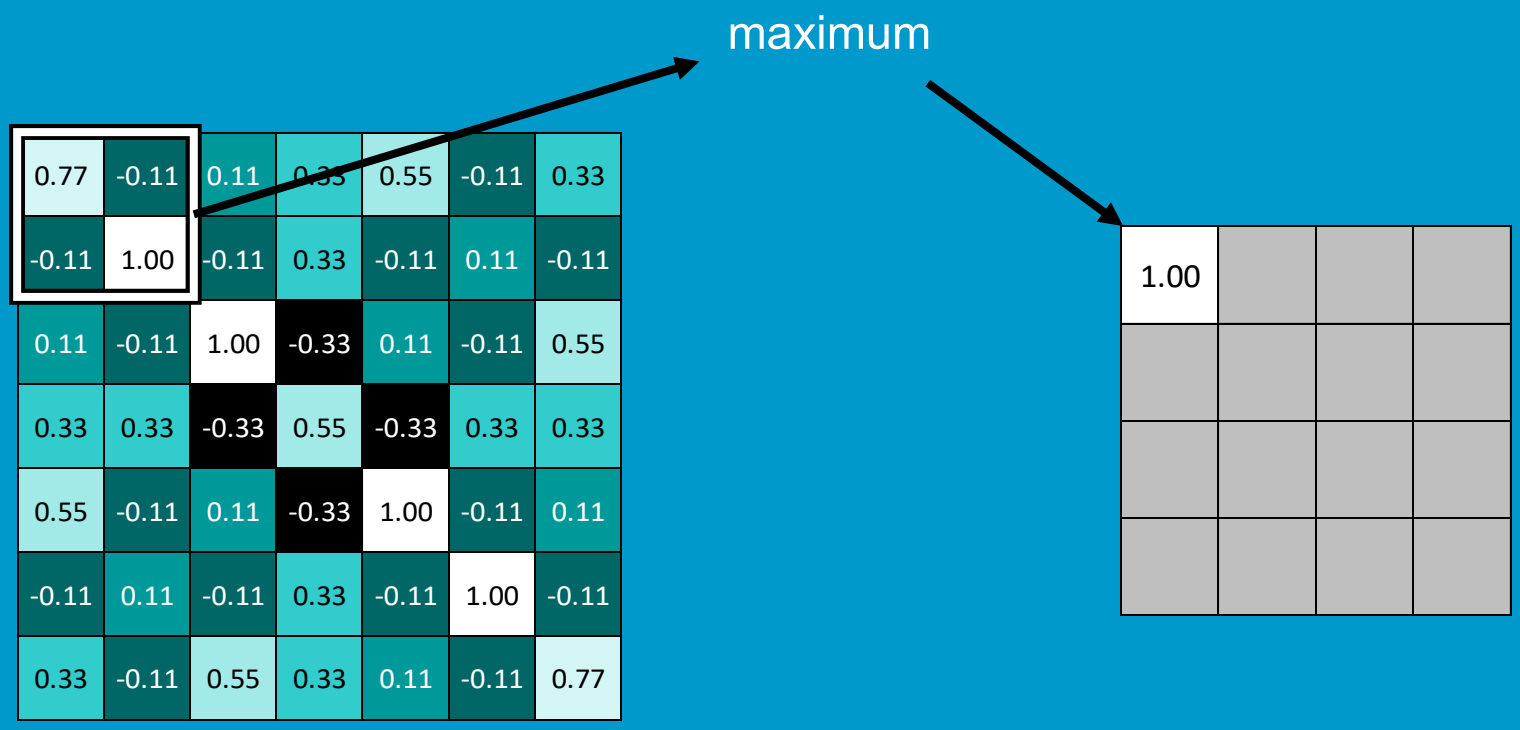

Max pooling
Average pooling
Max in a 2x2
filter
Average in a
2x2 filter


224x224x64
pool
112x112x64
224
224
downsampling
112
112

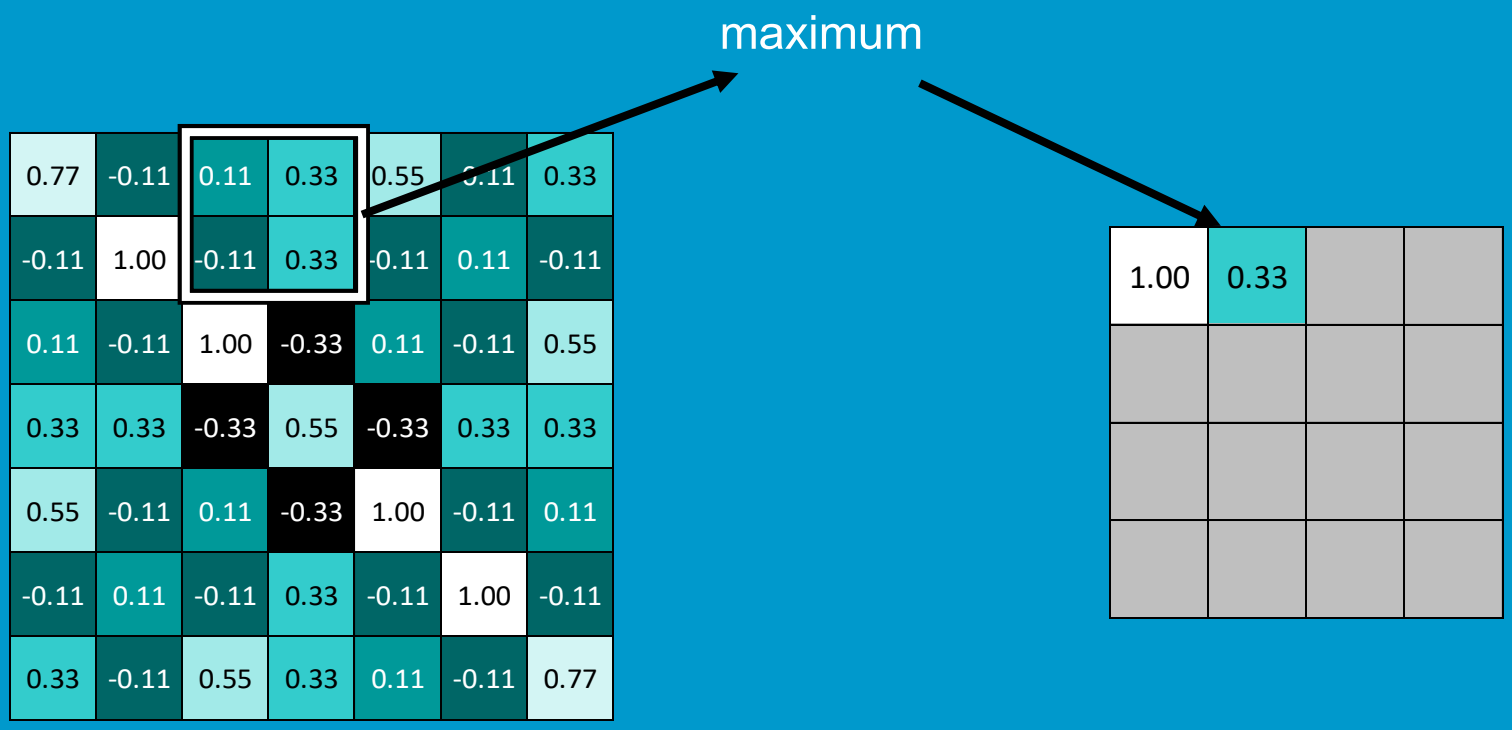
Pooling: Algoritmo

1. Escolha um tamanho de janela (2 ou 3).
2. Caminhe sua janela no sinal.
3. Para cada janela, pegue o valor máximo (para os caso do Max-pooling.

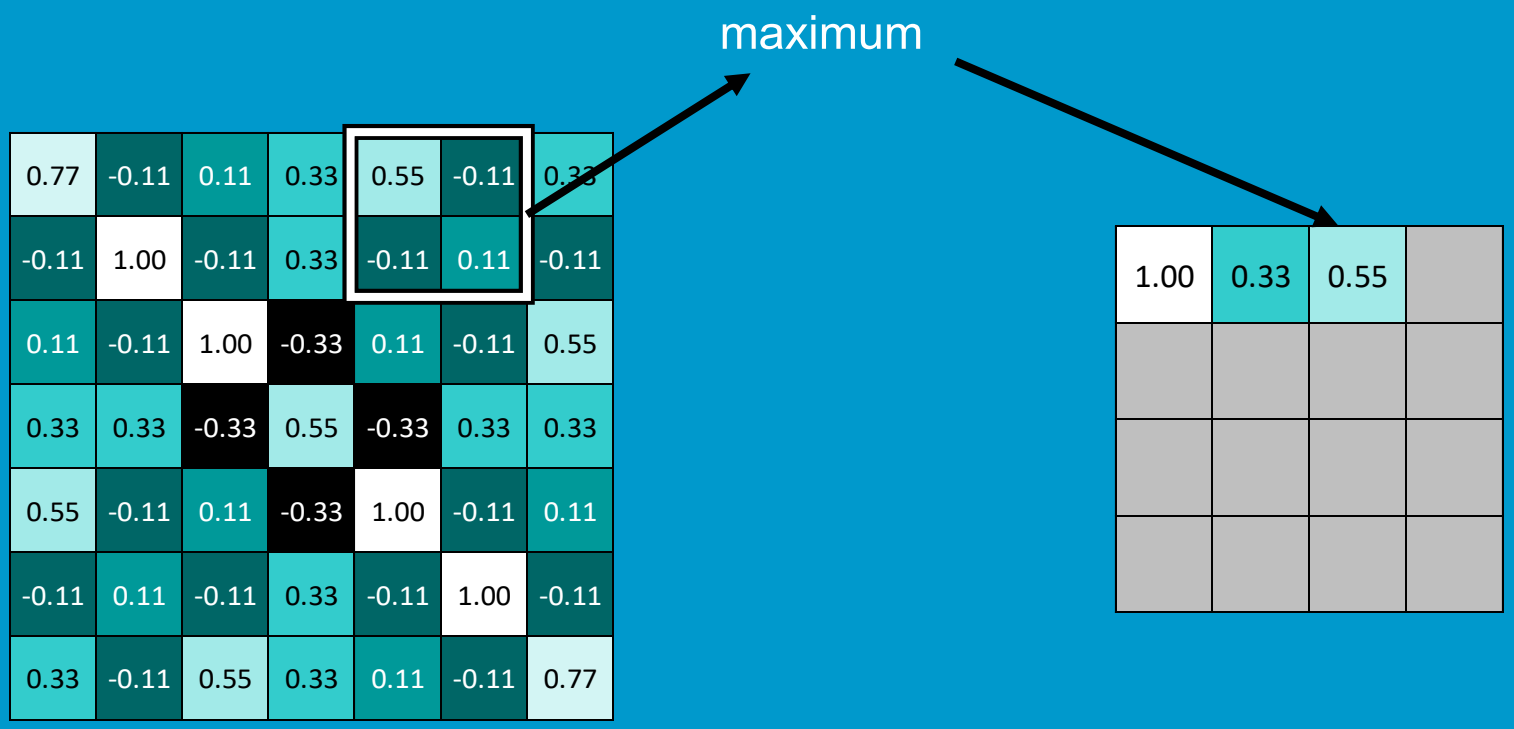
Pooling


maximum
0.77 -0.11 0.11 0.33 0.55 -0.11 0.33
-0.11 1.00 -0.11 0.33 -0.11 0.11 -0.11
0.11 -0.11 1.00 -0.33 0.11 -0.11 0.55
0.33 0.33 -0.33 0.55 -0.33 0.33 0.33
0.55 -0.11 0.11 -0.33 1.00 -0.11 0.11
-0.11 0.11 -0.11 0.33 -0.11 1.00 -0.11
0.33 -0.11 0.55 0.33 0.11 -0.11 0.77
1.00

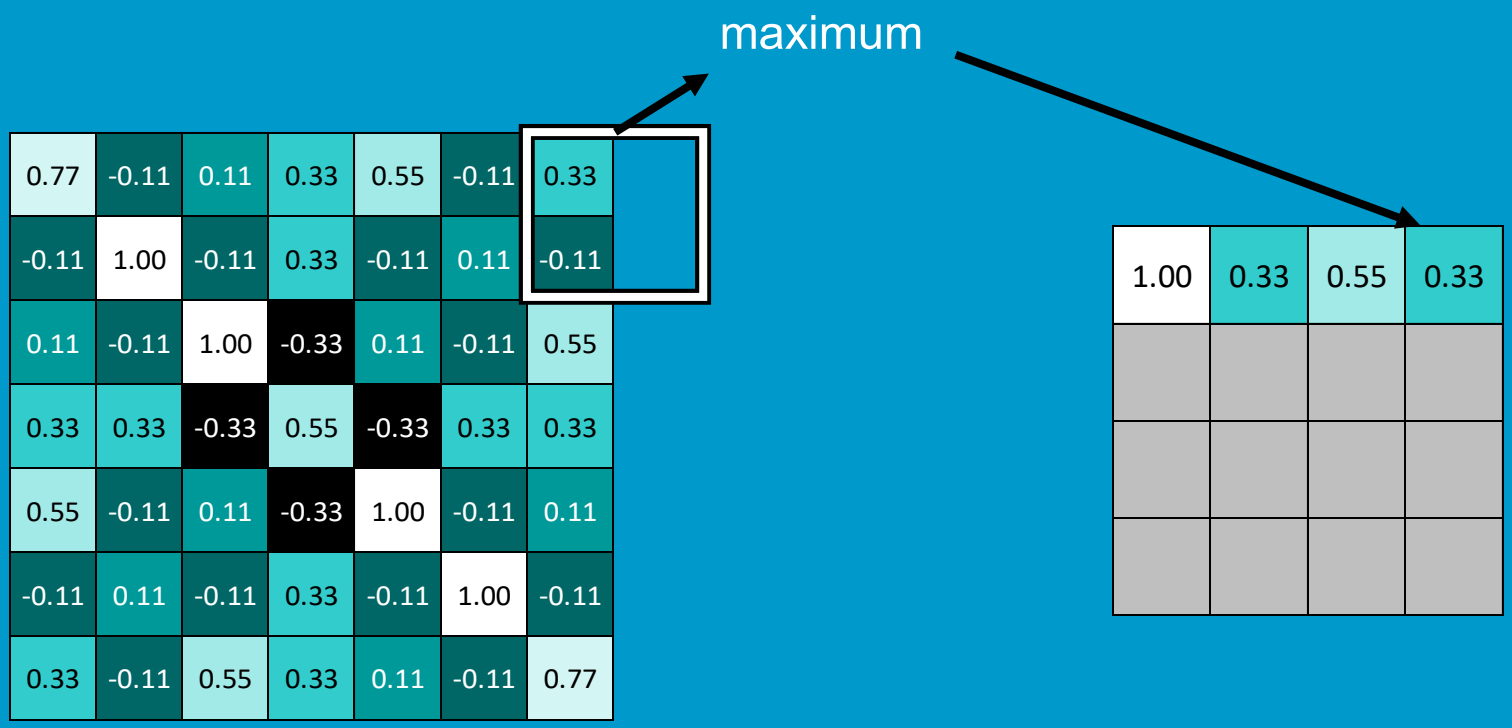
Pooling


maximum
0.77 -0.11 0.11 0.33 0.55 -0.11 0.33
-0.11 1.00 -0.11 0.33 -0.11 0.11 -0.11
0.11 -0.11 1.00 -0.33 0.11 -0.11 0.55
0.33 0.33 -0.33 0.55 -0.33 0.33 0.33
0.55 -0.11 0.11 -0.33 1.00 -0.11 0.11
-0.11 0.11 -0.11 0.33 -0.11 1.00 -0.11
0.33 -0.11 0.55 0.33 0.11 -0.11 0.77
1.00 0.33

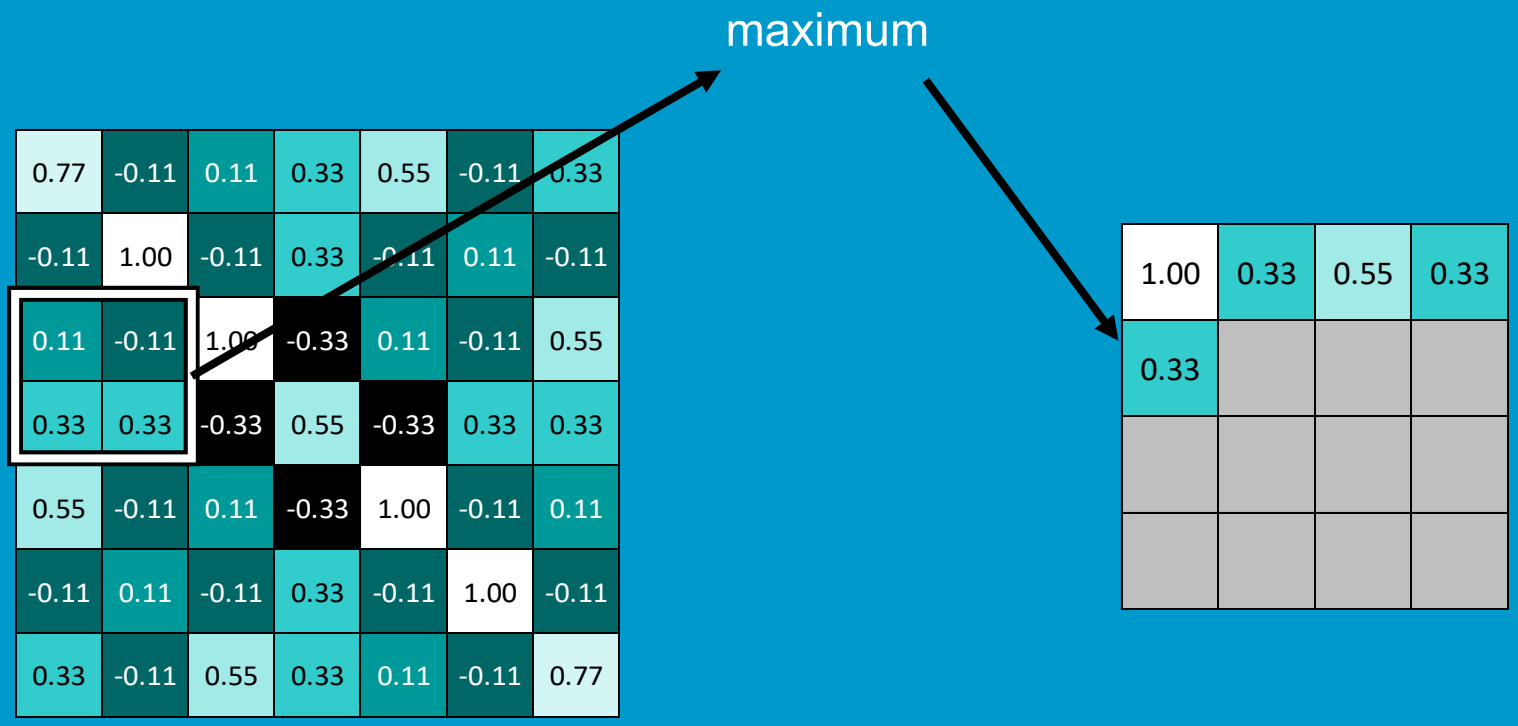
Pooling


maximum
0.77 -0.11 0.11 0.33 0.55 -0.11 0.33
-0.11 1.00 -0.11 0.33 -0.11 0.11 -0.11
0.11 -0.11 1.00 -0.33 0.11 -0.11 0.55
0.33 0.33 -0.33 0.55 -0.33 0.33 0.33
0.55 -0.11 0.11 -0.33 1.00 -0.11 0.11
-0.11 0.11 -0.11 0.33 -0.11 1.00 -0.11
0.33 -0.11 0.55 0.33 0.11 -0.11 0.77
1.00 0.33 0.55

Pooling


maximum
0.77 -0.11 0.11 0.33 0.55 -0.11 0.33
-0.11 1.00 -0.11 0.33 -0.11 0.11 -0.11
0.11 -0.11 1.00 -0.33 0.11 -0.11 0.55
0.33 0.33 -0.33 0.55 -0.33 0.33 0.33
0.55 -0.11 0.11 -0.33 1.00 -0.11 0.11
-0.11 0.11 -0.11 0.33 -0.11 1.00 -0.11
0.33 -0.11 0.55 0.33 0.11 -0.11 0.77
1.00 0.33 0.55 0.33

