IntroML
ML. 7.3. Convolutional neural nets

DataLab CSIC

Objectives and schedule

Introduce key concepts about convolutional neural networks (CNNs, Convnets)

CASI 18, Goodfellow et al 9, Chollet and Allaire 5

Case by Nacho Villanueva (ICMAT, UCM) on forecasting eolic energy production

http://srdas.github.io/DLBook/ConvNets.html

https://www.youtube.com/watch?v=BFdMrDOx_CM

Labs

- MNST
  - logreg
  - fully connected network
    - With L2 regularization
    - With dropout
  - Model maintenance
  - Random forest
  - CNN

- Drago, Artemisa
- Lovelace, Carlitos
- Google Collab

Conv NNs. Motivation

Motivation

- Fully connected NNs can approximate any function….
- But training can be super slow and may require lots of data
- In some domains, lots gained through specific architectures
- In vision, convolutional neural nets

History

- Hubel and Wiesel (60’s) visual perception of cats
- Fukushima (late 70’s) introduces neocognitron (without training algo)
- Le Cun et al (90’s) ‘neocognitron+backprop’ leads to convnets to handle MNIST dataset. Le Net 5
- Alexnet (2012) (1.3 M images to recognise 1000 objects)
- VGGNet (2014), Googlenet (2015) win the Imagenet competition leading to explosion of interest

Towards convnets

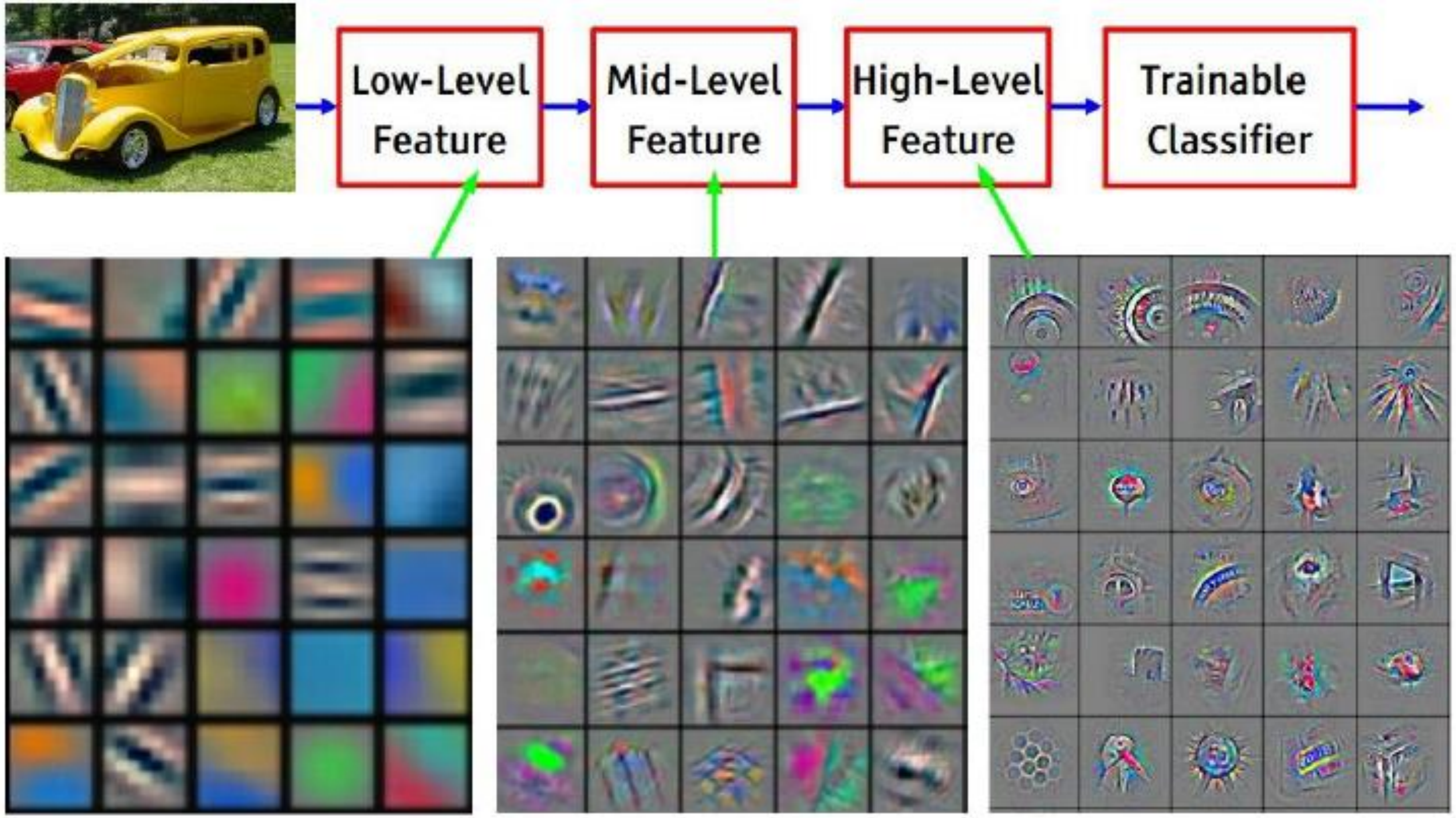
Before

- Objects to be classified ----> Extract features ‘manually’ ----> Trainable classifier

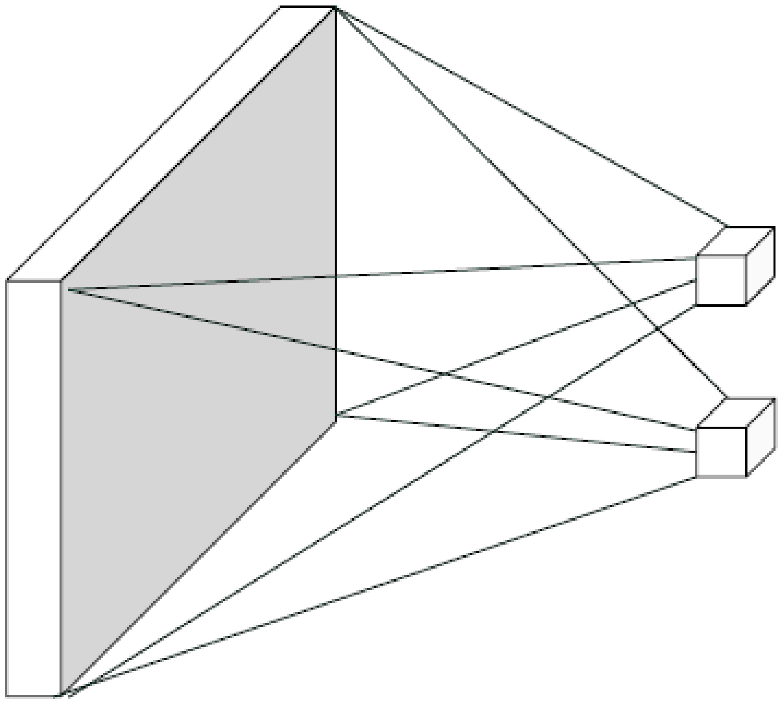
Today

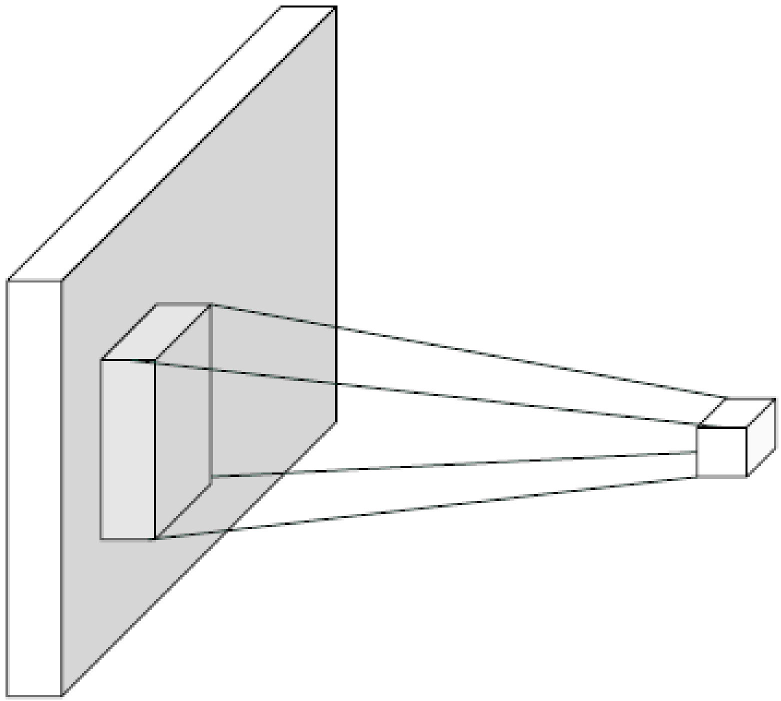
- Objects to be classified ----> Trainable feature extractor ----> Trainable classifier (even integrated)

