THE UNIVERSITY OF TEXAS AT DALLAS

# Convolutional Neural Networks I

CS 4391 Introduction to Computer Vision
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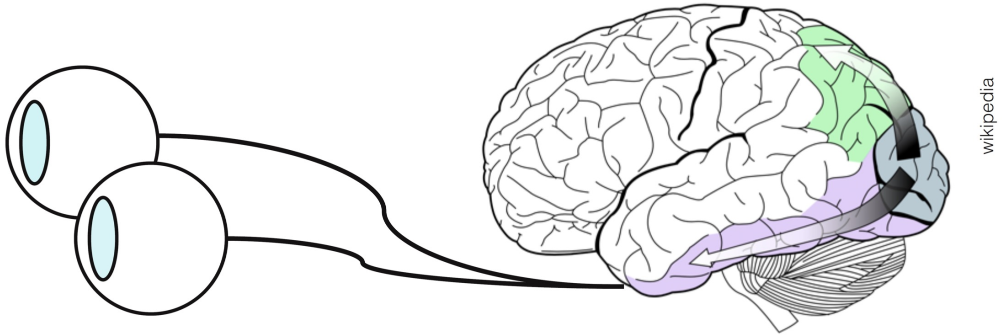
Department of Computer Science

Slides borrowed from Professor Yu Xiang

# Visual Perception vs. Computational Perception




sensors → network → compute

low-level processing    high-level processing

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

$x$ $\Rightarrow$  $\Rightarrow$ $y$

Image — $f(x)$ — Object class

# Mathematic Models

What is the form of the function $f(x)$ ?

- No idea!
- Concatenate simple functions (neurons)

$x$

$$f(x)$$

$$y \in \{+1, -1\}$$

Dog

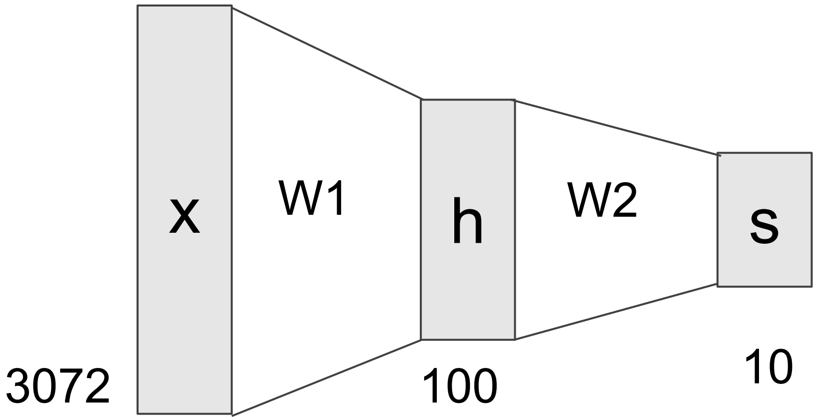
# Neural Network: Concatenation of functions

Linear score function: $f = Wx$

2-layer Neural Network

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

Non-linearity




$$h = f_1(X)$$

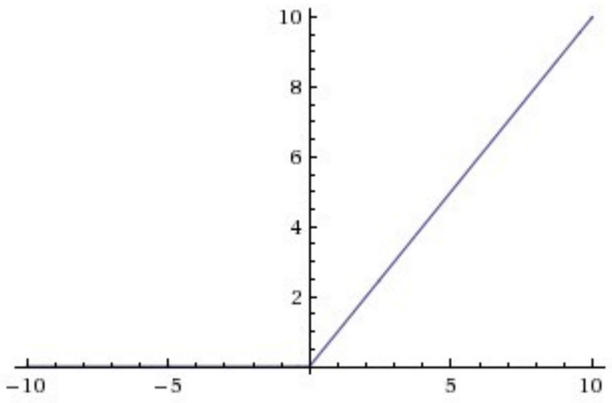
$$s = f_2(h)$$

# 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)

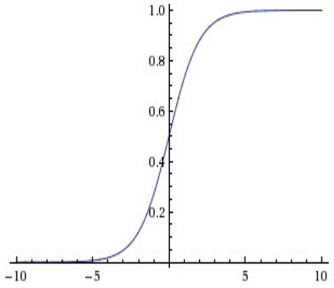



Introduce non-linearity to the network

# Activation Functions

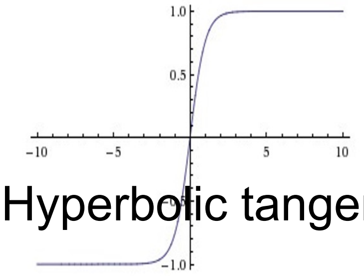
**Sigmoid**

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



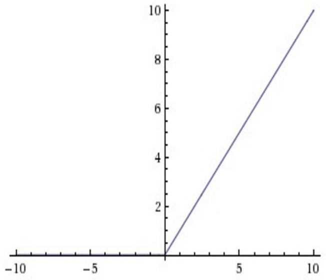
**tanh** tanh(x)

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

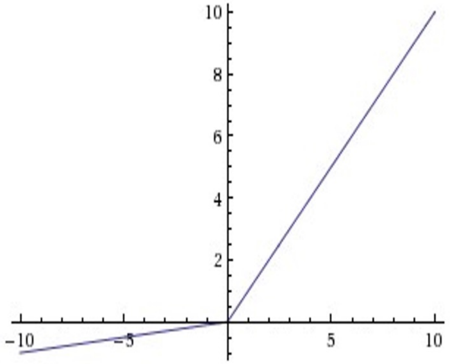


Hyperbolic tangent

**ReLU** max(0,x)



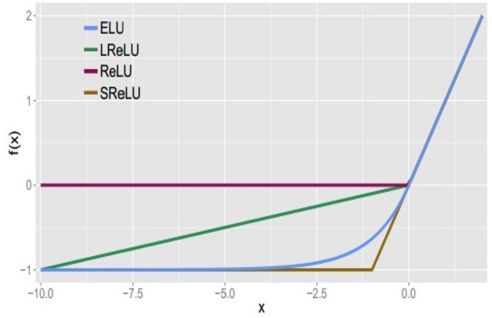
**Leaky ReLU**
max(0.1x, x)



