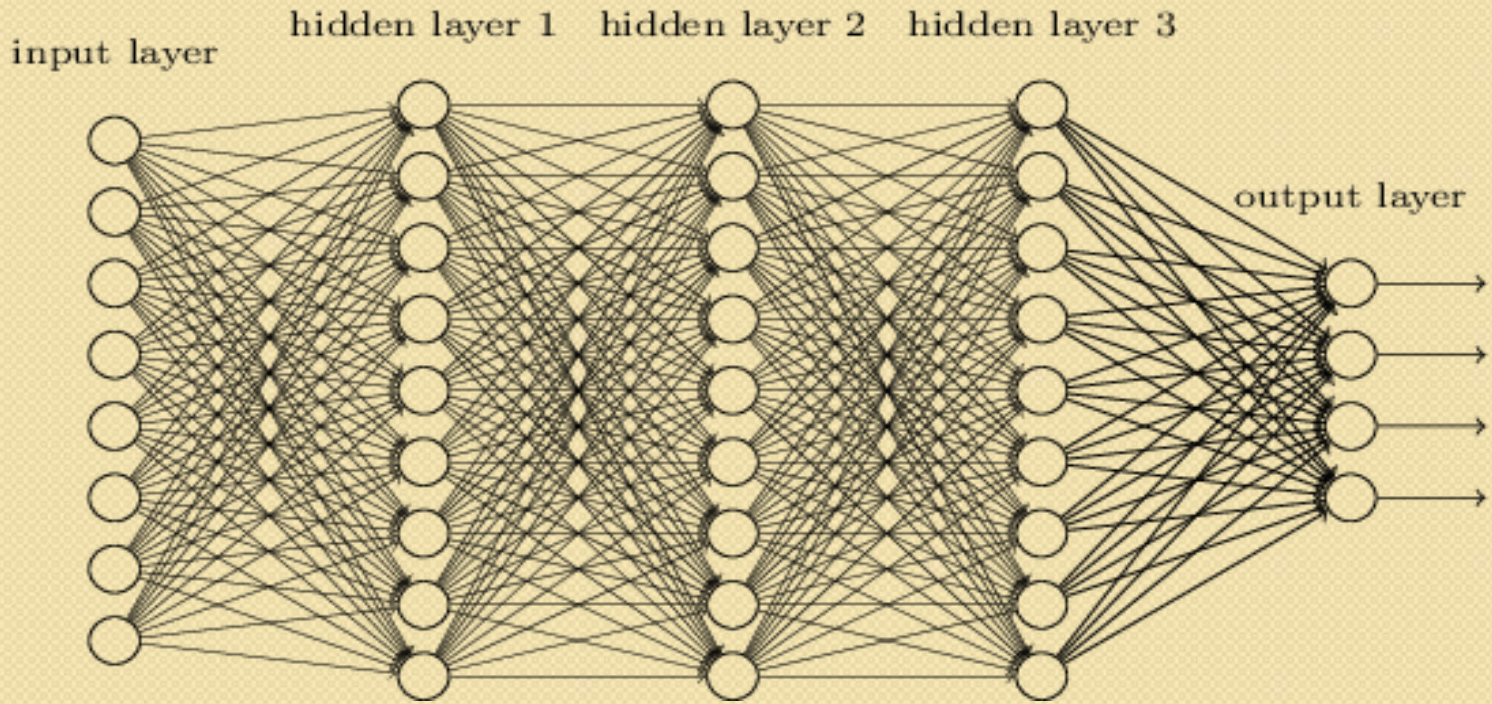
Redes Convolucionais e *Deep Learning*

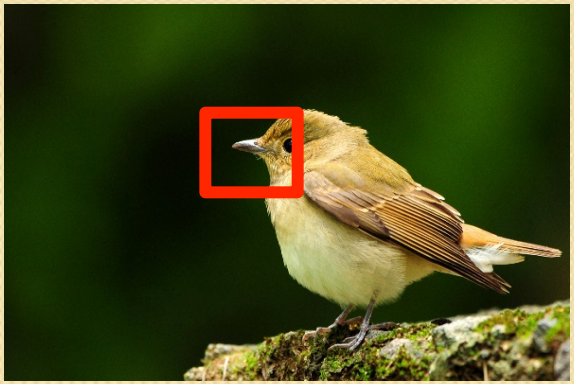
Germano C. Vasconcelos
Centro de Informática - UFPE

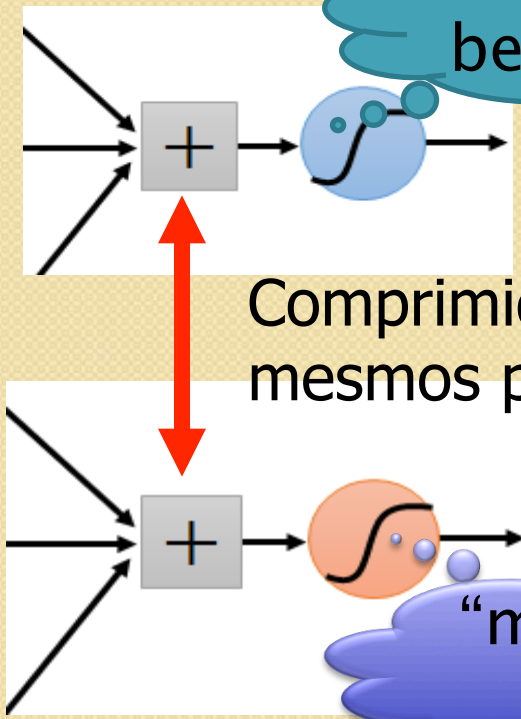
Estrutura Feedforward Tradicional

- Rede Totalmente Conectada (Fully Connected)



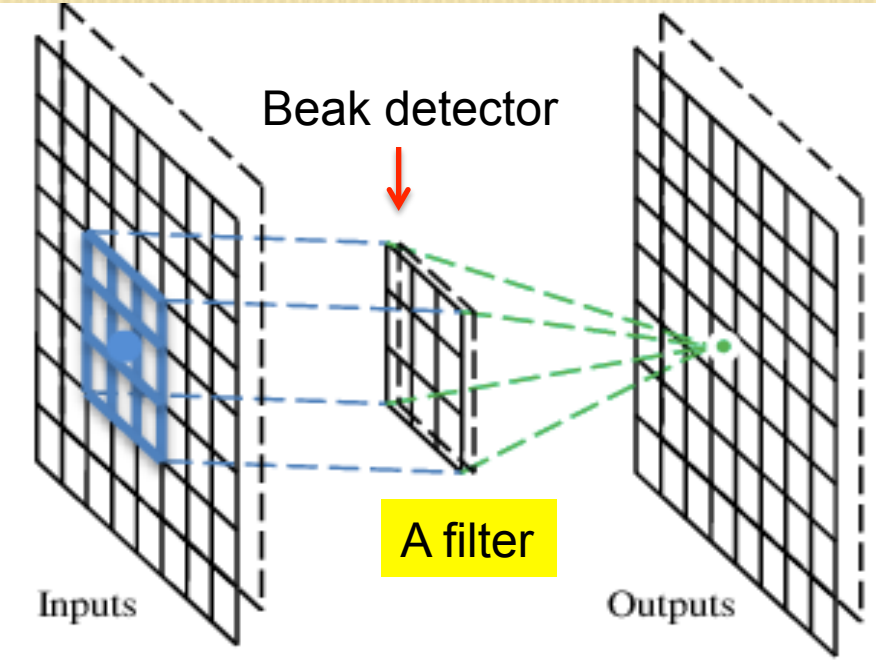
Como Lidar com Padrões em Áreas Diferentes?
Que tal detectores em áreas diferentes?





1o Passo: Camada Convolucional

- CNN: rede neural com camadas convolucionais e outras camadas
- Camada convolucional: filtros que fazem operação de convolução



Convolução

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

6 x 6 image

Parâmetros a serem aprendidos!

1	−1	−1
−1	1	−1
−1	−1	1

Filtro 1

−1	1	−1
−1	1	−1
−1	1	−1

Filtro 2

⋮ ⋮

Cada filtro detecta pequeno padrão(3 x 3)

Convolução

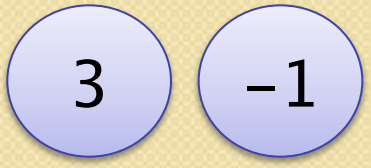
1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

stride=1

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

Dot product →



6 x 6 image

Convolução

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

Filter 1

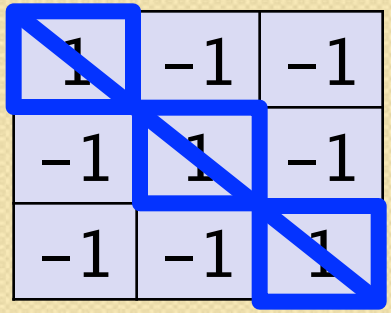
If stride=2

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

6 x 6 image

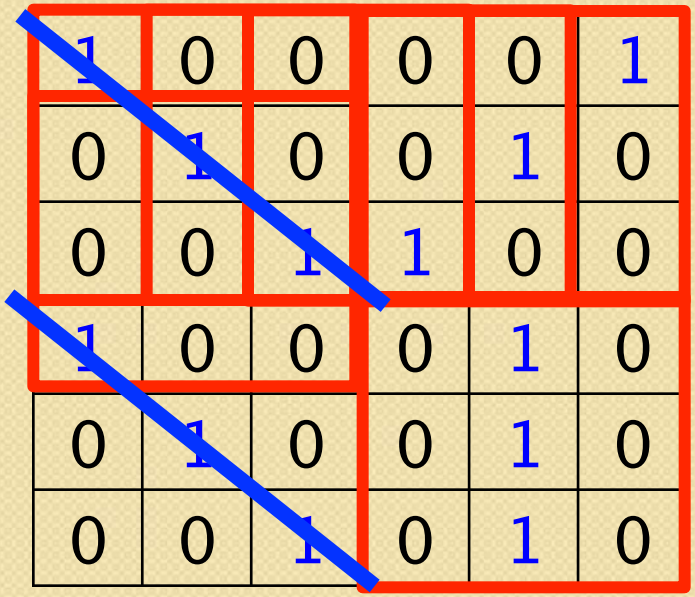
3 -3

Convolução

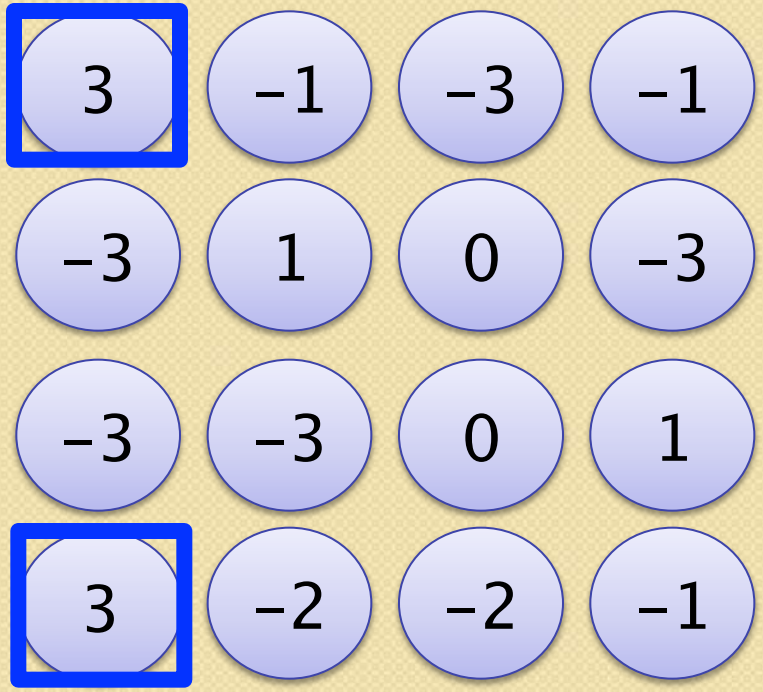


Filtro 1

stride=1



6 x 6 image



Convolução

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

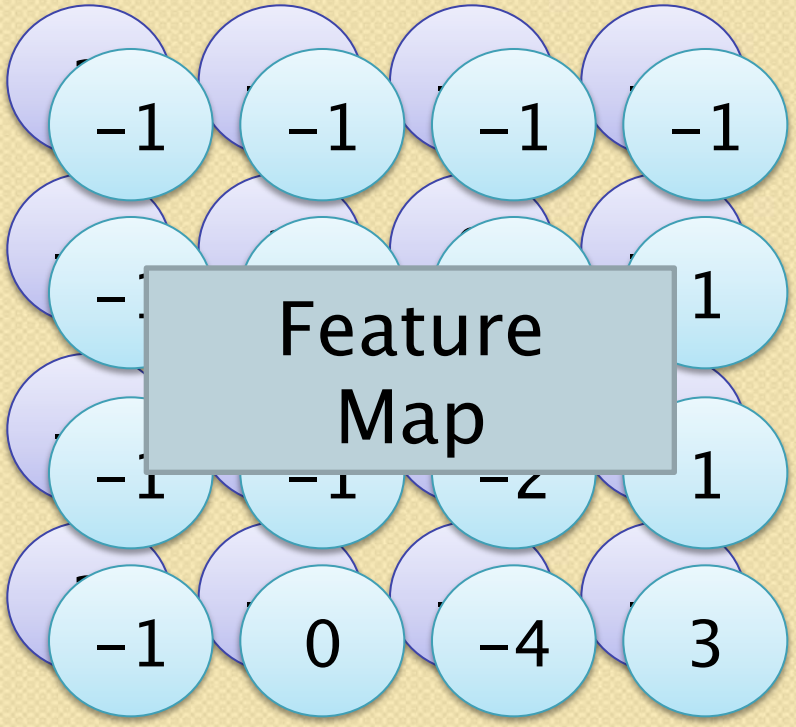
Filtro 2

stride=1

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

6 x 6 image

Repita para cada filtro



Duas imagens 4 x 4

Formando matriz 2 x 4 x 4

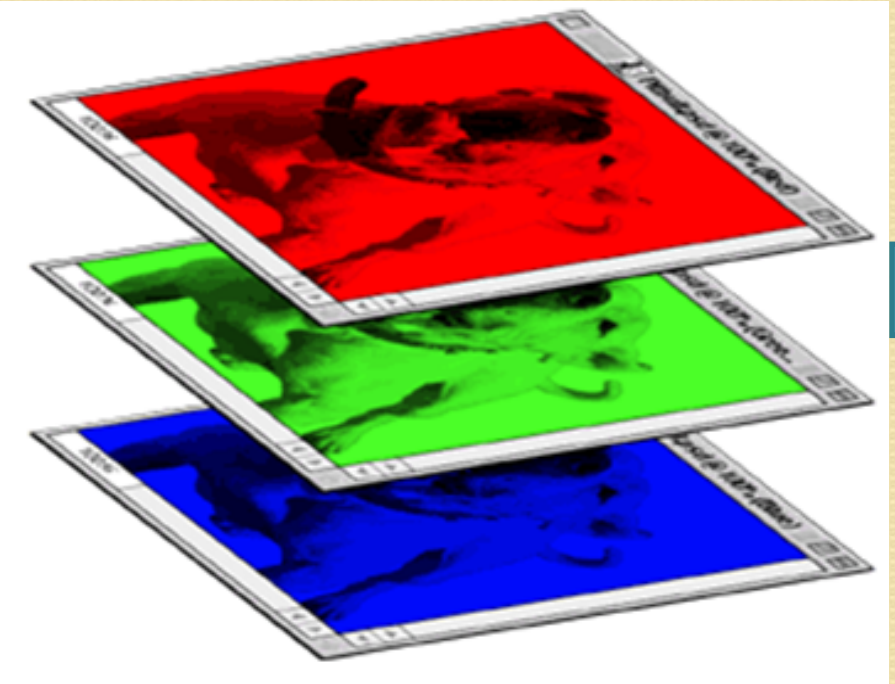
Imagem Colorida: 3 Canais RG

1	−1	−1
−1	1	−1
−1	−1	1

Filtro 1

−1	1	−1
−1	1	−1
−1	1	−1

Filtro 2



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

Convolução vs Totalmente Conectada

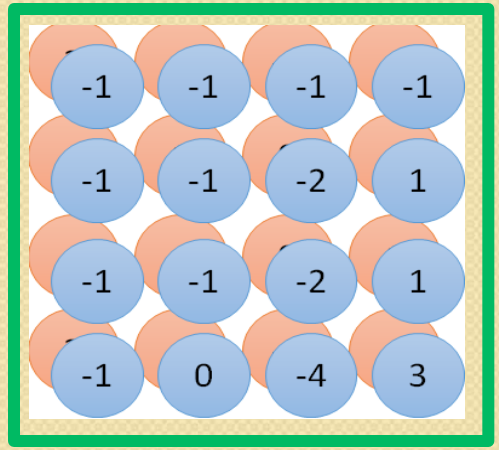
1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