CNNs. Typical structure



From fully connected DNs to convolutional (deep) nets



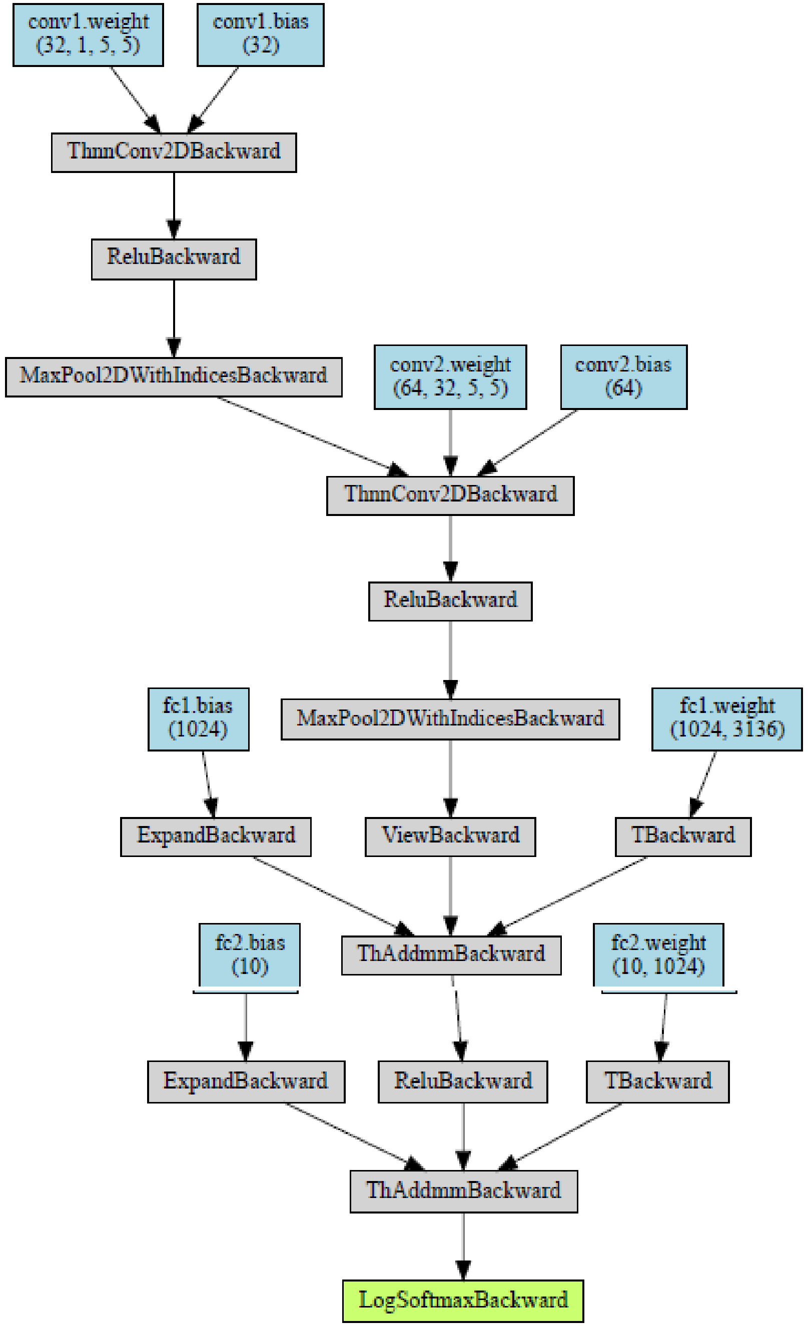


Towards convolutional networks

- Three concepts
  - Convolution
  - RELU
  - MaxPool

- Applications
  - Image recognition (e.g., security)
  - Video analysis (e.g., ADS)
  - Sound analysis

  - Pharma discovery
  - ….. And others



Core concepts

Convolution

CNNs: Neural nets which include convolution in at least one of the layers

Convolution. Linear operator. For measurement x(t), weighted w(a) (a, past time)

$$s(t) = (x * w)(t) = \sum_{a=-\infty}^{\infty} x(a)w(t-a)$$

x, input; w, kernel

Convolution

In DL: Input. Multidimensional matrix (tensor) (eg, piece of an image)

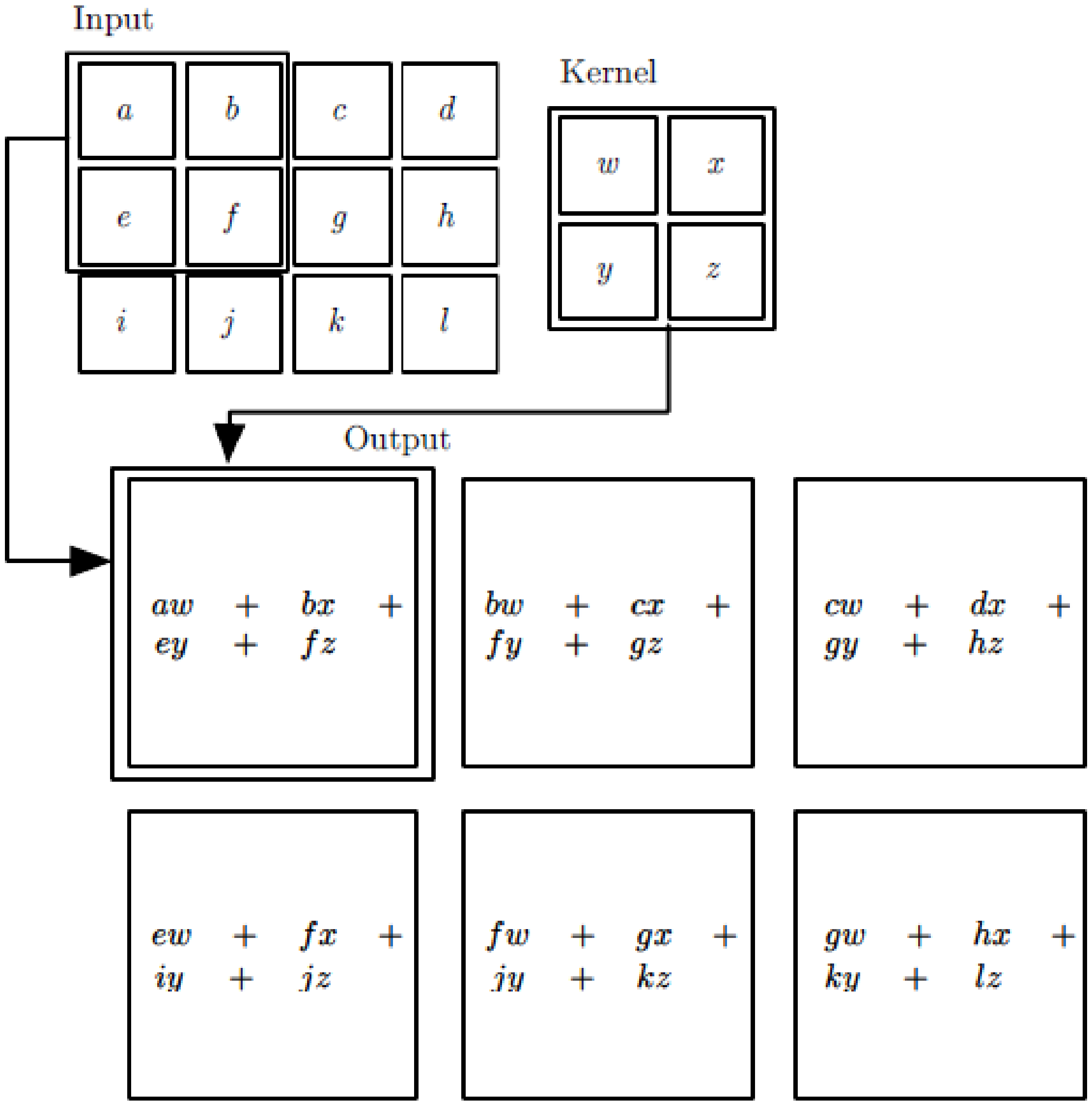
Kernel. Multidimensional matrix (tensor)

