

## Aula 06 – Redes Neurais Convolucionais

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#### Roteiro

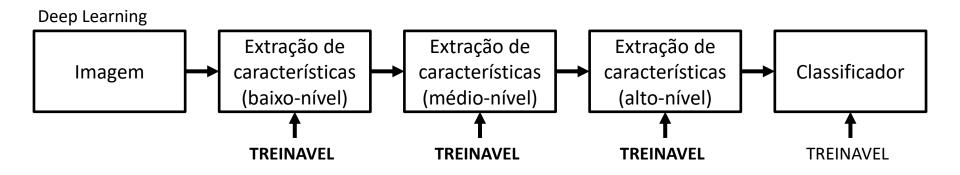


- Pipelines de classificação
- Perceptron de múltiplas camadas (MLP)
- Redes Neurais Convolucionais (CNNs)
- Camada convolucional
- Camada de pooling
- Função de ativação
- Camada completamente conectada
- Camada de saída softmax
- Função de perda (loss)
- Otimizadores
- Arquiteturas
- Bibliotecas e desenvolvimento
- Conjuntos de imagens

# Pipelines de classificação



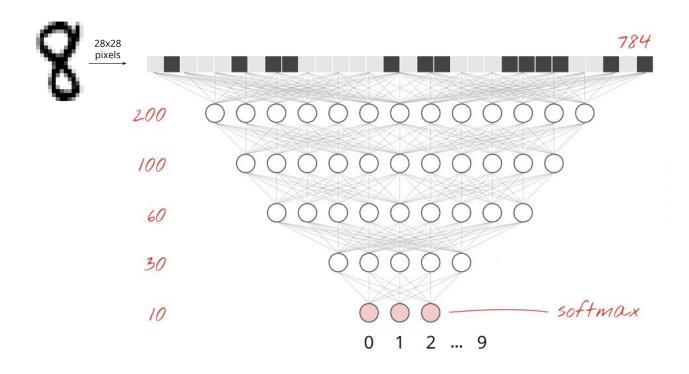




Yann LeCun's Deep Learning Course at CDS - SPRING 2021

# Perceptron de múltiplas camadas (MLP)

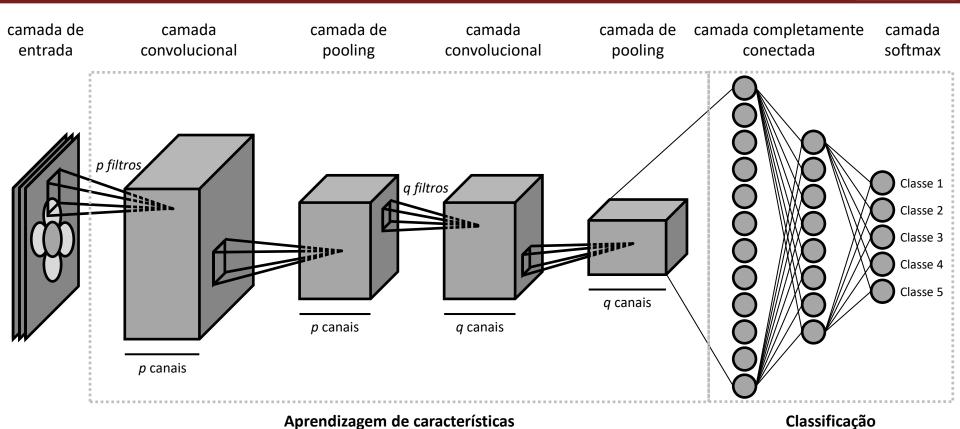




Learn TensorFlow and deep learning, without a Ph.D.

## Redes Neurais Convolucionais (CNNs)

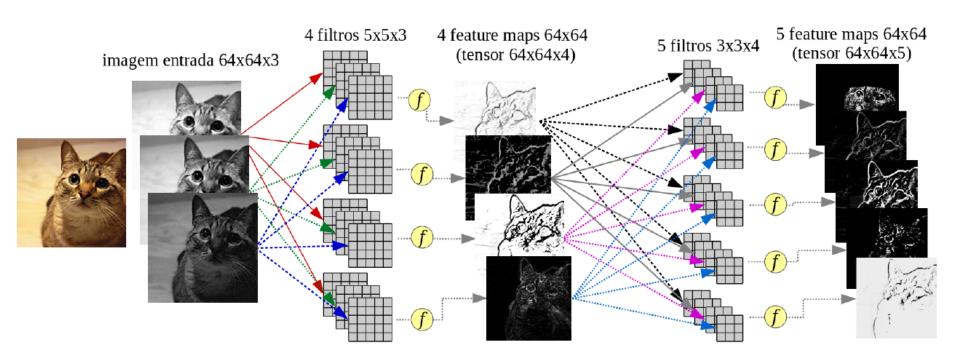






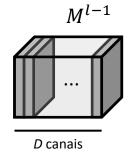
# **CAMADA CONVOLUCIONAL**



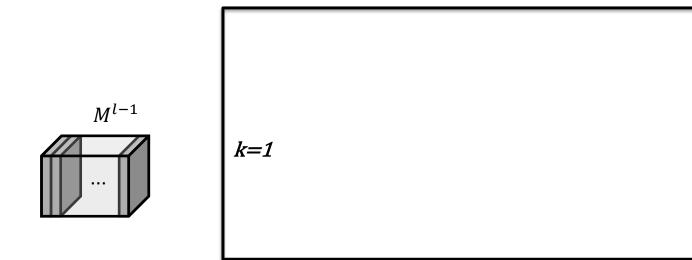


Moacir Ponti. <a href="http://conteudo.icmc.usp.br/pessoas/moacir/p17sibgrapi-tutorial/">http://conteudo.icmc.usp.br/pessoas/moacir/p17sibgrapi-tutorial/</a>