imagem

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

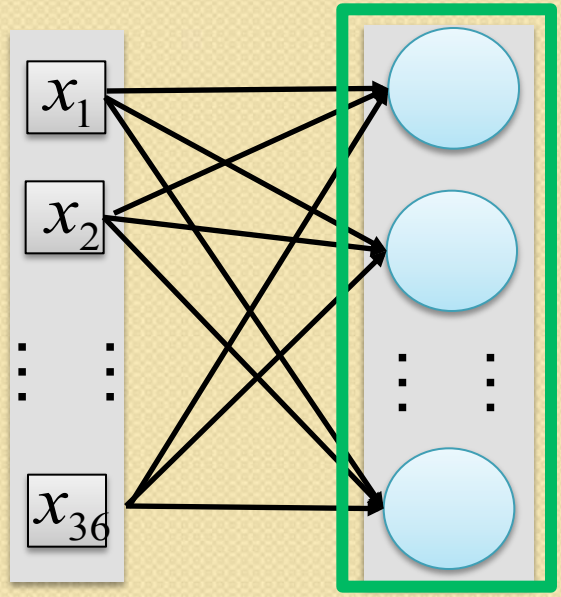
-1	1	-1
-1	1	-1
-1	1	-1

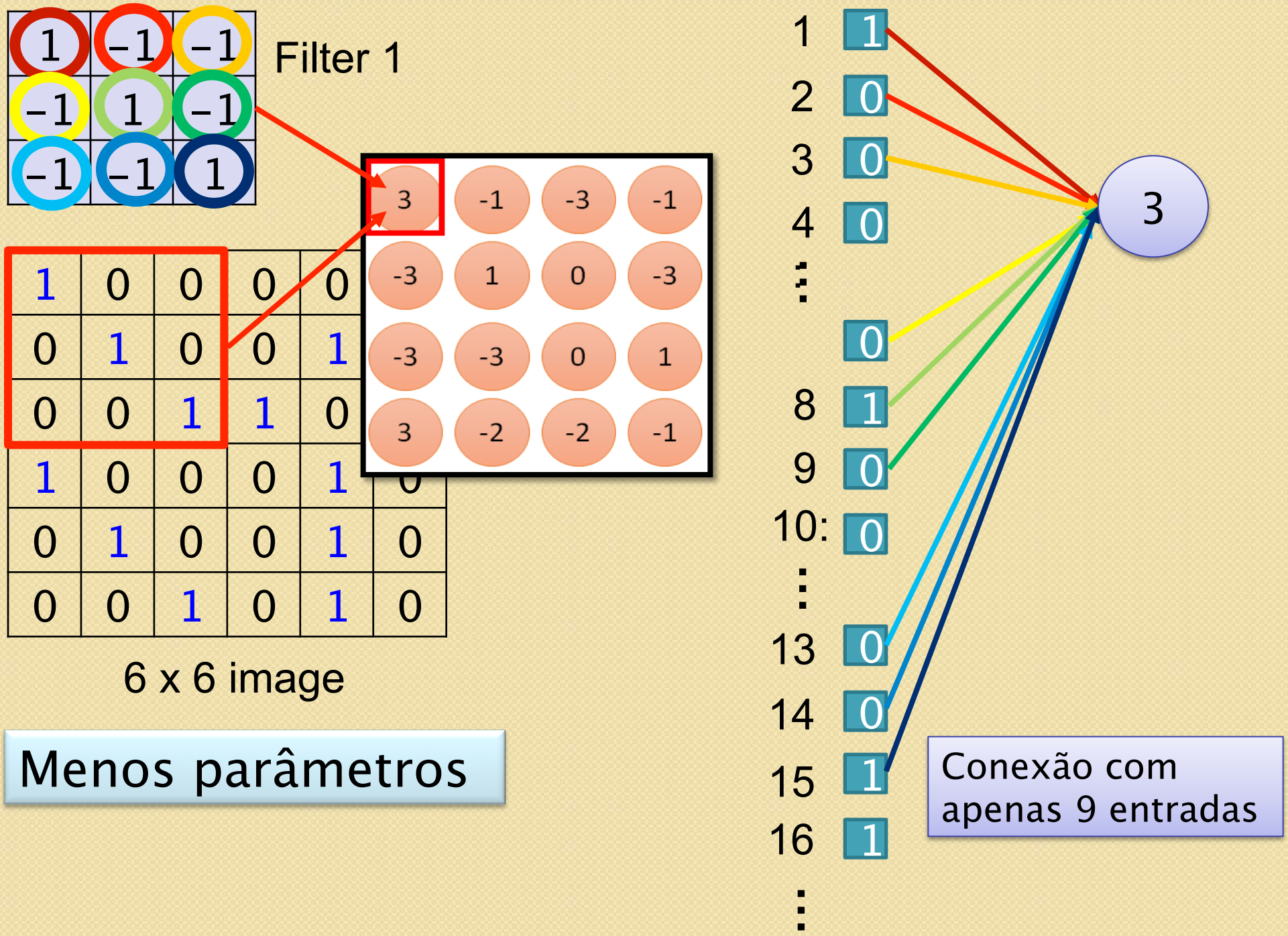
convolução

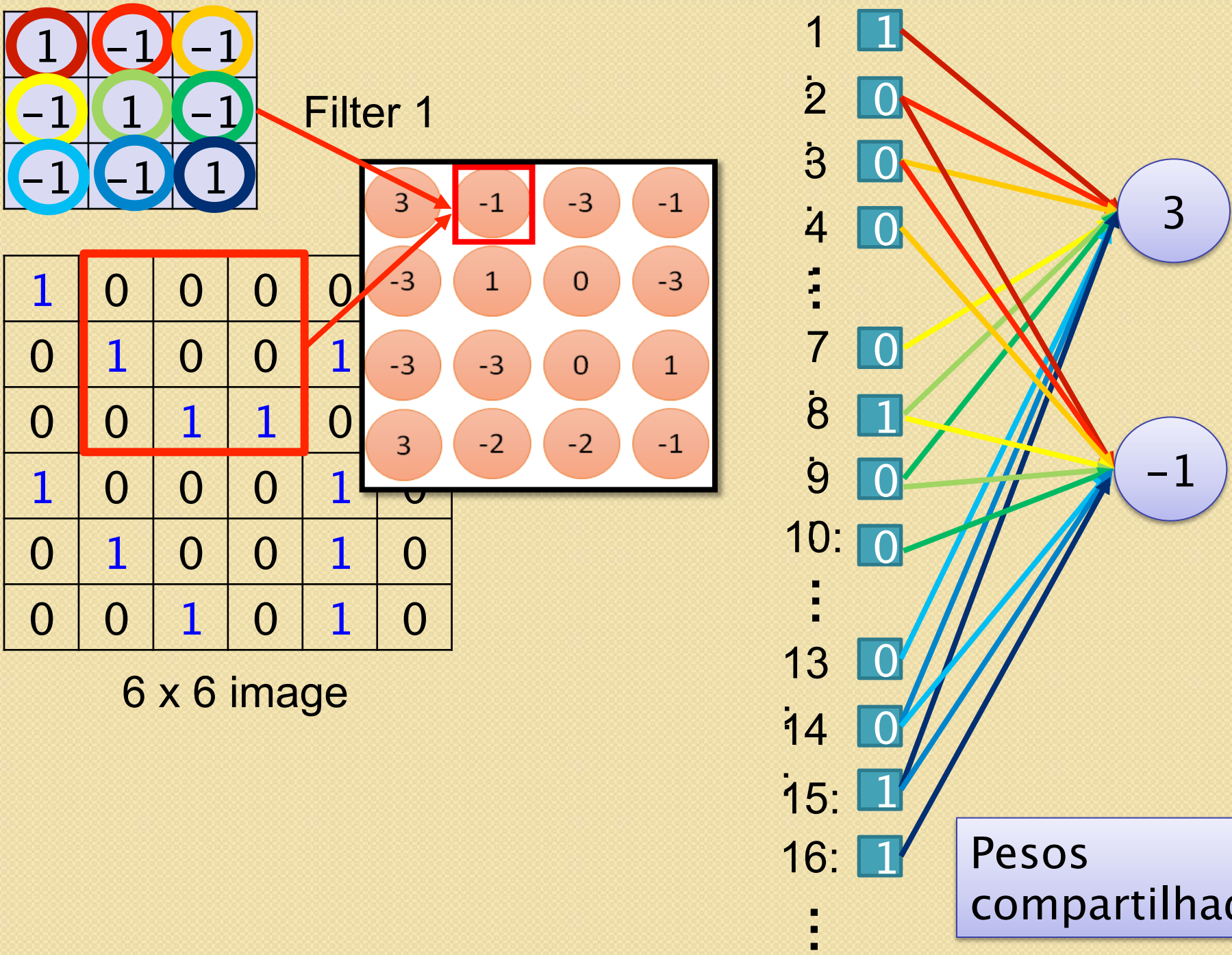


Fully-connected

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




1 -1 -1
-1 1 -1
-1 -1 1
Filter 1
3 -1 -3 -1
-3 1 0 -3
-3 -3 0 1
3 -2 -2 -1
1 0 0 0 0
0 1 0 0 1
0 0 1 1 0
1 0 0 0 1 0
0 1 0 0 1 0
0 0 1 0 1 0
6 x 6 image
1
2
3
4
8
9
10:
13
14
15
16
1
0
0
0
0
1
0
0
0
0
1
3
Menos parâmetros
Conexão com apenas 9 entradas


1 -1 -1
-1 1 -1
-1 -1 1
Filter 1
3 -1 -3 -1
-3 1 0 -3
-3 -3 0 1
3 -2 -2 -1
1 0 0 0 0
0 1 0 0 1
0 0 1 1 0
1 0 0 0 1
0 1 0 0 1 0
0 0 1 0 1 0
6 x 6 image
1
2
3
4
7
8
9
10:
13
14
15:
16:
1 0 0 0 1 0 1 0 0 1
3
-1
Pesos compartilhados