Convolution in more than one dimension (eg I bidimensional image, K bidimensional kernel)

$$S(i,j) = (I * K)(i,j) = \sum_m \sum_n I(i+m, j+n)K(m,n)$$

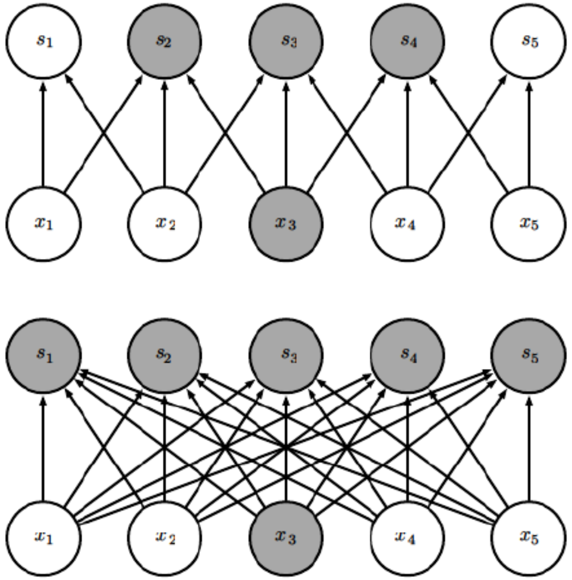
Multiplication by a circulating matrix, frequently sparse (many zeros)

