Big Data Technology

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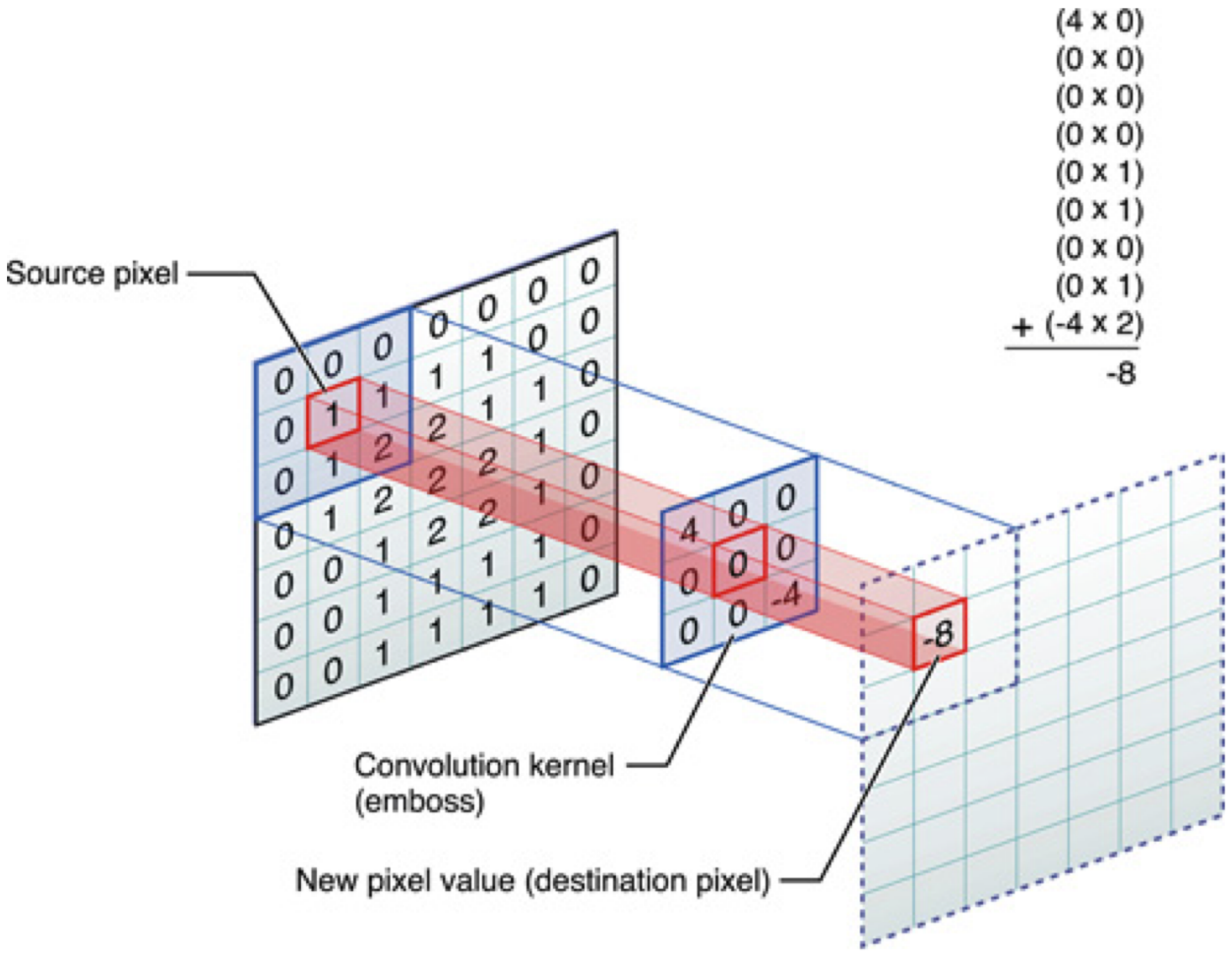
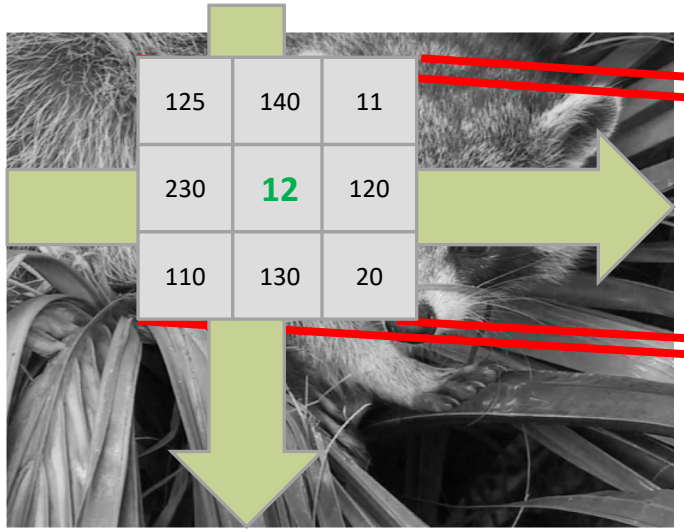
2-Dimensional Convolution