Pooling


maximum
0.77 -0.11 0.11 0.33 0.55 -0.11 0.33
-0.11 1.00 -0.11 0.33 -0.11 0.11 -0.11
0.11 -0.11 1.00 -0.33 0.11 -0.11 0.55
0.33 0.33 -0.33 0.55 -0.33 0.33 0.33
0.55 -0.11 0.11 -0.33 1.00 -0.11 0.11
-0.11 0.11 -0.11 0.33 -0.11 1.00 -0.11
0.33 -0.11 0.55 0.33 0.11 -0.11 0.77
1.00 0.33 0.55 0.33
0.33

Pooling

0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77

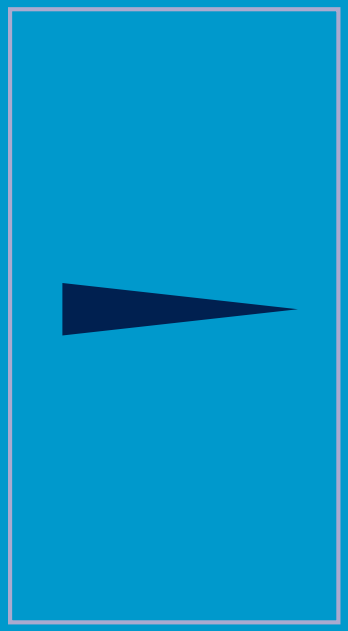
max pooling

1.00	0.33	0.55	0.33
0.33	1.00	0.33	0.55
0.55	0.33	1.00	0.11
0.33	0.55	0.11	0.77

Entendendo a camada Pooling

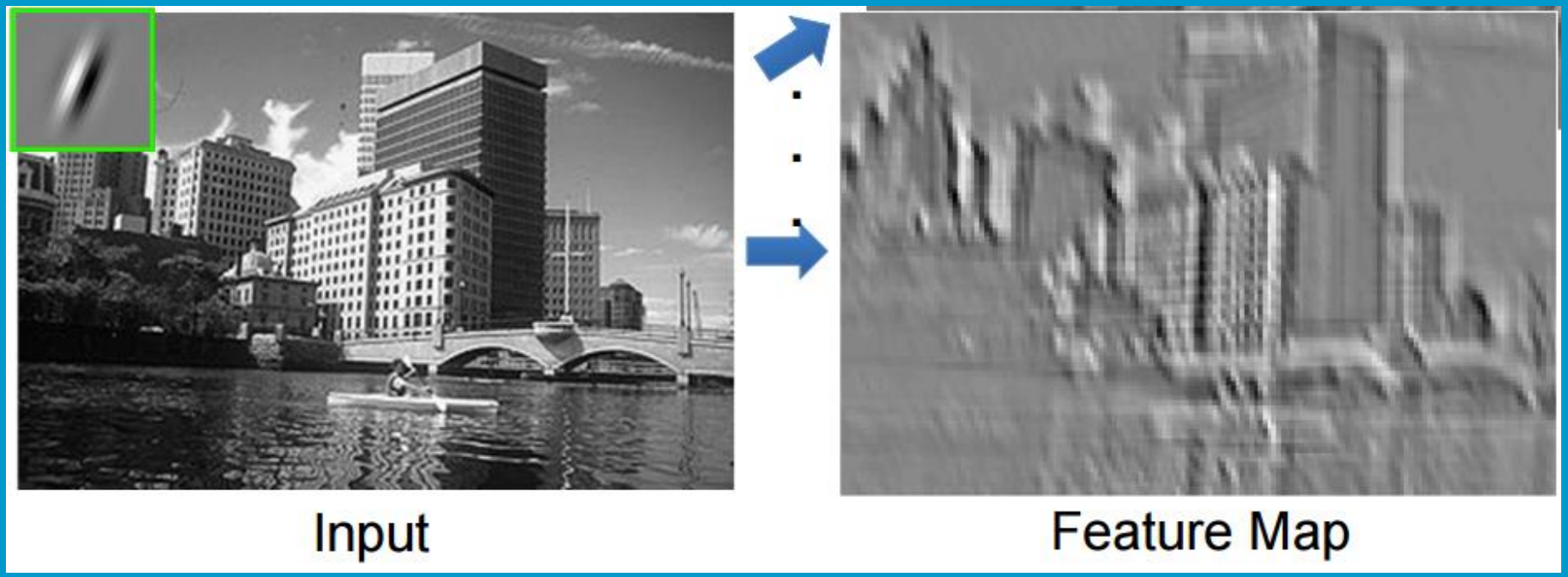
Um conjunto de entradas gera saídas menores

0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.55	0.11	-0.11	0.11	-0.55	0.33
-0.55	0.55	-0.55	0.33	-0.55	0.55	-0.55
0.11	-0.55	0.55	-0.77	0.55	-0.55	0.11
-0.11	0.33	-0.77	1.00	-0.77	0.33	-0.11
0.11	-0.55	0.55	-0.77	0.55	-0.55	0.11
-0.55	0.55	-0.55	0.33	-0.55	0.55	-0.55
0.33	-0.55	0.11	-0.11	0.11	-0.55	0.33



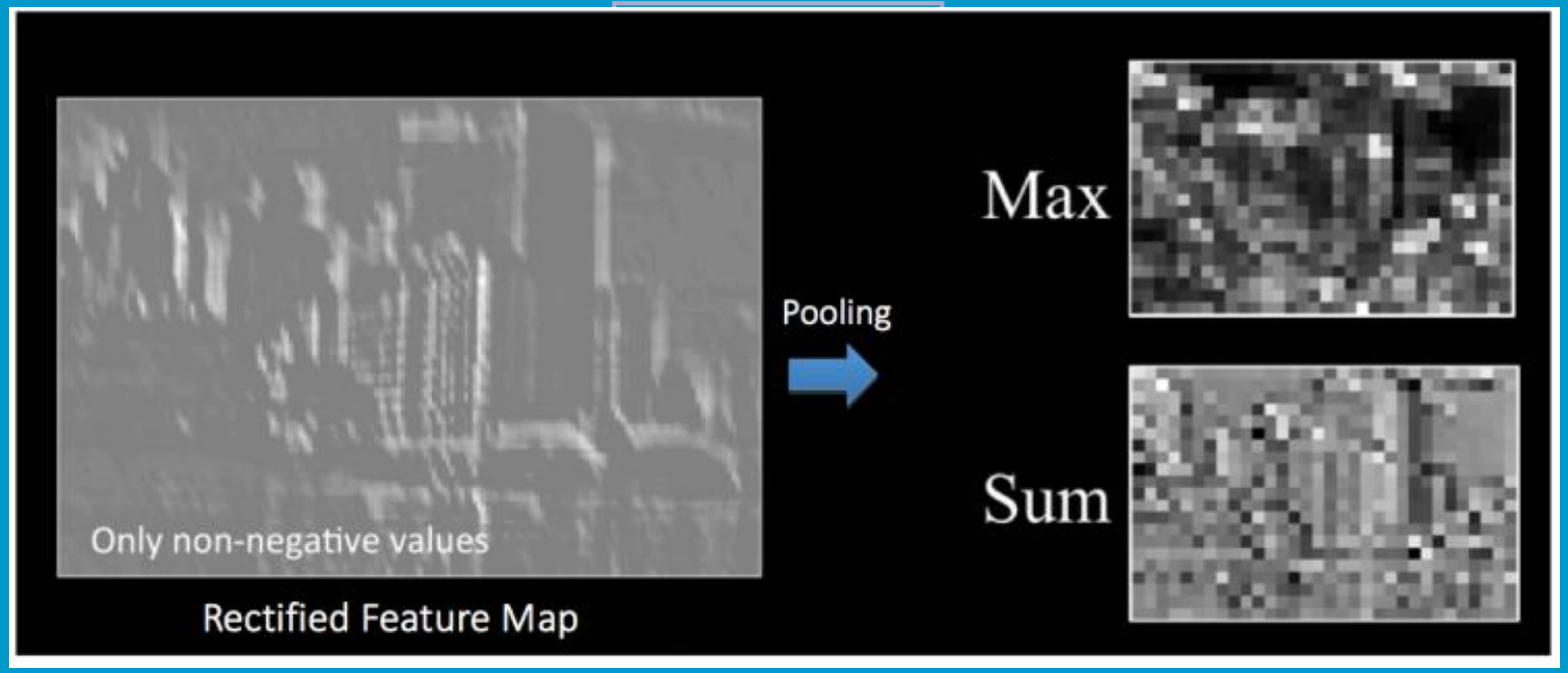
1.00	0.33	0.55	0.33
0.33	1.00	0.33	0.55
0.55	0.33	1.00	0.11
0.33	0.55	0.11	0.77
0.55	0.33	0.55	0.33
0.33	1.00	0.55	0.11
0.55	0.55	0.55	0.11
0.33	0.11	0.11	0.33

Entendendo a camada Pooling

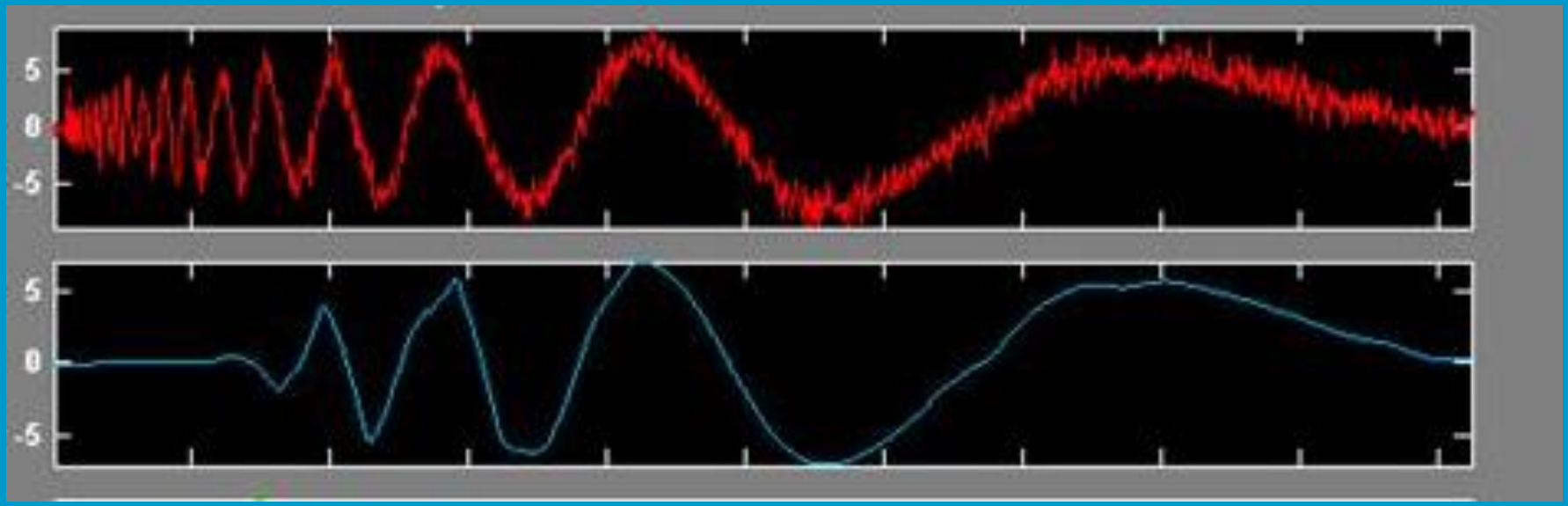


Entendendo a camada Pooling

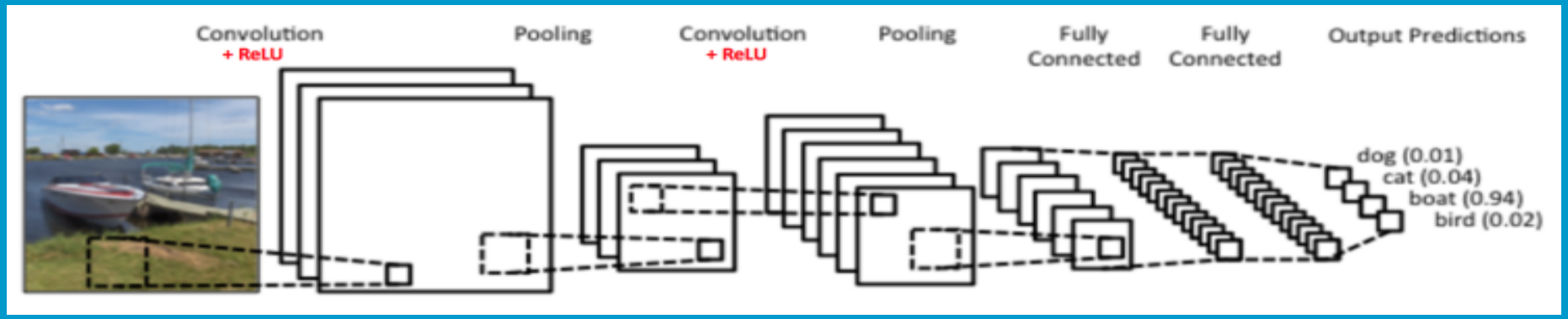
Um conjunto de entradas gera saídas menores



