Convolutional Neural Networks I

CS 6384 Computer Vision

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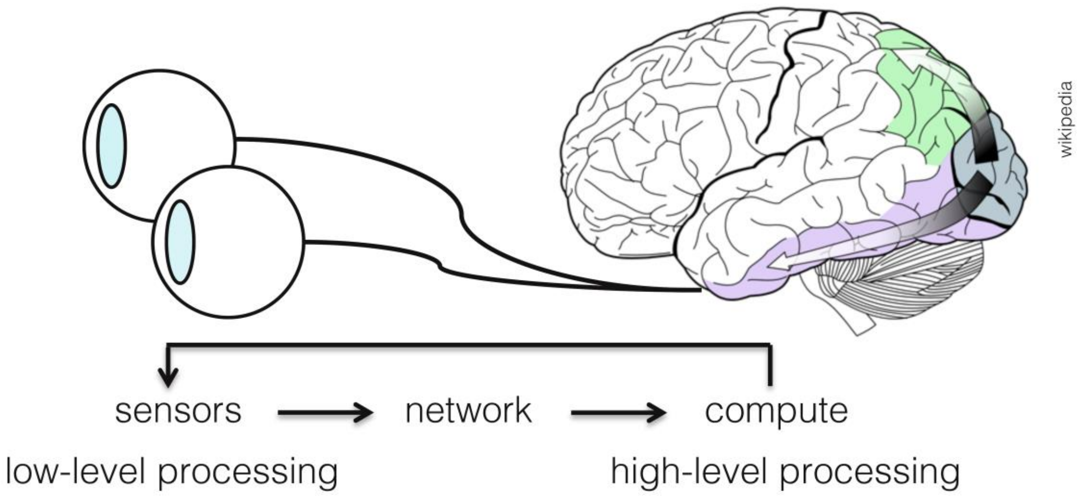
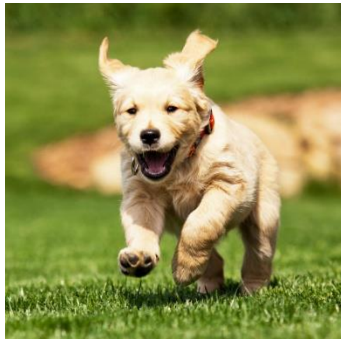
The University of Texas at Dallas

Some slides of this lecture are courtesy Stanford CS231n

Visual Perception vs. Computational Perception





Image

Neural Network

High-level information
- Depth
- Motion
- Object classes
- Object poses
- Etc.

Mathematic Models

- Try to model the human brain with computational models, e.g., neural networks

x

Image

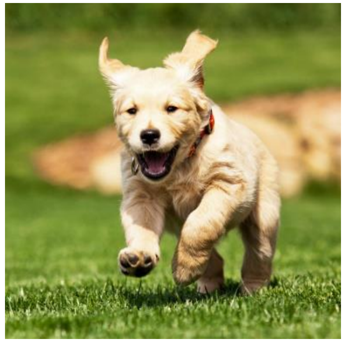
$f(x)$

y

Object class

Mathematic Models

- What is the form of the function $f(x)$?
  - No idea!
  - Concatenate simple functions (neurons)



x

$$f(x) \Rightarrow y \in \{+1, -1\}$$

Dog

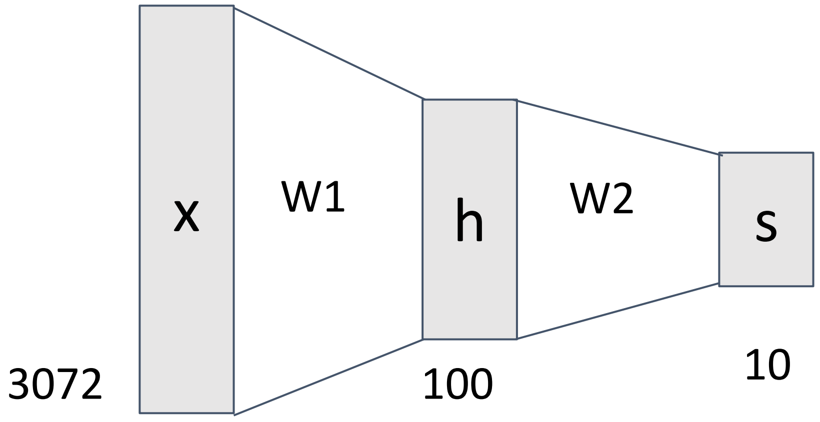
Neural Network: Concatenation of functions

Linear score function: $$f = Wx$$

2-layer Neural Network

$$f = f_2(f_1(x)) = W_2 \max(0, W_1 x)$$

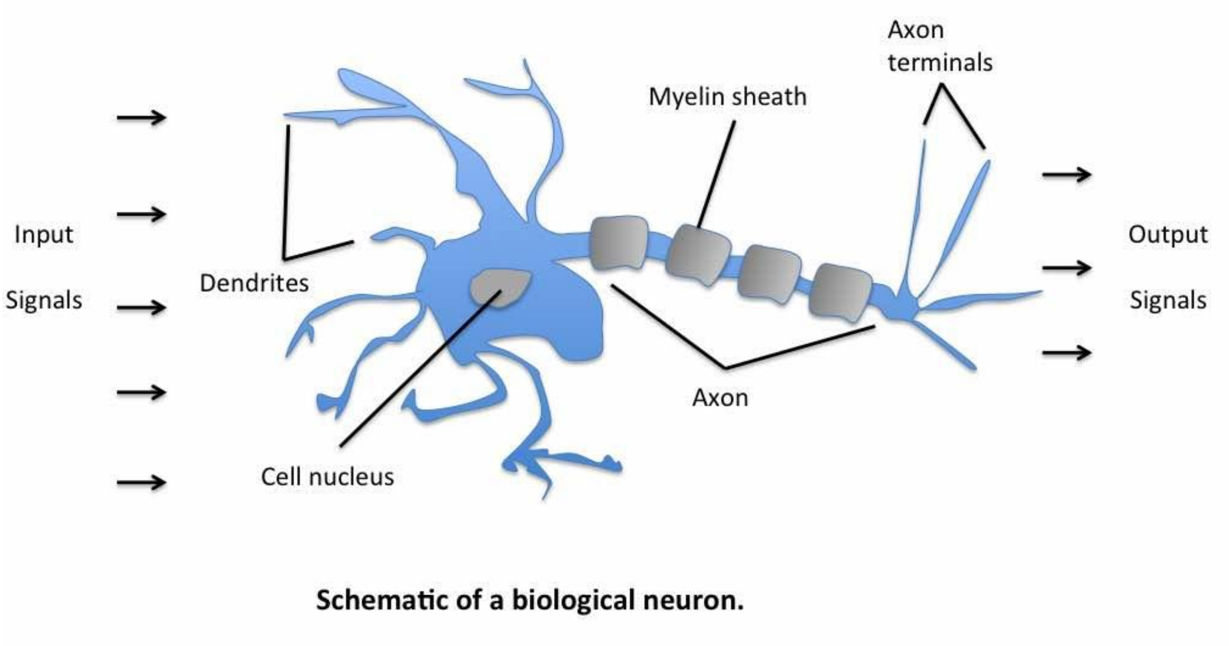
Non-linearity



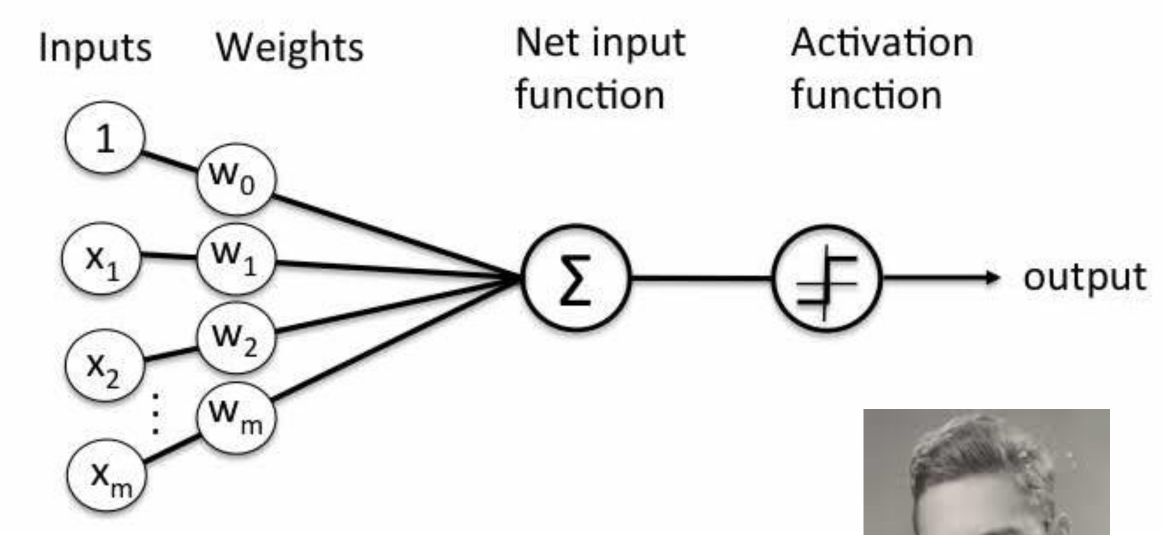
$$h = f_1(X)$$
$$s = f_2(h)$$

Need to learn the weights!

Frank Rosenblatt’s Perceptron



Schematic of a biological neuron.



$$\sigma(\mathbf{w}^T\mathbf{x} + b) = \begin{cases} 1 \text{ if } \mathbf{w}^T\mathbf{x} + b \geq 0, \\ 0 \text{ otherwise.} \end{cases}$$

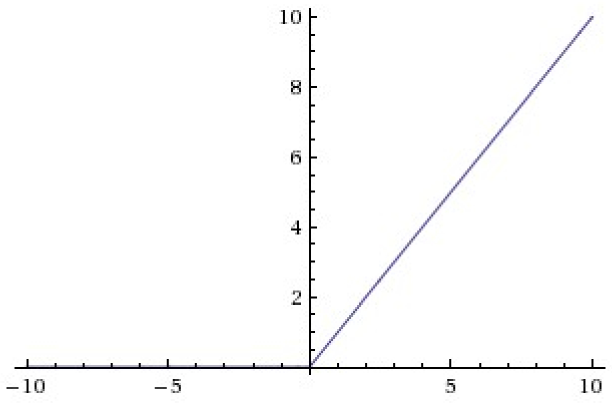
Frank Rosenblatt
(1928-1971)

Activation Functions

2-layer Neural Network

$$f = f_2(f_1(x)) = W_2 \max(0, W_1 x)$$

Rectified Linear Unit (ReLU)
max(0,x)

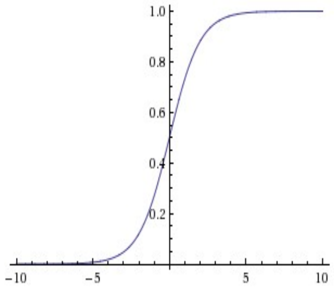


Introduce non-linearity to the network

Activation Functions

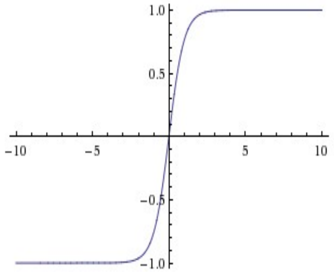
Sigmoid

$$\sigma(x) = 1/(1+e^{-x})$$

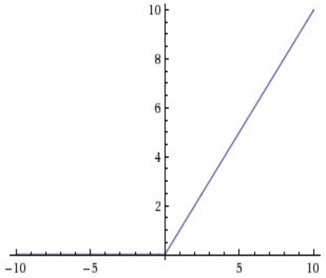


tanh tanh(x)

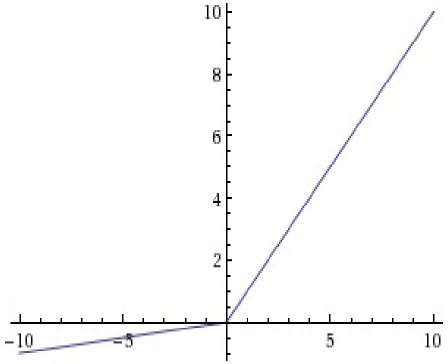
$$\frac{e^{2x}-1}{e^{2x}+1}$$



ReLU max(0,x)



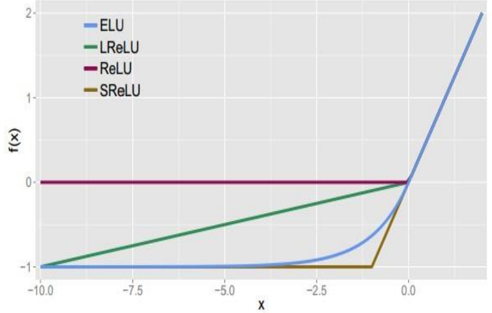
Leaky ReLU
max(0.1x, x)



Maxout $\max(w_1^T x + b_1, w_2^T x + b_2)$

ELU Exponential Linear Unit

$$f(x) = \begin{cases} x & \text{if } x > 0 \\ \alpha\,(\exp(x) - 1) & \text{if } x \le 0 \end{cases}$$

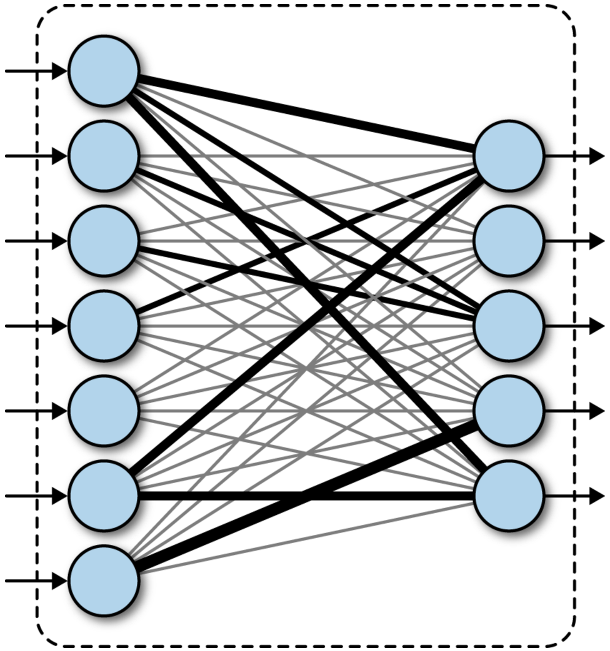


Fully Connected Layer

$$y = Wx$$

$x : n \times 1$ $\quad W : m \times n$ $\quad y : m \times 1$

$W : m \times n$



$x : n \times 1$ $\quad y : m \times 1$

Fully Connected Layer

- What is the drawback of only using fully connected layers?

$$y = Wx$$

- Consider an image with 640 x 480
  - x is with dimension 307,200
  - The weight matrix of the fully connect layer is too large

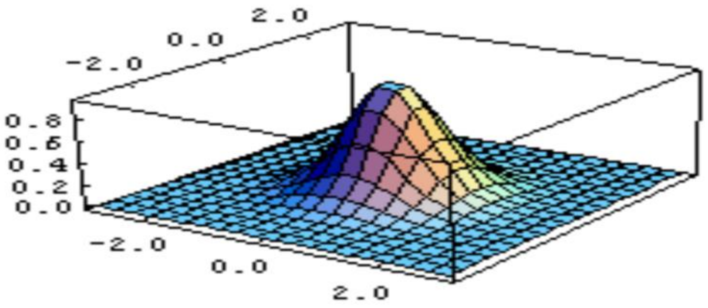
Convolutional Layers

- Consist of convolutional filters

- Share weights among different image locations

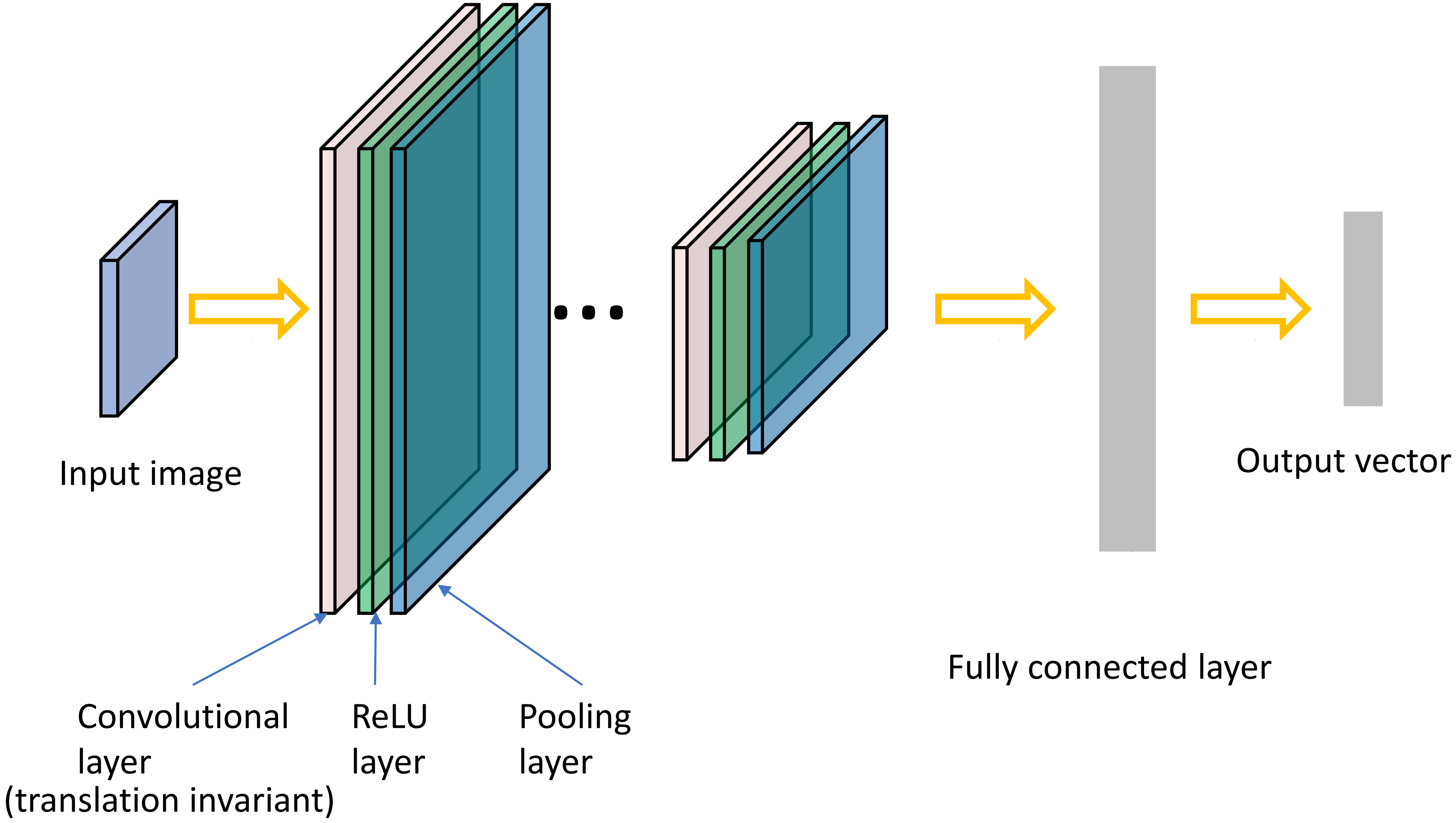
$$g(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

Gaussian Filter

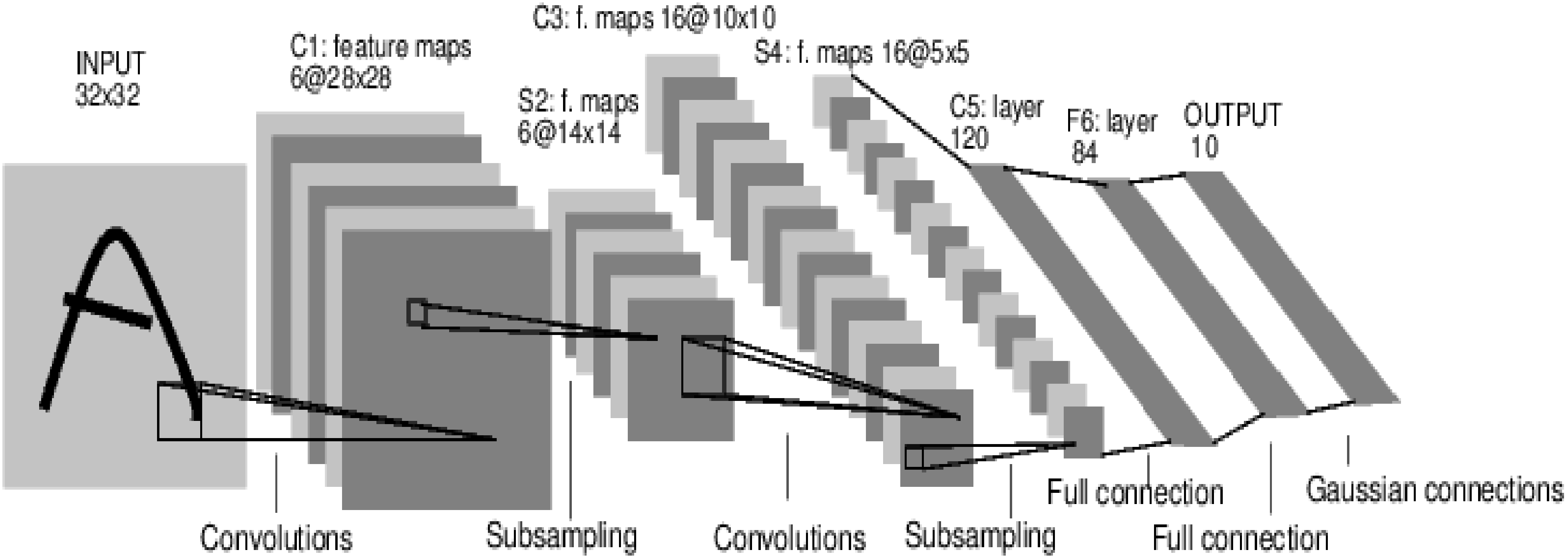


Learn the weights!