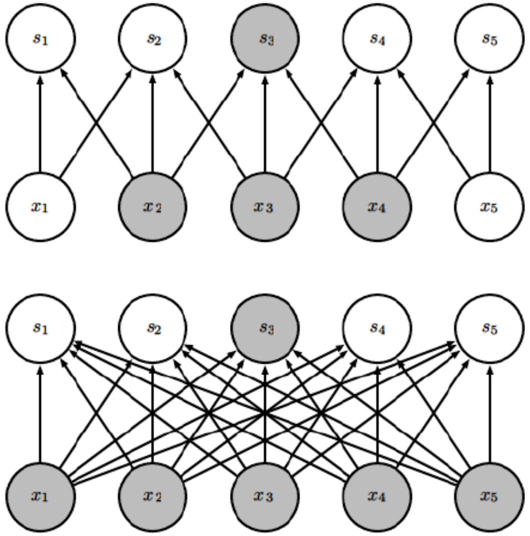
Convolution

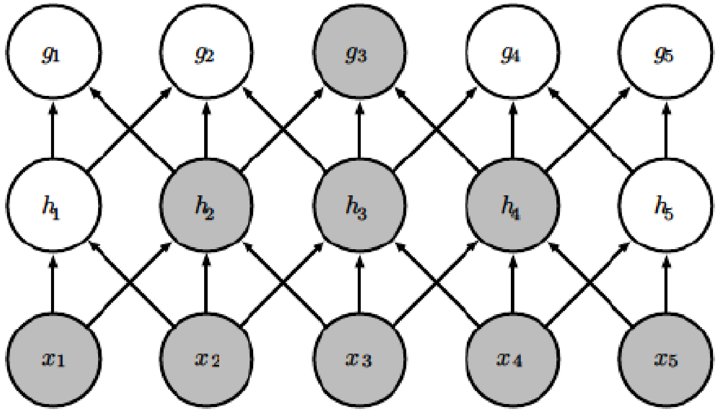


Convolution

- Less dense interactions

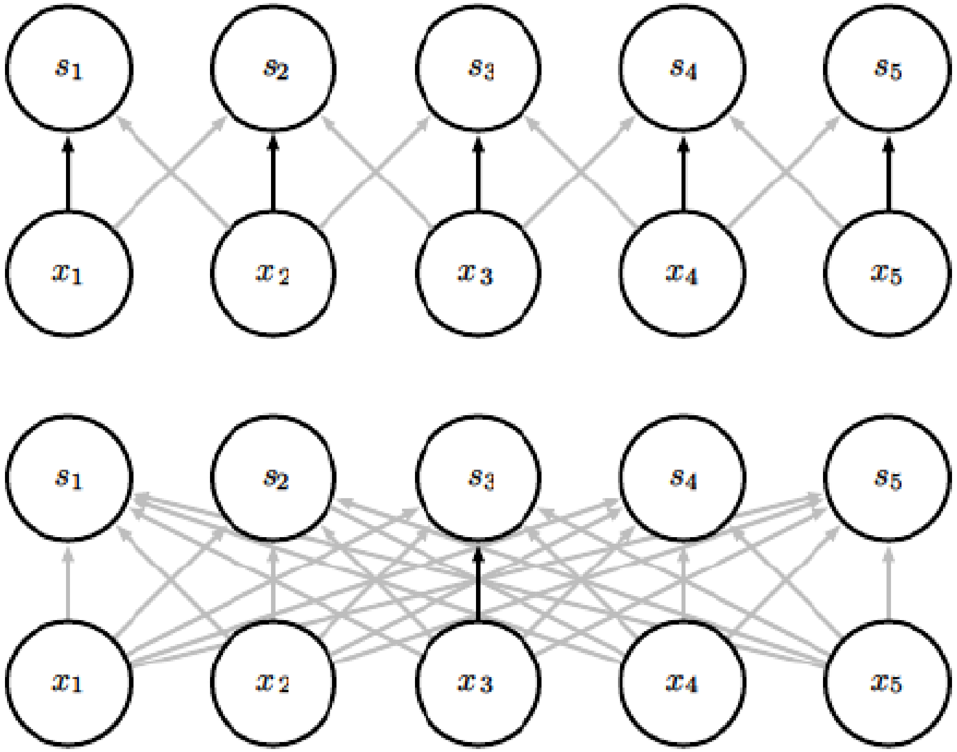






Convolution

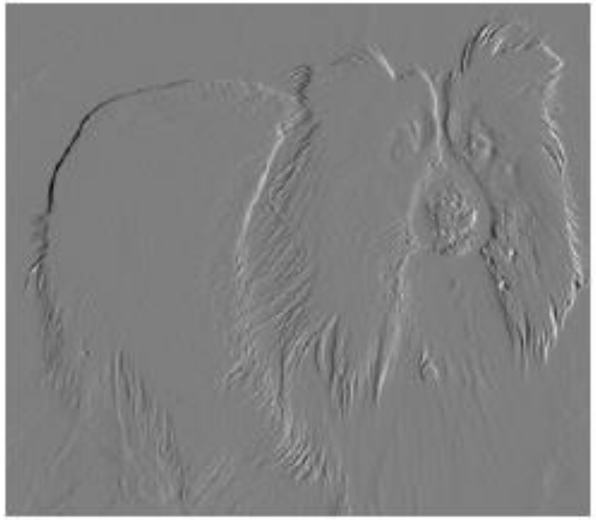
- Parameter sharing

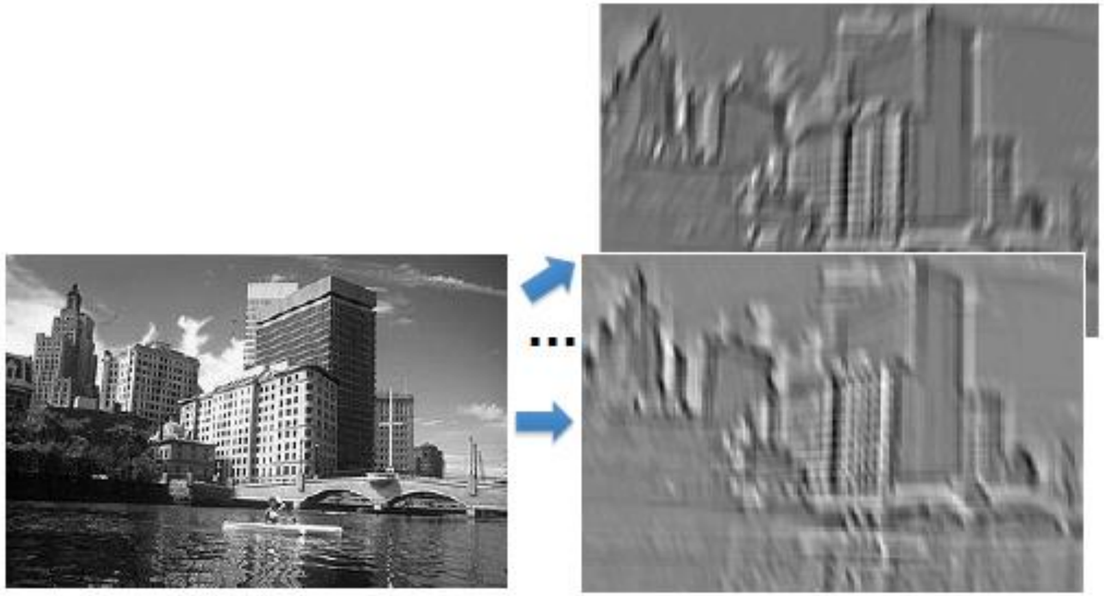


Convolution

Low density+sharing   -> Edge detection, feature extraction

Remove to each pixel that on its left

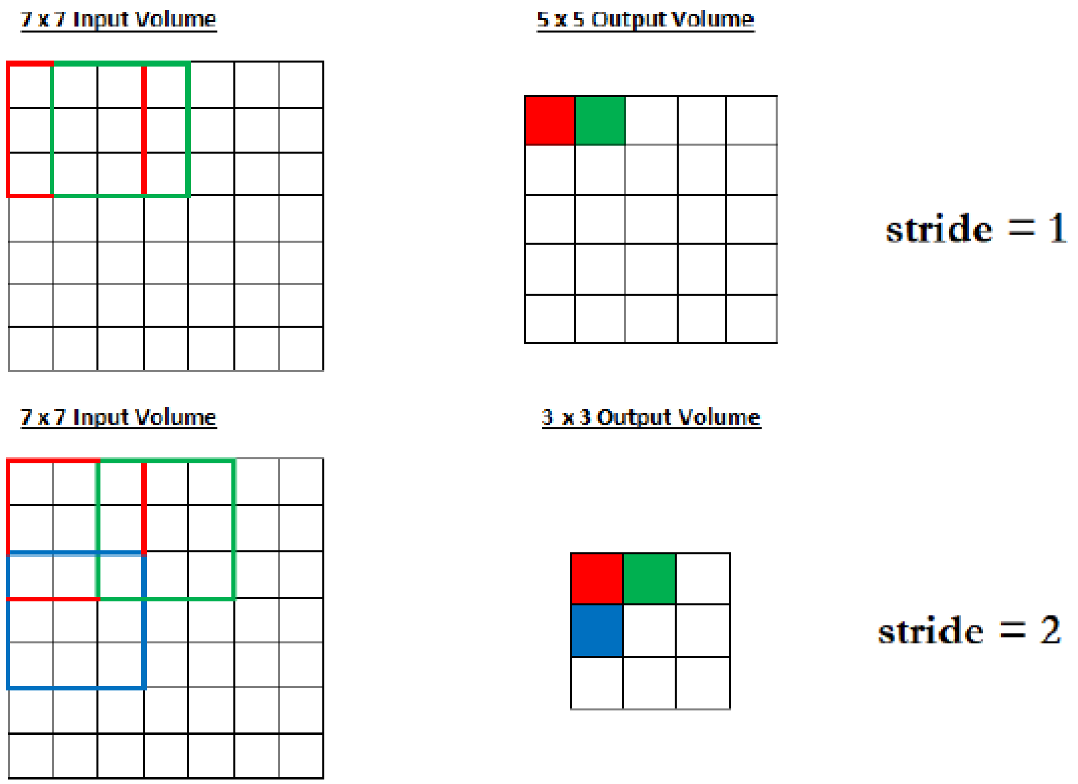




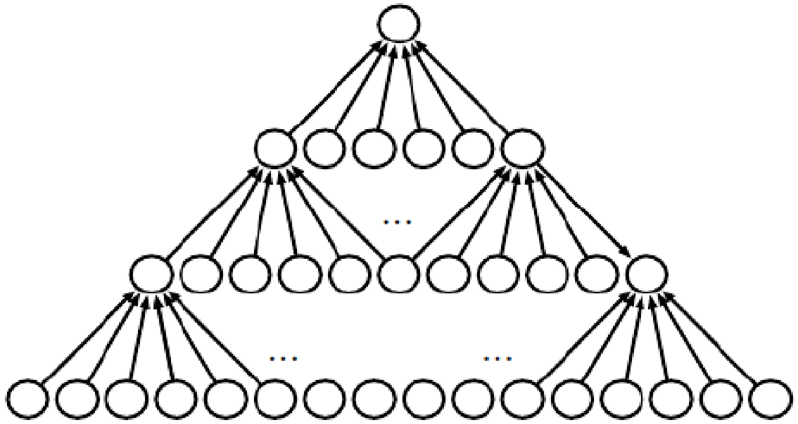
- Equivariance against traslations

Convolution stride

- Stride of the kernels sliding window

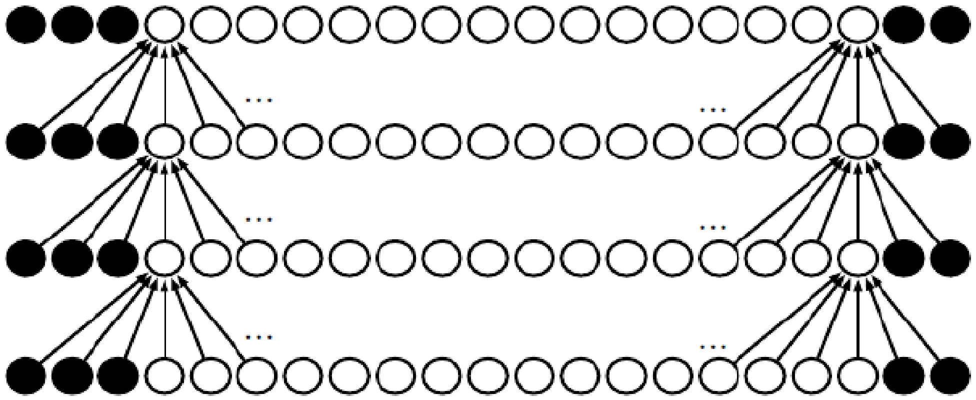


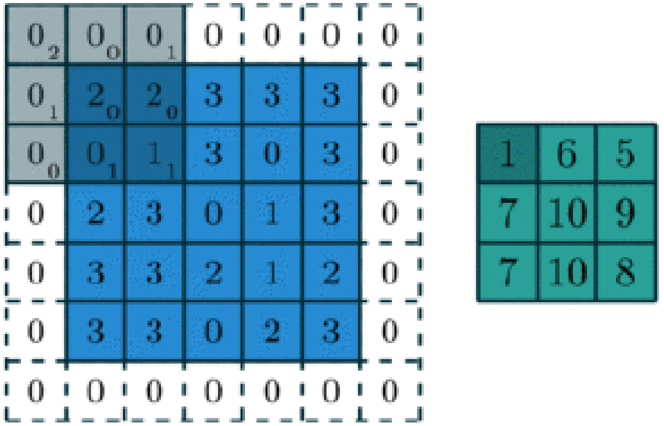
Zero padding



- What if we apply a **5x5** filter to a **32x32** image?
- The resulting image is **28x28** !!