Entendendo a camada Pooling

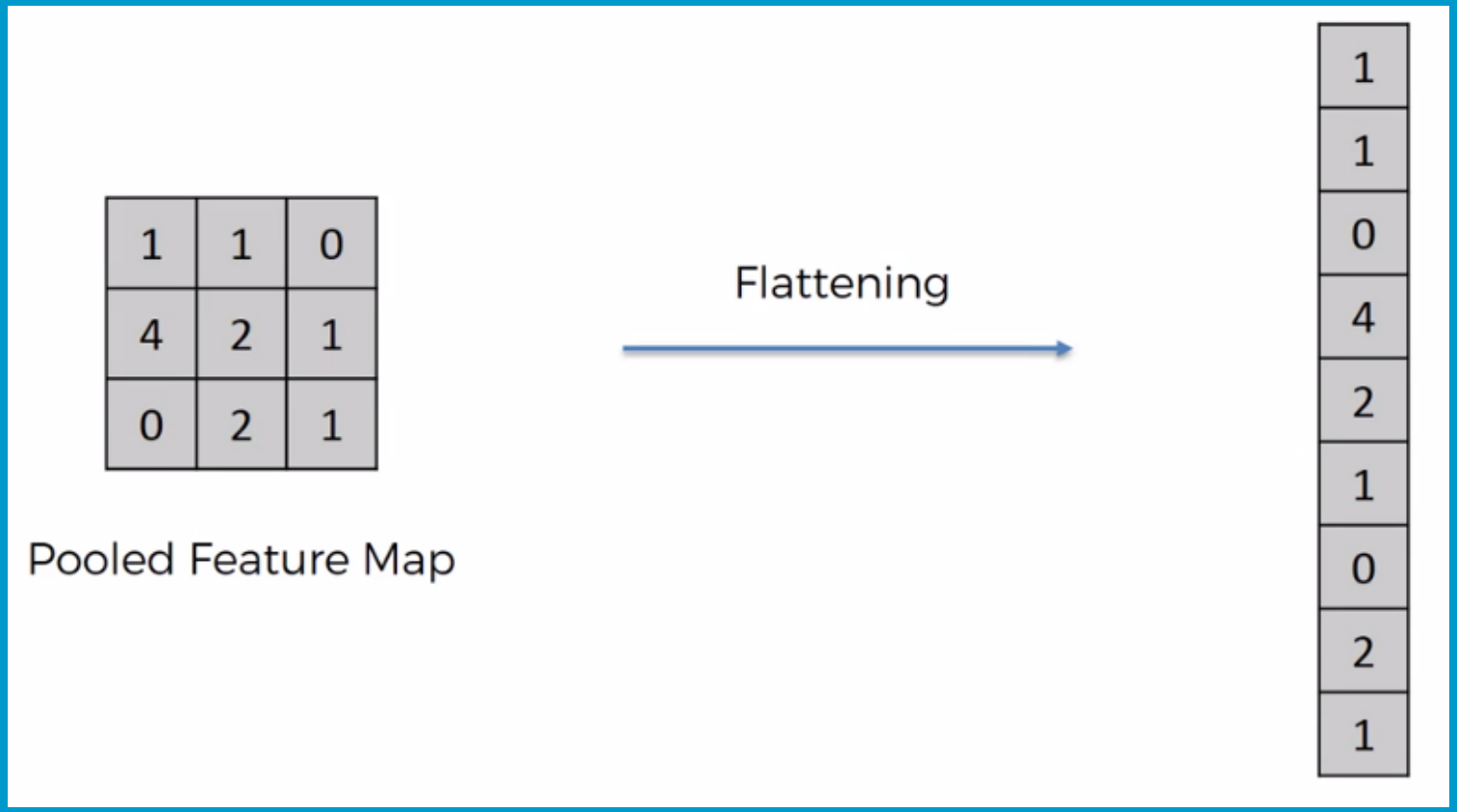


Entendendo a camada Pooling

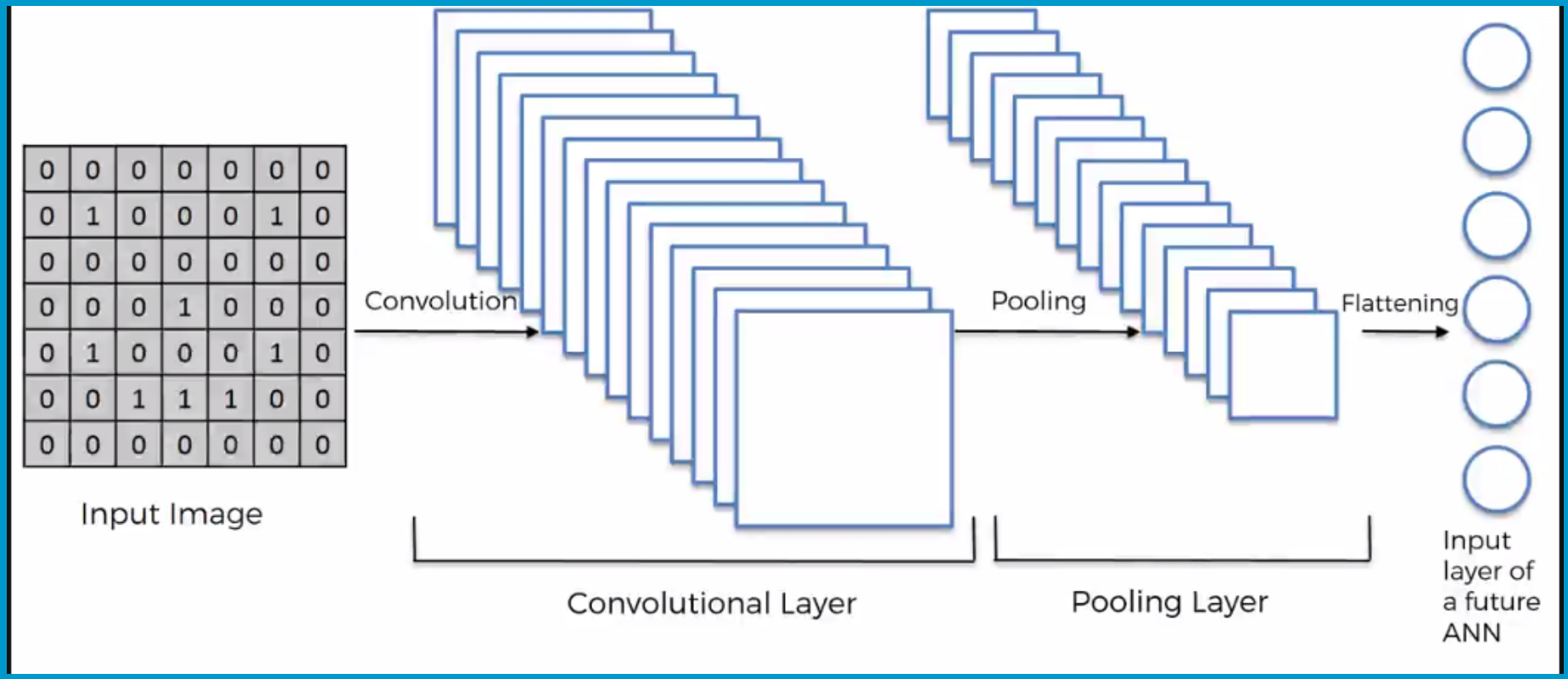


Entendendo a camada Fully Connected

Fully connected layer

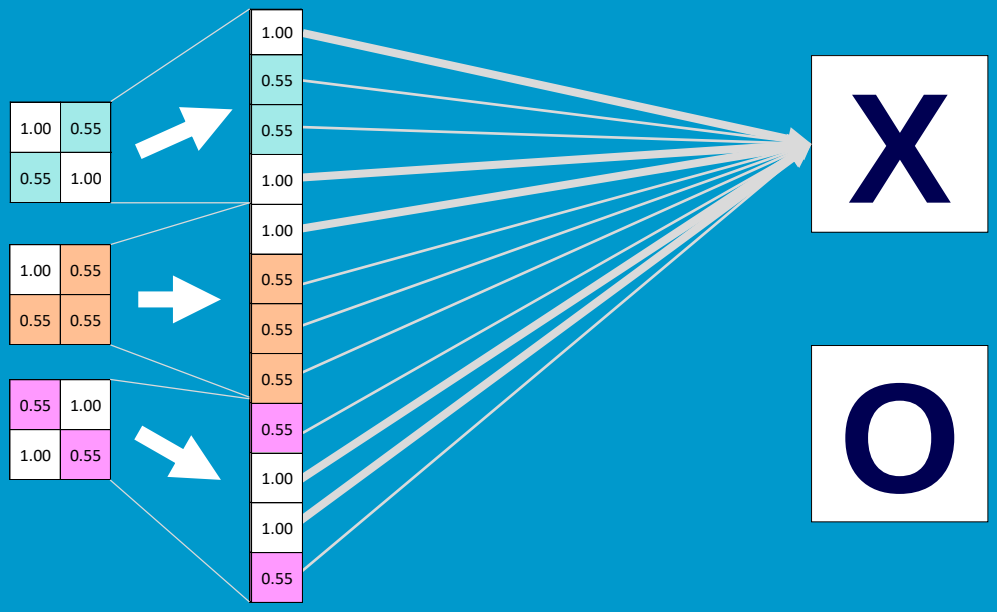


Fully connected layer



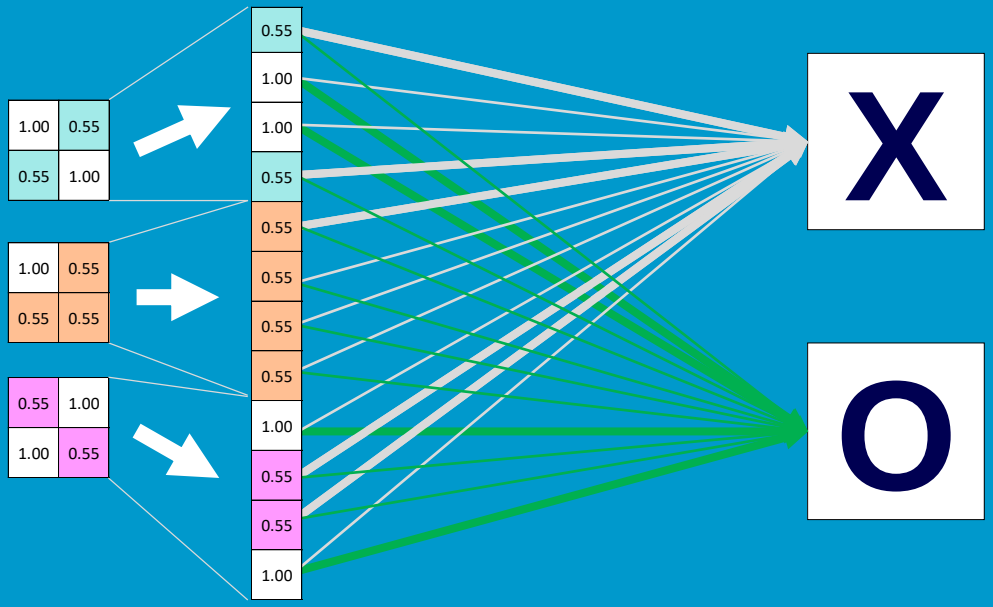
Fully connected layer

Cada valor recebido da camada pooling expressa um valor



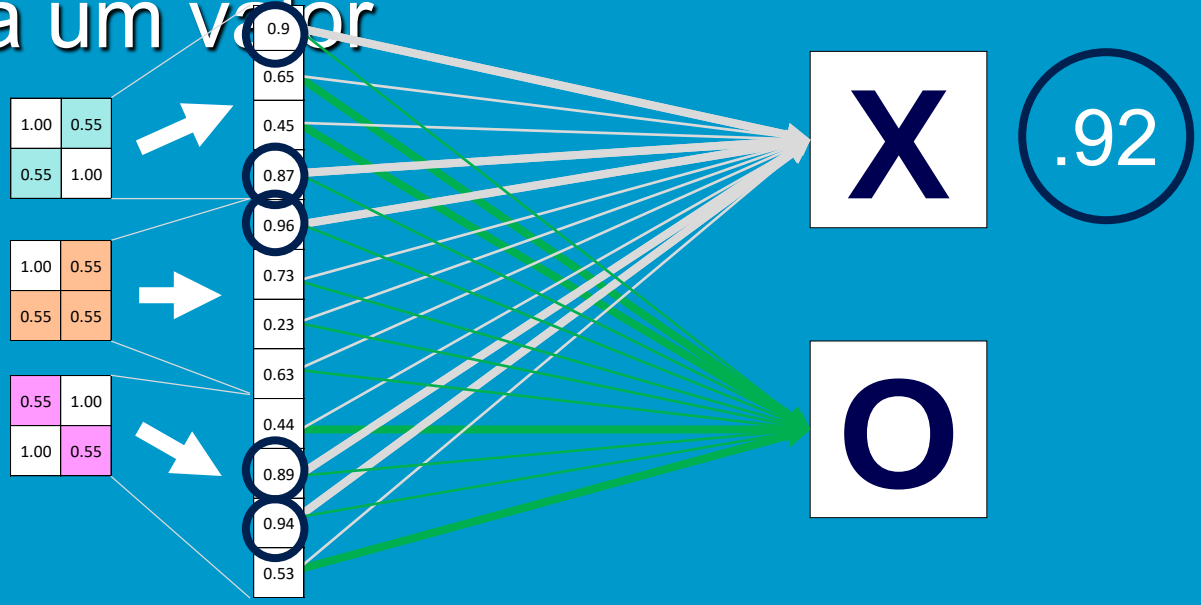
Fully connected layer

Cada valor recebido da camada pooling expressa um valor



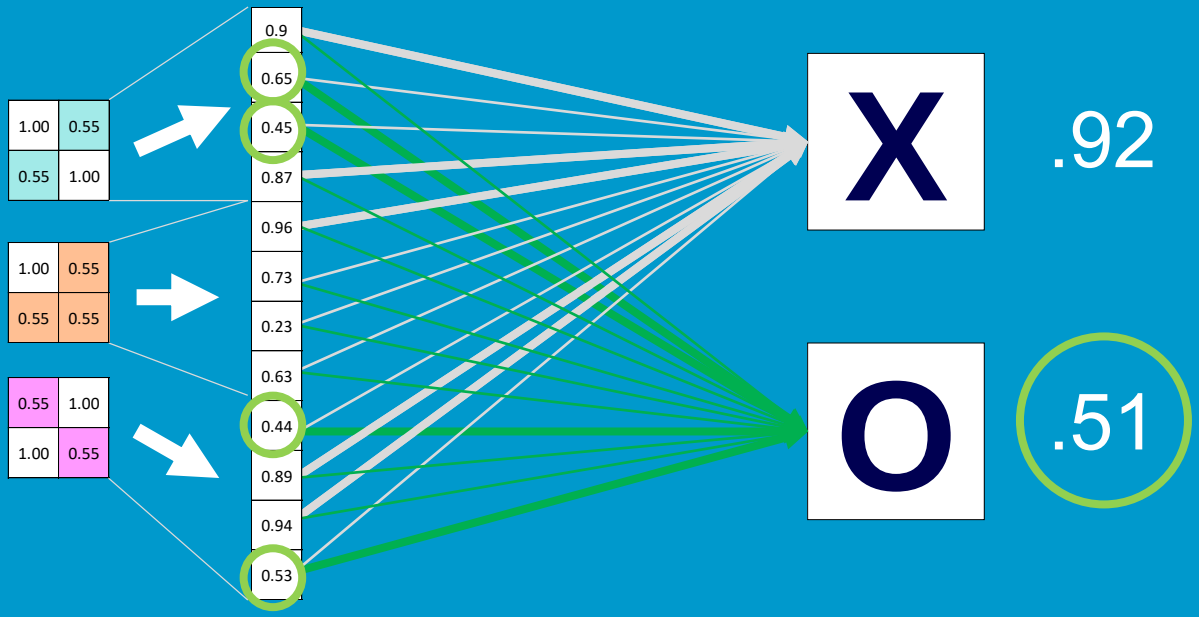
Fully connected layer

Cada valor recebido da camada pooling expressa um valor



Fully connected layer

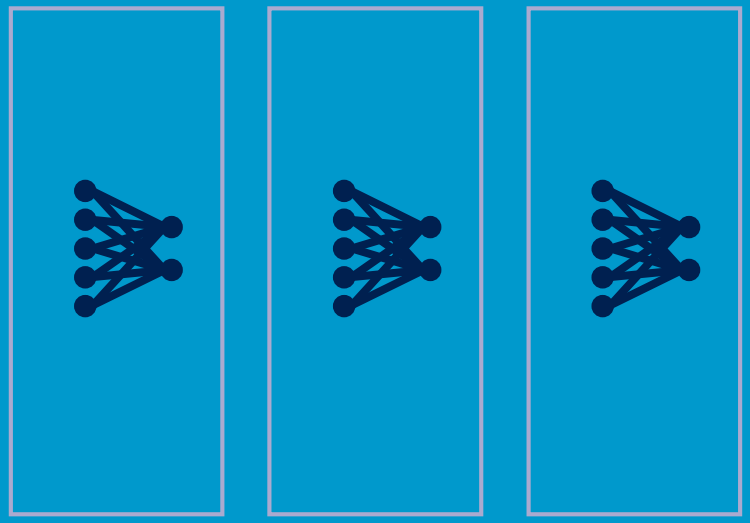
Cada valor recebido da camada pooling expressa um valor



Fully connected layer

0.9
0.65
0.45
0.87
0.96
0.73
0.23
0.63
0.44
0.89
0.94
0.53

Também pode ser “empilhada”



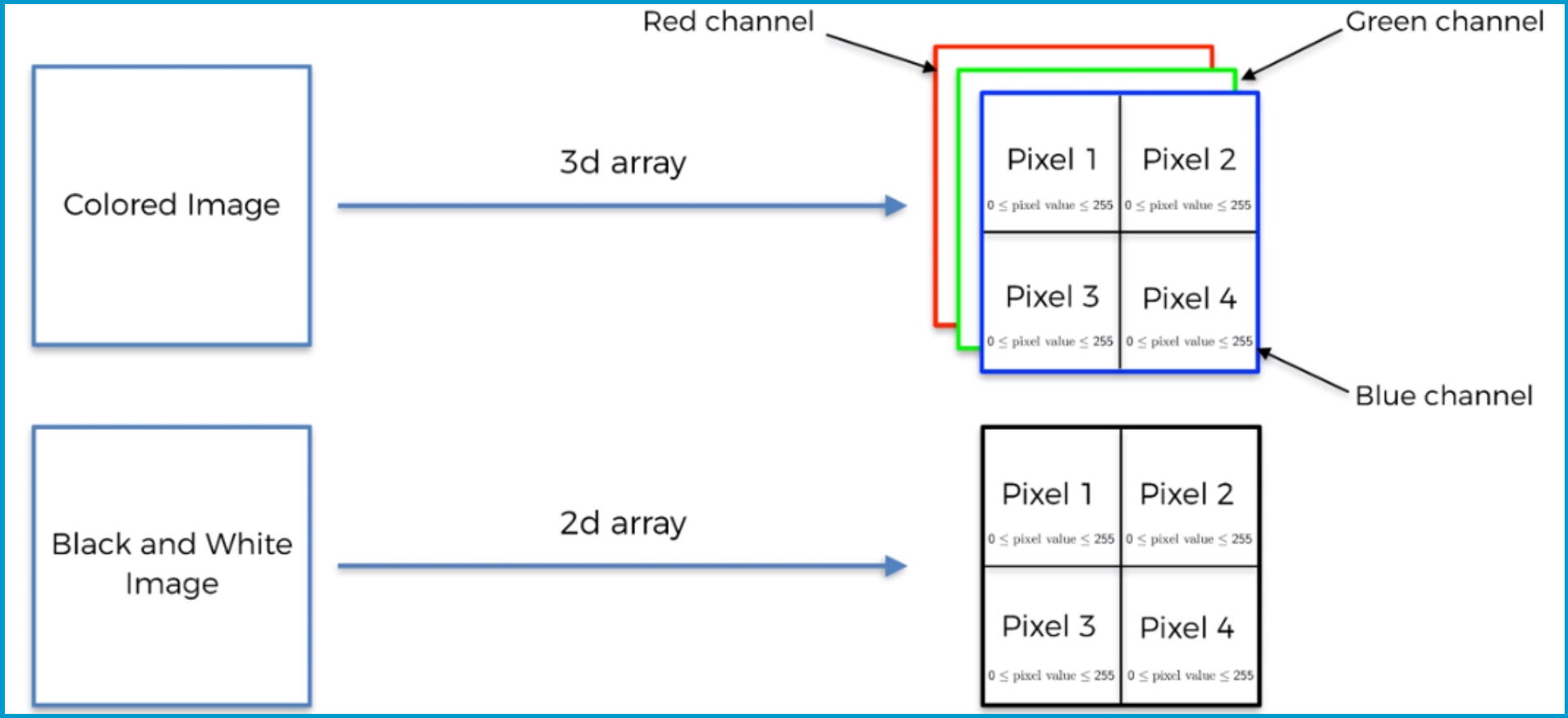
X

O

Codificando...

```
#Considerando o problema de reconhecimento de dígitos
# MNIST é um vetor 1-D de 784 features (28*28 pixels)
# Reshape para [Height x Width x Channel]
# Tensor será 4-D: [Batch Size, Height, Width, Channel]
x = tf.reshape(x, shape=[-1, 28, 28, 1])
```

Codificando...



Codificando...

```
# Camada de convolução com 32 filtros e kernel de tamanho 5
conv1 = tf.layers.conv2d(x, 32, 5, activation=tf.nn.relu)
# Max Pooling (down-sampling) com strides 2 e kernel 2
conv1 = tf.layers.max_pooling2d(conv1, 2, 2)

# Camada de convolução com 64 filtros e kernel de tamanho 3
conv2 = tf.layers.conv2d(conv1, 64, 3, activation=tf.nn.relu)
# Max Pooling (down-sampling) com stride 2 kernel 2
conv2 = tf.layers.max_pooling2d(conv2, 2, 2)

# Fully connected layer
fc1 = tf.layers.dense(fc1, 1024)
# Camada de saída, predição de classe
saida = tf.layers.dense(fc1, n_classes)
```

Softmax e Entropia cruzada

Softmax
Por enquanto: pense como uma outra função de ativação

$$L\left(\hat{f}(x), y\right) = -\frac{e^{z_j}}{\sum e^{z_k}}$$

Softmax e Entropia cruzada

Estamos comparando distribuições de probabilidade, logo usaremos função de entropia cruzada como a função de perda:

$$L\left(\hat{f}(x), y\right) = -\log\left(\frac{e^{z_j}}{\sum e^{z_k}}\right)$$

$$L\left(\hat{f}(x), y\right) = -\sum y_i \log f_i(x)$$

A entropia cruzada procura encontrar as hipóteses de máxima verossimilhança sob o pressuposto de que a saída observada é uma função probabilística da instância de entrada.

Softmax e Entropia cruzada

Detalharemos na próxima aula, para os ansiosos…

Leitura adicional:

A Friendly Introduction to Cross-Entropy Loss

https://rdipietro.github.io/friendly-intro-to-cross-entropy-loss/

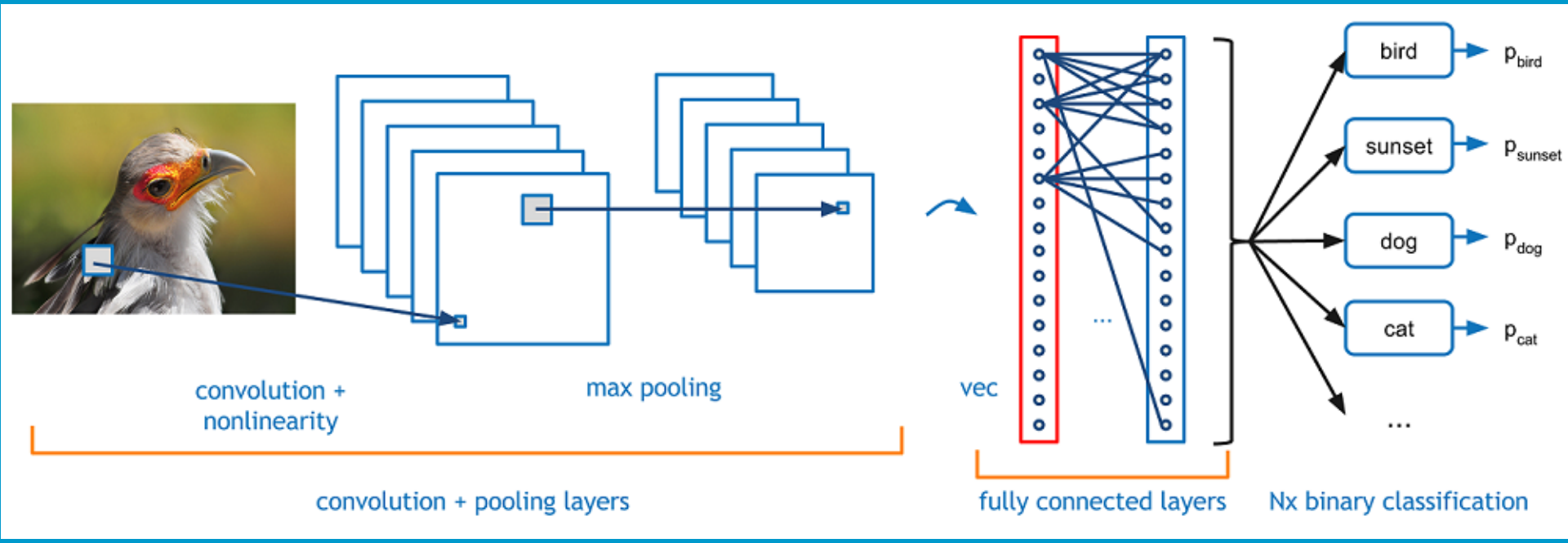
Codificando...

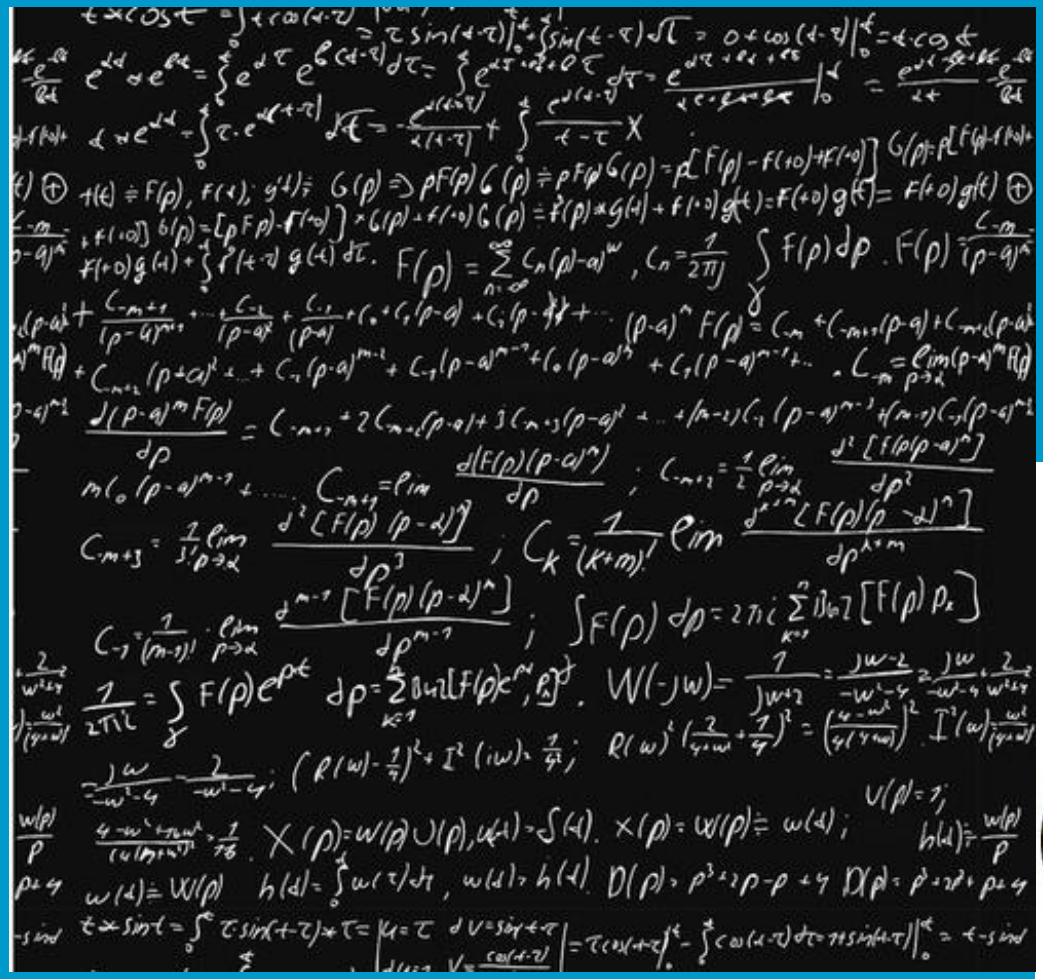
```
 logits_train = conv_net(features, num_classes, dropout,
reuse=False,is_training=True)
 logits_test = conv_net(features, num_classes, dropout,
reuse=True, is_training=False)

# Predictions
pred_classes = tf.argmax(logits_test, axis=1)
pred_probas = tf.nn.softmax(logits_test)
```

Codificando...