Example: 2-Dimensional Convolution

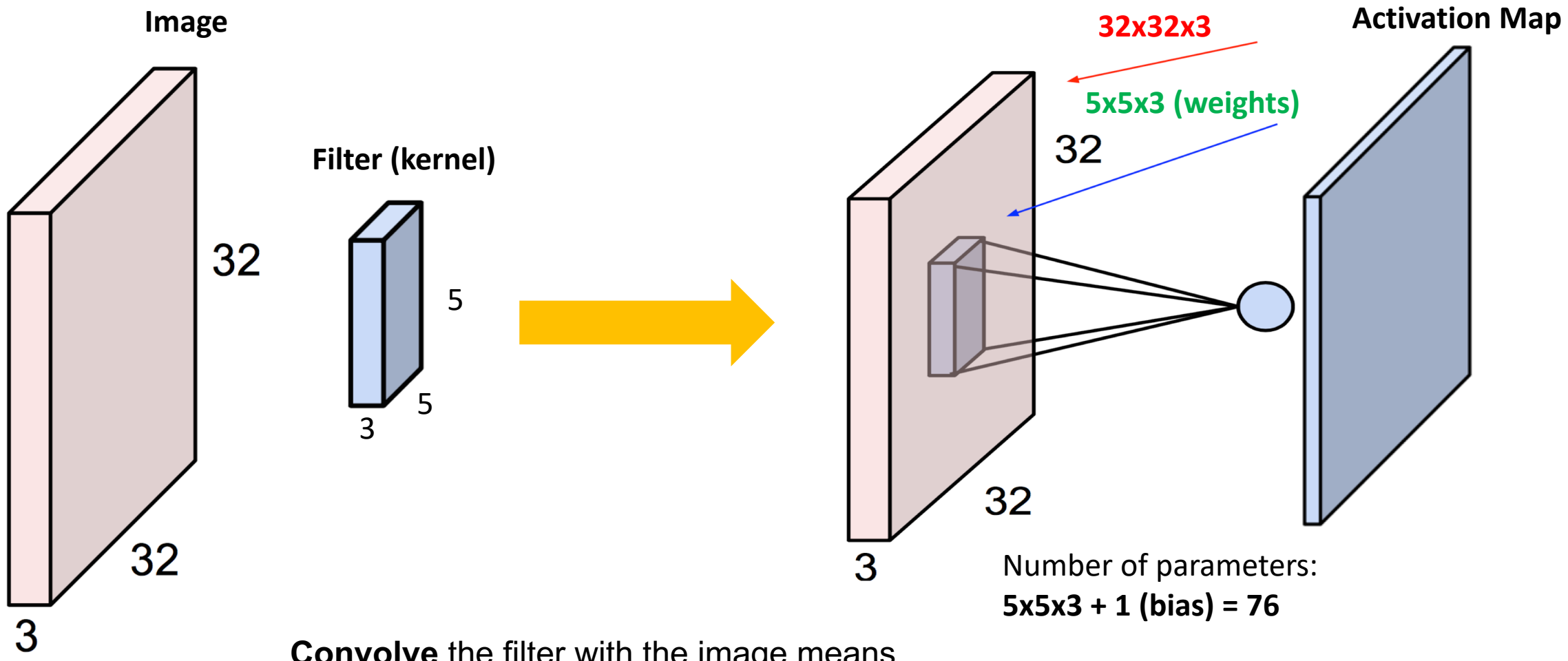
A convolution is an integral (discrete signals :Matrix Dot Product) that expresses the amount of overlap of one function as it is shifted over another function