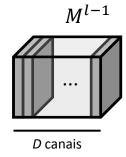


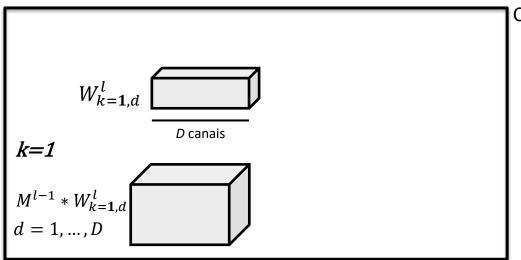




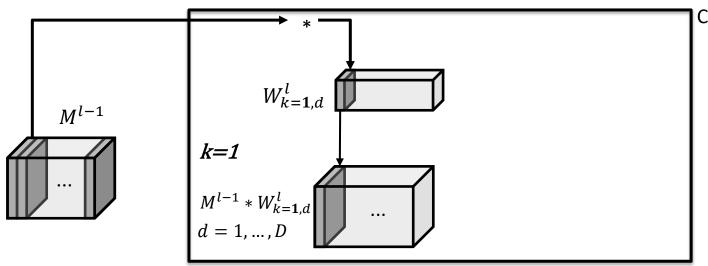




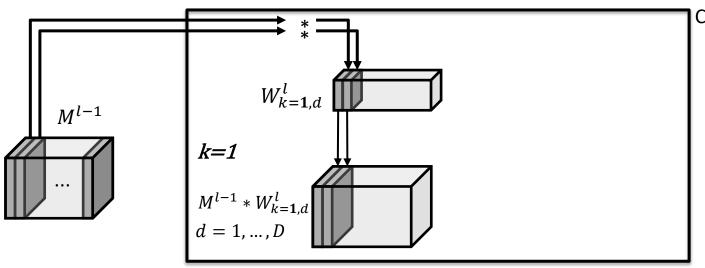






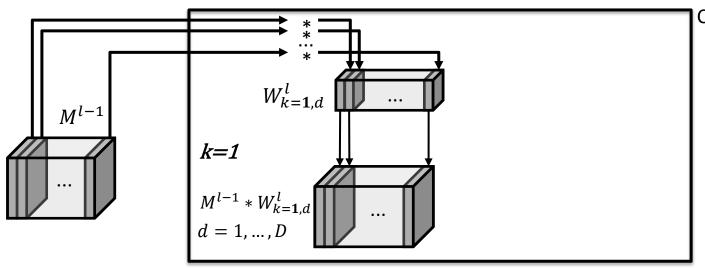






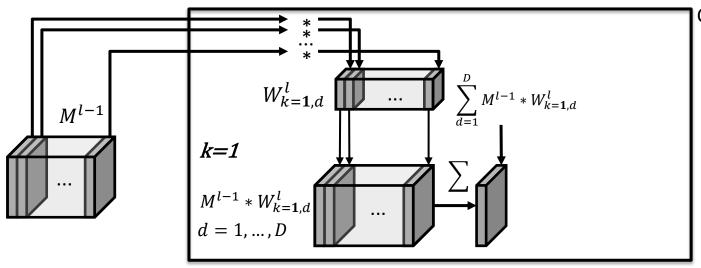
Camada convolucional  $\mathcal{C}^l$ 



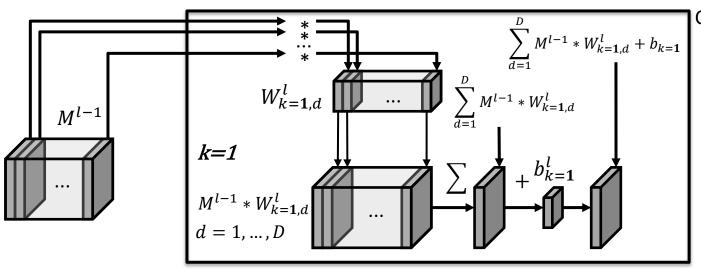


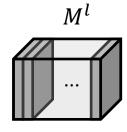
Camada convolucional  $\mathcal{C}^l$ 



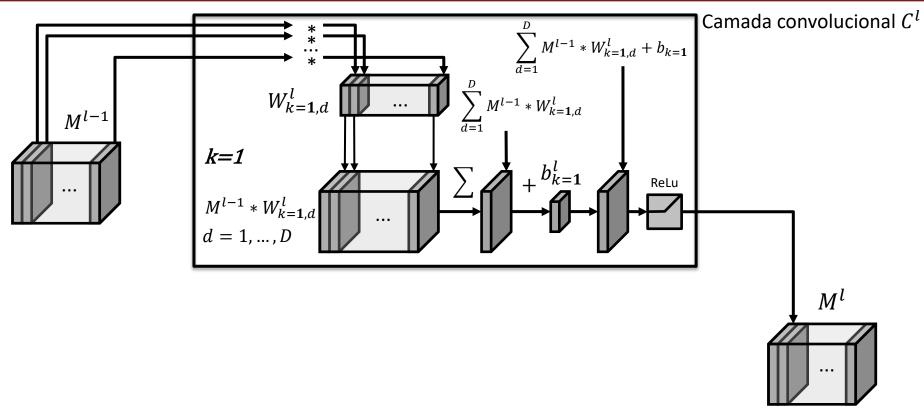




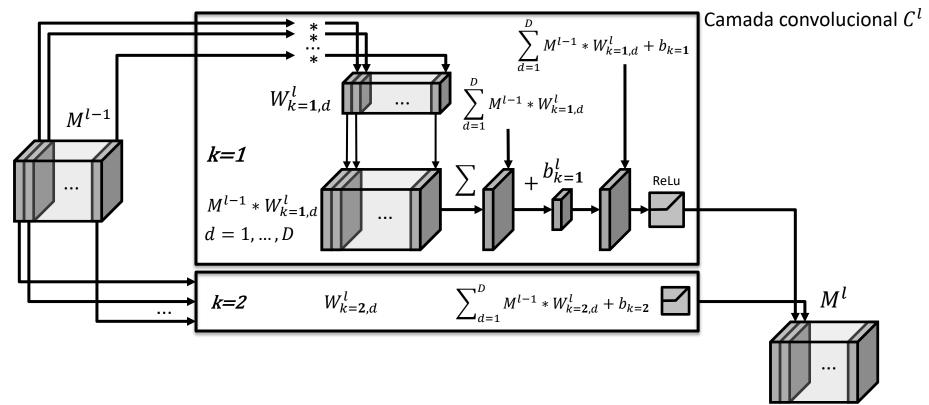




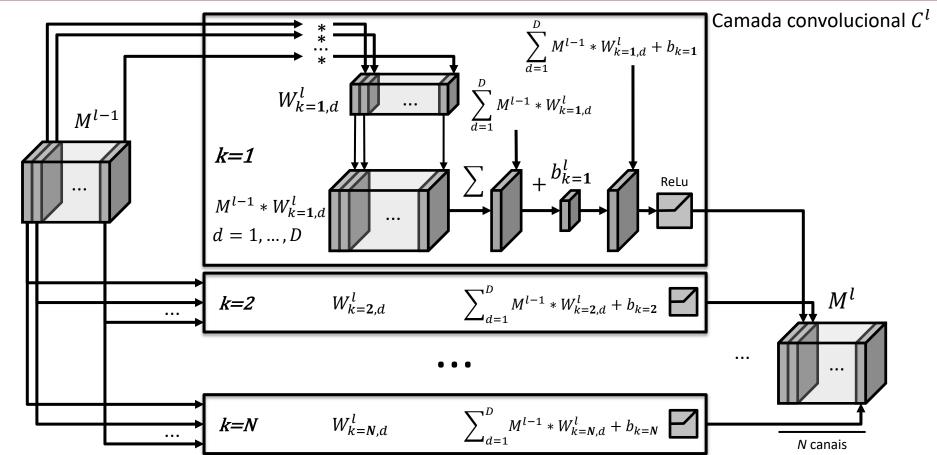




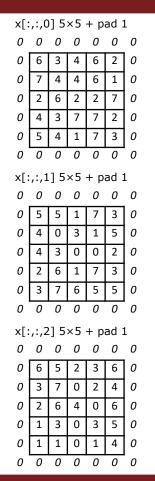


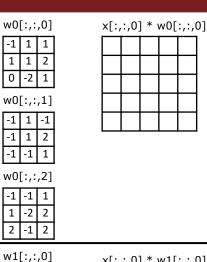


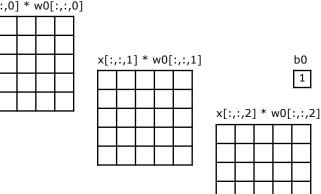


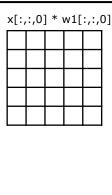


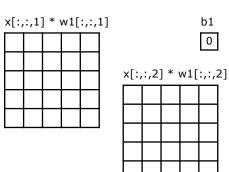












1

https://cs231n.github.io/convolutional-networks/

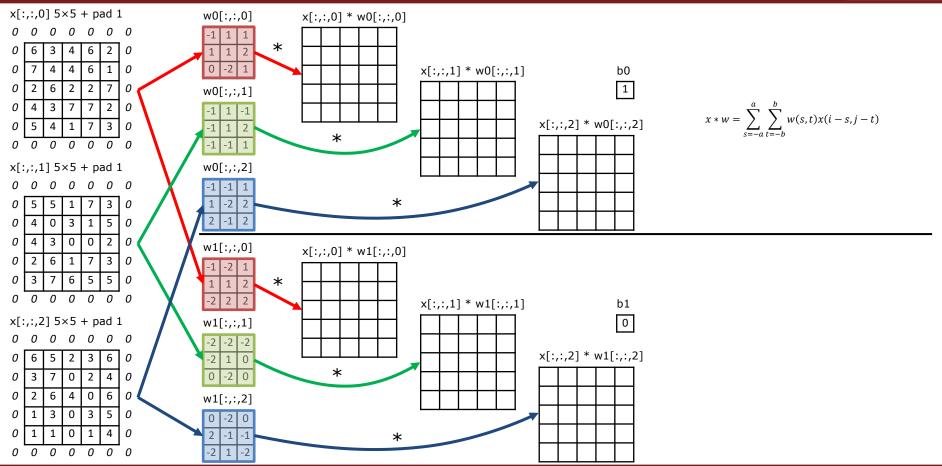
w1[:,:,1] -2 | -2 | -2

-2 1 0 0 -2 0

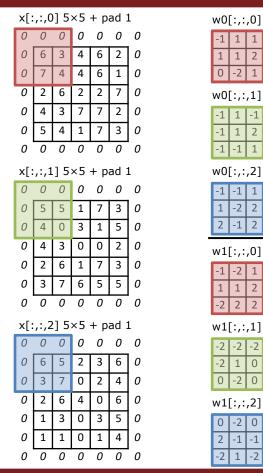
w1[:,:,2] 0 -2 0

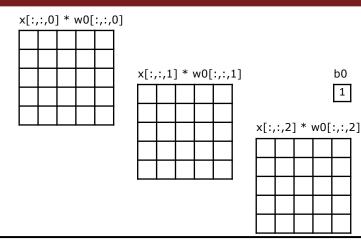
2 -1 -1

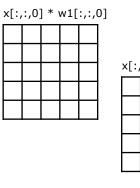


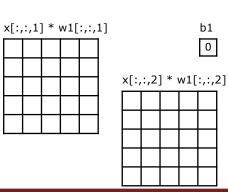




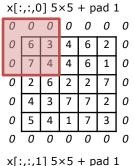


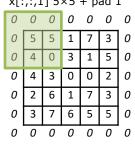


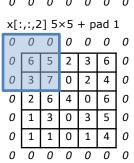










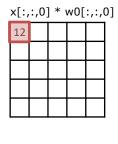


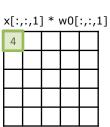
w0[:,:,0]							
-1	1	1					
1	1	2					
0	-2	1					
	_						
w0		,1]					
w0		,1] -1					
	[:,:						

w0[:,:,2]

0 -2 0

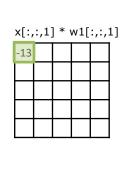
2 -1 -1

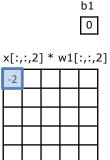




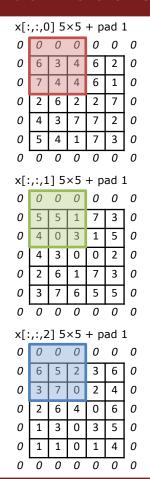
-	 						
						1	
		x[:,	:,2	] * '	]0w	:,:,	2]
		-17					
•							

w1	[:,:	,0]	] x[:,:,0] * w1[:,:,0]							0]
-1	-2	1			-9					ĺ
1	1	2				_				
-2	2	2			Н					
w1	[:,:	,1]								
-2	-2	-2								
-2	1	0								l
0	-2	0								
w1	[:,:	,2]	•							

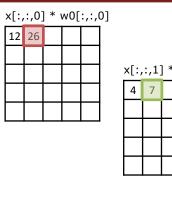




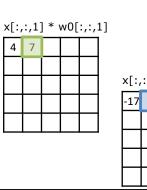


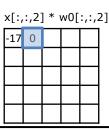




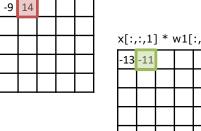


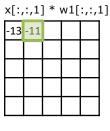
x[:,:,0] \* w1[:,:,0]





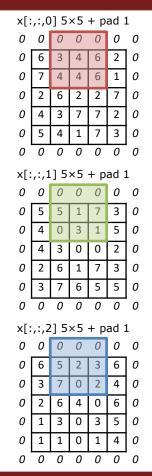
b0 1

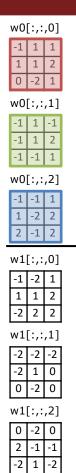