Convolutional Neural Networks



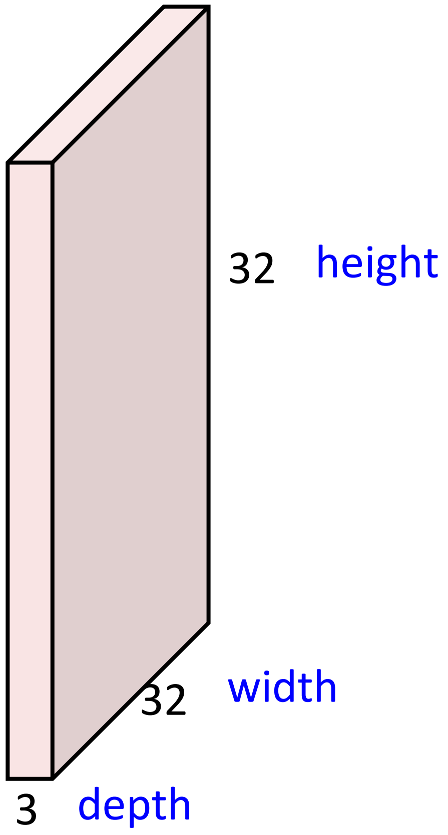
Convolutional Neural Networks



[LeNet-5, LeCun 1980]

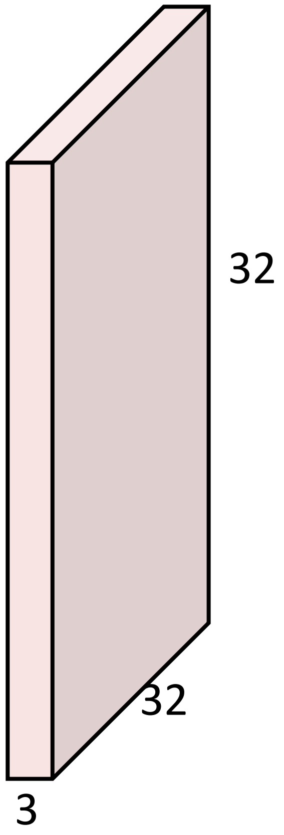
Convolutional Layer

32x32x3 image

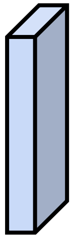


Convolutional Layer

32x32x3 image

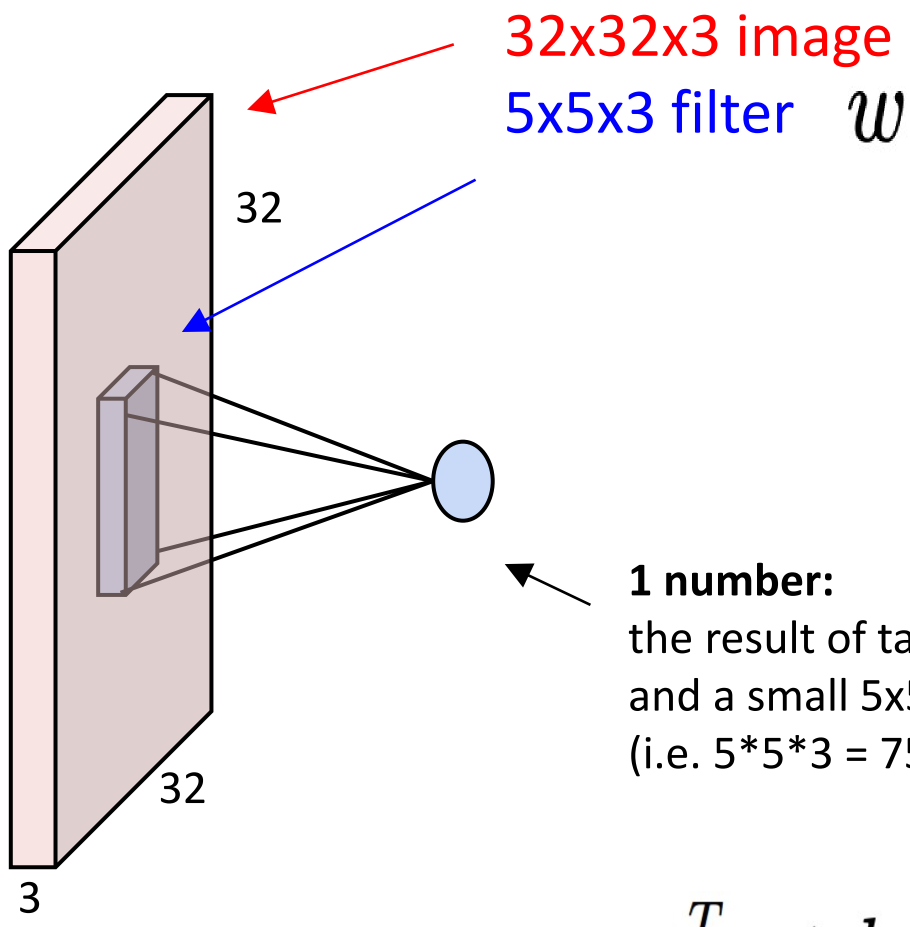


5x5x3 filter



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

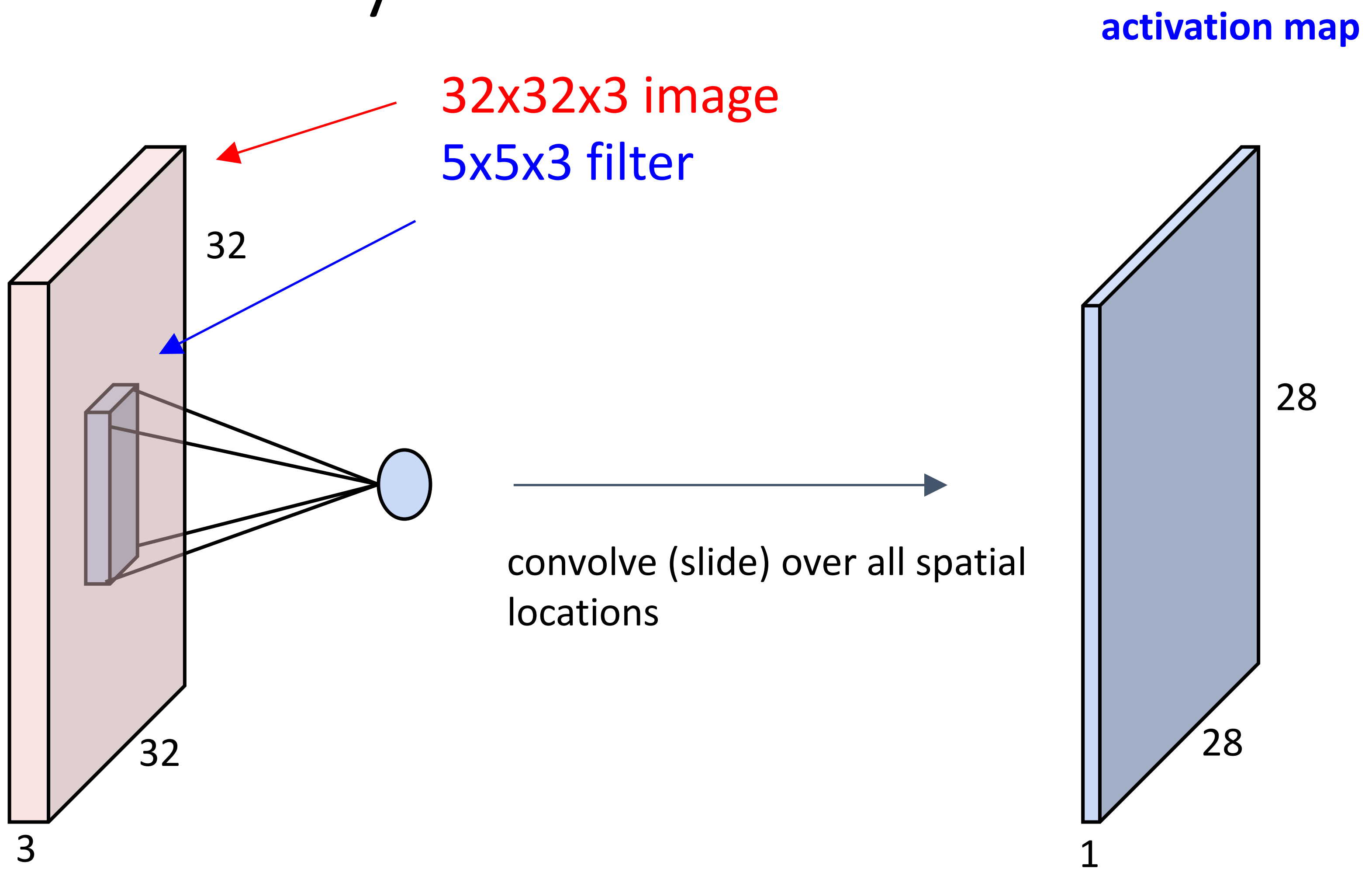
Convolutional Layer



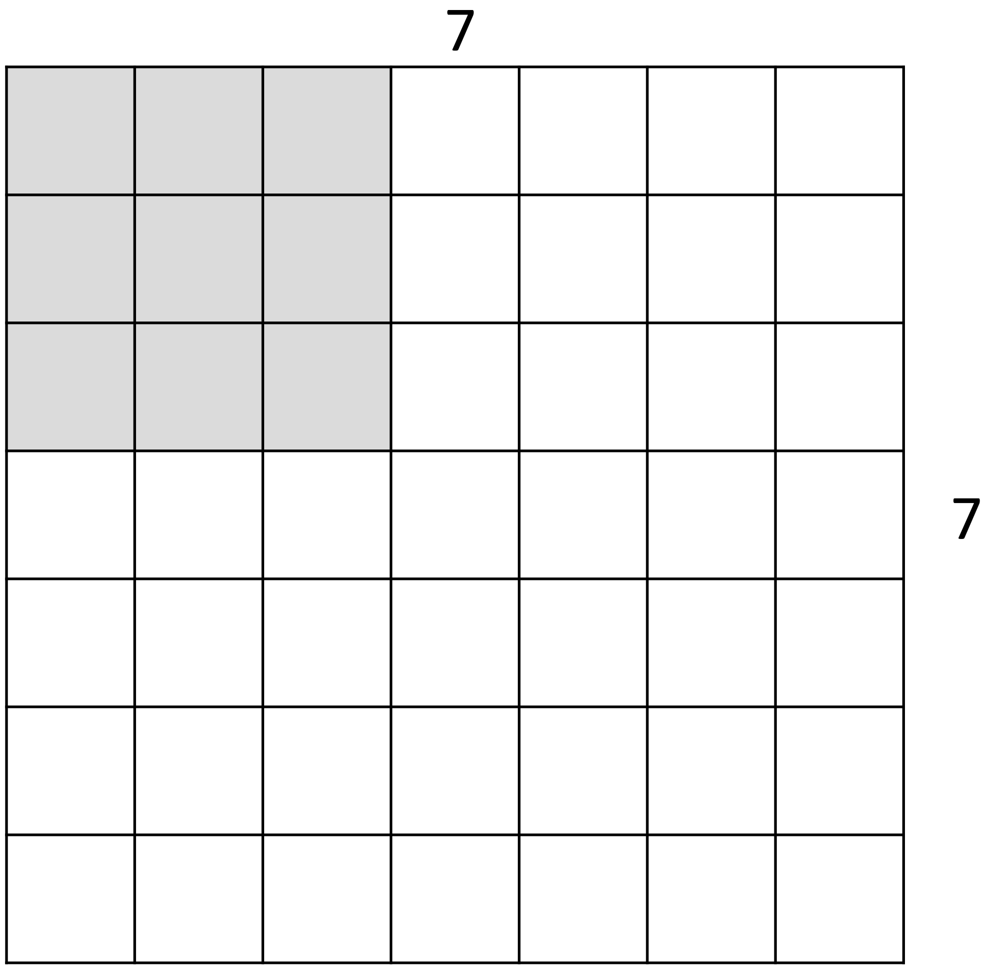
1 number:
the result of taking a dot product between the filter and a small 5x5x3 chunk of the image
(i.e. 5*5*3 = 75-dimensional dot product + bias)

$$w^T x + b$$

Convolutional Layer



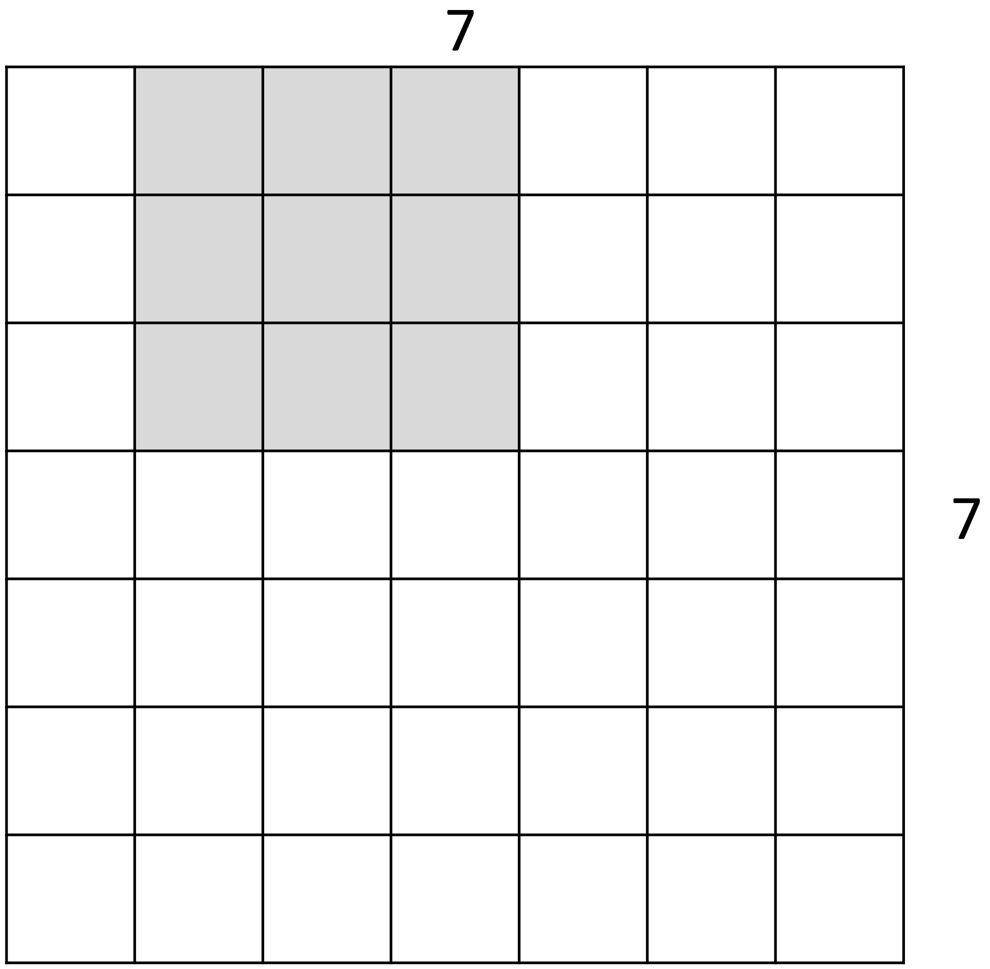
Convolutional Layer



A closer look at spatial dimensions:

7x7 input (spatially)
assume 3x3 filter, with stride 1

Convolutional Layer



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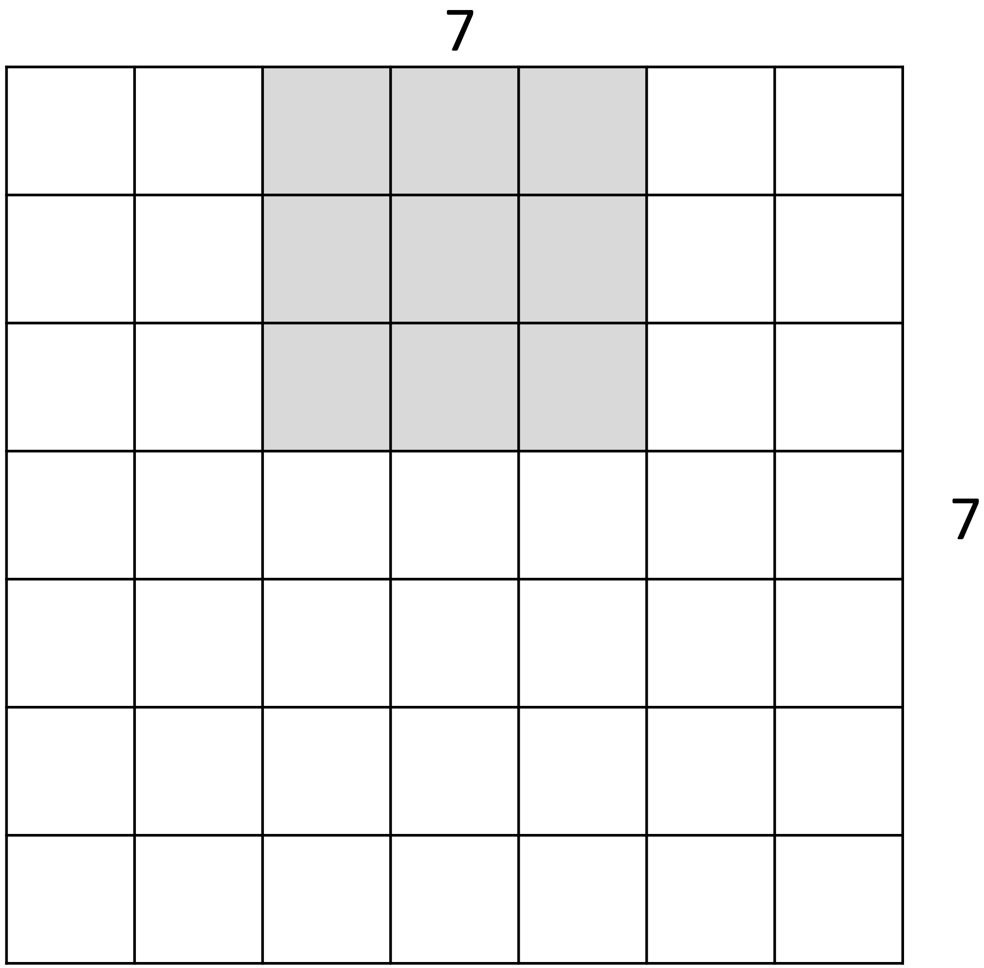