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

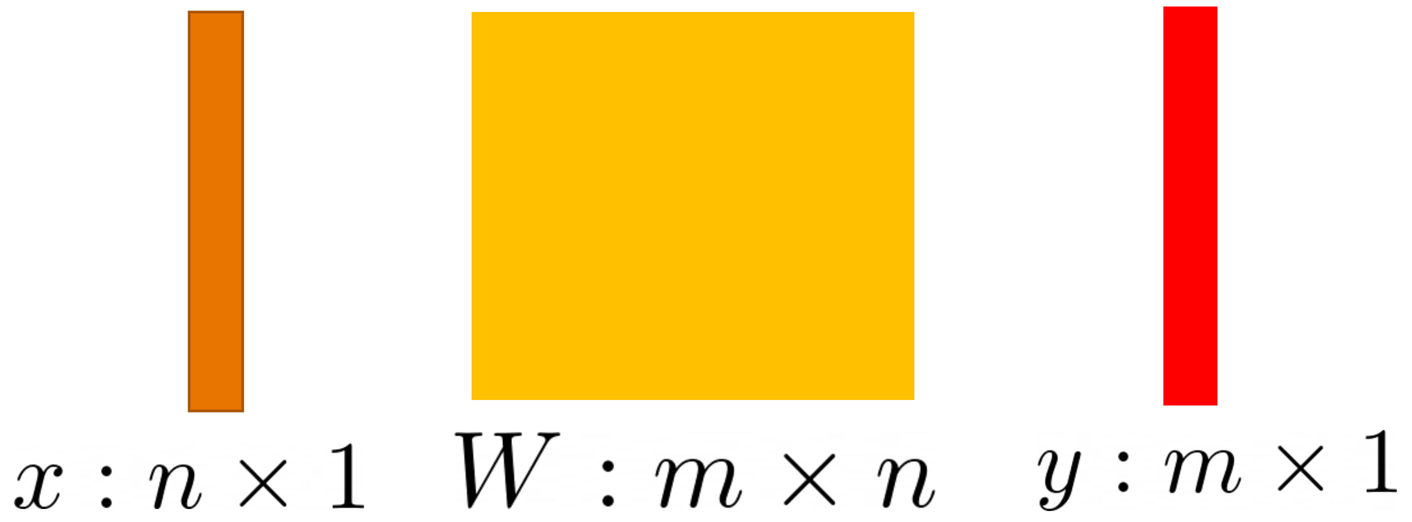
**ELU** Exponentia
Linear Unit

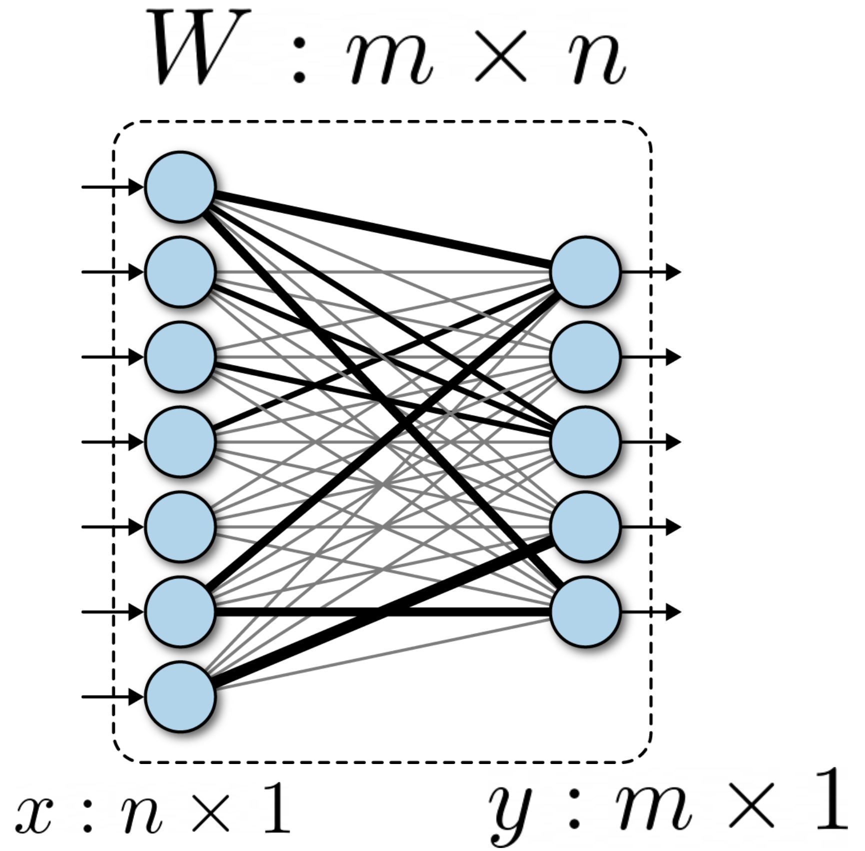
$$f(x) = \begin{cases} x & \text{if } x > 0 \\ \alpha\,(\exp(x) - 1) & \text{if } x \le 0 \end{cases}$$



# Fully Connected Layer

$$y = Wx$$



# 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

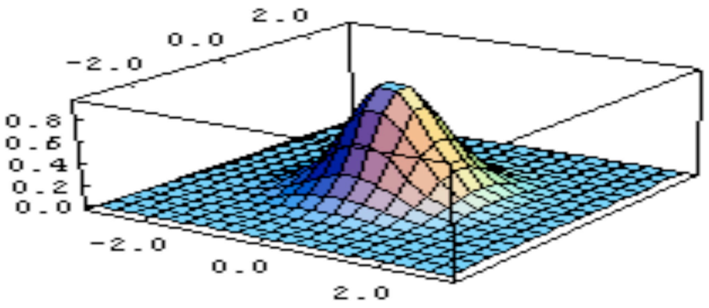
# Convolutional Layers

Consist of convolutional filters

Share weights among different image locations

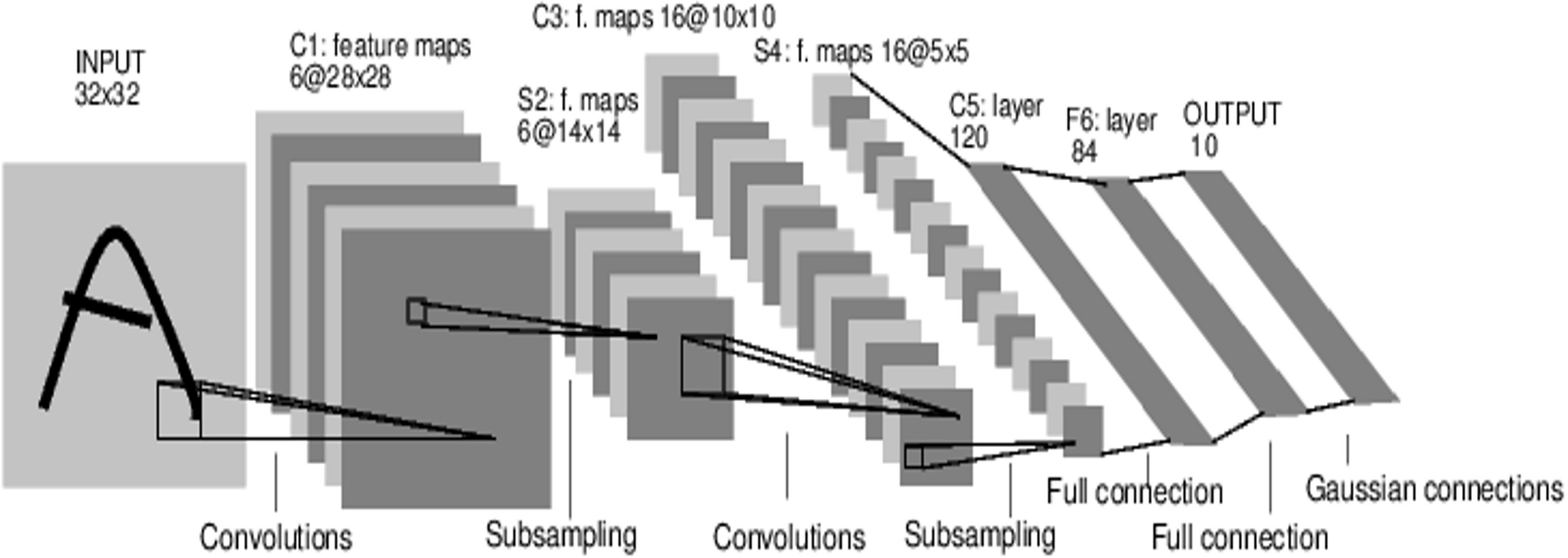
$$g(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

Gaussian Filter



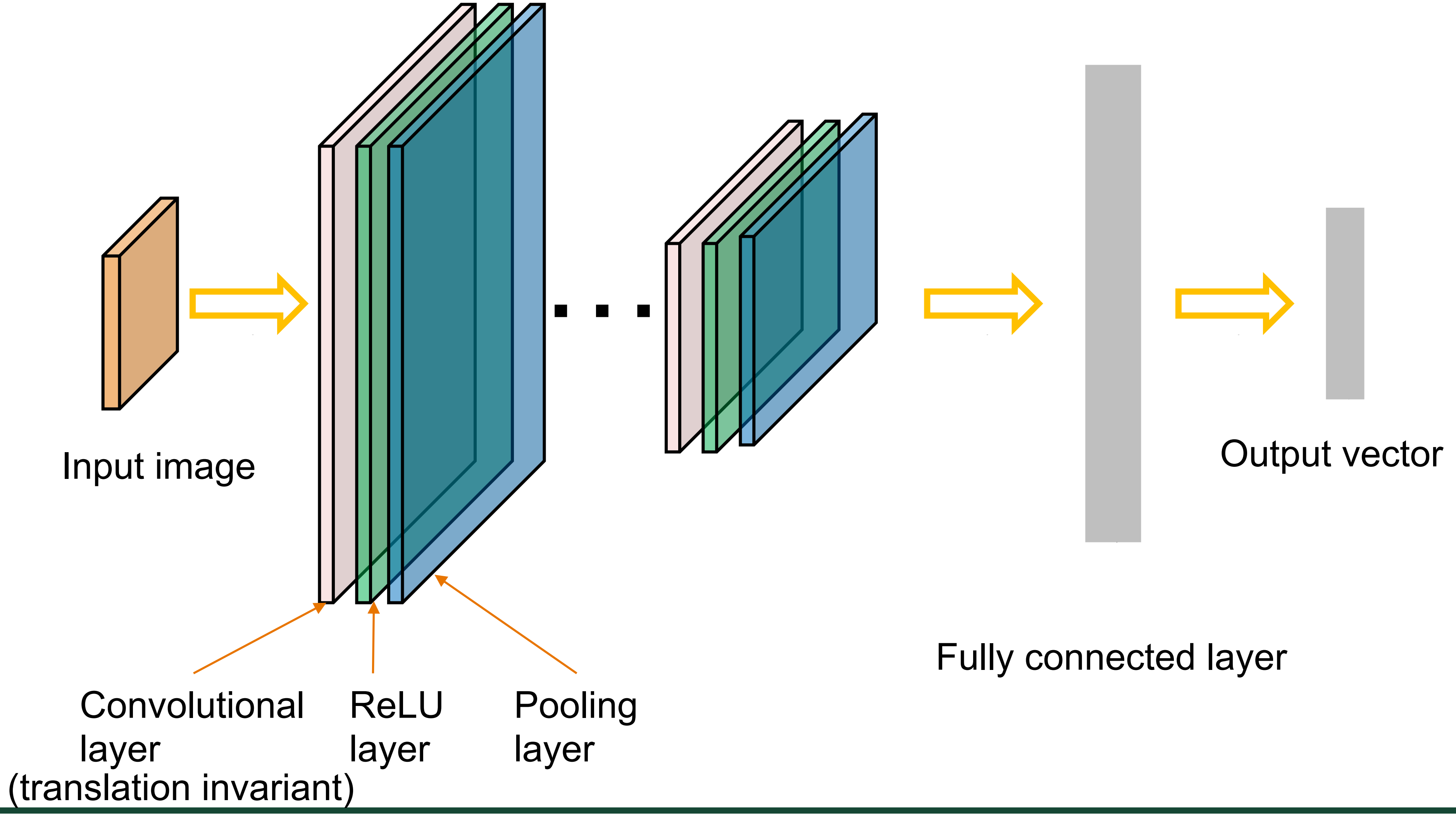

Learn the weights!

