RECOD
reasoning for complex data

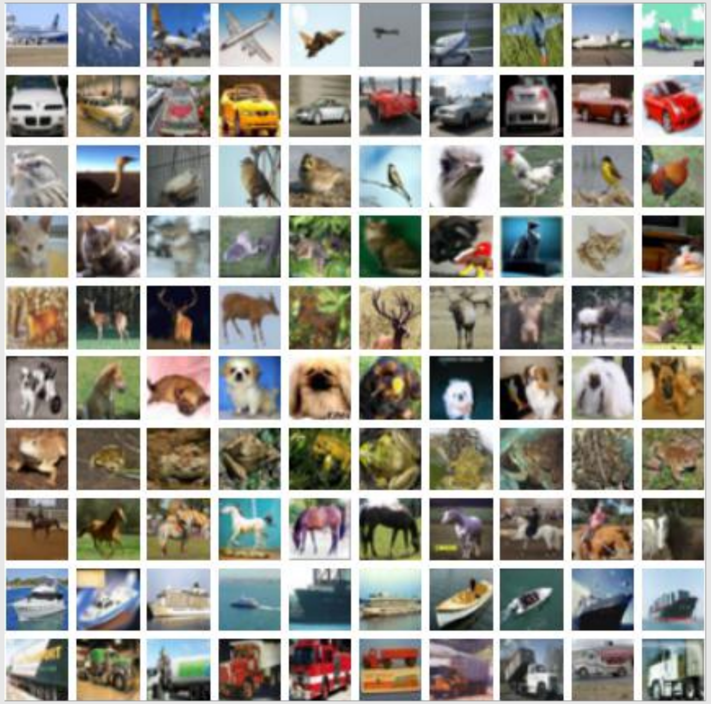
Machine Learning and Pattern Recognition
A High Level Overview

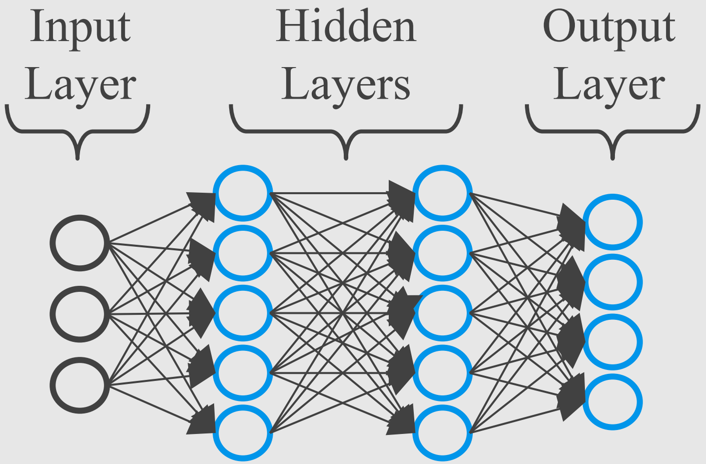
Prof. Anderson Rocha
(Main bulk of slides kindly provided by **Prof. Sandra Avila**
and based on materials by Fei-Fei Li & Justin Johnson & Serena Yeung)
Institute of Computing (IC/Unicamp)

MC886/MO444

Convolutional Neural Networks (CNNs)

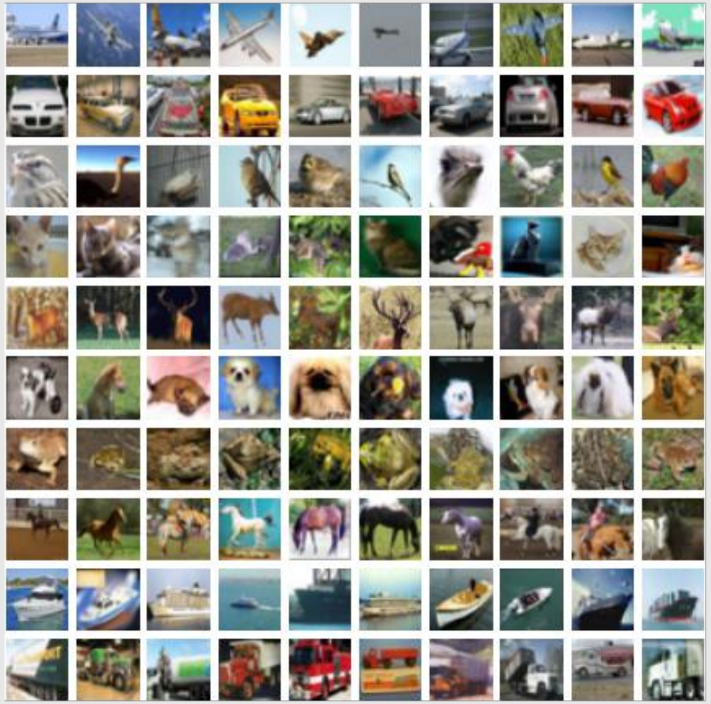
Fully Connected Layer


CIFAR-10

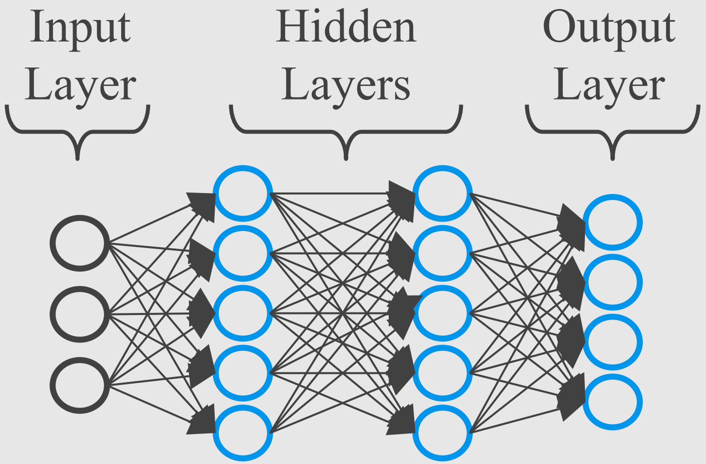


$32 \times 32 \times 3$ image $\Rightarrow$ stretch to 3072×1

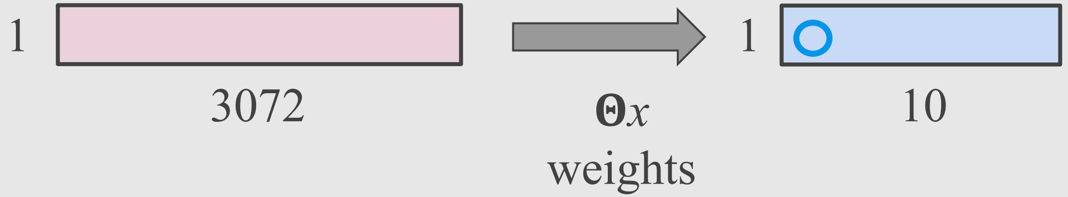
Fully Connected Layer

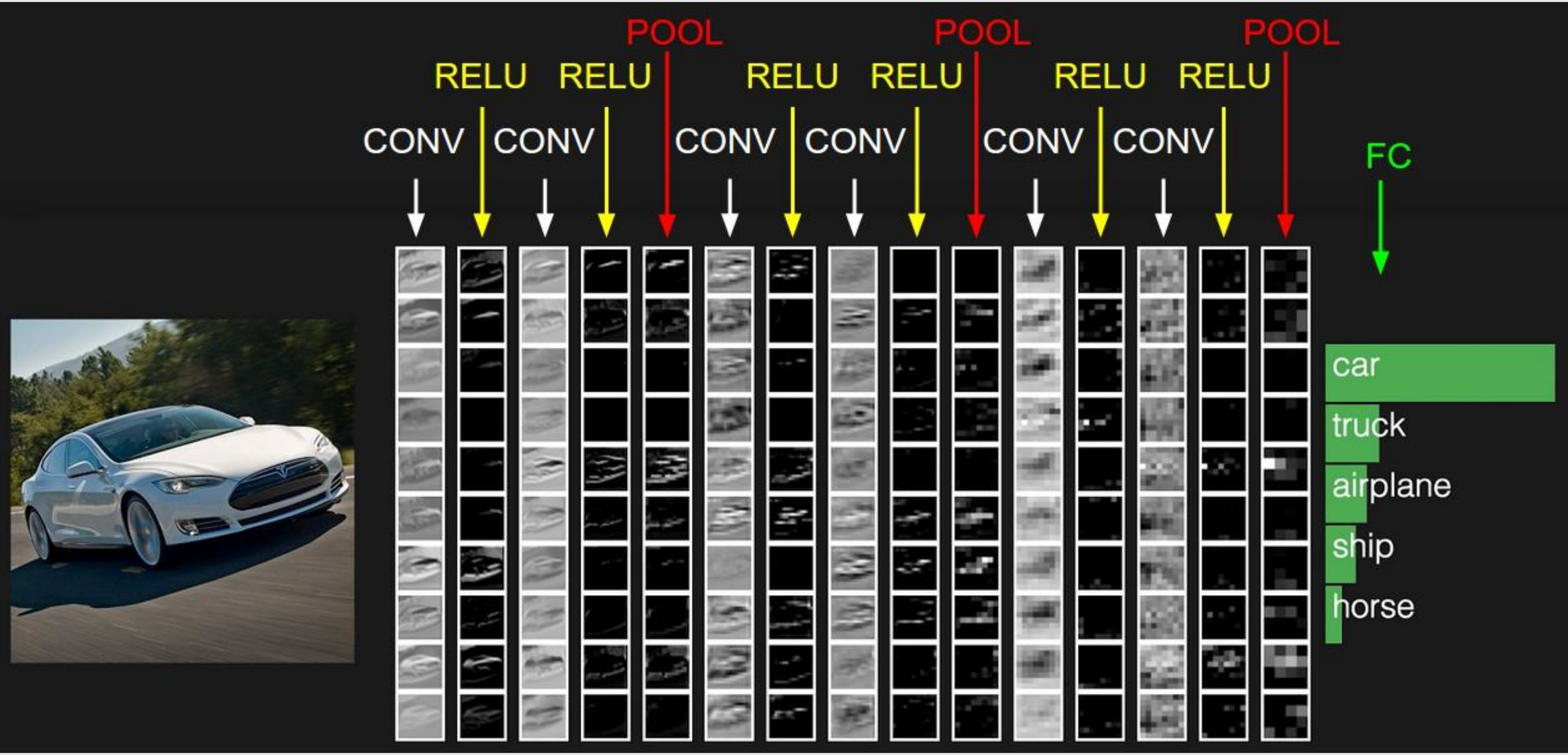


CIFAR-10



$32 \times 32 \times 3$ image $\Rightarrow$ stretch to 3072×1





Credit: http://cs231n.github.io/convolutional-networks/

What is a Convolution?

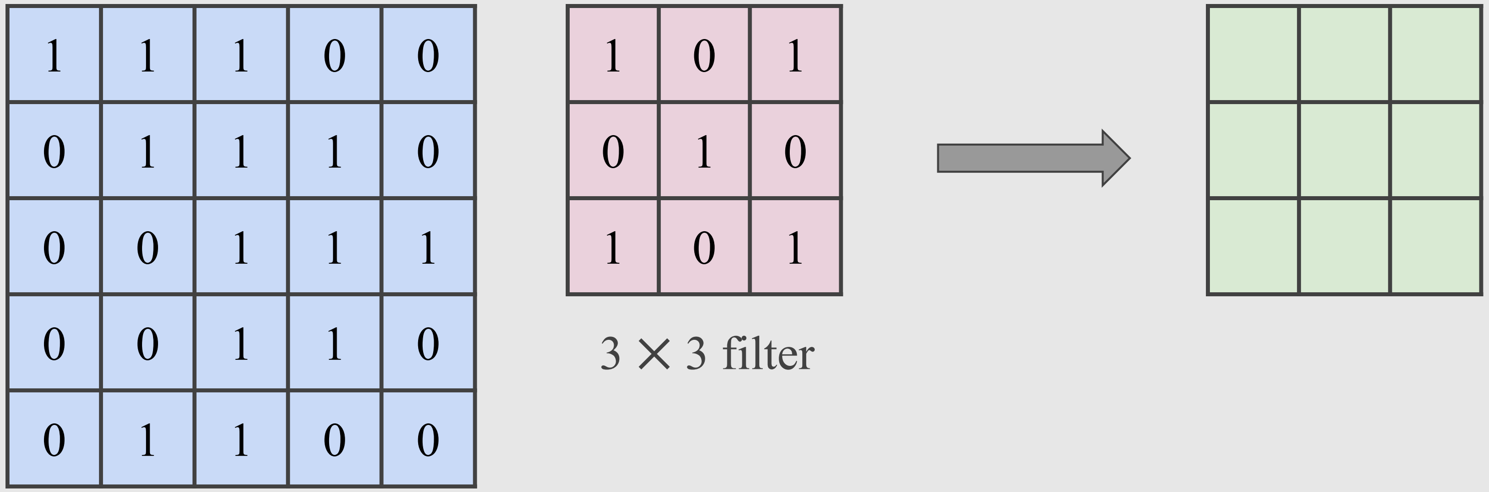
1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

5×5 matrix

1	0	1
0	1	0
1	0	1

3×3 filter

What is a Convolution?

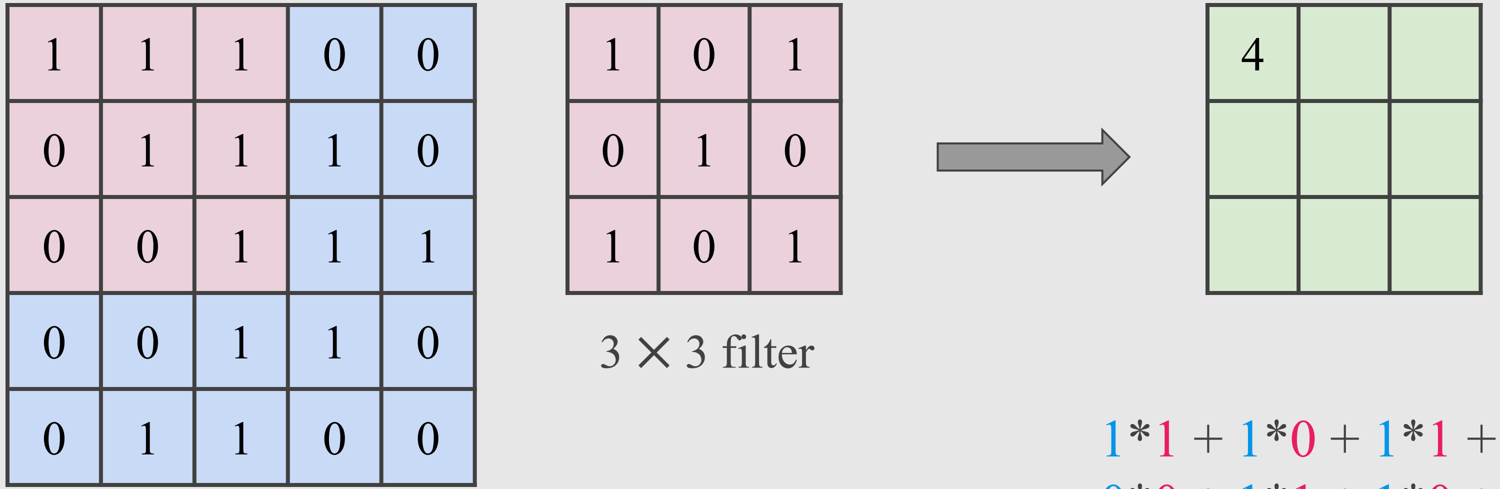


$$\begin{bmatrix} 1 & 1 & 1 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 & 0 \\ 0 & 1 & 1 & 0 & 0 \end{bmatrix} \quad \begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix} \quad \longrightarrow \quad \begin{bmatrix} \; & \; & \; \\ \; & \; & \; \\ \; & \; & \; \end{bmatrix}$$

5×5 matrix

3×3 filter

What is a Convolution?