- As we pile convolutional layers, the representation size gets reduced (info loss, specially in first layers)
- Mitigate by padding with zero's the image edge

Input 5x5, kernel 3x3, Stride 2



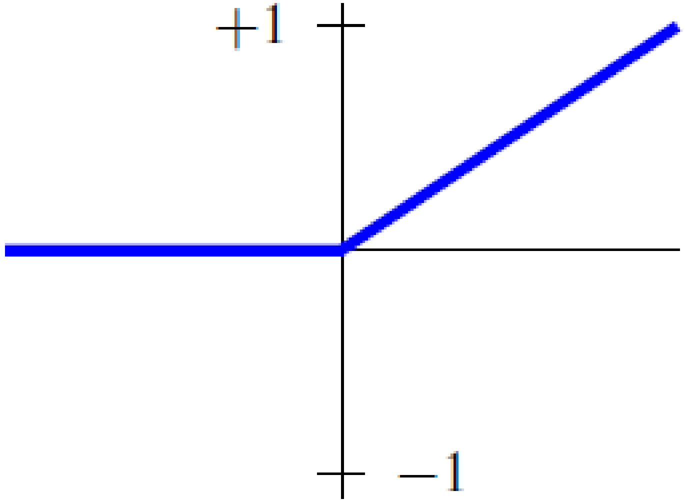


Pars defining convolution

- Stride
- Kernel size (usually square)
- Depth (number of kernels)
- Padding

Rectified linear unit. RELU

$$f(x) = \begin{cases} 0, & x < 0 \\ x, & x \geq 0 \end{cases}$$



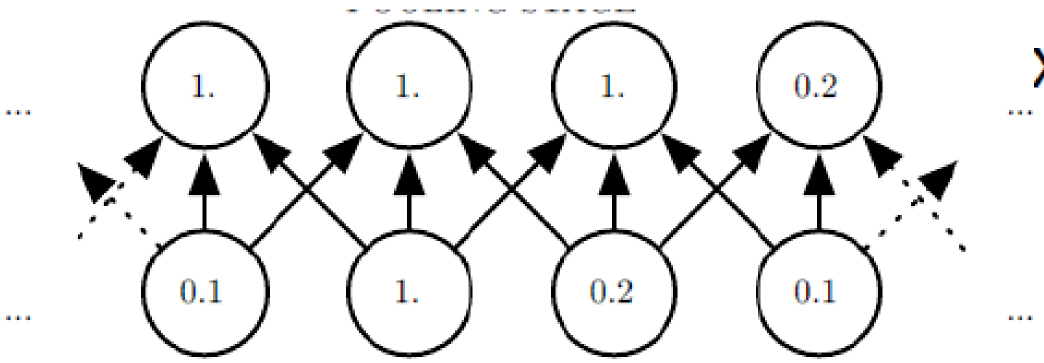
Lineal rectificada (ReLU)

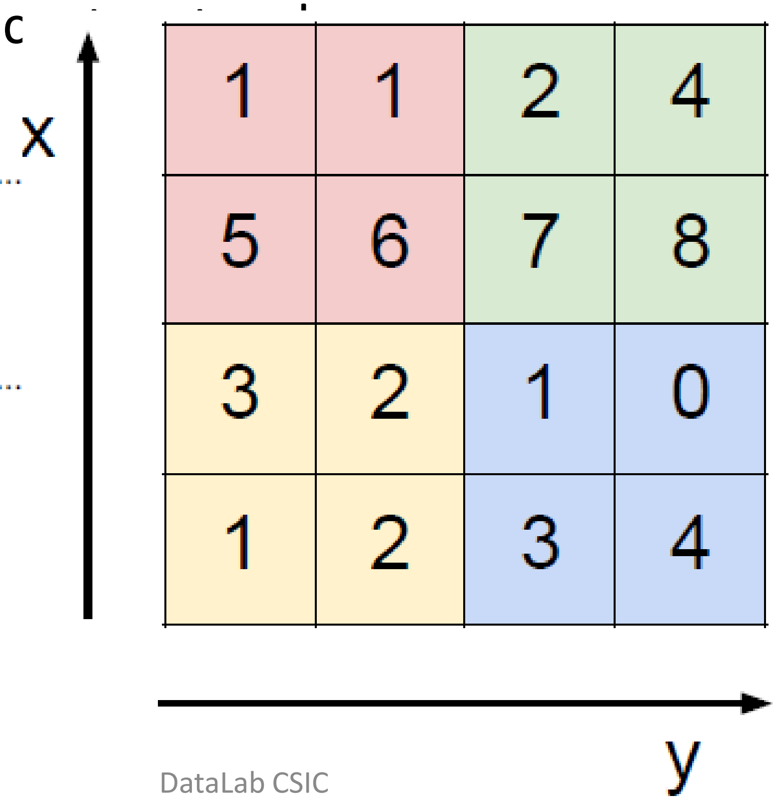
- More efficient computationally than other nonlinear functions (e.g. derivative simple, derivative??)
- Alleviating *vanishing gradient*

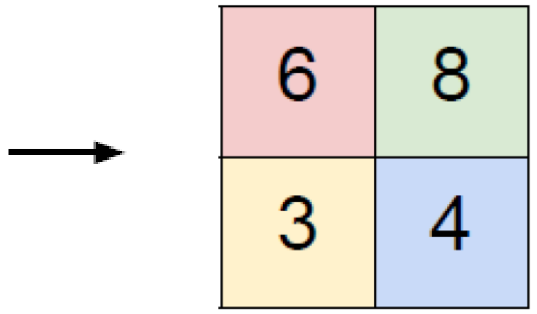
MaxPooling

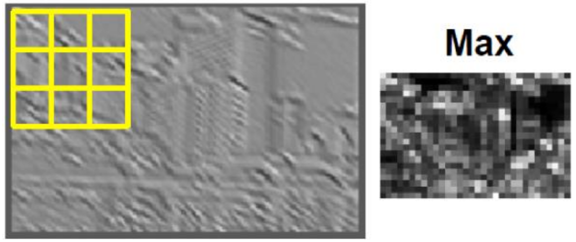
Pooling. Replaces output in a position by outputs in adjacent positions. Reduces number of pars. Is a feature present?