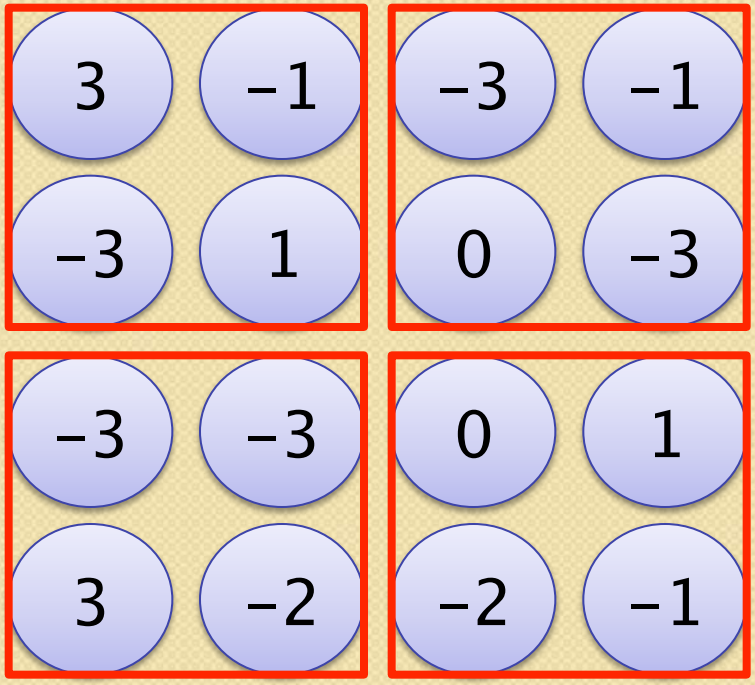
Max Pooling

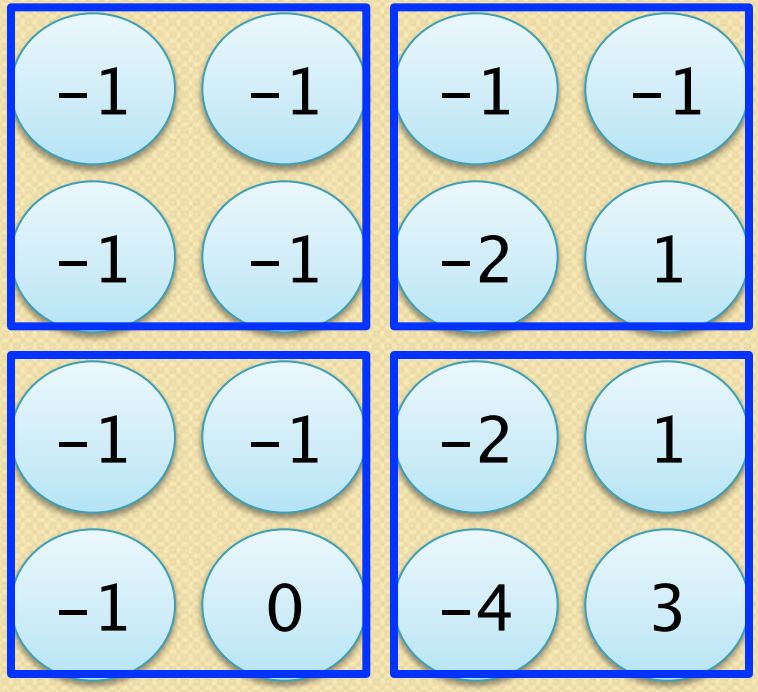
1	−1	−1
−1	1	−1
−1	−1	1

Filtro 1

−1	1	−1
−1	1	−1
−1	1	−1

Filtro 2

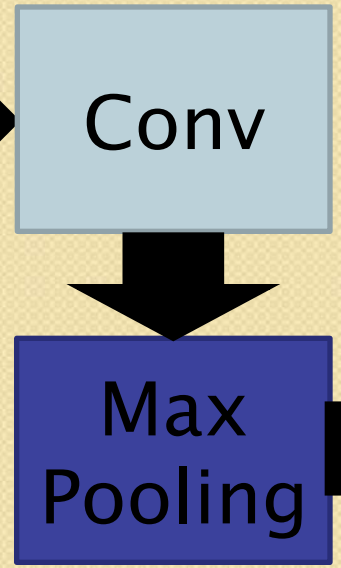




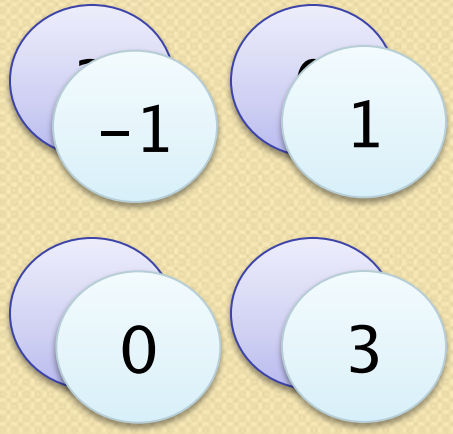
Max Pooling

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

6 x 6 image



Nova imagem menor



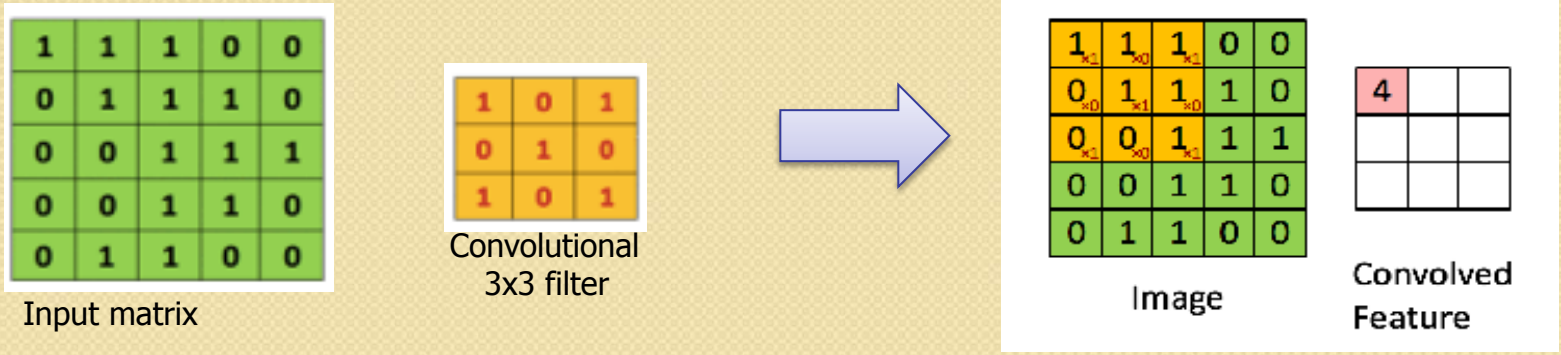
2 x 2 image

Cada filtro é um canal

Convolução…

Main CNN idea for text:
Compute vectors for n-grams and group them afterwards

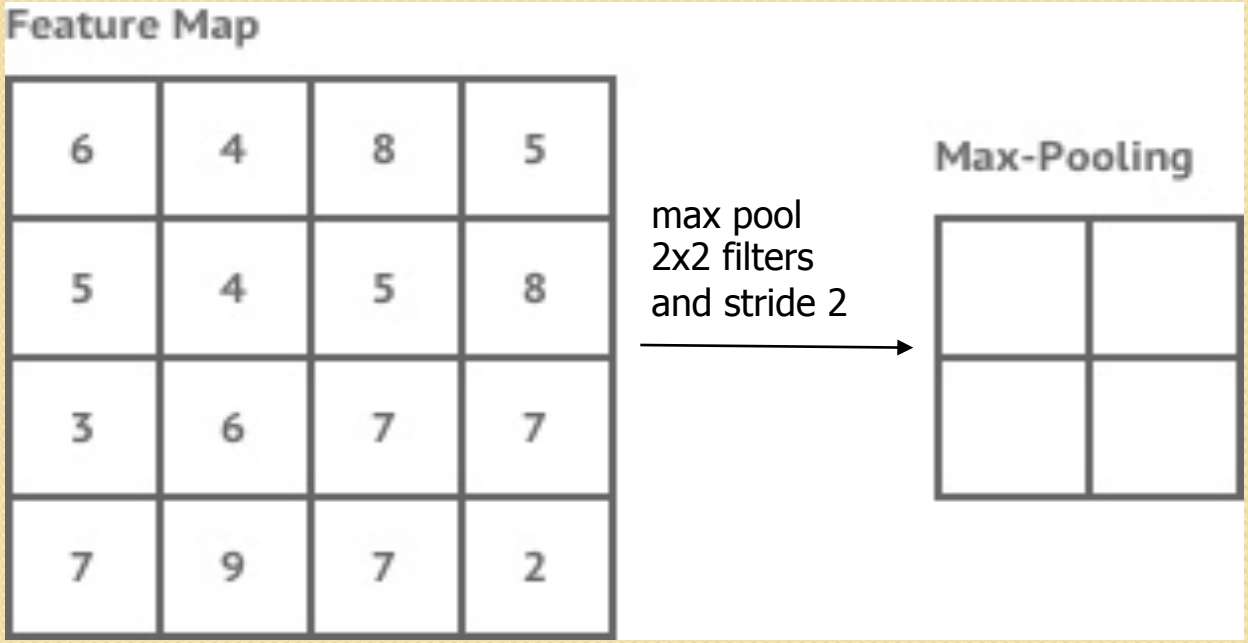
Example: "this takes too long" compute vectors for:
This takes, takes too, too long, this takes too, takes too long, this takes too long



http://deeplearning.stanford.edu/wiki/index.php/Feature_extraction_using_convolution

Max Pooling

Main CNN idea for text:
Compute vectors for n-grams and **group them afterwards**



https://shafeentejani.github.io/assets/images/pooling.gif

Por Que Fazer *Pooling*?

- Subsampling não muda o objeto

pássaro

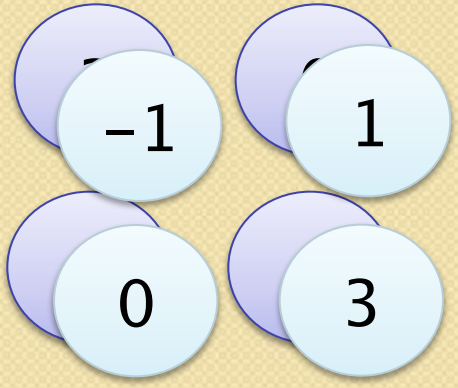
Subsampling

pássaro

Subamostrar pixels para tornar imagem menor

Menos parâmetros para caracterizar a imagem

CNN Completa



Convolution

Max Pooling

Convolution

Max Pooling

Pode se repetir várias vezes

Uma nova imagem

Menor que a original

Número de canais=Número de Filtros

CNN Completa

Convolution

Max Pooling

Nova imagem

Convolution

Max Pooling

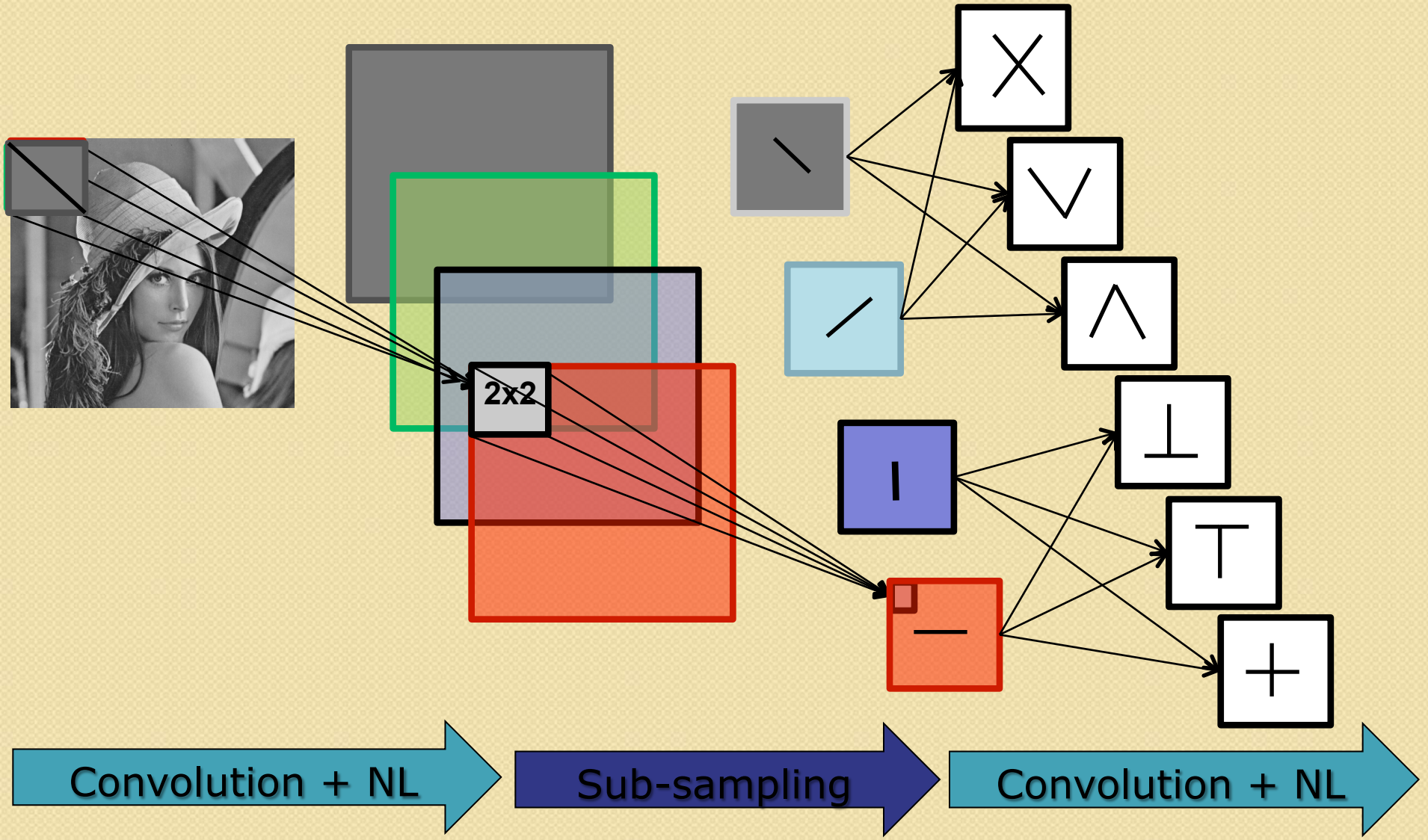
Nova imagem

Flattened

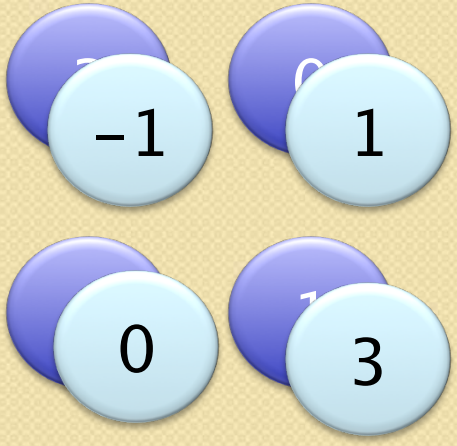
Rede Feedforward
Totalmente Conectada

cat dog ……

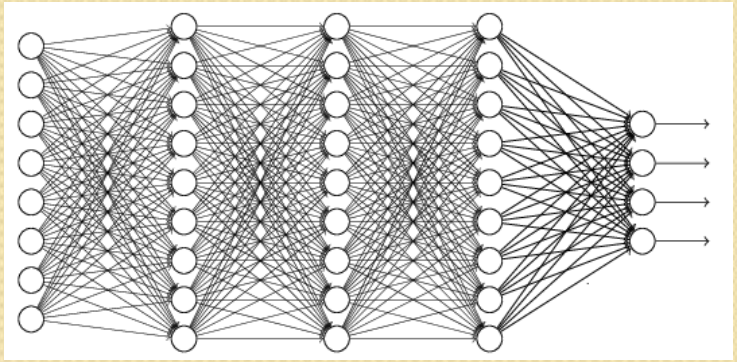
Rede Neural CNN



Achatamento (Flattening)