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

5 × 5 matrix

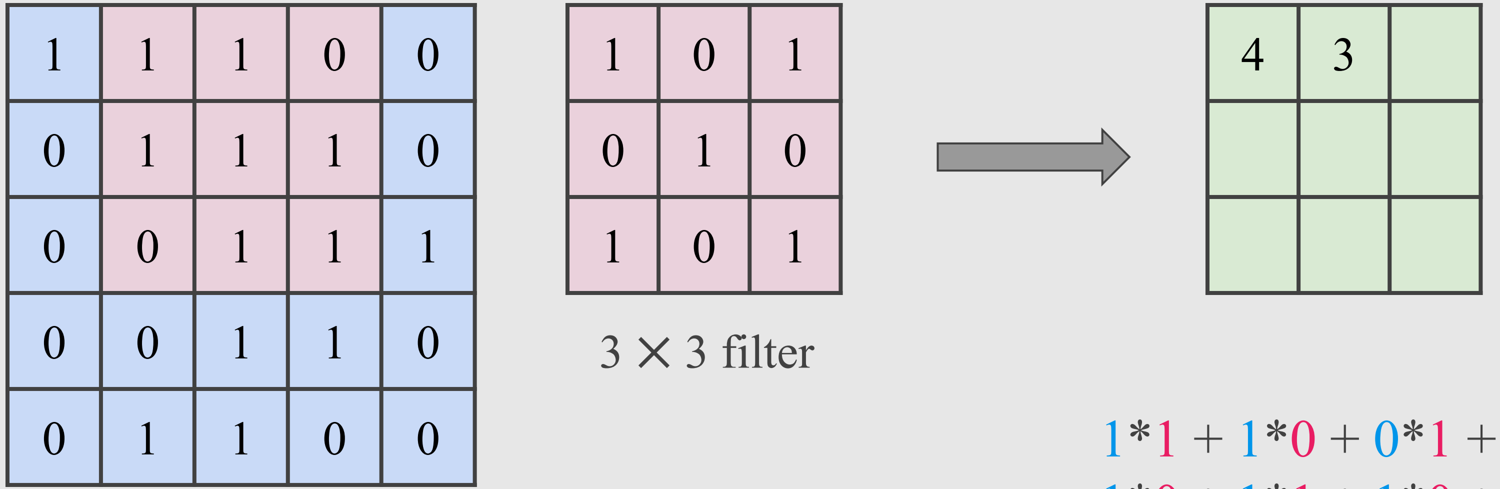
1	0	1
0	1	0
1	0	1

3 × 3 filter

4		

$$1*1 + 1*0 + 1*1 + \\ 0*0 + 1*1 + 1*0 + \\ 0*1 + 0*0 + 1*1 = 4$$

What is a Convolution?

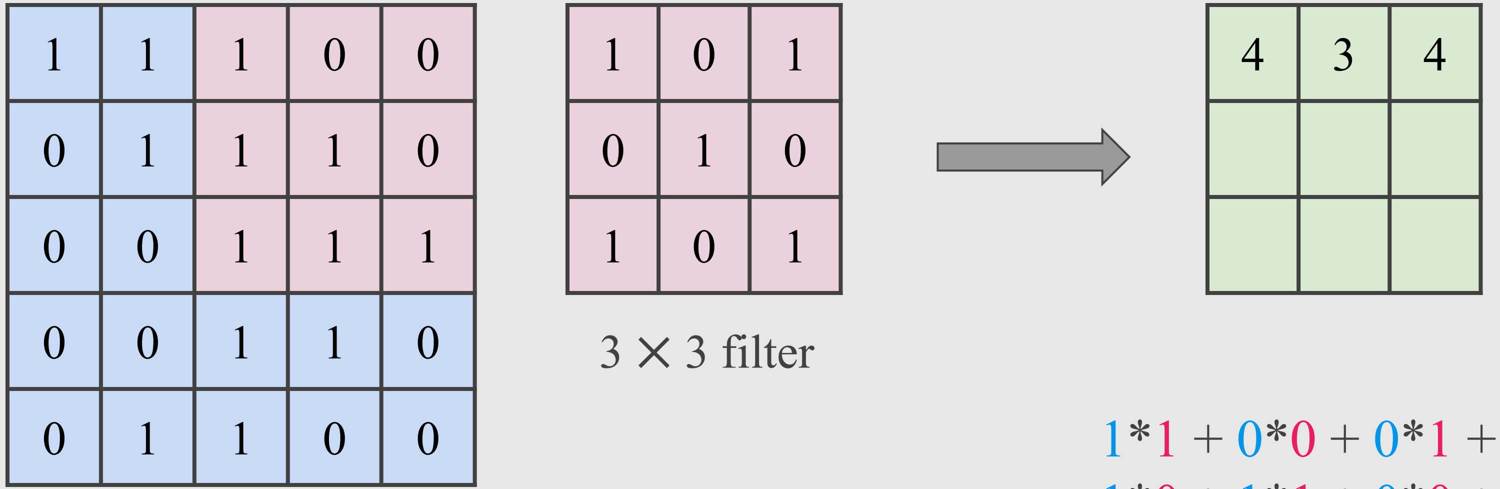


5 × 5 matrix

3 × 3 filter

1*1 + 1*0 + 0*1 +
1*0 + 1*1 + 1*0 +
0*1 + 1*0 + 1*1 = 3

What is a Convolution?



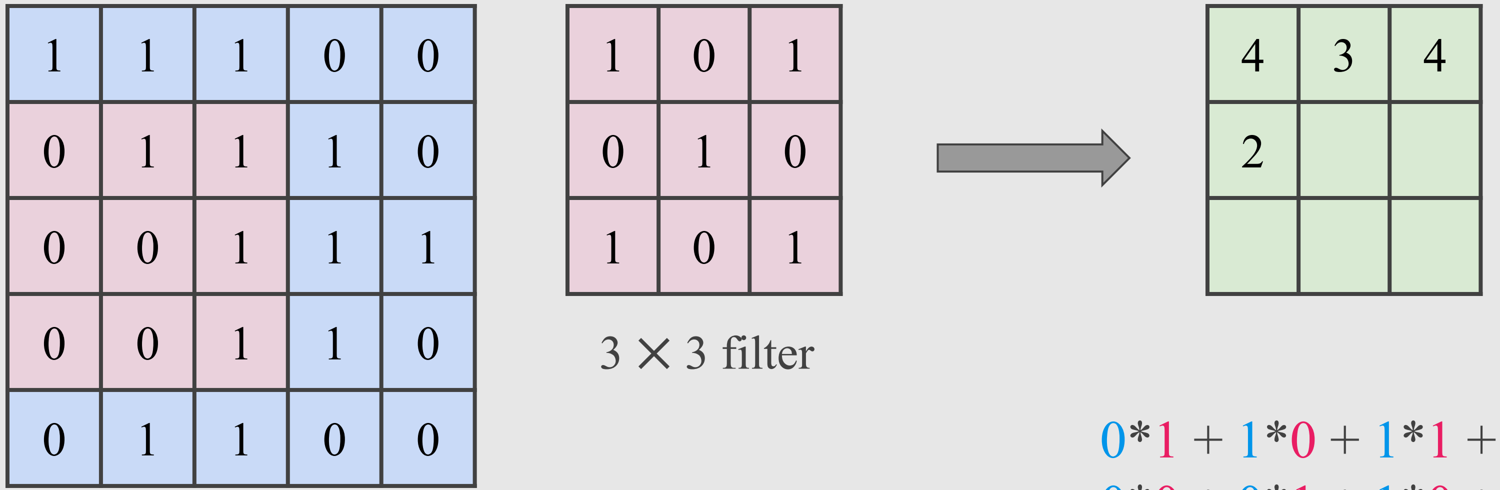
$$\begin{bmatrix}1&1&1&0&0\\0&1&1&1&0\\0&0&1&1&1\\0&0&1&1&0\\0&1&1&0&0\end{bmatrix} \quad \begin{bmatrix}1&0&1\\0&1&0\\1&0&1\end{bmatrix} \rightarrow \begin{bmatrix}4&3&4\\ & & \\ & & \end{bmatrix}$$

5 × 5 matrix

3 × 3 filter

$$1*1 + 0*0 + 0*1 +$$
$$1*0 + 1*1 + 0*0 +$$
$$1*1 + 1*0 + 1*1 = 4$$

What is a Convolution?



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

5 × 5 matrix

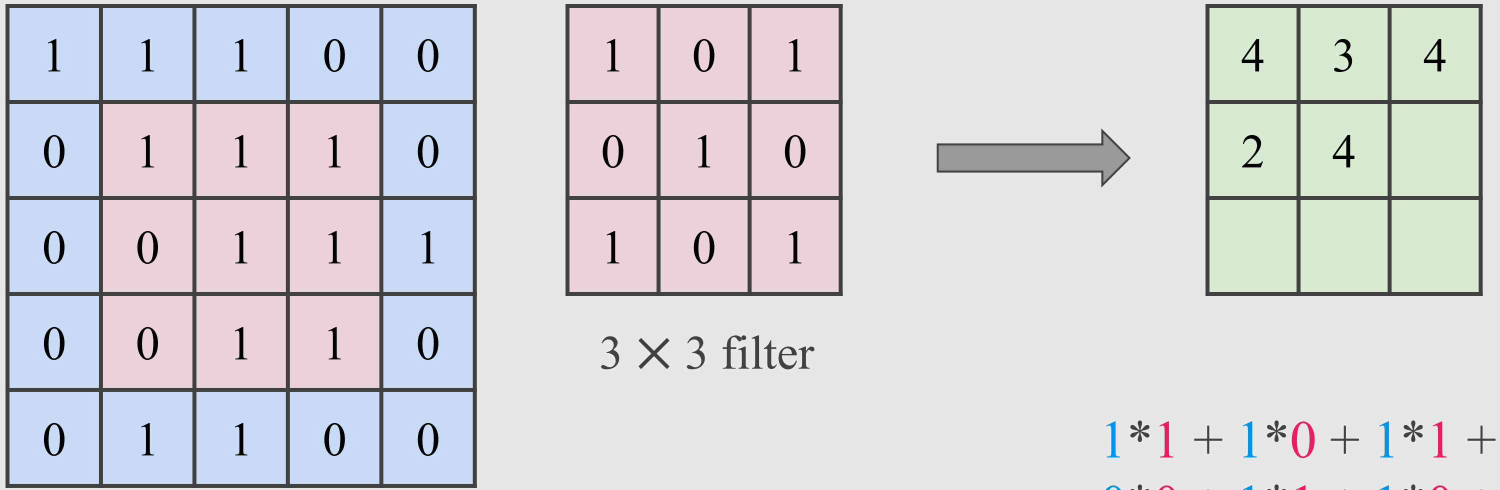
1	0	1
0	1	0
1	0	1

3 × 3 filter

4	3	4
2		

0*1 + 1*0 + 1*1 +
0*0 + 0*1 + 1*0 +
0*1 + 0*0 + 1*1 = 2

What is a Convolution?



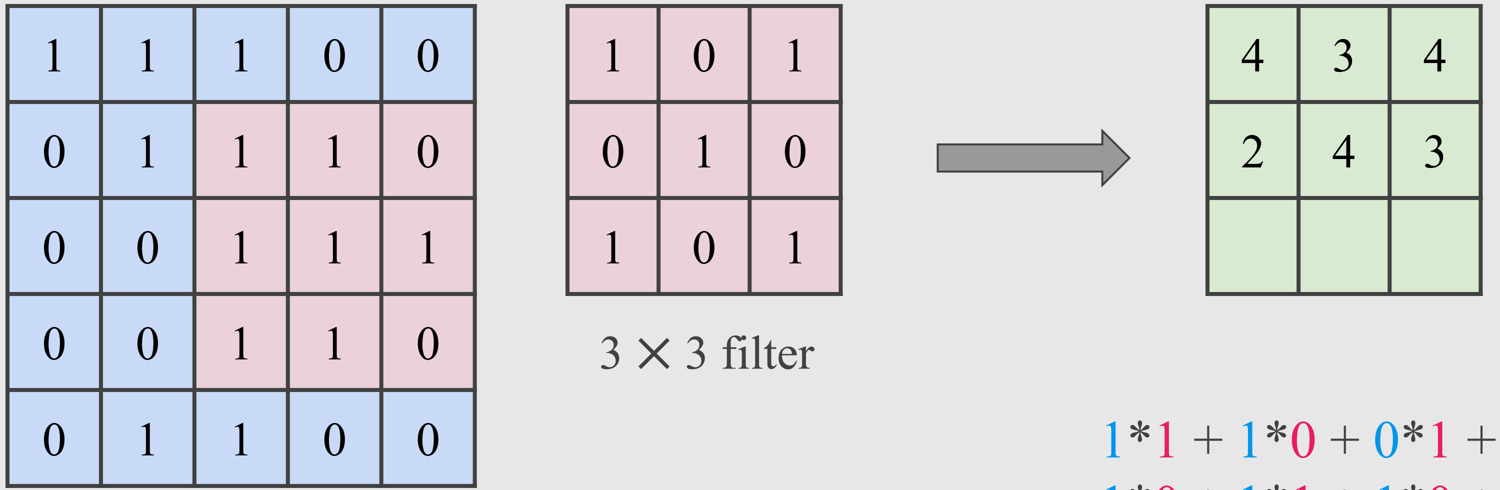
$$\begin{array}{|c|c|c|c|c|}\hline 1&1&1&0&0\\\hline 0&1&1&1&0\\\hline 0&0&1&1&1\\\hline 0&0&1&1&0\\\hline 0&1&1&0&0\\\hline\end{array} \quad \begin{array}{|c|c|c|}\hline 1&0&1\\\hline 0&1&0\\\hline 1&0&1\\\hline\end{array} \quad \longrightarrow \quad \begin{array}{|c|c|c|}\hline 4&3&4\\\hline 2&4&\\\hline &&\\\hline\end{array}$$

3 × 3 filter

5 × 5 matrix

$1*1 + 1*0 + 1*1 +$
$0*0 + 1*1 + 1*0 +$
$0*1 + 1*0 + 1*1 = 4$

What is a Convolution?