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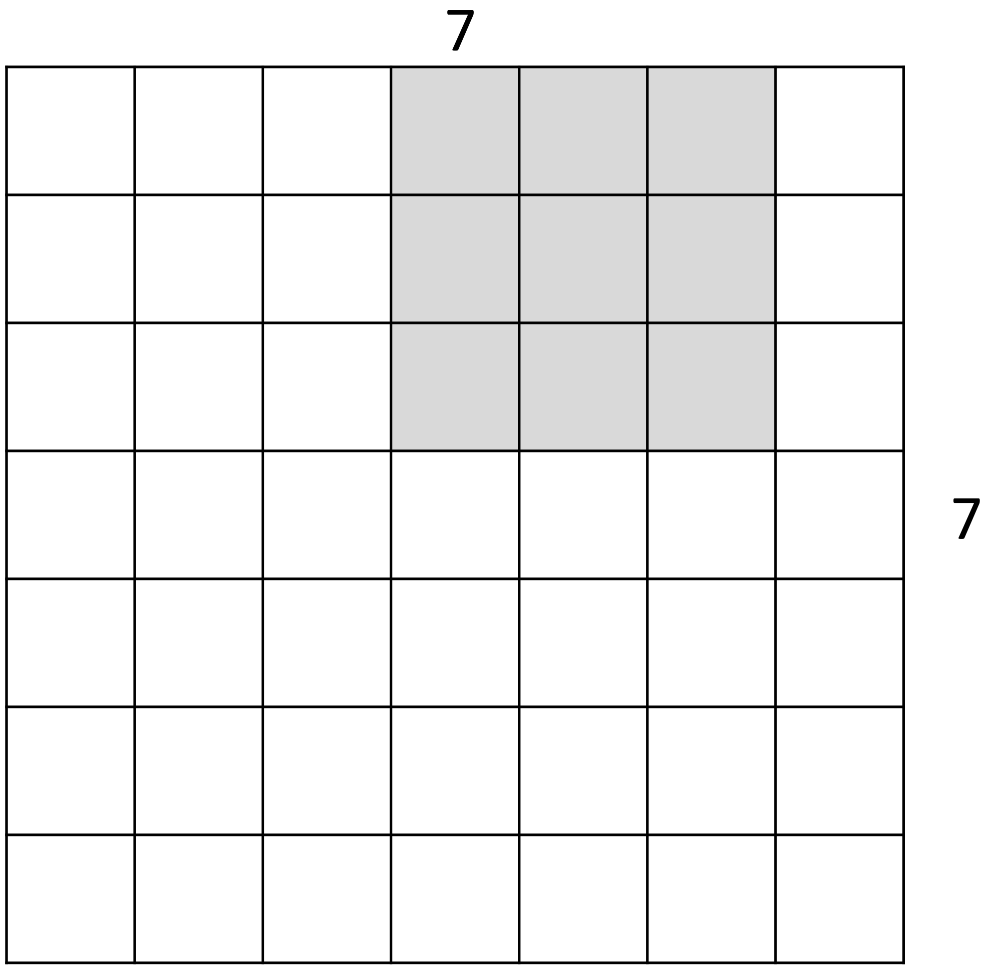

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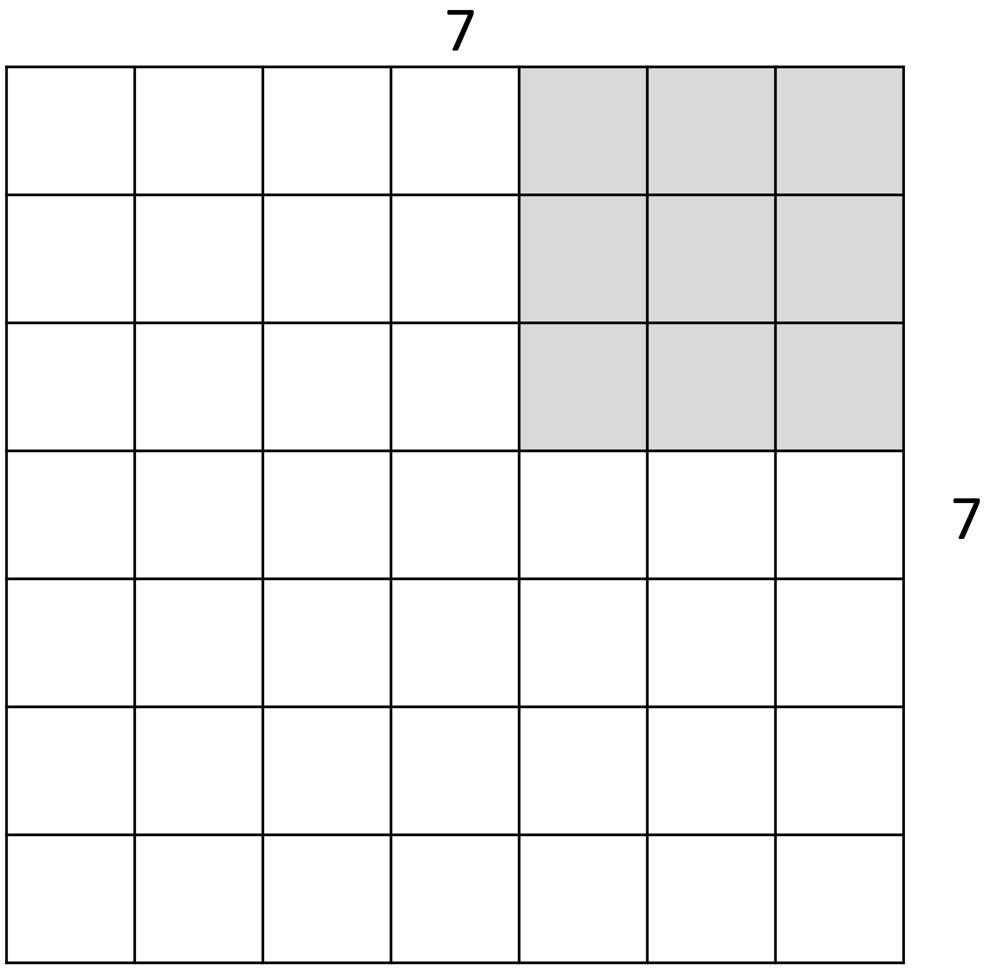

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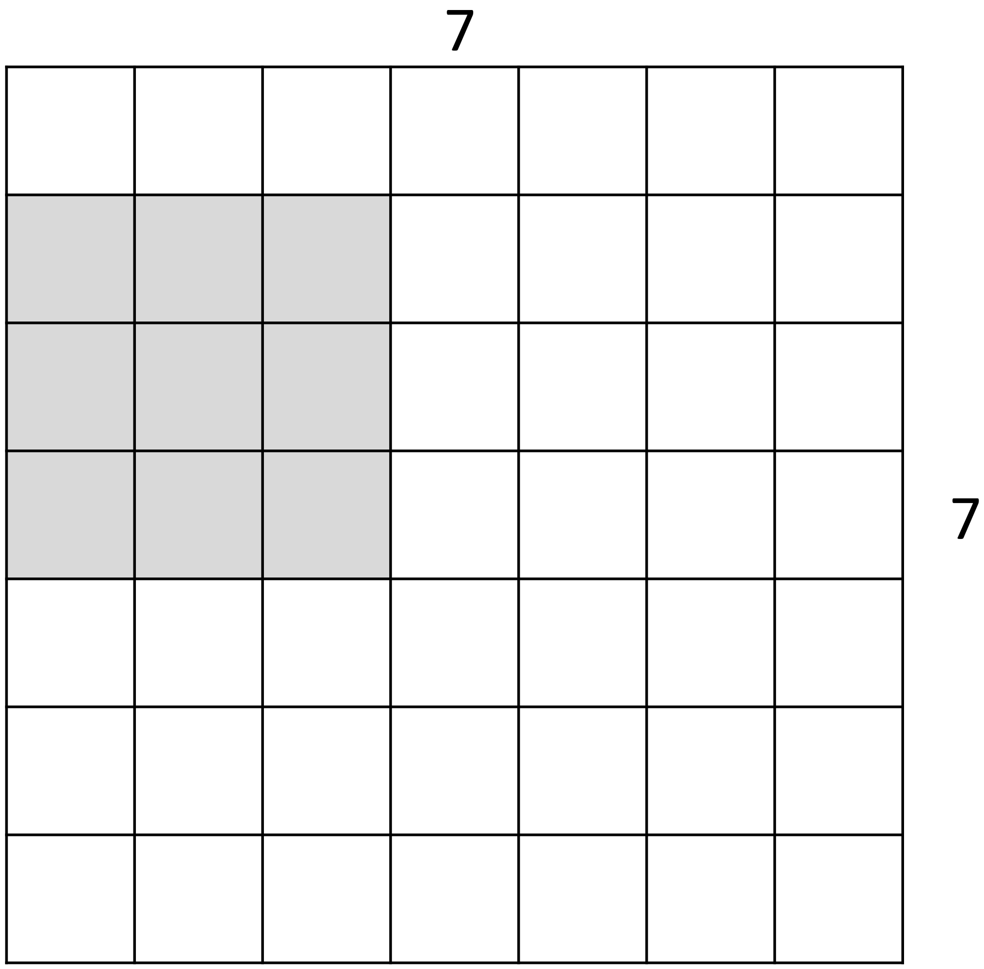
Convolutional Layer



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7x7 input (spatially)
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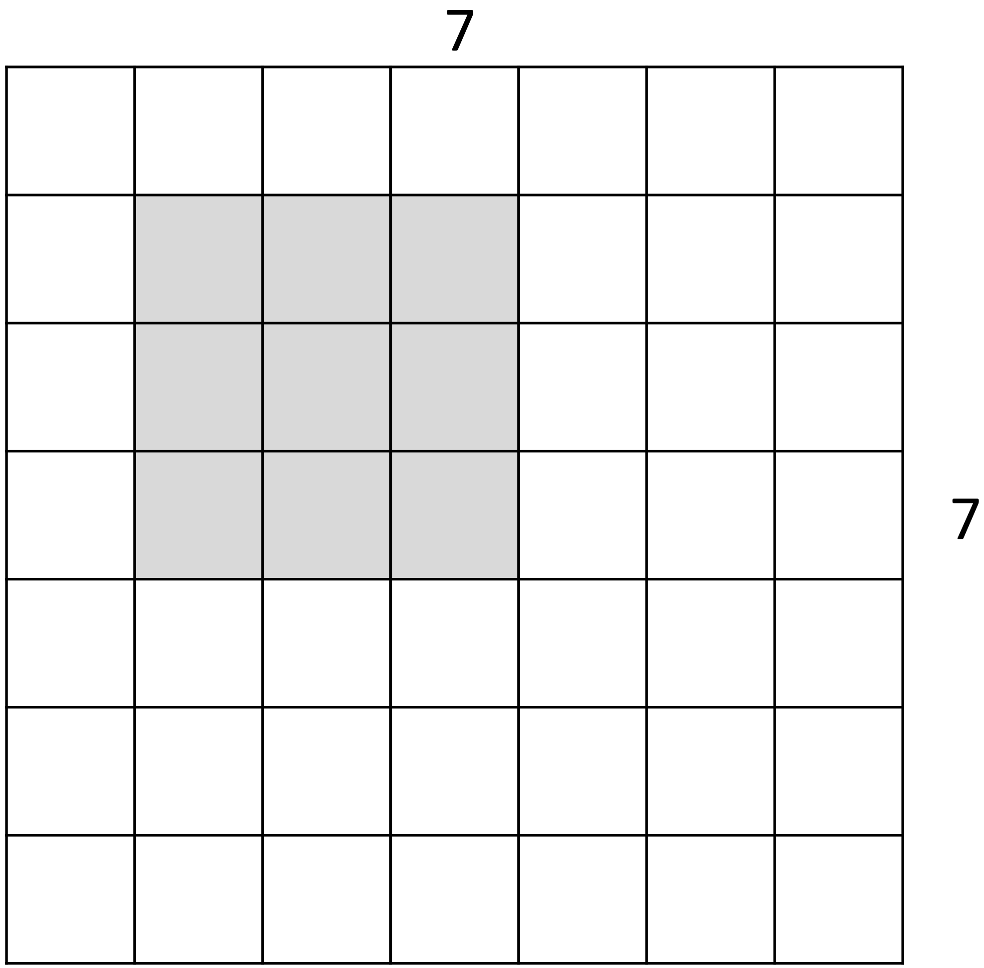
Convolutional Layer



A closer look at spatial dimensions:

7x7 input (spatially)
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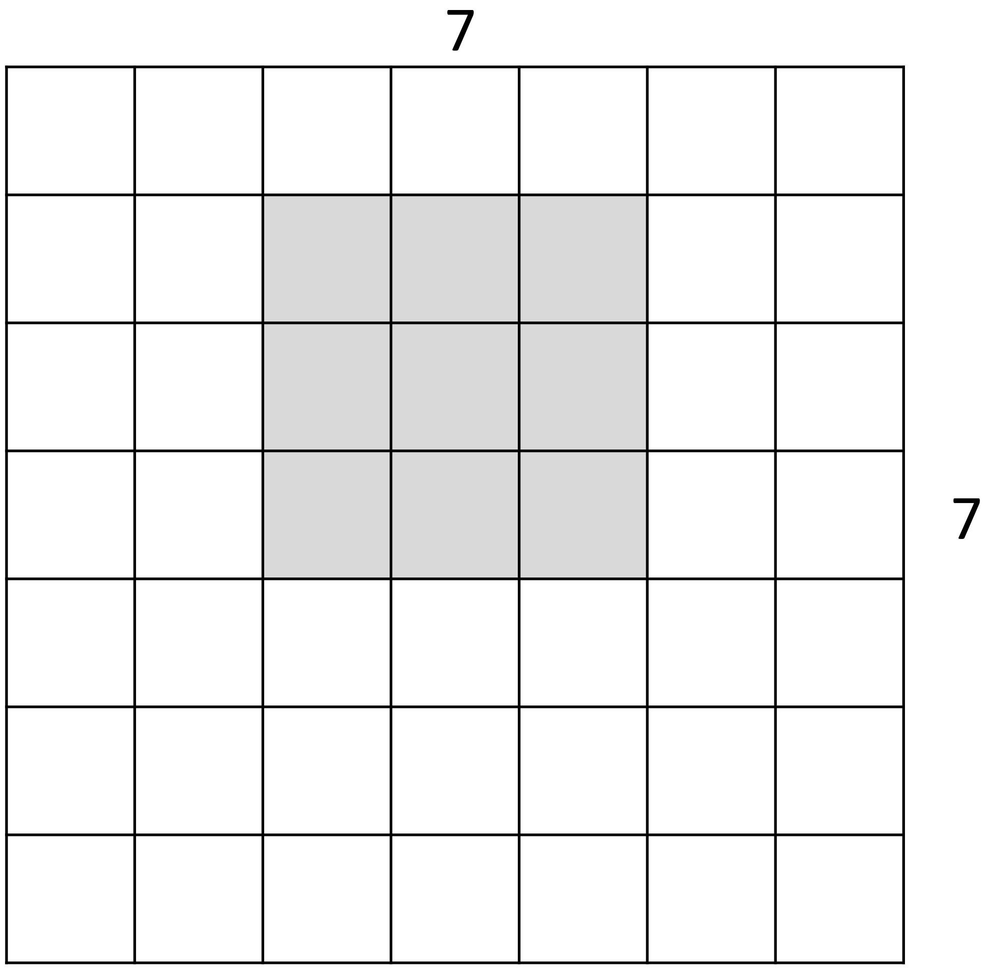
Convolutional Layer



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7x7 input (spatially)
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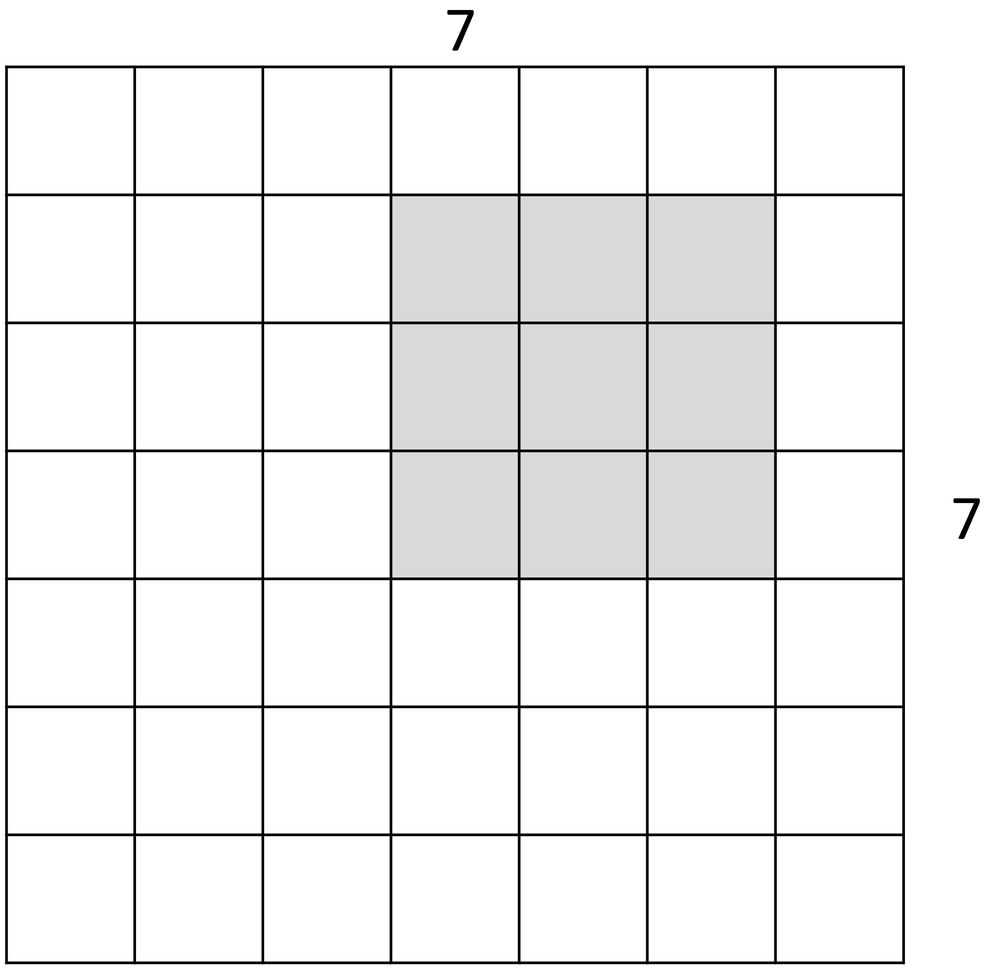
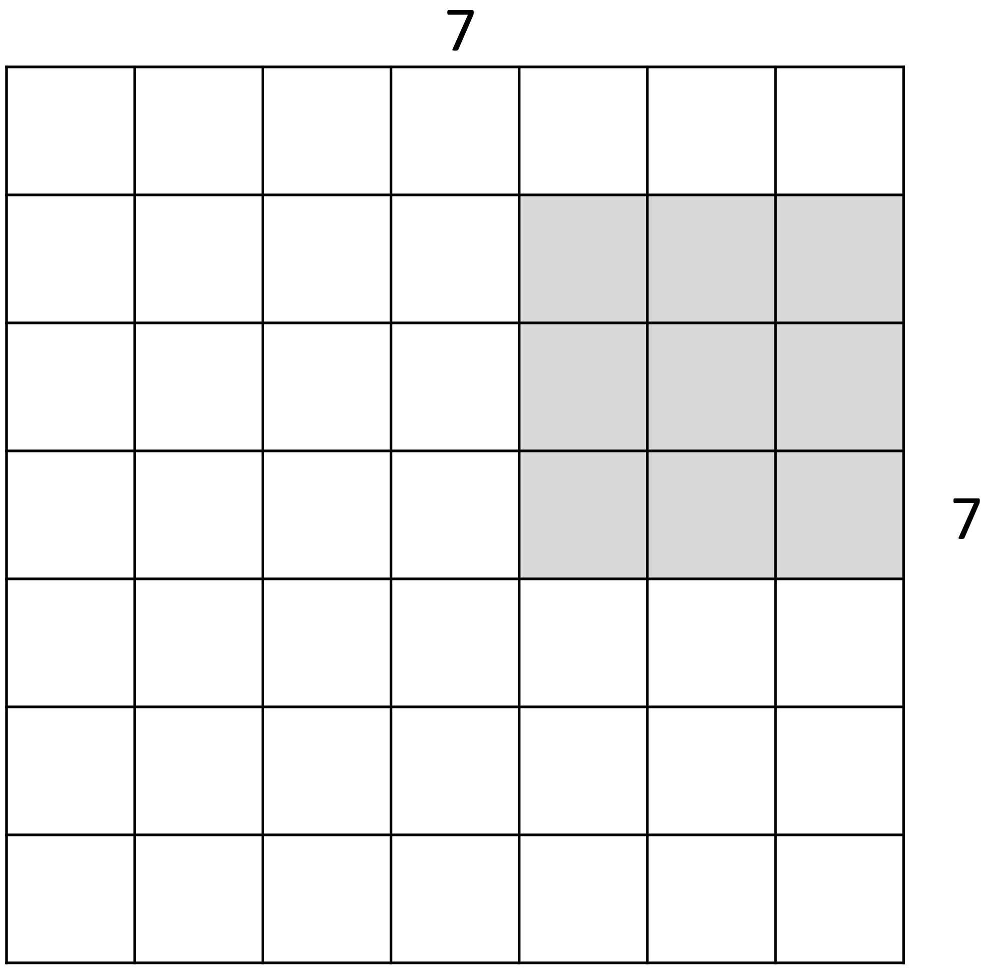
Convolutional Layer