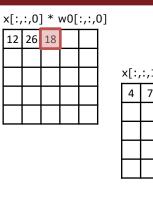


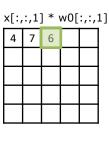
				ب	l
[:,	.:,2	] * '	w1[	:,:,	2]
-2	-21				

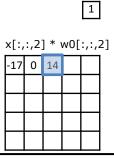






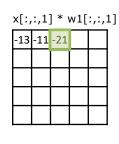


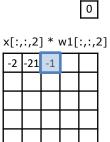




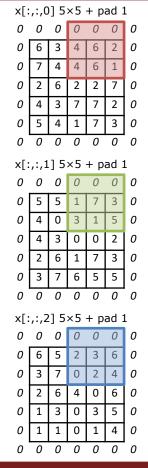
b0

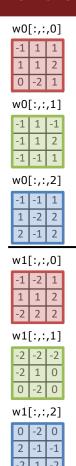
x[:,:,0] * w1[:,:,0]					
-9	14	6			

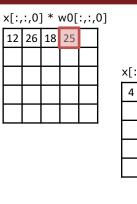


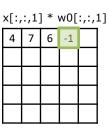








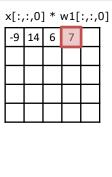


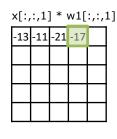


				1	
x[:,	:,2	] * ;	w0[	:,:,:	2]
-17	0	14	-2		

b0

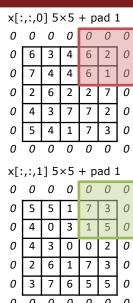
b1





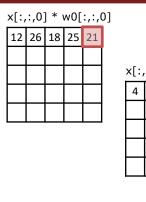
x[:,:,2] \* w1[:,:,2] -2 -21 -1 3

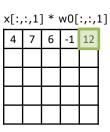




0	4	0	3	1	5	0	
0	4	3	0	0	2	0	,
0	2	6	1	7	3	0	
0	3	7	6	5	5	0	
0	0	0	0	0	0	0	
x[:	,:,2	2] 5	×5	+ p	ad 1	1	
0	0	0	0	0	0	0	
0	6	5	2	3	6	0	
0	3	7	0	2	4	0	
0	2	6	4	0	6	0	,
0	1	3	0	3	5	0	
0	1	1	0	1	4	0	
0	0	0	0	0	0	0	



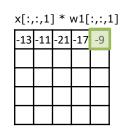




				_	
x[:,	:,2	] * ,	]0w	:,:,:	2]
-17	0	14	-2	-8	

b0

x[:,	x[:,:,0] * w1[:,:,0]						
-9	14	6	7	18			



				0	
x[:,	.,2	] * ,	w1[	:,:,2	2
-2	-21	-1	3	-17	
					ĺ



$x[:,:,0] 5 \times 5 + pad 1$									
0	0	0	0	0	0	0			
0	6	3	4	6	2	0			
0	7	4	4	6	1	0			
0	2	6	2	2	7	0			
0	4	3	7	7	2	0			
0	5	4	1	7	3	0			
0	0	0	0	0	0	0			
-	_		_						

- x[:,:,1] 5×5 + pad 1
  0 0 0 0 0 0 0 0
  0 5 5 1 7 3 0
  0 4 0 3 1 5 0
  0 4 3 0 0 2 0
  0 2 6 1 7 3 0
  0 3 7 6 5 5 0
- 0 0 0 0 0 0 0 0

  x[:,:,2] 5×5 + pad 1

  0 0 0 0 0 0 0 0

  0 6 5 2 3 6 0

  0 3 7 0 2 4 0

  0 2 6 4 0 6 0

  0 1 3 0 3 5 0

  0 1 1 0 1 4 0

w0[:,:,0]
-1 1 1
1 1 2
0 -2 1
w0[:,:,1]
-1 1 -1
-1 1 2

x[:	x[:,:,0] * w0[:,:,0]						
12	26	18	25	21			
-5							

	x[:,:,1] * w0[:,:,1					
	4	7	6	-1	12	
	-5					
Ī						
ĺ						

				<u> </u>			
x[:,:,2] * w0[:,:,2]							
-17	0	14	-2	-8			
-3							

b0

b1

w1[:,:,0]			
-1	-2	1	
1	1	2	
-2	2	2	

w0[:,:,2]

w1[:,:,1]					
-2	-2	-2			
-2	1	0			
0	-2	0			

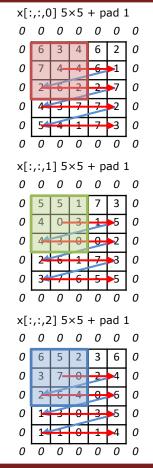
w1	[:,:	,2]
0	-2	0
2	-1	-1
-2	1	-2

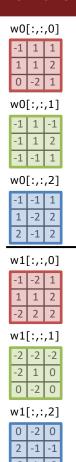
x[:,:,0] * w1[:,:,0]						
-9	14	6	7	18		
7						