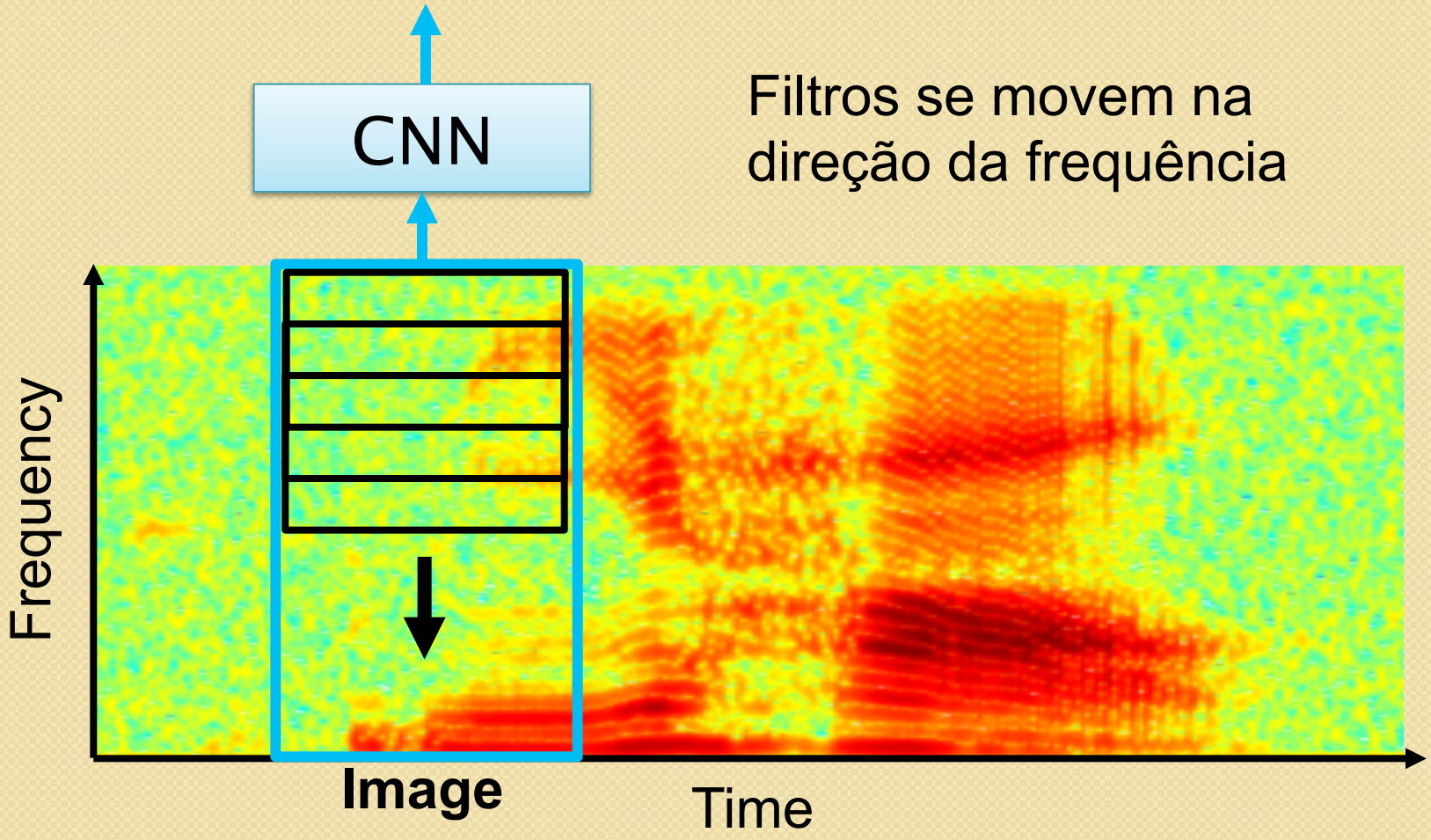


Achatada

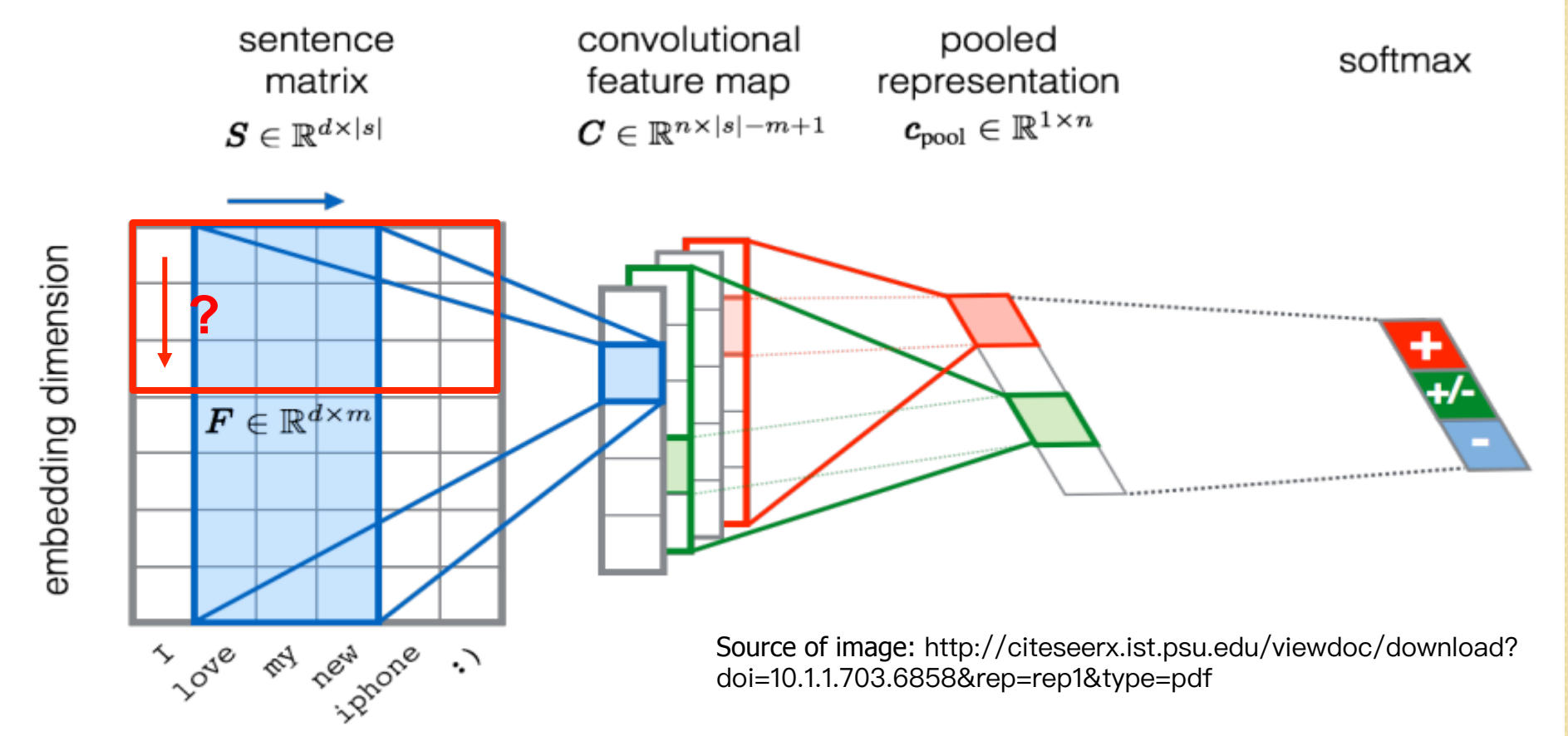


Rede Feedfoward
Totalmente Conectada

CNN em Reconhecimento da Fala



CNN em Classificação de Textos



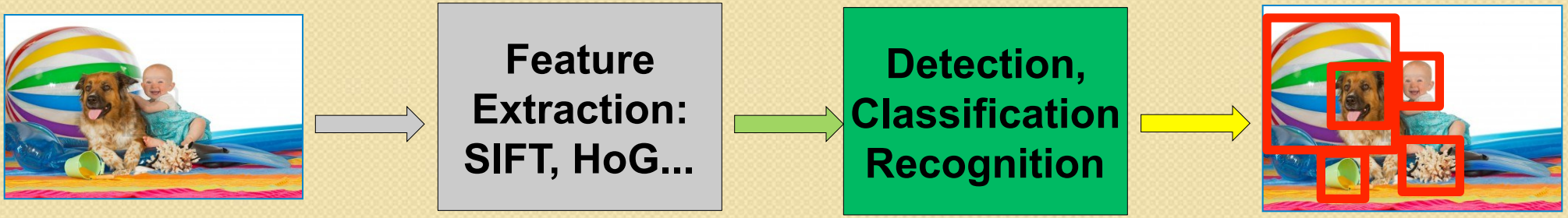
Source of image: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.703.6858&rep=rep1&type=pdf

Solução Típica em Visão Computacional

Para reconhecer coisas?

Solução Típica em Visão Computacional

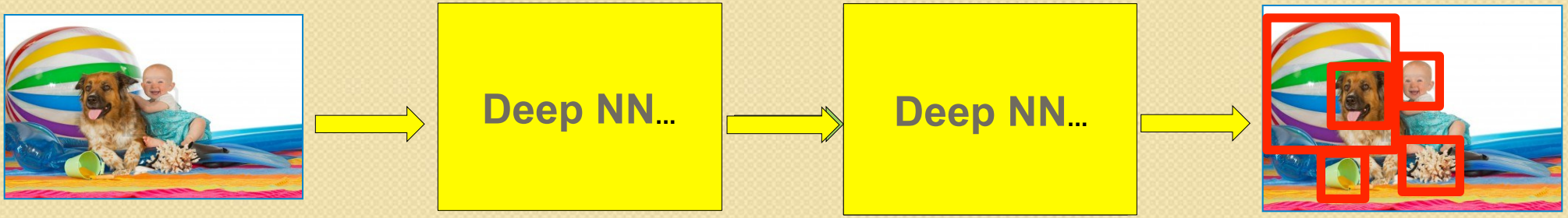
1. Definir e selecionar características:
2. SURF, HoG, SIFT, RIFT.
3. Acrescentar classificadores



Definição de características é dependente do domínio e consome tempo

Solução em Deep Learning: Pipeline Baseado em Visão

- Extrair características automaticamente baseado nos dados
- Combina a extração com classificação
- Papel do especialista: definir topologia e treinamento



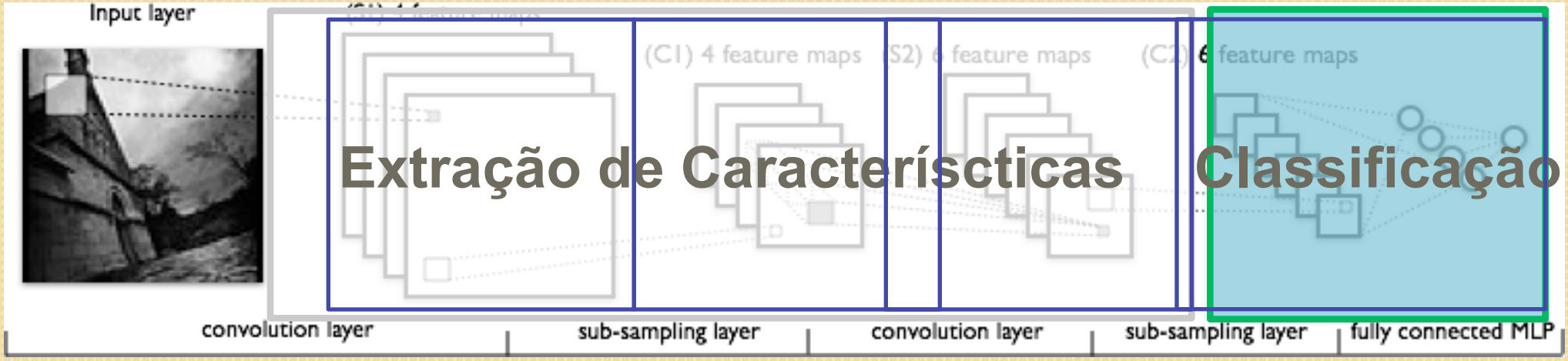
Promessa do Deep Learning?
Treinar boas características automaticamente
Mesmo método para diferentes domínios

Visão Computacional + Deep Learning + Machine Learning

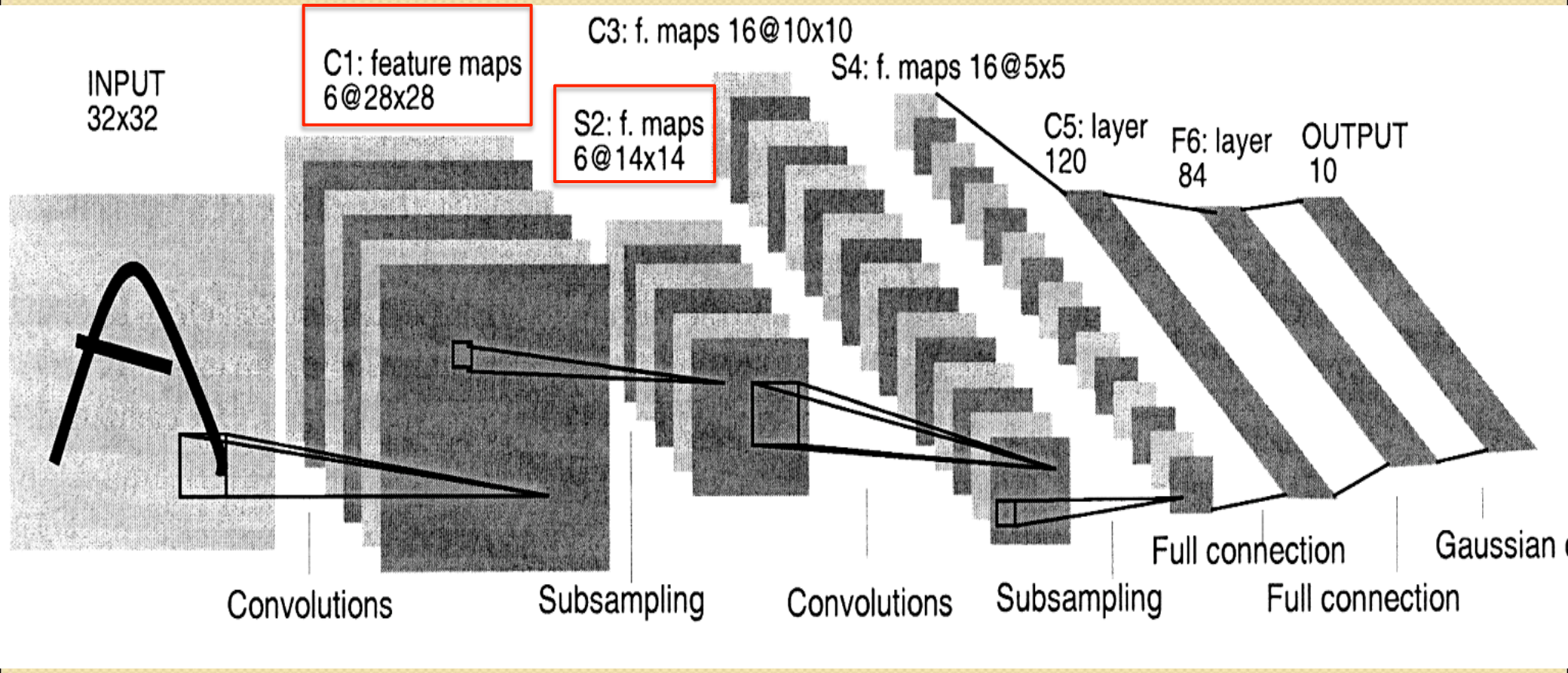
- Combinar características pré-definidas com características aprendidas
- Melhores métodos para classificação de múltiplas classes
- Especialistas em CV+DL+ML necessários para criar melhores soluções

