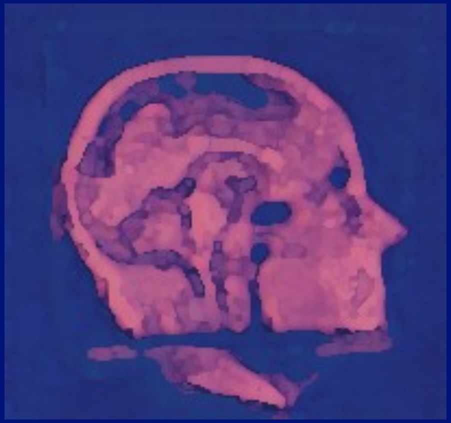
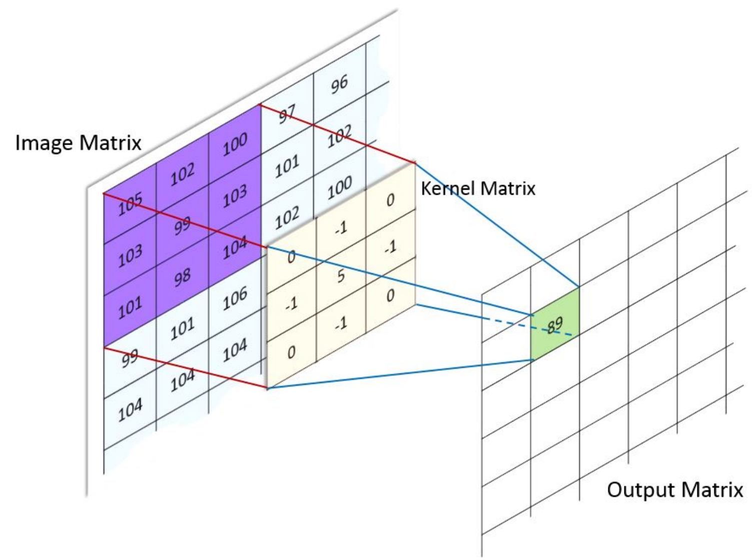
Deep Learning in Computer Vision



Alexei Manso Corrêa Machado
Pontifical Catholic University of Minas Gerais – D. Computer Science

2/2020

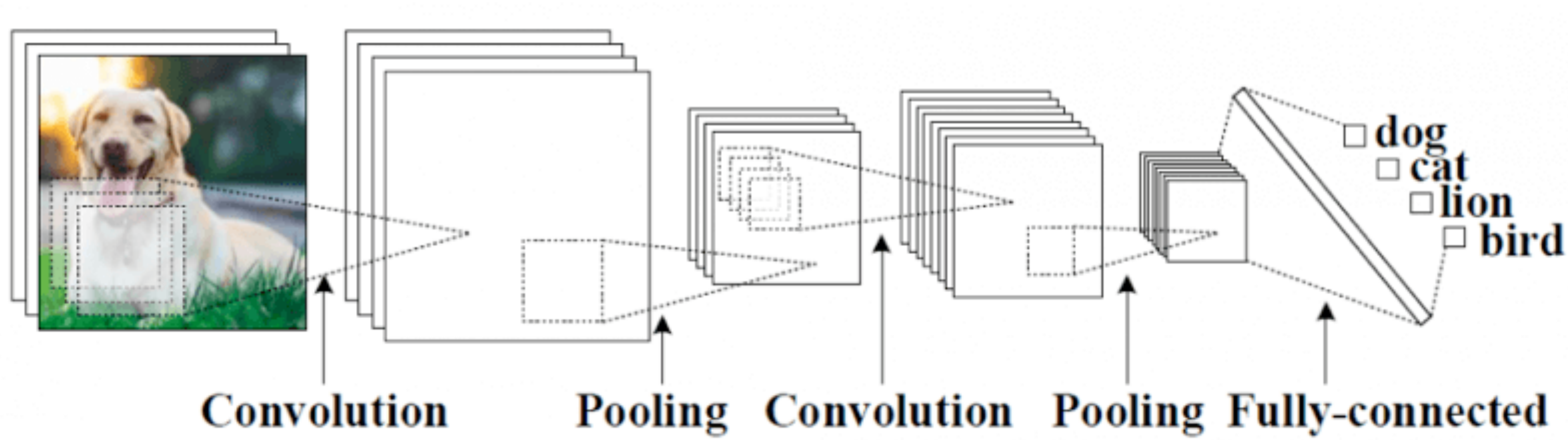
Convolutional Neural Networks



machinelearninguru.com

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

Convolutional Neural Networks



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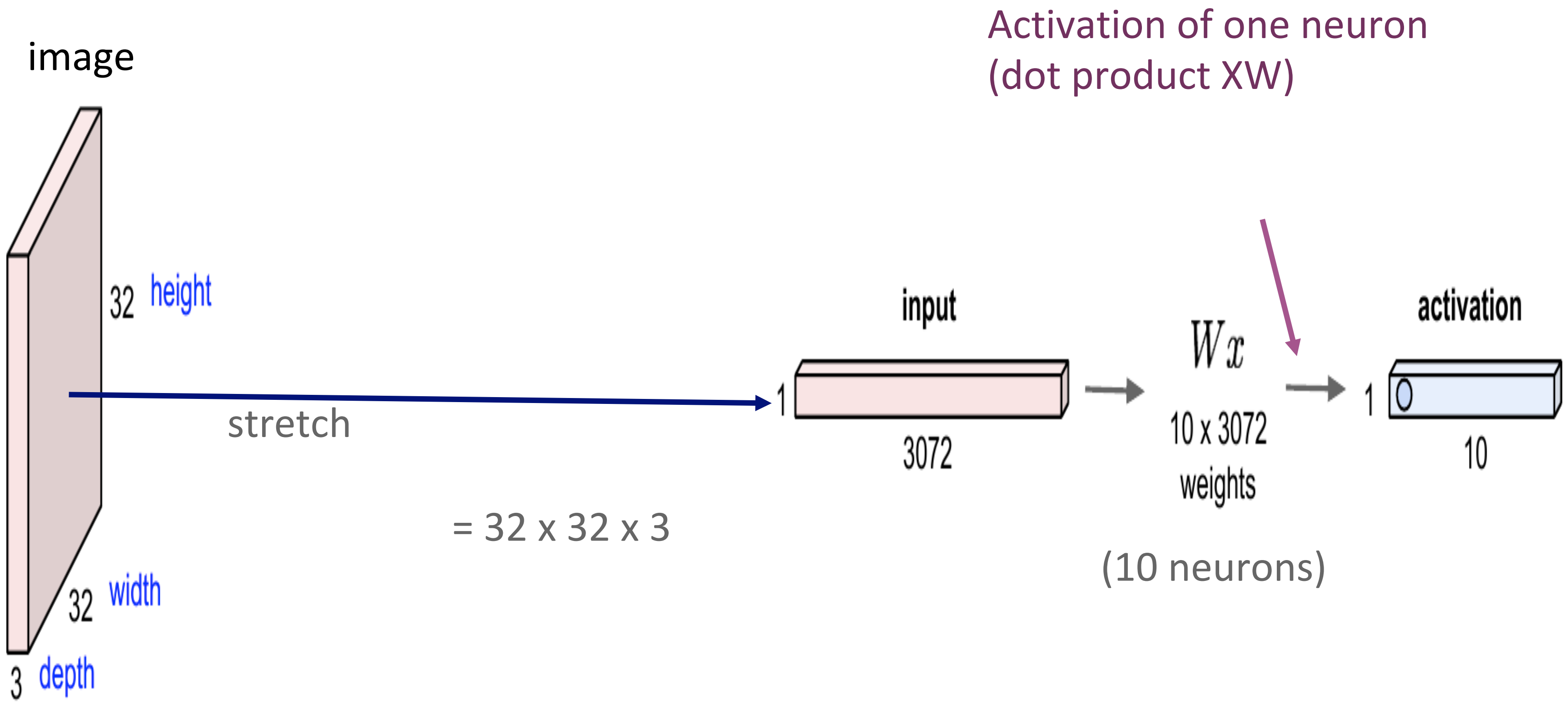
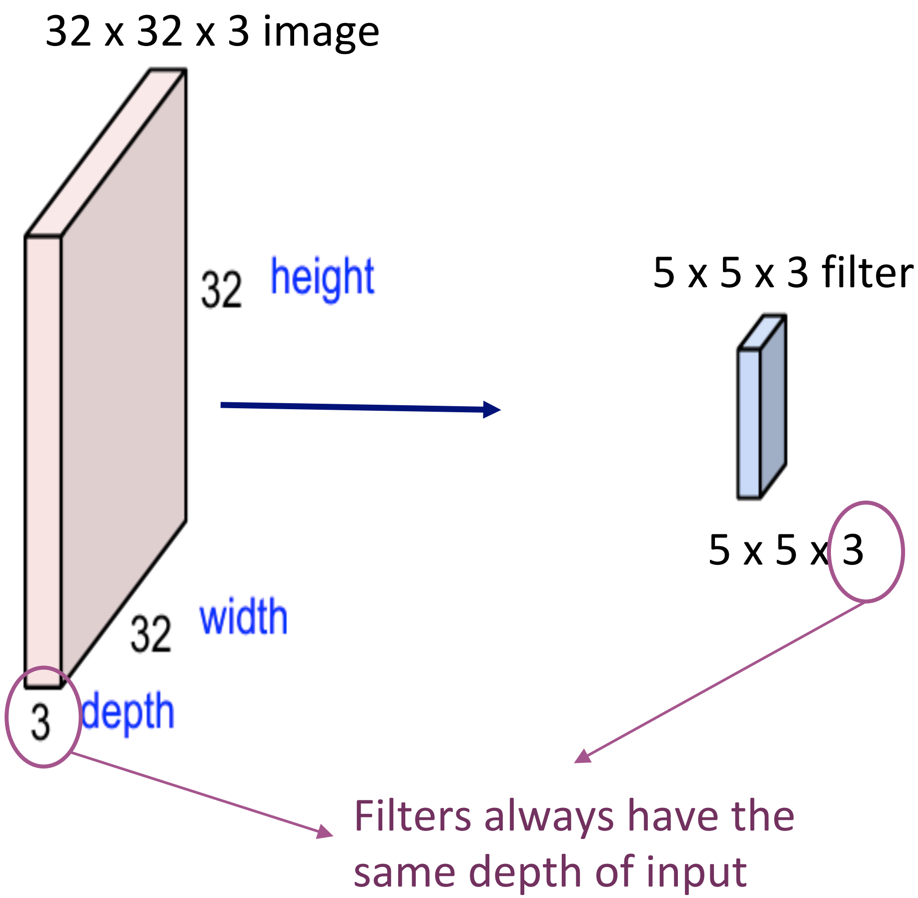
Fully-connected layers