A closer look at spatial dimensions:

7x7 input (spatially)
assume 3x3 filter, with stride 1

Convolutional Layer

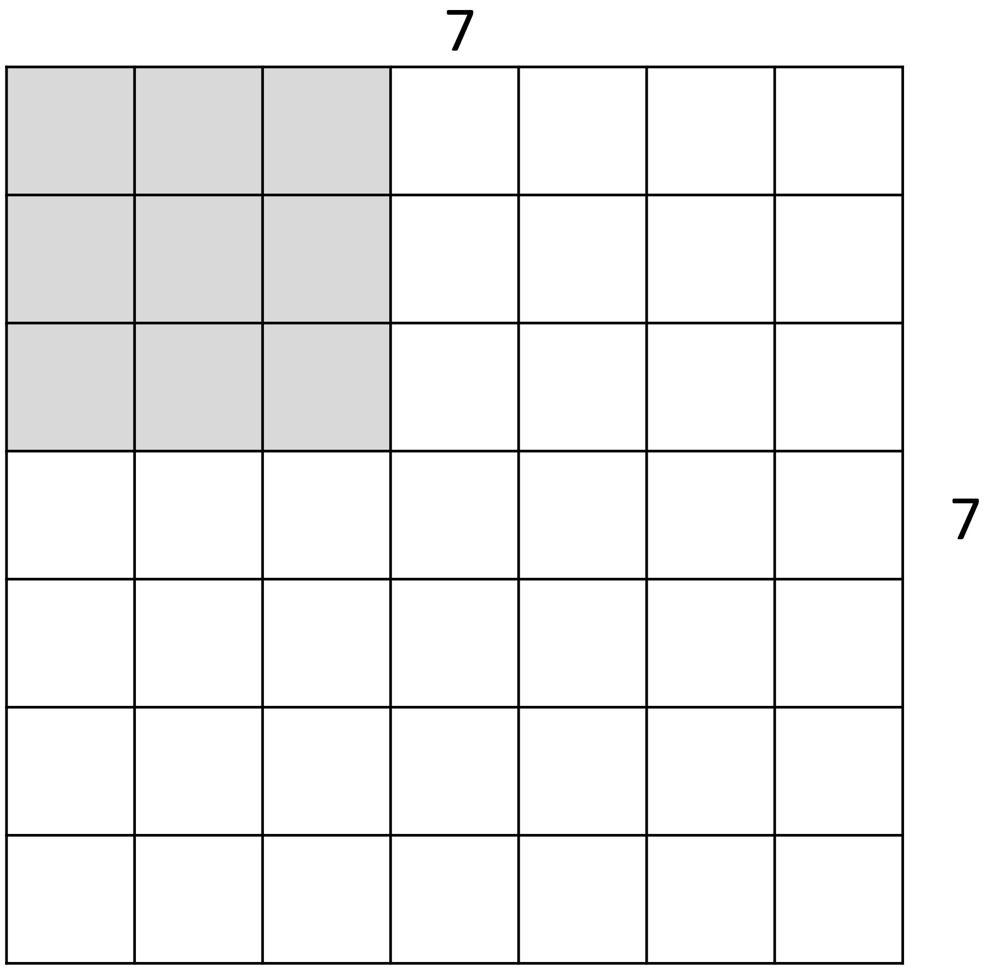


A closer look at spatial dimensions:

7x7 input (spatially)
assume 3x3 filter, with stride 1

=> 5x5 output

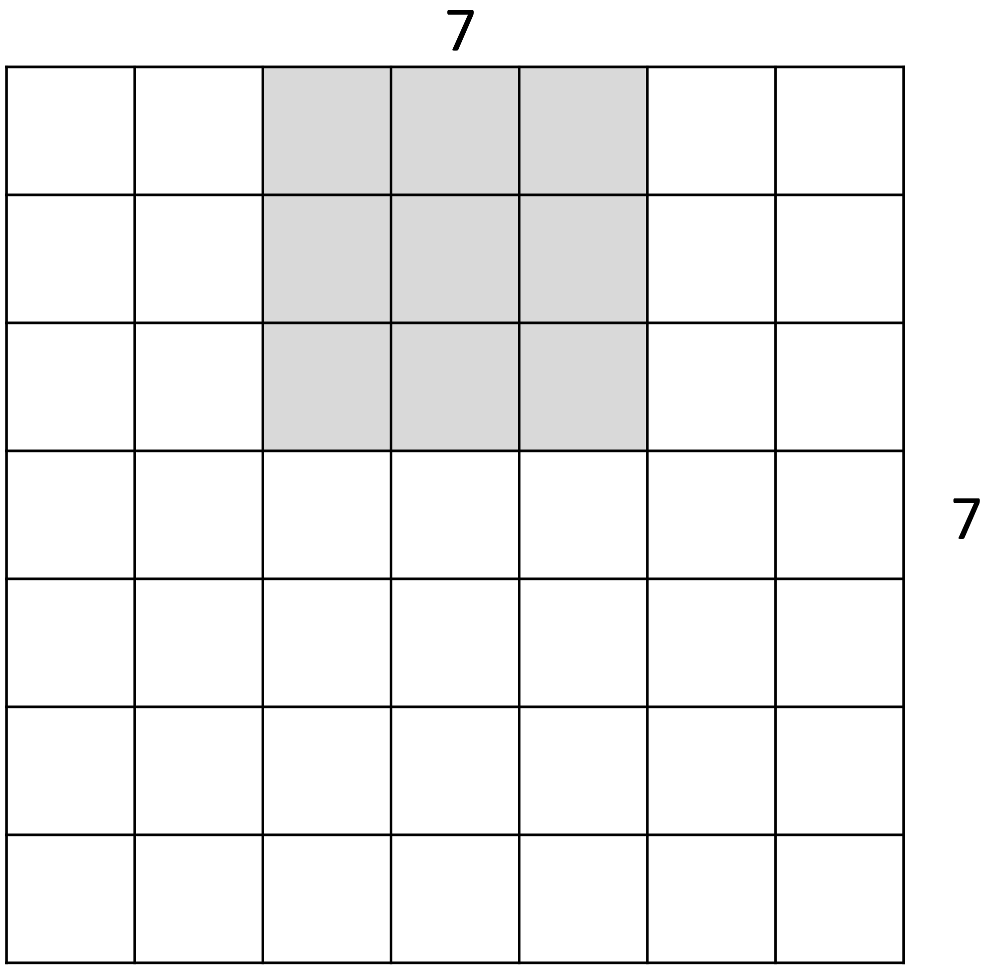
Convolutional Layer



A closer look at spatial dimensions:

7x7 input (spatially)
assume 3x3 filter, **with stride 2**

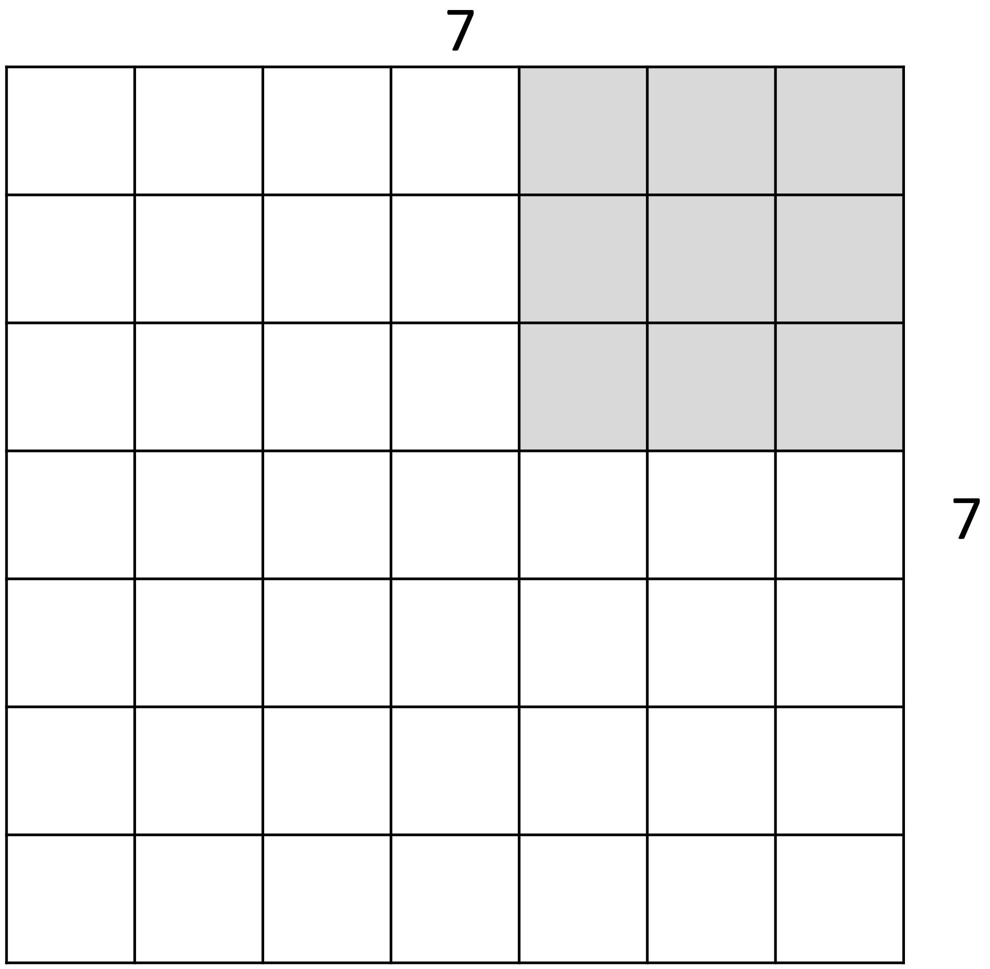
Convolutional Layer



A closer look at spatial dimensions:

7x7 input (spatially)
assume 3x3 filter, **with stride 2**

Convolutional Layer

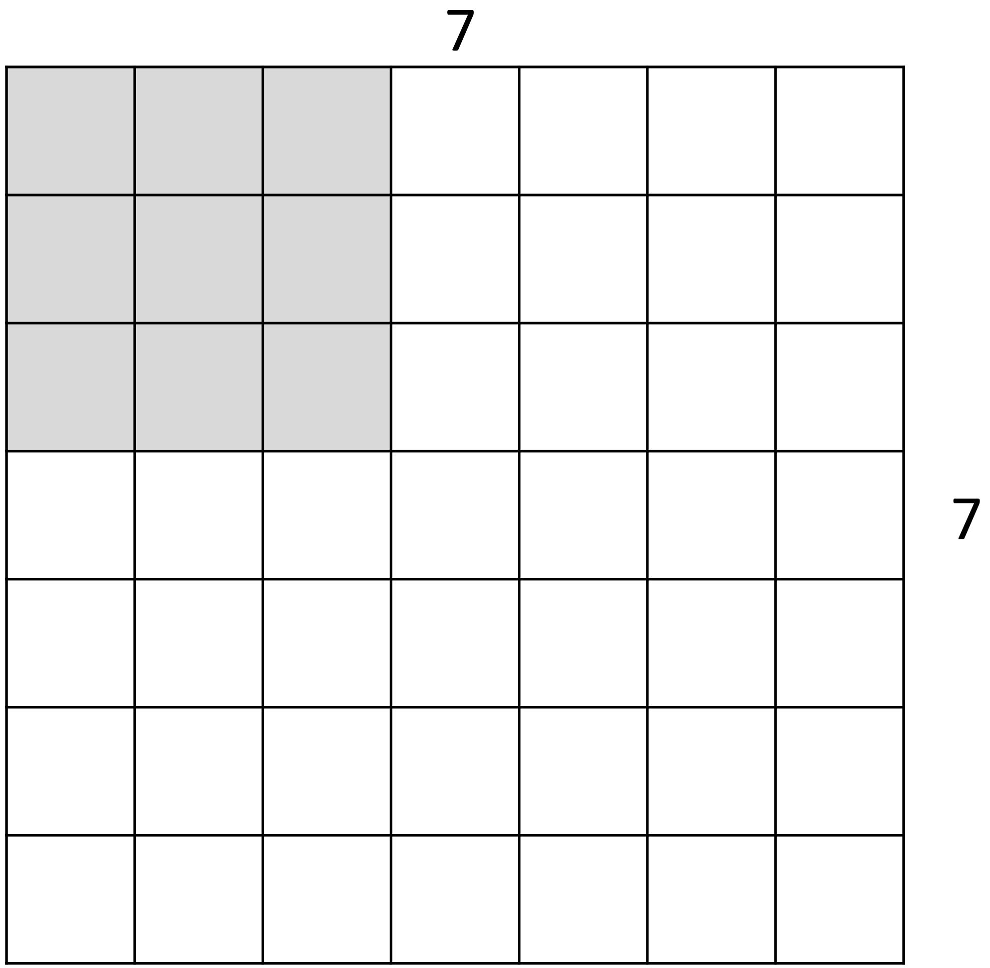


A closer look at spatial dimensions:

7x7 input (spatially)
assume 3x3 filter, **with stride 2**

=> 3x3 output!

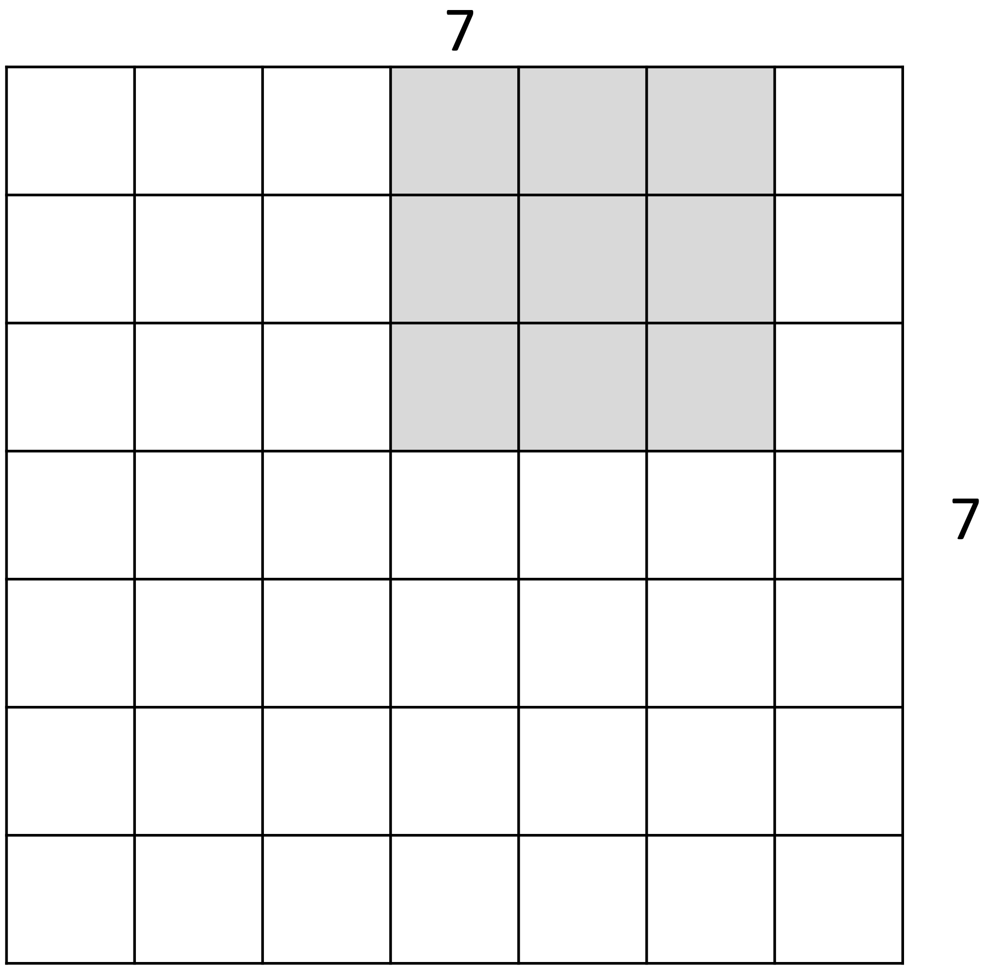
Convolutional Layer



A closer look at spatial dimensions:

7x7 input (spatially)
assume 3x3 filter, **with stride 3**

Convolutional Layer

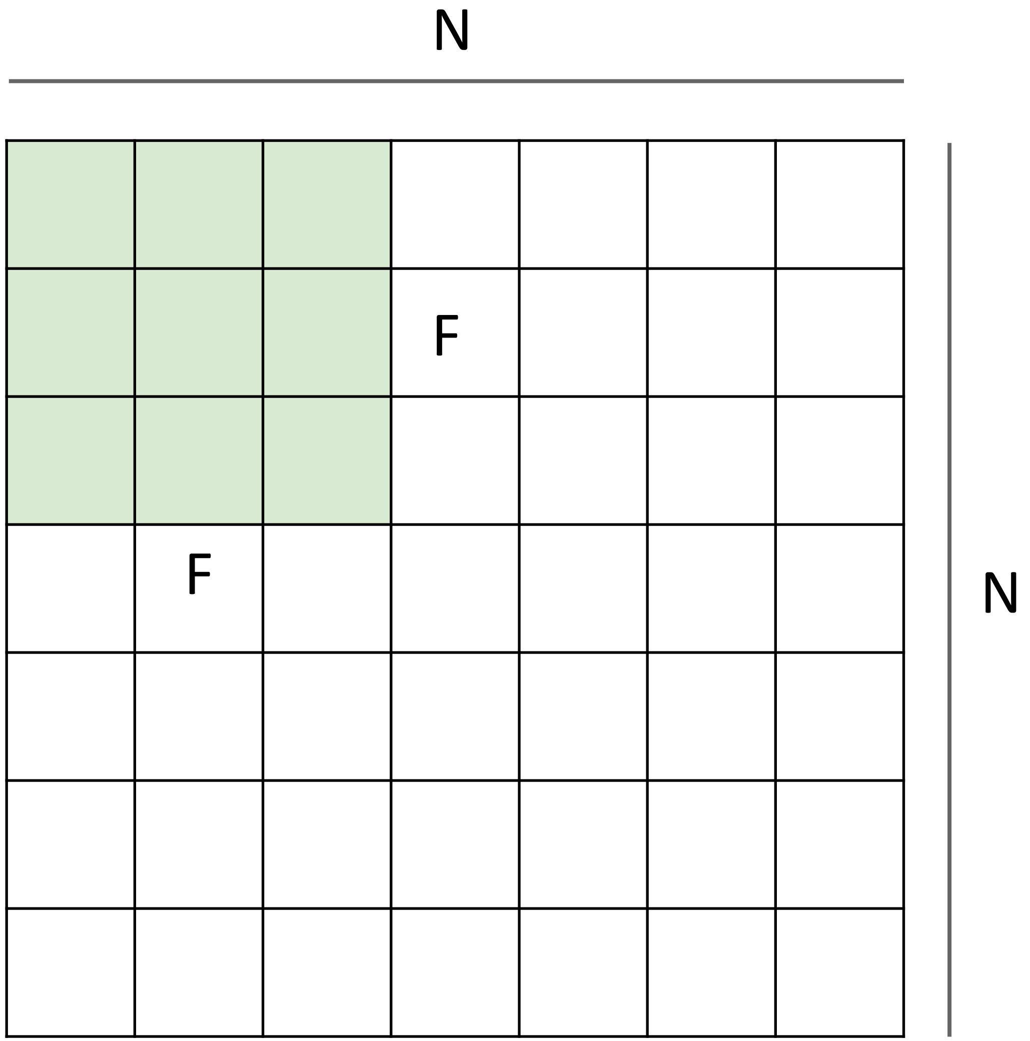


A closer look at spatial dimensions:

7x7 input (spatially)
assume 3x3 filter, **with stride 3**

doesn't fit!
cannot apply 3x3 filter on 7x7 input with stride 3.