-1	-2	-1
0	0	0
1	2	1

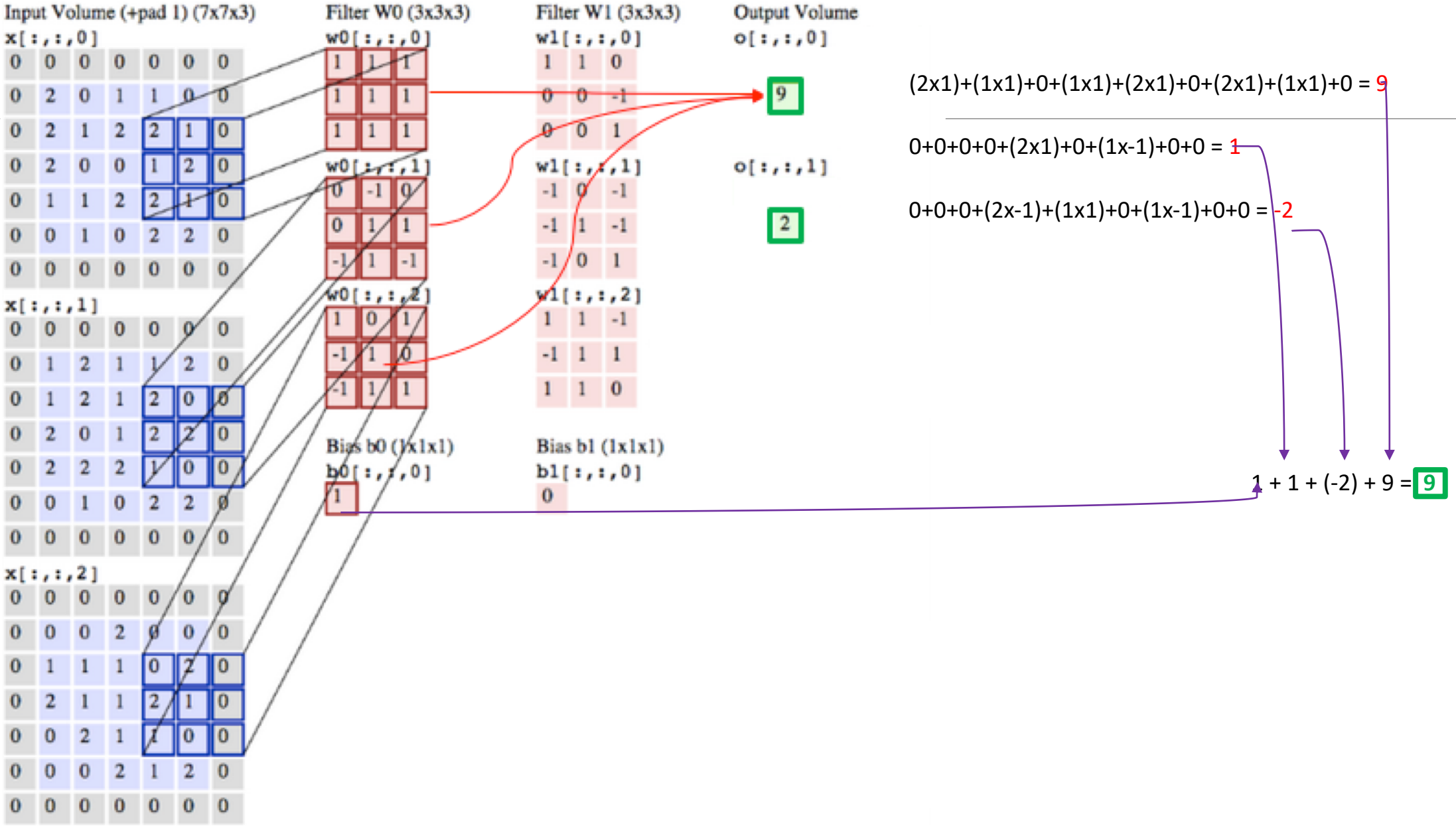
-1	0	1
-2	0	2
-1	0	1

Convolution Layer



Number of parameters:
5x5x3 + 1 (bias) = 76

Convolve the filter with the image means
"slide over the image spatially, compute dot products"


Input Volume (+pad 1) (7x7x3)
x[:,:,0]
0 0 0 0 0 0 0
0 2 0 1 1 0 0
0 2 1 2 2 1 0
0 2 0 0 1 2 0
0 1 1 2 2 1 0
0 0 1 0 2 2 0
0 0 0 0 0 0 0
x[:,:,1]
0 0 0 0 0 0 0
0 1 2 1 1 2 0
0 1 2 1 2 0 0
0 2 0 1 2 2 0
0 2 2 2 1 0 0
0 0 1 0 2 2 0
0 0 0 0 0 0 0
x[:,:,2]
0 0 0 0 0 0 0
0 0 0 2 0 0 0
0 1 1 1 0 2 0
0 2 1 1 2 1 0
0 0 2 1 1 0 0
0 0 0 2 1 2 0
0 0 0 0 0 0 0
Filter W0 (3x3x3)
w0[:,:,0]
1 1 1
1 1 1
1 1 1
w0[:,:,1]
0 -1 0
0 1 1
-1 1 -1
w0[:,:,2]
1 0 1
-1 1 0
-1 1 1
Filter W1 (3x3x3)
w1[:,:,0]
1 1 0
0 0 -1
0 0 1
w1[:,:,1]
-1 0 -1
-1 1 -1
-1 0 1
w1[:,:,2]
1 1 -1
-1 1 1
1 1 0
Bias b0 (1x1x1)
b0[:,:,0]
1
Bias b1 (1x1x1)
b1[:,:,0]
0
Output Volume
o[:,:,0]
9
o[:,:,1]
2
(2x1)+(1x1)+0+(1x1)+(2x1)+0+(2x1)+(1x1)+0 = 9
0+0+0+0+(2x1)+0+(1x-1)+0+0 = 1
0+0+0+(2x-1)+(1x1)+0+(1x-1)+0+0 = -2
1 + 1 + (-2) + 9 = 9