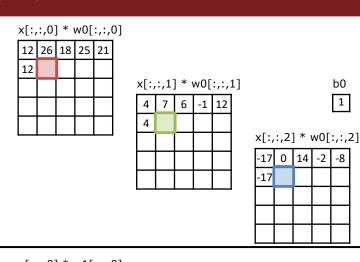
x[:,:,1] * w1[:,:,1					
-13	-11	-21	-17	-9	
-20					

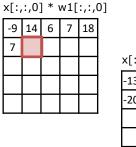
				0	
x[:,	.,2	] * ,	w1[	:,:,:	2
-2	-21	-1	3	-17	
3					
					l

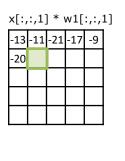


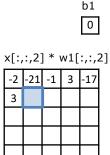






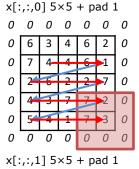






1





- $x[:,:,2] 5 \times 5 + pad 1$ 0 0

w0[:,:,0]				
	-1	1	1	
	1	1	2	
	0	-2	1	
	w0[::1]			

0	-2	1	
w0	[:,:	,1]	
-1	1	-1	
-1	1	2	
-1	-1	1	
w0[· · 2]			

WU[.,.,2]					
-1	-1	1			
1	-2	2			
2	-1	2			

w1[:,:,0]

w1[:,:,1]

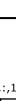
0 -2 0 w1[:,:,2] 0 -2 0 2 -1 -1

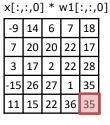
x[:,:,0] * w0[:,:,0						
12	26	18	25	21		
-5	28	19	4	24		
-5	11	15	17	24		
4	16	20	26	14		
1	16	5	5	20		

x[:,	:,1	] * v	0[	:,:,
4	7	6	-1	12
-5	3	-4	-9	13
-7	15	-10	-2	-6
-15	8	3	-2	15
-12	2	13	3	19
			,	

κ[:,	:,1	] * ·	]0w	:,:,	1]	
4	7	6	-1	12		
-5	3	-4	-9	13		
-7	15	-10	-2	-6		x[:
-15	8	3	-2	15		-17
-12	2	13	3	19		-3
			_		•	۵

				b0 1	
[:,	:,2	] * '	w0[	:,:,	2]
١7	0	14	-2	-8	
3	-5	32	11	-10	





	x[:,	:,1	* ı	w1[	:,:,
	-13	-11	-21	-17	-9
	-20	-30	-7	-27	-5
	-26	-15	-34	-28	-28
	-38	-34	-49	-31	-21
	-15	-17	-6	-19	-1
١				_	_

b1 0

15

⟨[:,	:,2	] * \	W1[	:,:,2	2
-2	-21	-1	3	-17	
3	-33	-25	-7	-18	
-3	-5	-28	-4	-16	
-7	-12	-5	-15	-10	
-4	-1	-11	0	-6	



x[:	,:,0	] 5	×5	+ p	ad :	1
0	0	0	0	0	0	0
0	6	3	4	6	2	0
0	7	4	4	6	1	0
0	2	6	2	2	7	0
0	4	3	7	7	2	0
0	5	4	1	7	3	0
0	0	0	0	0	0	0

- $x[:,:,1] 5 \times 5 + pad 1$ 4 0 4 6 3 6 5
- $x[:,:,2] 5 \times 5 + pad 1$ 2 3 6 0 6 5 3 0 0 3 1 0 1

- w0[:,:,0] w0[:,:,1]
- w0[:,:,2] 1 -2 2

w1[:,:,2]

0 -2 0

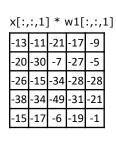
2 -1 -1

x[:,	:,0	] * \	w0[	:,:,	0]
12	26	18	25	21	
-5	28	19	4	24	
-5	11	15	17	24	
4	16	20	26	14	
1	16	5	5	20	

x[:,	:,1	] * \	w0[	:,:,
4	7	6	-1	12
-5	3	-4	-9	13
-7	15	-10	-2	-6
-15	8	3	-2	15
-12	2	13	3	19

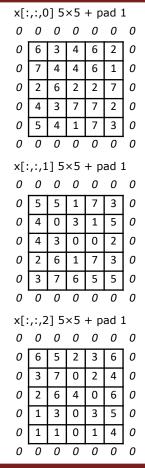
:,	:,1	] * \	w0[	:,:,	1]					b0	
ļ	7	6	-1	12						1	
5	3	-4	-9	13							
7	15	-10	-2	-6		x[:,	:,2	] * '	]0w	:,:,2	2]
5	8	3	-2	15		-17	0	14	-2	-8	
2	2	13	3	19		-3	-5	32	11	-10	
						9	-7	22	12	-14	
						9	2	17	14	-13	
						4	-1	15	9	-5	

w1[:,:,0] x[:,:,0] \* w1[:,:,0] -9 14 6 7 18 20 20 22 17 w1[:,:,1] -15 26 27 11 15 22 36 35 0 -2 0



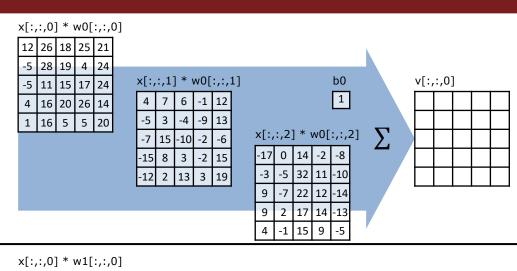
0 x[:,:,2] \* w1[:,:,2] -2 |-21 | -1 | 3 |-17 |-33|-25| -7 |-18 -28 -4 -16 -7 -12 -5 -15 -10 -1 -11 0

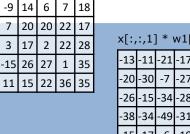


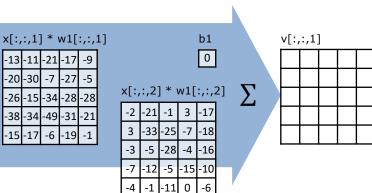


w0[:,:	,0]	
-1 1	1	
1 1	2	
0 -2	1	
w0[:,:	,1]	•
-1 1	-1	
-1 1	2	
-1 -1	1	
w0[:,:	,2]	
-1 -1	1	
1 -2	2	
2 -1	2	
2 -1 w1[:,:		
w1[:,:	,0]	
w1[:,:	,0] 1	
w1[:,:	,0] 1 2	
w1[:,: -1 -2 1 1 -2 2	,0] 1 2	
w1[:,: -1 -2 1 1 -2 2 w1[:,:	,0] 1 2 2 ,1]	
w1[:,: -1 -2 1 1 -2 2 w1[:,:	,0] 1 2 2 ,1]	
w1[:,: -1 -2 1 1 -2 2 w1[:,:	,0] 1 2 2 ,1] -2 0	
w1[:,: -1 -2 1 1 -2 2 w1[:,: -2 -2 -2 1 0 -2	,0] 1 2 2 ,1] -2 0	