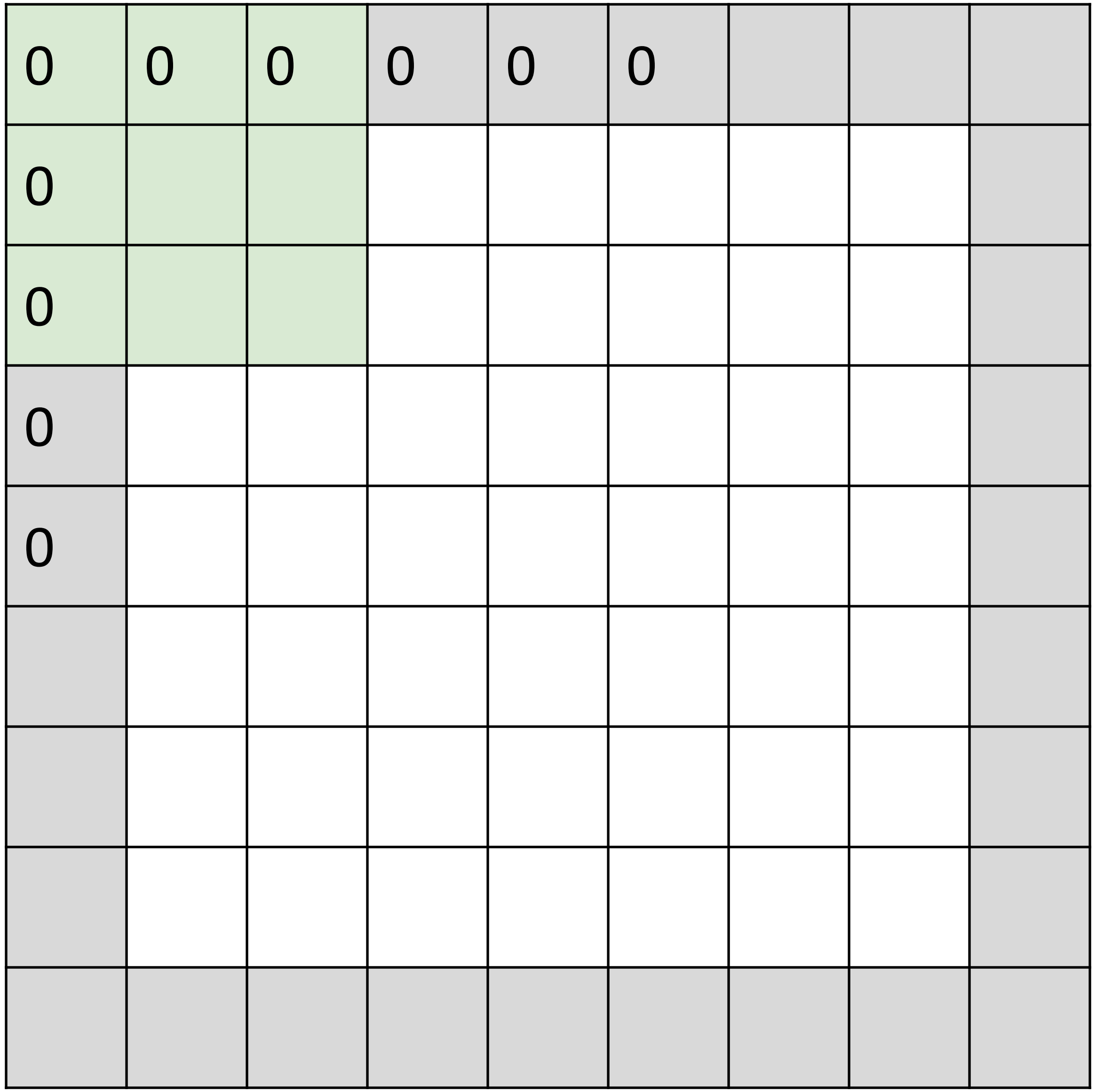
Convolutional Layer



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

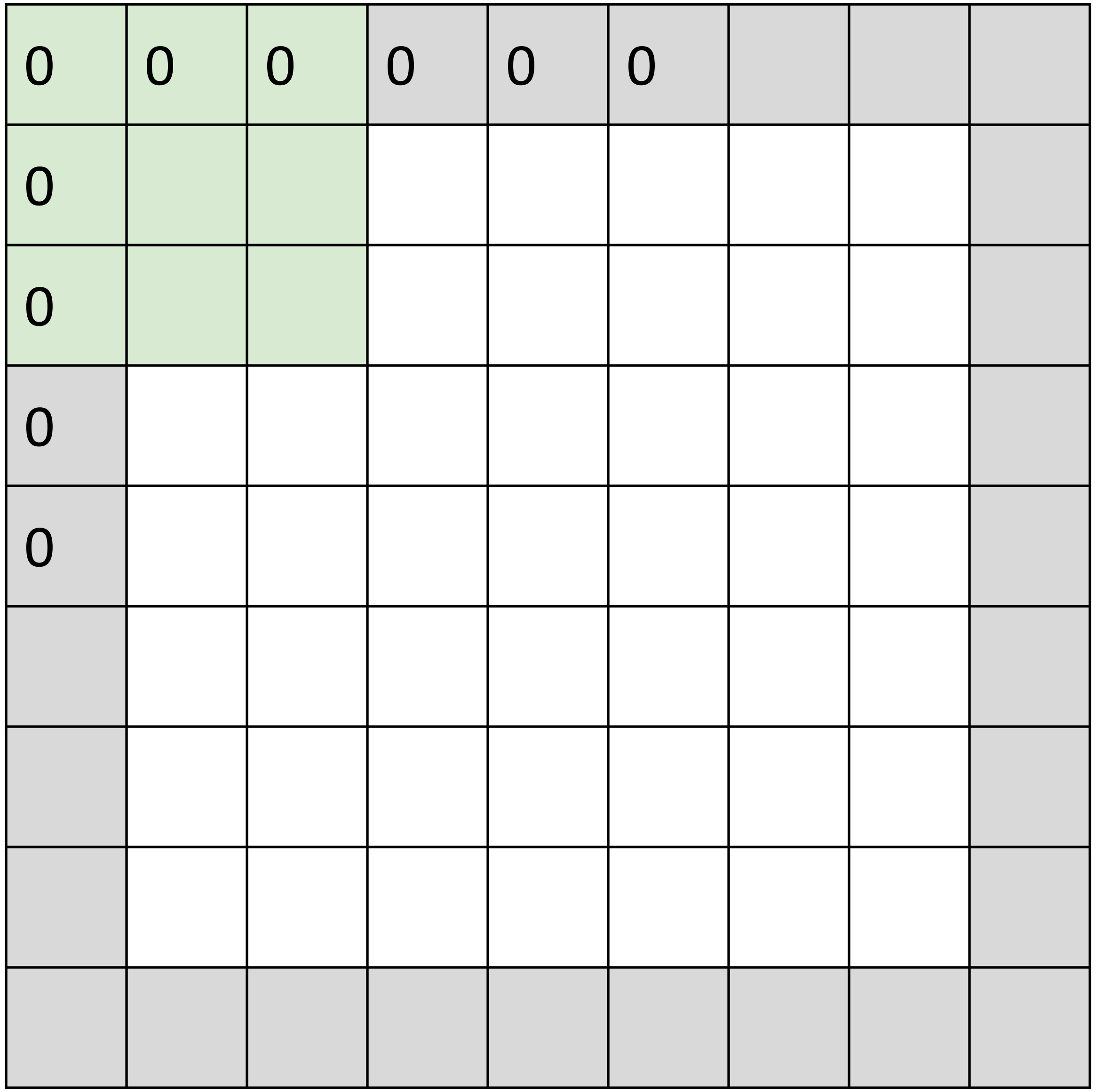


In practice: Common to zero pad the border

e.g. input 7x7
3x3 filter, applied with **stride 1**
pad with 1 pixel border => what is the output?

(recall:)
(N - F) / stride + 1

Convolutional Layer

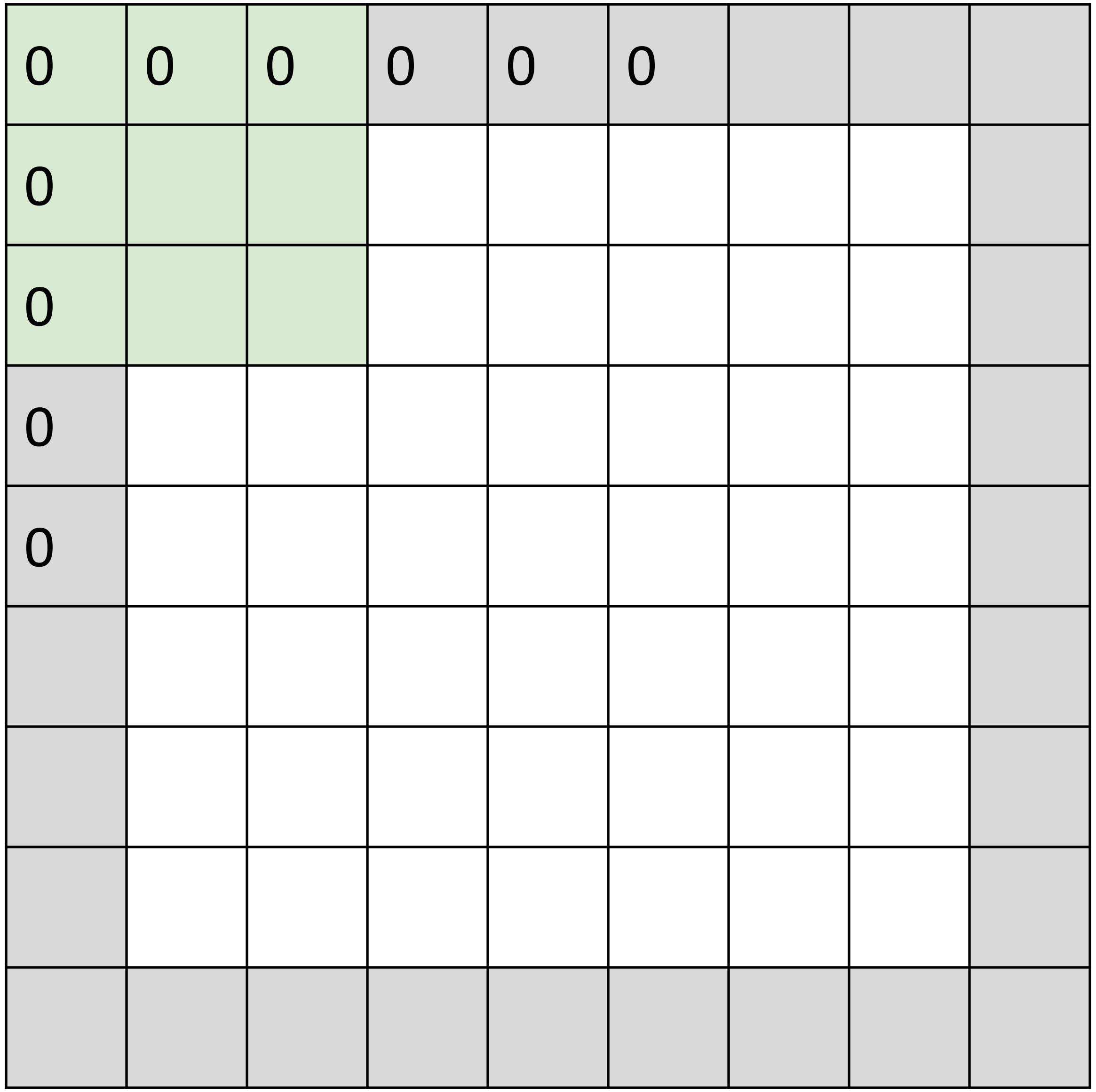


In practice: Common to zero pad the border

e.g. input 7x7
3x3 filter, applied with **stride 1**
pad with 1 pixel border => what is the output?

7x7 output!

Convolutional Layer

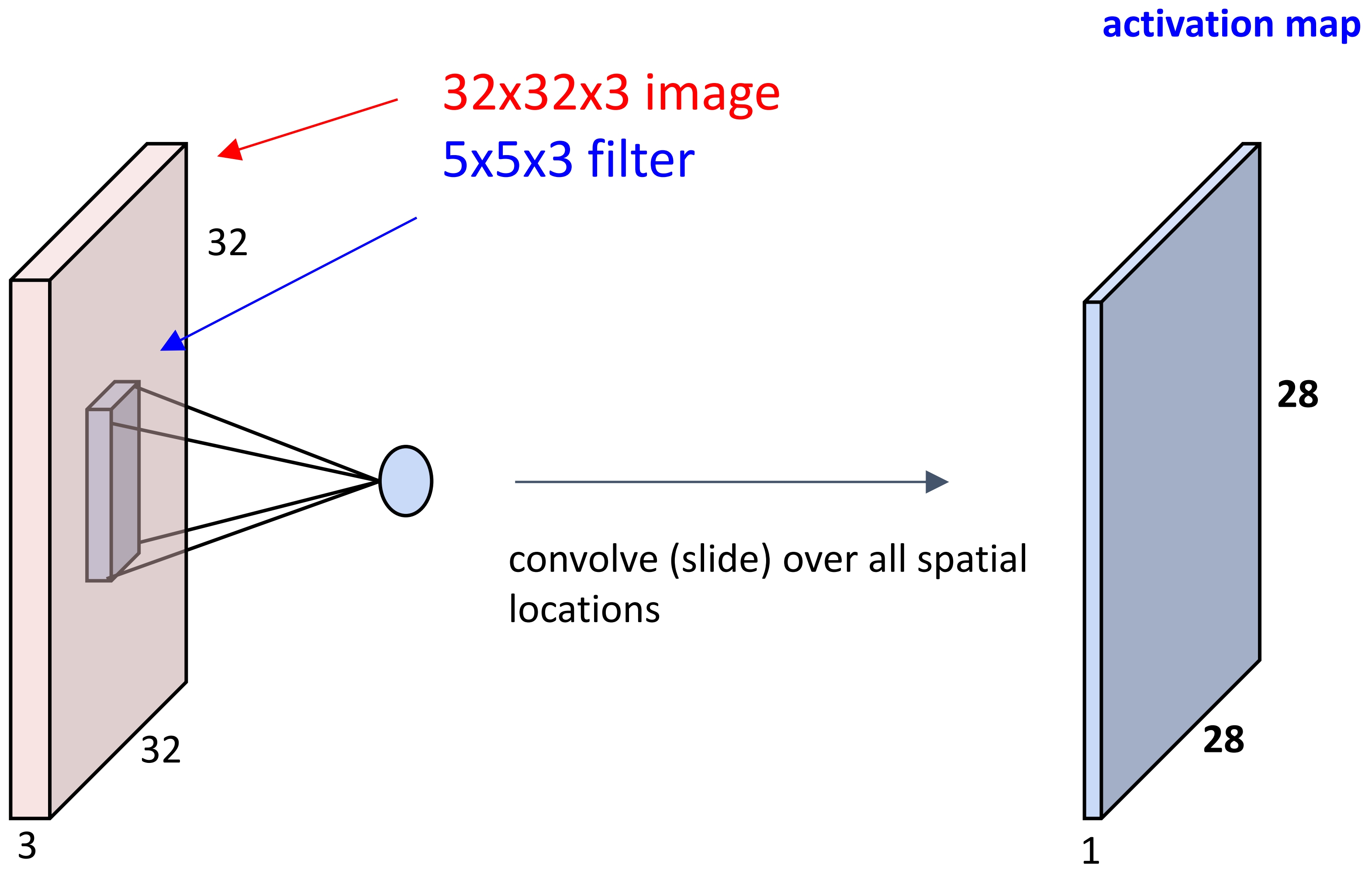


In practice: Common to zero pad the border

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

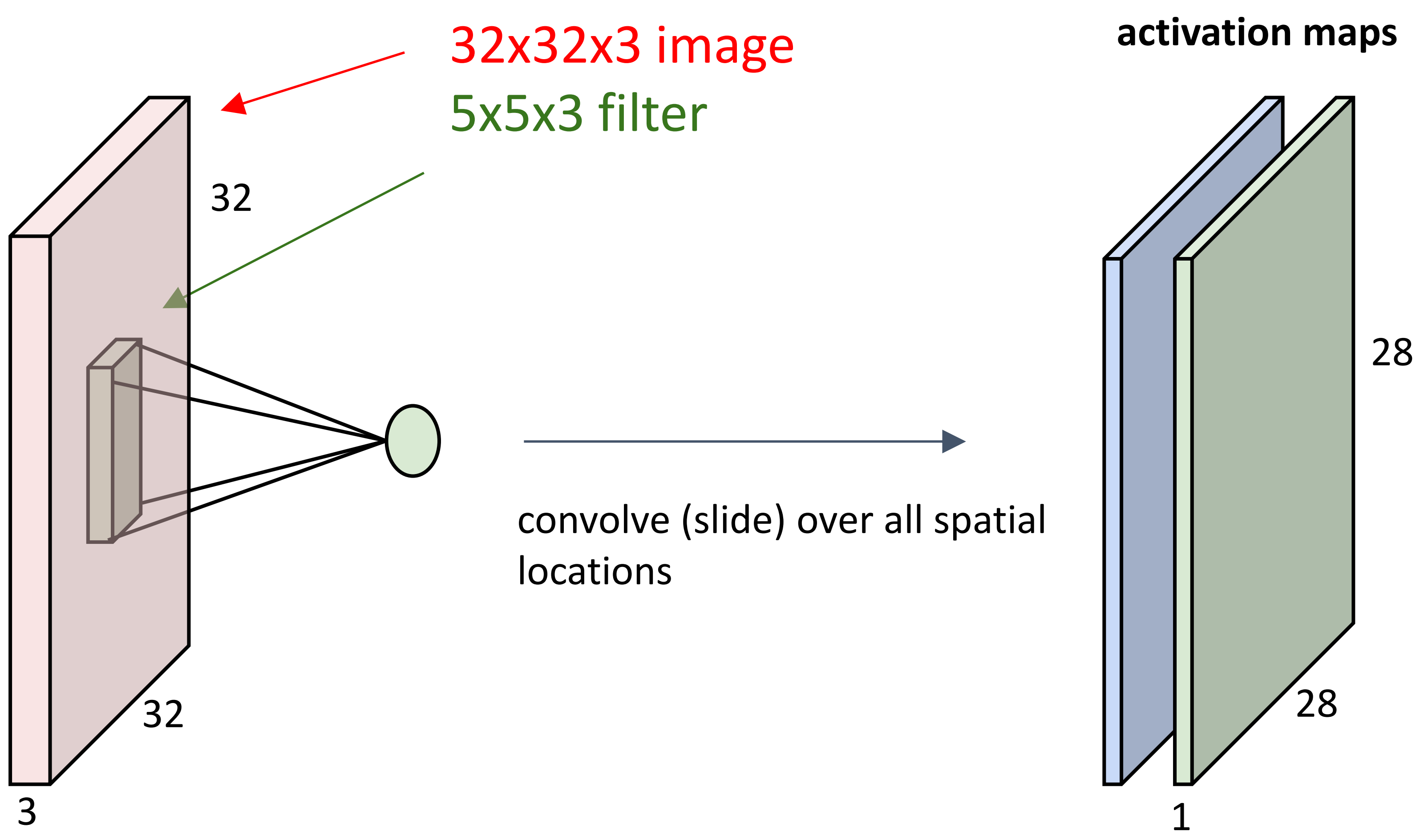
e.g. F = 3 => zero pad with 1
F = 5 => zero pad with 2
F = 7 => zero pad with 3