MaxPooling. Maximum of outputs in adjac









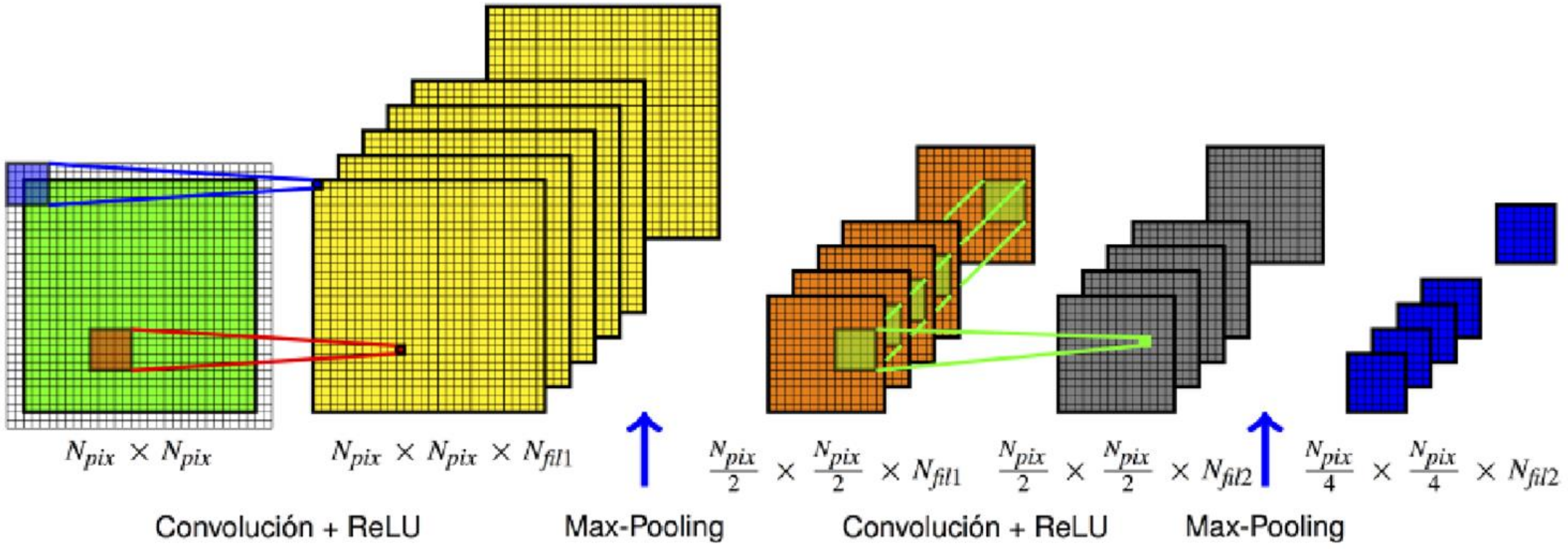
Average Pooling

CNN. Typical structures

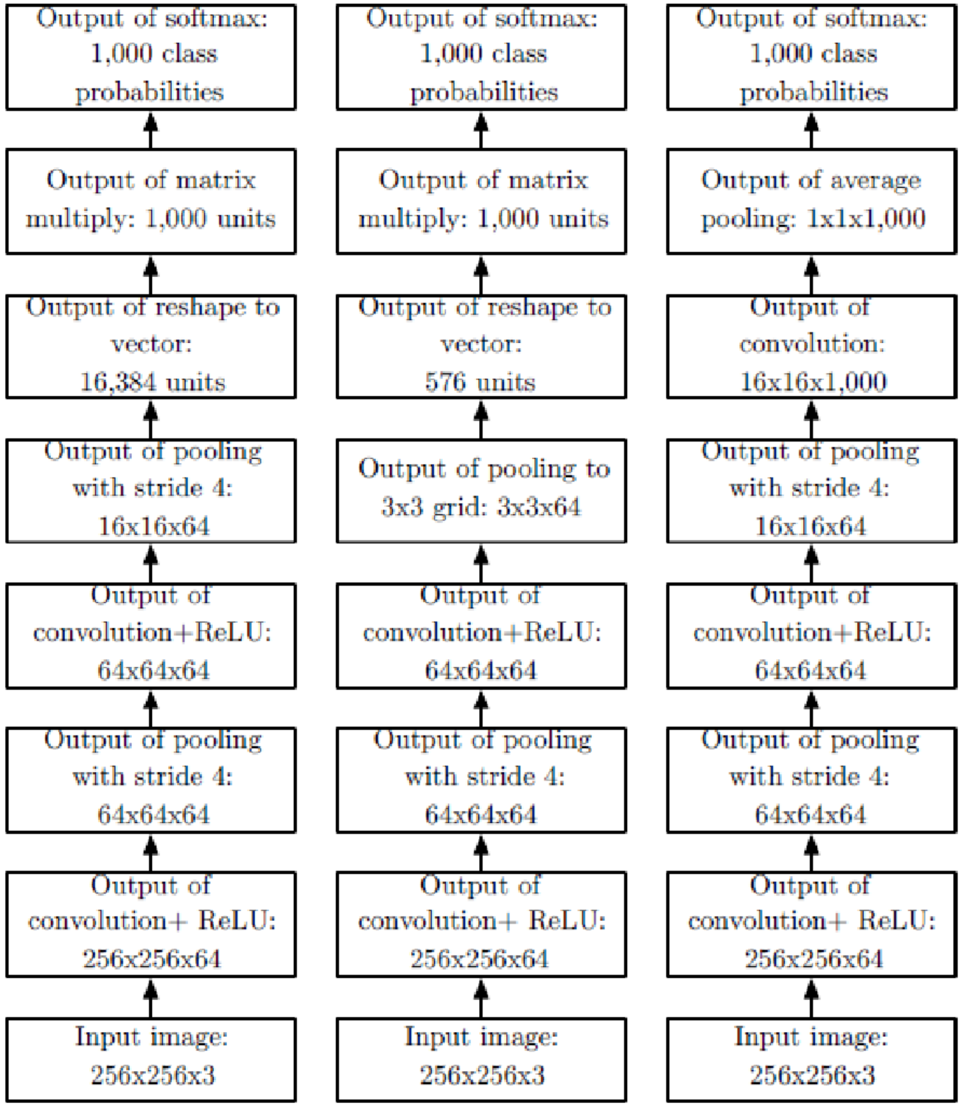
CNNs. Typical structure

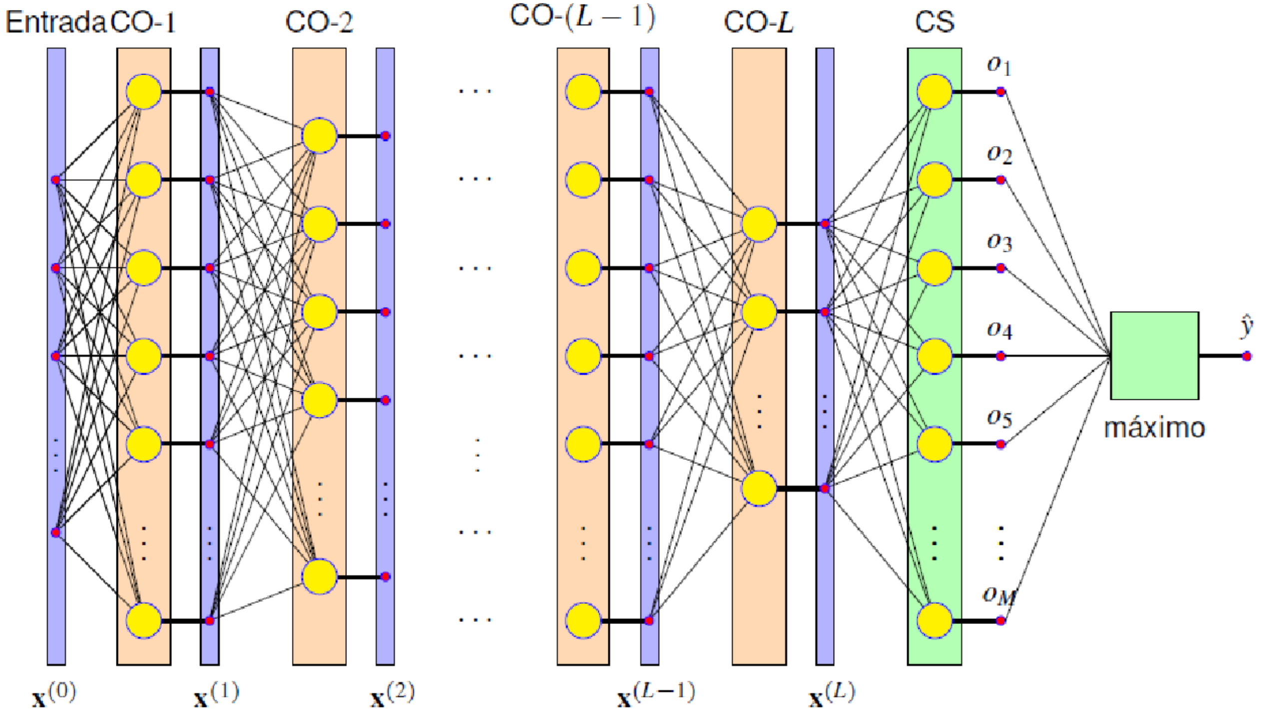
- Input to layer
- (Convolutional) Layer
  - Convolutional phase. Affine transformation
  - Detection phase. Non linearity, e.g. RELU
  - Pooling phase
- Output of layer