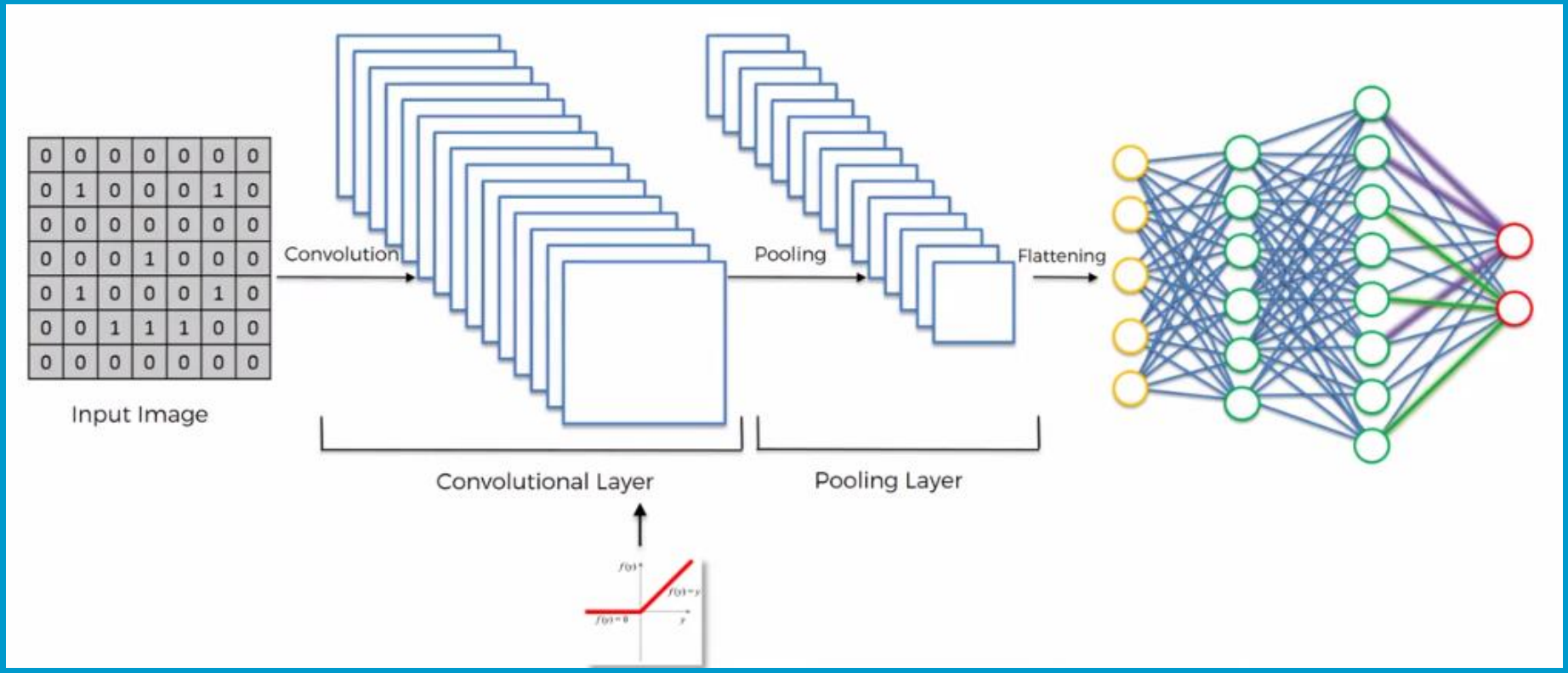
```
 # Define a função de perda
loss_op =
tf.reduce_mean(tf.nn.sparse_softmax_cross_entropy_with_logits(
            logits=logits_train, labels=tf.cast(labels, dtype=tf.int32)))

#Define o otimizador
optimizer =tf.train.GradientDescentOptimizer(learning_rate=0.001)
train_op = optimizer.minimize(
      loss_op, global_step=tf.train.get_global_step())
```

Fully connected layer





Resumindo...


0 0 0 0 0 0 0
0 1 0 0 0 1 0
0 0 0 0 0 0 0
0 0 0 1 0 0 0
0 1 0 0 0 1 0
0 0 1 1 1 0 0
0 0 0 0 0 0 0
Input Image
Convolution
Pooling
Flattening
Convolutional Layer
Pooling Layer

Resumindo...

```
# Camada de convolução com 32 filtros e kernel de tamanho 5
conv1 = tf.layers.conv2d(x, 32, 5, activation=tf.nn.relu)
# Max Pooling (down-sampling) com strides 2 e kernel 2
conv1 = tf.layers.max_pooling2d(conv1, 2, 2)
```

```
# Camada de convolução com 64 filtros e kernel de tamanho 3
conv2 = tf.layers.conv2d(conv1, 64, 3, activation=tf.nn.relu)
# Max Pooling (down-sampling) com stride 2 kernel 2
conv2 = tf.layers.max_pooling2d(conv2, 2, 2)
```

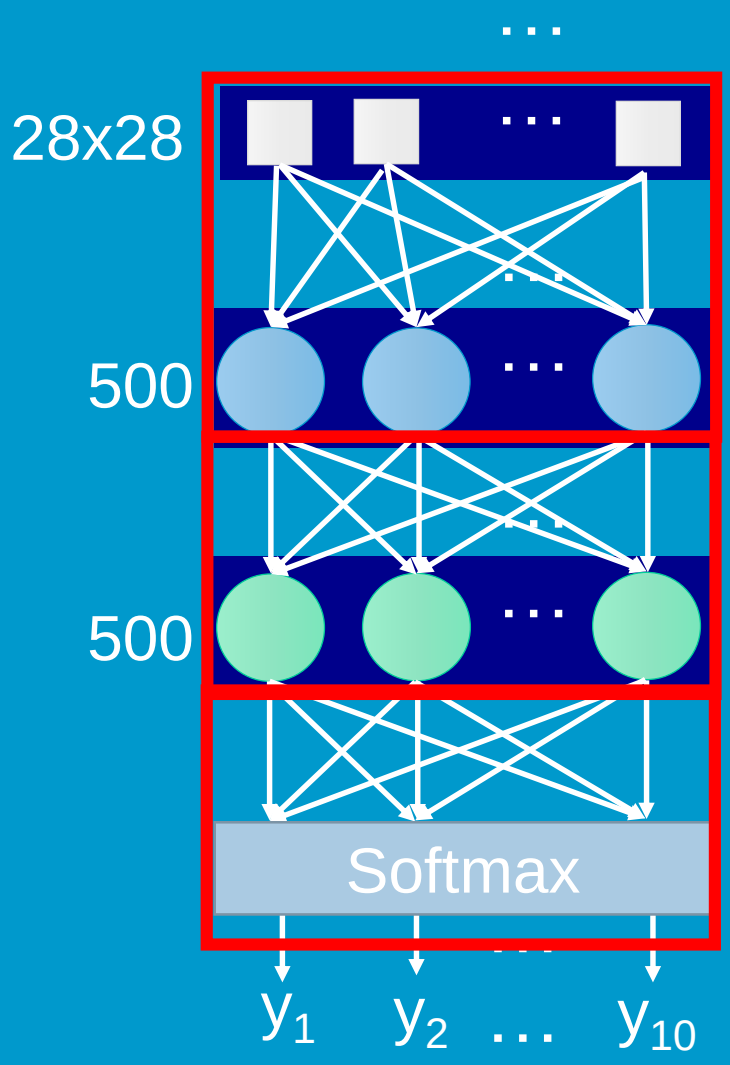
Keras

Interface para
TensorFlow ou Theano

keras

Documentação: http://keras.io/
Exemplos:
https://github.com/fchollet/keras/tree/master/examples

Keras




```
model = Sequential()
```

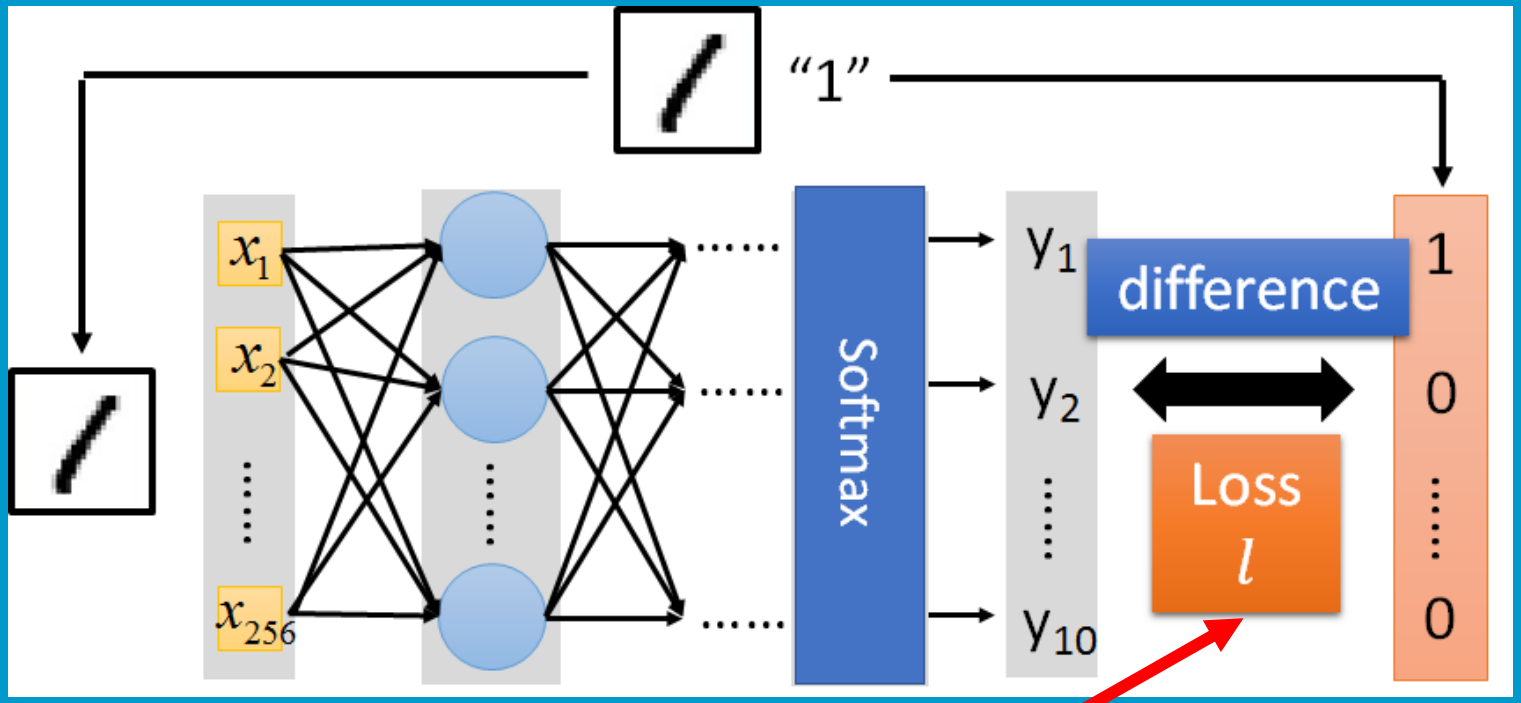
```
model.add( Dense( input_dim=28*28,
                  output_dim=500 ))
model.add( Activation('sigmoid') )
```

softplus, softsign, relu, tanh, hard_sigmoid, linear

```
model.add( Dense( output_dim=500 )
model.add( Activation('sigmoid') )
```

```
model.add( Dense(output_dim=10 ) )
model.add( Activation('softmax') )
```

Keras




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

Several alternatives: https://keras.io/objectives/

Keras

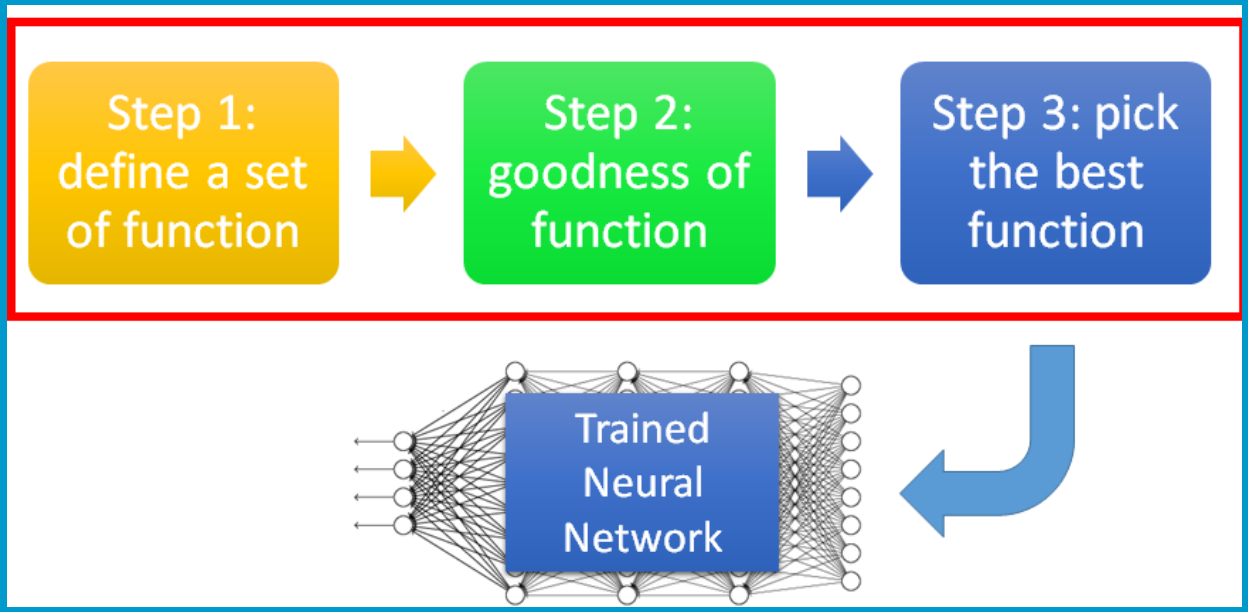
```
model.compile(loss='categorical_crossentropy',
              optimizer='adam',
              metrics=['accuracy'])
```

SGD, RMSprop, Adagrad, Adadelta, Adam, Adamax, Nadam

```
model.fit(x_train, y_train, batch_size=100, nb_epoch=20)
```

Entrada (Imagens)

Labels (digitos)



Salvando a rede neural
http://keras.io/getting-started/faq/#how-can-i-save-a-keras-model

```
score = model.evaluate(x_test,y_test)
print('Total loss on Testing Set:', score[0])
print('Accuracy of Testing Set:', score[1])
```

```
result = model.predict(x_test)
```

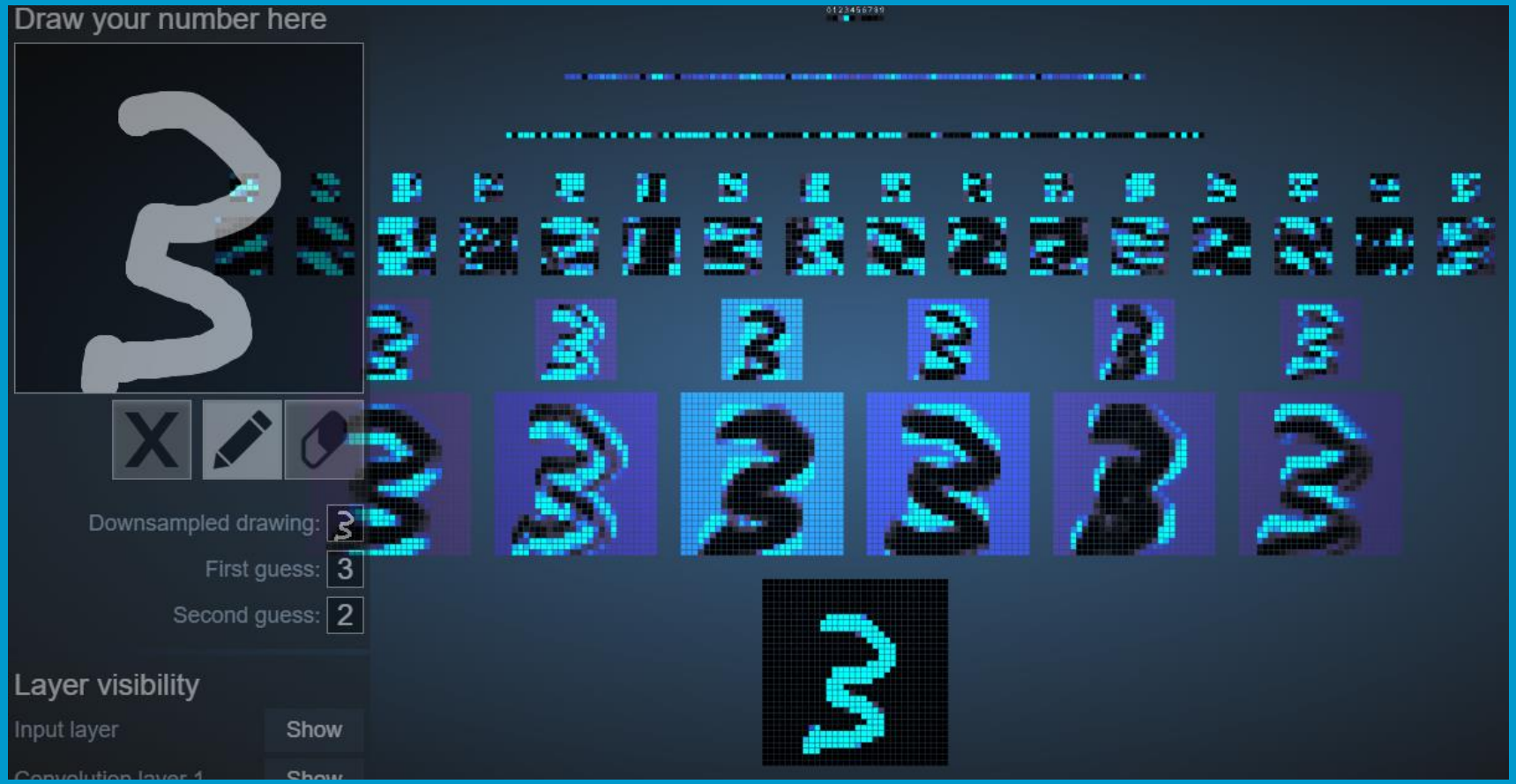
Keras

```
model = Sequential()

model.add(Conv2D(32, (3, 3), padding='same',
                 input_shape=x_train.shape[1:]))
model.add(Activation('relu'))
model.add(Conv2D(32, (3, 3)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))

model.add(Conv2D(64, (3, 3), padding='same'))
model.add(Activation('relu'))
model.add(Conv2D(64, (3, 3)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
```

Keras

```
model.add(Flatten())
model.add(Dense(512))
model.add(Activation('relu'))
model.add(Dense(num_classes))
model.add(Activation('softmax'))

# Inicializa o otimizador
opt = keras.optimizers.SGD(lr=0.0001)

# Treina o modelo
model.compile(loss='categorical_crossentropy',
              optimizer=opt,
              metrics=['accuracy'])
```