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

5 × 5 matrix

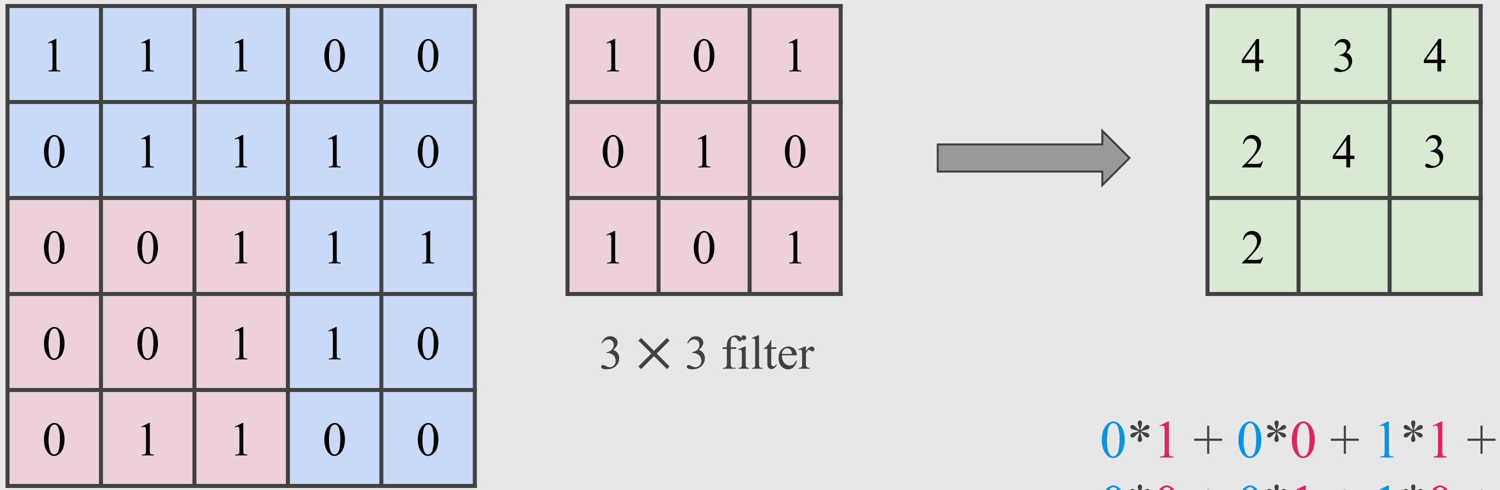
1	0	1
0	1	0
1	0	1

3 × 3 filter

4	3	4
2	4	3

$$1*1 + 1*0 + 0*1 +$$
$$1*0 + 1*1 + 1*0 +$$
$$1*1 + 1*0 + 0*1 = 3$$

What is a Convolution?



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

5 × 5 matrix

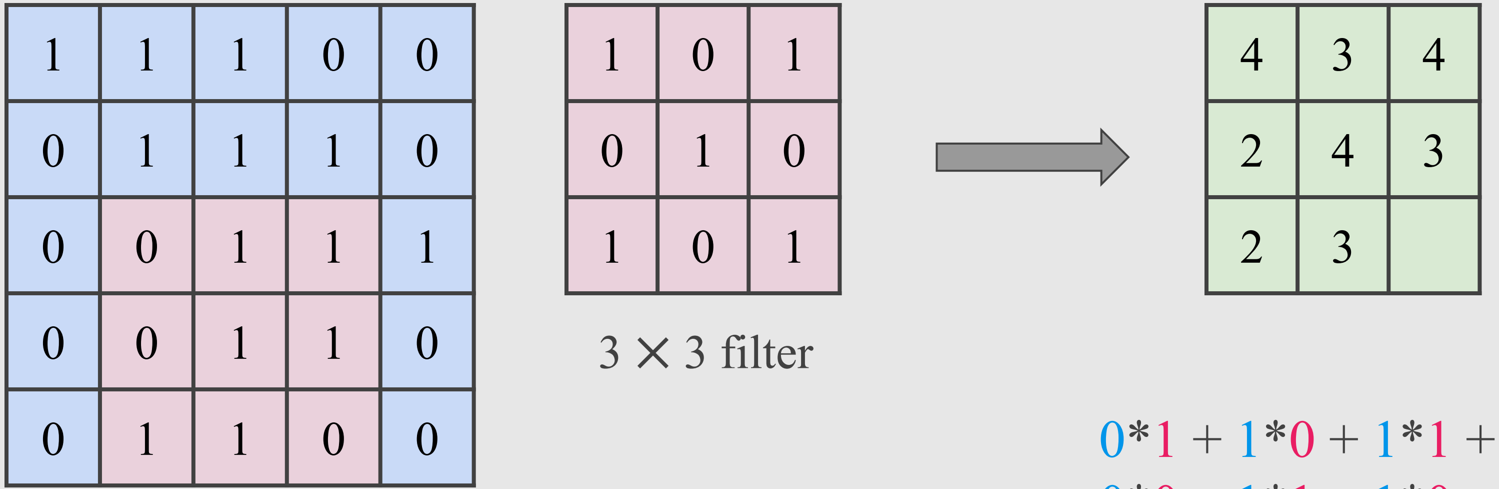
1	0	1
0	1	0
1	0	1

3 × 3 filter

4	3	4
2	4	3
2		

$$0*1 + 0*0 + 1*1 +$$
$$0*0 + 0*1 + 1*0 +$$
$$0*1 + 1*0 + 1*1 = 2$$

What is a Convolution?



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

5 × 5 matrix

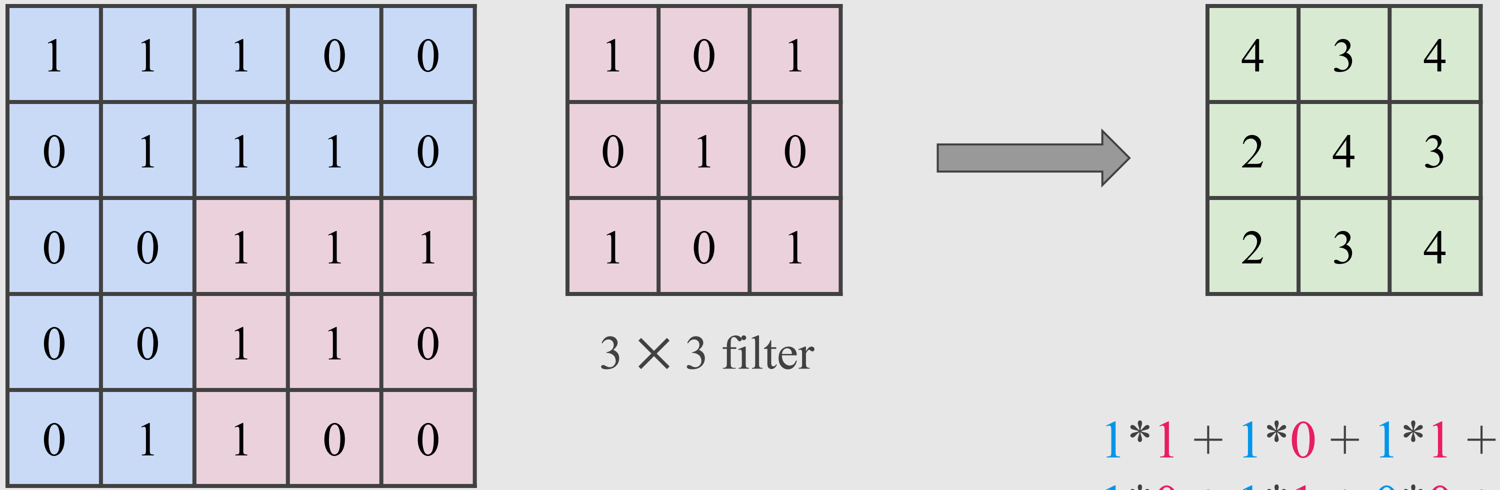
1	0	1
0	1	0
1	0	1

3 × 3 filter

4	3	4
2	4	3
2	3	

0*1 + 1*0 + 1*1 +
0*0 + 1*1 + 1*0 +
1*1 + 1*0 + 0*1 = 3

What is a Convolution?



$$\begin{bmatrix} 1 & 1 & 1 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 & 0 \\ 0 & 1 & 1 & 0 & 0 \end{bmatrix} \quad \begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix} \longrightarrow \begin{bmatrix} 4 & 3 & 4 \\ 2 & 4 & 3 \\ 2 & 3 & 4 \end{bmatrix}$$

5 × 5 matrix

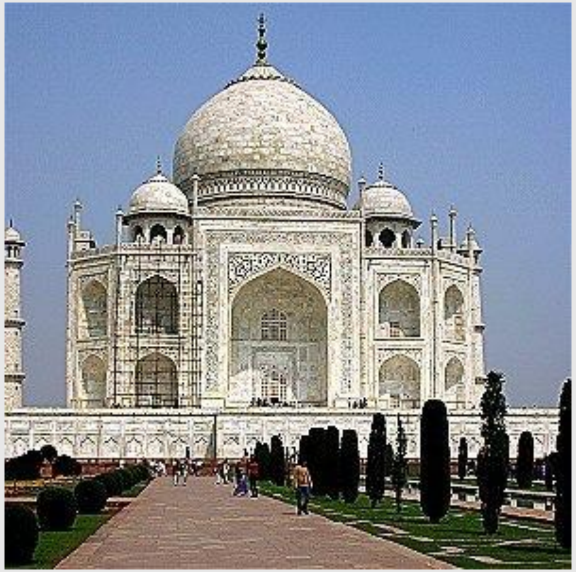
3 × 3 filter

1*1 + 1*0 + 1*1 +
1*0 + 1*1 + 0*0 +
1*1 + 0*0 + 0*1 = 4

What is a Convolution?

0	1	0
1	-4	1
0	1	0

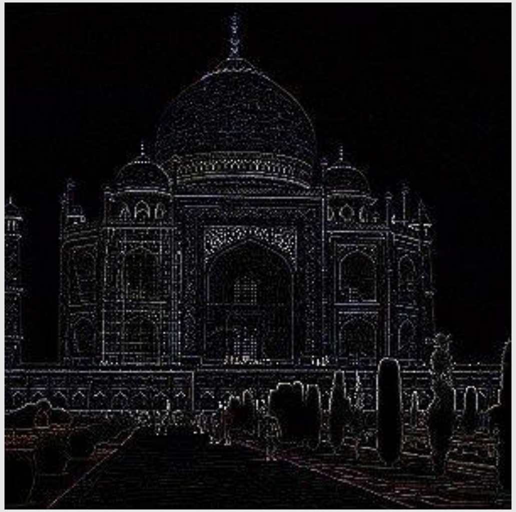
What is a Convolution?



Edge Detection

0	1	0
1	-4	1
0	1	0

$\rightarrow$

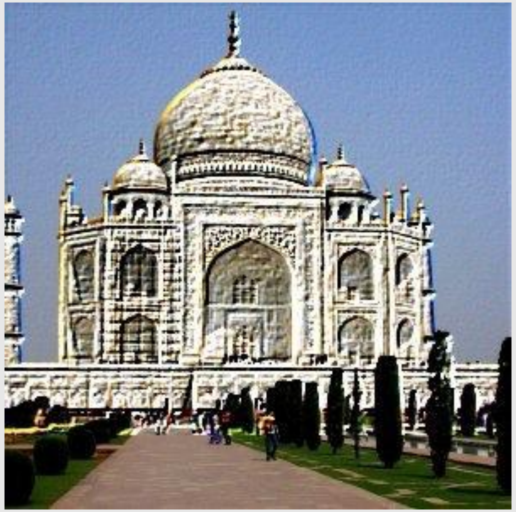


What is a Convolution?

Emboss

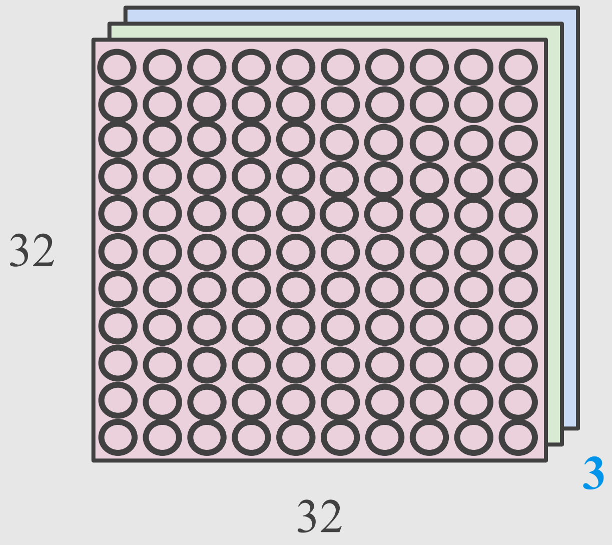
-2	-1	0
-1	1	1
0	1	2

$\longrightarrow$



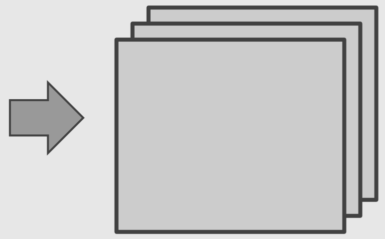
Convolution Layer

$32 \times 32 \times 3$ image $\Rightarrow$ preserve spatial structure



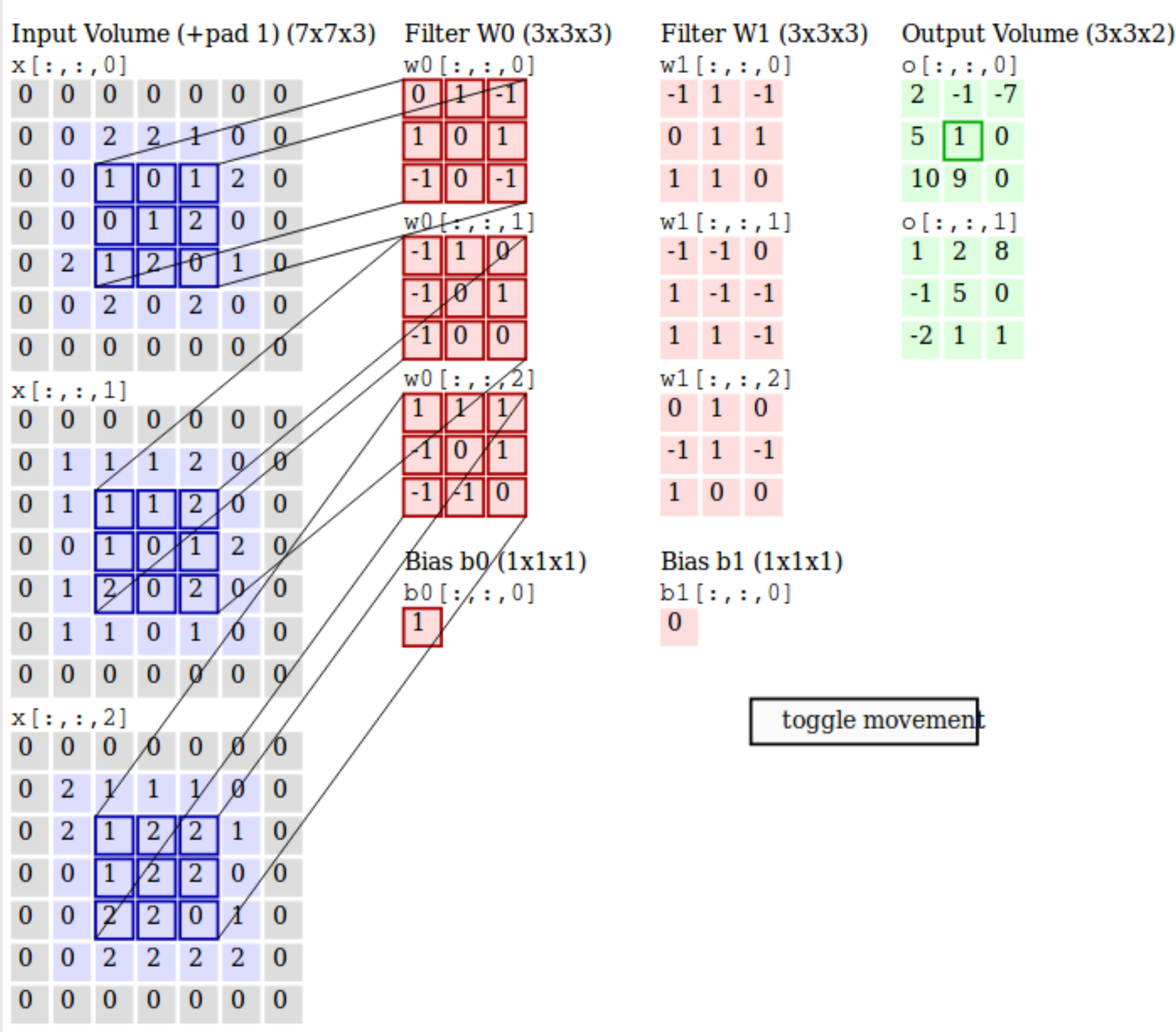
Convolve the filter with the image i.e. “slide over the image spatially, computing dot products”