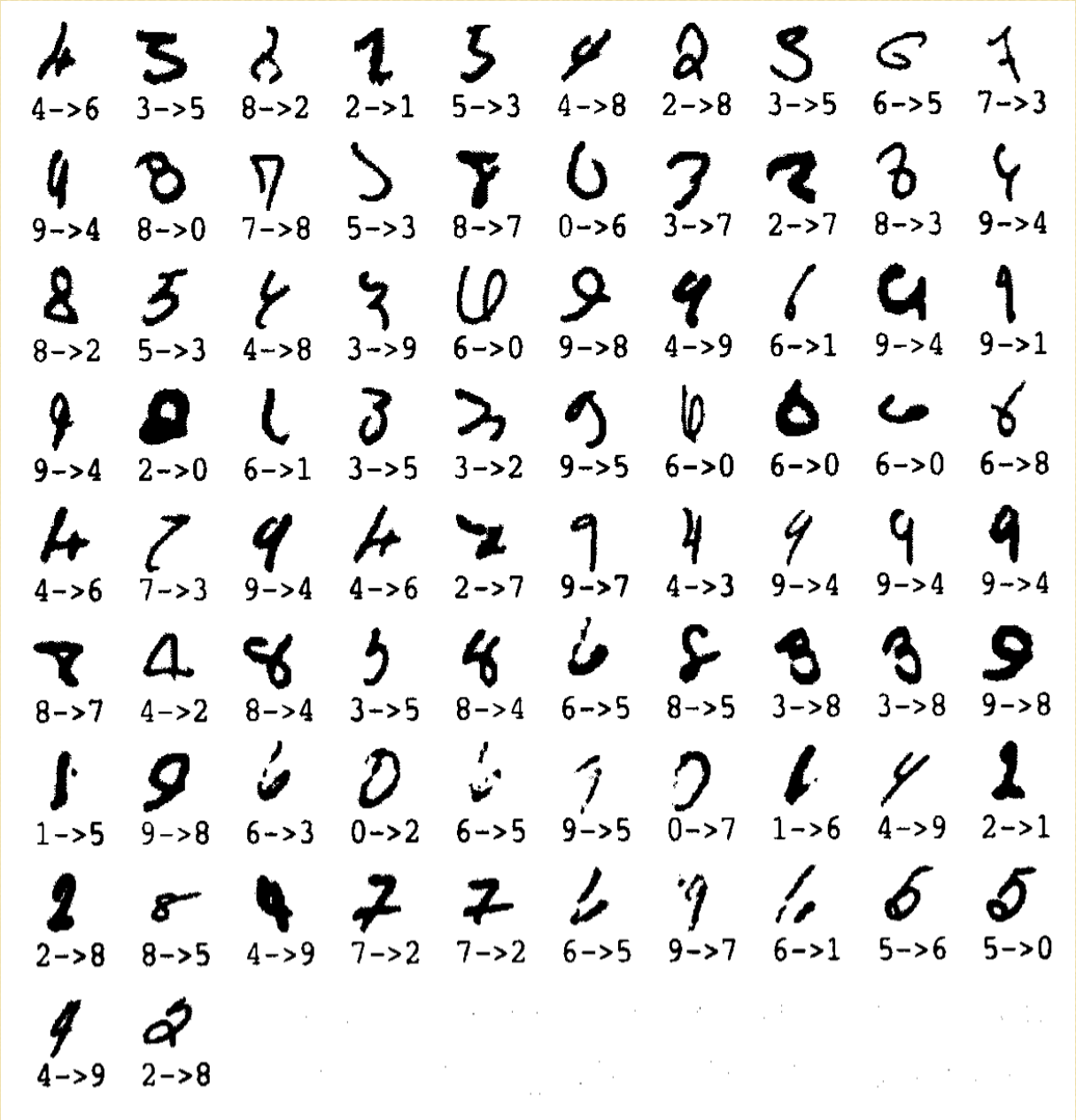
CNN Multi-camadas

- Convolutional + Non-Linear Layer
- Sub-sampling Layer
- Convolutional +Non-Linear Layer
- Fully connected layers
- Supervised



Como Tudo Começou? LeNet5



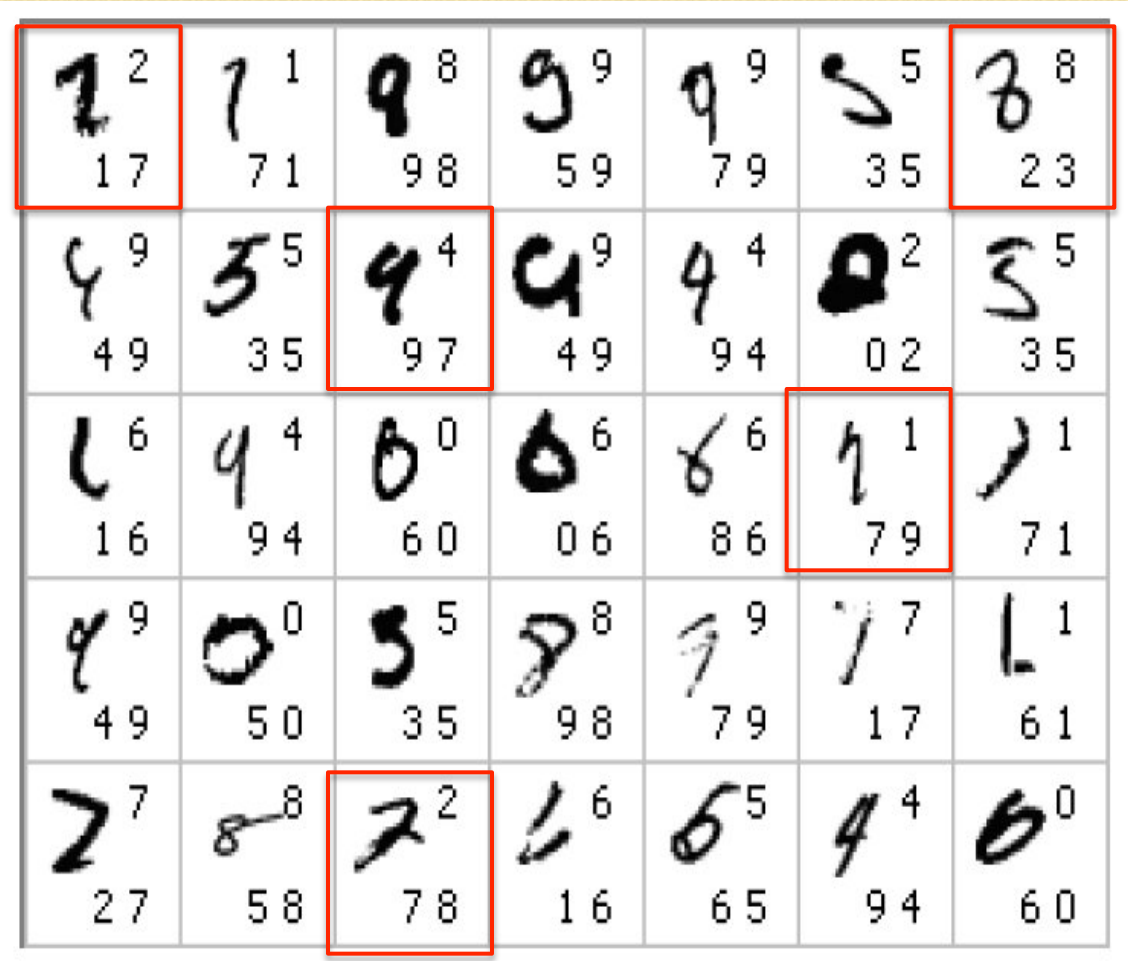


Os 82 erros da LeNet5

Muitos casos facilmente reconhecidos por humanos

Taxa de erro humana estimada em 20 a 30 erros

Erros na Rede de Ciresan *et.al.*



Digito em cima: resposta certa. Dígitos de baixo: 2 melhores apostas da rede.

Resposta certa quase sempre nas 2 melhores apostas.

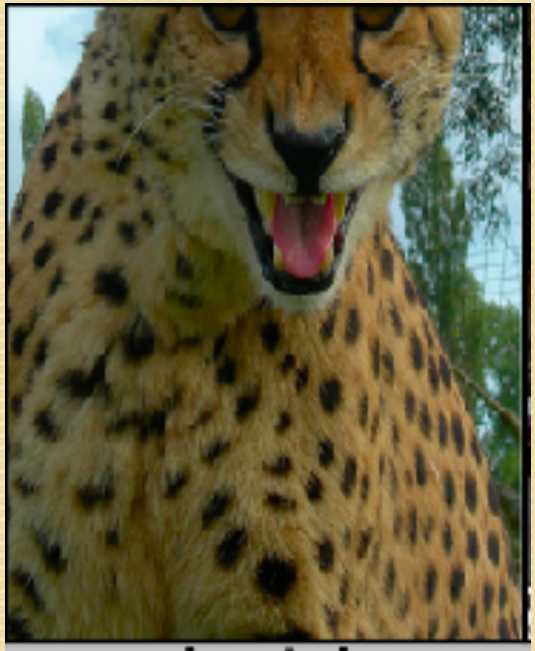
Tirando a média, performance aumentou para 25 erros.

Competição ILSVRC-2012 no Dataset ImageNet

- 1.2 milhões de imagens em alta resolução.
- Tarefa de classificação:
  - Encontre a classe correta nas suas 5 melhores apostas. 1000 classes.
- Tarefa de localização:
  - Para cada aposta, desenhe uma caixa entorno do objeto. Sua caixa tem de ter pelo menos 50% de sobreposição com a caixa correta.

- Alguns dos melhores métodos de visão computacional (VC) foram usados: Oxford, INRIA, XRCE, Tokio
  - Systemas de VC tarefas complicadas de múltiplos estágios
  - Estágios iniciais envolvem refinamento a mão de parâmetros

Exemplos de Apostas



cheetah

cheetah
leopard
snow leopard
Egyptian cat

bullet train

bullet train
passenger car
subway train
electric locomotive

hand glass

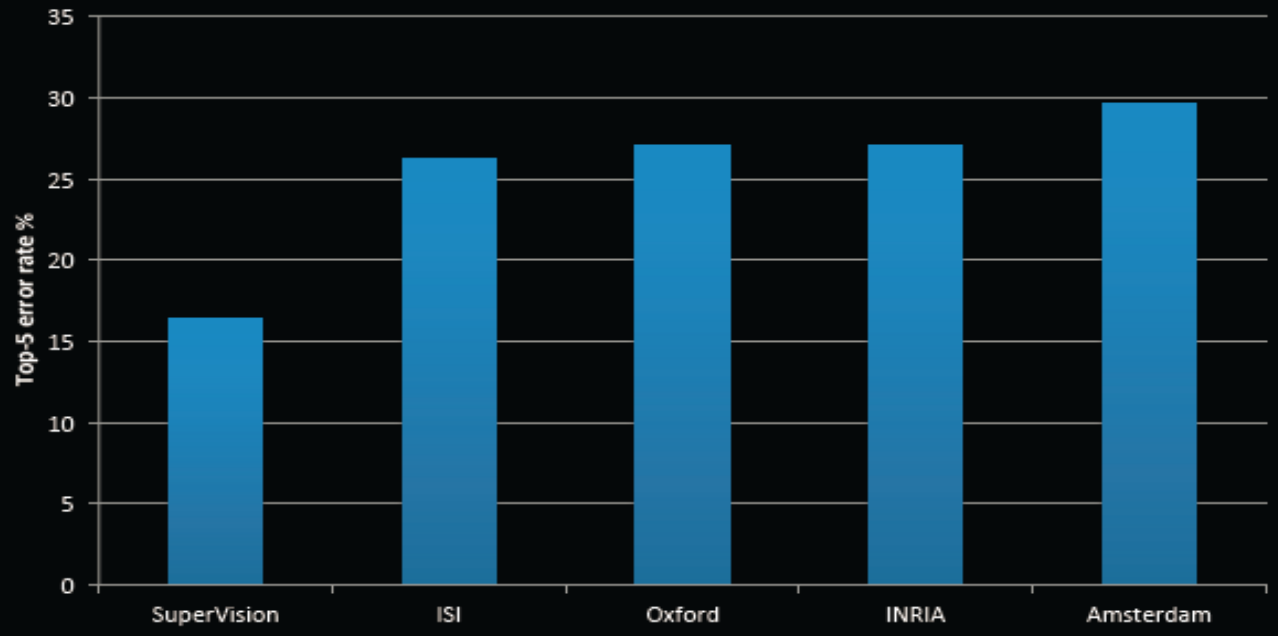
scissors
hand glass
frying pan
stethoscope

Taxas de Erros: ILSVRC-2012

	classification	classification &localization
University of Tokyo	26.1%	53.6%
Oxford University Computer Vision Group	26.9%	50.0%
INRIA (French national research institute in CS) + XRCE (Xerox Research Center Europe)	27.0%	
University of Amsterdam	29.5%	
University of Toronto (Alex Krizhevsky)	16.4%	34.1%

Classificações na Imagenet 2012

- Krizhevsky et al. -- 16.4% error (top-5)
- Next best (non-convnet) – 26.2% error

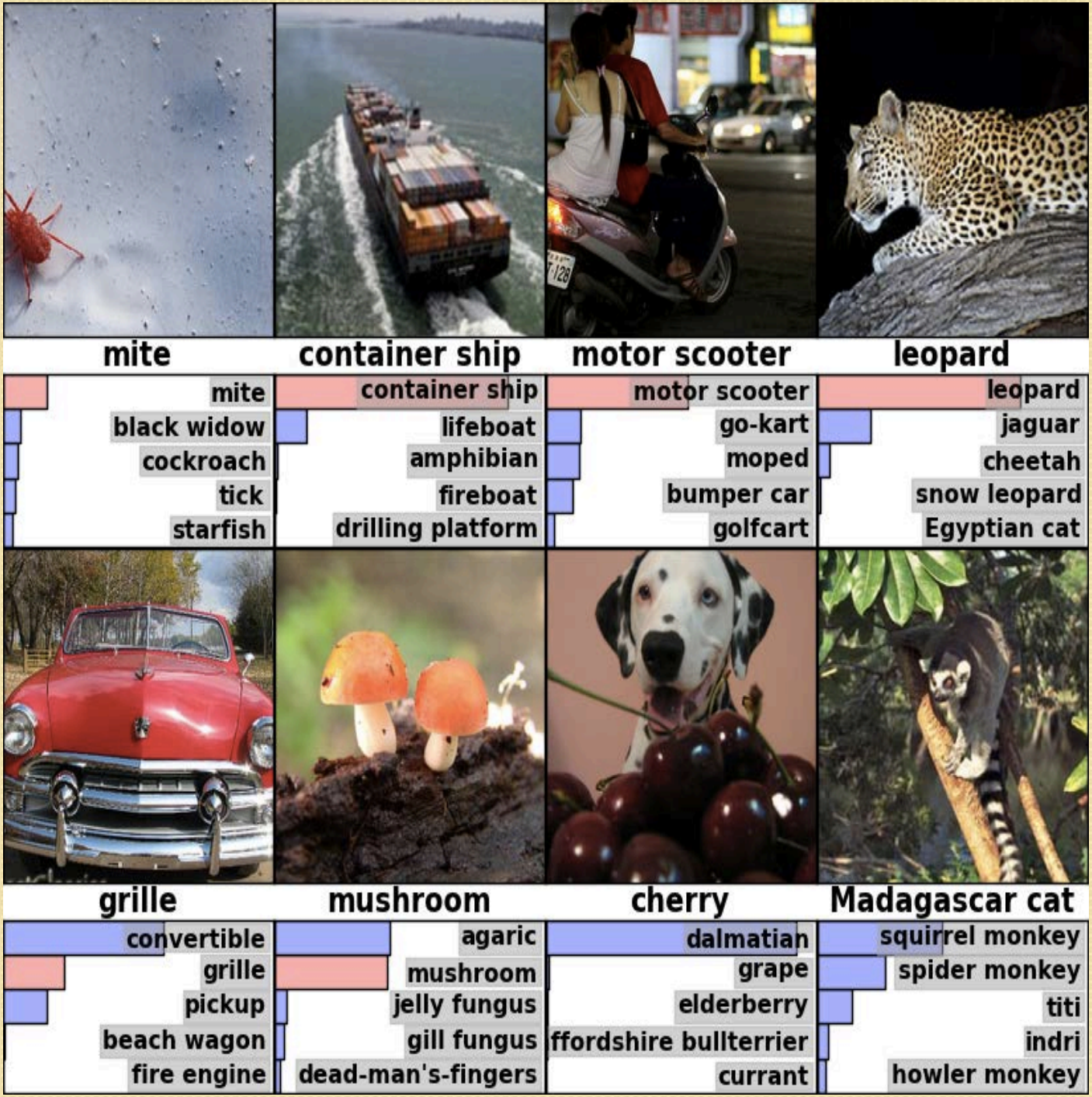


Rede Neural CNN para ImageNet

- Alex Krizhevsky (NIPS 2012): rede muito profunda baseada no trabalho de Yann Le Cun
  - 7 camadas intermediárias sem contar camadas de max pooling
  - Primeiras camadas convolucionais
  - Últimas 2 totalmente conectadas