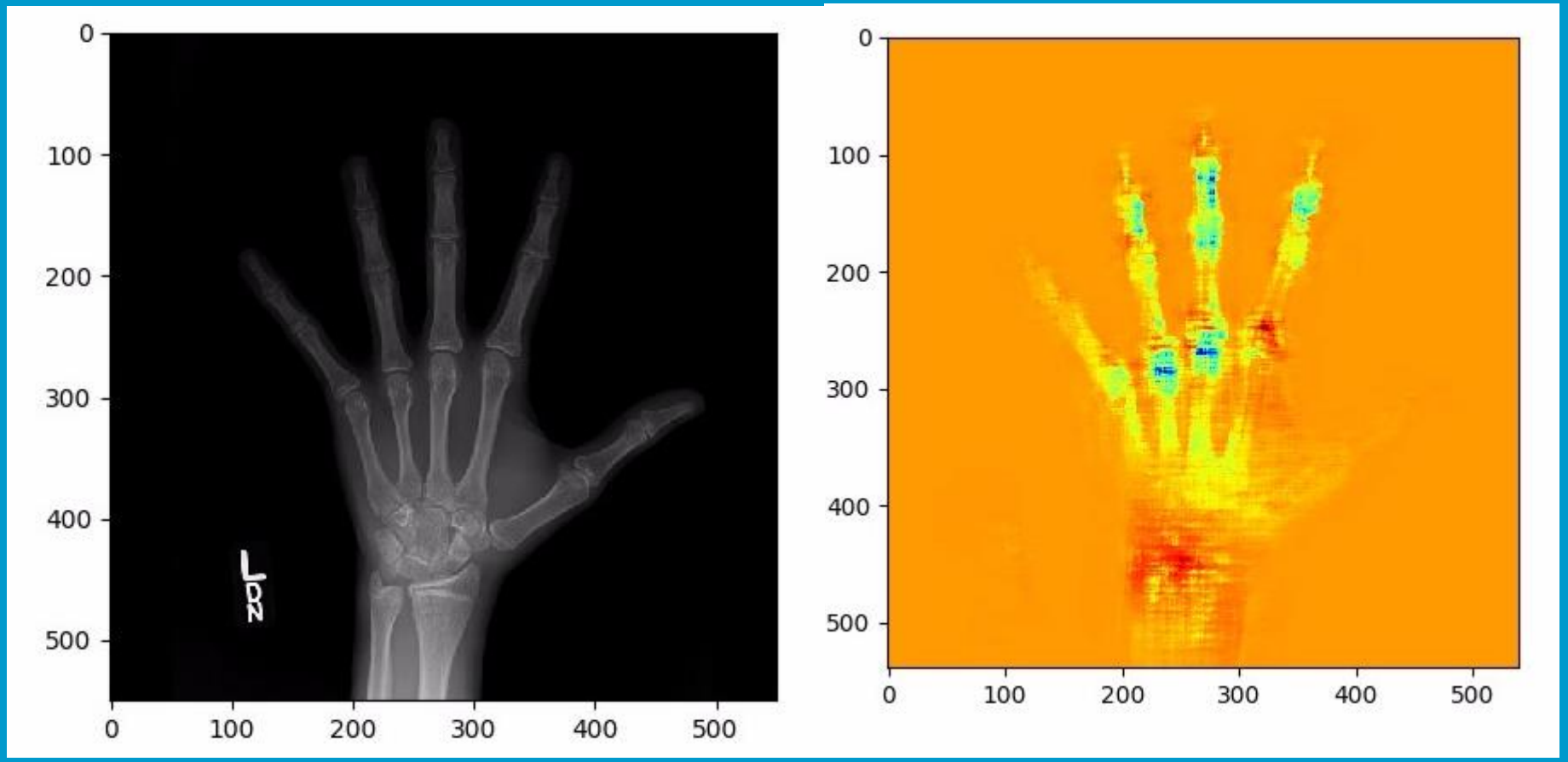
Juntando tudo...



http://www.cs.cmu.edu/~aharley/vis/

Demonstração vídeo


E


0
100
200
300
400
500
0
100
200
300
400
500
0
100
200
300
400
500
0
100
200
300
400
500

Resumindo a primeira parte dos parâmetros

Convolution

- Filtro a ser utilizado

Pooling

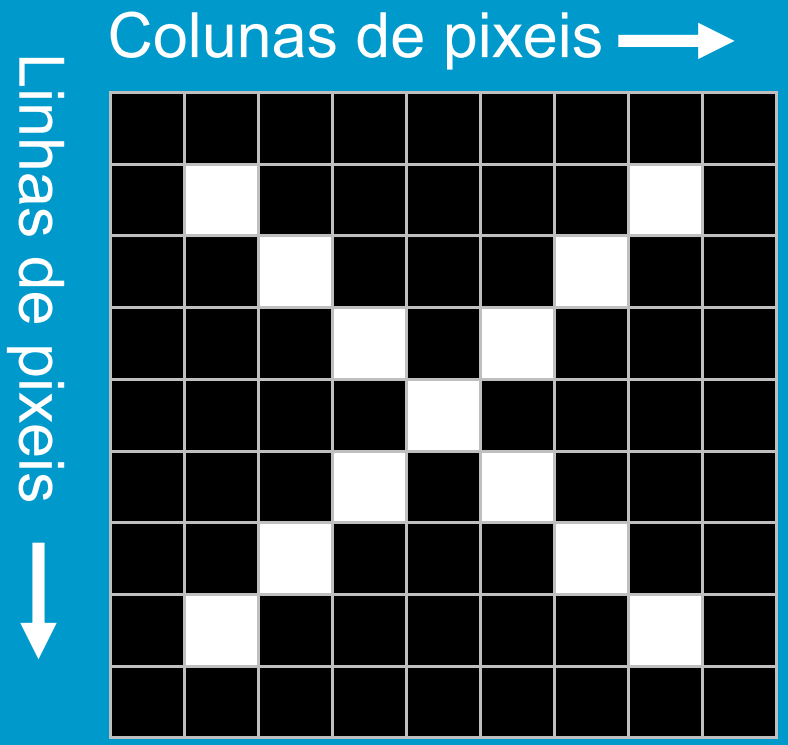
- Tamanho da janela

Fully Connected

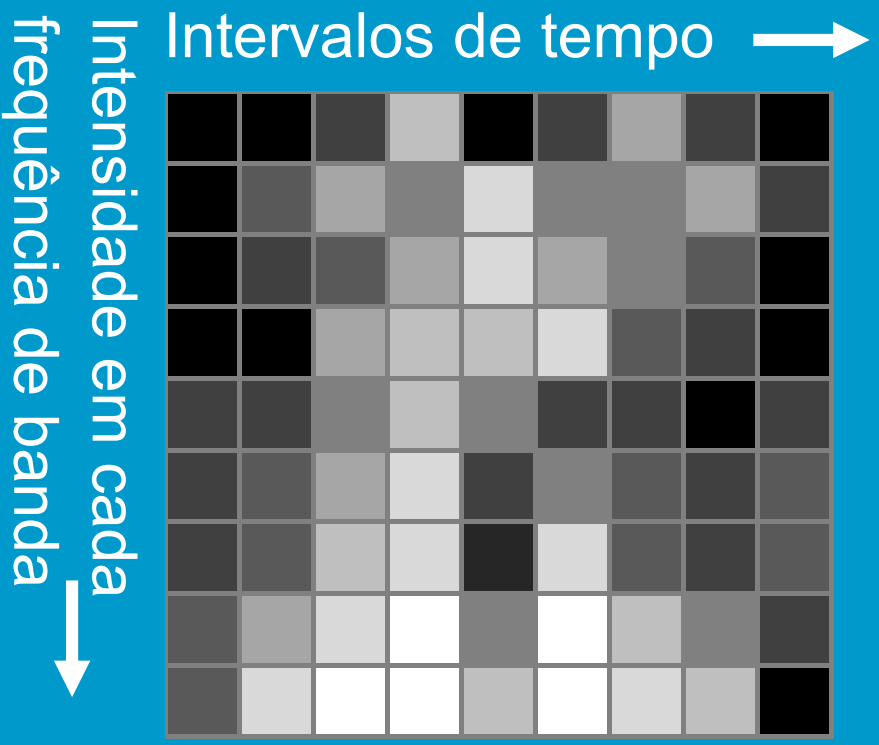
- Número de neurônios

Possibilidades de aplicações

Imagens



Sons


Intervalos de tempo
Intensidade em cada frequência de banda

Texto

Dados de cliente

Nome, idade,
endereço, email,
financeiro,
Atividade na internet,…

Clientes

A	22	1A	a@a	1	aa	a1.a	123	aa1
B	33	2B	b@b	2	bb	b2.b	234	bb2
C	44	3C	c@c	3	cc	c3.c	345	cc3
D	55	4D	d@d	4	dd	d4.d	456	dd4
E	66	5E	e@e	5	ee	e5.e	567	ee5
F	77	6F	f@f	6	ff	f6.f	678	ff6
G	88	7G	g@g	7	gg	g7.g	789	gg7
H	99	8H	h@h	8	hh	h8.h	890	hh8
I	111	9I	i@i	9	ii	i9.i	901	ii9

Uma nova era....

Digit Recognizer

Facial Keypoints Detection

Grasp-and-Lift EEG Detection

Diabetic Retinopathy Detection

National Data Science Bowl

Right Whale Recognition

The Merck Molecular Activity Challenge

The Job Salary prediction challenge

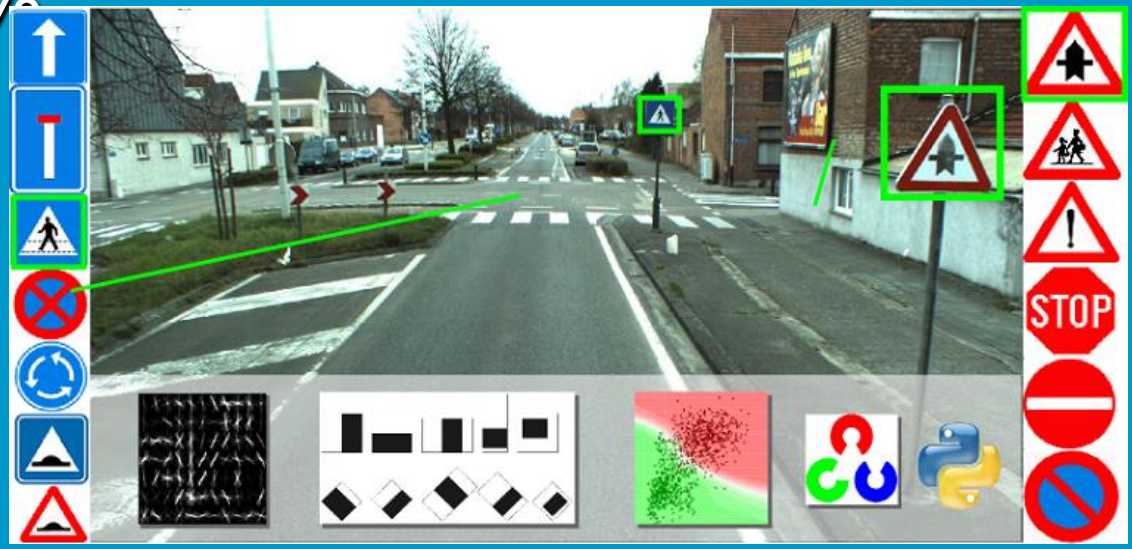
Uma nova era....

Traffic Sign Recognition Competition

Deep learning: 0,56%

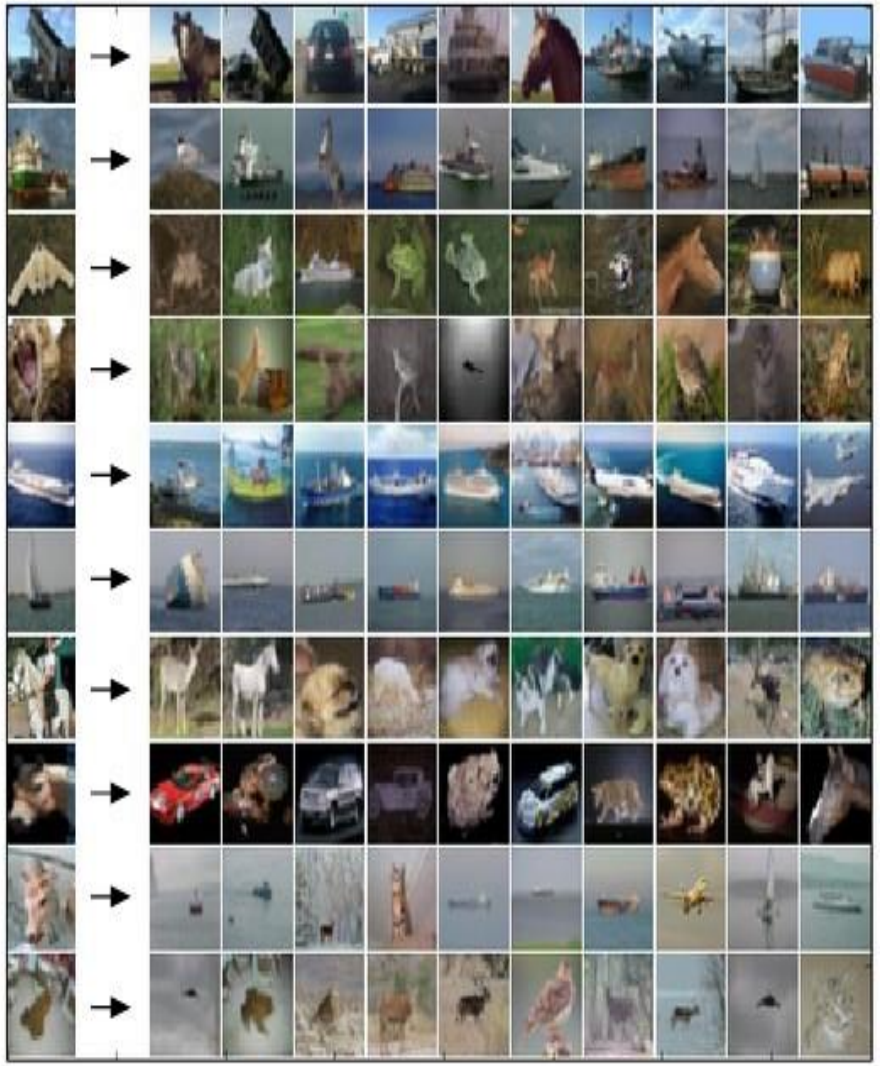
Humanos: 1,16%

Outros: 1,69%



CIFAR-10

10 categorias
50,000 Imagens de treinamento, imagens de 32x32x3
10,000 imagens de teste.



Uma nova era....

ImageNet Challenge 2012

- ~14 milhões de imagens,
- 20 mil classes
- Obtidas na internet
- Desafio: 1.2 milhões de imagens para treinamento,
- 1000 classes

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

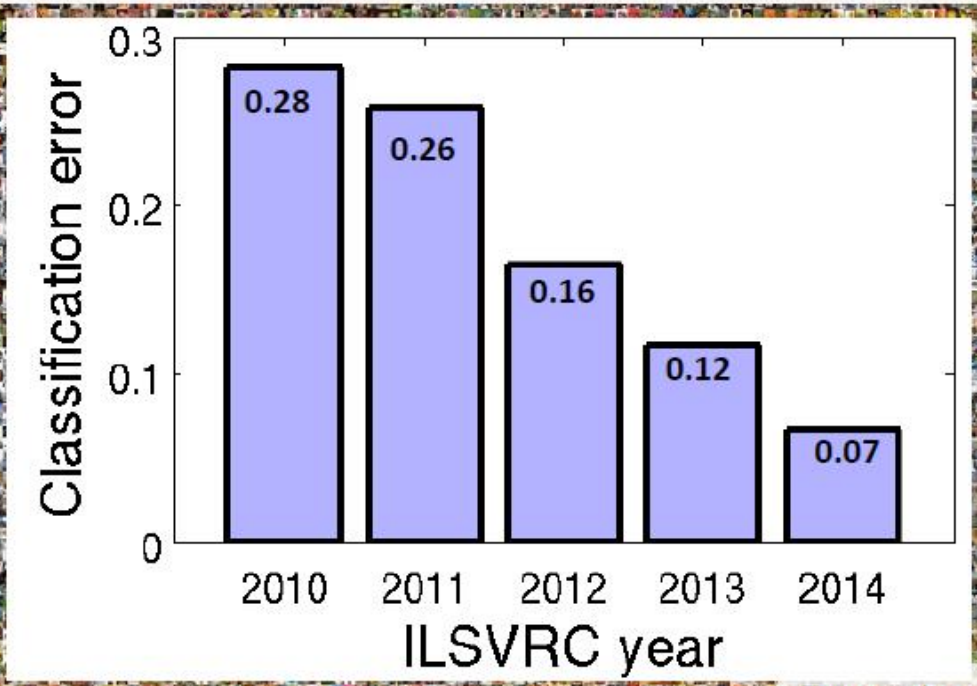
Deng, Dong, Socher, Li, Li, & Fei-Fei, 2009

IMAGENET Large Scale Visual Recognition Challenge

The Image Classification Challenge:

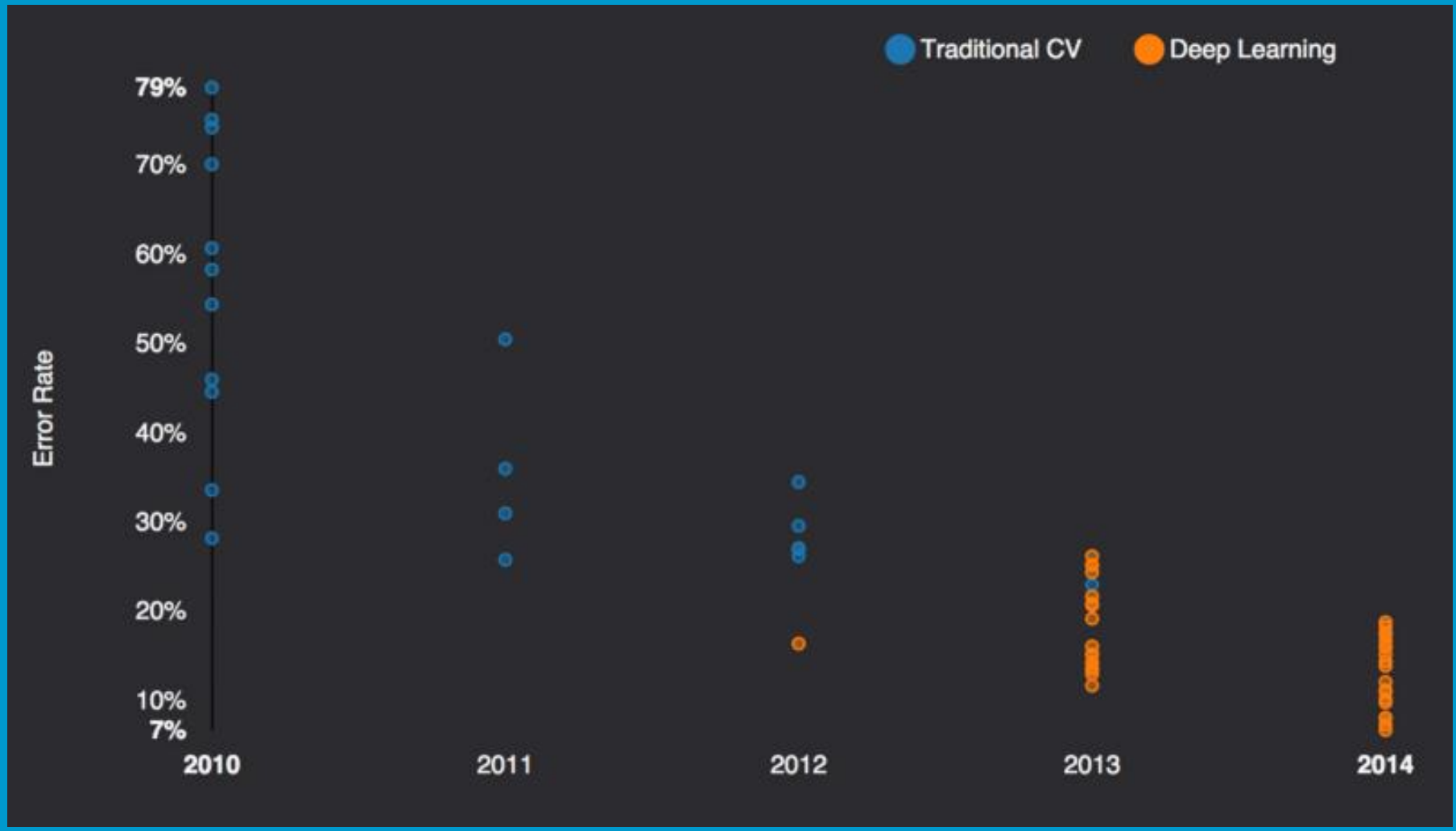
1,000 object classes

1,431,167 images



Russakovsky et al. arXiv, 2014

Uma nova era....