CNNs. Typical structure

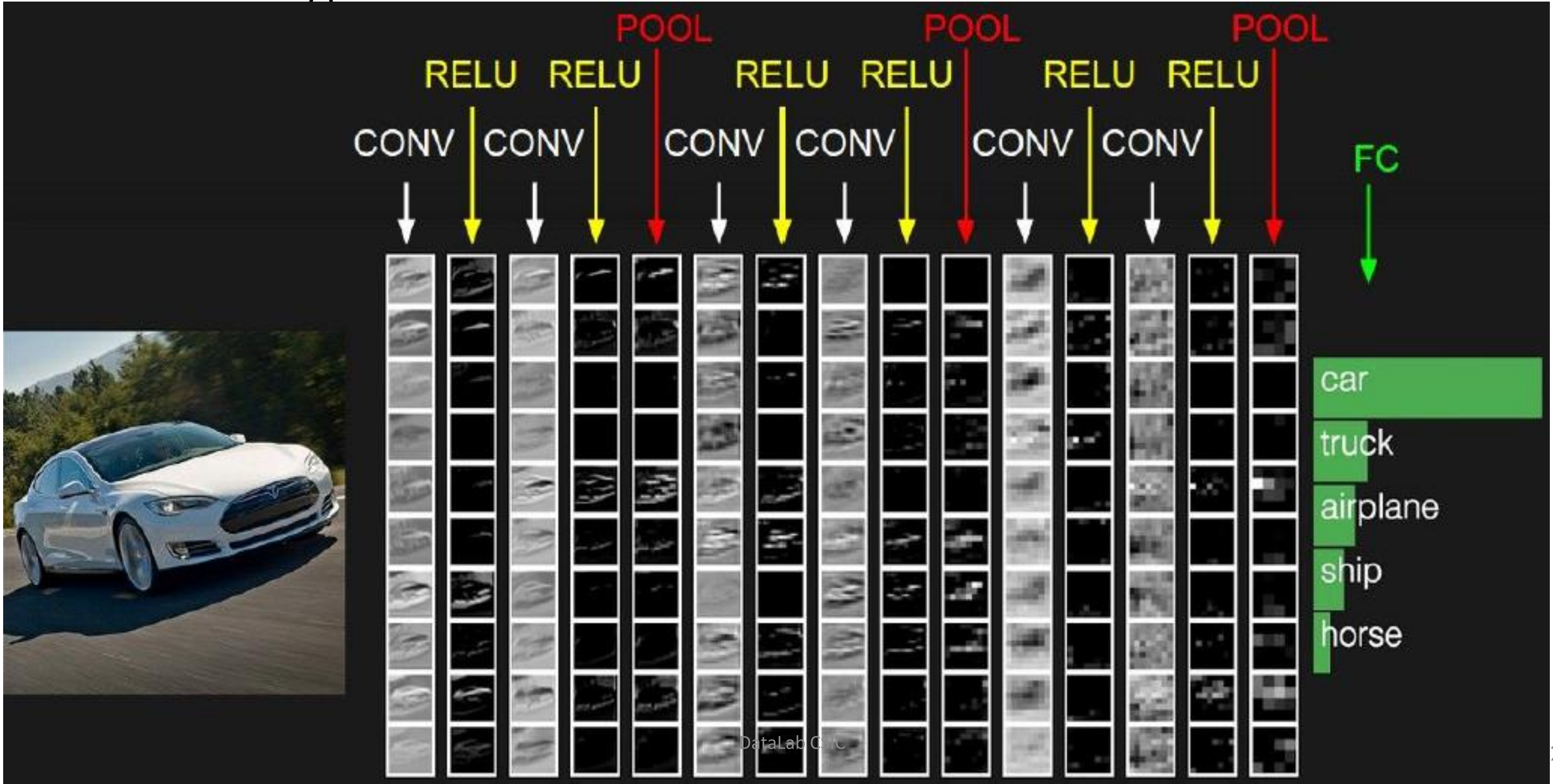


CNNs. Some typical structures





Convnets. Typical structure

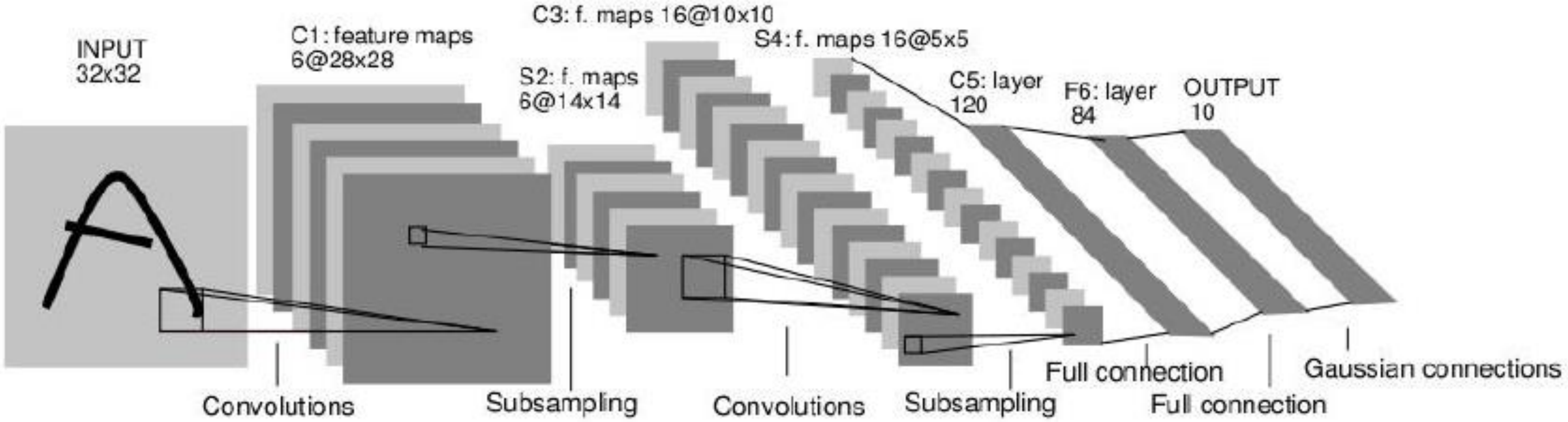


CNN in the lab

1. Conv layer, 32 filters, kernel 3×3, ReLU
2. Conv layer 64 filters, kernel 3×3, ReLU
3. Max pooling 2×2
4. Dropout (0.25)
5. Dense 128 units, ReLU
6. Dropout (0.5)
7. Output layer