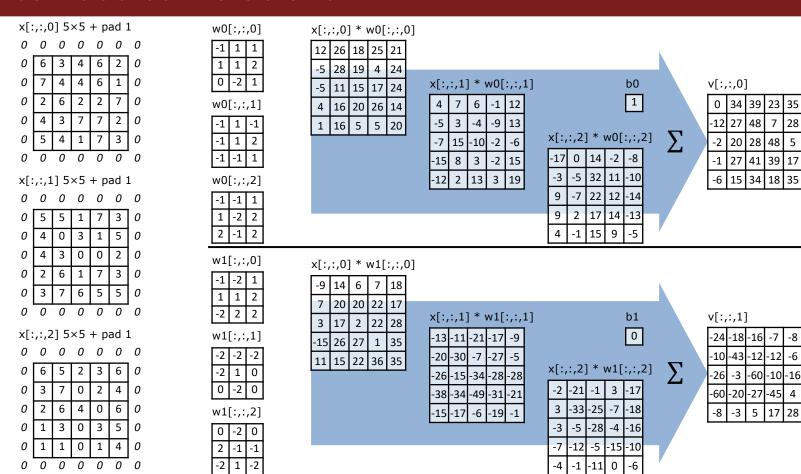
-2 1 -2



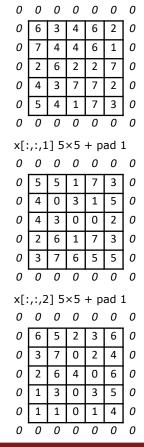








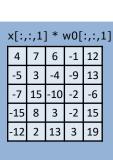


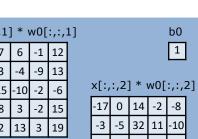


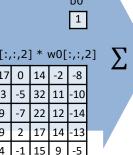
 $x[:,:,0] 5 \times 5 + pad 1$ 

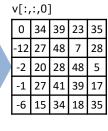
w0[:,:,0]  -1
w0[:,:,1]
-1 1 -1
-1 1 2
-1 -1 1
w0[:,:,2]
-1 -1 1
1 -2 2
2   -1   2
2 -1 2
w1[:,:,0]
w1[:,:,0]
w1[:,:,0]
w1[:,:,0] -1 -2 1 1 1 2
w1[:,:,0] -1 -2 1 1 1 2 -2 2 2
w1[:,:,0] -1 -2 1 1 1 2 -2 2 2 w1[:,:,1]
w1[:,:,0] -1 -2 1 1 1 2 -2 2 2 w1[:,:,1] -2 -2 -2
w1[:,:,0] -1 -2 1 1 1 2 -2 2 2 w1[:,:,1] -2 -2 -2 -2 1 0
w1[:,:,0] -1 -2 1 1 1 2 -2 2 2 w1[:,:,1] -2 -2 -2 -2 1 0 0 -2 0
w1[:,:,0] -1 -2 1 1 1 2 -2 2 2 w1[:,:,1] -2 -2 -2 -2 1 0 0 -2 0 w1[:,:,2]

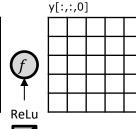


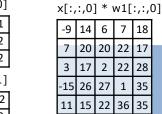


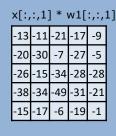


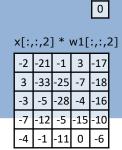


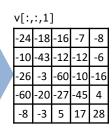


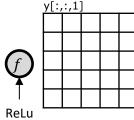




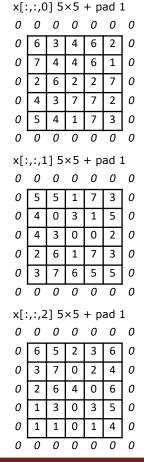










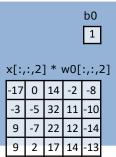


	w0	[:,:	,0]	
	-1	1	1	
	1	1	2	
	0	-2	1	
	w0	[:,:	,1]	
ĺ	-1	1	-1	
	-1	1	2	
	-1	-1	1	
	w0	[:,:	,2]	
	-1	-1	1	
	1	-2	2	
	`			
	2	-1	2	
_		-1 [:,:	_	
1			_	
_	w1	[:,:	,0]	
_	w1 -1	[:,: -2	,0] 1	
	w1 -1 1 -2	[:,: -2 1	,0] 1 2 2	
	w1 -1 1 -2	[:,: -2 1 2	,0] 1 2 2	
	w1 -1 1 -2 w1	[:,: -2 1 2	,0] 1 2 2 ,1]	
	w1 -1 -2 w1	[:,: -2 1 2 [:,:	,0] 1 2 2 ,1]	
	w1 1 -2 w1 -2 -2	[:,: -2 1 2 [:,: -2 1	,0] 1 2 2 ,1] -2 0 0	
	w1 1 -2 w1 -2 -2	[:,: -2 1 2 [:,: -2 1 -2	,0] 1 2 2 ,1] -2 0 0	
	w1 -1 1 -2 w1 -2 0	[:,: -2 1 2 [:,: -2 1 -2	,0] 1 2 2 ,1] -2 0 0	

-2 1 -2

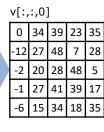


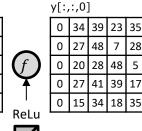


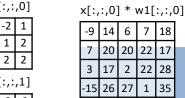


15 9

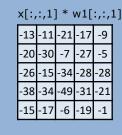
b1

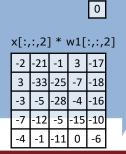


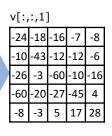


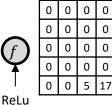


15 22 36 35









y[:,:,1]