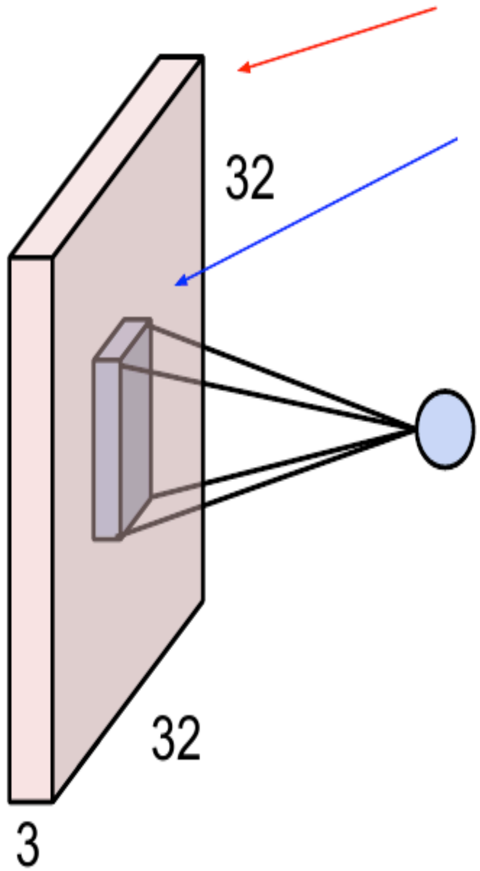
Convolutional layers



Convolutional layers

32x32x3 image

5x5x3 filter w

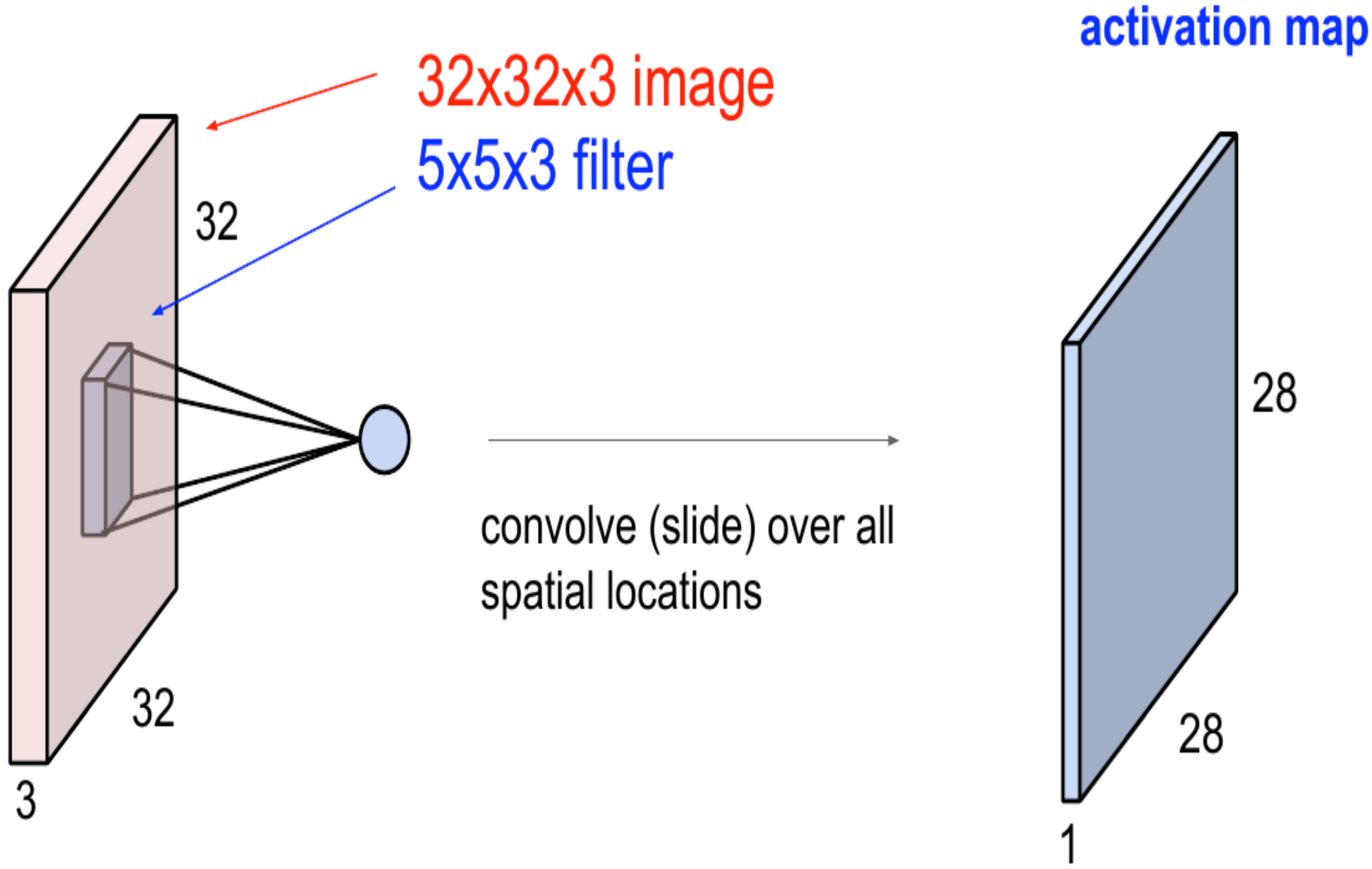


1 number:

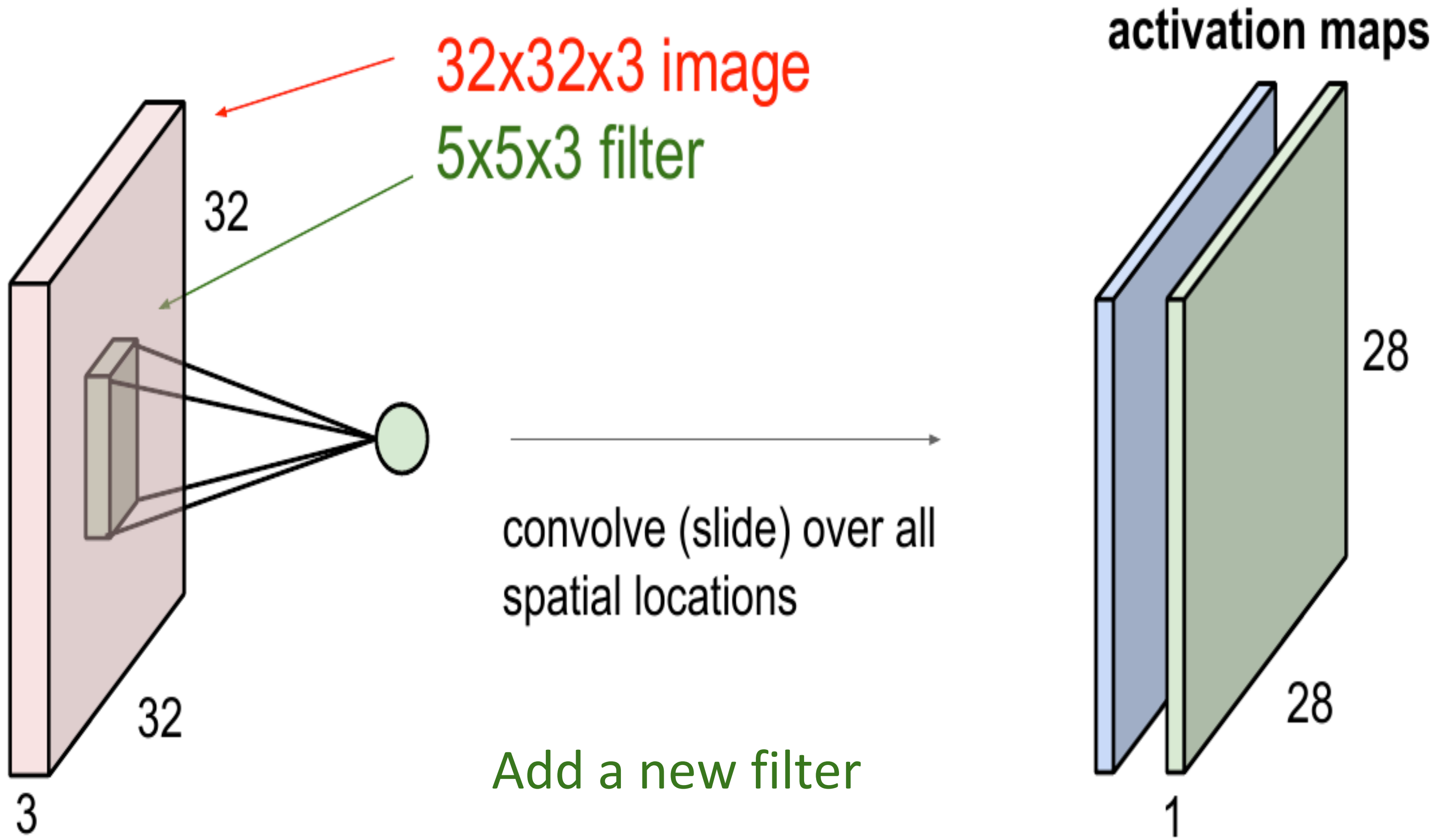
the result of taking a dot product between the filter and a small 5x5x3 chunk of the image (i.e. 5*5*3 = 75-dimensional dot product + bias)