$5 \times 5 \times \mathbf{3}$ filter



Filters always extend the full depth of the input volume

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



Input Volume (+pad 1) (7x7x3)

x[:,:,0]

0	0	0	0	0	0	0
0	0	2	2	1	0	0
0	0	1	0	1	2	0
0	0	0	1	2	0	0
0	2	1	2	0	1	0
0	0	2	0	2	0	0
0	0	0	0	0	0	0

x[:,:,1]

0	0	0	0	0	0	0
0	1	1	1	2	0	0
0	1	1	1	2	0	0
0	0	1	0	1	2	0
0	1	2	0	2	0	0
0	1	1	0	1	0	0
0	0	0	0	0	0	0

x[:,:,2]

0	0	0	0	0	0	0
0	2	1	1	1	0	0
0	2	1	2	2	1	0
0	0	1	2	2	0	0
0	0	2	2	0	1	0
0	0	2	2	2	2	0
0	0	0	0	0	0	0

Filter W0 (3x3x3)

w0[:,:,0]

0	1	-1
1	0	1
-1	0	-1

w0[:,:,1]

-1	1	0
-1	0	1
-1	0	0

w0[:,:,2]

1	1	1
-1	0	1
-1	-1	0

Bias b0 (1x1x1)

b0[:,:,0]

1

Filter W1 (3x3x3)

w1[:,:,0]

-1	1	-1
0	1	1
1	1	0

w1[:,:,1]

-1	-1	0
1	-1	-1
1	1	-1

w1[:,:,2]

0	1	0
-1	1	-1
1	0	0

Bias b1 (1x1x1)

b1[:,:,0]

0

Output Volume (3x3x2)

o[:,:,0]

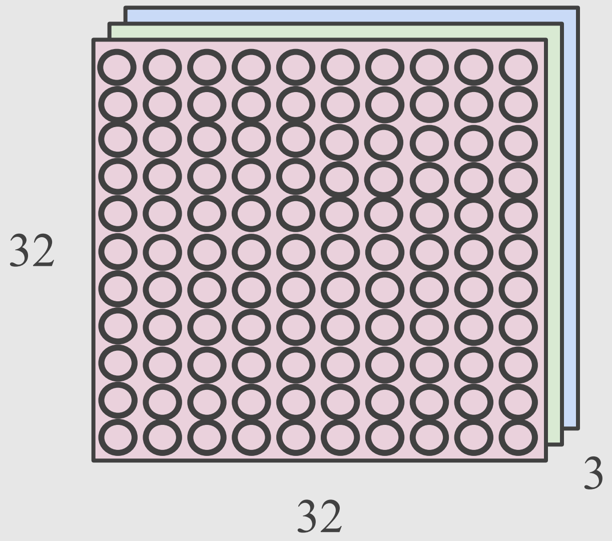
2	-1	-7
5	1	0
10	9	0

o[:,:,1]

1	2	8
-1	5	0
-2	1	1

Convolution Layer

$32 \times 32 \times 3$ image $\Rightarrow$ preserve spatial structure

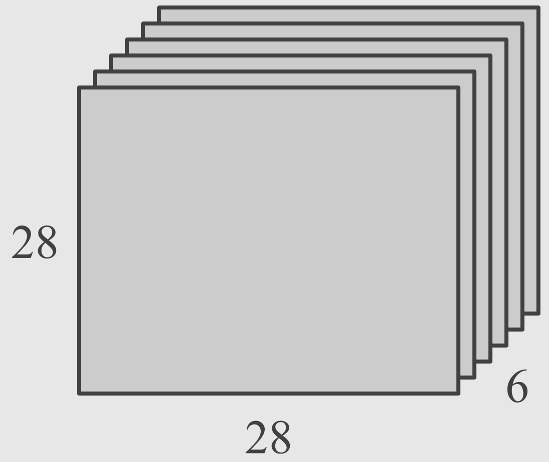


Convolve (slide) over all spatial locations

$32 \times 32 \times 3$ image
$5 \times 5 \times 3$ filter

If we had 6 $5 \times 5 \times 3$ filters ...

6 activation maps



Convolutional Layer

The size of the **Activation Map** (or Feature Map or Convolved Feature) is controlled by three parameters:

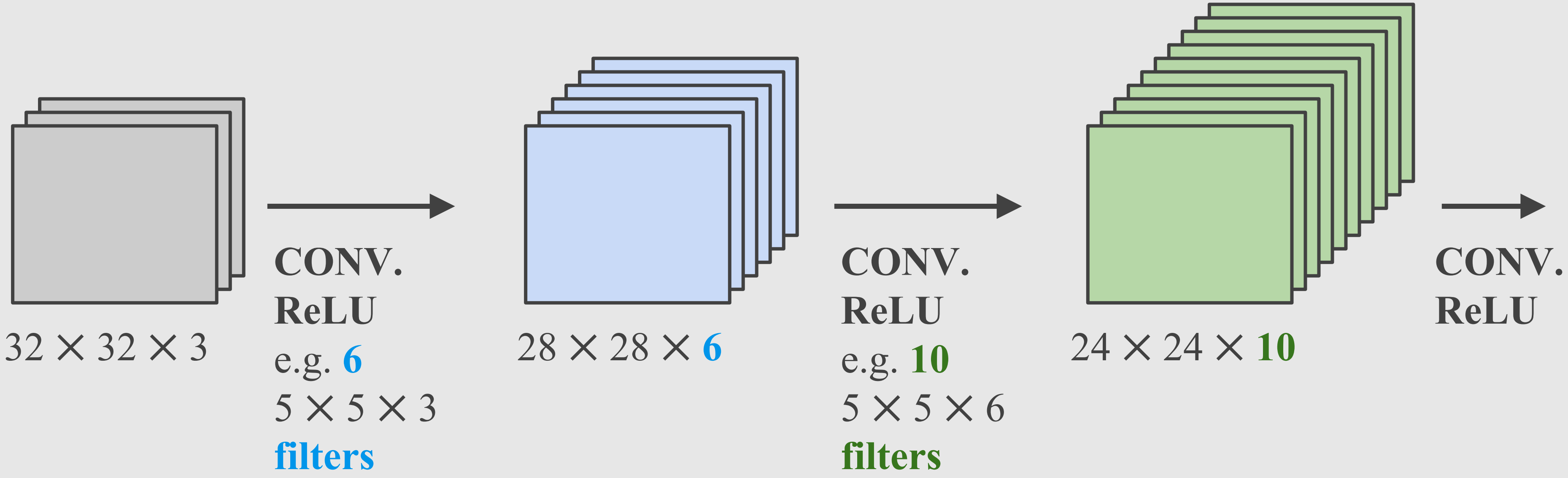
Convolutional Layer

The size of the **Activation Map** (or Feature Map or Convolved Feature) is controlled by three parameters:

- **Depth**: corresponds to the **number of filters** we use for the convolution operation.

Convolutional Layers

Sequence of Convolutional Layers, interspersed with activation functions.

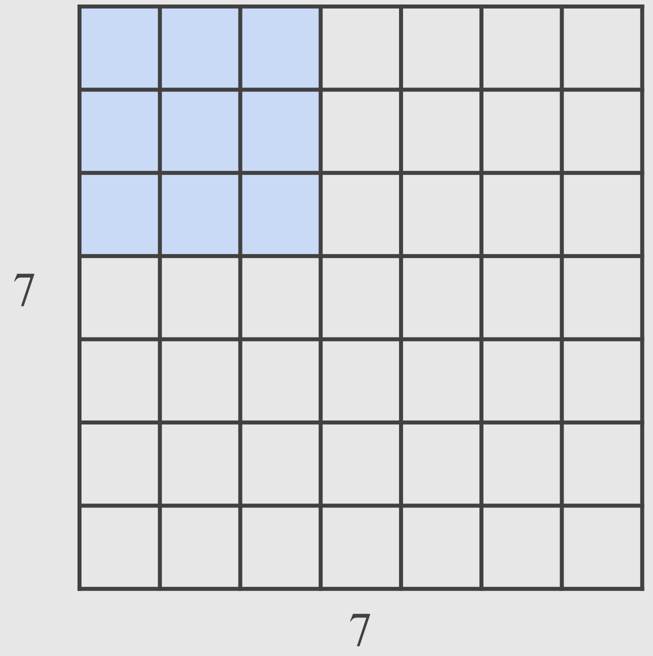


Convolutional Layer

The size of the **Activation Map** (or Feature Map or Convolved Feature) is controlled by three parameters:

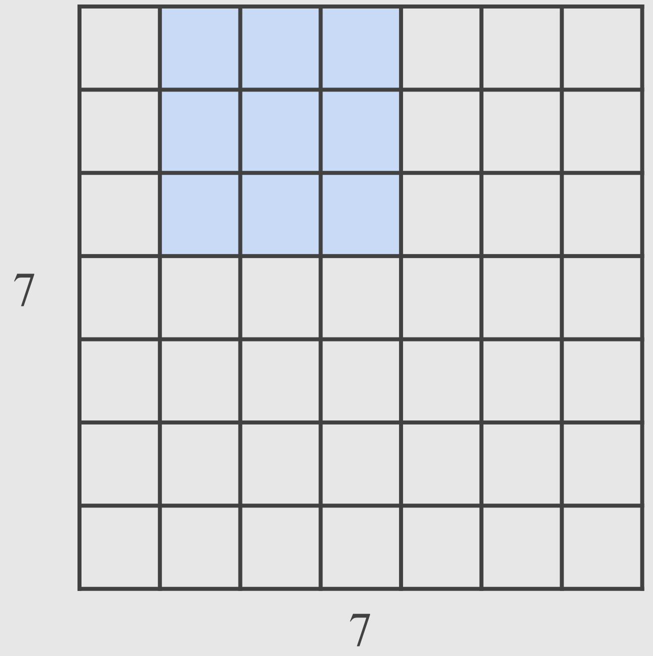
- **Depth**: corresponds to the **number of filters** we use for the convolution operation.
- **Stride**: the **number of pixels by which we slide** our filter matrix over the input matrix.

Convolutional Layer: Stride



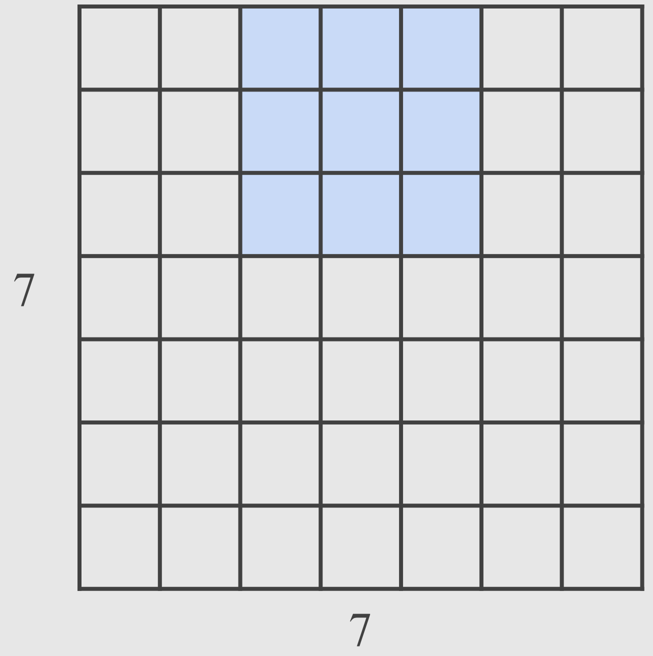
7×7 input (spatially)
assume 3×3 filter
applied with **stride 1**

Convolutional Layer: Stride



7×7 input (spatially)
assume 3×3 filter
applied with **stride 1**

Convolutional Layer: Stride



7×7 input (spatially)
assume 3×3 filter
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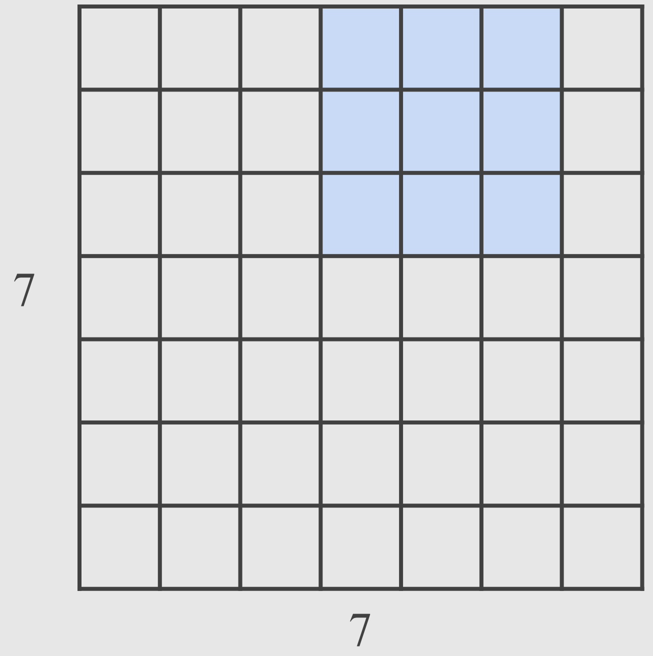
Convolutional Layer: Stride



7×7 input (spatially)
assume 3×3 filter
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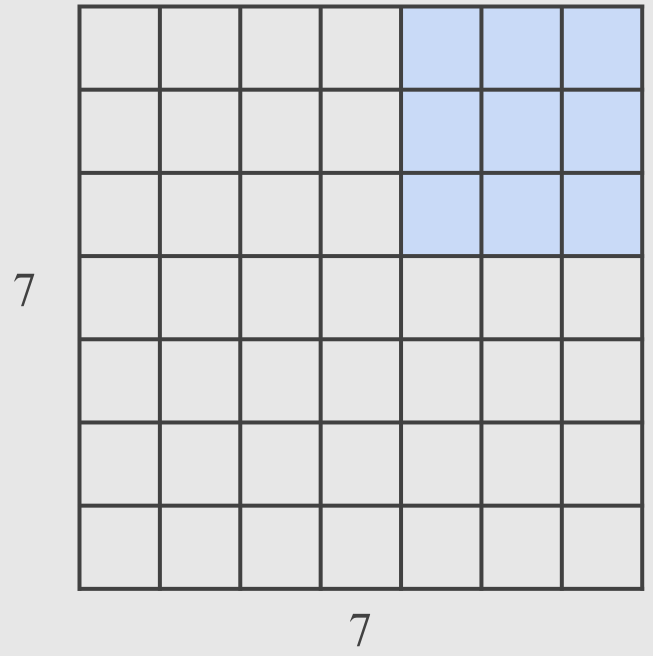
Convolutional Layer: Stride