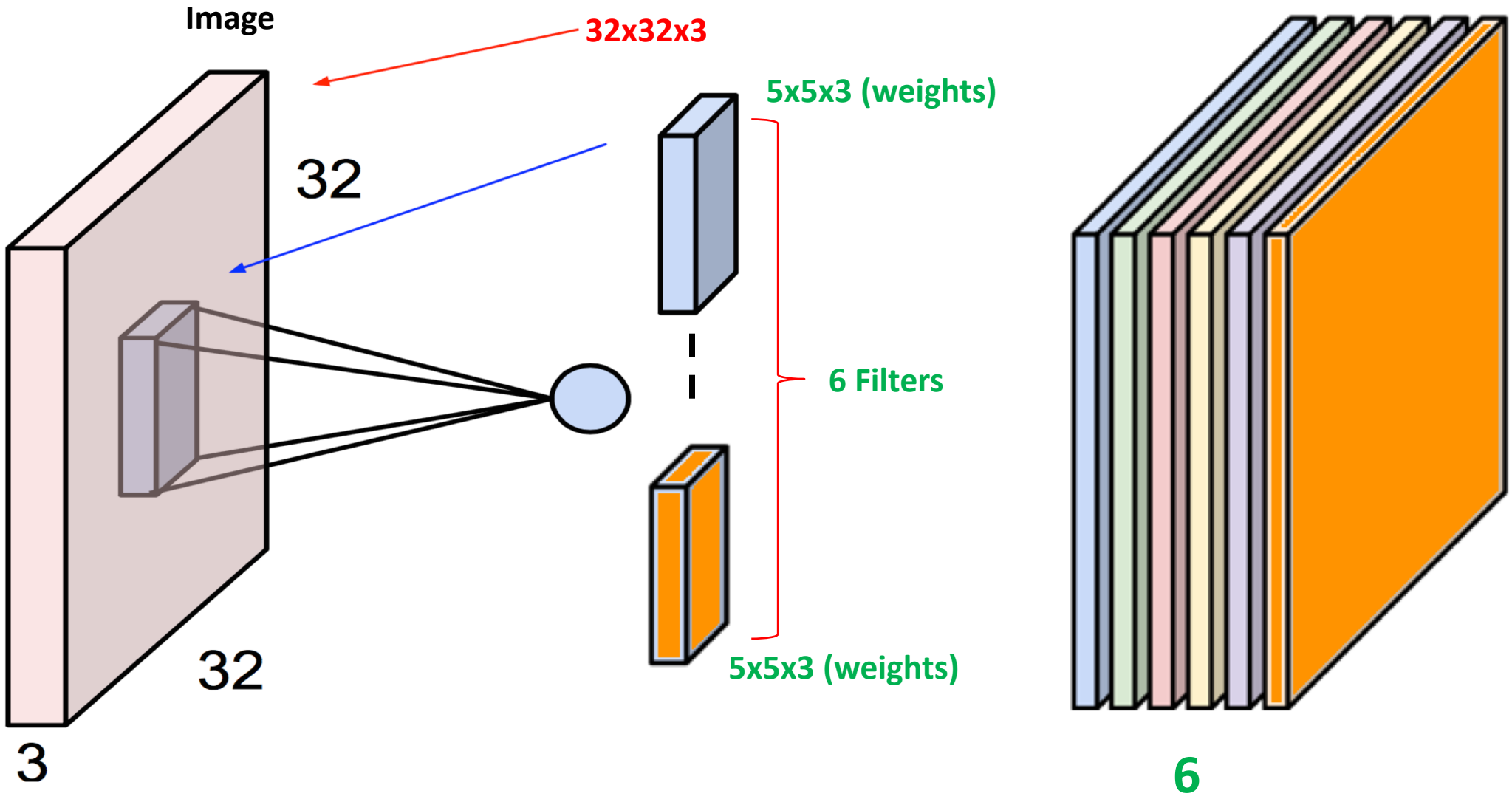
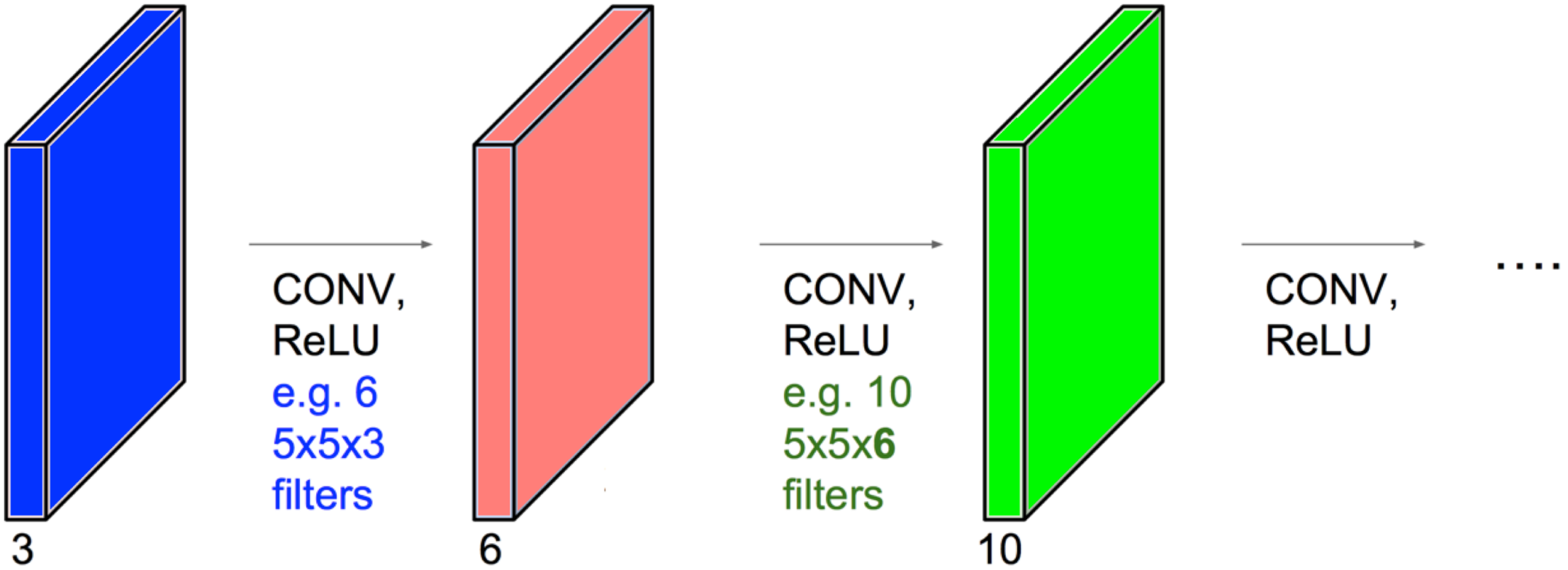