$$w^T x + b$$

Convolutional layers

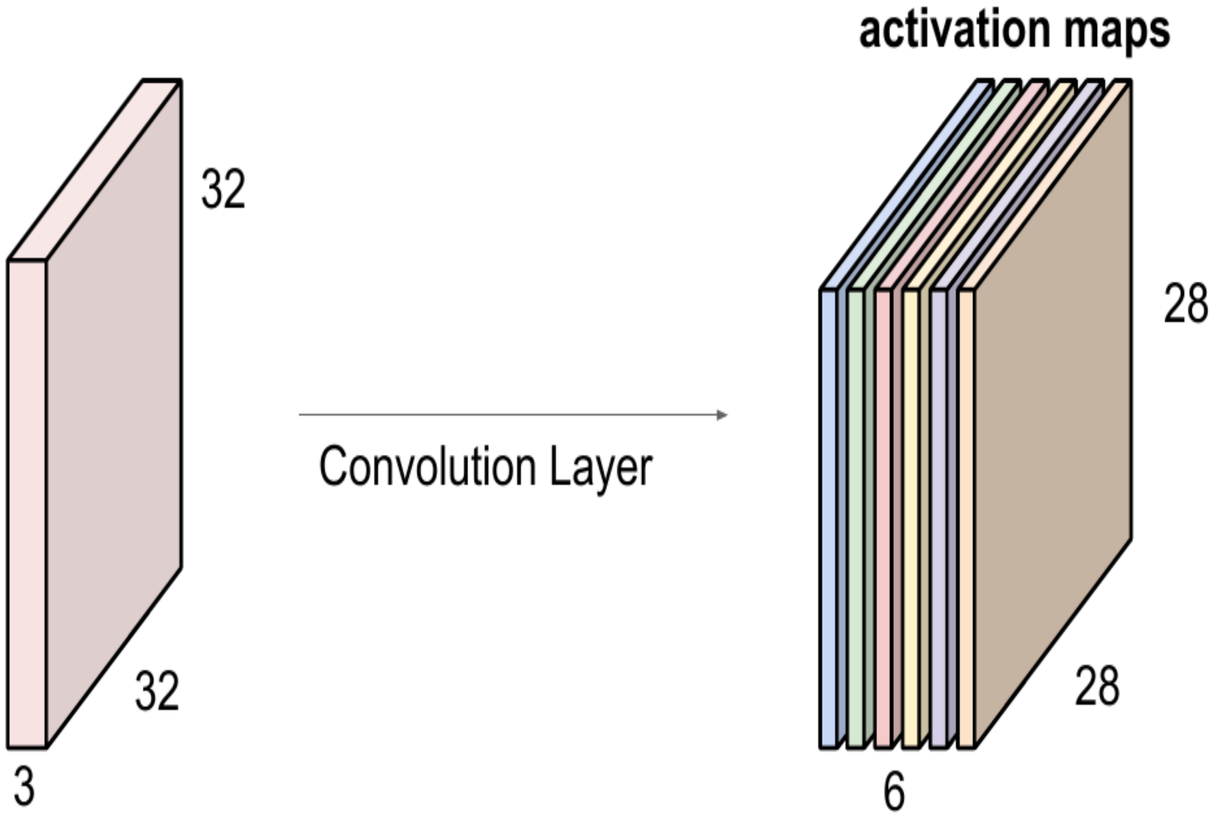


Convolutional layers



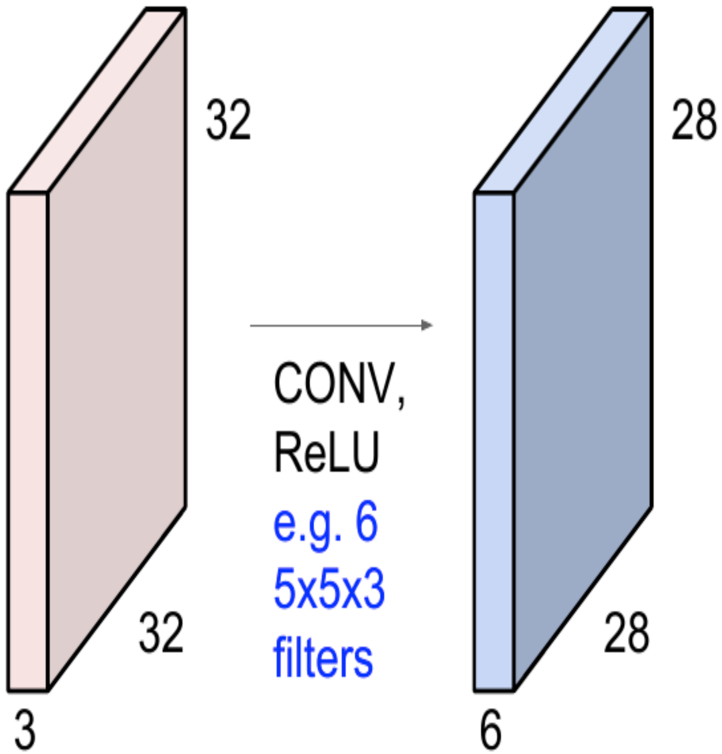
Convolutional layers

If we have 6 filters (5x5x3), there will be 6 activation maps:



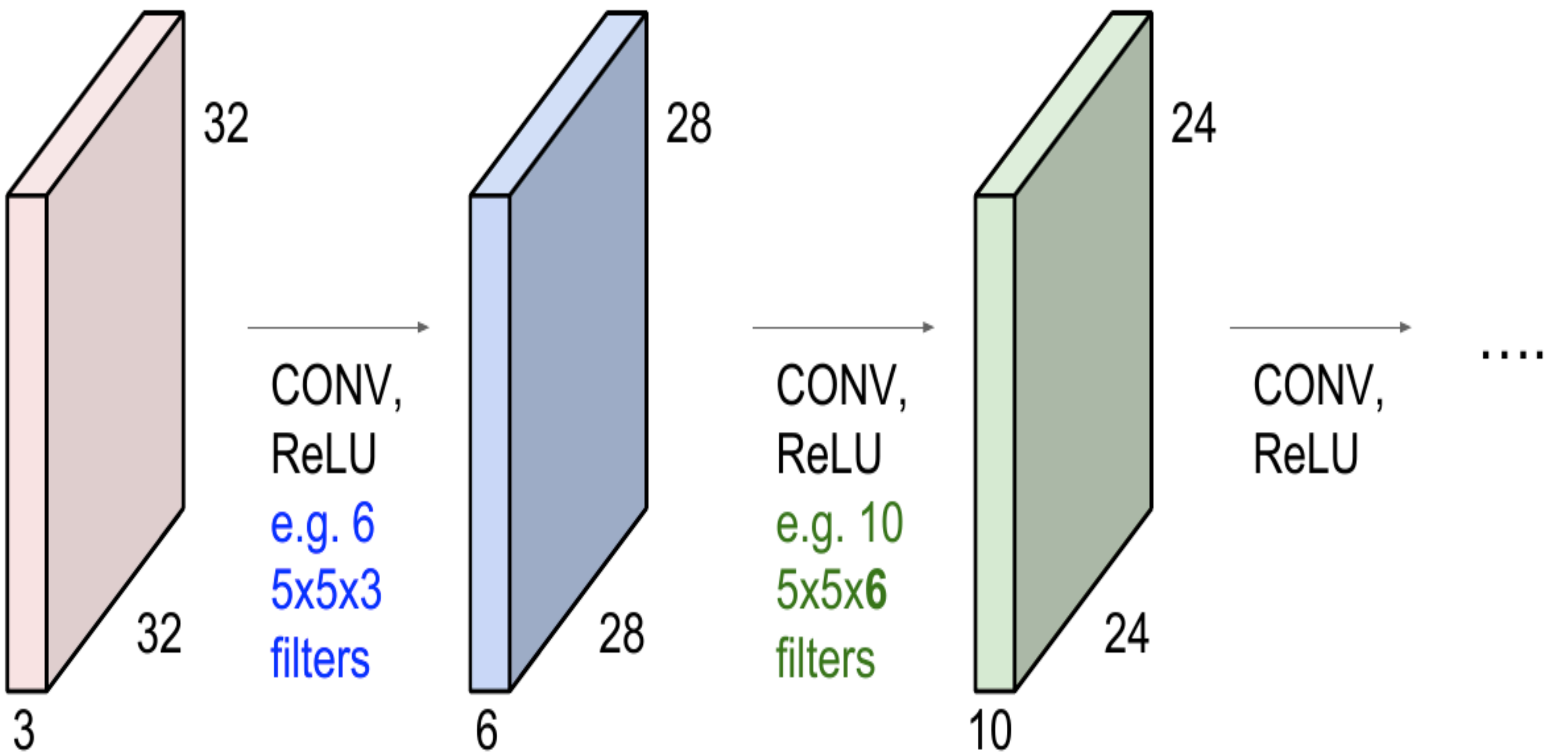
Convolutional layers

A ConvNet is a sequence of convolutional layers, each followed by an activation function:

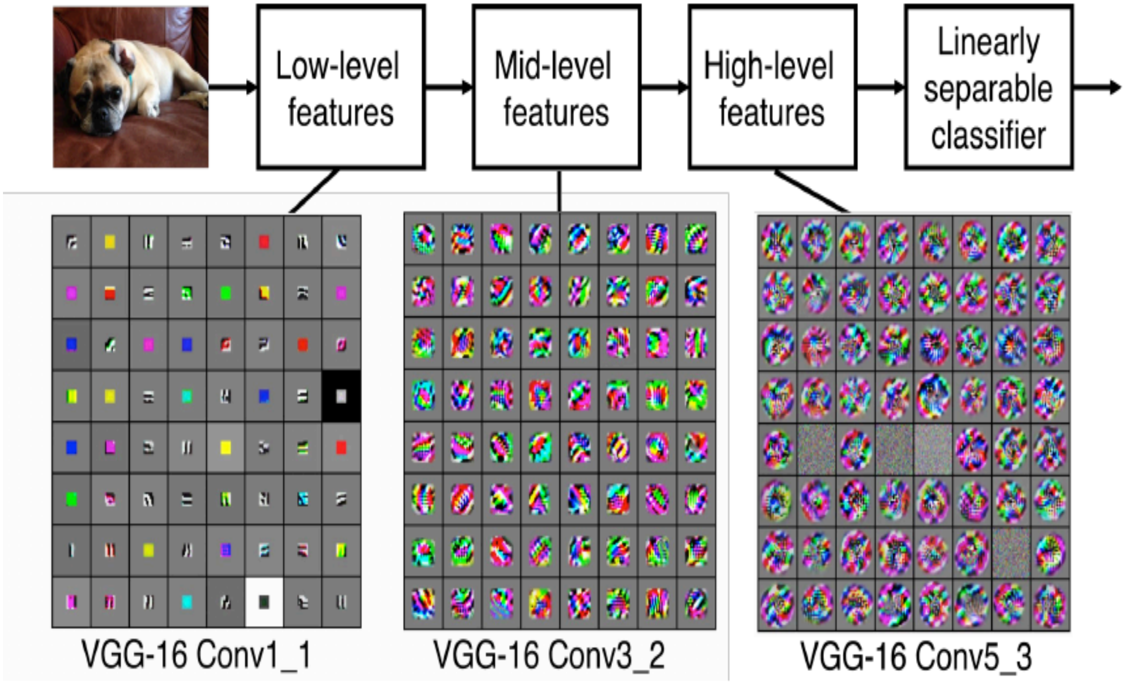


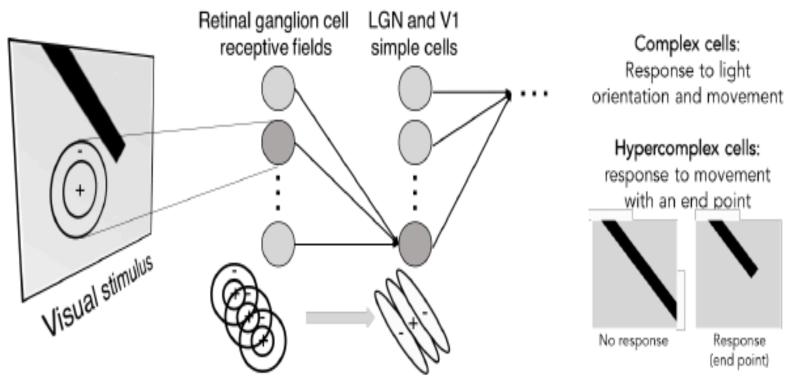
Convolutional layers

A ConvNet is a sequence of convolutional layers, each followed by an activation function:

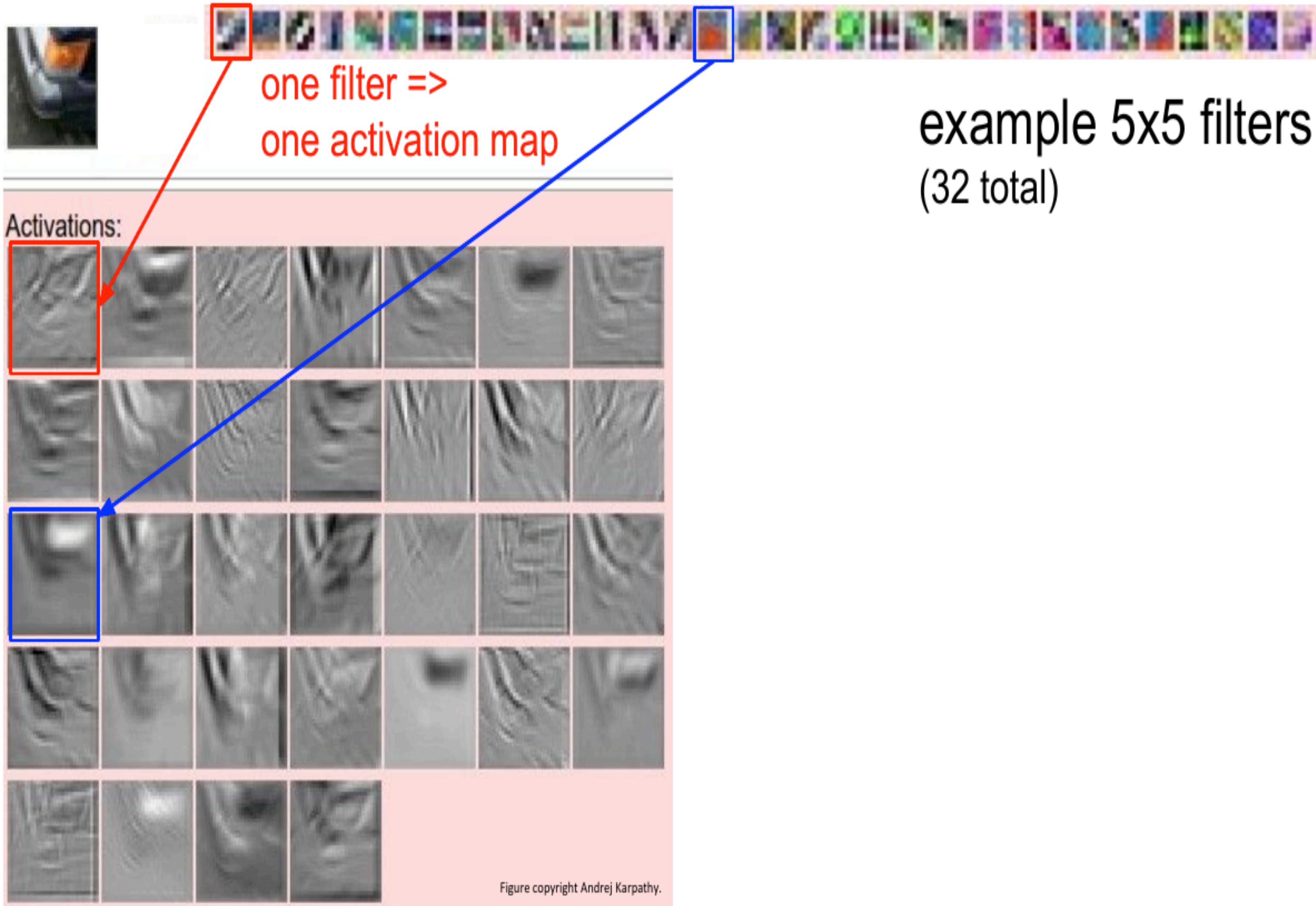


Filter hierarchy



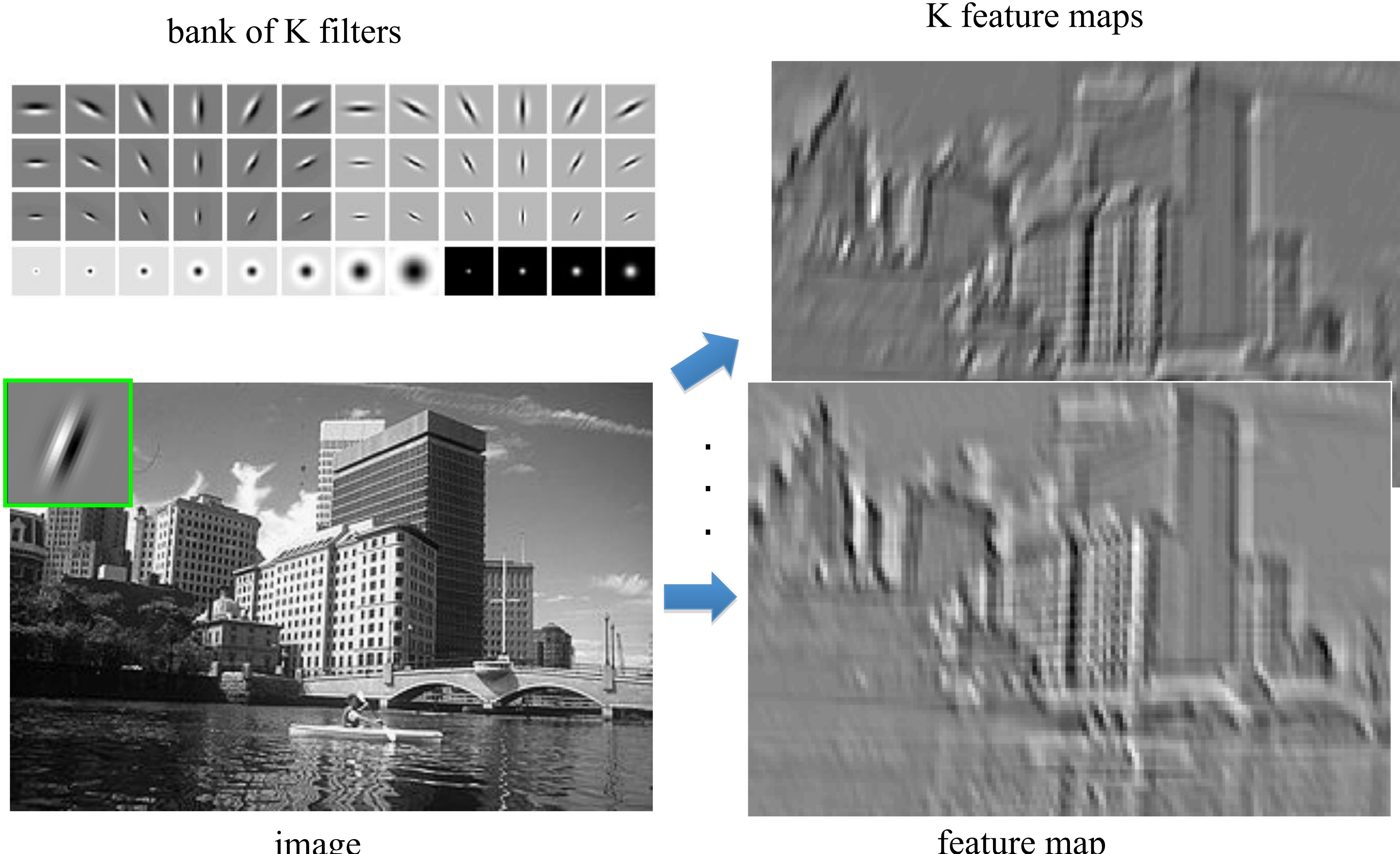


Activation maps

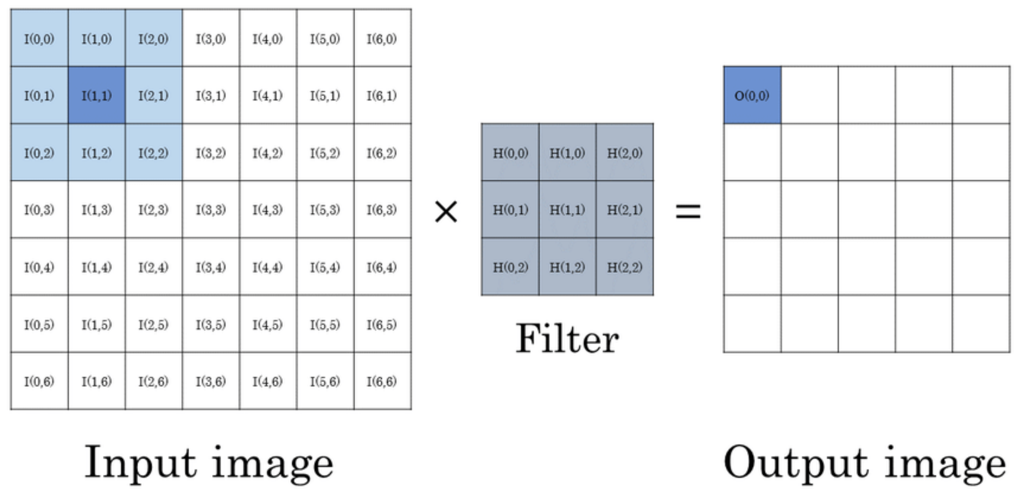


example 5x5 filters
(32 total)

Convolution as feature extraction

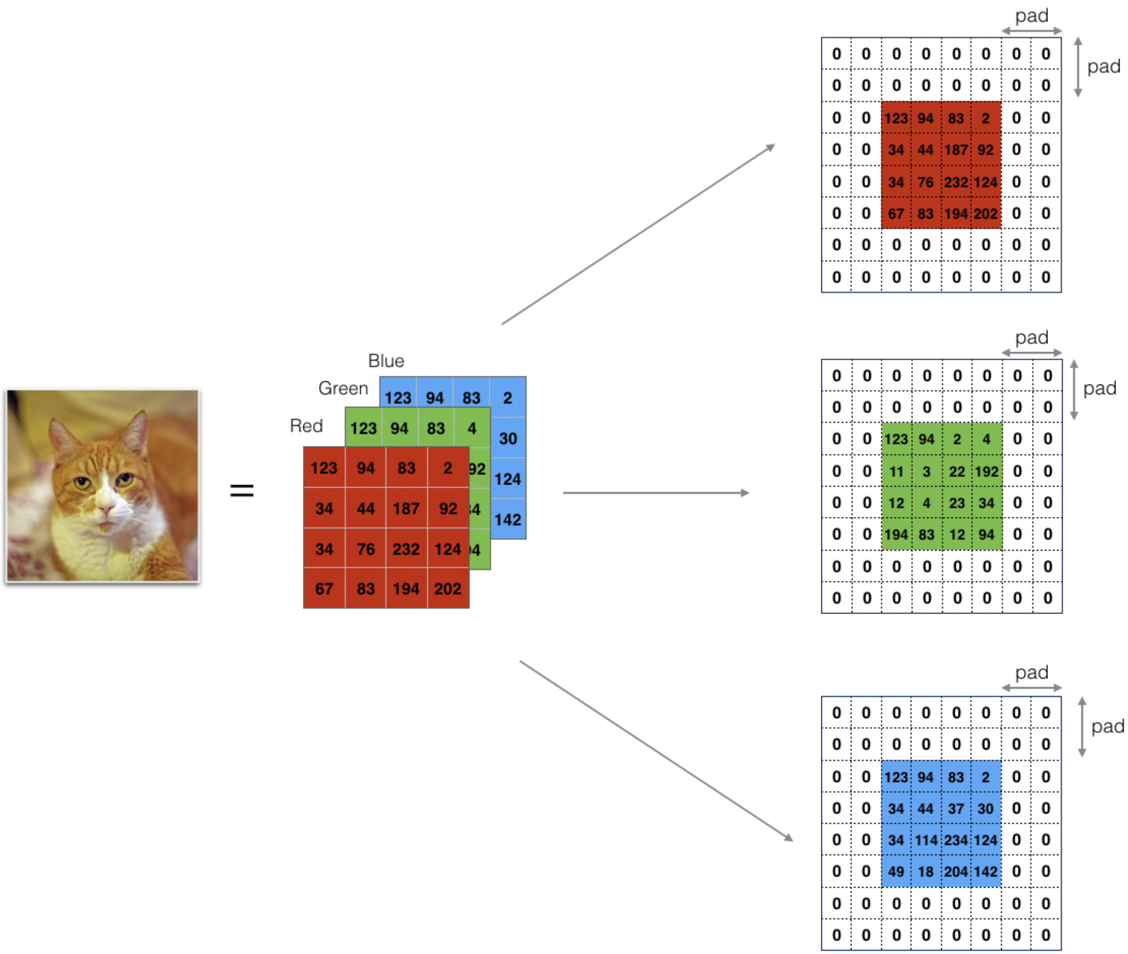


Padding

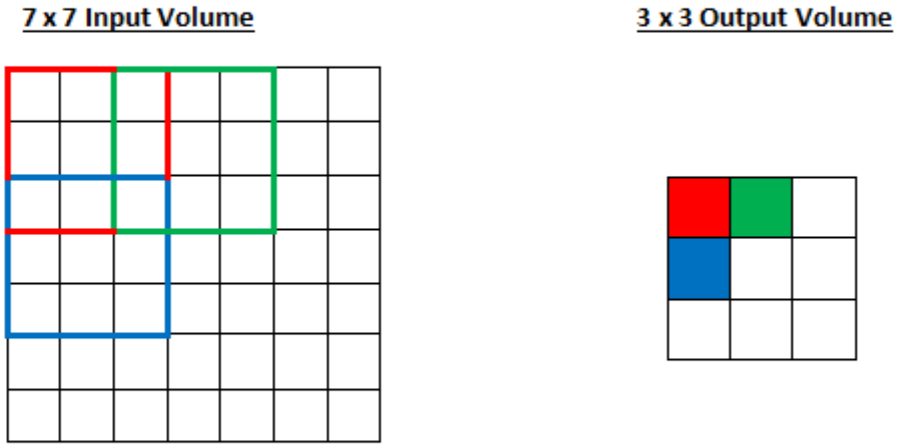


- When an image nxn is convolved by a filter fxf, it loses rows and columns, resulting in a n-f+1 x n-f+1 image
- In order for the image to keep the same dimensions, p columns and rows must be added prior to convolution, resulting in a n+2p-f+1 x n+2p-f+1 image

Padding


=
Blue
Green
Red
123 94 83 2
30
124
142
123 94 83 4
123 94 83 2
34 44 187 92
34 76 232 124
67 83 194 202
pad
pad
0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0
0 0 123 94 83 2 0 0
0 0 34 44 187 92 0 0
0 0 34 76 232 124 0 0
0 0 67 83 194 202 0 0
0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0
pad
pad
0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0
0 0 123 94 2 4 0 0
0 0 11 3 22 192 0 0
0 0 12 4 23 34 0 0
0 0 194 83 12 94 0 0
0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0
pad
pad
0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0
0 0 123 94 83 2 0 0
0 0 34 44 37 30 0 0
0 0 34 114 234 124 0 0
0 0 49 18 204 142 0 0
0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0

Striding



- When an image nxn is convolved by a filter fxf using stride s, it loses rows and columns, resulting in a (n-f)/s+1 x (n-f)/s+1 image

Padding and striding

- When an image nxn is convolved by a filter fxf using stride s and pad p the resulting image is

$$(n+2p-f)/s+1 \text{ x } (n+2p-f)/s+1$$

- In order for the image to keep original dimensions (“same” padding):

$$p = (ns - n + f - s) / 2$$

Convolution over volumes

- A convolutional layer may receive an image with multiple channels to be convolved by multiple filters
- The number of channels of the image and the filters must be the same
- Example: Input image of **6x6x3** and **10** filters **3x3x3** resulting in a **4x4x10** output (with **p = 0**,   **s = 1**)

Convolution over volumes

- Each layer receives a volume of $\mathbf{W_1}$ x $\mathbf{H_1}$ x $\mathbf{D_1}$
- Requires 4 hyperparameters:
  - Number of filters $\mathbf{n_c}$
  - Size of filter **f**
  - *Stride* **s**
  - *Padding* **p**
- Outputs a volume of $\mathbf{W_2}$ x $\mathbf{H_2}$ x $\mathbf{D_2}$, where:
  - $\mathbf{W_2} = (\mathbf{W_1} - \mathbf{f} + 2\mathbf{p})/\mathbf{s} + 1$
  - $\mathbf{H_2} = (\mathbf{H_1} - \mathbf{f} + 2\mathbf{p})/\mathbf{s} + 1$
  - $\mathbf{D_2} = \mathbf{n_c}$
- Must compute **f** x **f** x $\mathbf{D_1}$ weights per filter, a total of **f** x **f** x $\mathbf{D_1}$ x $\mathbf{n_c}$ weights and $\mathbf{n_c}$ *biases*
- In the output volume, the d-th slice of size $\mathbf{W_2}$ x $\mathbf{H_2}$ is the result of the convolution between the d-th filter and the image with *stride* **s**, and applying an offset related to the d-th *bias*