Alguns Exemplos de Classificação: ILSVRC

Outros


mite
container ship
motor scooter
leopard
mite
black widow
cockroach
tick
starfish
container ship
lifeboat
amphibian
fireboat
drilling platform
motor scooter
go-kart
moped
bumper car
golfcart
leopard
jaguar
cheetah
snow leopard
Egyptian cat
grille
mushroom
cherry
Madagascar cat
convertible
grille
pickup
beach wagon
fire engine
agaric
mushroom
jelly fungus
gill fungus
dead-man's-fingers
dalmatian
grape
elderberry
ffordshire bullterrier
currant
squirrel monkey
spider monkey
titi
indri
howler monkey

Topologia da CNN de Krizhevsky

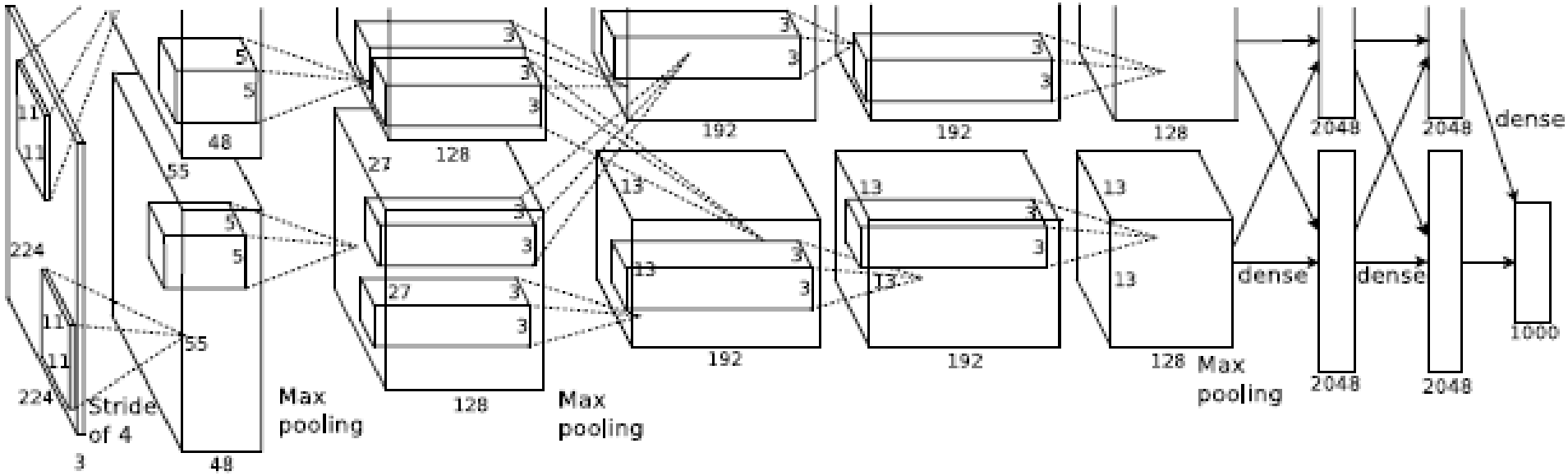
- 5 convolutional layers
- 3 fully connected layers + soft-max
- 650K neurons , 60 Mln weights

ImageNet Classification with Deep Convolutional Neural Networks

Alex Krizhevsky
University of Toronto
kriz@cs.utoronto.ca

Ilya Sutskever
University of Toronto
ilya@cs.utoronto.ca

Geoffrey E. Hinton
University of Toronto
hinton@cs.utoronto.ca



Explosão

MIT Technology Review, April 23rd, 2013

ILSVRC 2012: Top Rankers

http://www.image-net.org/challenges/LSVRC/2012/results.html

N	Error-5	Algorithm	Team	Authors
1	0.153	Deep Conv. Neural Network	Univ. of Toronto	Krizhevsky et al
2	0.262	Features + Fisher Vectors + Linear classifier	ISI	Gunji et al
3	0.270	Features + FV + SVM	OXFORD_VGG	Simonyan et al
4	0.271	SIFT + FV + PQ + SVM	XRCE/INRIA	Perronin et al
5	0.300	Color desc. + SVM	Univ. of Amsterdam	van de Sande et al

Imagenet 2013: Top Rankers

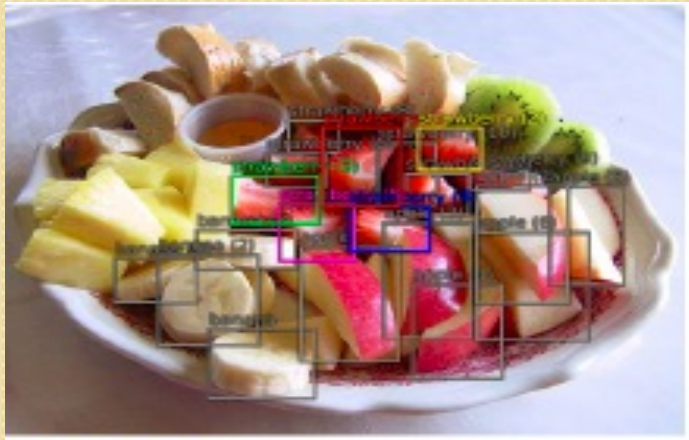
http://www.image-net.org/challenges/LSVRC/2013/results.php

N	Error-5	Algorithm	Team	Authors
1	0.117	Deep Convolutional Neural Network	Clarifi	Zeiler
2	0.129	Deep Convolutional Neural Networks	Nat.Univ Singapore	Min LIN
3	0.135	Deep Convolutional Neural Networks	NYU	Zeiler Fergus
4	0.135	Deep Convolutional Neural Networks		Andrew Howard
5	0.137	Deep Convolutional Neural Networks	Overfeat NYU	Pierre Sermanet et al

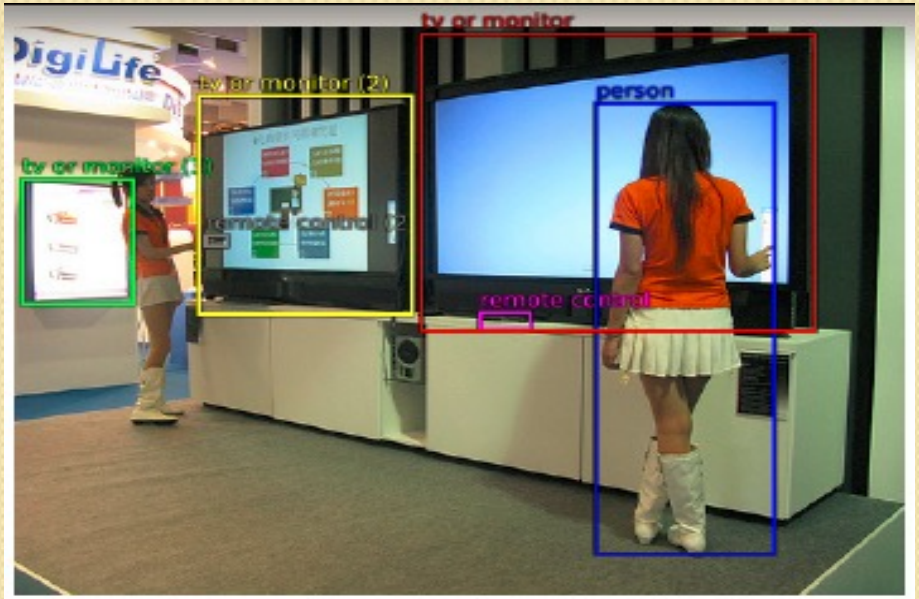
CNN: Detecção de Ações

Taylor, ECCV 2010

CNN: Detecção



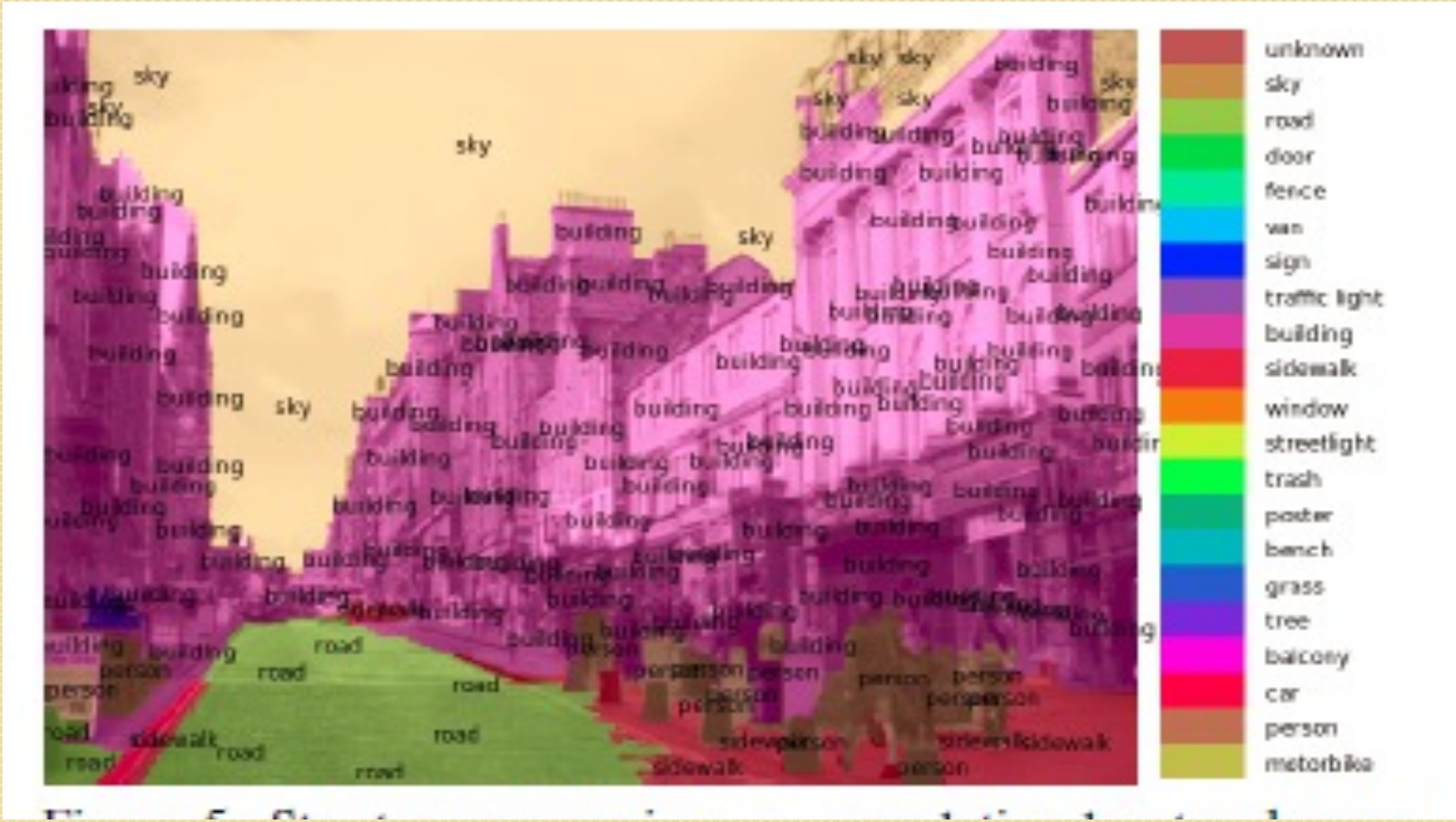
Groundtruth:
strawberry
strawberry (2)
strawberry (3)
strawberry (4)
strawberry (5)
strawberry (6)
strawberry (7)
strawberry (8)
strawberry (9)
strawberry (10)
apple
apple (2)
apple (3)



Groundtruth:
tv or monitor
tv or monitor (2)
tv or monitor (3)
person
remote control
remote control (2)