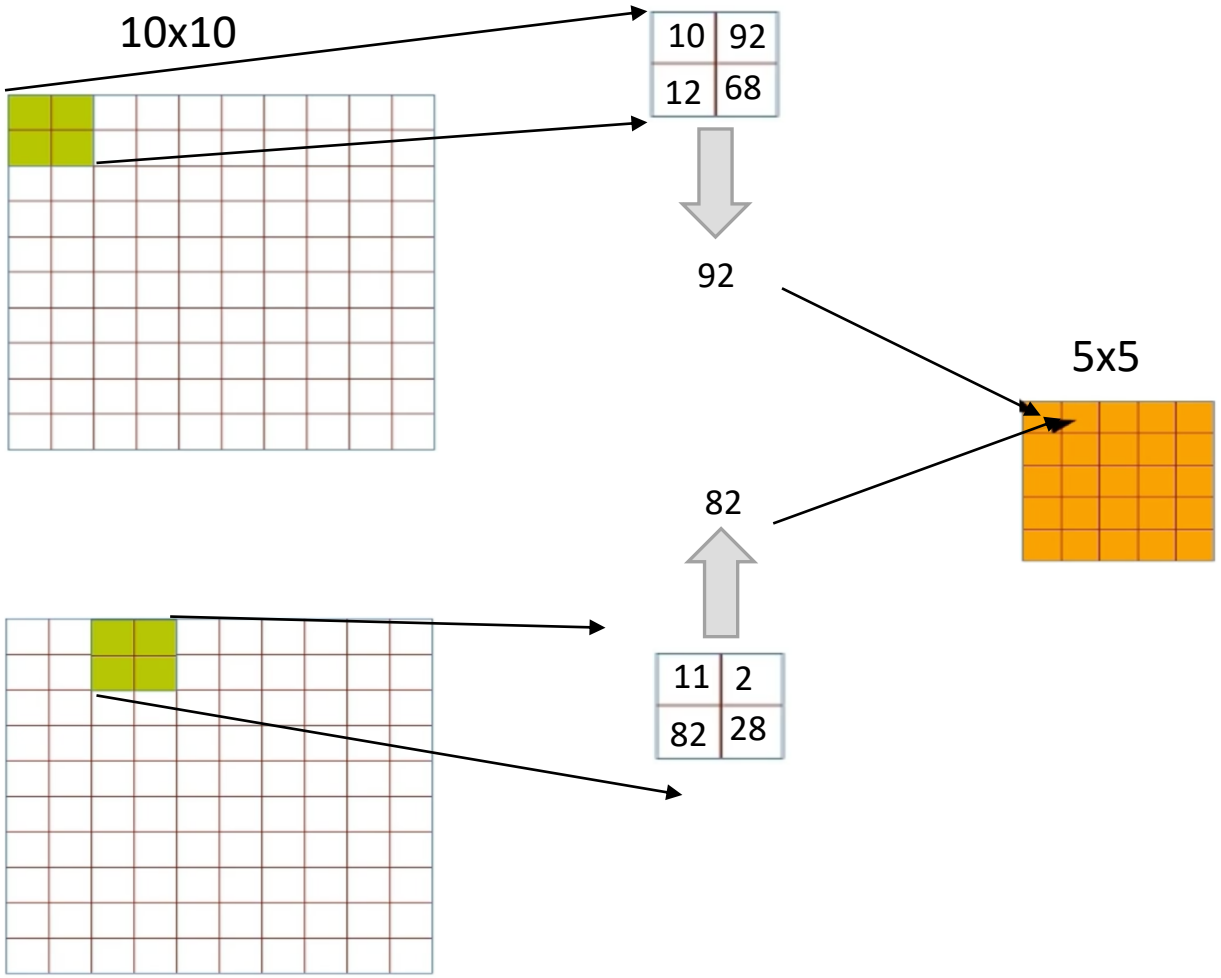