7×7 input (spatially)
assume 3×3 filter
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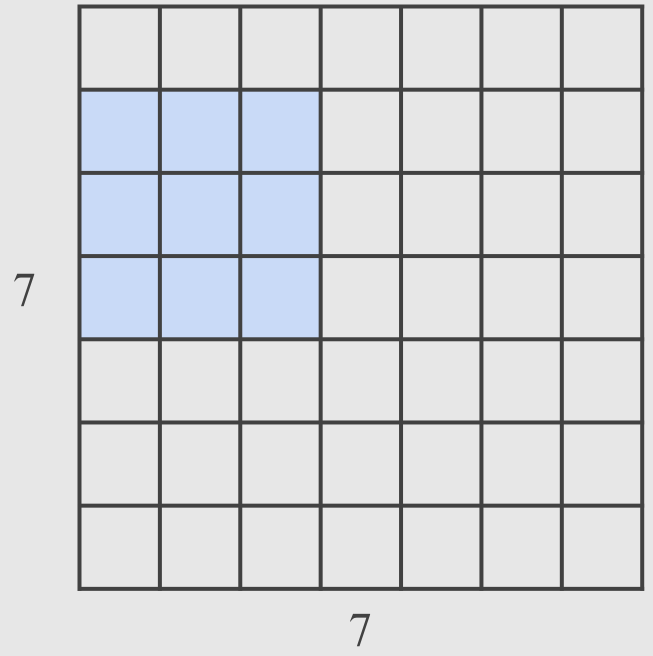
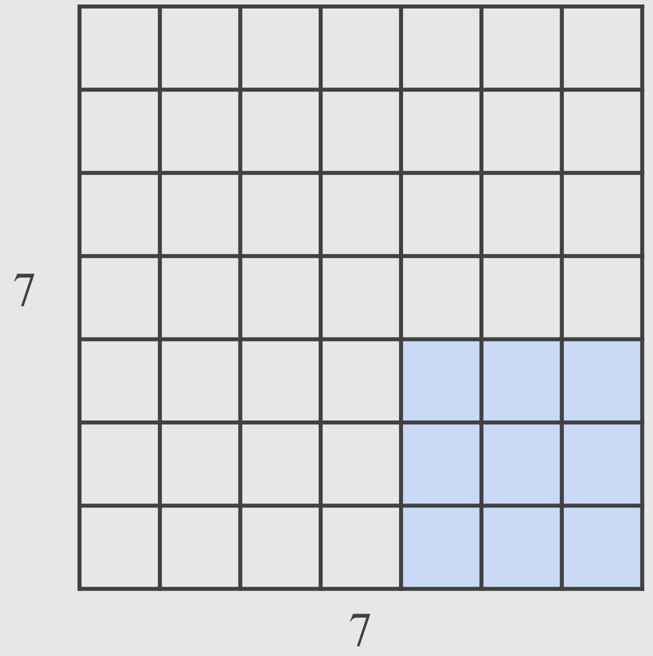
Convolutional Layer: Stride



7×7 input (spatially)
assume 3×3 filter
applied with **stride 1**

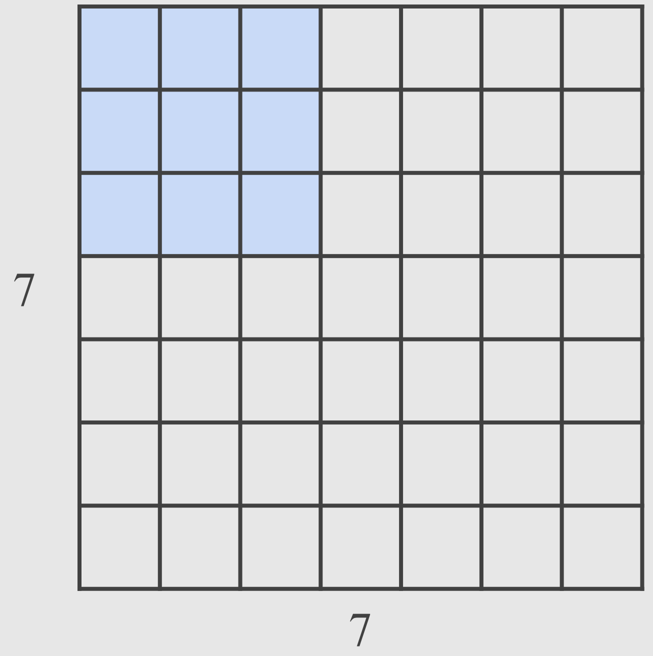
Convolutional Layer: Stride



7×7 input (spatially)
assume 3×3 filter
applied with **stride 1**

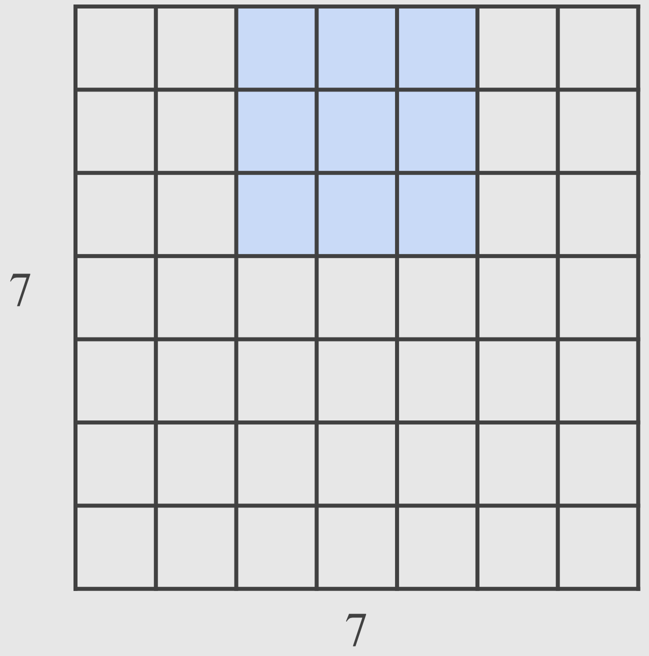
$\Rightarrow$ **5×5 output**

Convolutional Layer: Stride



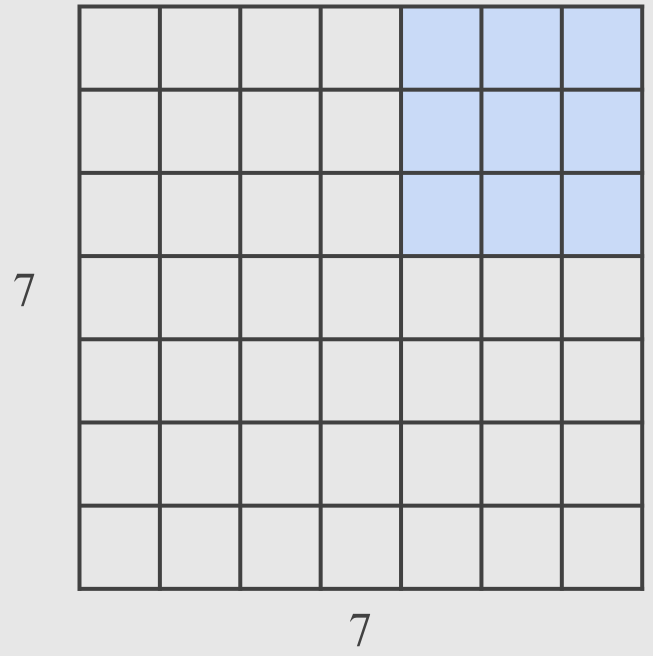
7×7 input (spatially)
assume 3×3 filter
applied with **stride 2**

Convolutional Layer: Stride



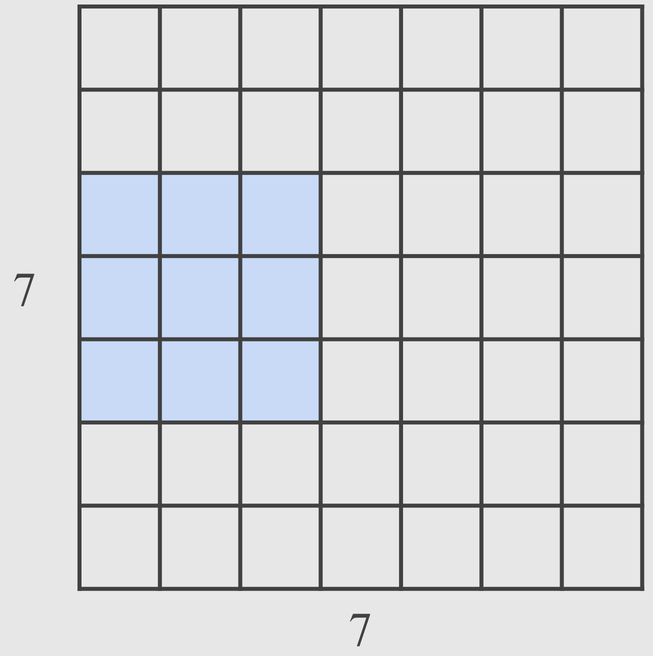
7×7 input (spatially)
assume 3×3 filter
applied with **stride 2**

Convolutional Layer: Stride



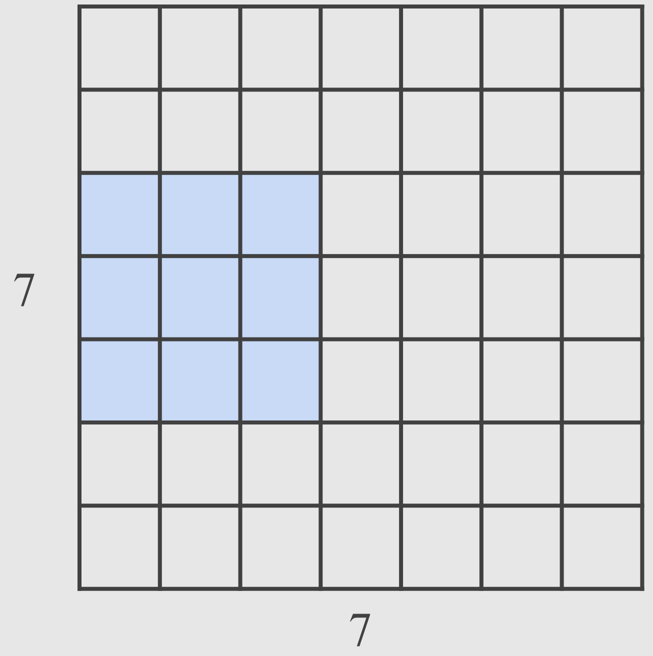
7×7 input (spatially)
assume 3×3 filter
applied with **stride 2**

Convolutional Layer: Stride



7×7 input (spatially)
assume 3×3 filter
applied with **stride 2**

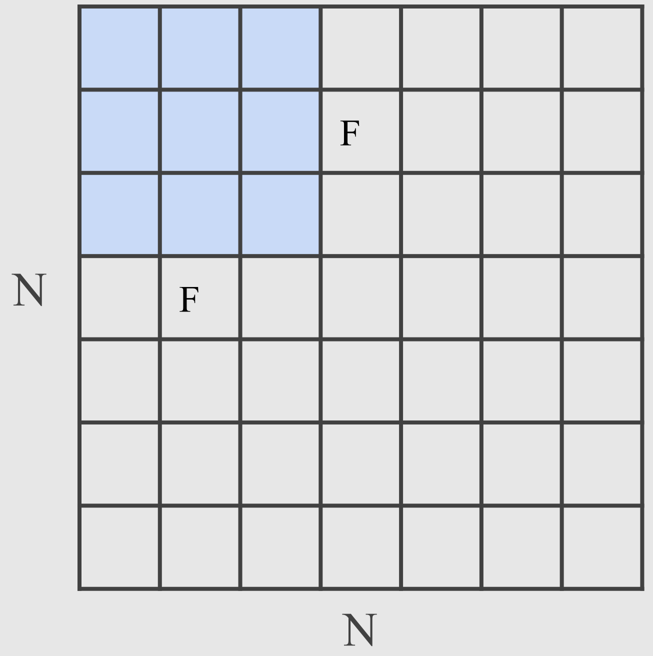
Convolutional Layer: Stride



7×7 input (spatially)
assume 3×3 filter
applied with **stride 2**

$\Rightarrow$ 3 $\times$3 output

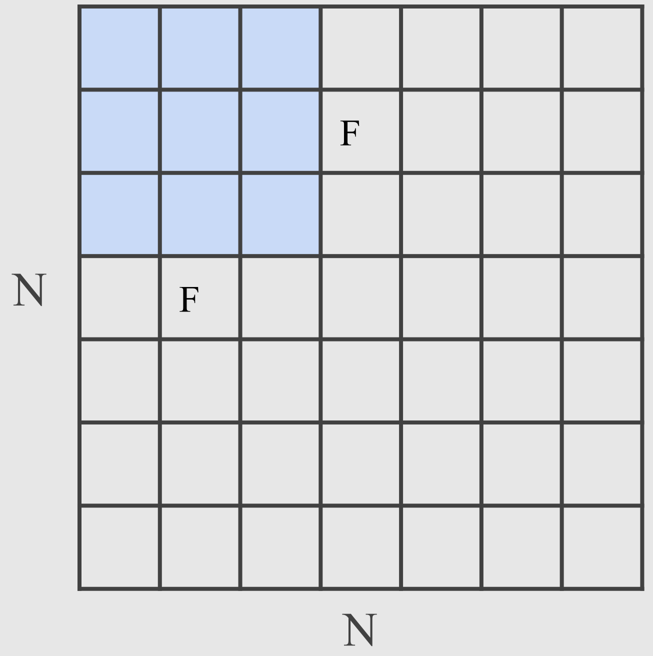
Convolutional Layer: Stride



Output size:

(N - F) / stride + 1

Convolutional Layer: Stride



Output size:

(N - F) / stride + 1

e.g. N = 7, F = 3:

stride 1 ⇒ (7 - 3)/1 + 1 = 5

stride 2 ⇒ (7 - 3)/2 + 1 = 3

stride 3 ⇒ (7 - 3)/3 + 1 = 2.33

Convolutional Layer

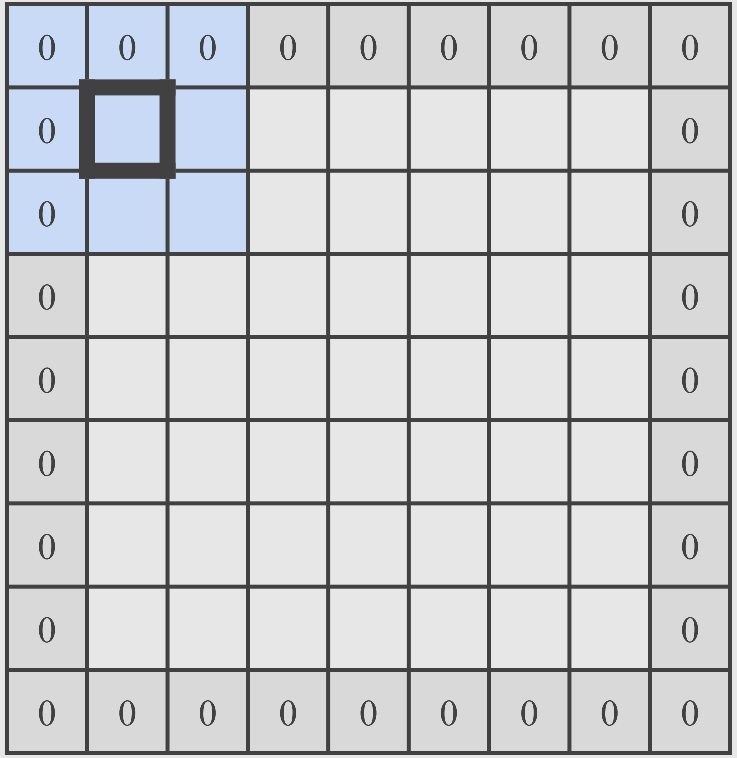
The size of the **Activation Map** (or Feature Map or Convolved Feature) is controlled by three parameters:

- **Depth**: corresponds to the **number of filters** we use for the convolution operation.
- **Stride**: the **number of pixels by which we slide** our filter matrix over the input matrix.
- **Zero-padding**: sometimes, it is convenient to pad the input matrix with **zeros around the border**.