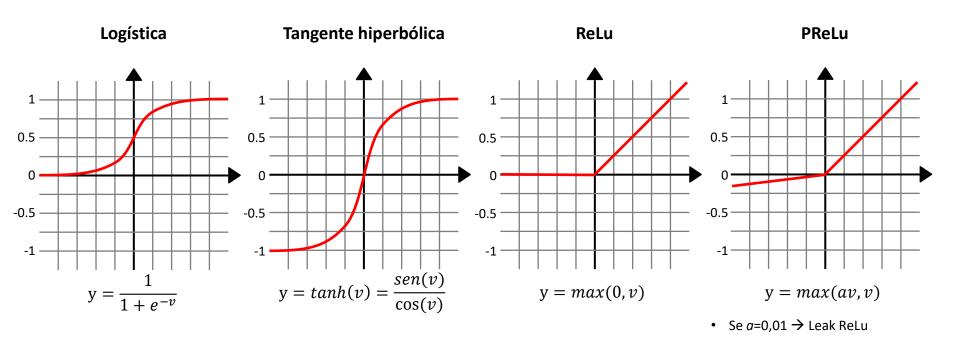




# FUNÇÃO DE ATIVAÇÃO

# Função de ativação

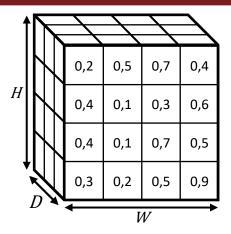




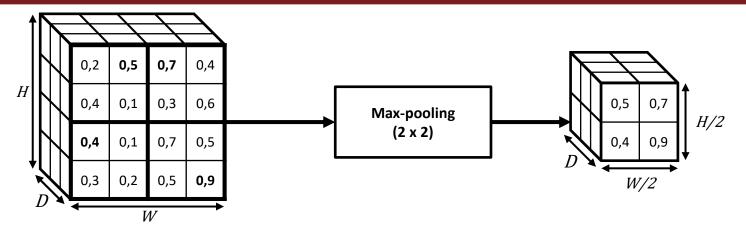


# **CAMADA DE POOLING**

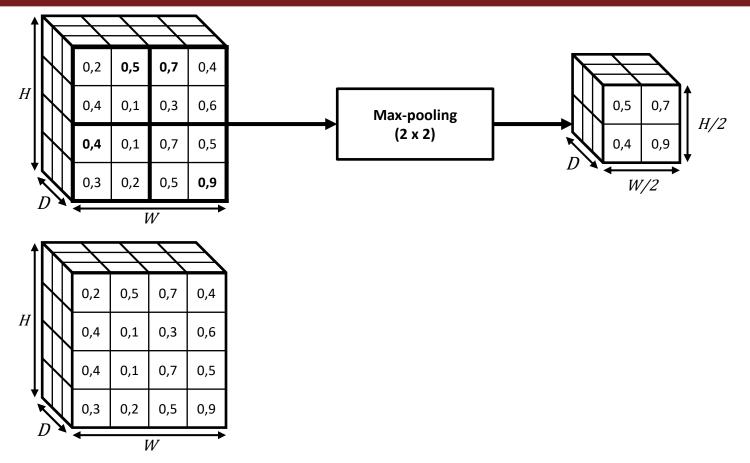




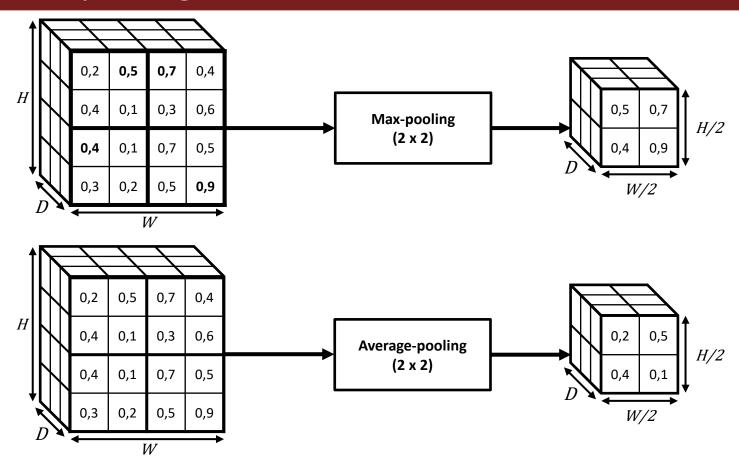










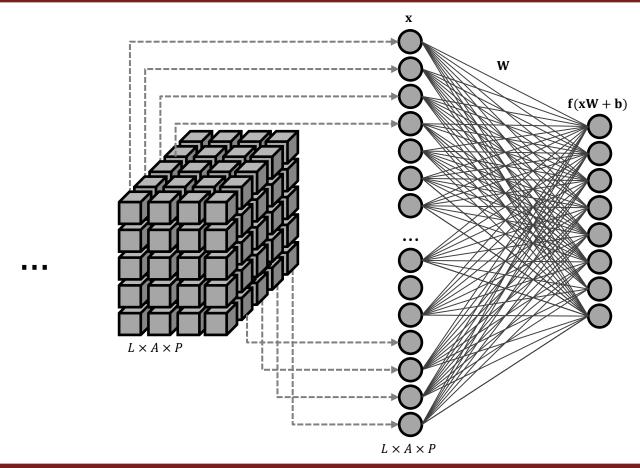




### CAMADA COMPLETAMENTE CONECTADA

# Camada completamente conectada







# CAMADA DE SAÍDA - SOFTMAX

#### Camada de saída – softmax



Função softmax para M classes:

$$- softmax(x_i) = \frac{e^{x_i}}{\sum_{j=0}^{M-1} e^{x_j}}$$

#### Exemplo:

- $\mathbf{x} = [-0.8 \ 2.0 \ 6.0 \ -2.7 \ 0.8]$ 
  - $\sum_{j=0}^{M-1} x_j = 5.3$
  - Soma != de 1,0. N\u00e3o pode ser interpretado como probabilidades.

$$-\sum_{j=0}^{M-1} e^{x_j} = 0,4493 + 7,3891 + 403,4288 + 0,0672 + 2,2255 = 413,5599$$

- $softmax(x_i) = [0.0011 \ 0.0179 \ 0.9755 \ 0.0002 \ 0.0054]$ 
  - $\sum_{i=0}^{M-1} softmax(x_i) = 1,0$
  - Representa a probabilidade da amostra pertencer a cada classe.



# FUNÇÃO DE PERDA (LOSS)

# Função de perda (loss)



Entropia cruzada para mais de 2 classes (M>2):

$$- L(\mathbf{y}, \widehat{\mathbf{y}}) = -\sum_{j=0}^{M-1} \mathbf{y}_j \cdot \log(\widehat{\mathbf{y}}_j)$$

Entropia cruzada para 2 classes (M=2):

$$-L(\mathbf{y},\widehat{\mathbf{y}}) = -(\mathbf{y} \cdot \log(\widehat{\mathbf{y}}) + (1-\mathbf{y})\log(1-\widehat{\mathbf{y}}))$$

#### Entropia cruzada para M>2



- 5 classes, classificação **correta**, com 72% de probabilidade:
  - $y = [0 \quad 0 \quad 0 \quad 1 \quad 0]$
  - $-\hat{y} = [0.20 \ 0.0 \ 0.05 \ 0.72 \ 0.03]$
  - $L(\mathbf{y}, \widehat{\mathbf{y}}) = -(0 \times \log 0.2 + 0 \times \log 0.0 + 0 \times \log 0.5 + 1 \times \log 0.72 + 0 \times \log 0.03)$
  - $L(\mathbf{y}, \widehat{\mathbf{y}}) = -(\log 0.72) = 0.14267$

#### Entropia cruzada para M>2



- 5 classes, classificação **correta**, com 72% de probabilidade:
  - $y = [0 \quad 0 \quad 0 \quad 1 \quad 0]$   $\hat{y} = [0,20 \quad 0,0 \quad 0,05 \quad 0,72 \quad 0,03]$   $L(y,\hat{y}) = -(0 \times \log 0,2 + 0 \times \log 0,0 + 0 \times \log 0,5 + 1 \times \log 0,72 + 0 \times \log 0,03)$   $L(y,\hat{y}) = -(\log 0,72) = 0,14267$
- 5 classes, classificação correta, com 52% de probabilidade:
  - $\mathbf{y} = [0 \quad 0 \quad 0 \quad 1 \quad 0]$   $\hat{\mathbf{y}} = [0,30 \quad 0,0 \quad 0,05 \quad 0,52 \quad 0,13]$   $L(\mathbf{y},\hat{\mathbf{y}}) = -(0 \times \log 0,3 + 0 \times \log 0,0 + 0 \times \log 0,5 + 1 \times \log 0,52 + 0 \times \log 0,13)$   $L(\mathbf{y},\hat{\mathbf{y}}) = -(\log 0,52) = 0,284$

#### Entropia cruzada para M>2



5 classes, classificação correta, com 72% de probabilidade:

$$- y = [0 \quad 0 \quad 0 \quad 1 \quad 0]$$

$$- \hat{y} = [0,20 \quad 0,0 \quad 0,05 \quad 0,72 \quad 0,03]$$

$$- L(y,\hat{y}) = -(0 \times \log 0,2 + 0 \times \log 0,0 + 0 \times \log 0,5 + 1 \times \log 0,72 + 0 \times \log 0,03)$$

$$- L(y,\hat{y}) = -(\log 0,72) = 0,14267$$

• 5 classes, classificação **correta**, com 52% de probabilidade:

$$- y = [0 \quad 0 \quad 0 \quad 1 \quad 0]$$

$$- \hat{y} = [0,30 \quad 0,0 \quad 0,05 \quad 0,52 \quad 0,13]$$

$$- L(y,\hat{y}) = -(0 \times \log 0,3 + 0 \times \log 0,0 + 0 \times \log 0,5 + 1 \times \log 0,52 + 0 \times \log 0,13)$$

$$- L(y,\hat{y}) = -(\log 0,52) = 0,284$$

5 classes, classificação incorreta:

$$- y = [0 \quad 0 \quad 0 \quad 1 \quad 0]$$

$$- \hat{y} = [0,60 \quad 0,0 \quad 0,07 \quad 0,30 \quad 0,03]$$

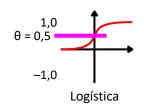
$$- L(y,\hat{y}) = -(0 \times \log 0,6 + 0 \times \log 0,0 + 0 \times \log 0,07 + 1 \times \log 0,3 + 0 \times \log 0,03)$$

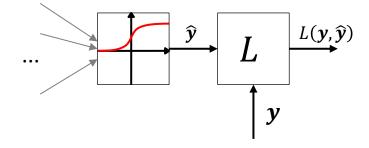
$$- L(y,\hat{y}) = -(\log 0,3) = 0,5229$$

#### Entropia cruzada para M=2



- 2 classes, classificação correta:
  - y = [0]
  - $\hat{y} = [0,20]$
  - $L(\mathbf{y}, \hat{\mathbf{y}}) = -(0 \times \log 0.2 + (1 0) \times \log(1 0.2))$
  - $L(\mathbf{y}, \hat{\mathbf{y}}) = -(0 \times \log 0.2 + (1) \times \log(0.8)) = -(\log(0.8)) = 0.09691$



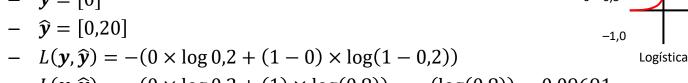


#### Entropia cruzada para M=2

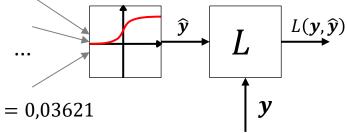


- 2 classes, classificação correta:
  - y = [0]