Summary of notation

f[l] = filter size

p[l] = padding

s[l] = stride

nc[l] = number of filters

Input: n[l-1] x n[l-1] x nc[l-1]	**Or**	nH[l-1] x nW[l-1] x nc[l-1]
Output: n[l] x n[l] x nc[l]	**Or**	nH[l] x nW[l] x nc[l]

Where n[l] = (n[l-1] + 2p[l] - f[l] / s[l]) + 1

Each filter is: f[l] x f[l] x nc[l-1]

Activations: a[l] is nH[l] x nW[l] x nc[l]

A[l] is m x nH[l] x nW[l] x nc[l]

Weights: f[l] * f[l] * nc[l-1] * nc[l]

bias: (1, 1, 1, nc[l])

Forward propagation

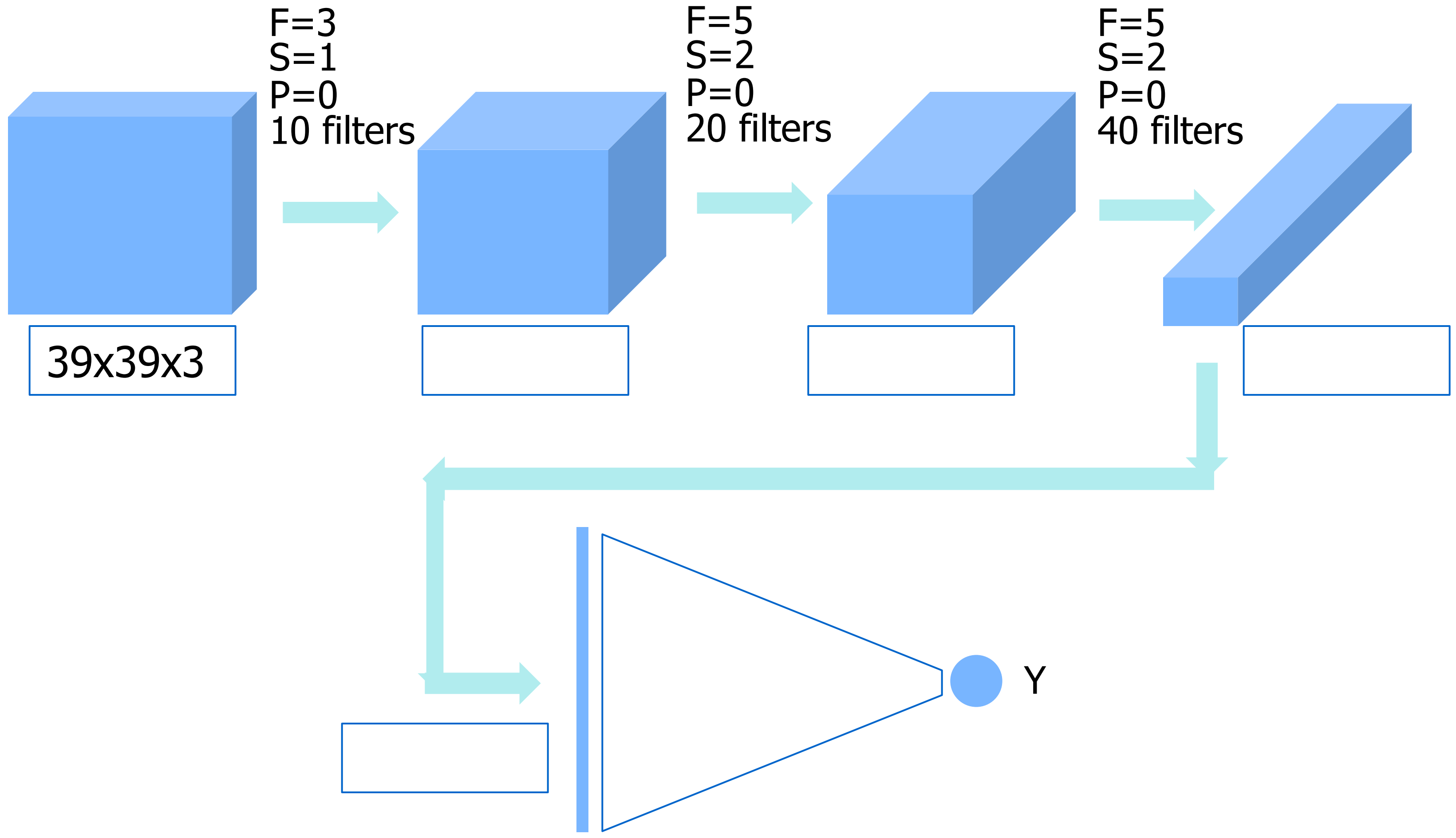
- Convolve the filters with the image
- Add a bias to the output of each filter
- Apply ReLU to the result

Forward propagation

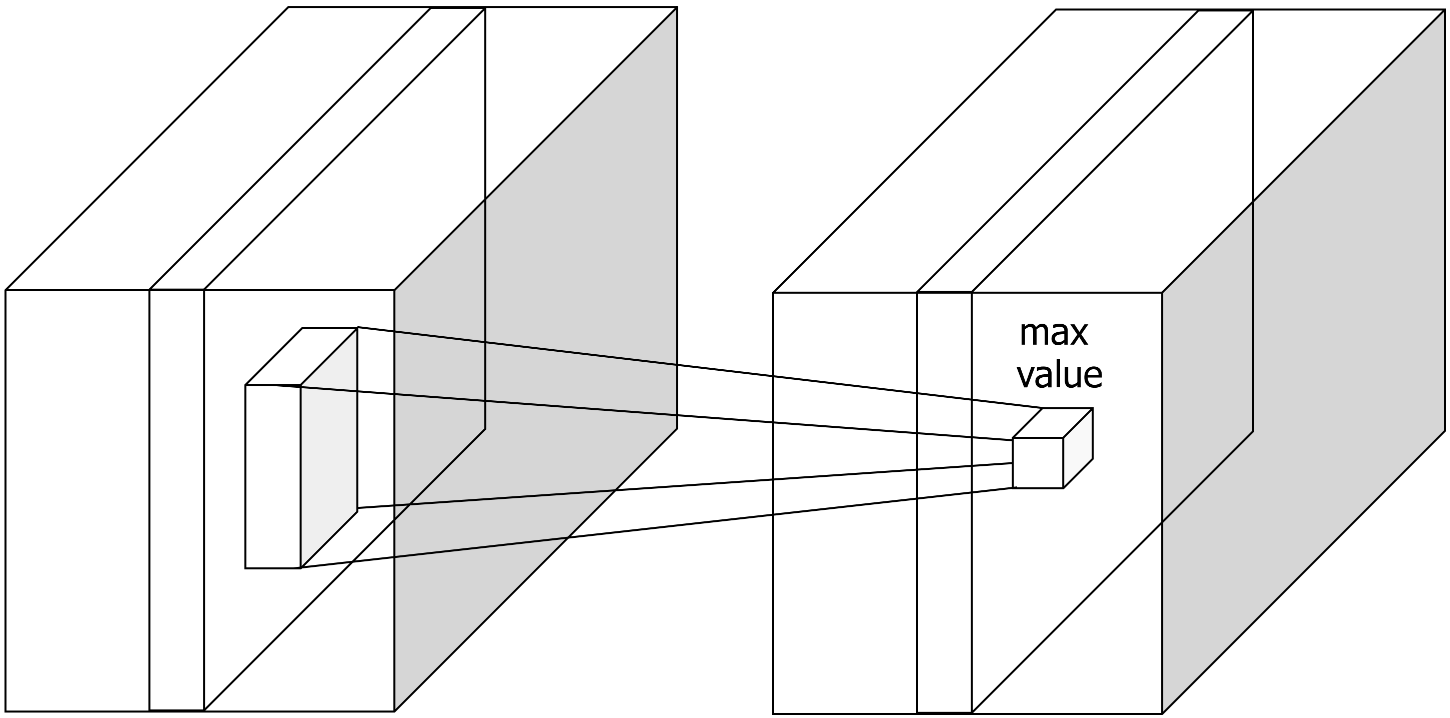
Example:

- Convolve the filters with the image:
  - Input image: **6x6x3** (a0)
  - 10 filters: **3x3x3** (W1)
  - Result: **4x4x10** (W1a0)
- Add a bias to the output of each filter
  - **b**, **10x1**: image **4x4x10** (W1a0 + b)
- Apply ReLU to the result
  - imagem **4x4x10** (A1 = RELU (W1a0 + b))
- Number of parameters: **(3x3x3x10) + 10 = 280**