Image
32x32x3
5x5x3 (weights)
32
6 Filters
32
5x5x3 (weights)
3
6

Convolution Network



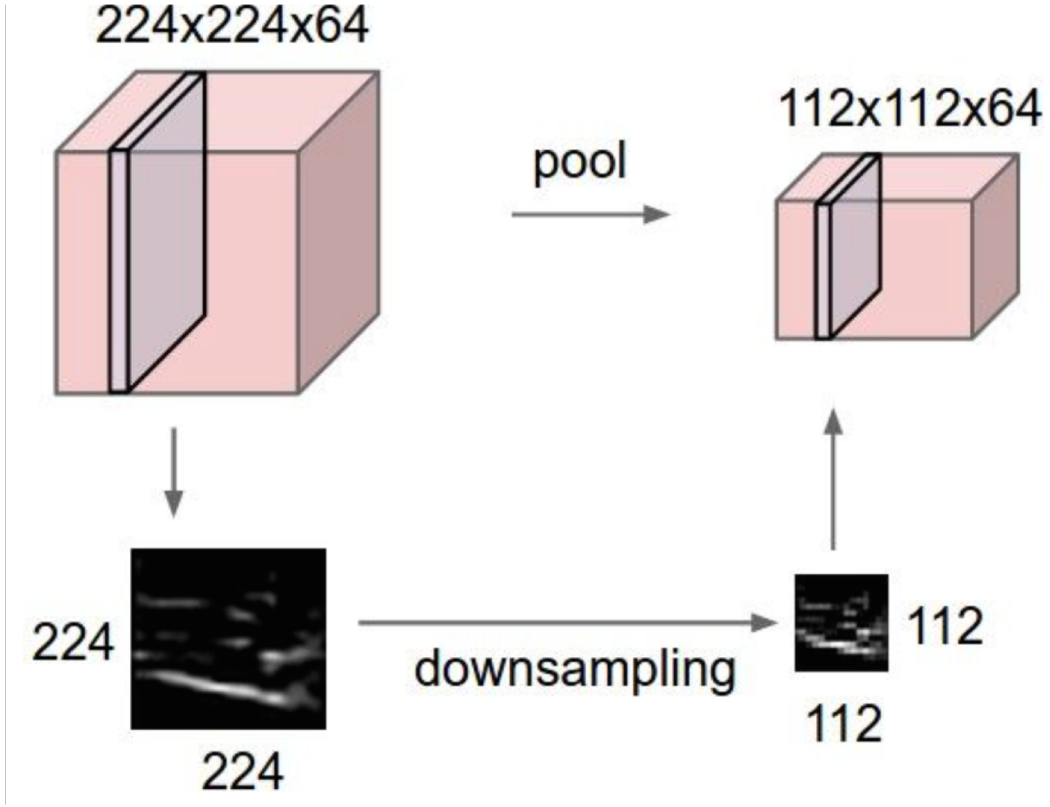
Downsampling = Max Pooling

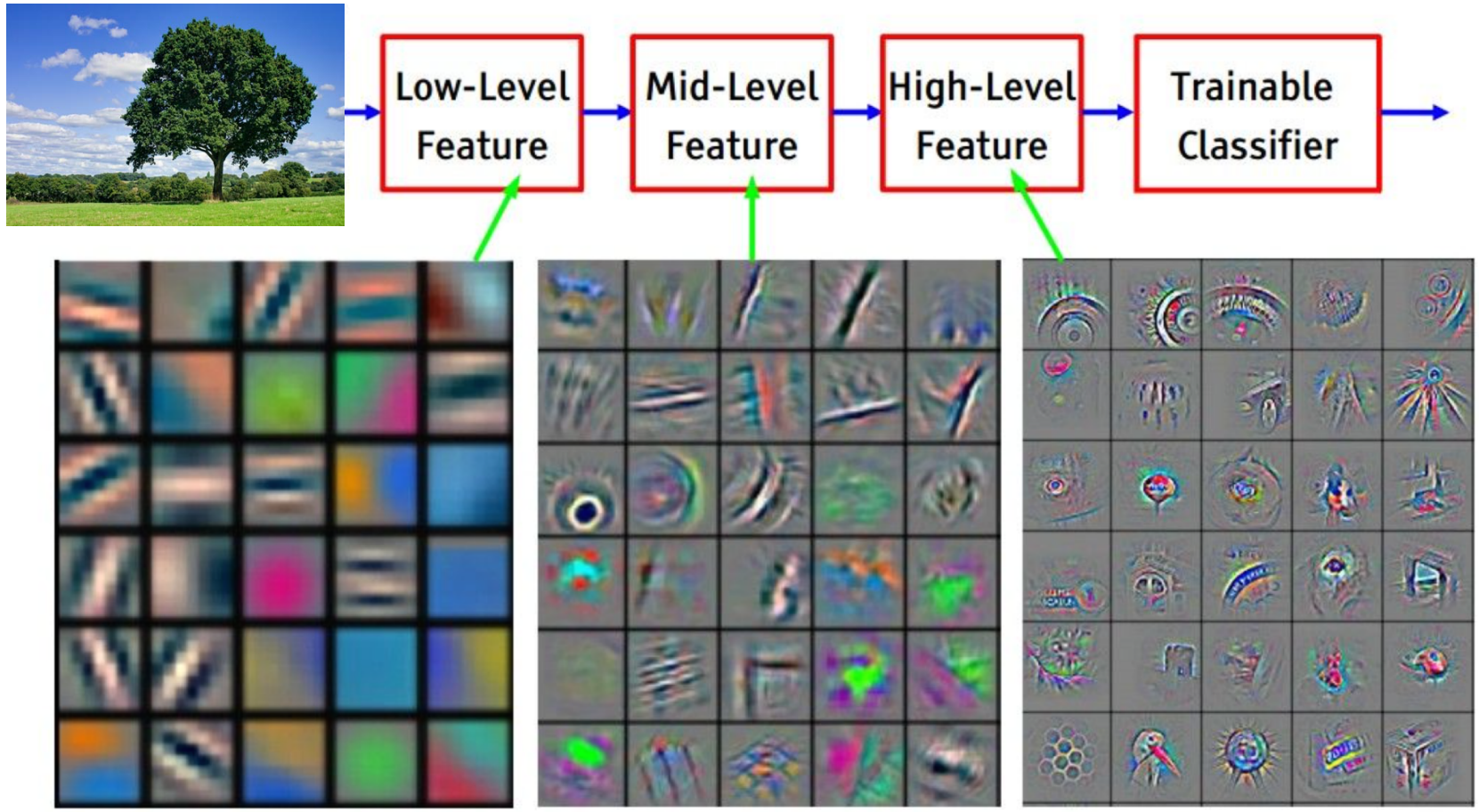


“Max Pooling” Layers to extract the “best” local feature

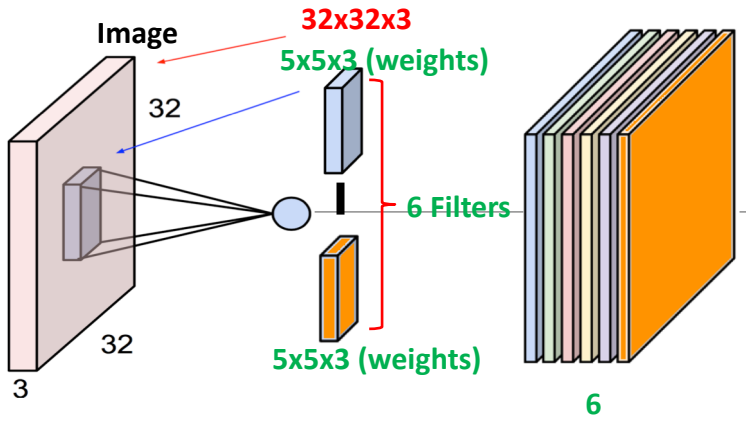
Pooling Layer

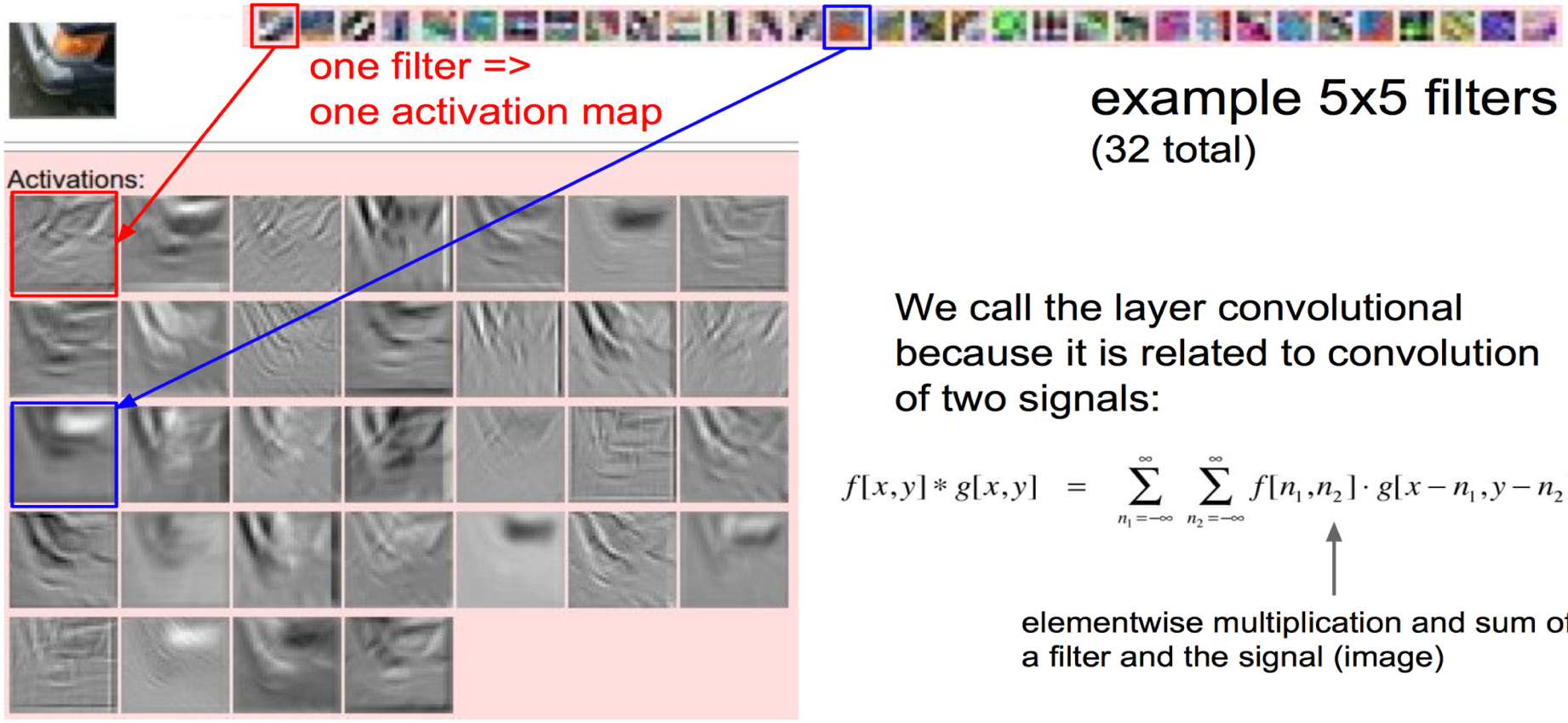
- Makes the representations smaller and more manageable
- Operates over each activation map independently





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





example 5x5 filters
(32 total)

We call the layer convolutional because it is related to convolution of two signals:

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

elementwise multiplication and sum of a filter and the signal (image)