 $-L(\mathbf{y}, \hat{\mathbf{y}}) = -(0 \times \log 0.2 + (1) \times \log(0.8)) = -(\log(0.8)) = 0.09691$ 



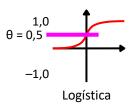
- 2 classes, classificação correta:
  - y = [1]
  - $-\hat{y} = [0.92]$
  - $-L(\mathbf{y}, \hat{\mathbf{y}}) = -(1 \times \log 0.92 + (1-1) \times \log(1-0.92))$
  - $-L(\mathbf{y}, \hat{\mathbf{y}}) = -(1 \times \log 0.92 + (0) \times \log(0.08)) = -(\log(0.92)) = 0.03621$



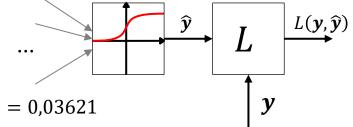
#### Entropia cruzada para M=2



- 2 classes, classificação correta:
  - y = [0]
  - $\hat{y} = [0,20]$
  - $L(\mathbf{y}, \hat{\mathbf{y}}) = -(0 \times \log 0.2 + (1 0) \times \log(1 0.2))$
  - $L(\mathbf{y}, \hat{\mathbf{y}}) = -(0 \times \log 0.2 + (1) \times \log(0.8)) = -(\log(0.8)) = 0.09691$



- 2 classes, classificação correta:
  - y = [1]
  - $-\hat{y} = [0.92]$
  - $L(\mathbf{y}, \hat{\mathbf{y}}) = -(1 \times \log 0.92 + (1 1) \times \log(1 0.92))$
  - $L(\mathbf{y}, \widehat{\mathbf{y}}) = -(1 \times \log 0.92 + (0) \times \log(0.08)) = -(\log(0.92)) = 0.03621$



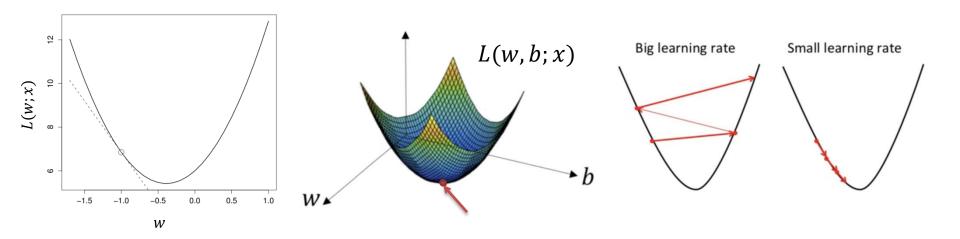
- 2 classes, classificação incorreta:
  - y = [0]
  - $\hat{y} = [0.65]$
  - $L(\mathbf{y}, \hat{\mathbf{y}}) = -(0 \times \log 0.65 + (1 0) \times \log(1 0.65))$
  - $L(\mathbf{y}, \hat{\mathbf{y}}) = -(0 \times \log 0.65 + (1) \times \log(0.35)) = -(\log(0.35)) = 0.45593$



# **OTIMIZADORES**



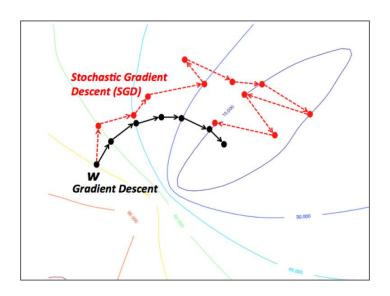
- Gradiente descendente (GD Gradient descent):
  - $W_{t+1} = W_t \eta \sum_{j=1}^N \nabla L(W; x_j)$
  - N é o tamanho do conjunto de treinamento



Donges. Gradient Descent in Machine Learning: A Basic Introduction. <u>https://builtin.com/data-science/gradient-descent</u>



- Gradiente descendente estocástico (SGD *Stochastic gradient descent*):
  - $W_{t+1} = W_t \eta \sum_{j=1}^{B} \nabla L(W; x_j^B)$
  - Bé o tamanho do mini-lote (mini-batch)

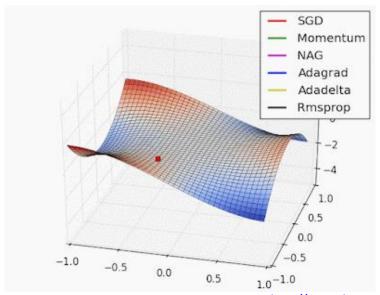


https://wikidocs.net/3413



- SGD com momentum:
  - $W_{t+1} = W_t \eta \sum_{j=1}^B \nabla L(W; x_j^B)$ 
    - *B* é o tamanho do mini-lote (*mini-batch*)

$$- W_{t+1} = W_t + \alpha (W_t - W_{t-1}) + (1 - \alpha) [-\eta \sum_{j=1}^B \nabla L(W; x_j^B)]$$



http://www.denizyuret.com/2015/03/alec-radfords-animations-for.html



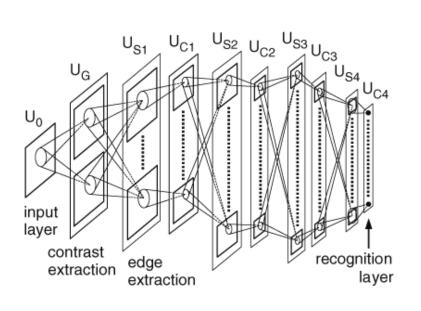
- Outros otimizadores:
  - AdaGrad Adaptive Gradient
  - AdaDelta Adaptive learning rate
  - RMSProp Root Mean Squared Propagation
  - Adam Adaptive moment estimation
  - **–** ...

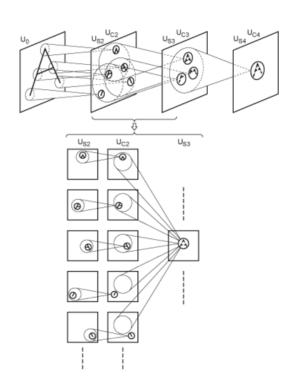


# **ARQUITETURAS**



Neocognitron (1979)





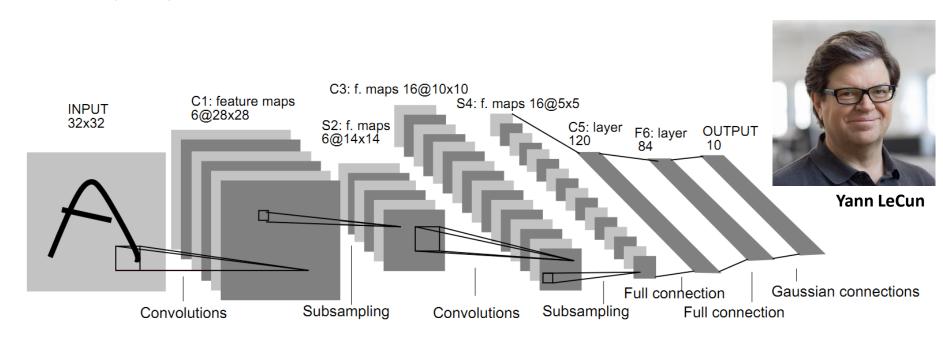


Kunihiko Fukushima

Fukushima, K. (1980). "Neocognitron: A self-organizing neural network model for a mechanism of pattern recognition unaffected by shift in position". Biological Cybernetics. 36 (4)



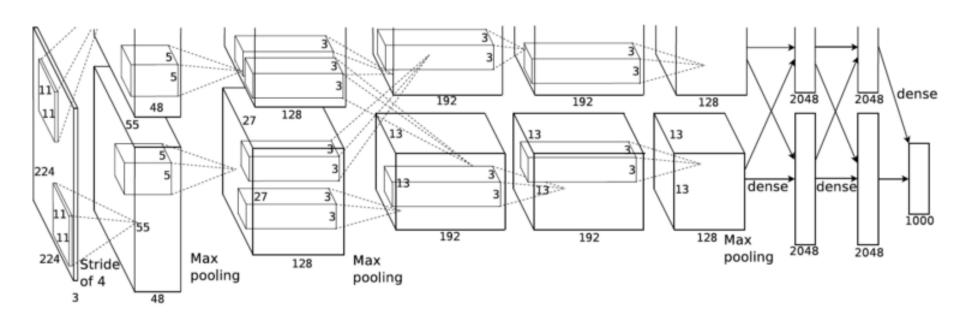
LeNet-5 (1998)



Lecun, Y. et al. (1998). "Gradient-based learning applied to document recognition". Proceedings of the IEEE. 86 (11): 2278–2324.