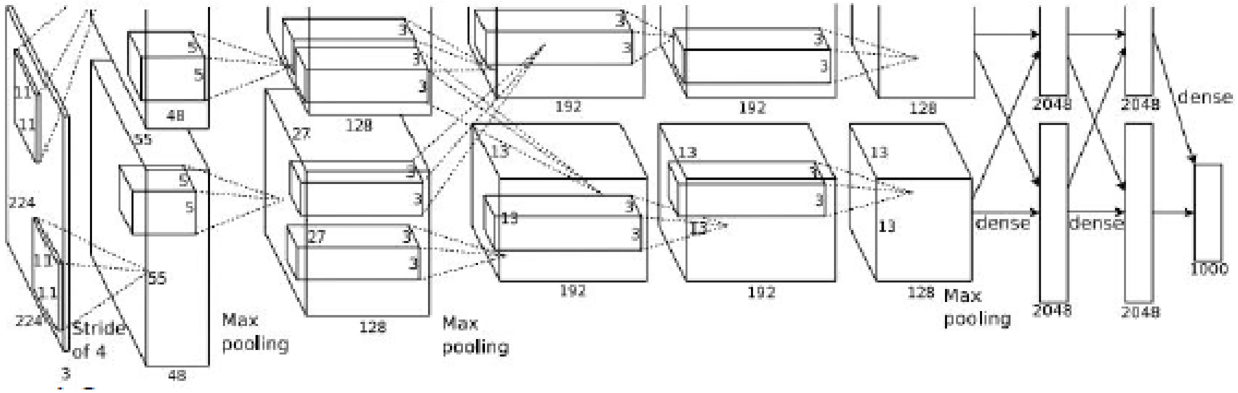
CNN. Some standards

LeNet 5


INPUT
32x32
C1: feature maps
6@28x28
S2: f. maps
6@14x14
C3: f. maps 16@10x10
S4: f. maps 16@5x5
C5: layer
120
F6: layer
84
OUTPUT
10
Convolutions
Subsampling
Convolutions
Subsampling
Full connection
Full connection
Gaussian connections

AlexNet

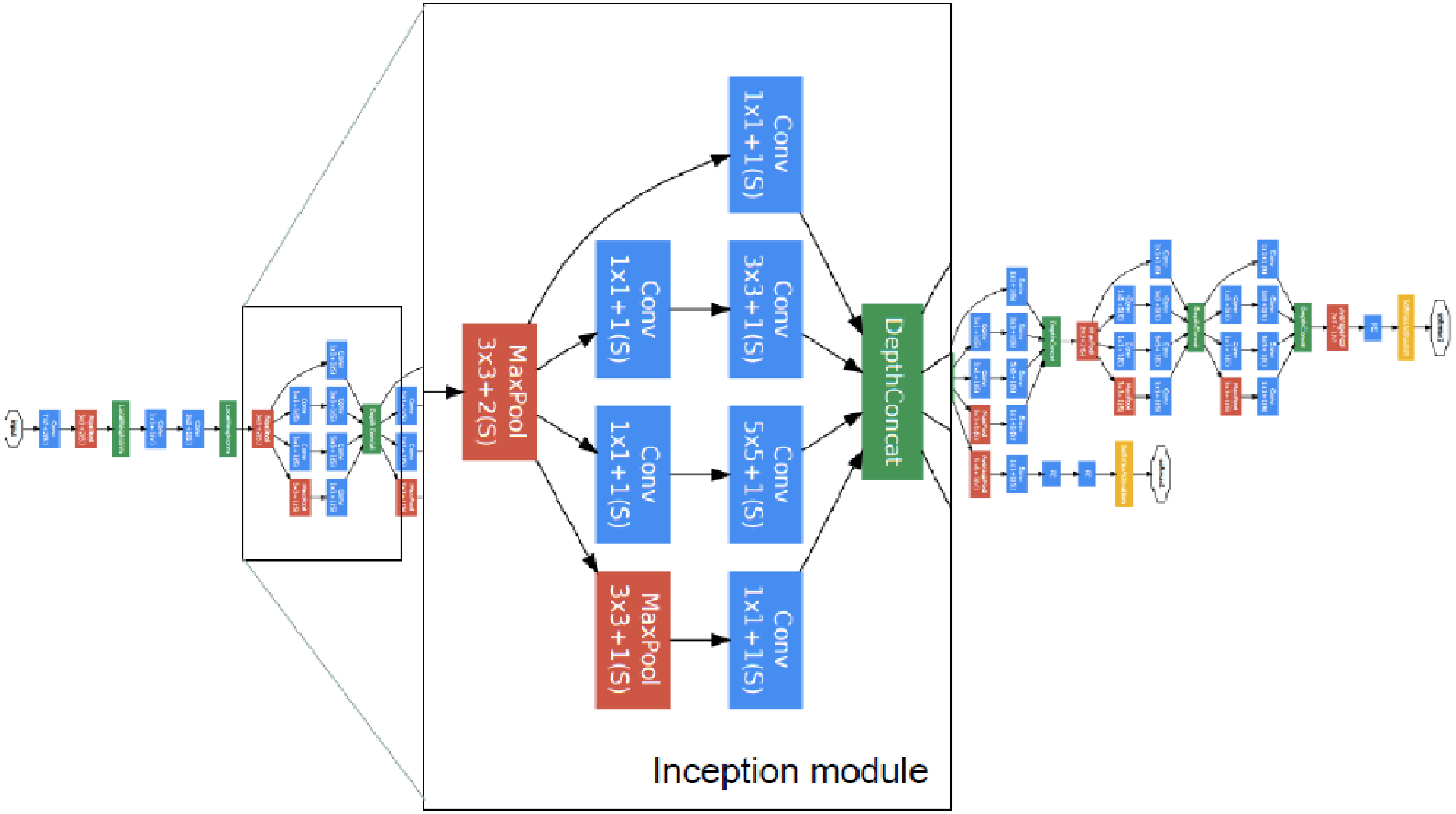
[227x227x3] INPUT
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] NORM2: Normalization layer
[13x13x384] 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)



VGGNet

INPUT: [224x224x3] memory: 224*224*3=150K params: 0 (not counting biases)
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*3)*64 = 1,728
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*64)*64 = 36,864
POOL2: [112x112x64] memory: 112*112*64=800K params: 0
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*64)*128 = 73,728
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*128)*128 = 147,456
POOL2: [56x56x128] memory: 56*56*128=400K params: 0
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*128)*256 = 294,912
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
POOL2: [28x28x256] memory: 28*28*256=200K params: 0
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*256)*512 = 1,179,648
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
POOL2: [14x14x512] memory: 14*14*512=100K params: 0
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
POOL2: [7x7x512] memory: 7*7*512=25K params: 0
FC: [1x1x4096] memory: 4096 params: 7*7*512*4096 = 102,760,448
FC: [1x1x4096] memory: 4096 params: 4096*4096 = 16,777,216
FC: [1x1x1000] memory: 1000 params: 4096*1000 = 4,096,000

GoogleNet



MaxPool 3x3+2(S)
Conv 1x1+1(S)
Conv 1x1+1(S)
Conv 1x1+1(S)
Conv 3x3+1(S)
Conv 1x1+1(S)
Conv 5x5+1(S)
MaxPool 3x3+1(S)
Conv 1x1+1(S)
DepthConcat
Inception module

Some architectures

Team	Year	Place	Error (top-5)	External data
SuperVision – Toronto (AlexNet, 7 layers)	2012	-	16.4%	no
SuperVision	2012	1st	15.3%	ImageNet 22k
Clarifai – NYU (7 layers)	2013	-	11.7%	no
Clarifai	2013	1st	11.2%	ImageNet 22k
VGG – Oxford (16 layers)	2014	2nd	7.32%	no
GoogLeNet (19 layers)	2014	1st	6.67%	no
ResNet (152 layers)	2015	1st	3.57%	
Human expert*			5.1%	

Final comments

From fully connected NNs to CNNs. ResNet

Other paradigms next (RNNs,…)

Once conceived the architecture, train by SGD+backprop

Keras

- Transfer learning based on standard architectures (e.g. available in Keras)
- Data augmentation
- Visualization as explanation