Traditional CV
Deep Learning
Error Rate
79%
70%
60%
50%
40%
30%
20%
10%
7%
2010
2011
2012
2013
2014

Uma nova era....

The ImageNet Large Scale Visual Recognition Challenge (ILSVRC) evaluates algorithms for object detection and image classification at large scale.

O vencedor de 2014 reconheceu corretamente 93 das 100 imagens de teste, um grande passo comparado a competição de 2010 em que o vencedor acertou 72/100 utilizando técnicas tradicionais de visão computacional.

Uma nova era…

- “Top-5 error” é a porcentagem de vezes que label apareceu entre os 5 com maior probabildiade

Name	Layers	Top-5 Error (%)	References
AlexNet	8	15.3	Krizhevsky et al. (2012)
VGG Net	19	7.3	Simonyan and Zisserman (2014)
ResNet	152	3.6	He et al. (2016)

- Nota: a performance de um humano é de 5.1% top-5

IMAGENET Large Scale Visual Recognition Challenge

Year 2010

NEC-UIUC

Dense grid descriptor: HOG, LBP

Coding: local coordinate, super-vector

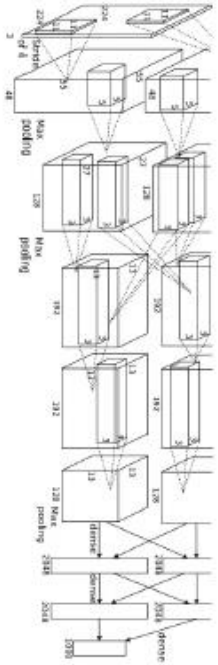
Pooling, SPM

Linear SVM

[Lin CVPR 2011]

Year 2012

SuperVision



[Krizhevsky NIPS 2012]

Year 2014

GoogLeNet

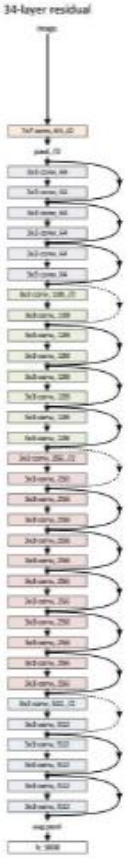
[Szegedy arxiv 2014]

VGG

[Simonyan arxiv 2014]

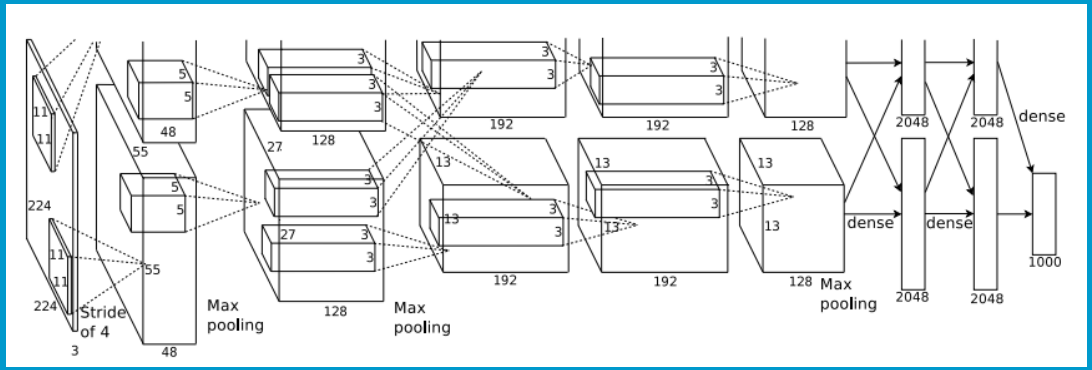
Year 2015

MSRA



Case Study: AlexNet

[Krizhevsky et al. 2012]



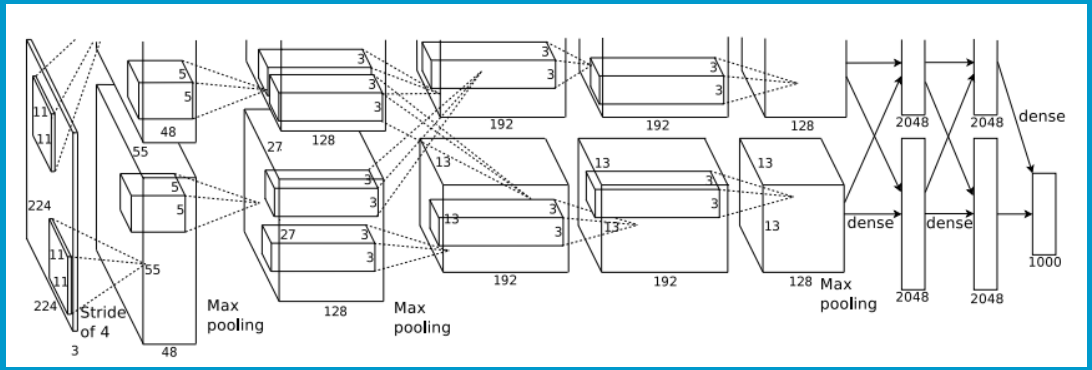
Input: 227x227x3 images

Primeira camada (CONV1): 96 11x11 filtros com stride 4

Saída: (227-11)/4+1 = 55

Case Study: AlexNet

[Krizhevsky et al. 2012]

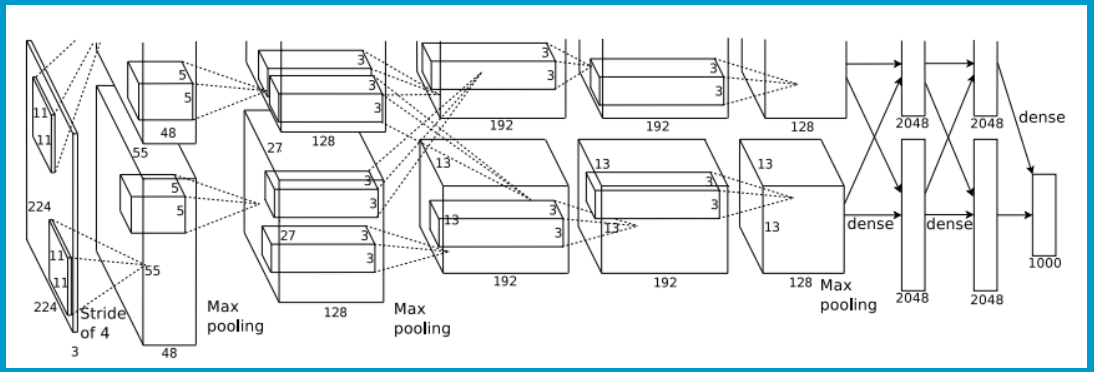


Input: 227x227x3 images

Primeira camada (CONV1): 96 11x11 filtros com stride 4
Saída **[55x55x96]**

Case Study: AlexNet

[Krizhevsky et al. 2012]



Input: 227x227x3 images

Primeira camada (CONV1): 96 11x11 filtros com stride 4

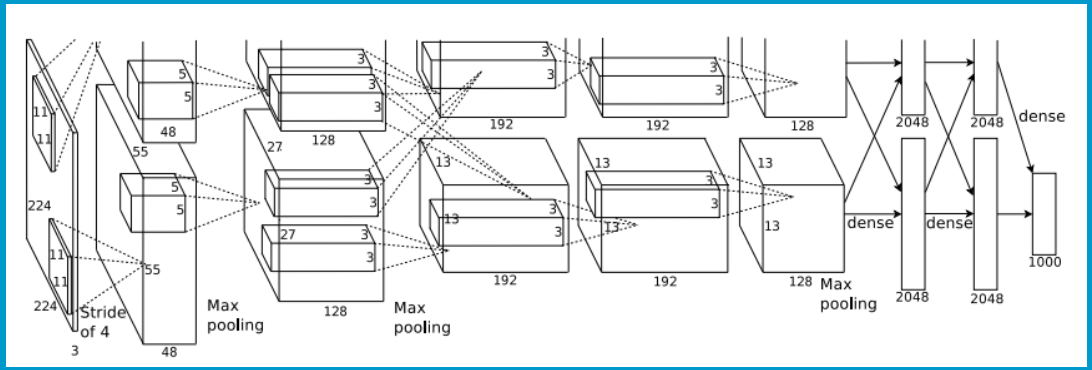
=>

Saída **[55x55x96]**

Parametros: (11*11*3)*96 = **35K**

Case Study: AlexNet

[Krizhevsky et al. 2012]



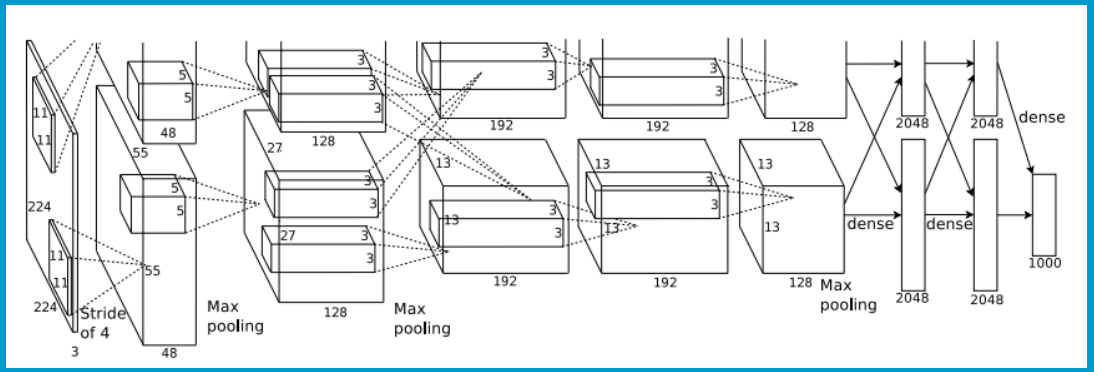
Input: 227x227x3 images
After CONV1: 55x55x96

Segunda camada (POOL1): 3x3 filtros com stride 2

Q: Qual o tamanho da saída? Hint: (55-3)/2+1 = 27

Case Study: AlexNet

[Krizhevsky et al. 2012]

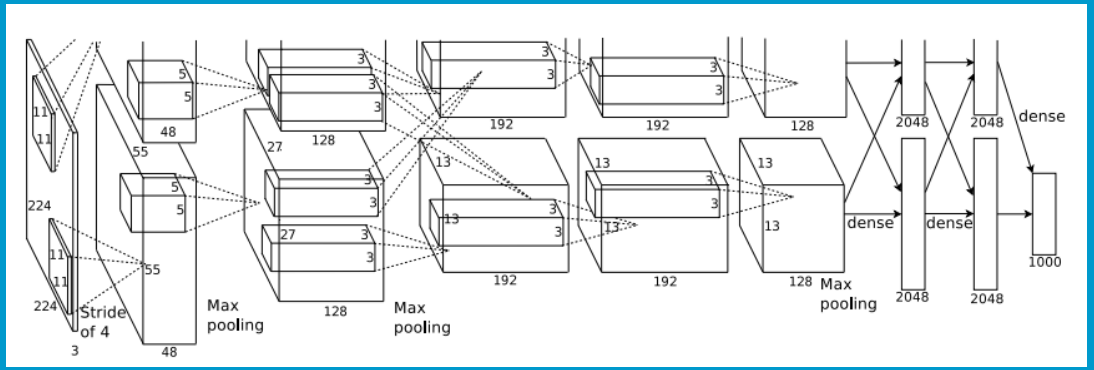


Input: 227x227x3 images
Depois da CONV1: 55x55x96

Segunda camada (POOL1): 3x3 filtros com stride 2
Saída: 27x27x96

Case Study: AlexNet

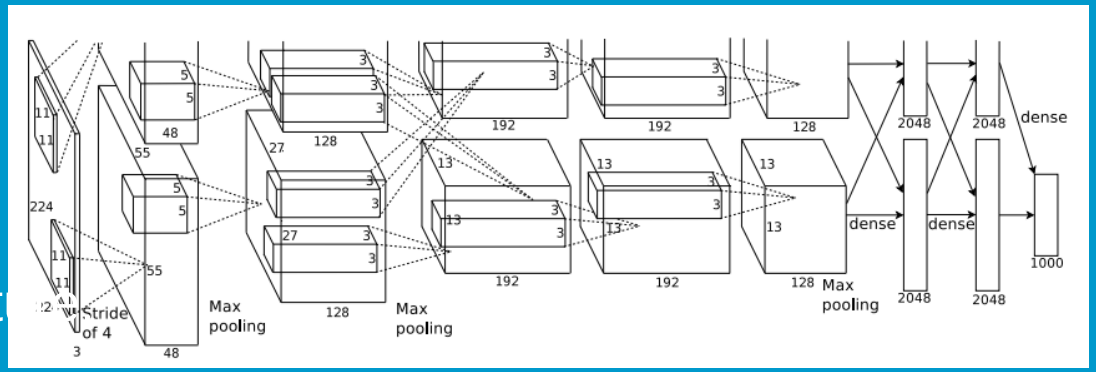
[Krizhevsky et al. 2012]



Input: 227x227x3 images
After CONV1: 55x55x96
After POOL1: 27x27x96
...

Case Study: AlexNet

[Krizhevsky et al. 2012]

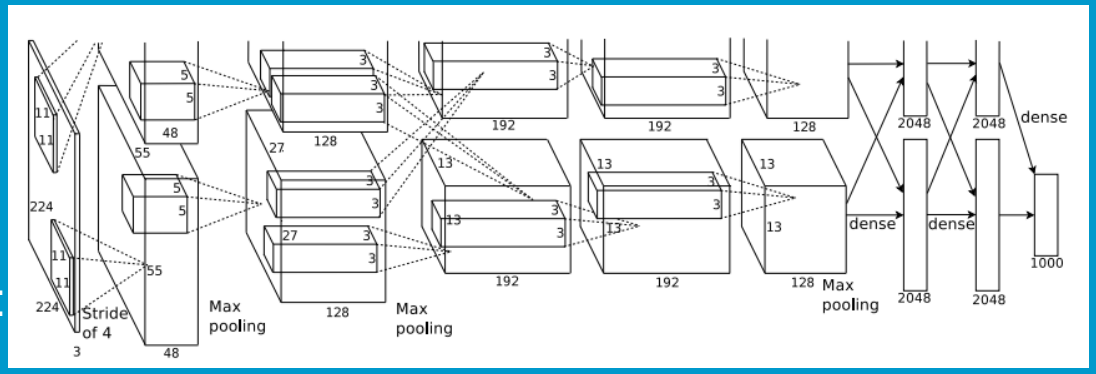


Full (simplified) AlexNet architect

[227x227x3] INPUT
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] NORM2: Normalization layer
[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1
[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1
[6x6x256] MAX POOL3: 3x3 filters at stride 2
[4096] FC6: 4096 neurons
[4096] FC7: 4096 neurons
[1000] FC8: 1000 neurons (class scores)

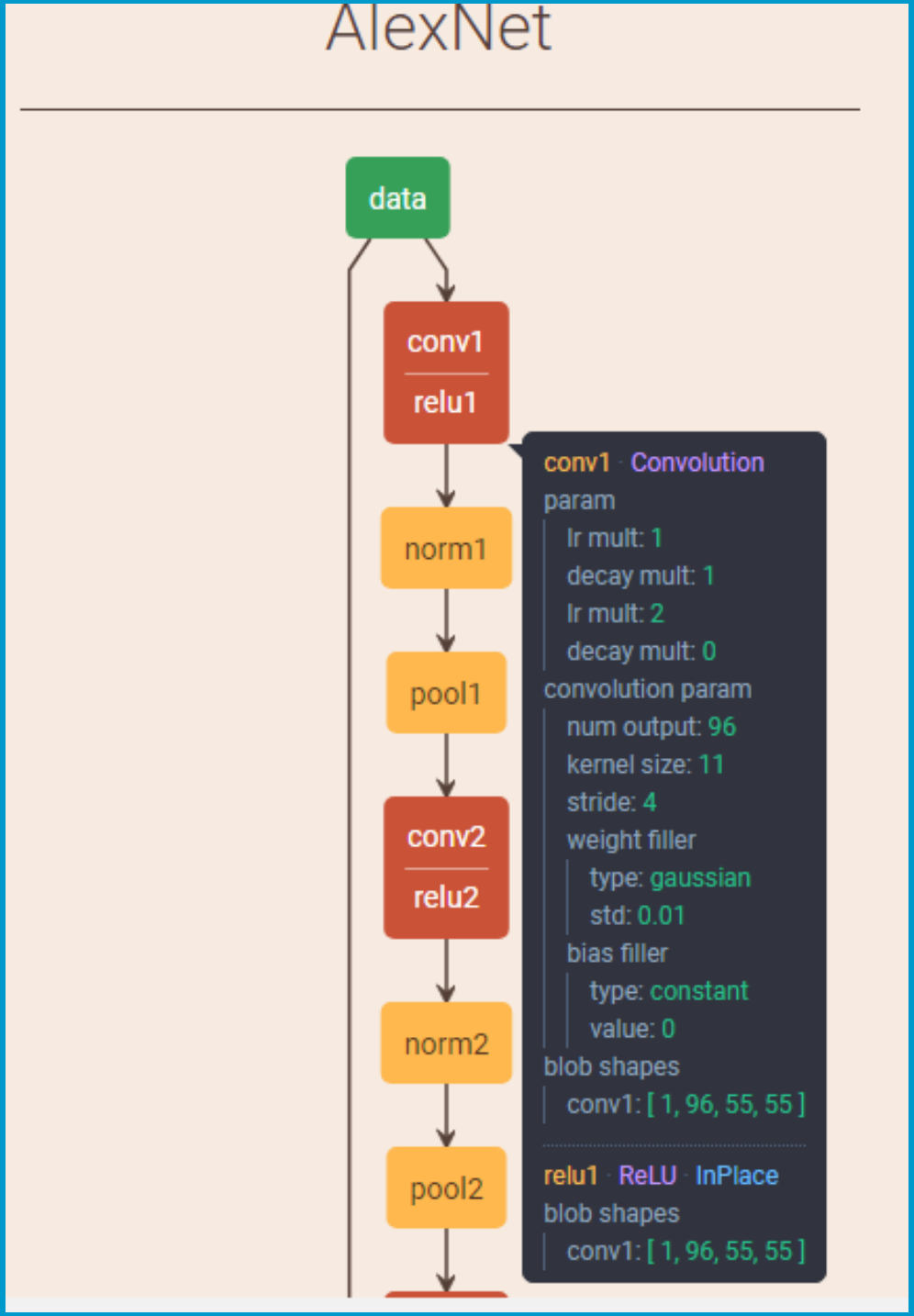
Case Study: AlexNet

[Krizhevsky et al. 2012]