Example of ConvNet



Pooling layers



F x F pooling filter, stride S

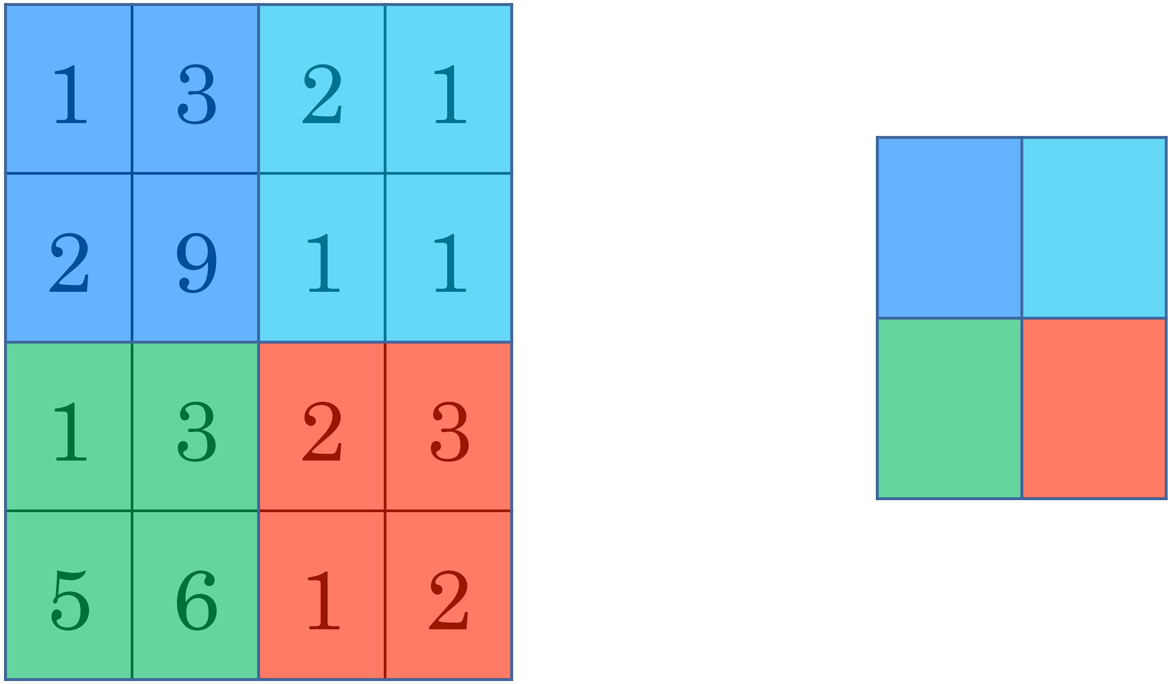
Usually: F=2 or 3, S=2

Backward pass: gradient from next layer is passed back only to the unit with max value

Pooling layers

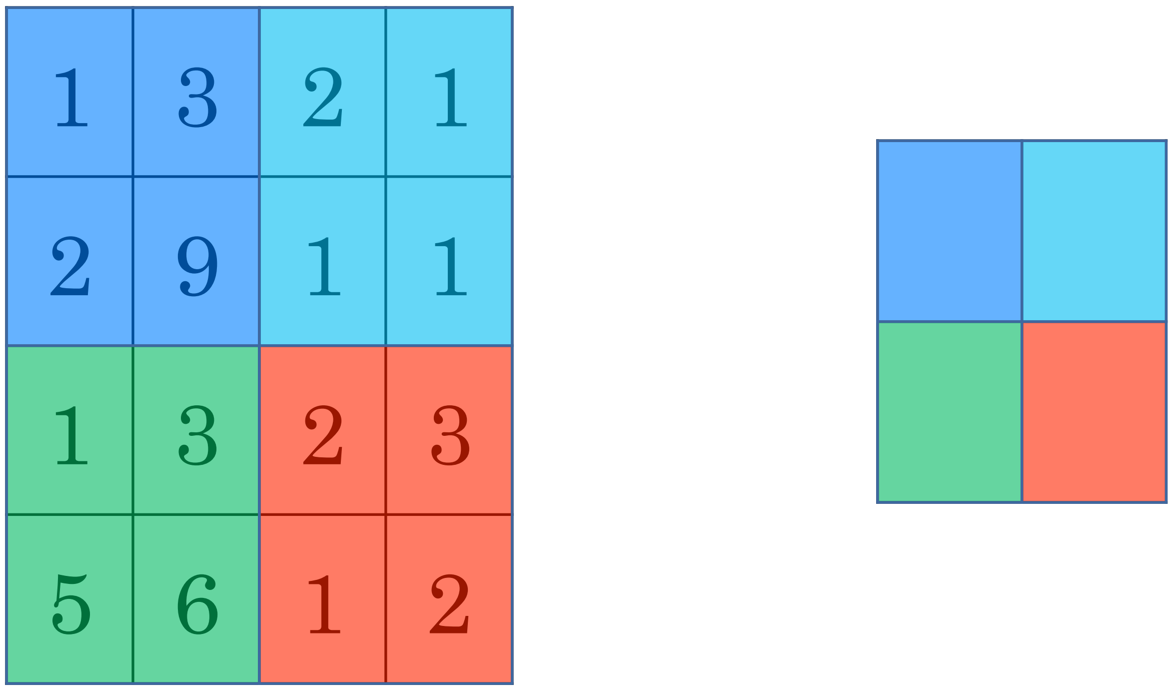
- In addition to the convolutional layers, CNNs usually use pooling layers to
  - Reduce the size of entries
  - Speed up computation
  - Make some detected features more robust
- Pooling layers have no parameteres to learn!

Max pooling layer



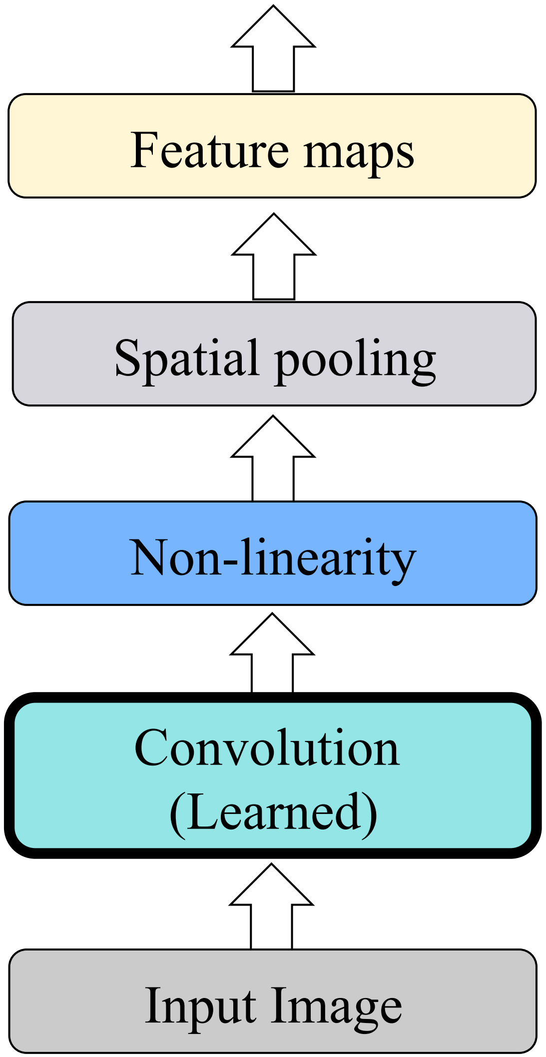
Max pooling says that if a feature is detected anywhere in the filter, keep it high to the next layer