Architecture of LeNet-5, Convolution Neural Network

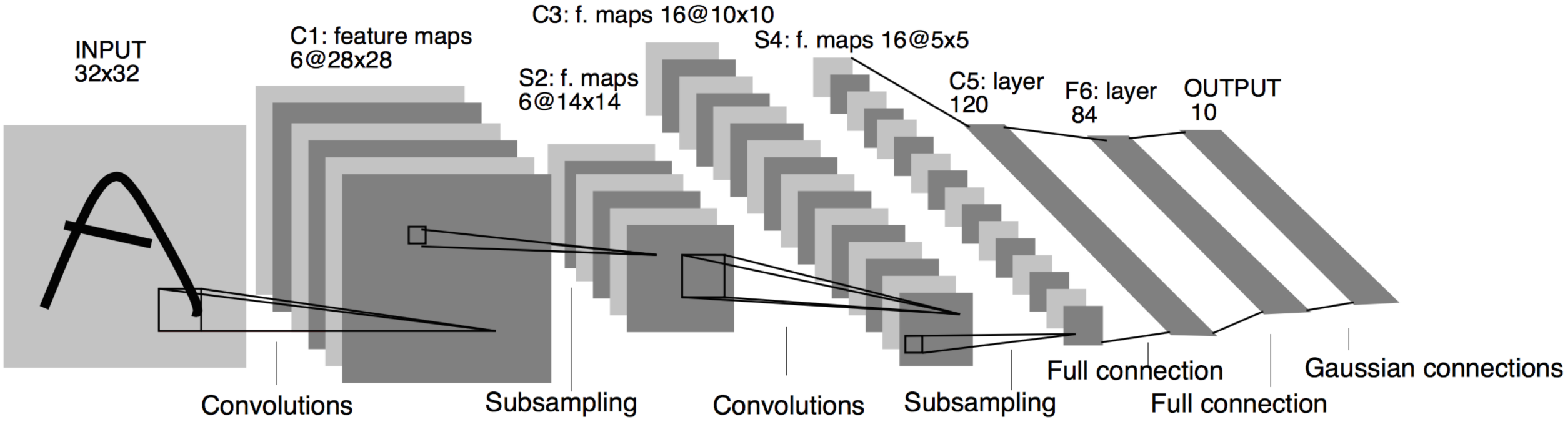
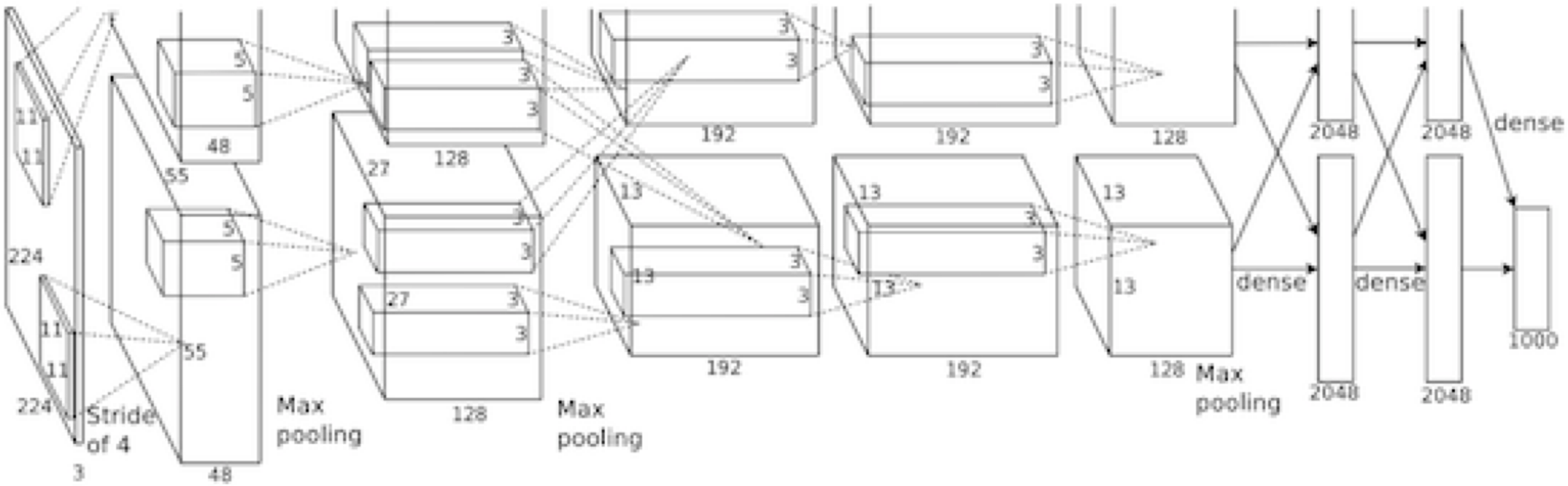


Fig. 2. Architecture of LeNet-5, a Convolutional Neural Network, here for digits recognition. Each plane is a feature map, i.e. a set of units whose weights are constrained to be identical.

Proc. Of the IEEE, November 1998, "Gradient-Based Learning Applied to Document Recognition"

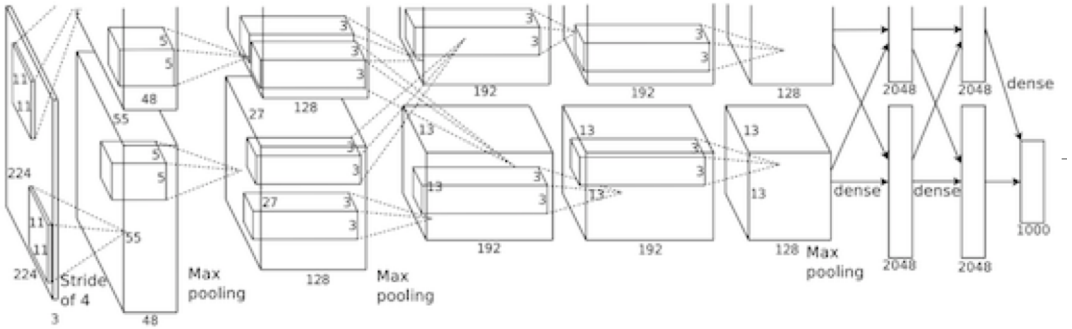
Case Study: AlexNet



Input 227x227x3 images
First Layer (Conv1): 96 11x11 filters applied at stride 4
What is the output volume size? (N-F)/stride+1=55
Output volume : [55x55x96]
Parameters: (11*11*3)*96 = 35k

https://papers.nips.cc/paper/4824-imagenet-classification-with-deep-convolutional-neural-networks.pdf

AlexNet



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 anymore)
- heavy data augmentation
- dropout 0.5
- batch size 128
- SGD Momentum 0.9
- Learning rate 1e-2, reduced by 10 manually when val accuracy plateaus
- L2 weight decay 5e-4
- 7 CNN ensemble: 18.2% -> 15.4%