# Convolutional Neural Networks



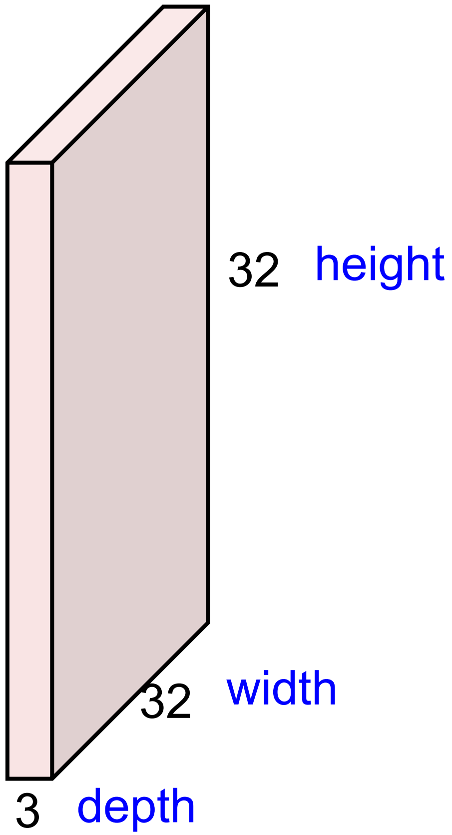

*[LeNet-5, LeCun 1980]*

# Convolutional Neural Networks



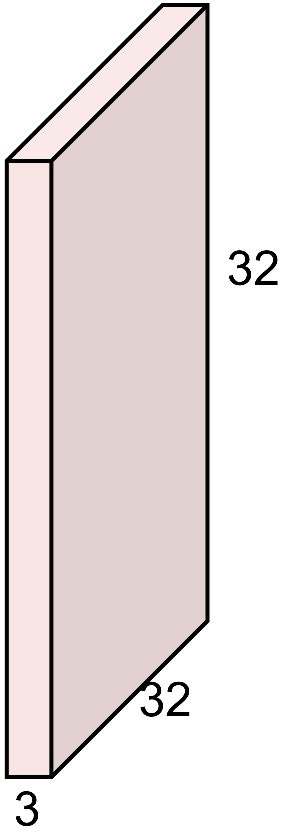
# Convolutional Layer

32x32x3 image

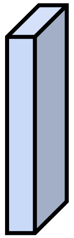


# Convolutional Layer

32x32x3 image

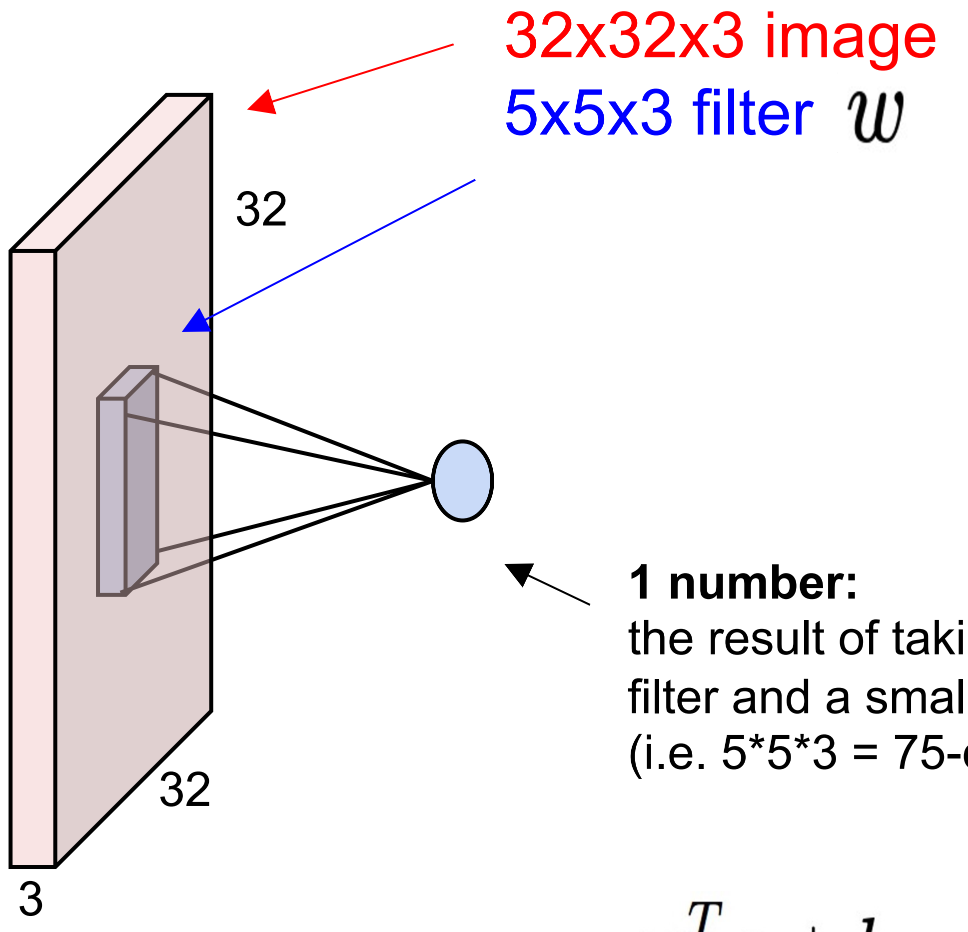



5x5x3 filter



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

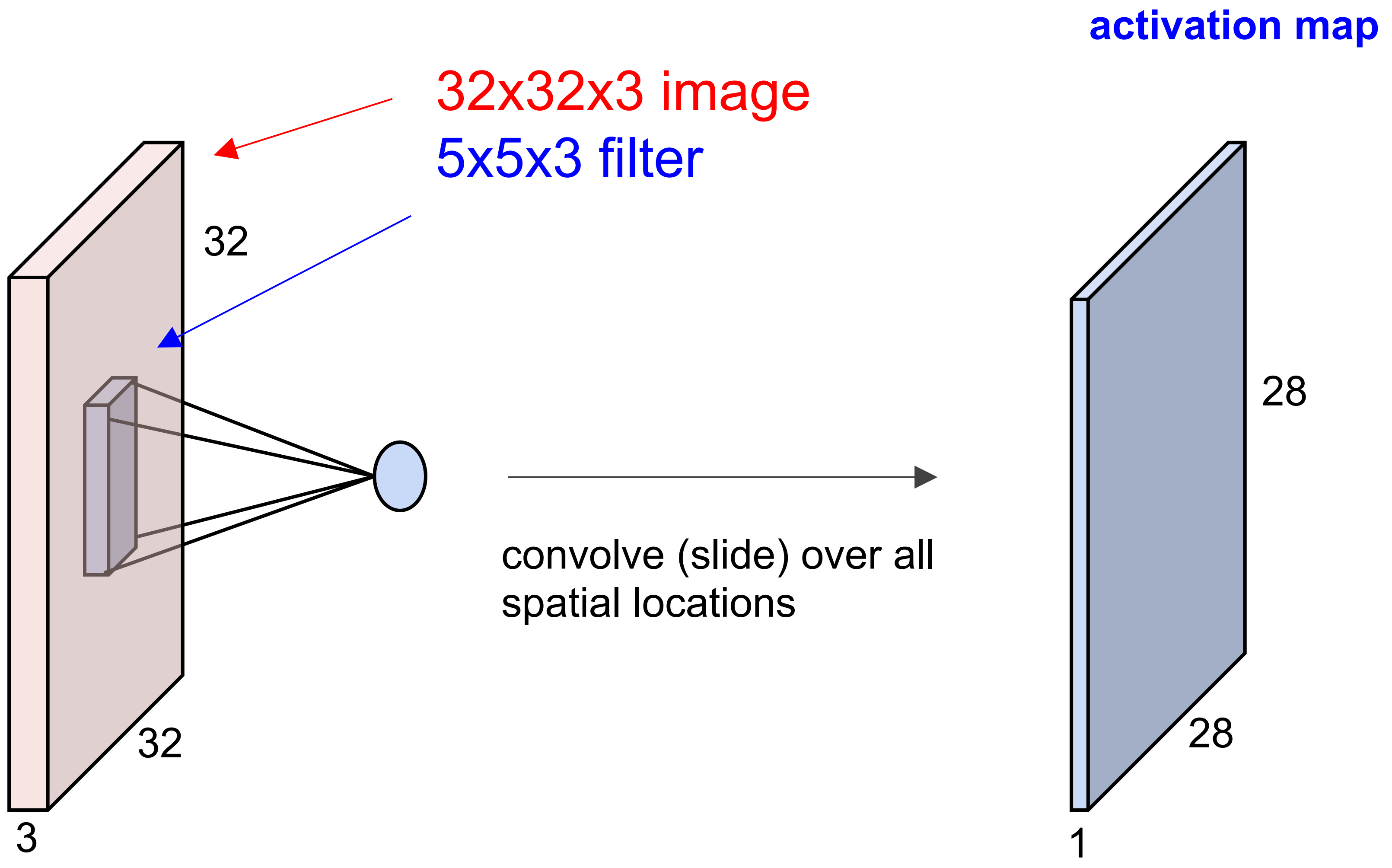
# Convolutional Layer



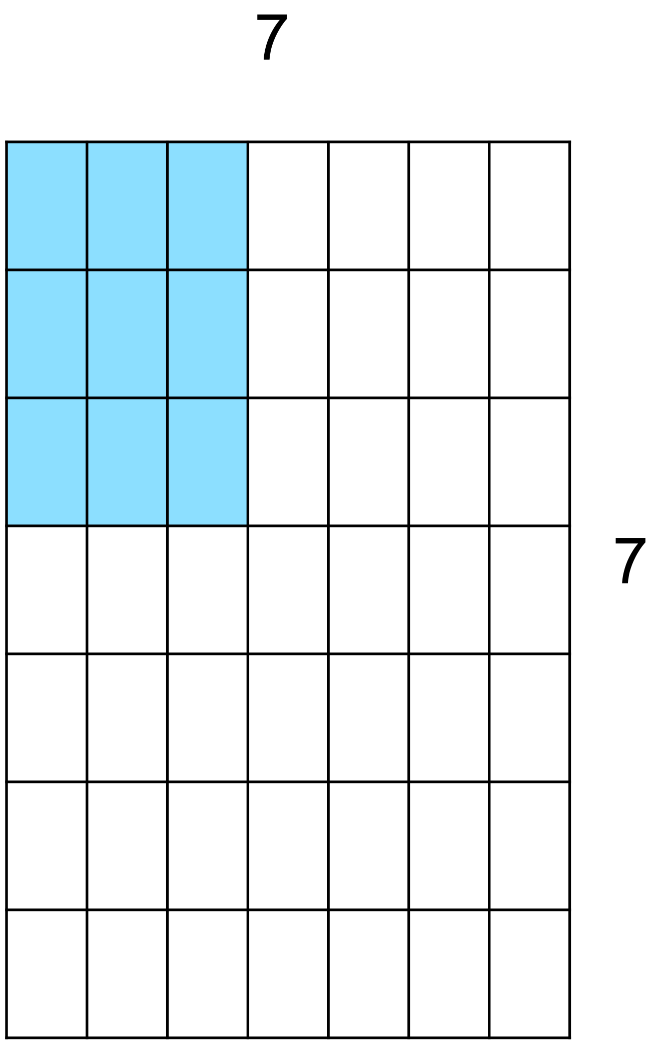