Sermanet, CVPR 2014

CNN: Descrição de Cenários



Farabet, PAMI 2013

CNN: Rotulamento Semântico Indoor em RGBD

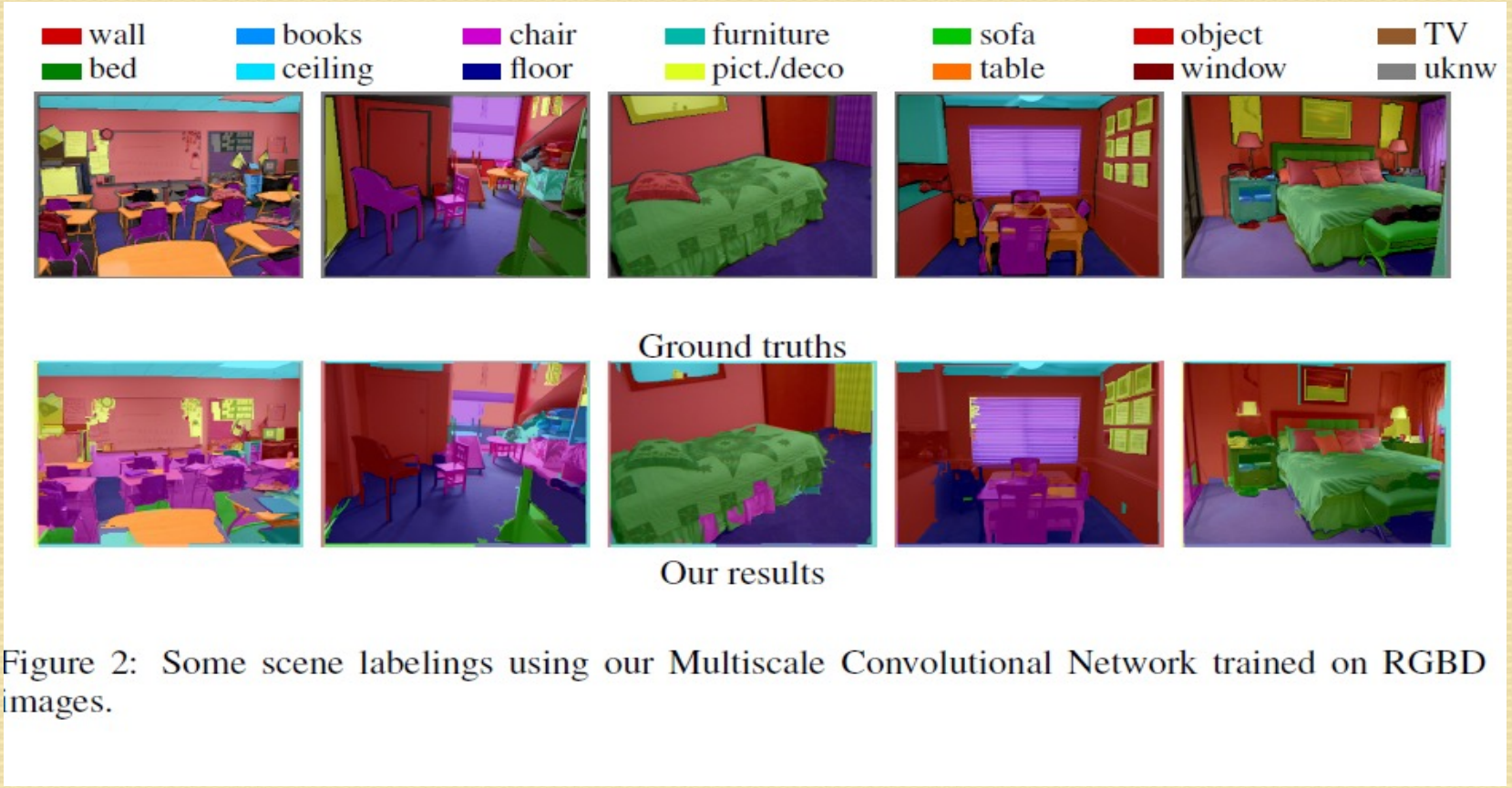
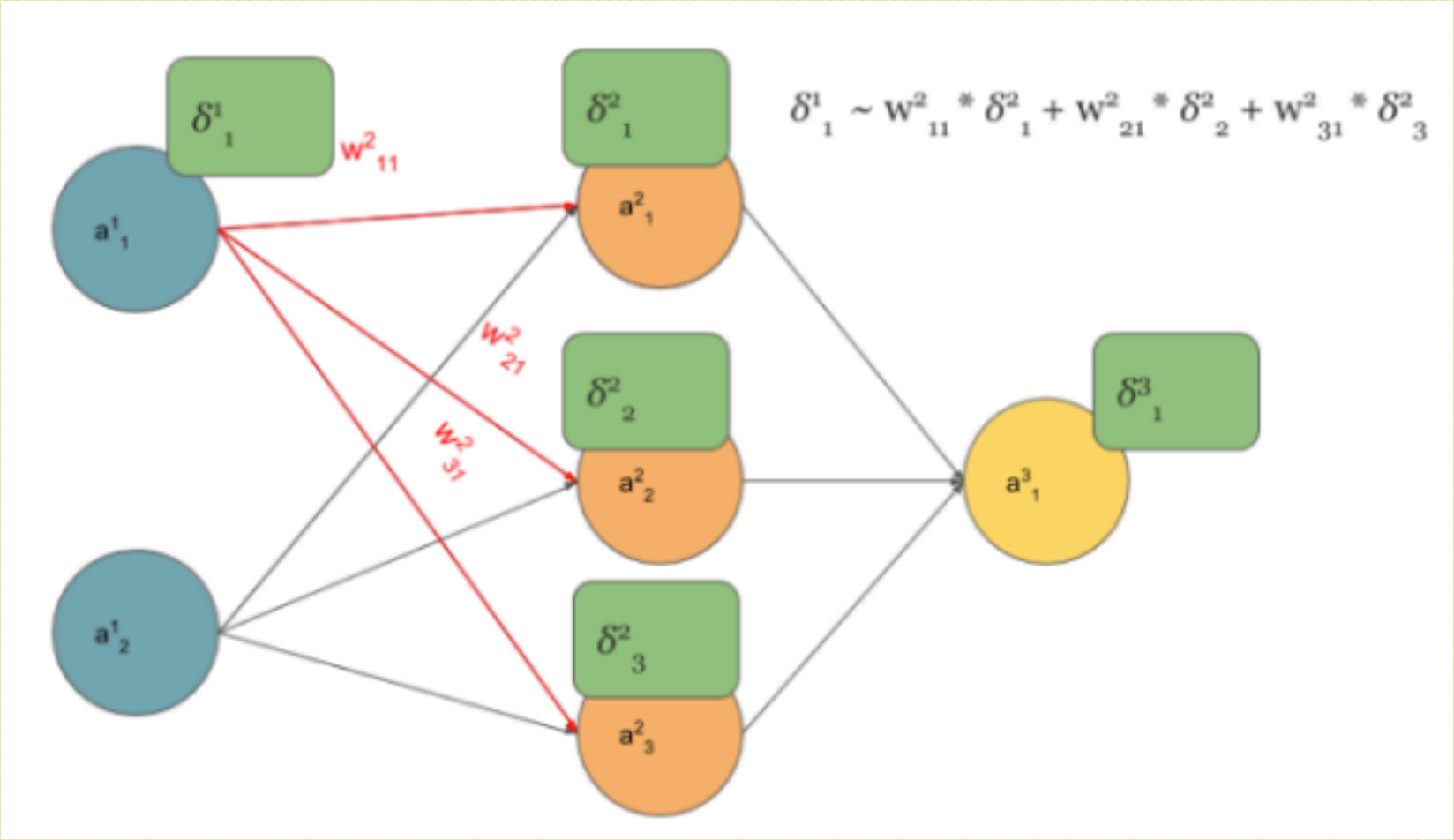


Figure 2: Some scene labelings using our Multiscale Convolutional Network trained on RGBD images.

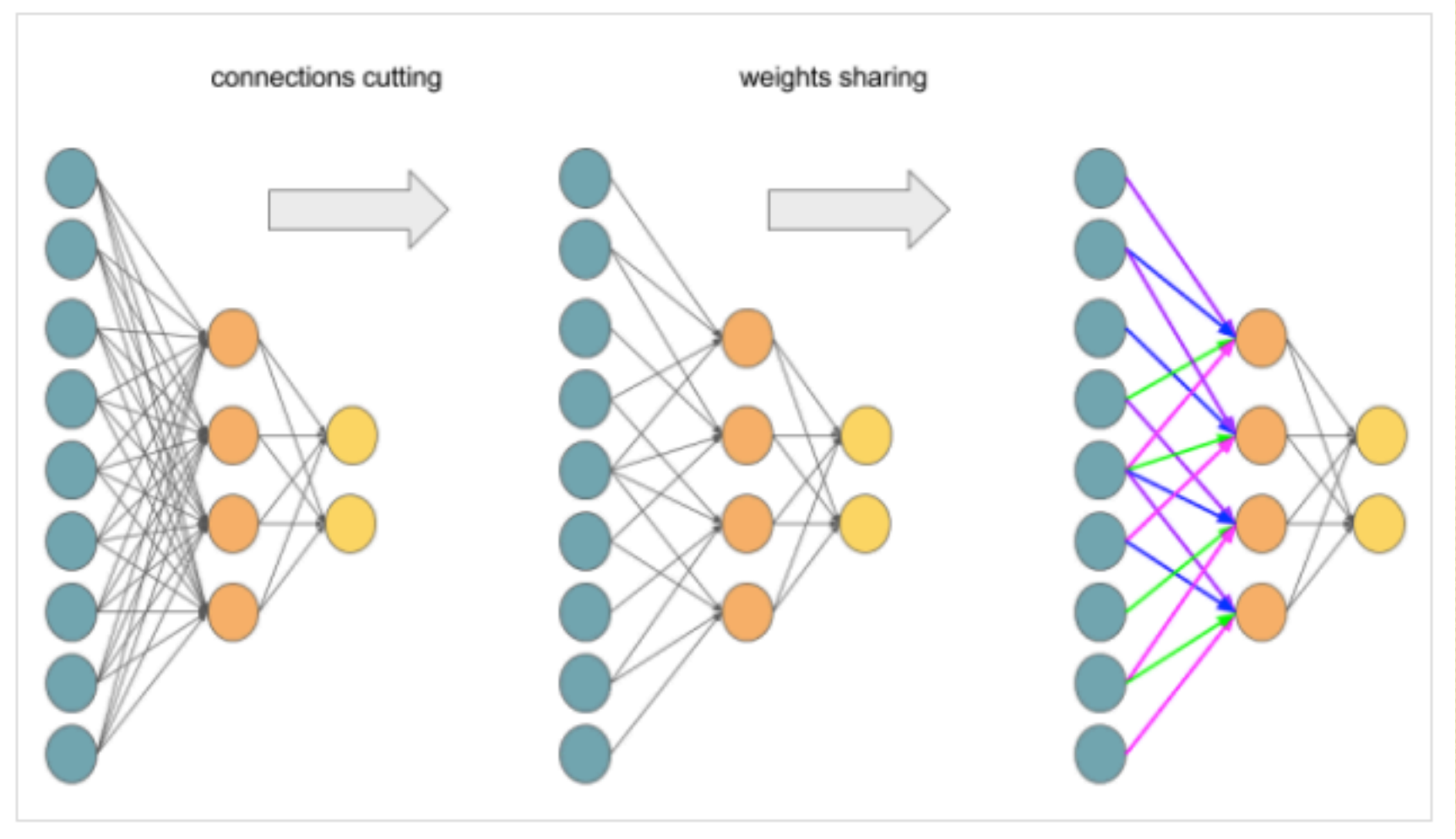
Farabet, 2013

Como se Treina uma CNN?

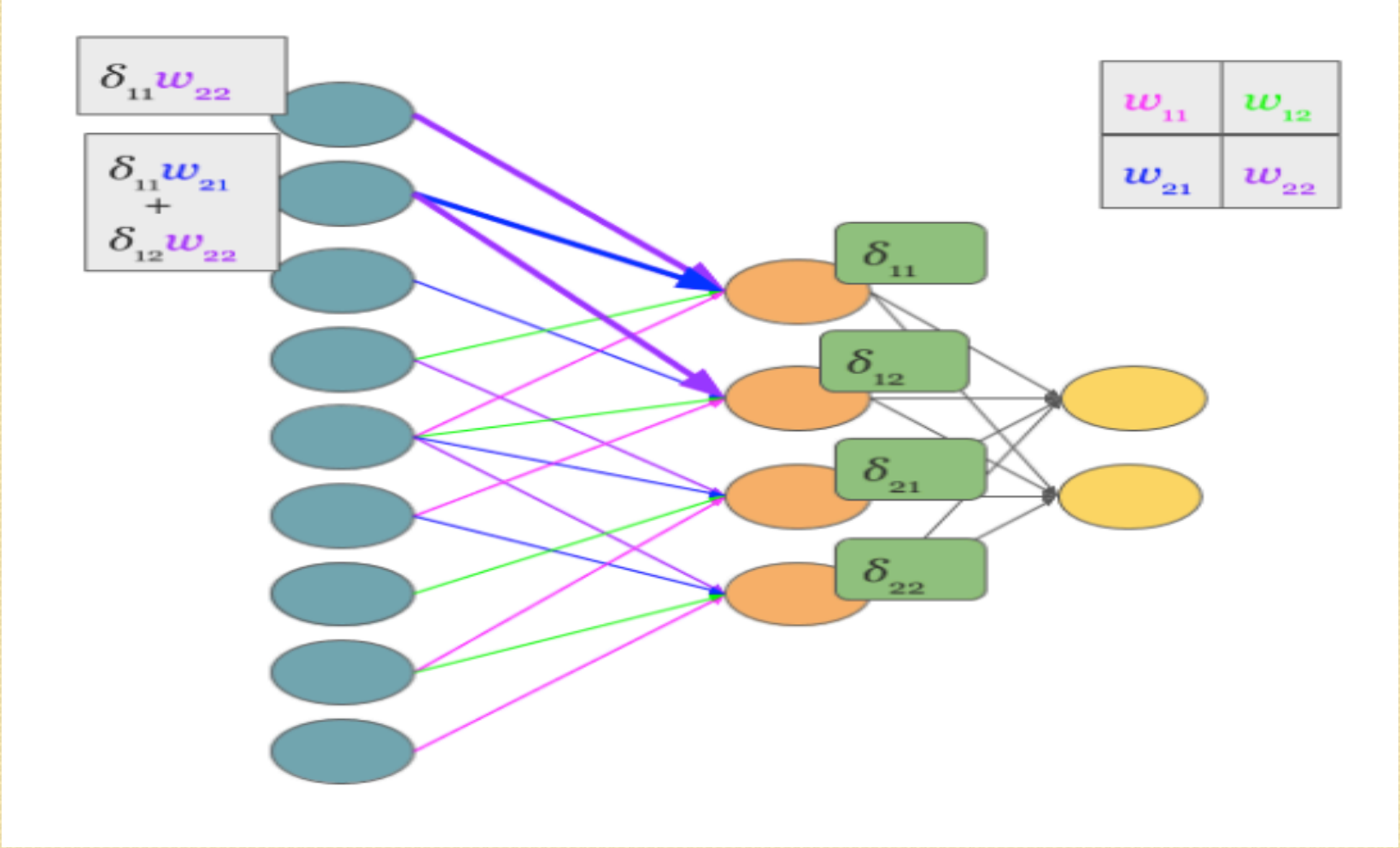
Lembrando Gradiente Descendente (Backpropagation)



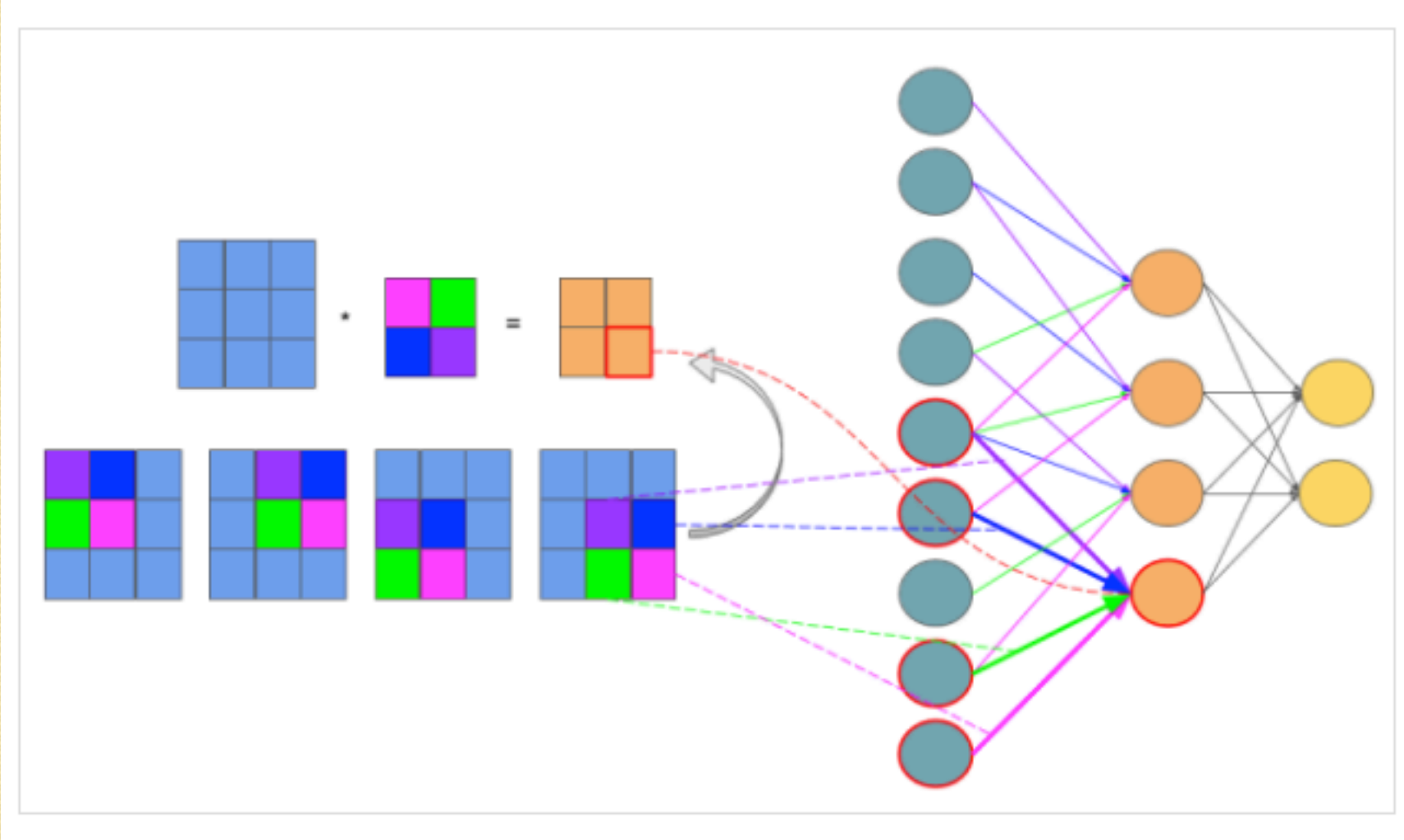
Transformando Rede Totalmente Conectada em CNN