Convolutional Layer: Zero-Padding

0	0	0	0	0	0	0	0	0
0								0
0								0
0								0
0								0
0								0
0								0
0								0
0	0	0	0	0	0	0	0	0

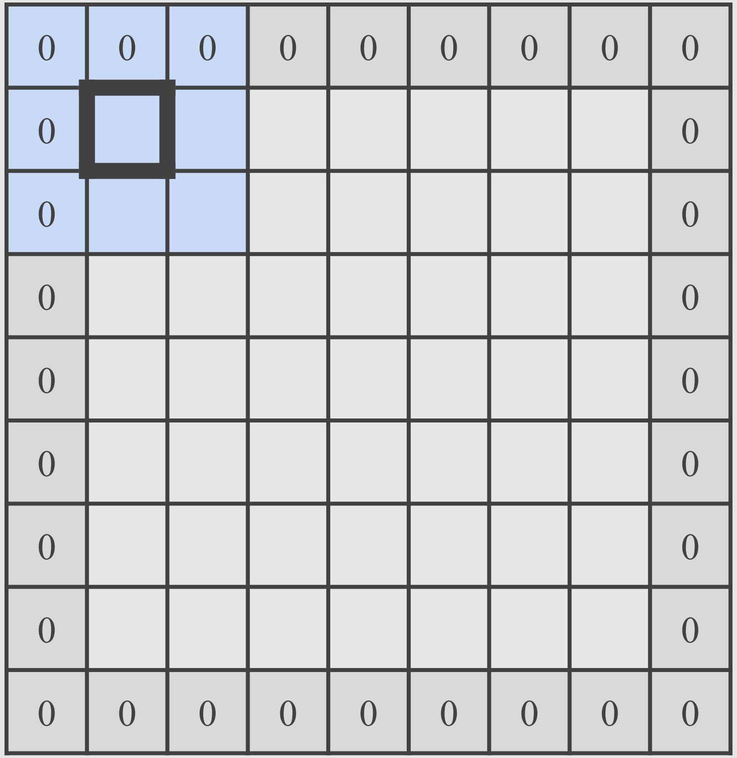
Convolutional Layer: Zero-Padding



7×7 input,
3×3 filter applied
with **stride 1 with pad 1**

What is the output?
7×7 output

Convolutional Layer: Zero-Padding

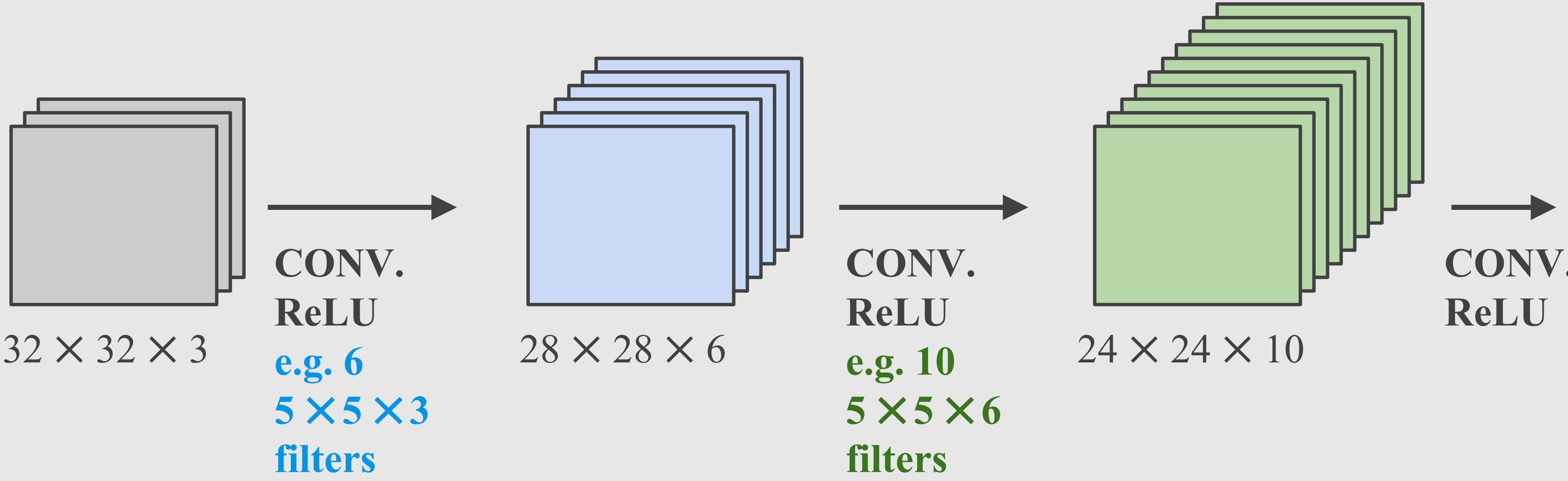


In general, common to see CONV layers with stride 1, filters of size F × F, and zero-padding with (F-1)/2 **(will preserve size spatially)**.

e.g. F = 3 ⇒ zero pad with 1
F = 5 ⇒ zero pad with 2
F = 7 ⇒ zero pad with 3

Shrinking too fast is not good, doesn't work well.

$32 \rightarrow 28 \rightarrow 24 \rightarrow \ldots$



Number of Parameters

Input volume: $\mathbf{32 \times 32 \times 3}$

10 5×5 filters with stride 1, pad 2

Number of parameters in this layer?

Number of Parameters

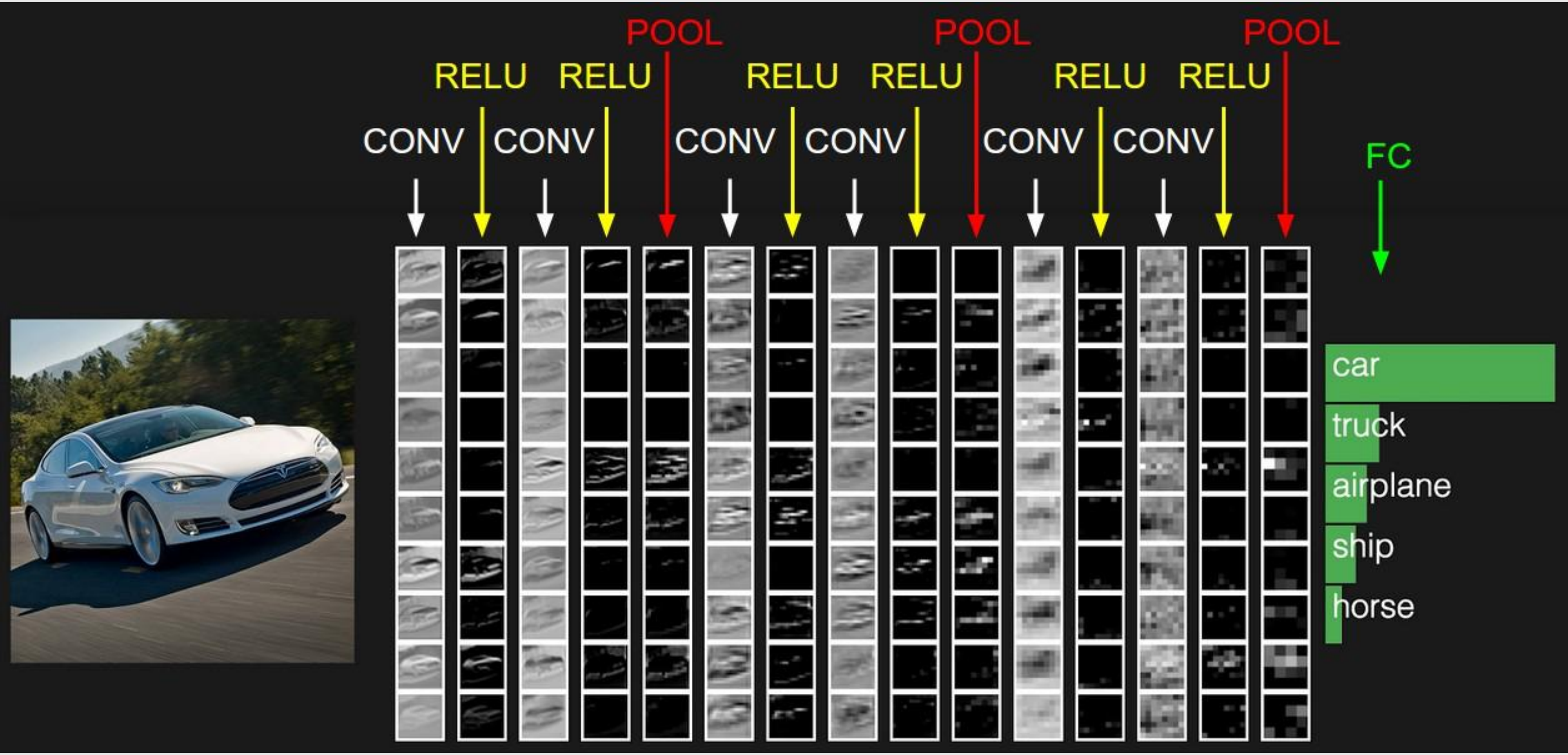
Input volume: $\mathbf{32 \times 32 \times 3}$

$\mathbf{10}$ $\mathbf{5 \times 5}$ filters with stride 1, pad 2

Number of parameters in this layer?

Each filter has $5*5*3 + 1 = \mathbf{76}$ parameters (+1 for bias)

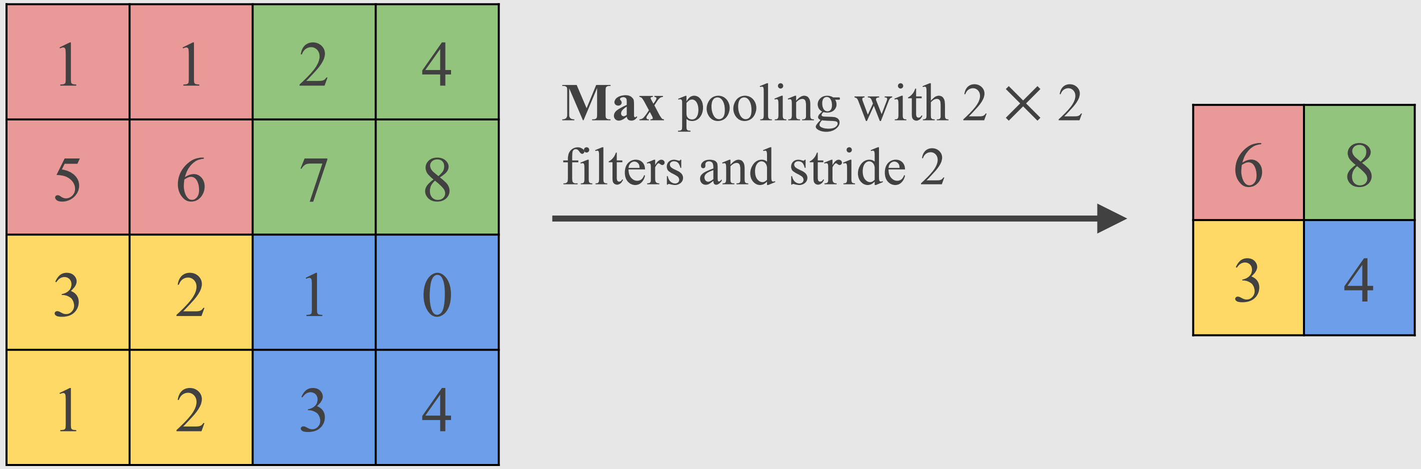
=> $\mathbf{76}*\mathbf{10} = 760$



Credit: http://cs231n.github.io/convolutional-networks/

Pooling Layer

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



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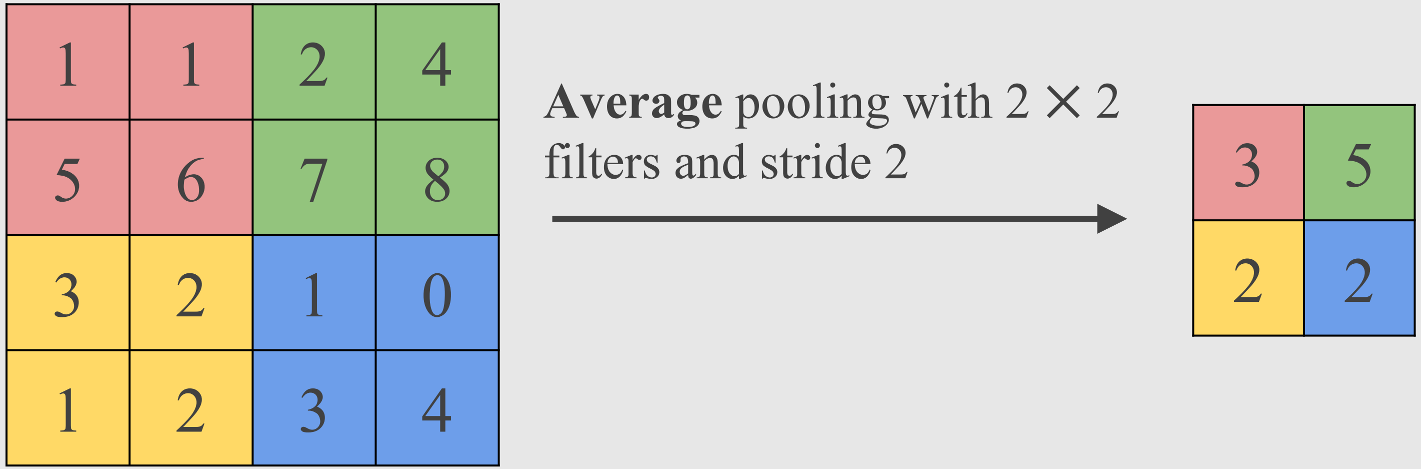


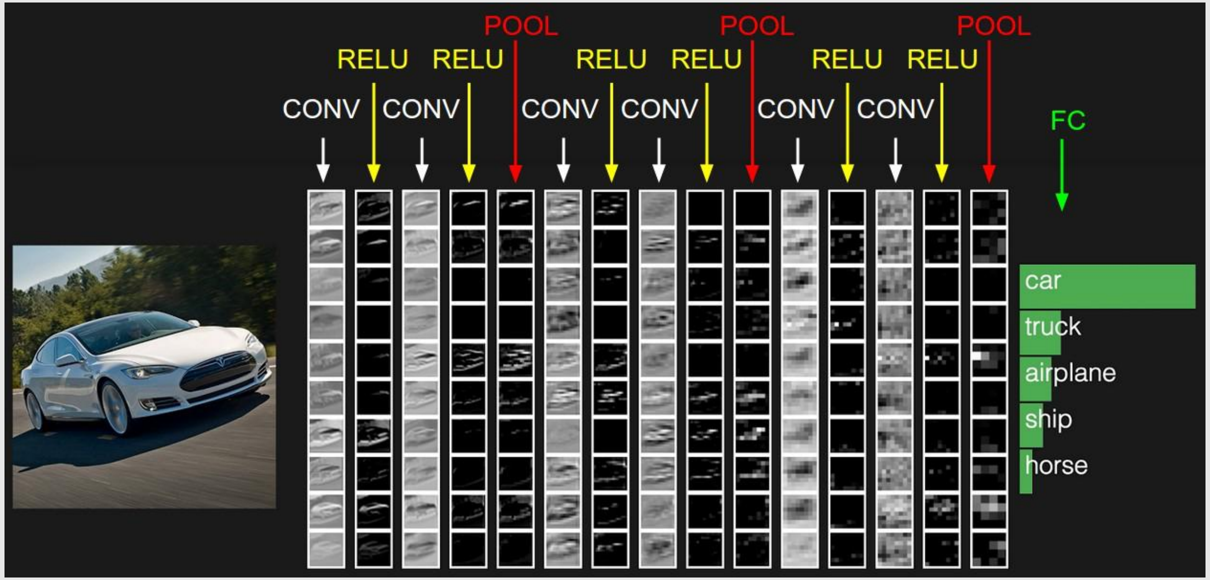
Pooling Layer

The function of Pooling is **to progressively reduce the spatial size of the input representation**. In particular, pooling