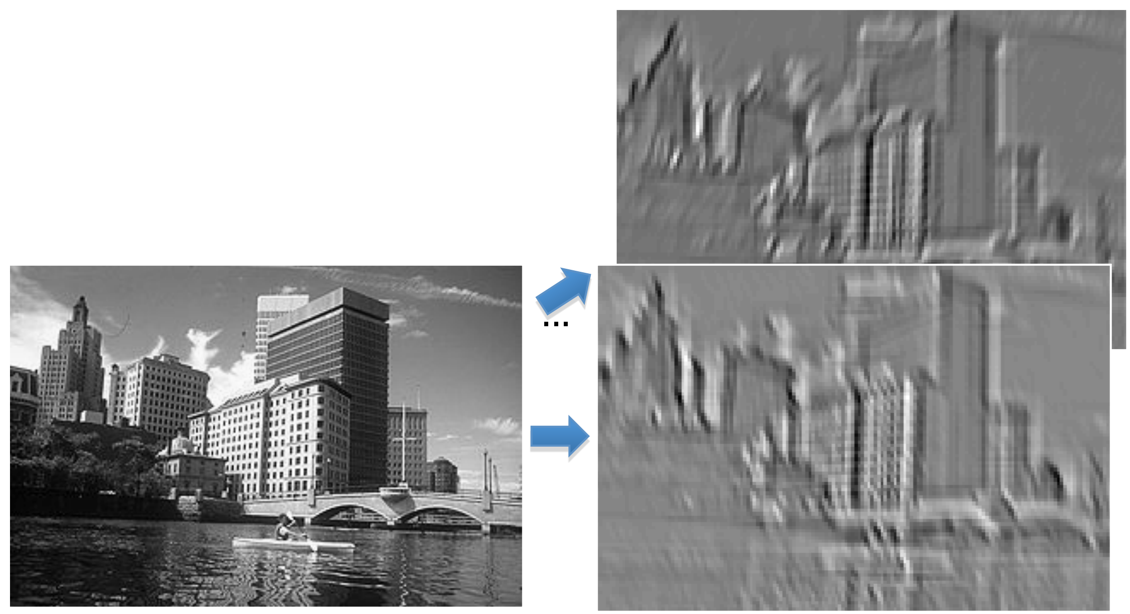
Average pooling layer



Average pooling takes the average of values and is less used than max pooling

Summary: CNN pipeline



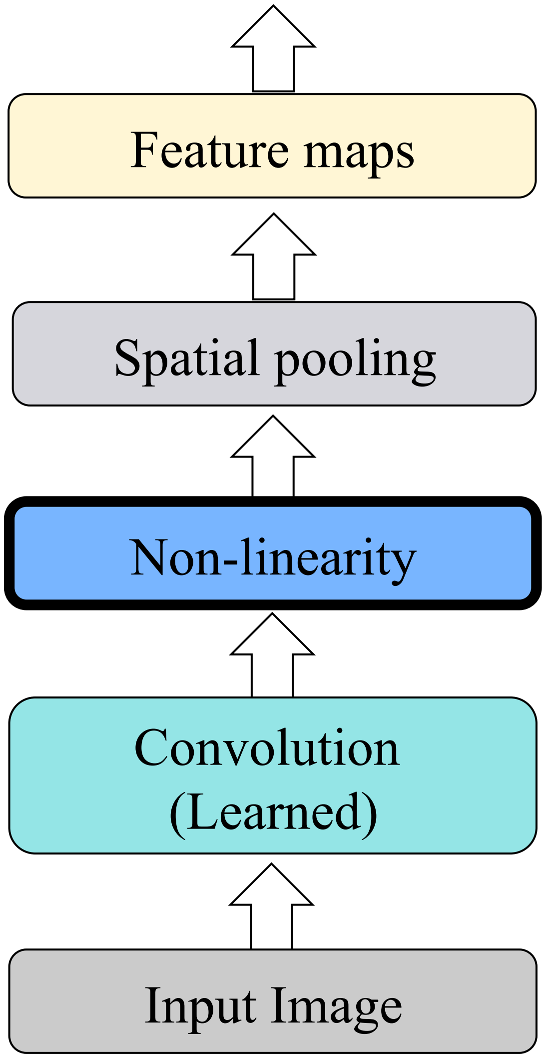


Input

Feature Map

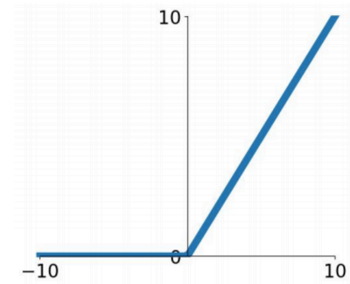
Source: R. Fergus, Y. LeCun

Summary: CNN pipeline



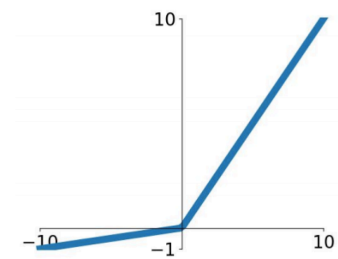
ReLU

$$\max(0, x)$$



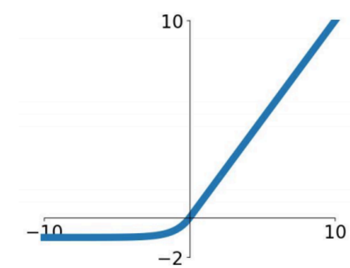
Leaky ReLU

$$\max(0.1x, x)$$



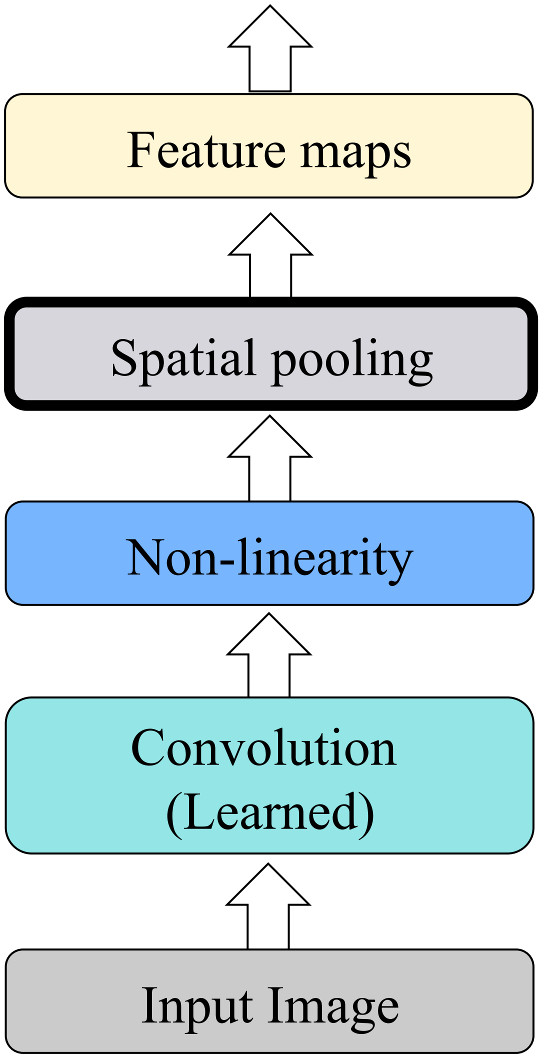
ELU

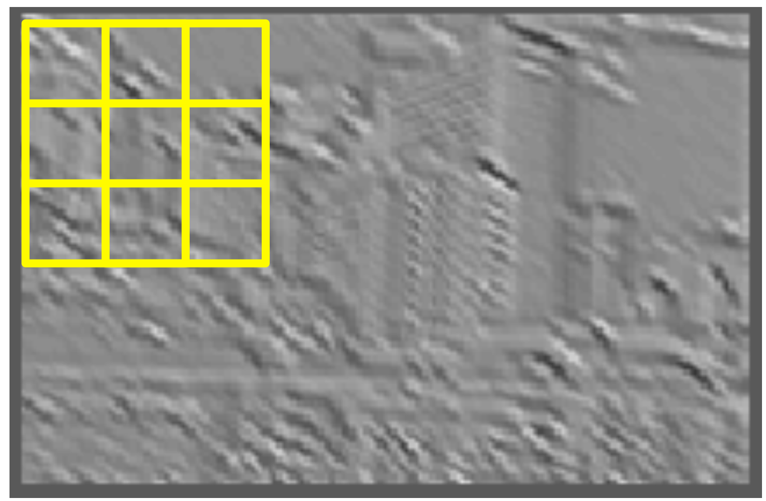
$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



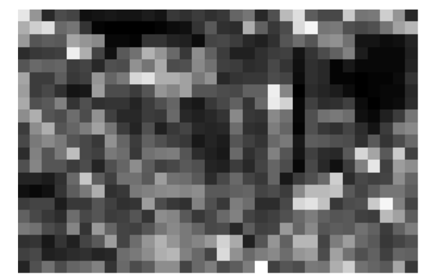
Source: R. Fergus, Y. LeCun

Summary: CNN pipeline



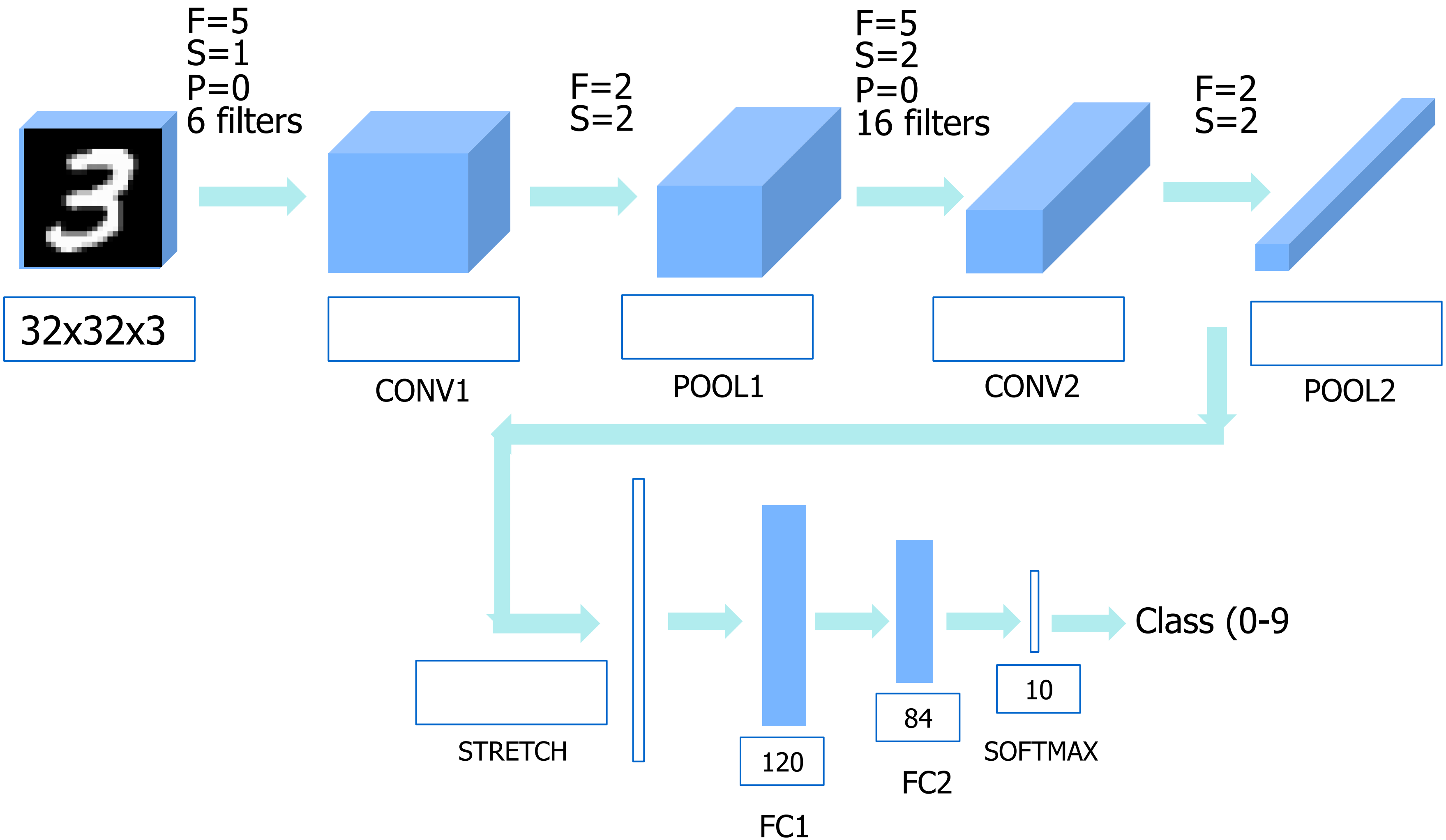


Max
(or Avg)



Source: R. Fergus, Y. LeCun

Example of CNN (LeNet-5)



References and acknowledgements

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Reference courses include *Machine Learning* and *Deep Learning* CS230 and CS231 from Stanford University, *Deep Learning* and *Hands-on Deep Learning* from UFMG, *Deep Learning* CS498 from Un. Of Illinois.