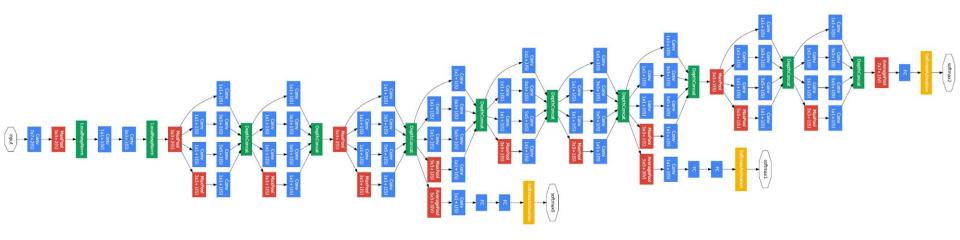
AlexNet (2012)



Krizhevsky, Sutskever e Hinton. ImageNet Classification with Deep Convolutional Neural Networks. NeuripIPS 2012



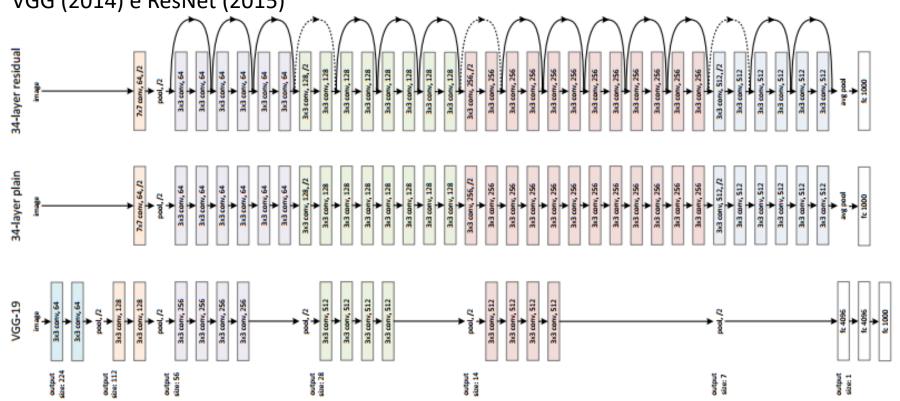
• Inception (GoogLeNet) (2015)



Szegedy, Christian (2015). "Going deeper with convolutions". CVPR2015.



VGG (2014) e ResNet (2015)



Simonyan e Zisserman. Very Deep Convolutional Networks for Large-Scale Image Recognition. 2014

He et al. Deep Residual Learning for Image Recognition. 2015.

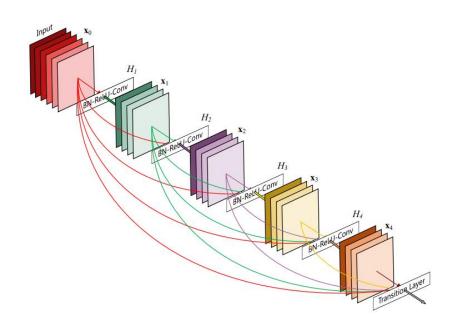


DenseNet (2017)



Transition (BN+Conv+Pool) BN

Figure 10. Illustration of a DenseBlock with 5 functions  $H_1$  and a Transition Layer.



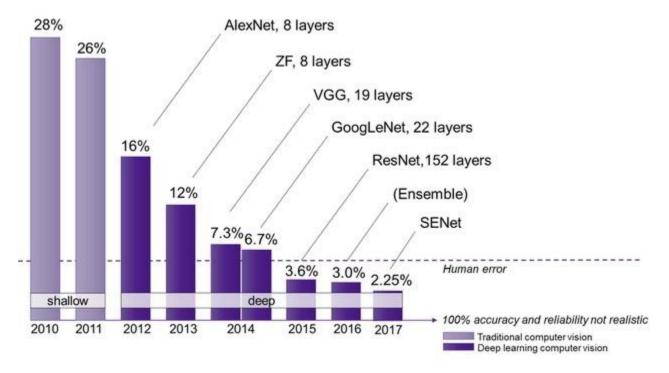
Huang et al. Densely Connected Convolutional Networks. CVPR 2017.

**Figure 1:** A 5-layer dense block with a growth rate of k = 4. Each layer takes all preceding feature-maps as input.

Ponti et al. Everything You Wanted to Know about Deep Learning for Computer Vision but Were Afraid to Ask. Sibgrapi 2017.



- ImageNet Large Scale Visual Recognition Challenge
  - https://image-net.org/challenges/LSVRC/



https://semiengineering.com/new-vision-technologies-for-real-world-applications/



# **BIBLIOTECAS E DESENVOLVIMENTO**

#### Bibliotecas e desenvolvimento



- O treinamento de CNNs possui alto custo computacional.
  - Recomenda-se que sejam treinados usando GPUs.
  - O Google Colab fornece acesso à GPUs (com algumas restrições).





#### Bibliotecas e desenvolvimento



- Principais bibliotecas para Deep Learning e Redes Neurais Convolucionais
  - PyTorch
    - https://pytorch.org/
  - Tensorflow
    - https://www.tensorflow.org/





#### Bibliotecas e desenvolvimento



- Anaconda Distribution:
  - Distribuição Python com suporte às principais bibliotecas
  - https://www.anaconda.com/products/distribution
- Google Colab:
  - Ambiente de execução em nuvem com GPUs.
  - https://colab.research.google.com







# **CONJUNTOS DE IMAGENS**



- MNIST
  - http://yann.lecun.com/exdb/mnist/
  - 60,000 training images
  - 10,000 testing images
  - 28 x 28 pixels
  - Níveis de cinza





#### Cats vs. Dogs:

- <a href="https://www.kaggle.com/c/dogs-vs-cats">https://www.kaggle.com/c/dogs-vs-cats</a>
- 25,000 images de treinamento
- 12,500 imagens de teste
- 2 classes
- Diversos tamanhos
- RGB

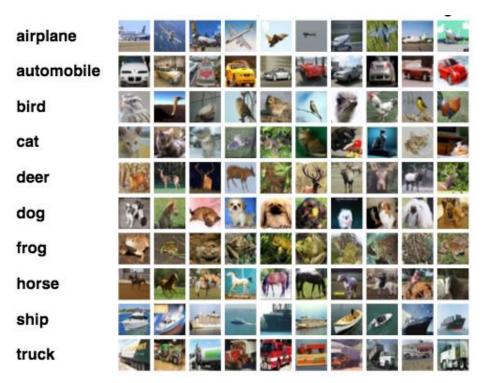


Sample of cats & dogs images from Kaggle Dataset



#### CIFAR10:

- https://www.cs.toronto.edu/~kriz/cifar.html
- 50,000 training images
- 10,000 testing images
- 10 classes
- 32 x 32 pixels
- RGB

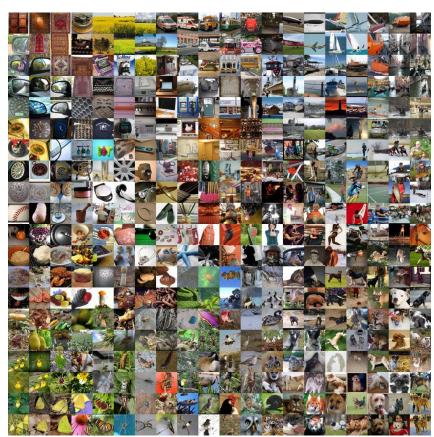




#### ImageNet:

- https://www.image-net.org/
- ~1,000,000 imagens
- 1,000 classes
- RGB





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# FIM