- makes the input representations (feature dimension) smaller and more manageable
- reduces the number of parameters and computations in the network, therefore, controlling overfitting
- makes the network invariant to small transformations, distortions and translations in the input image

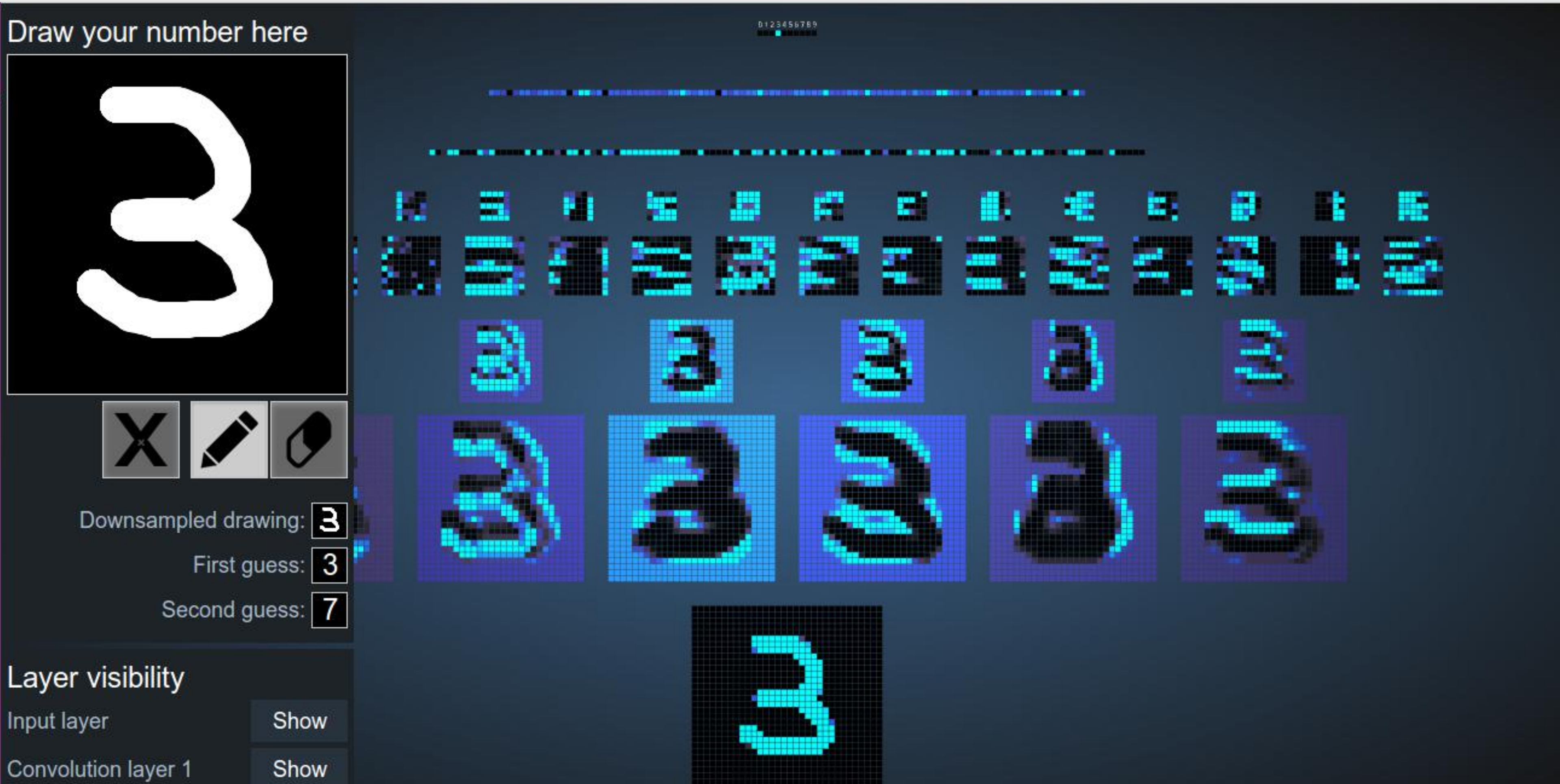
Fully Connected Layer

- Contains neurons that connect to the entire input volume, as in ordinary Neural Networks



Credit: http://cs231n.github.io/convolutional-networks/

http://scs.ryerson.ca/~aharley/vis/conv/flat.html



Visualizing a CNN trained on Handwritten Digits

- Input image: 1024 pixels (32 x 32 image)
- CONV 1 (+ RELU): 6 5 × 5 (stride 1) filters
- POOL 1: 2 × 2 max pooling (with stride 2)
- CONV 2 (+ RELU): 16 5 × 5 (stride 1) filters
- POOL 2: 2 × 2 max pooling (with stride 2)
- 3 FC layers:
  - 120 neurons in the first FC layer
  - 100 neurons in the second FC layer
  - 10 neurons in the third FC (Output layer)

DNNs Architectures

DNNs Architectures

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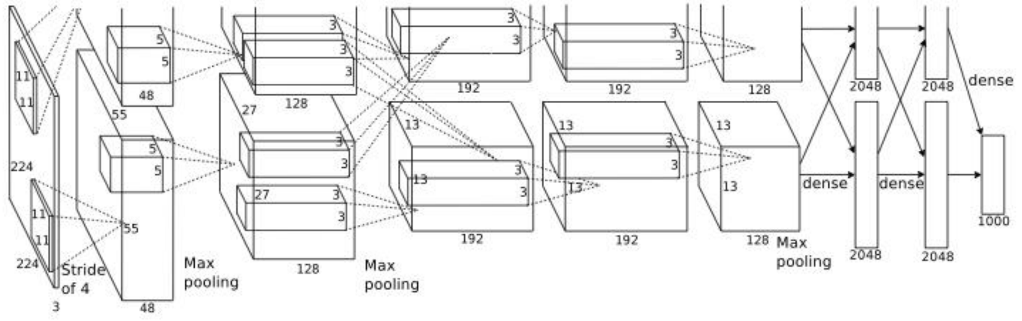
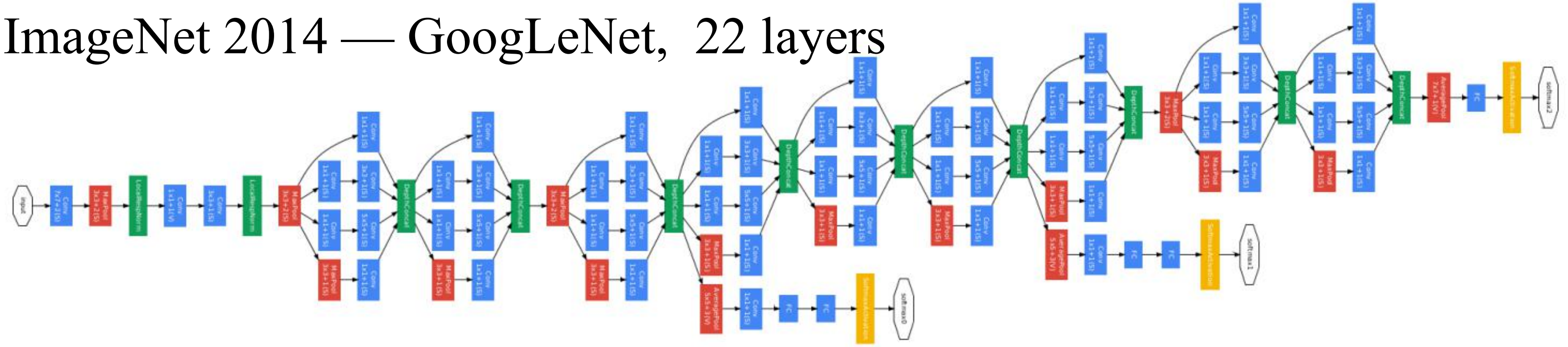
ImageNet 2012 — AlexNet, 8 layers



ImageNet 2014 — GoogLeNet, 22 layers



ImageNet 2015 — ResNet, 152 layers

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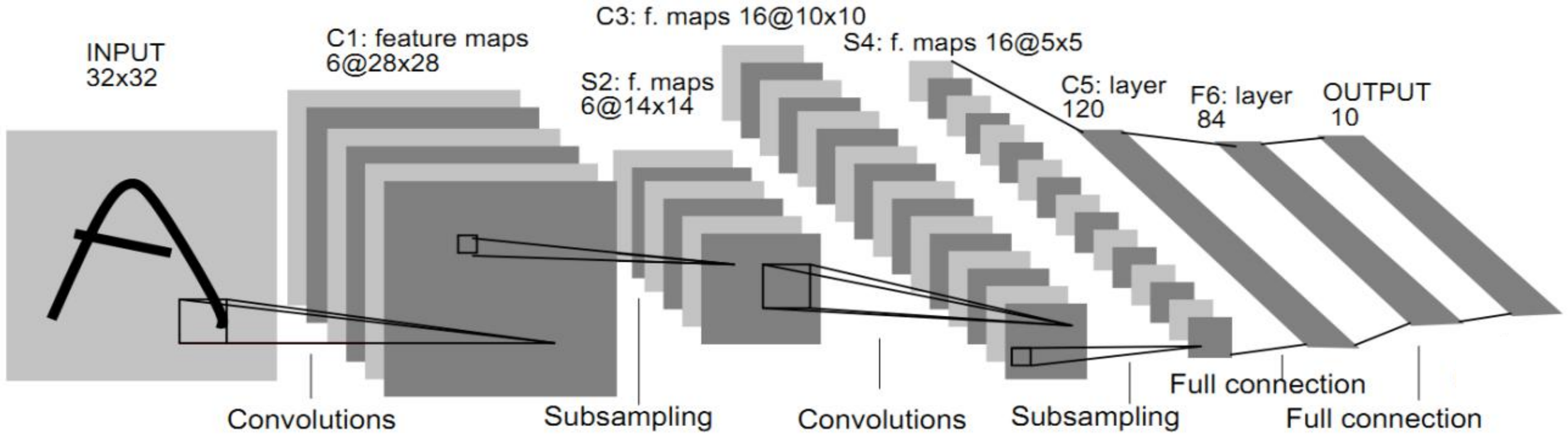
LeNet-5 [LeCun et al., 1998]

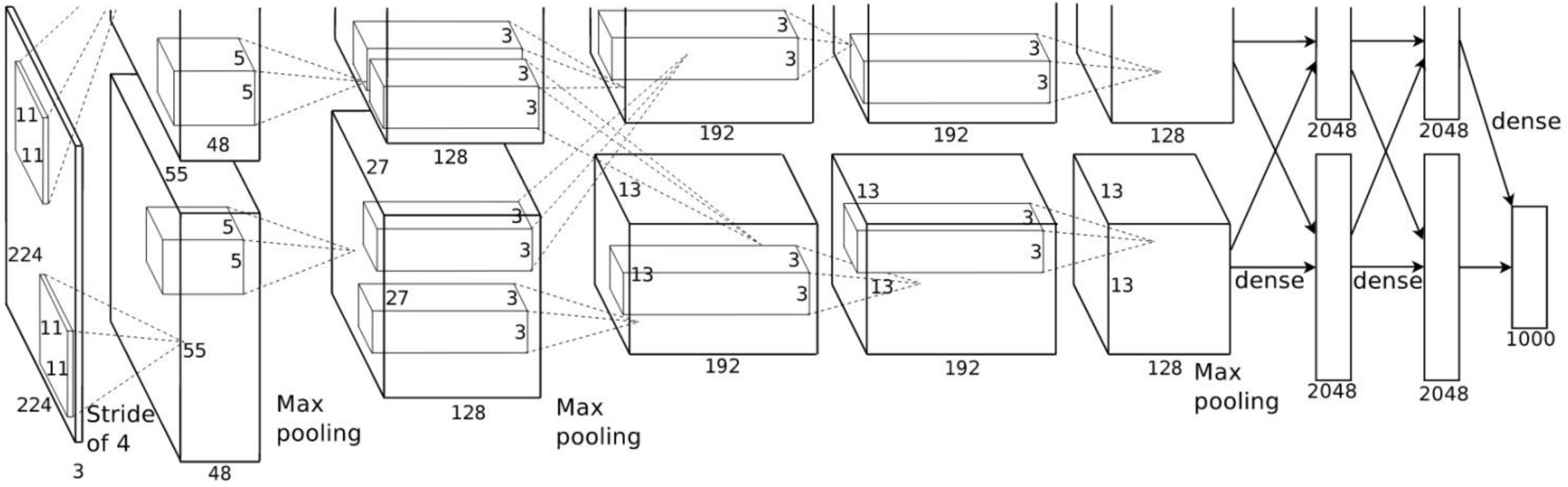


Convolution filters: 5x5 with stride 1

Subsampling (Pooling) layers: 2x2 with stride 2

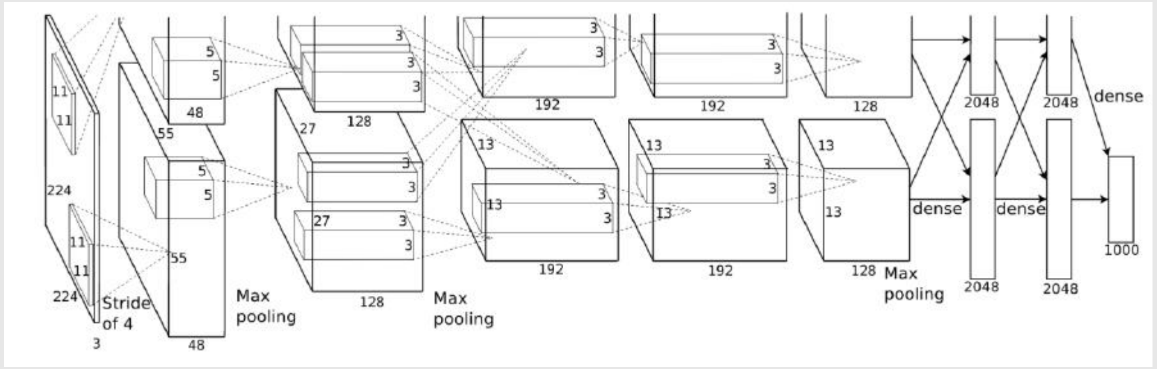
[CONV-POOL-CONV-POOL-FC-FC]

AlexNet [Krizhevsky et al., 2012]



AlexNet [Krizhevsky et al., 2012]