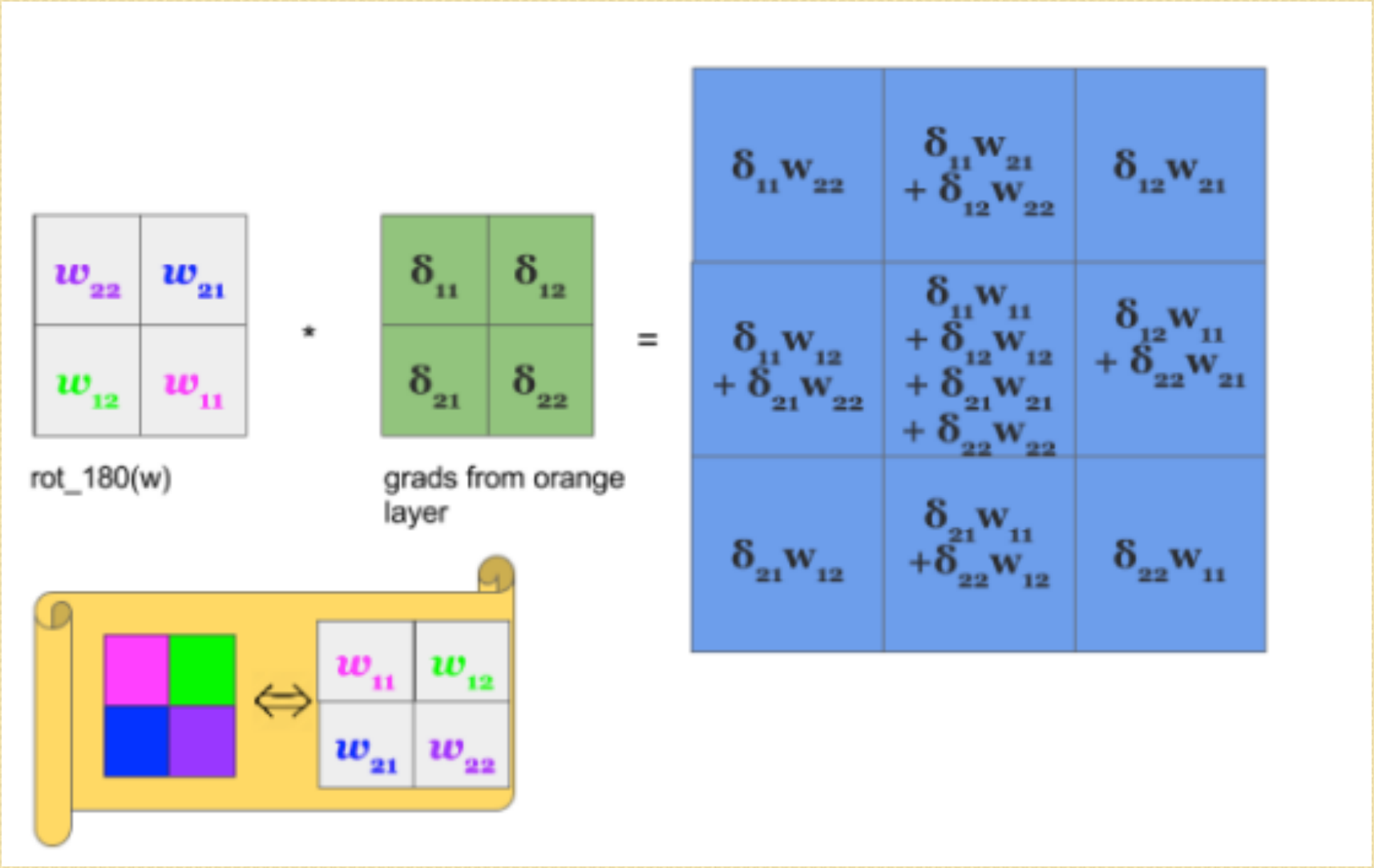
Transformando Rede Totalmente Conectada em CNN



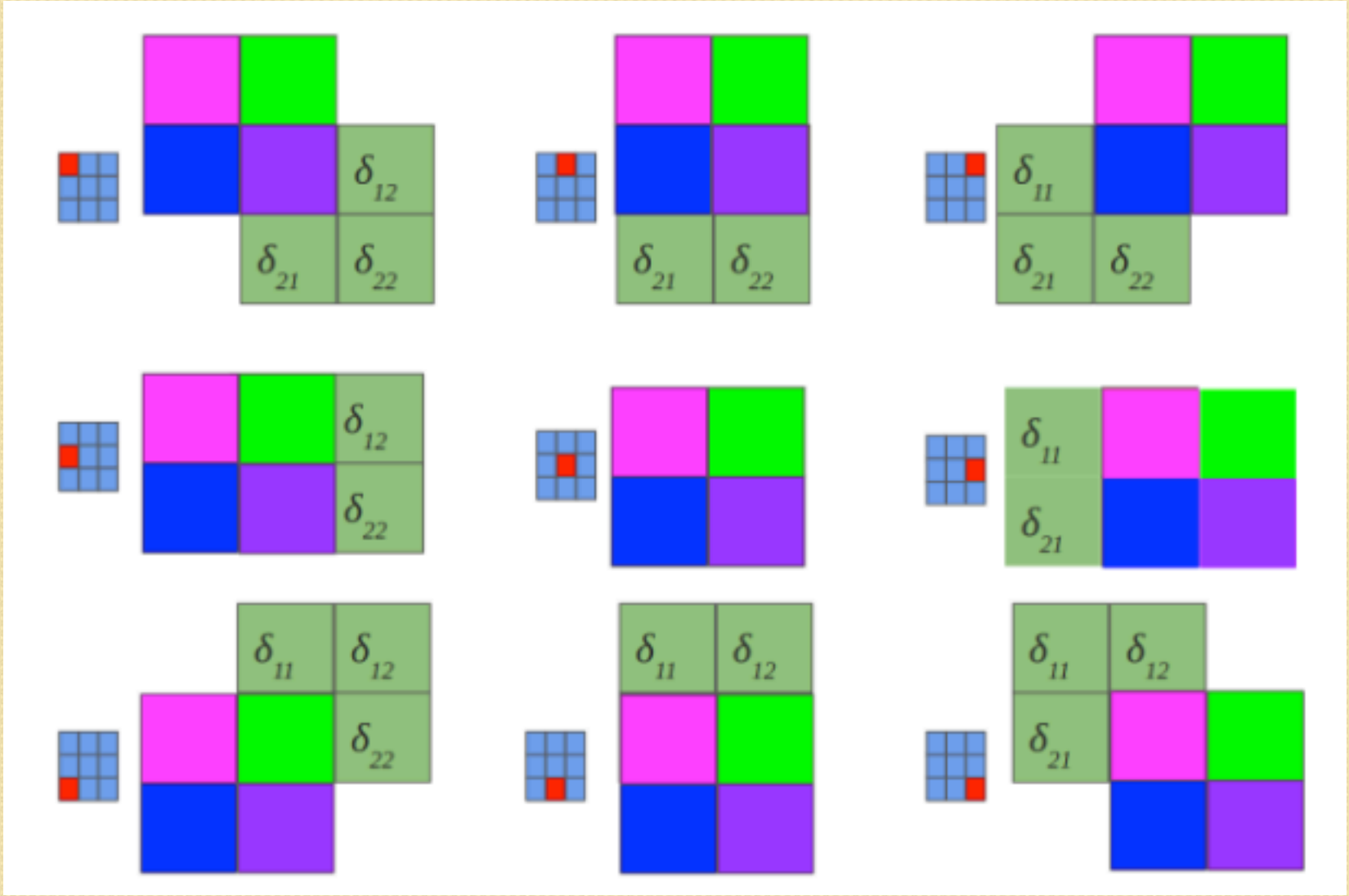
Operação de Convolução



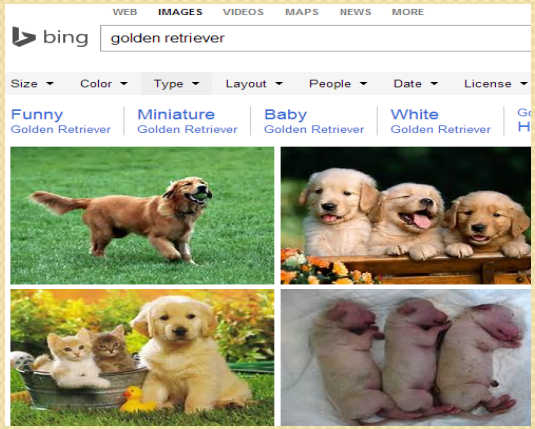
Definição do Erro para Ajuste de Cada Conexão

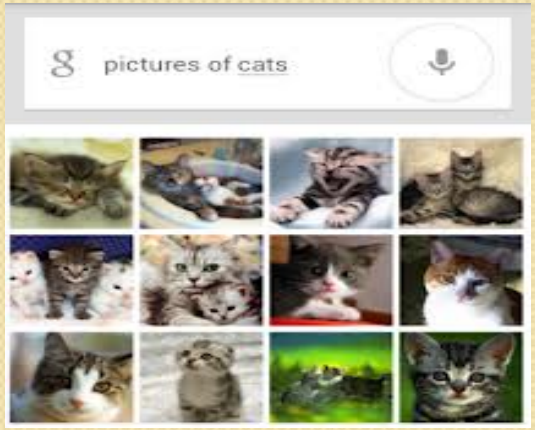


Definição do Erro para Ajuste de Cada Conexão



Da Pesquisa para Tecnologia

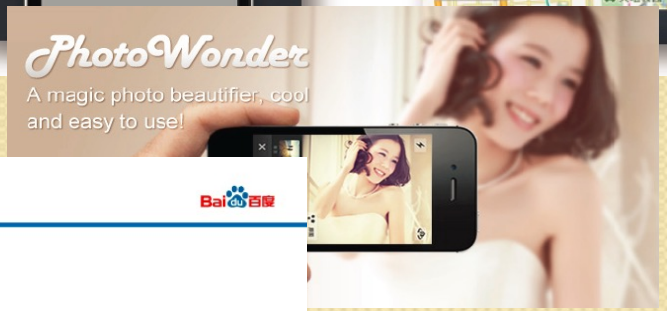


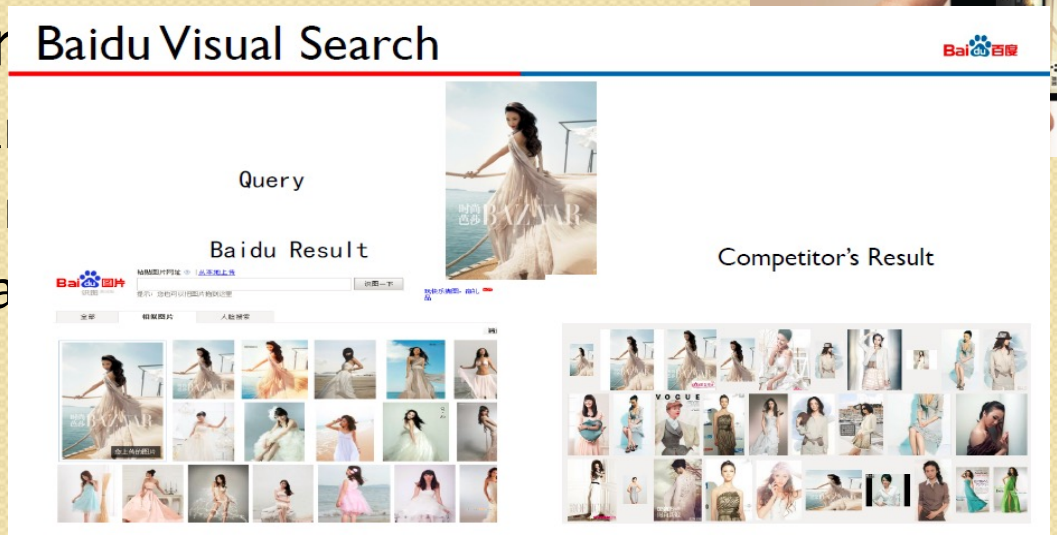


Deep Learning – breakthrough reconhecimento visual e da fala

Buzz

- July 2012 – Started DL lab
- Nov 2012– Big impr
  OCR:
  - Speech – reduce Erro
  - OCR – reduce Error rate by
- 2013 laur
  - Voice sea
  - Photo Wo
  - Visual sea





Baidu 百度

Buzz

Scientists See Promise in Deep-Learning Programs

A voice recognition program translated a speec
Chinese.

By JOHN MARKOFF
Published: November 23, 2012

The New York Times

[Microsoft On Deep Learning for Speech](#) goto 3:00-5:10

Buzz

Google Scoops Up Neural Networks Startup DNNresearch To Boost Its Voice And Image Search Tech

RIP EMPSON

Tuesday, March 12th, 2013 5 Comments

[Why Google invest in Deep Learning]

Buzz

Courant's LeCun to Lead Facebook's New Artificial Intelligence Group

December 9, 2013
143

Facebook has named New York University Professor Yann LeCun the director of a new laboratory devoted to research in artificial intelligence and deep learning.

"As one of the most respected thinkers in this field, Yann has done groundbreaking rese deep learning and computer vision," said Mike Schroepfer, Facebook's chief technology "We're thrilled to welcome him to Facebook."

Facebook is building the team across three locations: Facebook's headquarters in Menlo Calif., New York City, and London.

Machine learning is a branch of artificial intelligence that involves computers "learning" t extract knowledge from massive data sets and rendering informed analyses and judgme often predicting outcomes.

LeCun, a professor at NYU's Courant Institute of Mathematical Sciences, is a pioneer in t growing field. In the 1980s, LeCun proposed one of the early versions of the back-propa algorithm, the most popular method for training artificial neural networks. In the late 19 and early 1990s at AT&T Bell Laboratories, he developed the convolutional network mod

ENTERPRISE | research | uncategorized

Facebook Taps 'Deep Learning' Giant for New AI Lab

BY CADE METZ 12.09.13 3:14 PM
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Yann LeCun. *Photo: Josh Valcarcel/WIRED*

Facebook is building a research lab dedicated to the new breed of artificial intelligence, after hiring one of the preeminent researchers in the field: New York University professor Yann LeCun

NYU "Deep Learning" Professor LeCun Will Head Facebook's New Artificial Intelligence Lab, Dec 10, 2013

Por Hoje é Só…