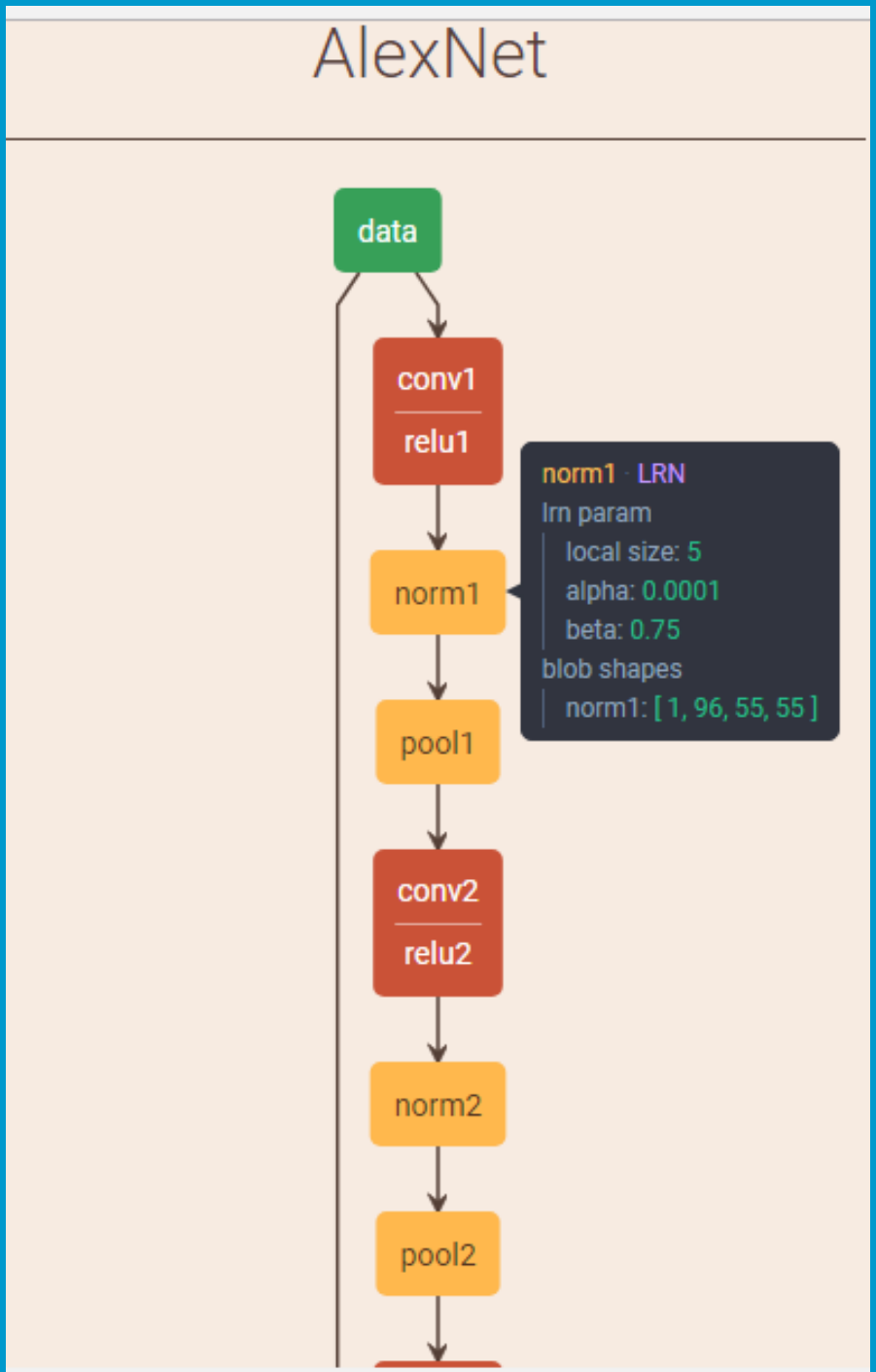
Full (simplified) AlexNet architecture:
[227x227x3] INPUT
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] NORM2: Normalization layer
[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1
[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1
[6x6x256] MAX POOL3: 3x3 filters at stride 2
[4096] FC6: 4096 neurons
[4096] FC7: 4096 neurons
[1000] FC8: 1000 neurons (class scores)

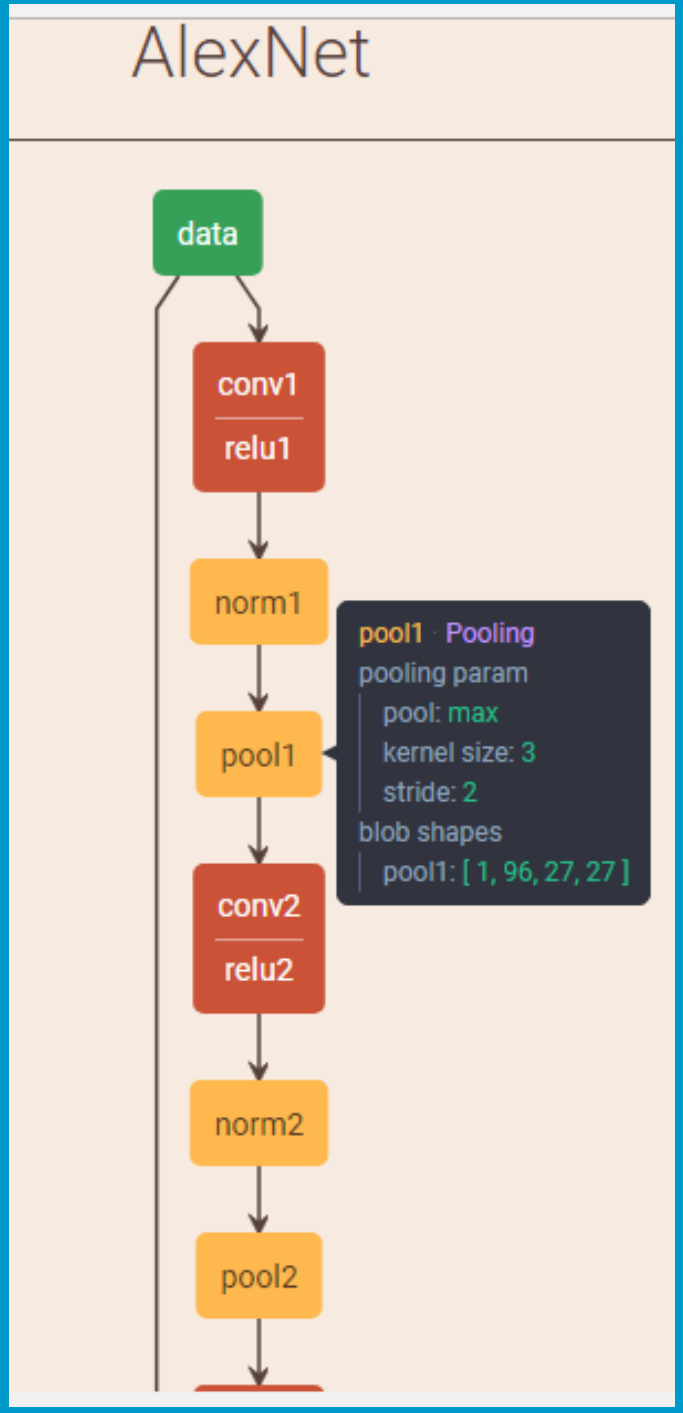
Details/Retrospectives:
- **first use of ReLU**
- **used Norm layers (not common anymor**
- **heavy data augmentation**
- **dropout 0.5**
- **batch size 128**
- **SGD Momentum 0.9**
- **L2 weight decay 5e-4**
- **7 CNN ensemble: 18.2% -> 15.4%**



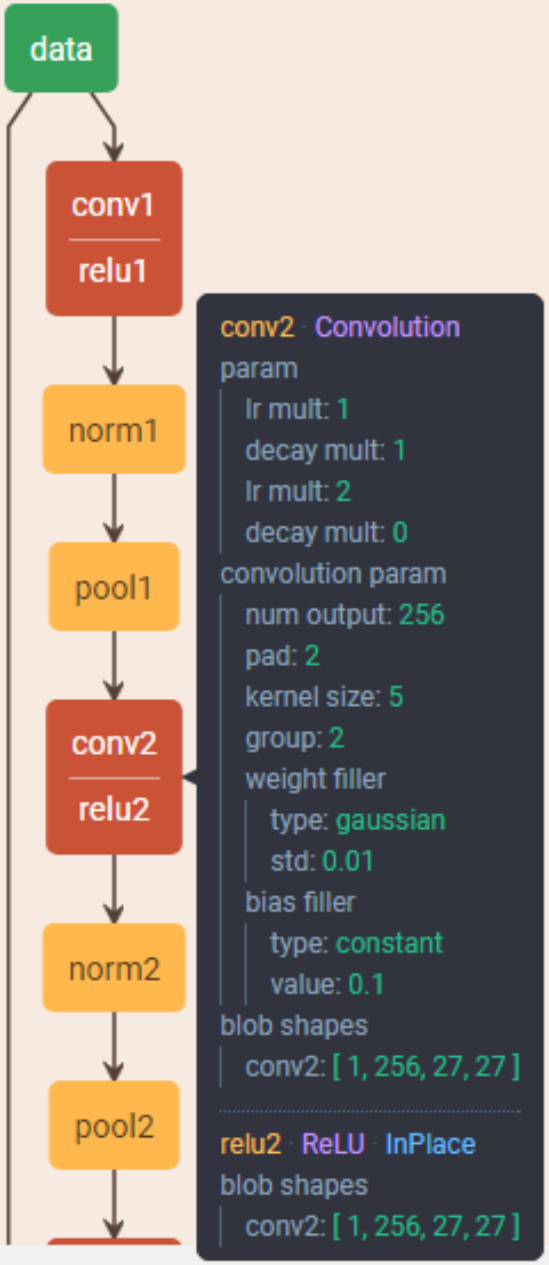
http://ethereon.github.io/netscope/quickstart.html

AlexNet


data
conv1
relu1
norm1
pool1
conv2
relu2
norm2
pool2
norm1 · LRN
lrn param
local size: 5
alpha: 0.0001
beta: 0.75
blob shapes
norm1: [1, 96, 55, 55]


AlexNet
data
conv1
relu1
norm1
pool1
conv2
relu2
norm2
pool2
pool1 · Pooling
pooling param
pool: max
kernel size: 3
stride: 2
blob shapes
pool1: [1, 96, 27, 27]

AlexNet

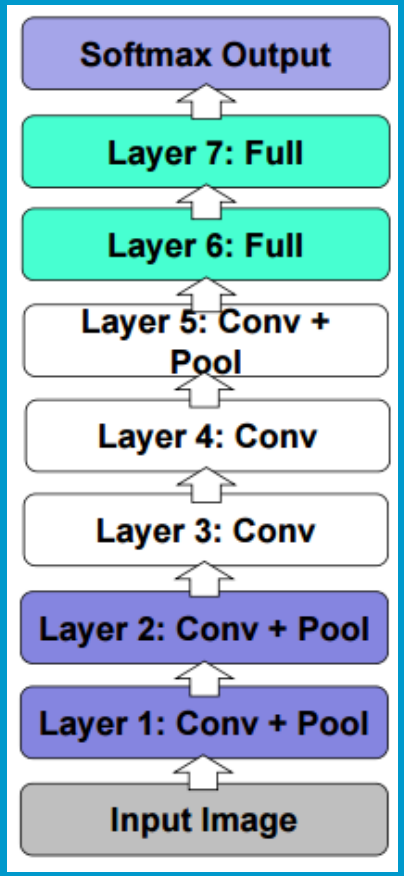

data
conv1
relu1
norm1
pool1
conv2
relu2
norm2
pool2
conv2 · Convolution
param
lr mult: 1
decay mult: 1
lr mult: 2
decay mult: 0
convolution param
num output: 256
pad: 2
kernel size: 5
group: 2
weight filler
type: gaussian
std: 0.01
bias filler
type: constant
value: 0.1
blob shapes
conv2: [1, 256, 27, 27]
relu2 · ReLU · InPlace
blob shapes
conv2: [1, 256, 27, 27]

Aspectos de projeto da rede

AlexNet 2012

8 camadas

Erro de 18.1% top-5



Aspectos de projeto da rede

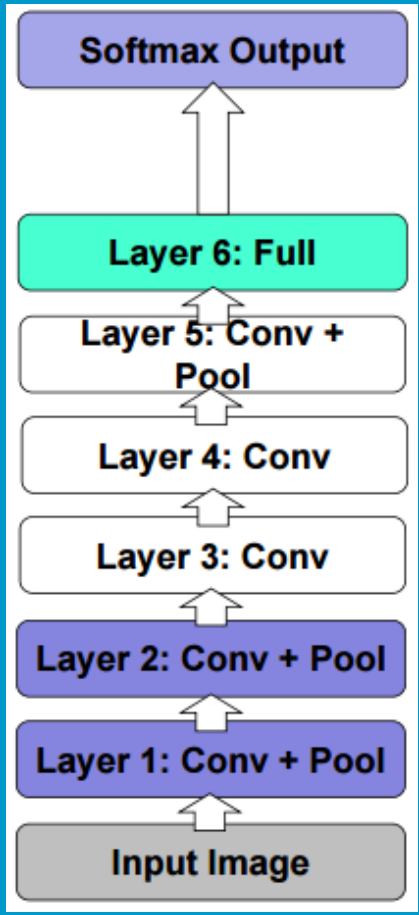
AlexNet 2012

7 camadas

Sem uma das Fully Layer

Menos 17 milhões de parâmetros

Erro de 19.2%



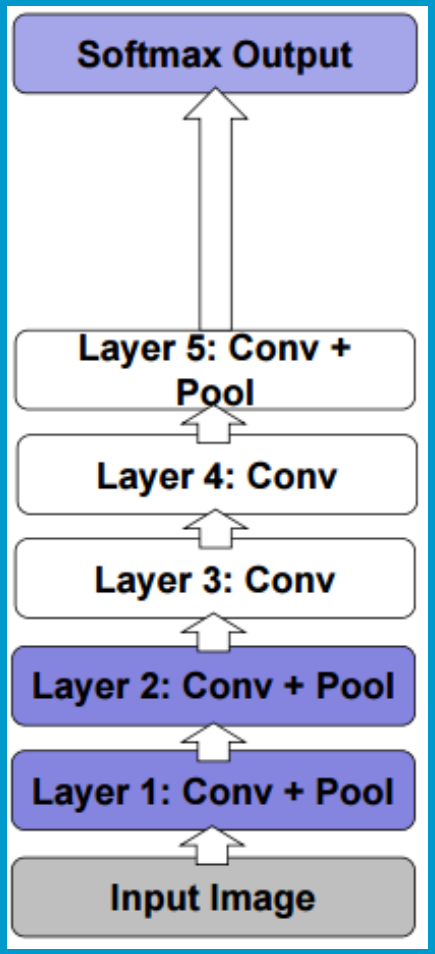
Aspectos de projeto da rede

AlexNet 2012

6 camadas

Menos ~50 milhões de parâmetros

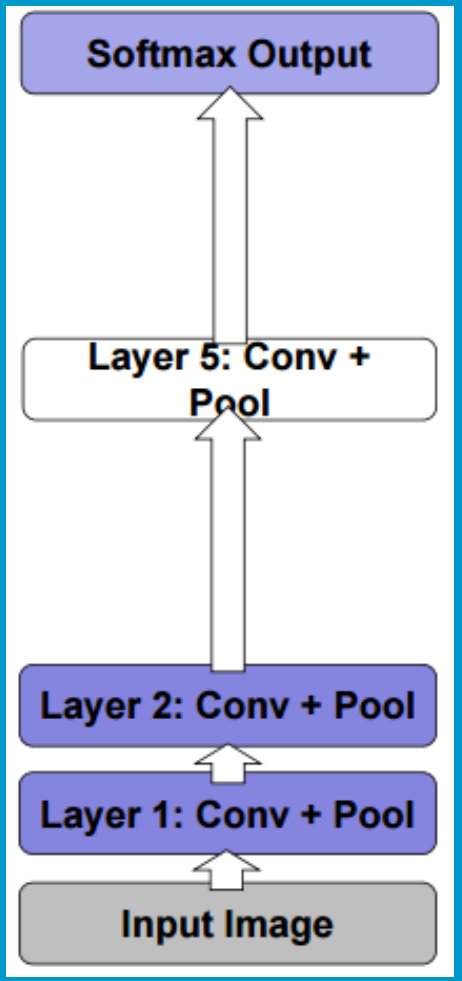
Erro ~24%



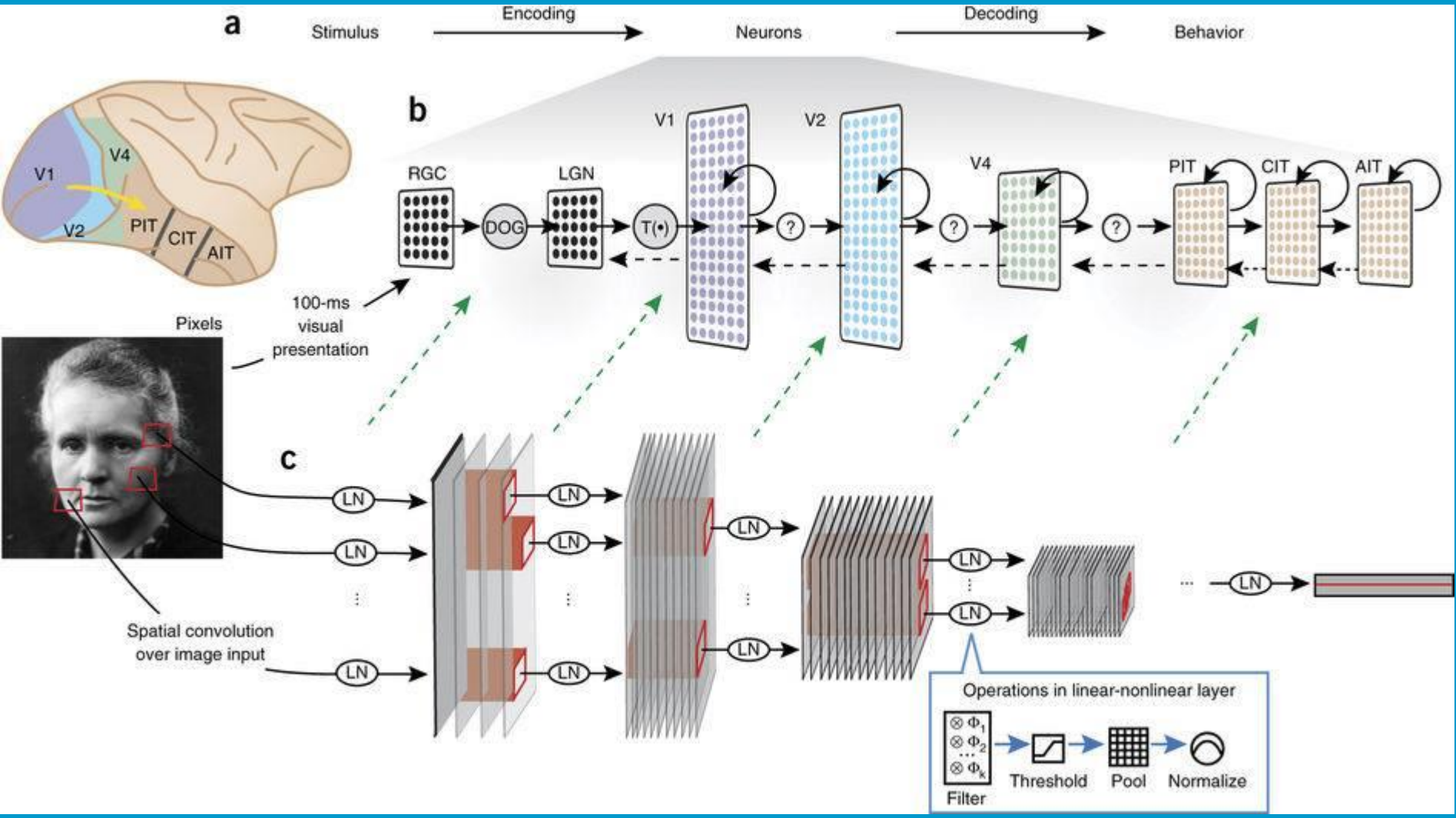
Aspectos de projeto da rede

AlexNet 2012

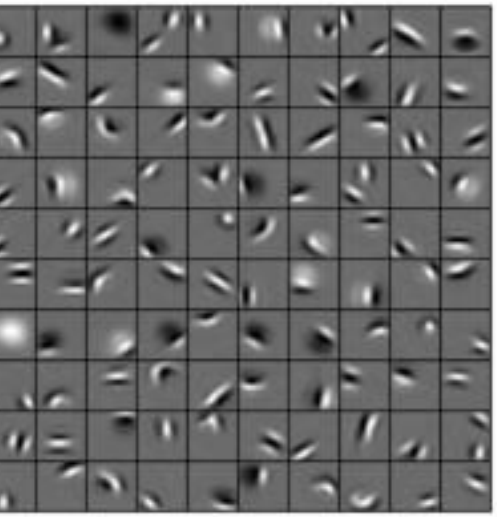
Erro ~33.8

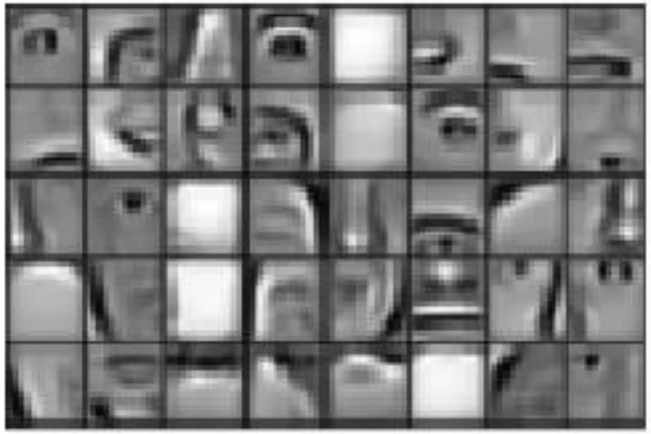


Resumindo...


a
Stimulus
Encoding
Neurons
Decoding
Behavior
b
V1
V4
V2
PIT
CIT
AIT
RGC
LGN
DOG
T(•)
?
100-ms
visual
presentation
Pixels
c
LN
Spatial convolution
over image input
Operations in linear-nonlinear layer
Filter
Threshold
Pool
Normalize

Resumindo...