Convolutional Layer

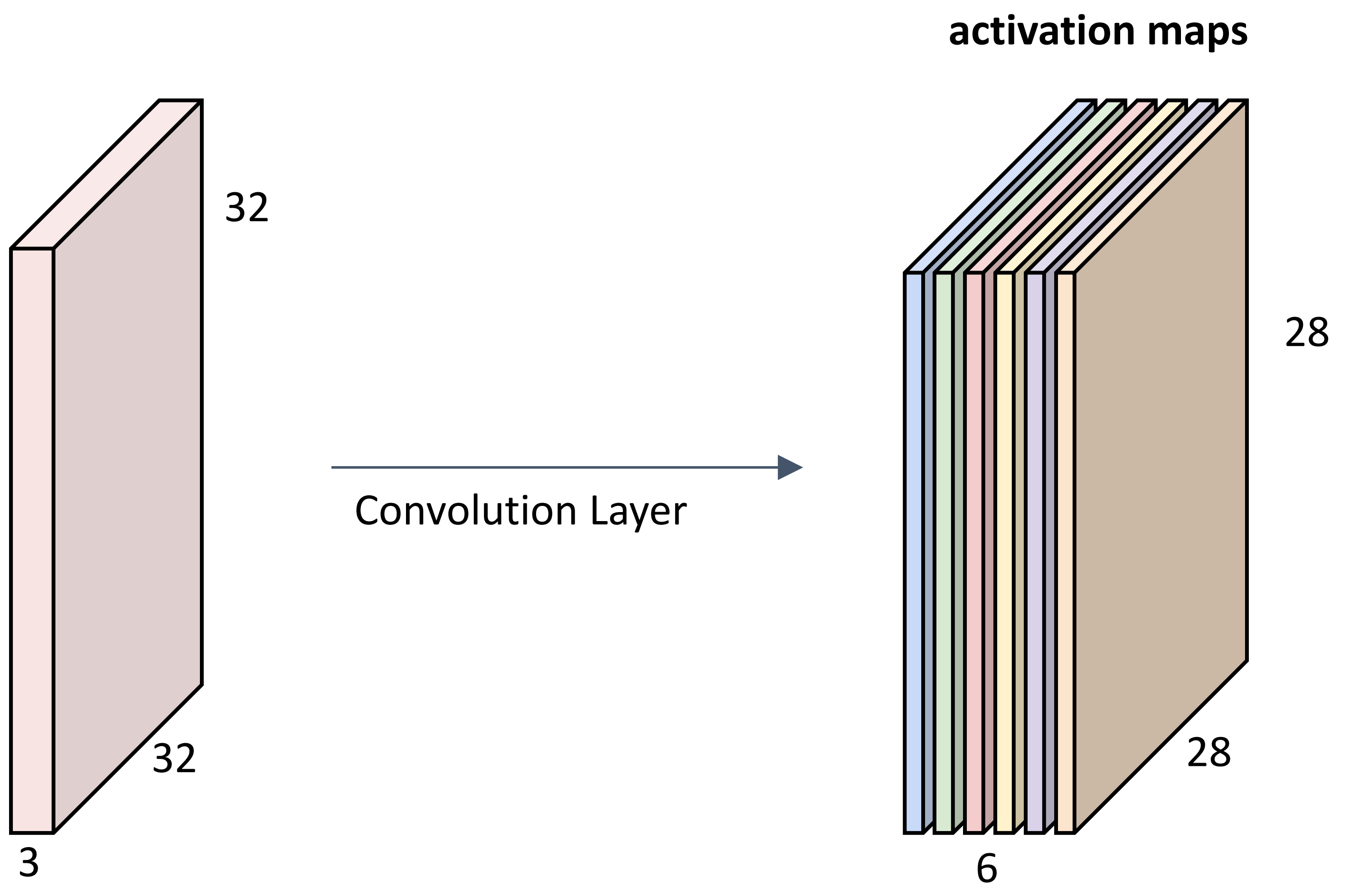


Convolutional Layer

consider a second, green filter



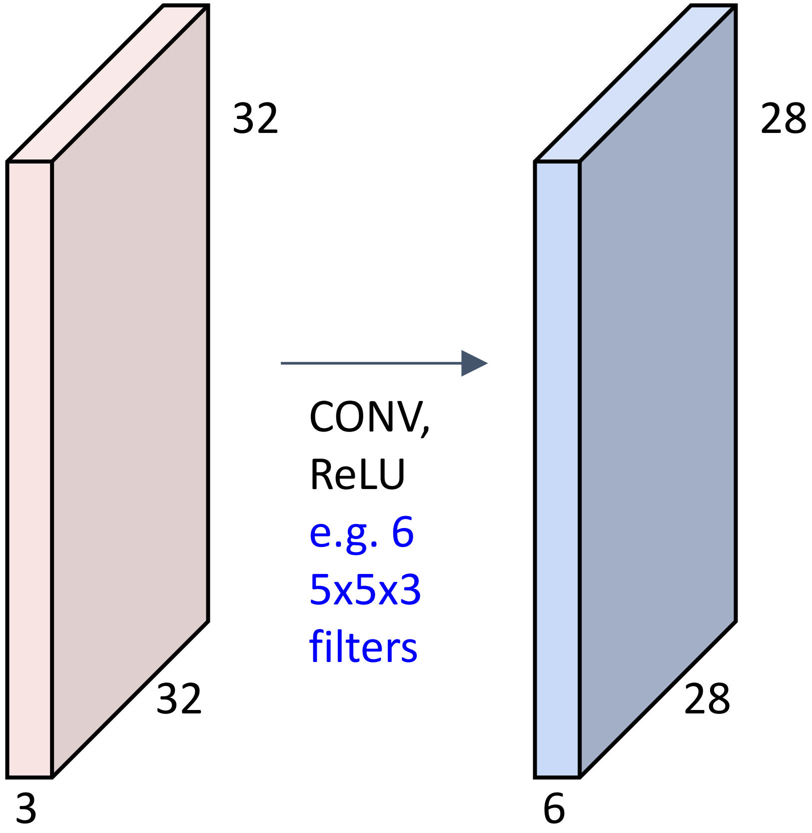
Convolutional Layer



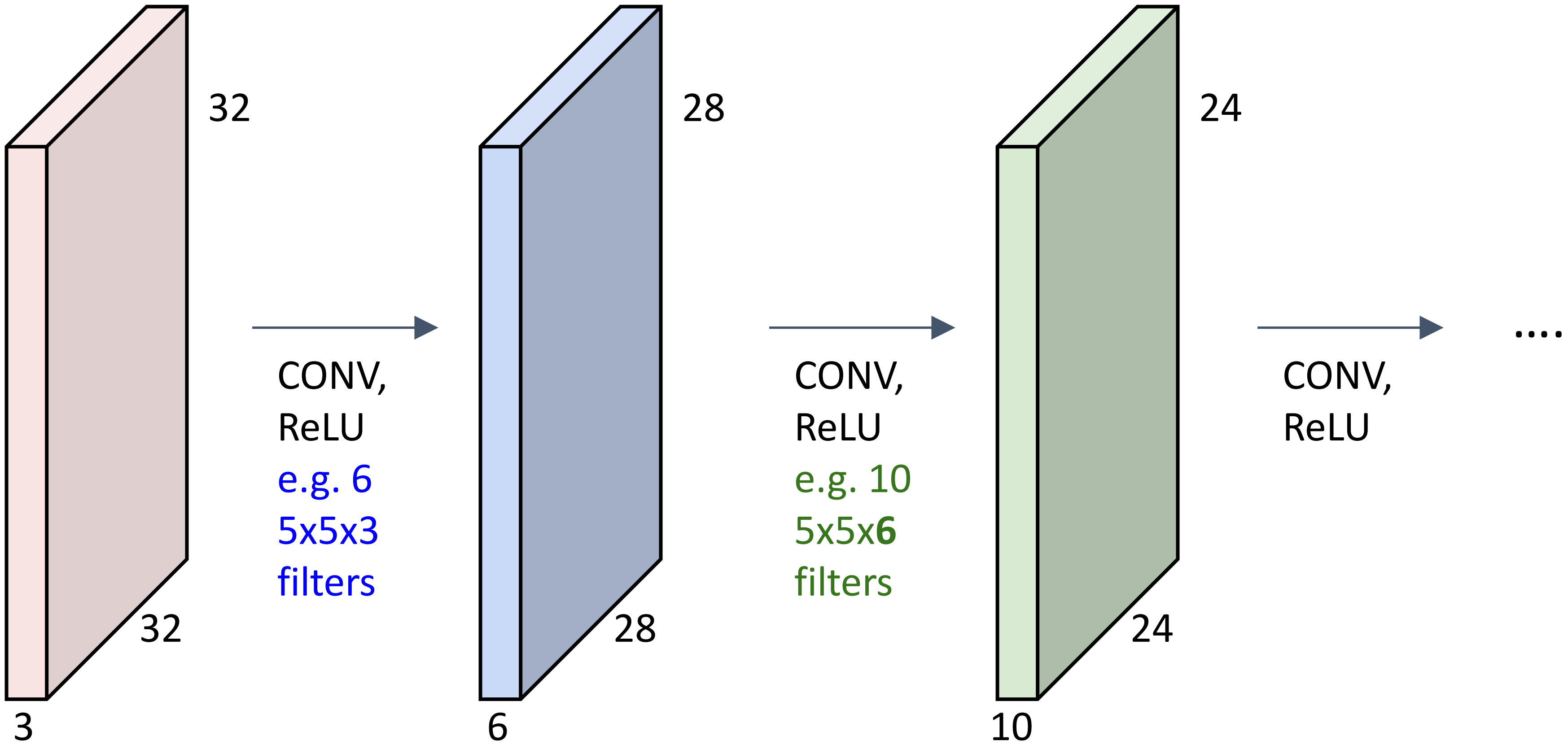
For example, if we had 6 5x5 filters, we'll get 6 separate activation maps

We stack these up to get a "new image" of size 28x28x6!

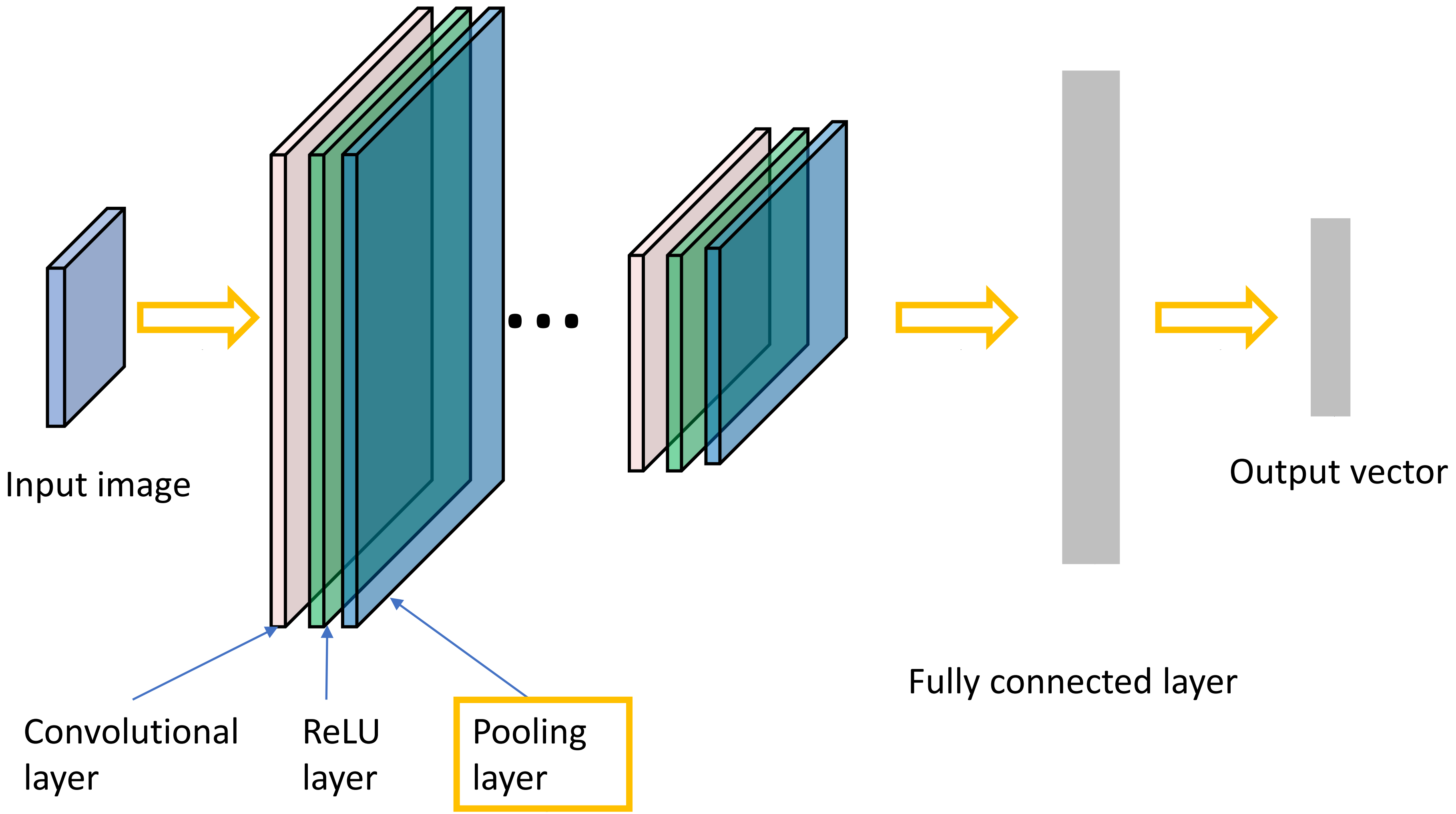
Preview: ConvNet is a sequence of Convolution Layers, interspersed with activation functions



Preview: ConvNet is a sequence of Convolutional Layers, interspersed with activation functions

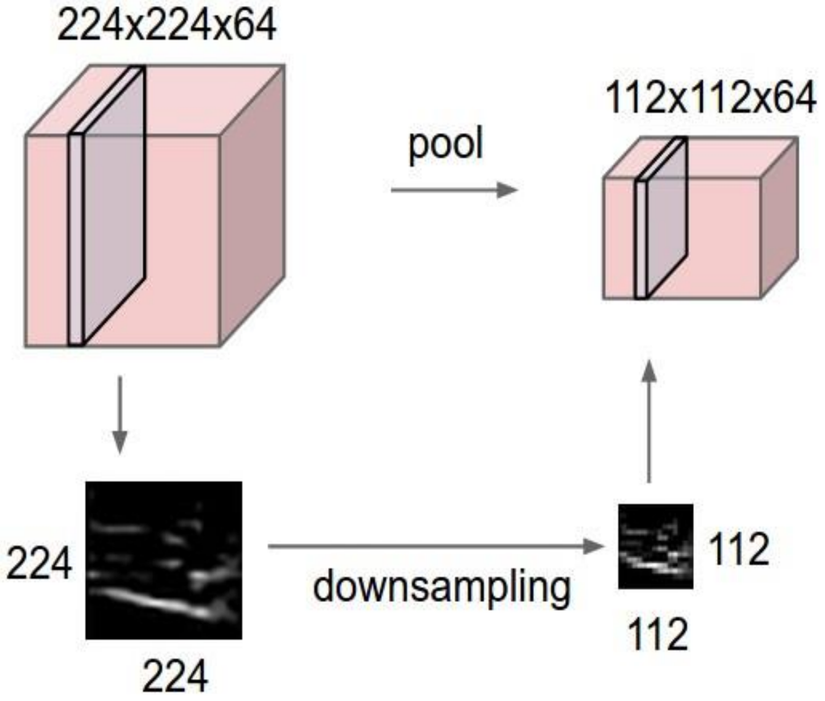


Convolutional Neural Networks



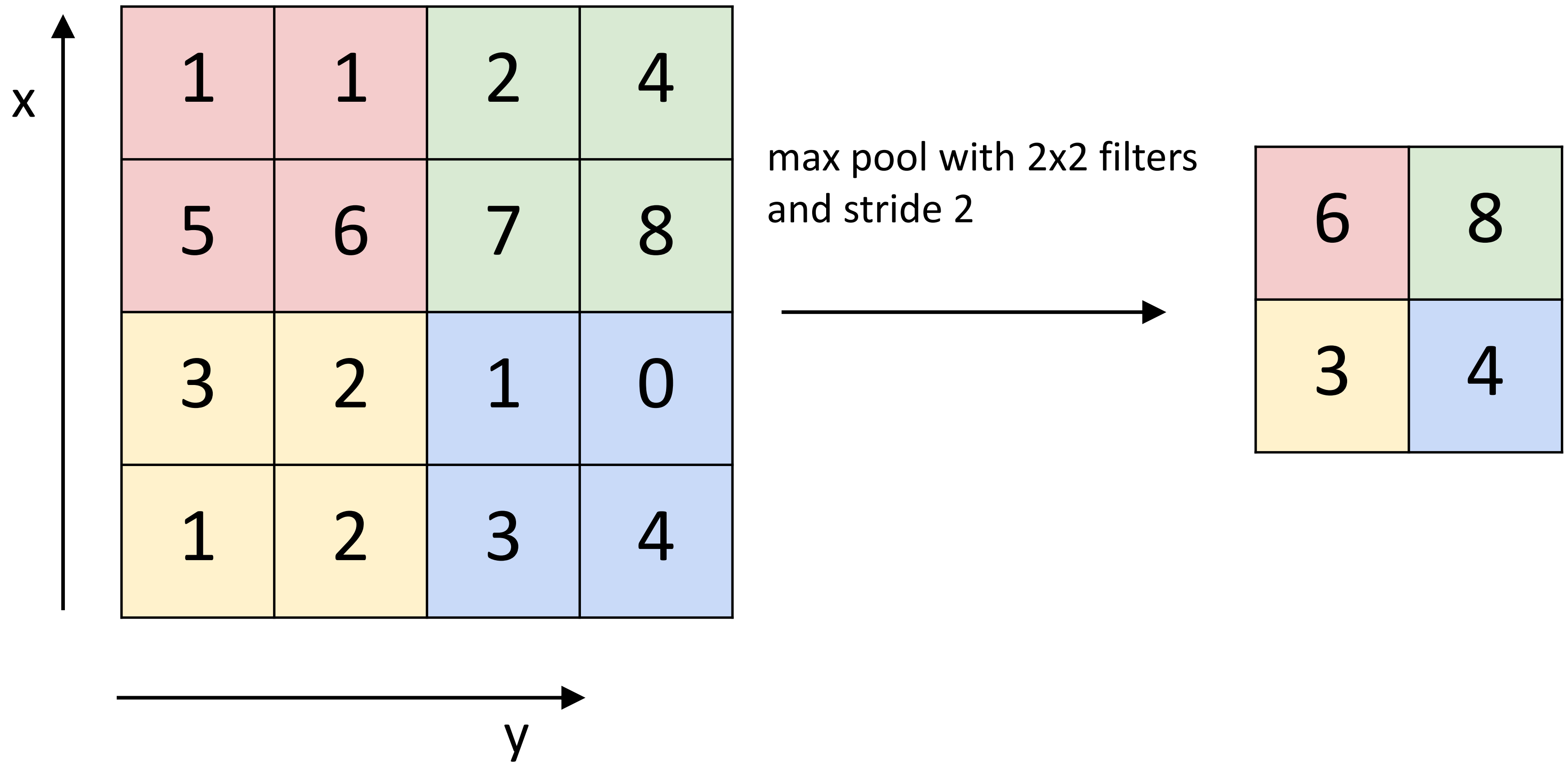
Pooling Layer

- makes the representations smaller and more manageable
- operates over each activation map independently:

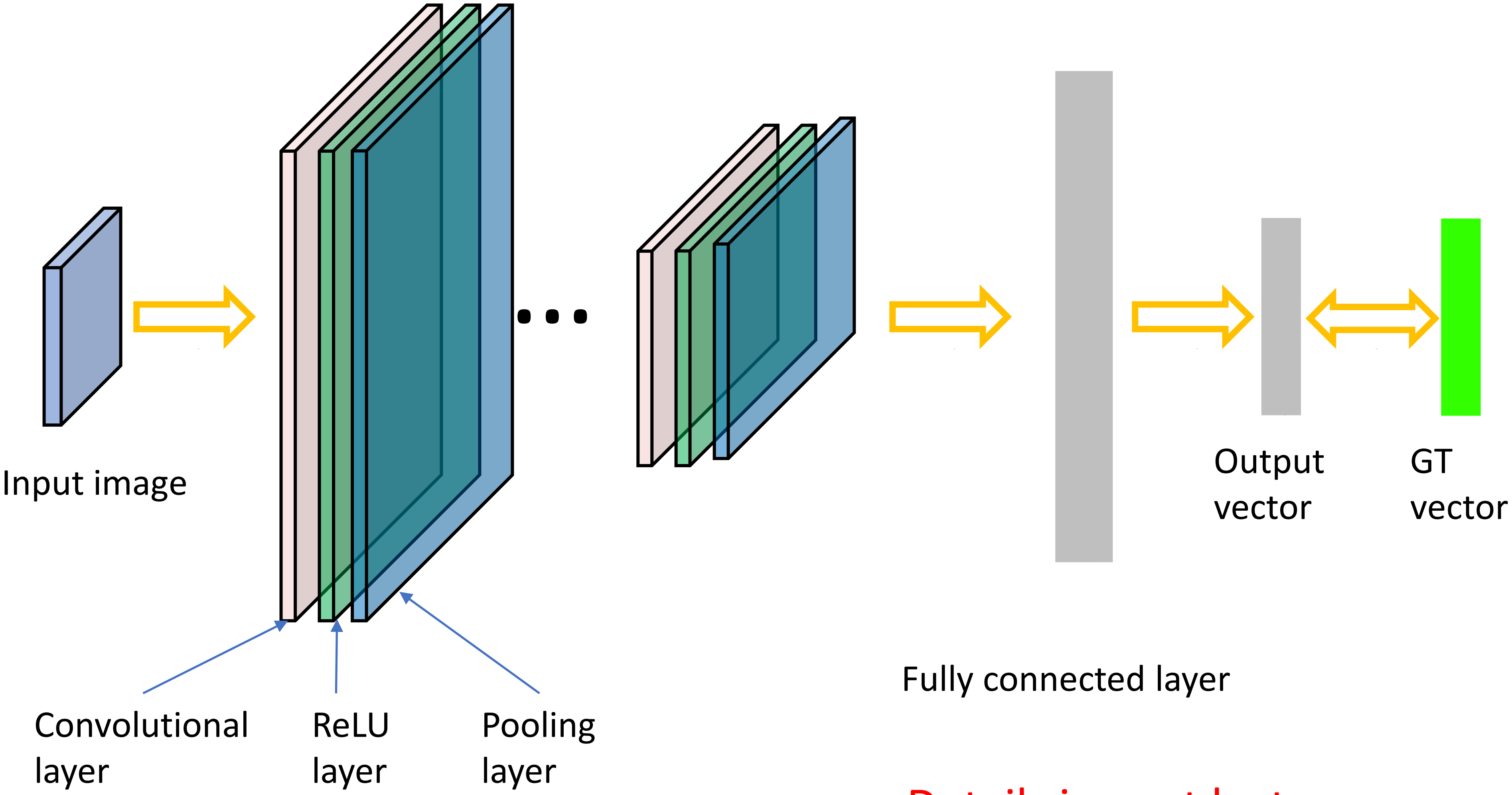


Max Pooling Layer

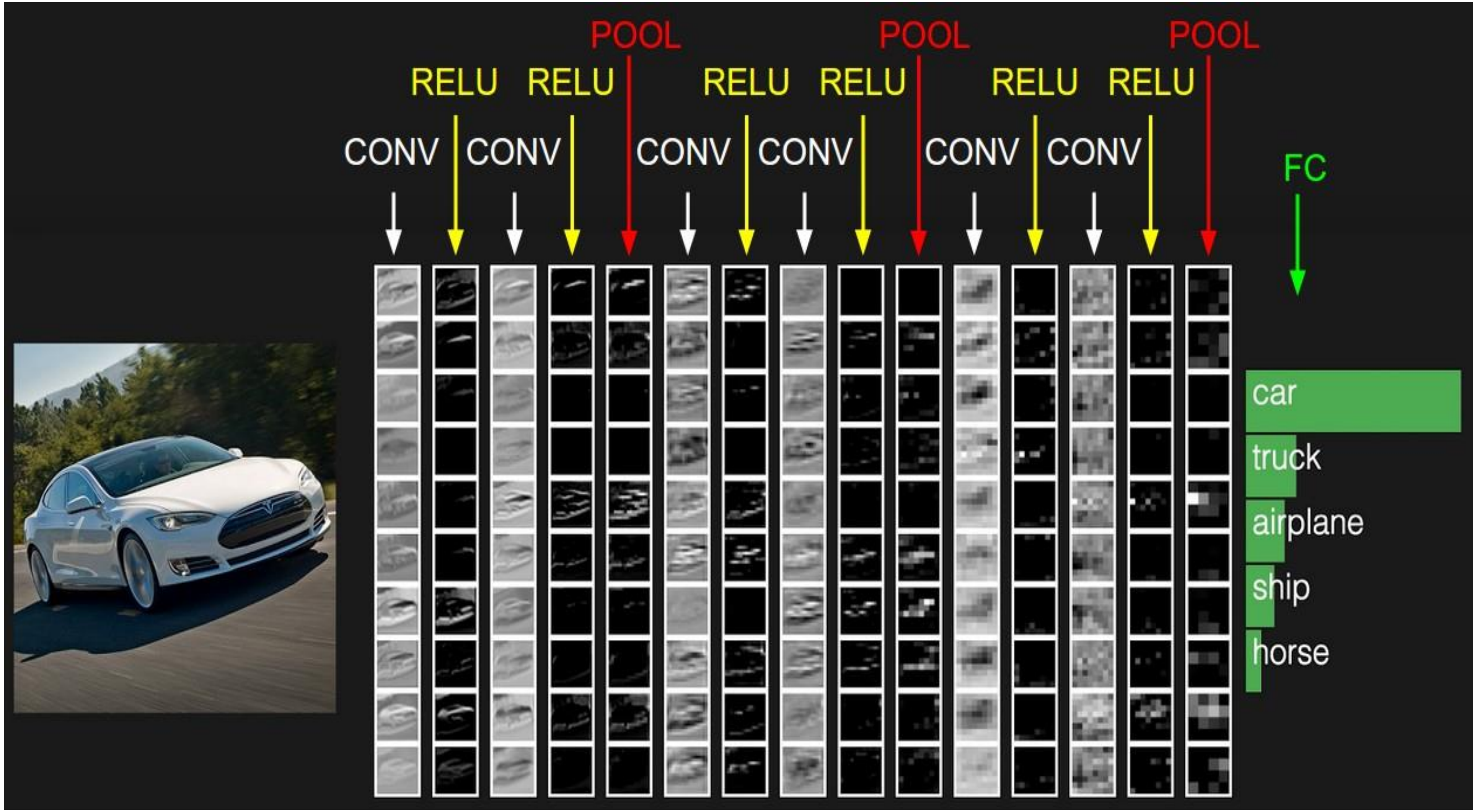
Single depth slice



Training: back-propagate errors

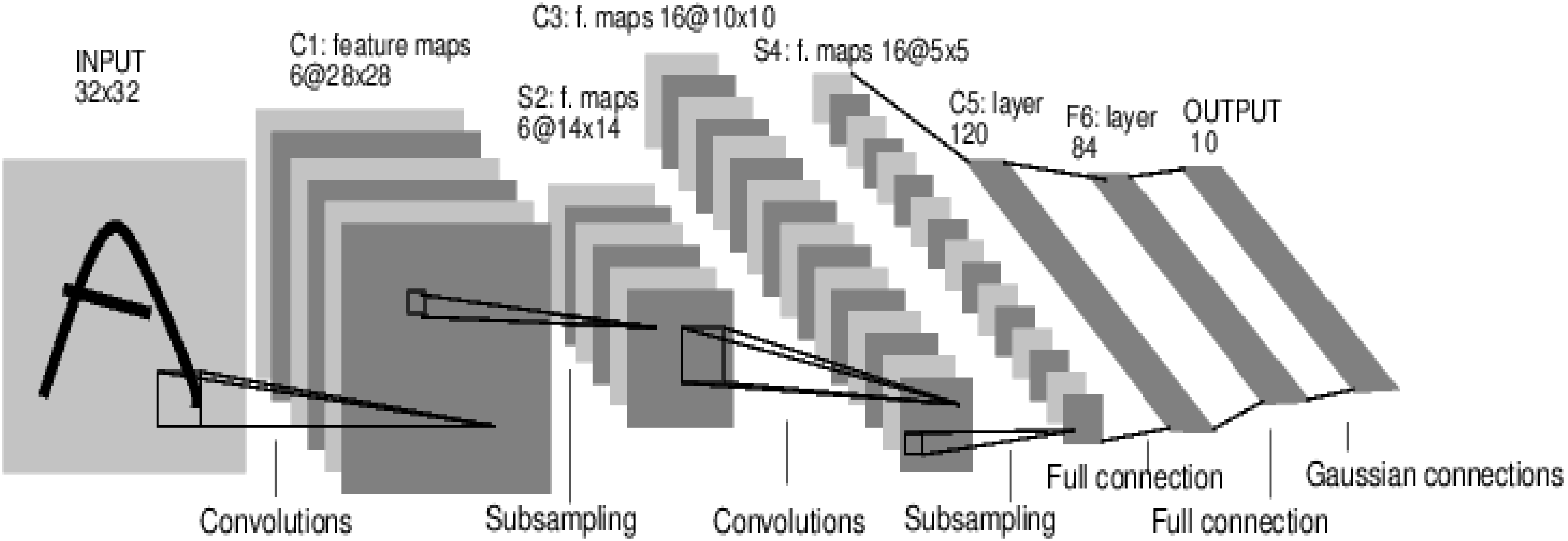


Details in next lecture


POOL
POOL
POOL
RELU
RELU
RELU
RELU
RELU
RELU
CONV
CONV
CONV
CONV
CONV
CONV
FC
car
truck
airplane
ship
horse

Case Study: LeNet-5

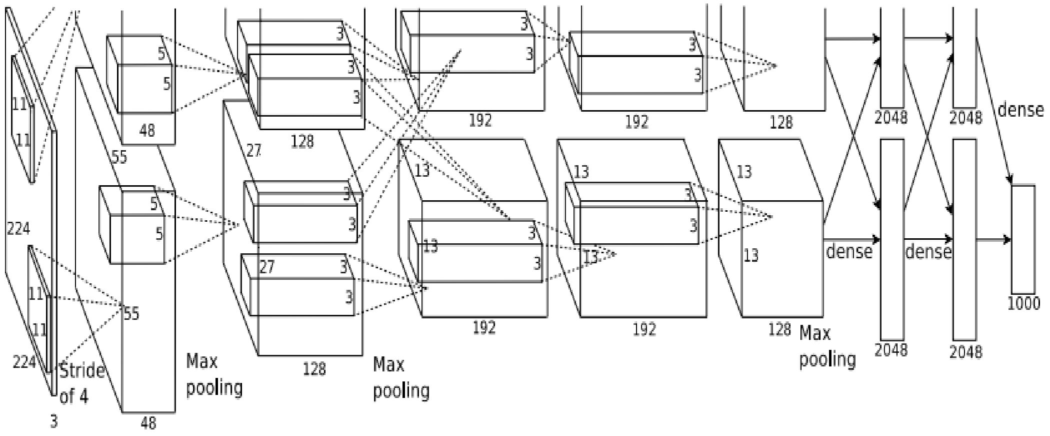
[LeCun et al., 1998]



Conv filters were 5x5, applied at stride 1
Subsampling (Pooling) layers were 2x2 applied at stride 2
i.e. architecture is [CONV-POOL-CONV-POOL-CONV-FC]

Case Study: AlexNet

[Krizhevsky et al. 2012]



Input: 227x227x3 images

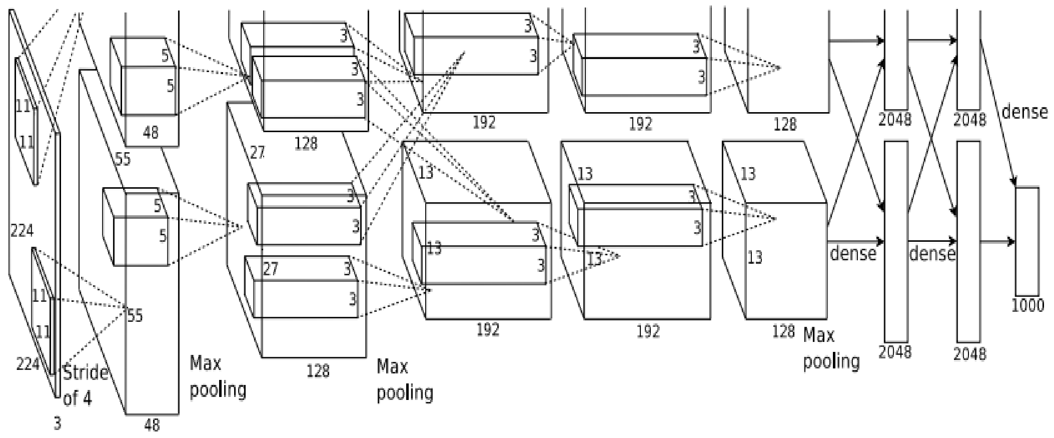
First layer (CONV1): 96 11x11 filters applied at stride 4

=>

Q: what is the output volume size? Hint: (227-11)/4+1 = 55

Case Study: AlexNet

[Krizhevsky et al. 2012]



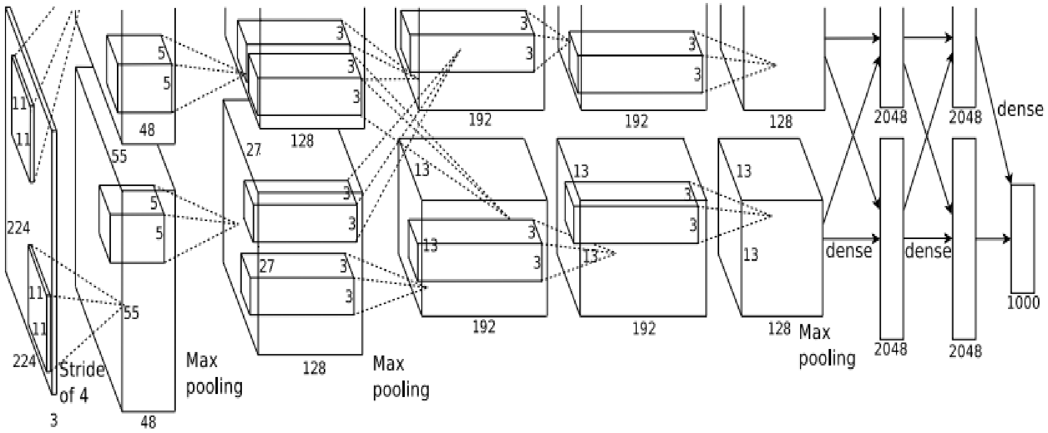
Input: 227x227x3 images

First layer (CONV1): 96 11x11 filters applied at stride 4
=>
Output volume **[55x55x96]**

Q: What is the total number of parameters in this layer?

Case Study: AlexNet

[Krizhevsky et al. 2012]

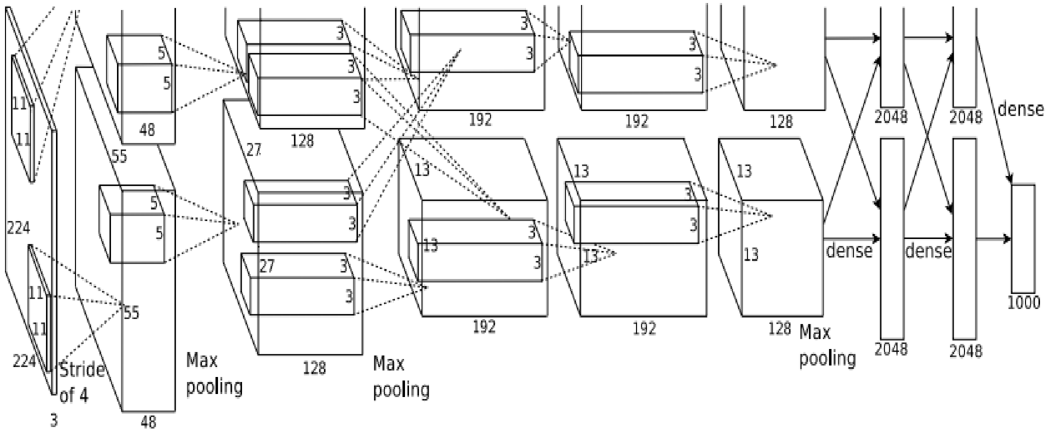


Input: 227x227x3 images

First layer (CONV1): 96 11x11 filters applied at stride 4
=>
Output volume **[55x55x96]**
Parameters: (11*11*3)*96 = **35K**

Case Study: AlexNet

[Krizhevsky et al. 2012]



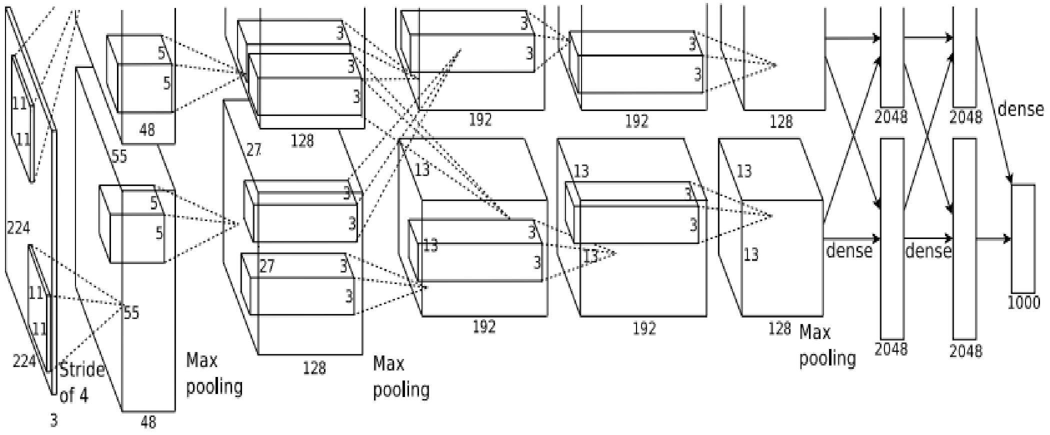
Input: 227x227x3 images
After CONV1: 55x55x96

Second layer (POOL1): 3x3 filters applied at stride 2

Q: what is the output volume size? Hint: (55-3)/2+1 = 27

Case Study: AlexNet

[Krizhevsky et al. 2012]



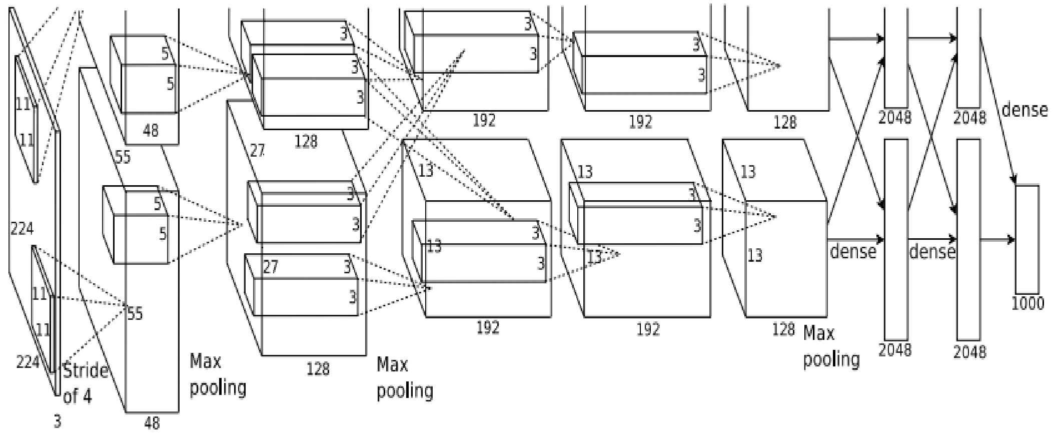
Input: 227x227x3 images
After CONV1: 55x55x96

Second layer (POOL1): 3x3 filters applied at stride 2
Output volume: 27x27x96

Q: what is the number of parameters in this layer?