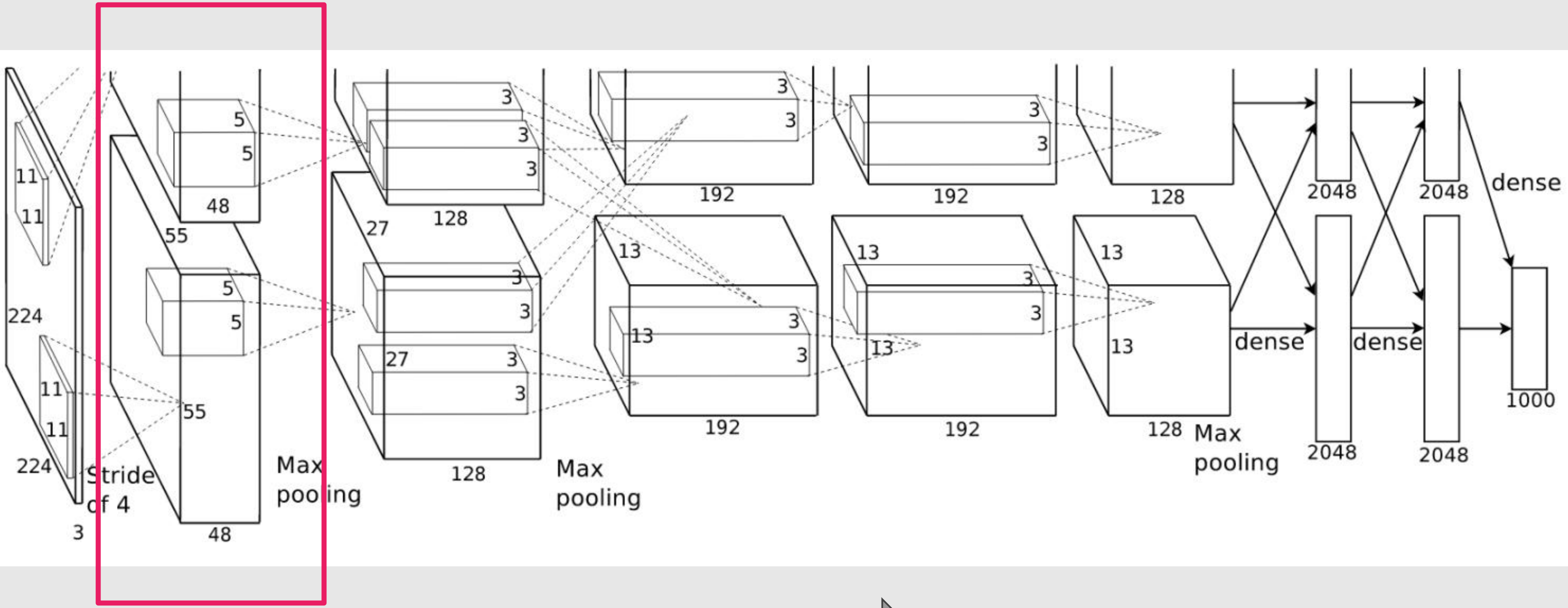
Architecture:
CONV1
MAX POOL1
NORM1
CONV2
MAX POOL2
NORM2
CONV3
CONV4
CONV5
MAX POOL3
FC6
FC7
FC8



AlexNet [Krizhevsky et al., 2012]

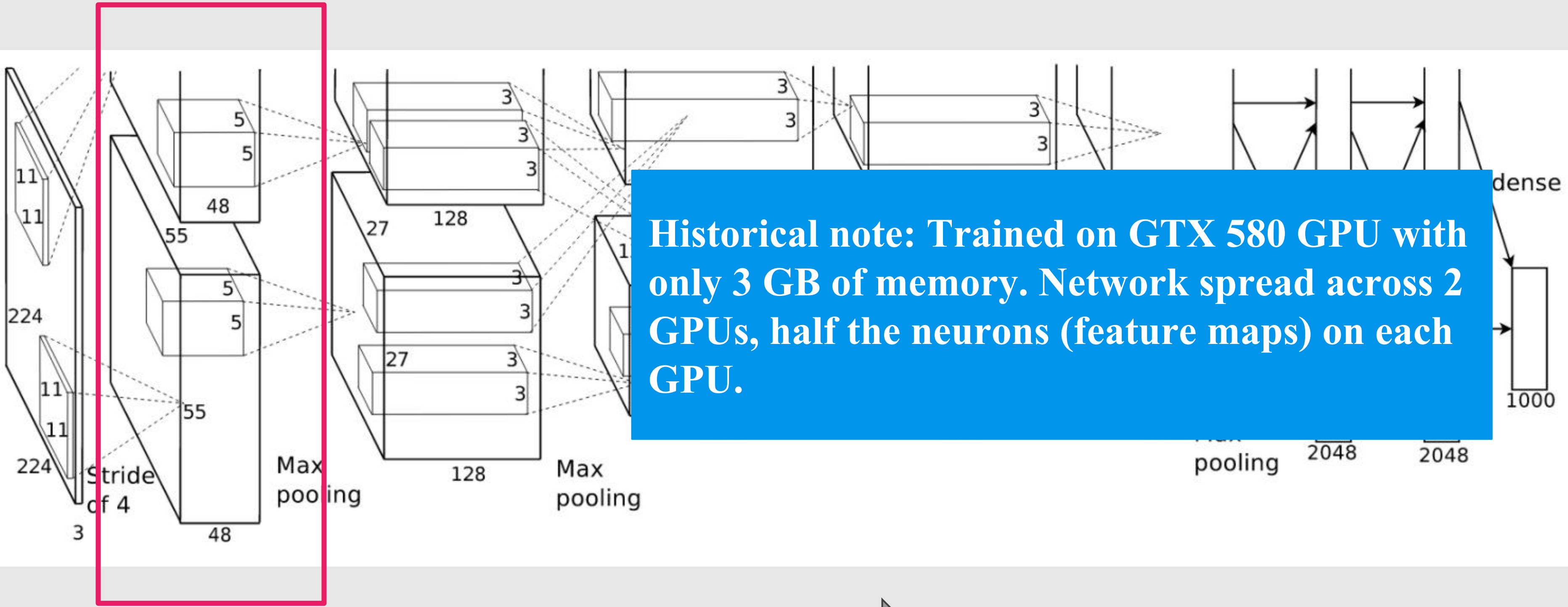
[227x227x3] INPUT
[55x55x96] **CONV1**: 96 11x11 filters at stride 4, pad 0
[27x27x96] **MAX POOL1**: 3x3 filters at stride 2
[27x27x96] **NORM1**: Normalization layer
[27x27x256] **CONV2**: 256 5x5 filters at stride 1, pad 2
[13x13x256] **MAX POOL2**: 3x3 filters at stride 2
[13x13x256] **NORM2**: Normalization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

AlexNet [Krizhevsky et al., 2012]



[55x55x96] **CONV1** ➡ [55x55x48] x 2

AlexNet [Krizhevsky et al., 2012]



Historical note: Trained on GTX 580 GPU with only 3 GB of memory. Network spread across 2 GPUs, half the neurons (feature maps) on each GPU.

[55x55x96] **CONV1** ⇨ [55x55x48] x 2

AlexNet [Krizhevsky et al., 2012]

Details:

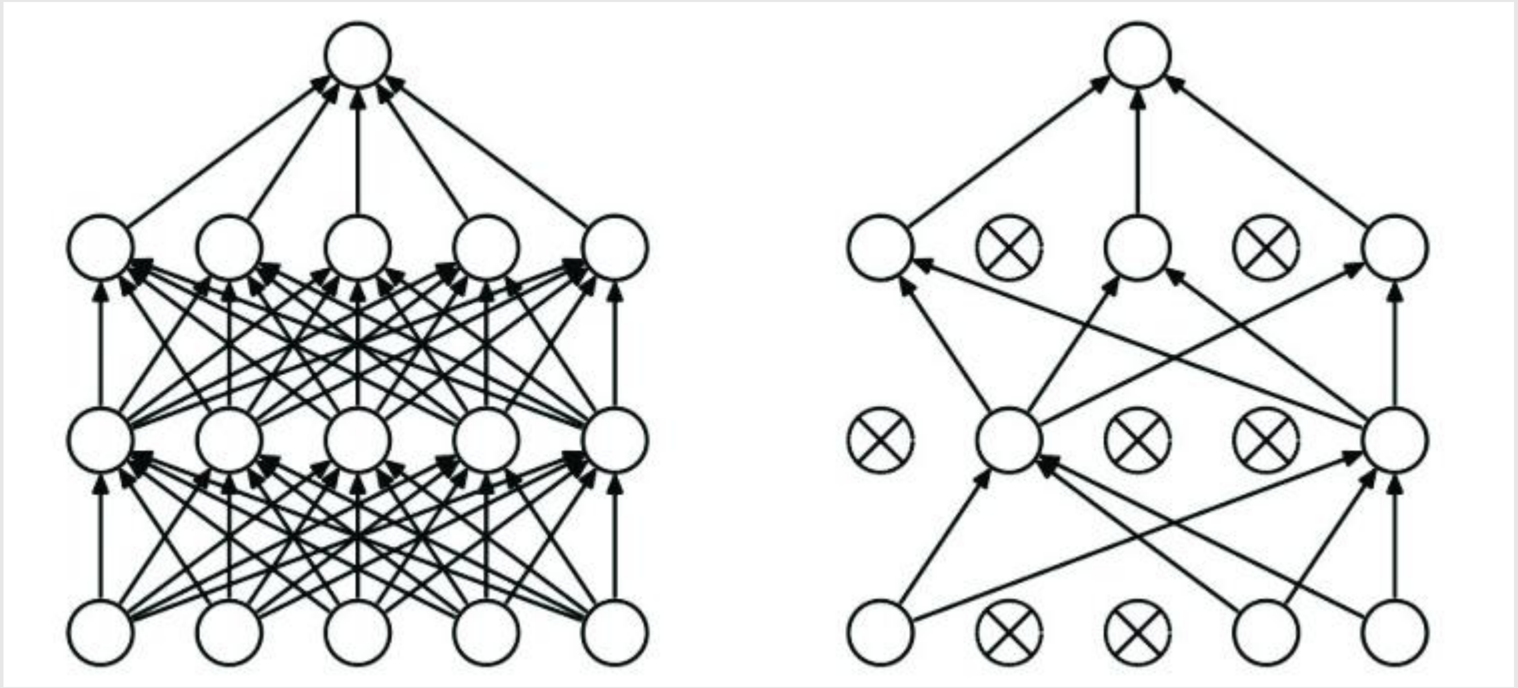
- 60 million learned parameters
- first use of ReLU
- used Norm layers (not common anymore)
- heavy data augmentation
- dropout 0.5
- batch size 128
- 7 CNN ensemble: 18.2% -> 15.4%

Dropout

- Dropout is a radically different technique for regularization.
- Dropout doesn't rely on modifying the cost function. Instead, **in dropout we modify the network itself**.

[Srivastava et al., 2014] Dropout: A Simple Way to Prevent Neural Networks from Overfitting
https://www.cs.toronto.edu/~hinton/absps/JMLRdropout.pdf

Dropout



Standard Network

After applying dropout

Dropout

- Heuristically, when we dropout different sets of neurons, it's rather like we're training different neural networks.
- The dropout procedure is like averaging the effects of a very large number of different networks.
- The different networks will overfit in different ways, and so, hopefully, the net effect of dropout will be to reduce overfitting.

AlexNet [Krizhevsky et al., 2012]

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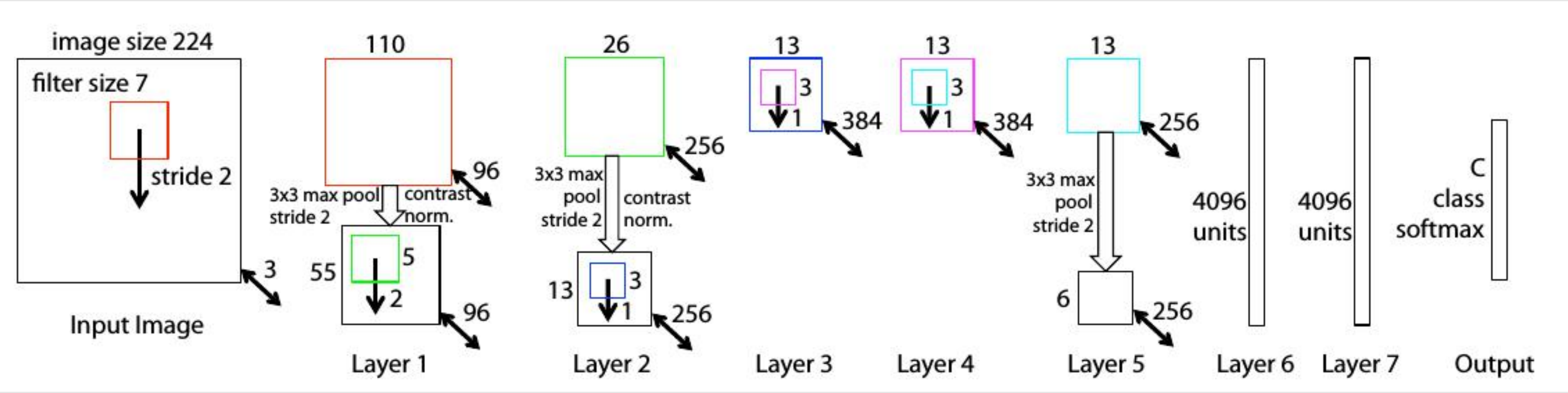
ZFNet [Zeiler & Fergus, 2013]



AlexNet but:

CONV1: change from (11x11 stride 4) to (7x7 stride 2)

CONV3,4,5: instead of 384, 384, 256 filters use 512, 1024, 512

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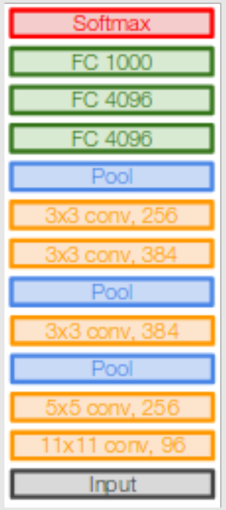
VGGNet [Simonyan & Zisserman, 2014]

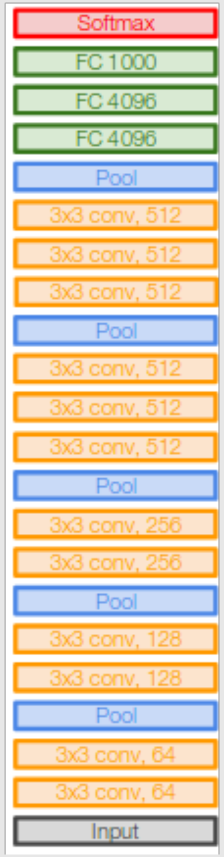
Small filters, Deeper networks
8 layers (AlexNet)
16 - 19 layers (VGG16Net)

Only 3x3 CONV stride 1, pad 1
and 2x2 MAX POOL stride 2

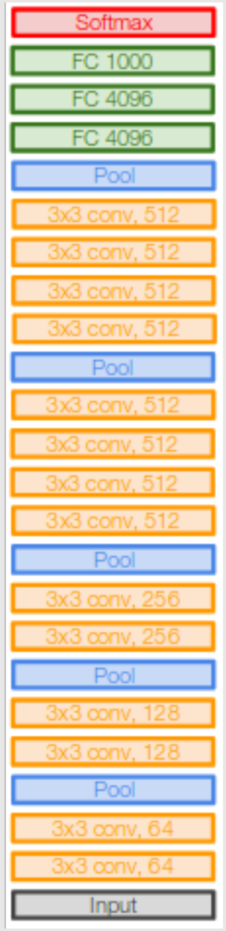
11.7% in ILSVRC’13 (ZFNet)
7.3% in ILSVRC’14



AlexNet



VGG16



VGG19

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- **ResNet** by Kaiming He et al. (2015)

To be continued ...

References

Machine Learning Books

- Hands-On Machine Learning with Scikit-Learn and TensorFlow, Chap. 11 & 13

Machine Learning Courses

- https://www.coursera.org/learn/neural-networks
- “The 3 popular courses on Deep Learning”: https://medium.com/towards-data-science/the-3-popular-courses-for-deeplearning-ai-ac37d4433bd