Exemplo de uma rede executando no browser

http://cs.stanford.edu/people/karpathy/convnetjs/demo/cifar10.html

Resumindo...

Uma nova era....

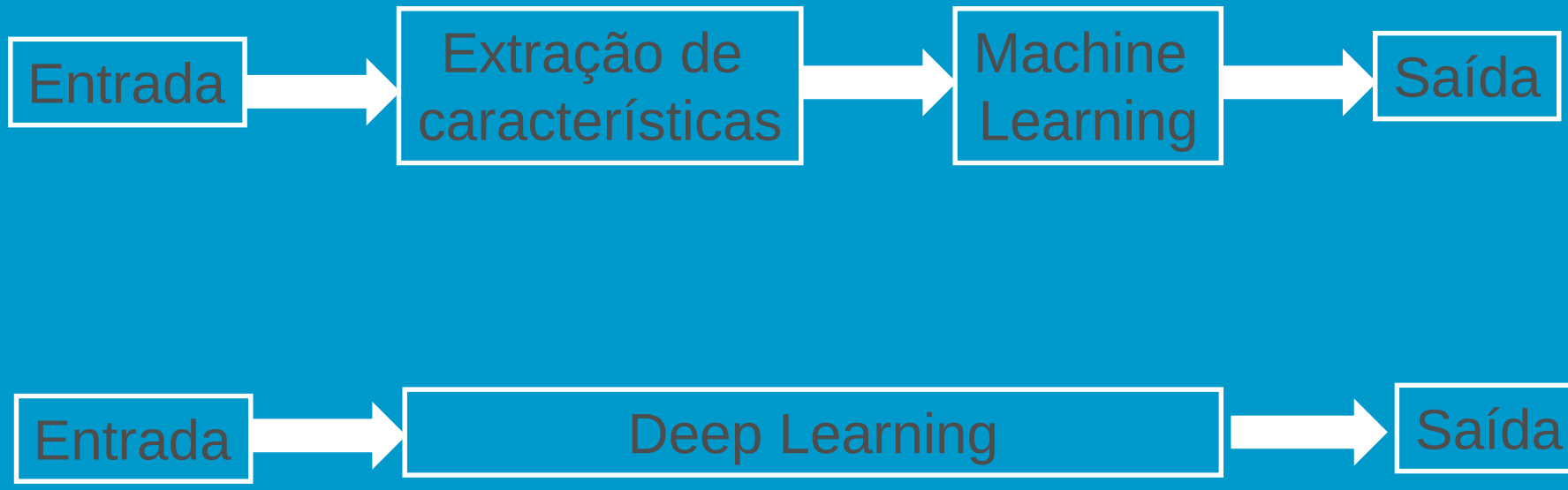
Auto-encoders

Aprendizado não-supervisionado + supervisionado

Altos níveis de abstração

Alta carga computacional

Resumindo...


Entrada
Extração de características
Machine Learning
Saída
Entrada
Deep Learning
Saída

Resumindo...

IA tradicional	Deep learning
Engenharia de variáveis	Modelo hierárquico com camadas de abstrações
Rótulos geralmente definidos por humanos	Dados não rotulados
Computação sequencial	Múltiplas decisões simultâneas

Lenet 5 - 1995

```
52  model = Sequential()
53  # For an explanation on conv layers see http://cs231n.github.io/convolutional-networks/#conv
54  # By default the stride/subsample is 1 and there is no zero-padding.
55  # If you want zero-padding add a ZeroPadding layer or, if stride is 1 use border_mode="same"
56  model.add(Convolution2D(12, 5, 5, activation = 'relu', input_shape=in_shape, init='he_normal'))
57
58  # For an explanation on pooling layers see http://cs231n.github.io/convolutional-networks/#pool
59  model.add(MaxPooling2D(pool_size=(2, 2)))
60
61  model.add(Convolution2D(25, 5, 5, activation = 'relu', init='he_normal'))
62
63  model.add(MaxPooling2D(pool_size=(2, 2)))
64
65  # Flatten the 3D output to 1D tensor for a fully connected layer to accept the input
66  model.add(Flatten())
67  model.add(Dense(180, activation = 'relu', init='he_normal'))
68  model.add(Dropout(0.5))
69  model.add(Dense(100, activation = 'relu', init='he_normal'))
70  model.add(Dropout(0.5))
71  model.add(Dense(nb_classes, activation = 'softmax', init='he_normal')) #Last layer with one output per
72  class
73
74  # The function to optimize is the cross entropy between the true label and the output (softmax) of the
75  model
76  # We will use adadelta to do the gradient descent see http://cs231n.github.io/neural-networks-3/#ada
77  model.compile(loss='categorical_crossentropy', optimizer='adamax', metrics=["accuracy"])
```

Fonte:
https://www.kaggle.com/ftence/keras-cnn-inspired-by-lenet-5

Próxima aula: parametrização de redes neurais profundas

Tarefa para casa: Explique pq o professor montou a imagem abaixo

Por hoje é só pessoal...

Backup slides

Compreendendo o treinamento...

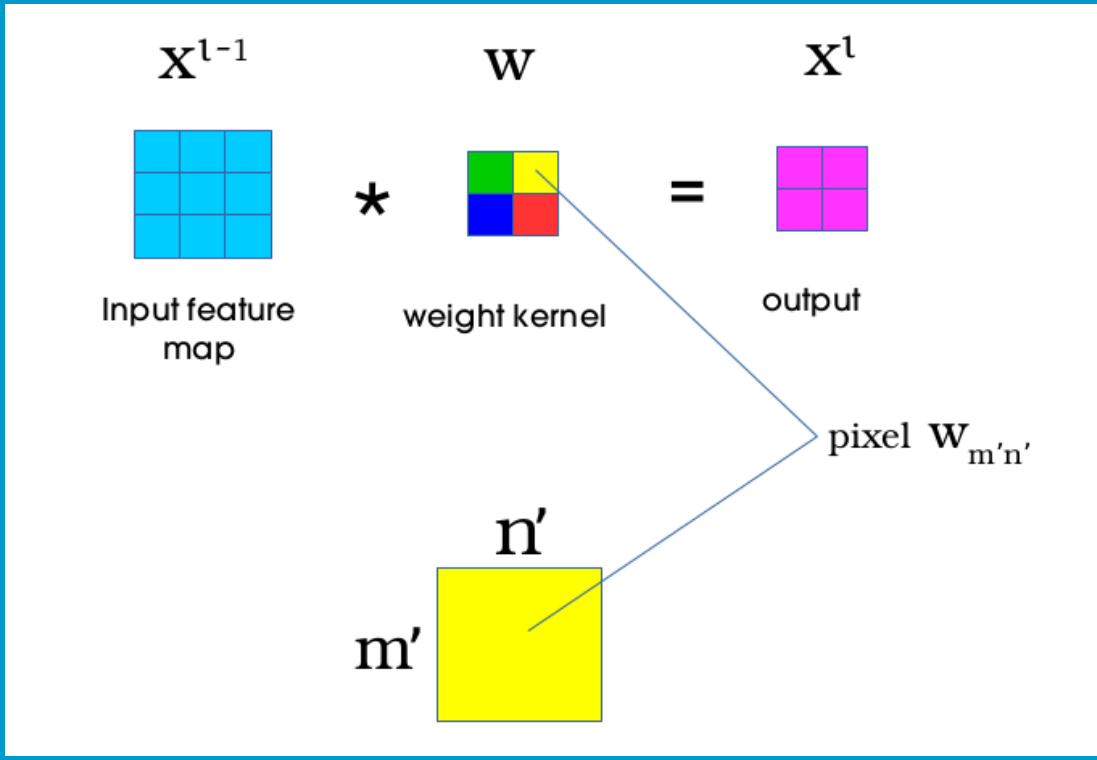
Tranquem a porta da sala...

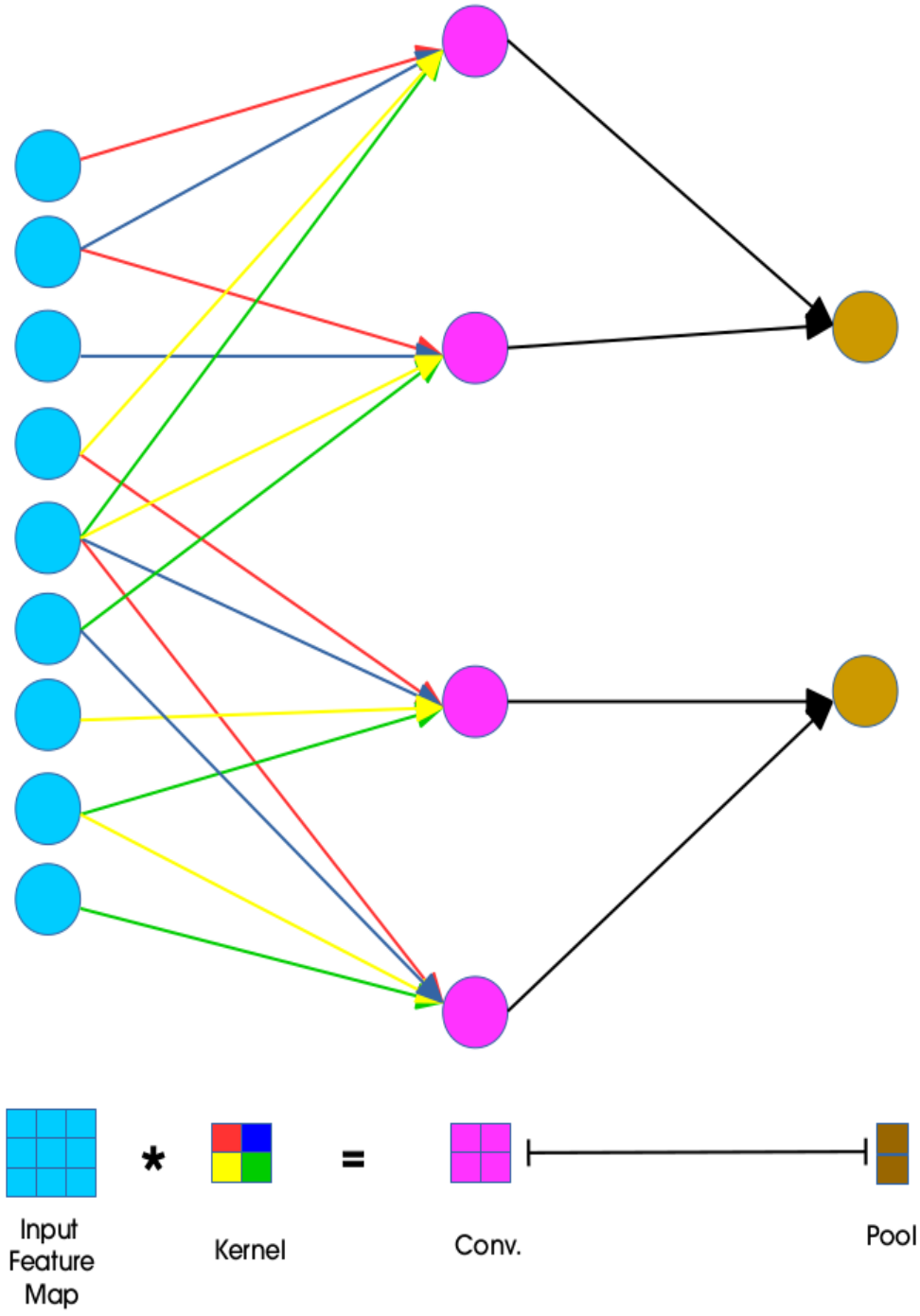
Compreendendo o treinamento...

Importante:

Atualização dos pesos e deltas.

Como uma mudança de um pixel no “weight kernel” afeta a função de perda?

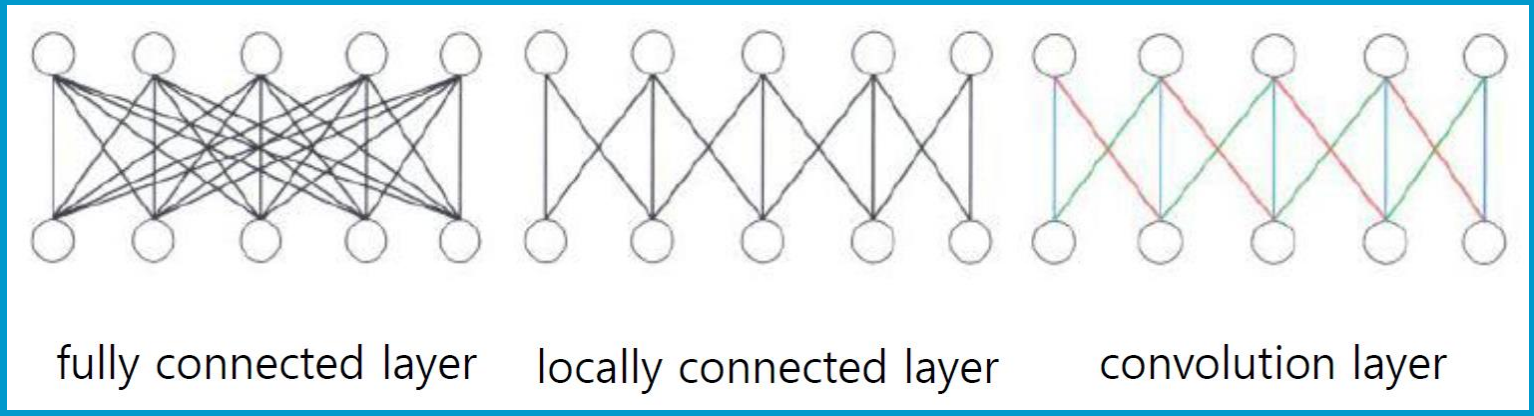




As unidades na camada convolucional têm campos receptivos de tamanho 4, portanto, somente estão conectados a 4 neurônios adjacentes na entrada.

Idéia de conectividade esparsa em CNNs onde existe padrão de conectividade local entre neurônios em camadas adjacentes.

Compreendendo o treinamento...



Pesos diferentes | Pesos diferentes | Pesos compartilhados

- **Logo, camada convolucional** possui um número muito menor de parâmetros em razão da conexão local e do compartilhamento de pesos

Compreendendo o treinamento...

No final teremos :

$$\frac{\partial E}{\partial w^l_{m',n'}} = \sum_{i=0}^{H-k_1} \sum_{j=0}^{W-k_2} \delta^l_{i,j} o^{l-1}_{i+m',j+n'}$$

$$= \mathrm{rot}_{180^\circ} \left\{ \delta^l_{i,j} \right\} * o^{l-1}_{m',n'}$$

$$\frac{\partial E}{\partial x^l_{i',j'}} = \sum_{m=0}^{k_1-1} \sum_{n=0}^{k_2-1} \delta^{l+1}_{i'-m,j'-n} w^{l+1}_{m,n} f' \left(x^l_{i',j'} \right)$$

$$= \mathrm{rot}_{180^\circ} \left\{ \sum_{m=0}^{k_1-1} \sum_{n=0}^{k_2-1} \delta^{l+1}_{i'+m,j'+n} w^{l+1}_{m,n} \right\} f' \left(x^l_{i',j'} \right)$$

$$= \delta^{l+1}_{i',j'} * \mathrm{rot}_{180^\circ} \left\{ w^{l+1}_{m,n} \right\} f' \left(x^l_{i',j'} \right)$$

Compreendendo o treinamento

Consiere o caso 1D:

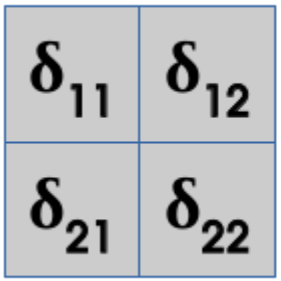
X^{l-1} = [a b c d e] (Entrada)

K = [k_1 k_2] (Kernel)

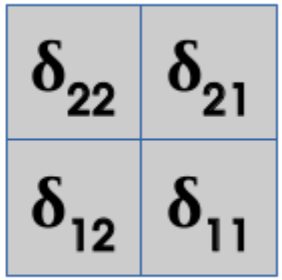
X^l = [a*k_1+b*k_2 b*k_1+c*k_2 c*k_1+d*k_2 d*k_1+e*k_2 e*k_1] (Saída)

Agora considere

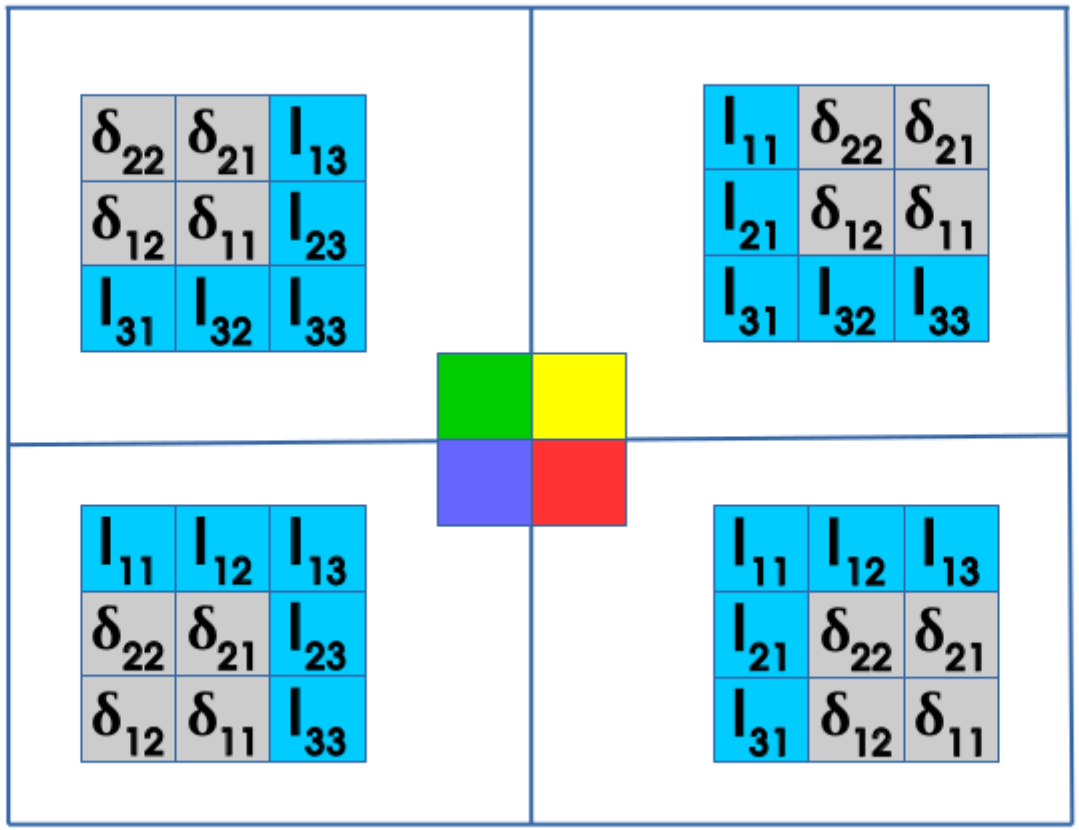
$\frac{\partial X^l}{\partial k_1}$ = [0 k_2 k_1 0 0] -- Kernel “flipped”.



Error matrix Flipped 180°



$$\delta_{i,j}^{l} = \frac{\partial E}{\partial x_{i,j}^{l}}$$



Compreendendo o treinamento...

Dicas de leitura:

A guide to convolution arithmetic for deep learning. stat 1050 (2016) - https://arxiv.org/pdf/1603.07285.pdf

http://jefkine.com/general/2016/09/05/backpropagation-in-convolutional-neural-networks/