Case Study: AlexNet

[Krizhevsky et al. 2012]

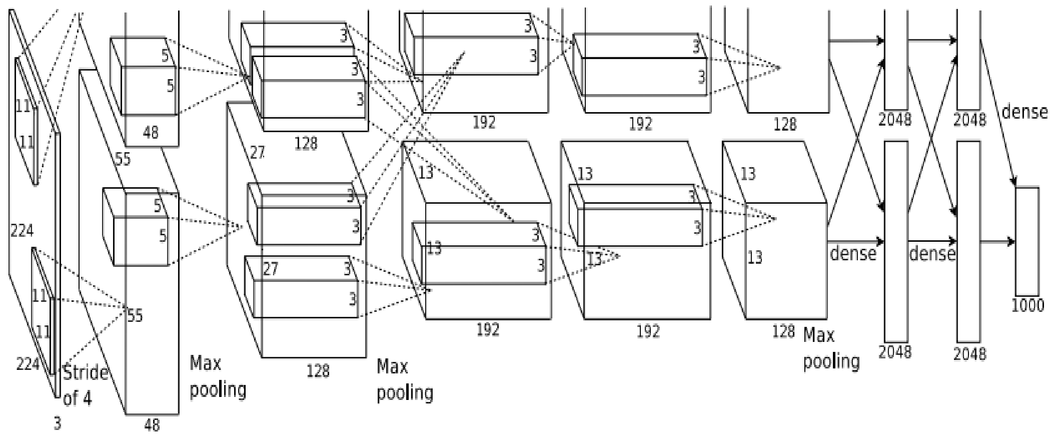


Input: 227x227x3 images
After CONV1: 55x55x96

Second layer (POOL1): 3x3 filters applied at stride 2
Output volume: 27x27x96
Parameters: 0!

Case Study: AlexNet

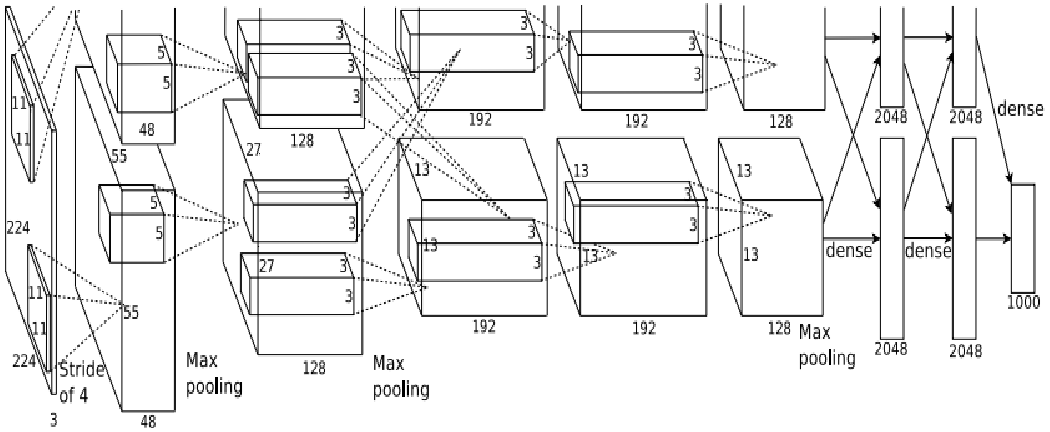
[Krizhevsky et al. 2012]



Input: 227x227x3 images
After CONV1: 55x55x96
After POOL1: 27x27x96
...

Case Study: AlexNet

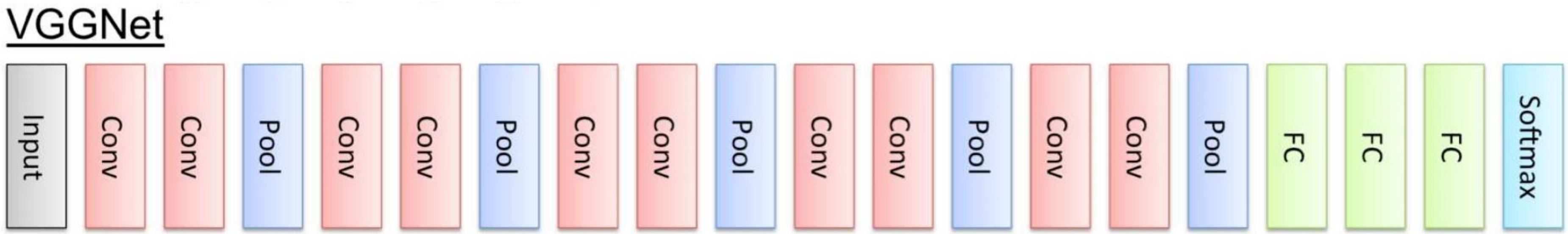
[Krizhevsky et al. 2012]



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)

Case Study: VGGNet

[Simonyan and Zisserman, 2014]



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

11.2% top 5 error in ILSVRC 2013
->
7.3% top 5 error

Case Study: VGGNet

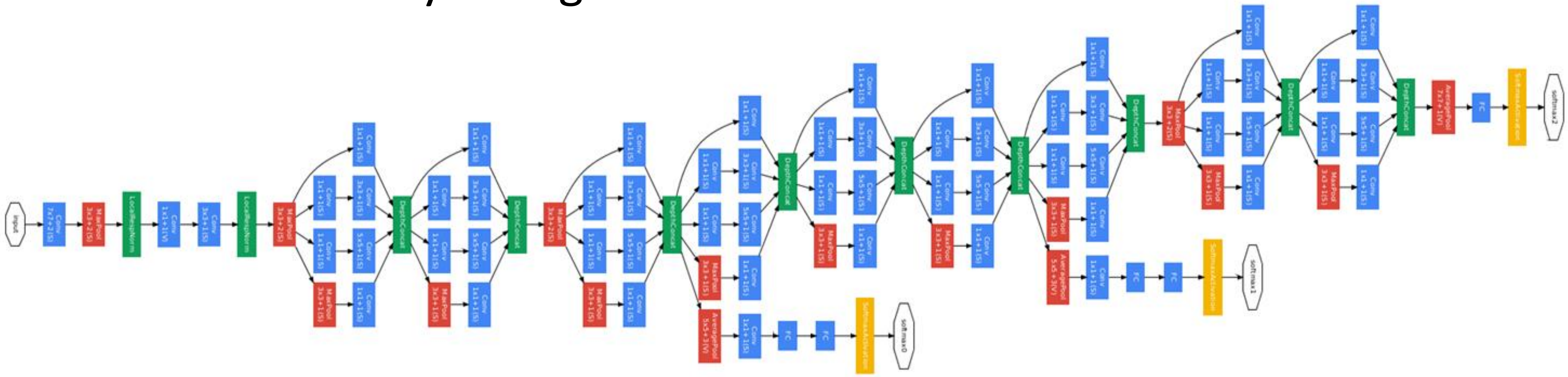
[Simonyan and Zisserman, 2014]

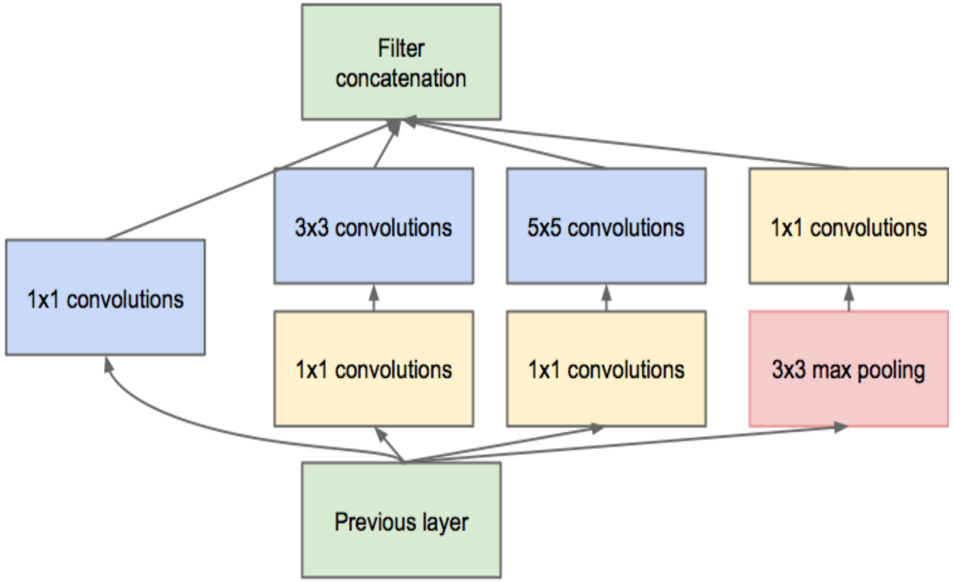
INPUT: [224x224x3] memory: 224*224*3=150K params: 0
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*3)*64 = 1,728
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*64)*64 = 36,864
POOL2: [112x112x64] memory: 112*112*64=800K params: 0
CONV3-128: [112x112x128] memory: 112*112*128=1.6M 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

(not counting biases)

Case Study: GoogLeNet

[Szegedy et al., 2014]





Inception module

ILSVRC 2014 winner (6.7% top 5 error)

Case Study: GoogLeNet

type	patch size/ stride	output size	depth	#1×1	#3×3 reduce	#3×3	#5×5 reduce	#5×5	pool proj	params	ops
convolution	7×7/2	112×112×64	1							2.7K	34M
max pool	3×3/2	56×56×64	0								
convolution	3×3/1	56×56×192	2		64	192				112K	360M
max pool	3×3/2	28×28×192	0								
inception (3a)		28×28×256	2	64	96	128	16	32	32	159K	128M
inception (3b)		28×28×480	2	128	128	192	32	96	64	380K	304M
max pool	3×3/2	14×14×480	0								
inception (4a)		14×14×512	2	192	96	208	16	48	64	364K	73M
inception (4b)		14×14×512	2	160	112	224	24	64	64	437K	88M
inception (4c)		14×14×512	2	128	128	256	24	64	64	463K	100M
inception (4d)		14×14×528	2	112	144	288	32	64	64	580K	119M
inception (4e)		14×14×832	2	256	160	320	32	128	128	840K	170M
max pool	3×3/2	7×7×832	0								
inception (5a)		7×7×832	2	256	160	320	32	128	128	1072K	54M
inception (5b)		7×7×1024	2	384	192	384	48	128	128	1388K	71M
avg pool	7×7/1	1×1×1024	0								
dropout (40%)		1×1×1024	0								
linear		1×1×1000	1							1000K	1M
softmax		1×1×1000	0								

Fun features:

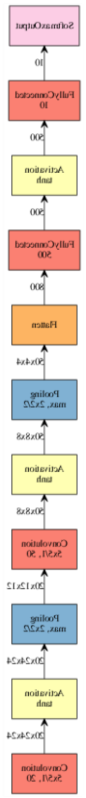
- Only 5 million params!

Compared to AlexNet:
- 12X less params
- 2x more compute
- 6.67% (vs. 16.4%)

Case Study: ResNet

[He et al., 2015]

ILSVRC 2015 winner (3.6% top 5 error)



LeNet
(5 layers)

AlexNet
(8 layers)

VGGNet
(19 layers)

GoogleNet

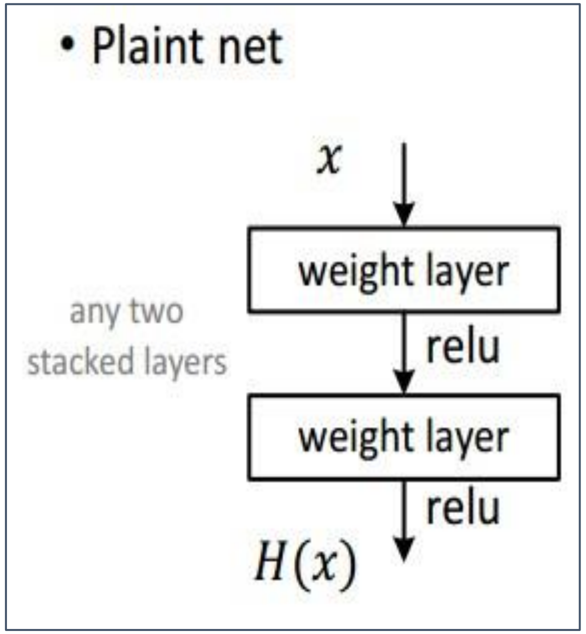
ResNet
(152 layers)

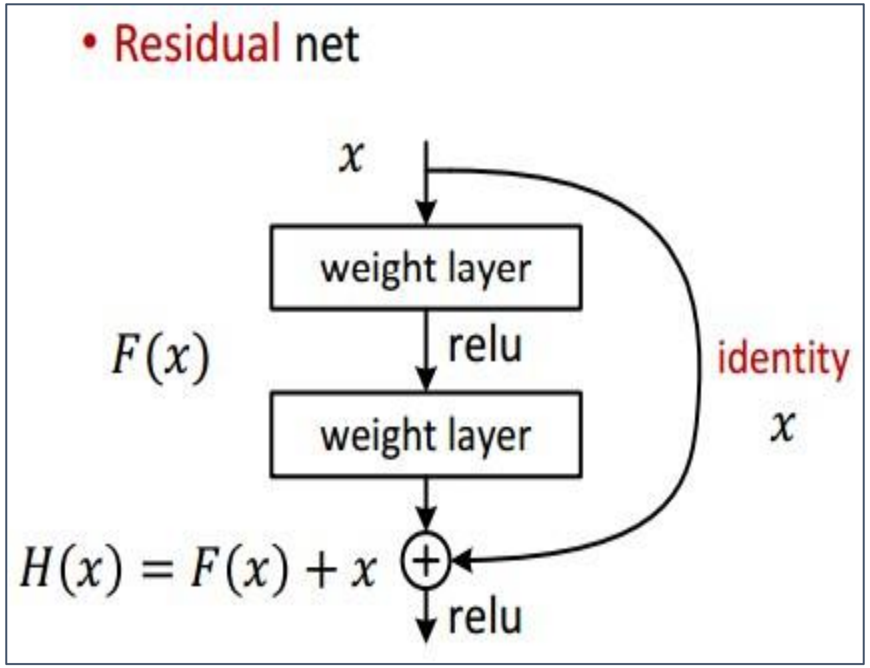
2-3 weeks of training on 8 GPU machine

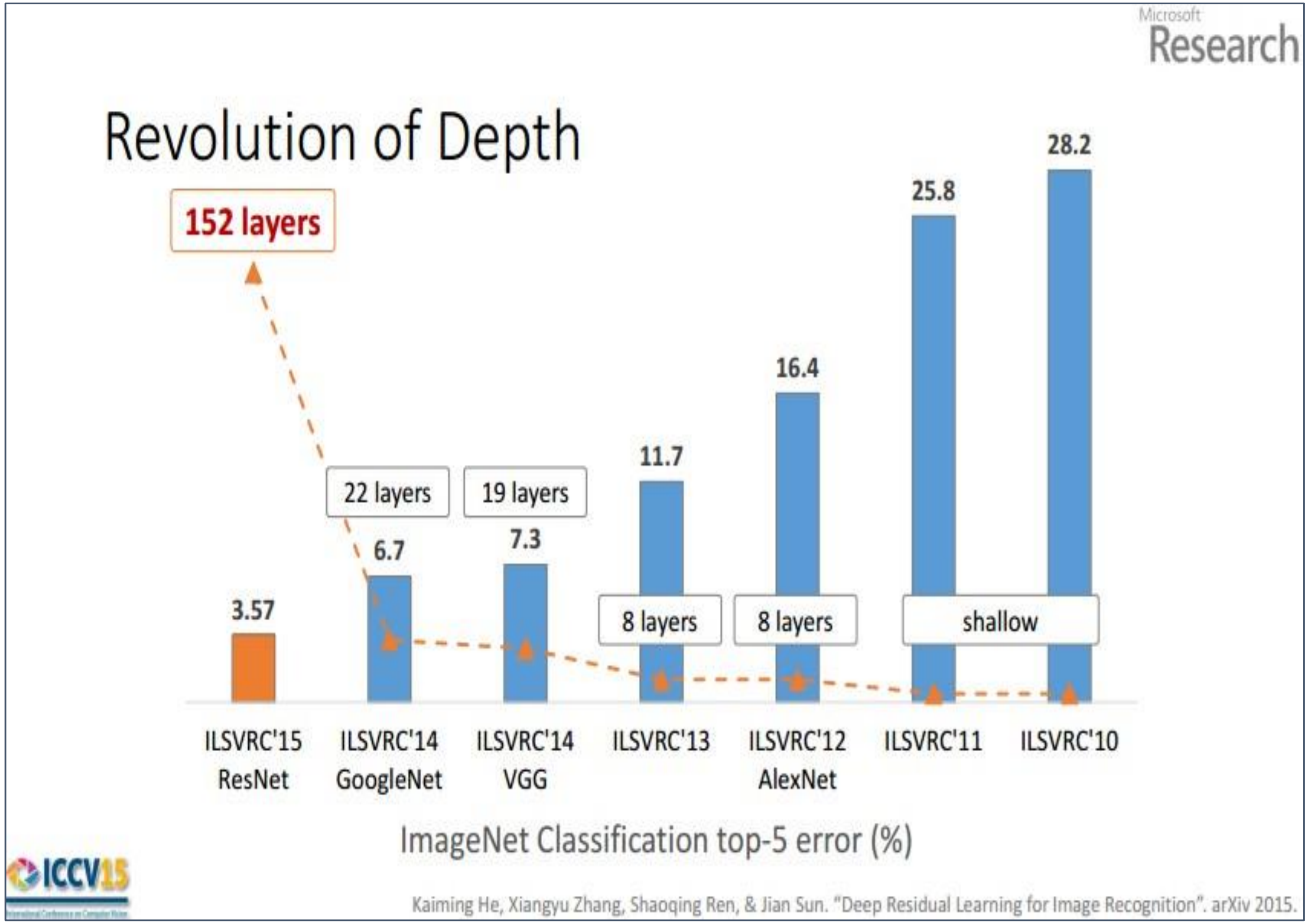
at runtime: faster than a VGGNet! (even though it has 8x more layers)

Case Study: ResNet

[He et al., 2015]







(slide from Kaiming He)

Further Reading

- Stanford CS231n, lecture 5, Convolutional Neural Networks
  http://cs231n.stanford.edu/schedule.html
- Deep learning with PyTorch
  https://pytorch.org/tutorials/beginner/deep_learning_60min_blitz.html
- AlexNet (2012):
  https://papers.nips.cc/paper/2012/hash/c399862d3b9d6b76c8436e924a68c45b-Abstract.html
- Vgg16 (2014): https://arxiv.org/abs/1409.1556
- GoogleNet (2014): https://arxiv.org/abs/1409.4842
- ResNet (2015): https://arxiv.org/abs/1512.03385