**1 number:**
the result of taking a dot product between the filter and a small 5x5x3 chunk of the image
(i.e. 5*5*3 = 75-dimensional dot product + bias)

$$w^T x + b$$

# Convolutional Layer

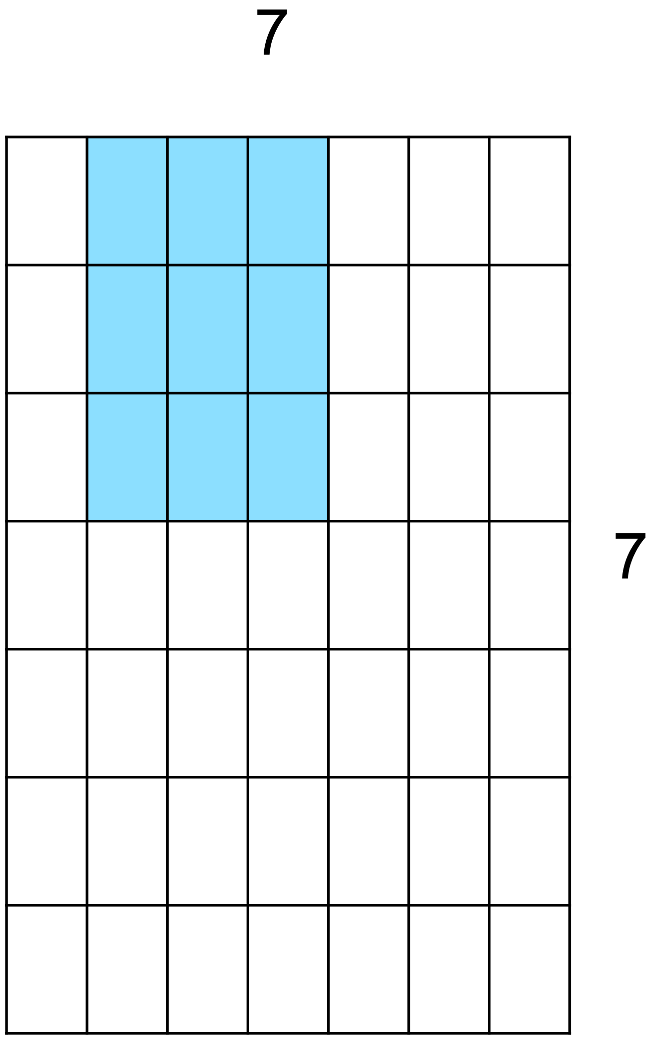


A closer look at spatial dimensions:



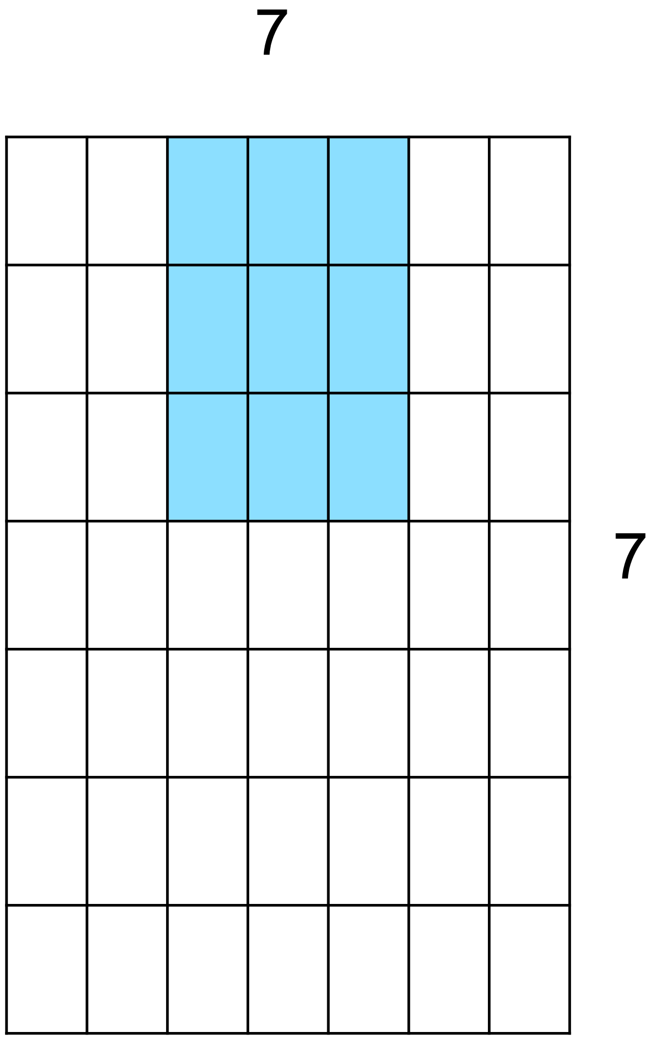

7x7 input (spatially)
assume 3x3 filter, with stride 1

A closer look at spatial dimensions:



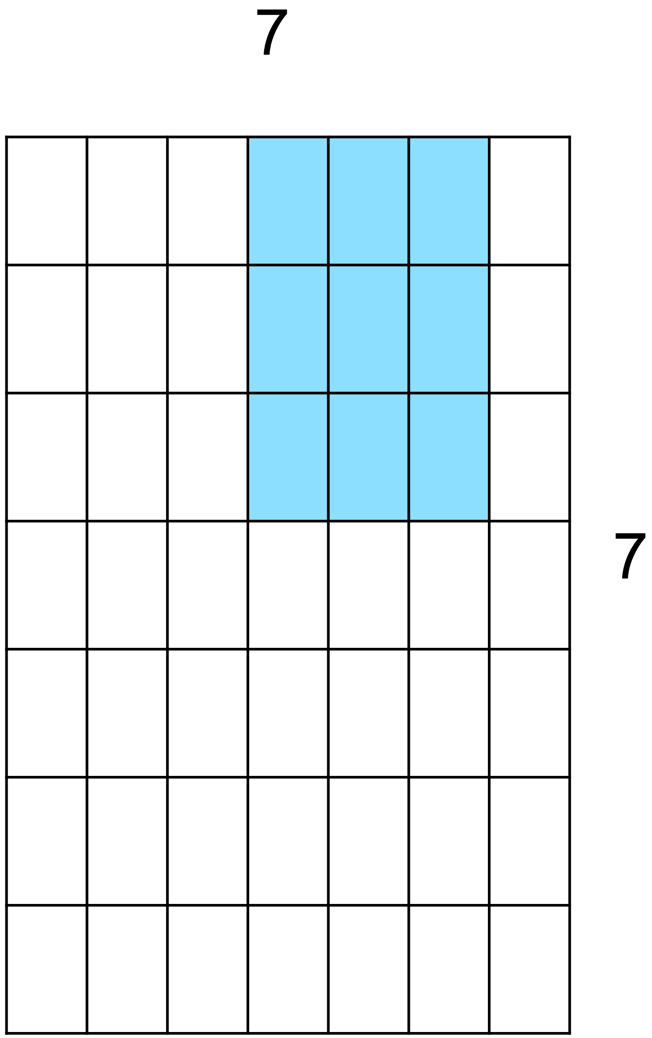

7x7 input (spatially)
assume 3x3 filter

A closer look at spatial dimensions:




7x7 input (spatially)
assume 3x3 filter

A closer look at spatial dimensions:




7x7 input (spatially)
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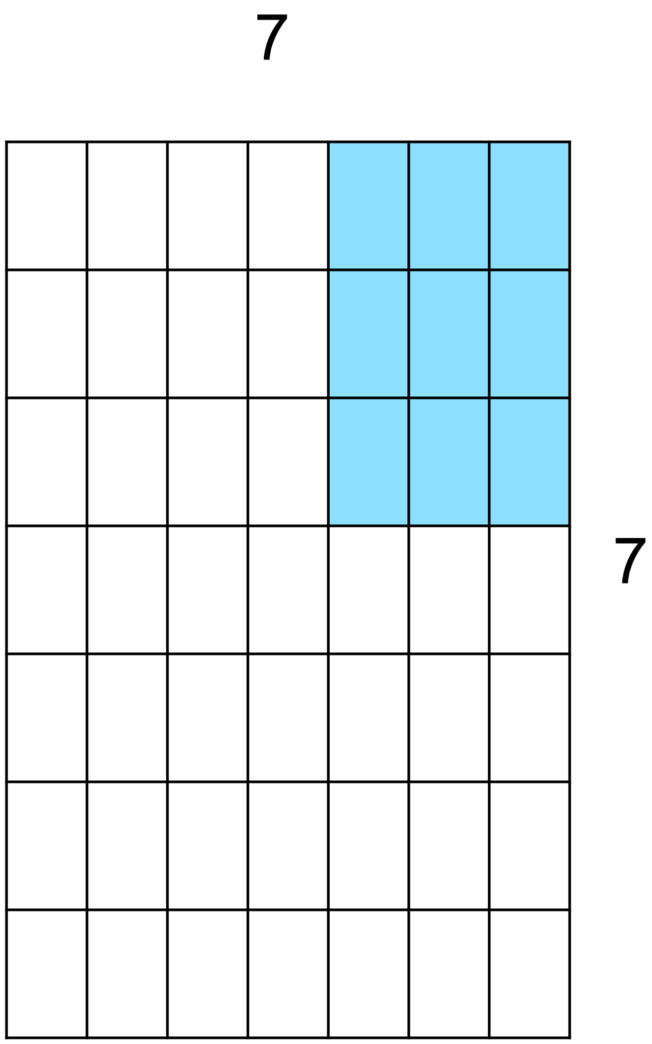


7x7 input (spatially)
assume 3x3 filter

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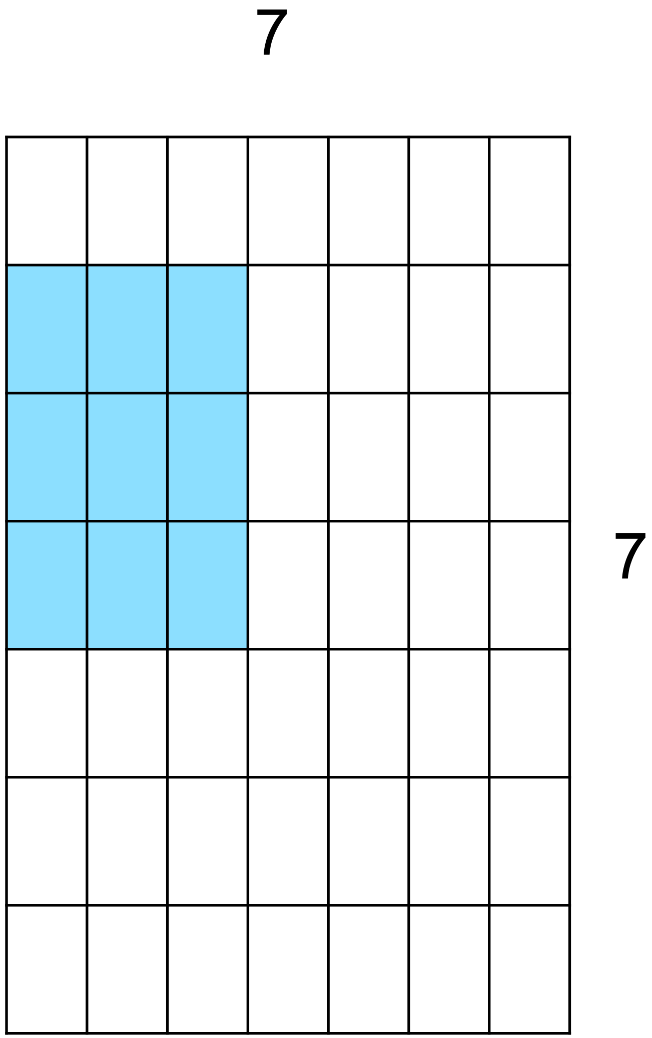
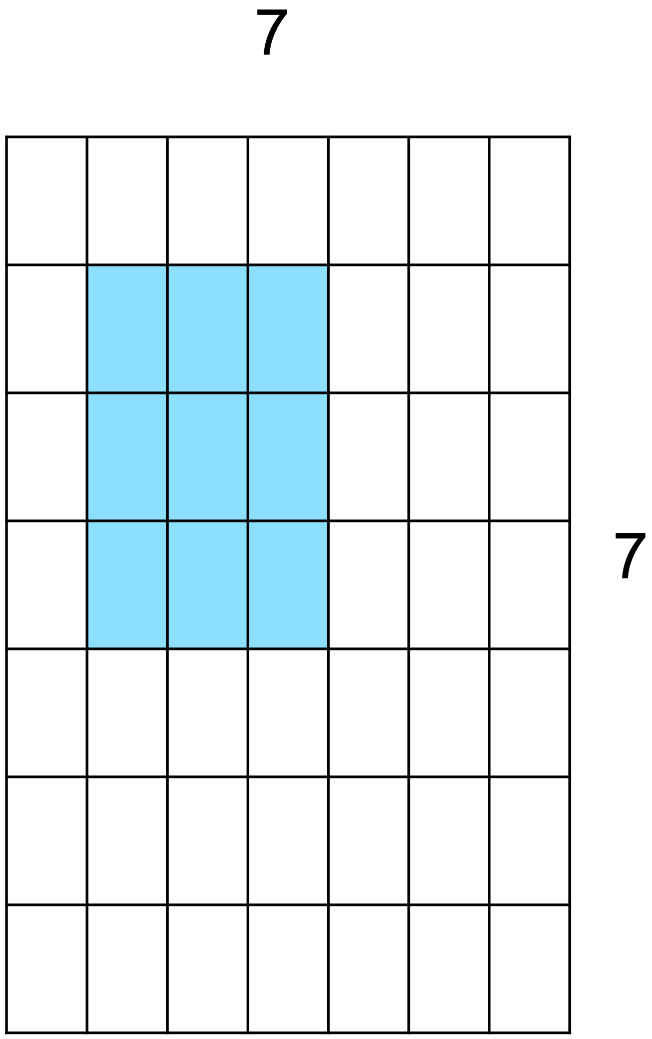


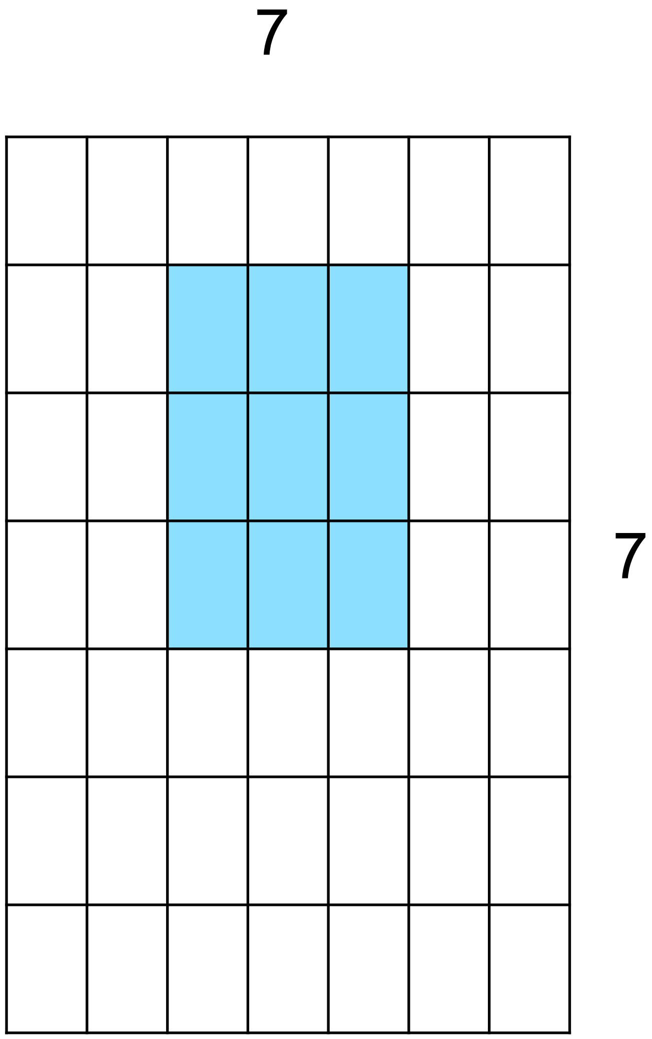

7x7 input (spatially)
assume 3x3 filter

A closer look at spatial dimensions:




7x7 input (spatially)
assume 3x3 filter

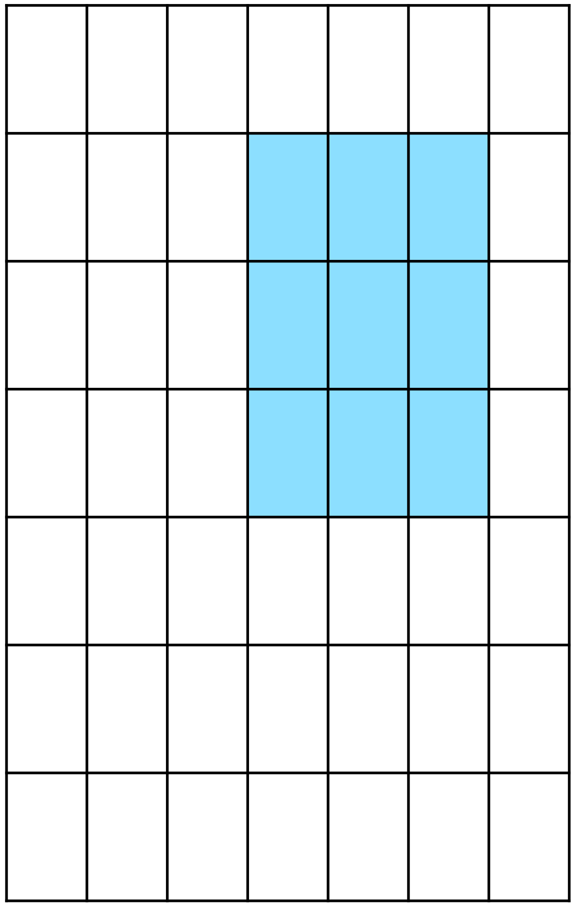
A closer look at spatial dimensions:




7x7 input (spatially)
assume 3x3 filter

A closer look at spatial dimensions:

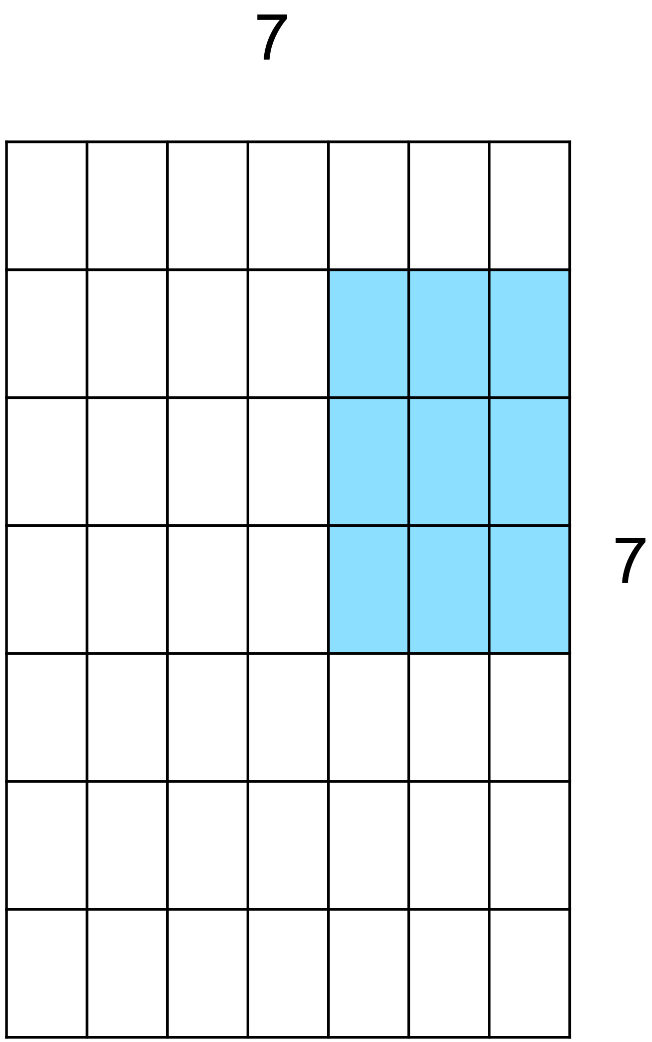
7



7

7x7 input (spatially)
assume 3x3 filter

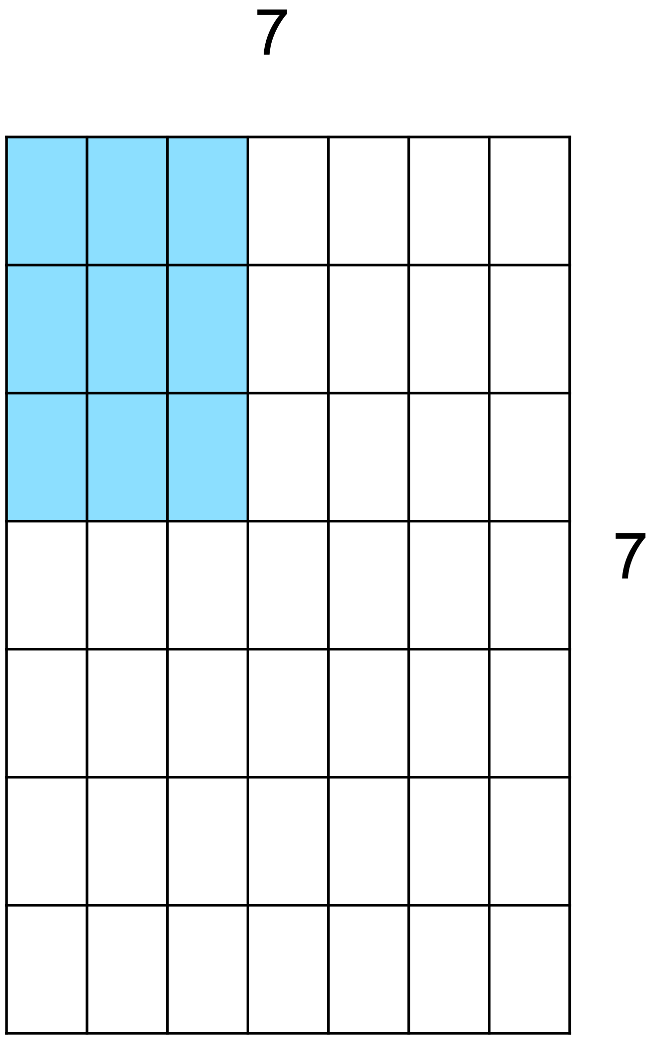
A closer look at spatial dimensions:




7x7 input (spatially)
assume 3x3 filter

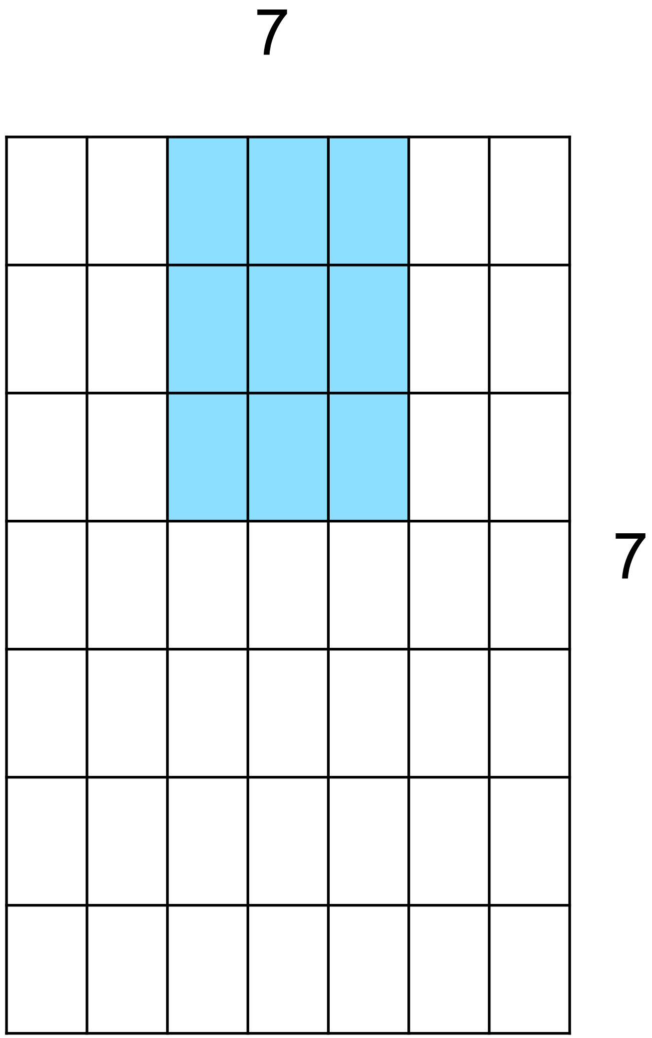
**=> 5x5 output**

A closer look at spatial dimensions:



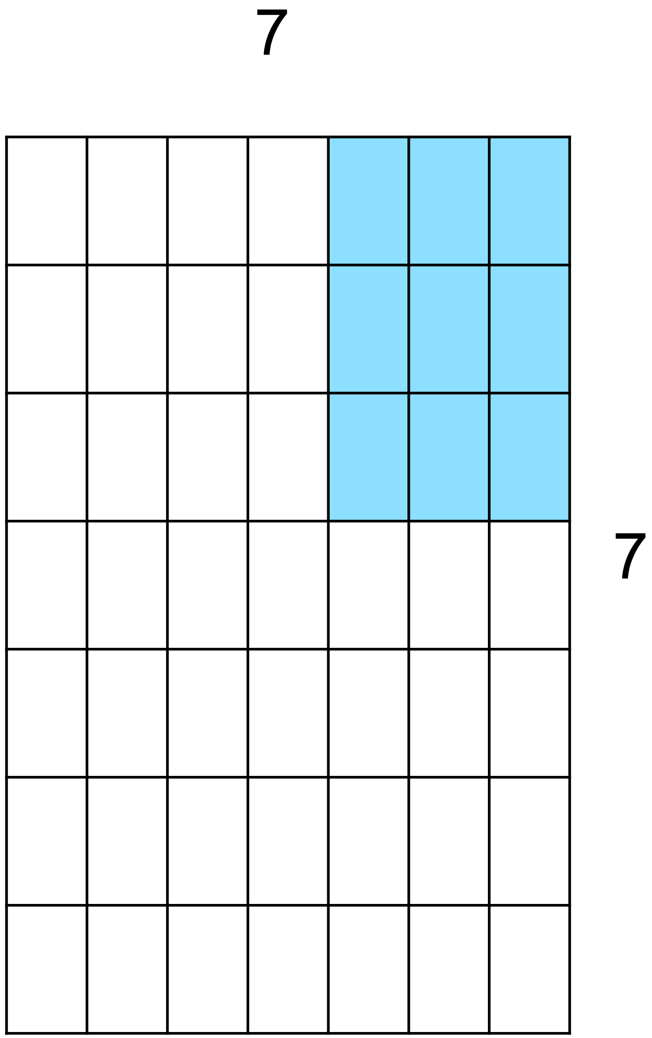

7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**

A closer look at spatial dimensions:




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

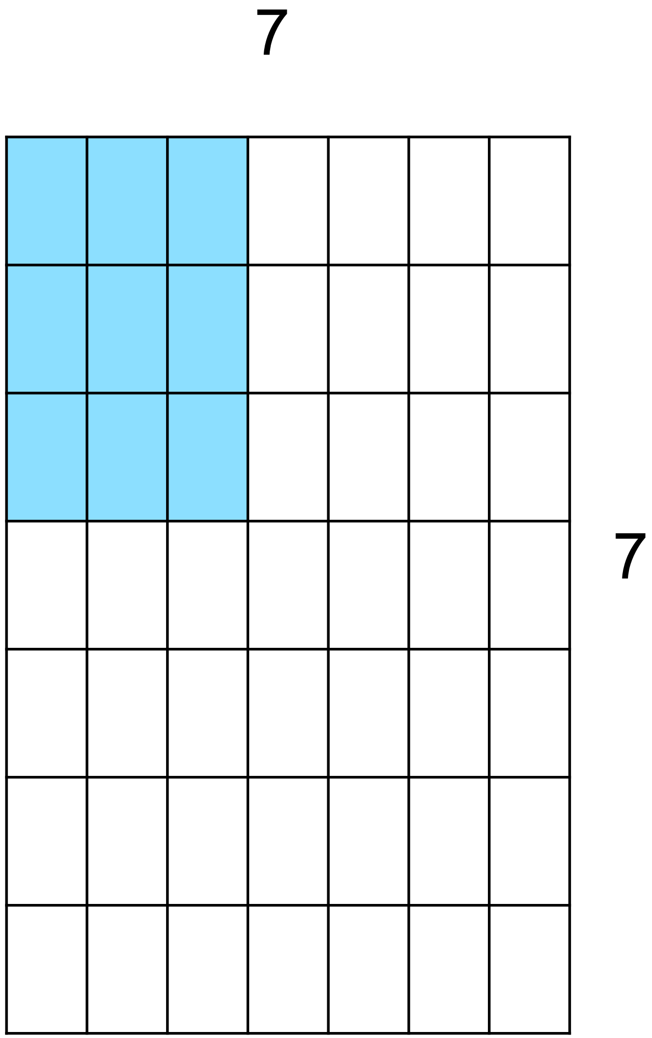
A closer look at spatial dimensions:




7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**
**=> 3x3 output!**

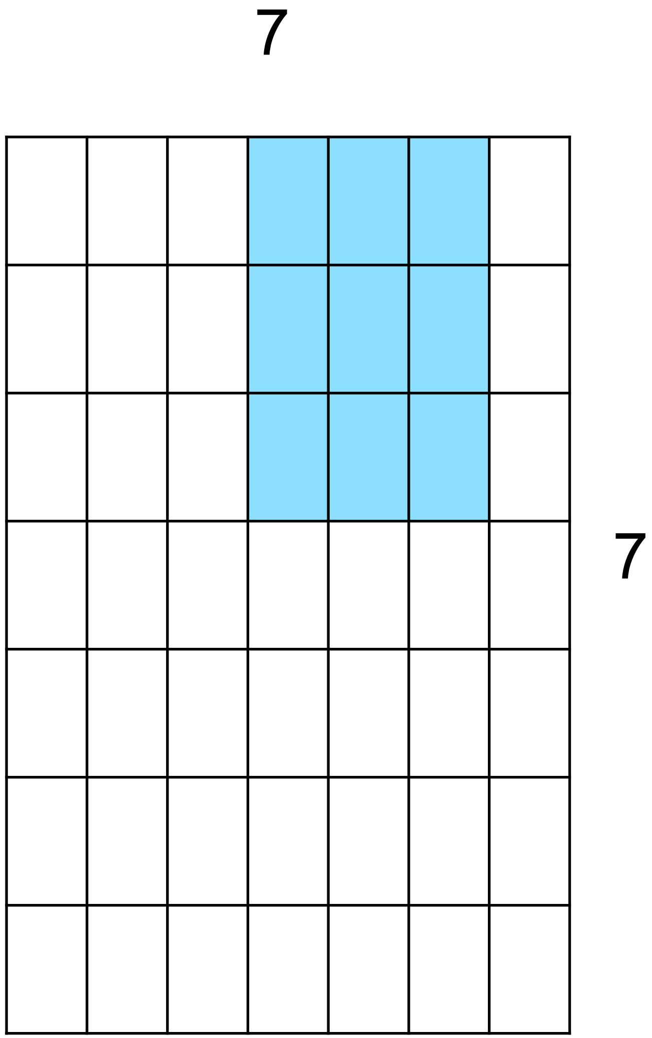
Output size:
**(N - F) / stride + 1**

A closer look at spatial dimensions:



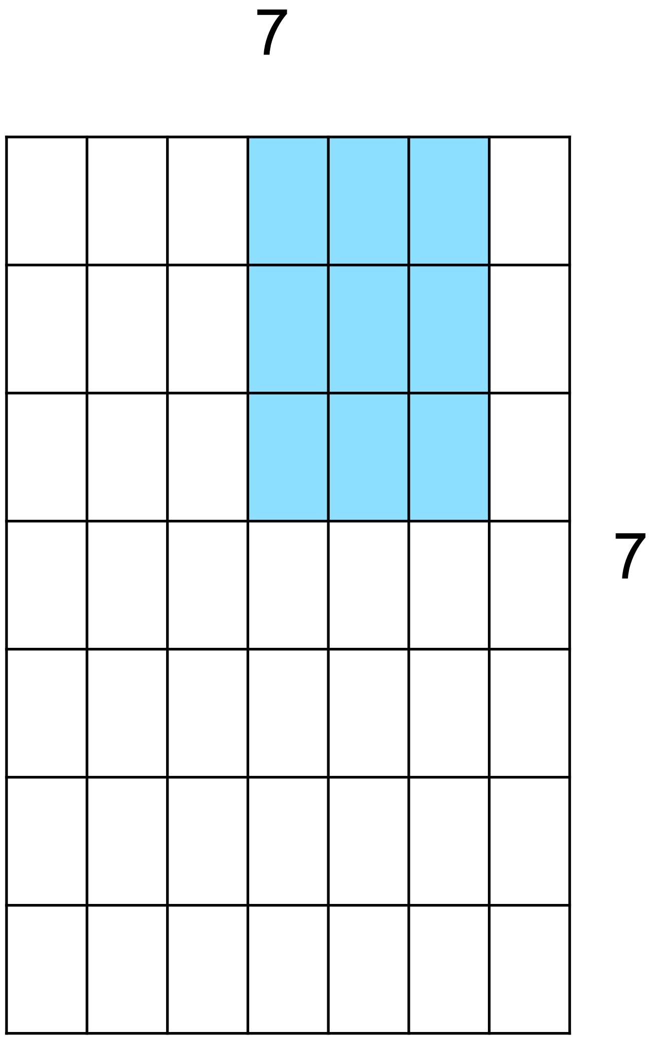
7x7 input (spatially)
assume 3x3 filter
applied **with stride 3?**

A closer look at spatial dimensions:



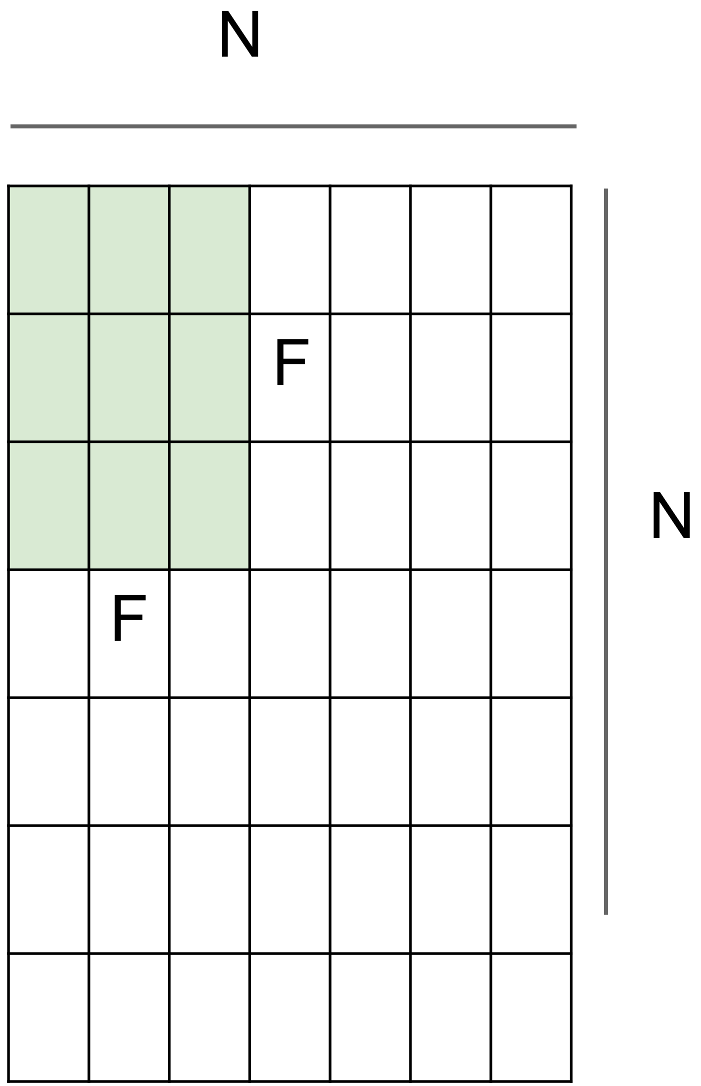

7x7 input (spatially)
assume 3x3 filter
applied **with stride 3?**

A closer look at spatial dimensions:




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

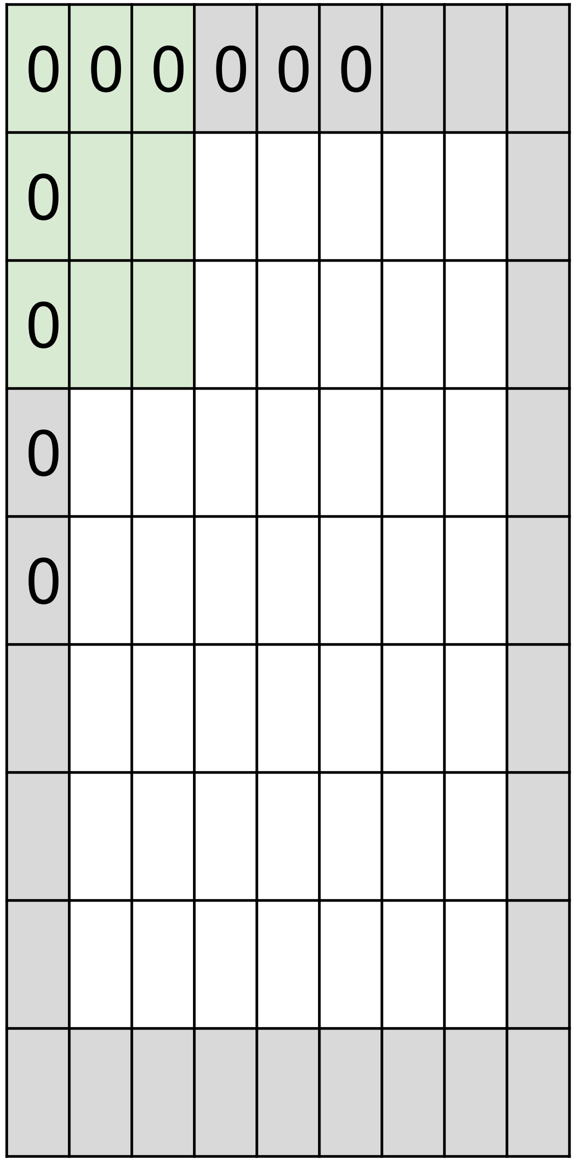
**doesn't fit!**
cannot apply 3x3 filter on
7x7 input with stride 3.




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

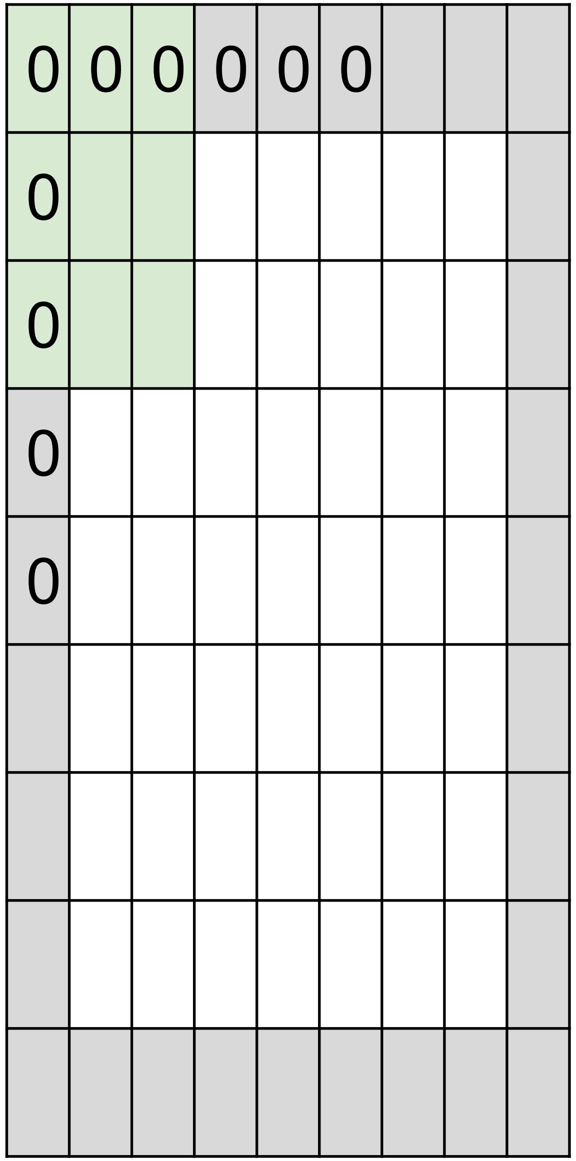
# In practice: Common to zero pad the border




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

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

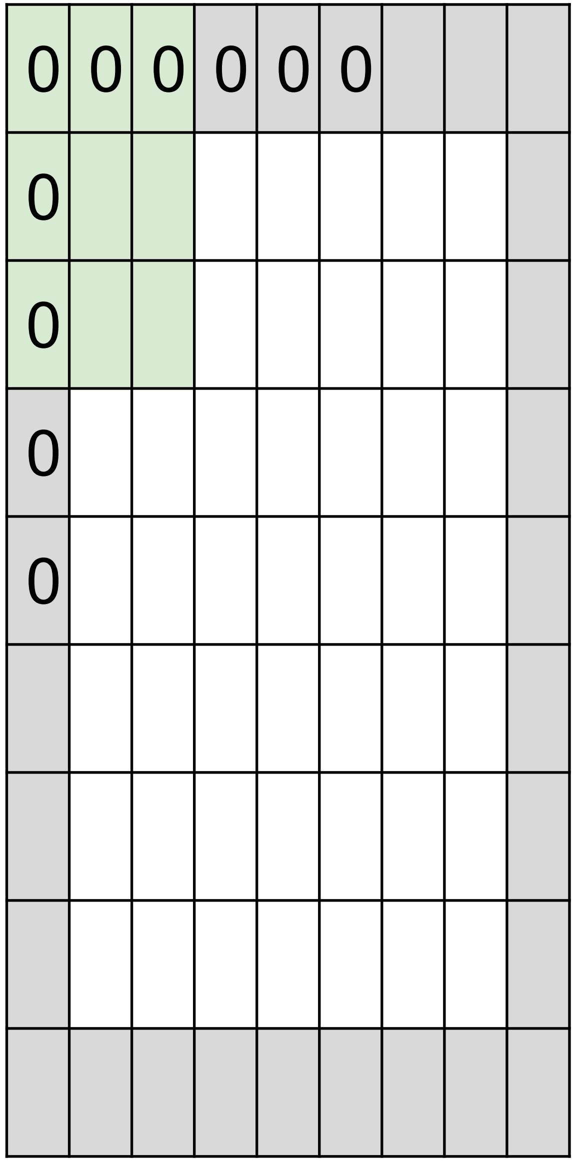
# In practice: Common to zero pad the border




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

**7x7 output!**

# In practice: Common to zero pad the border

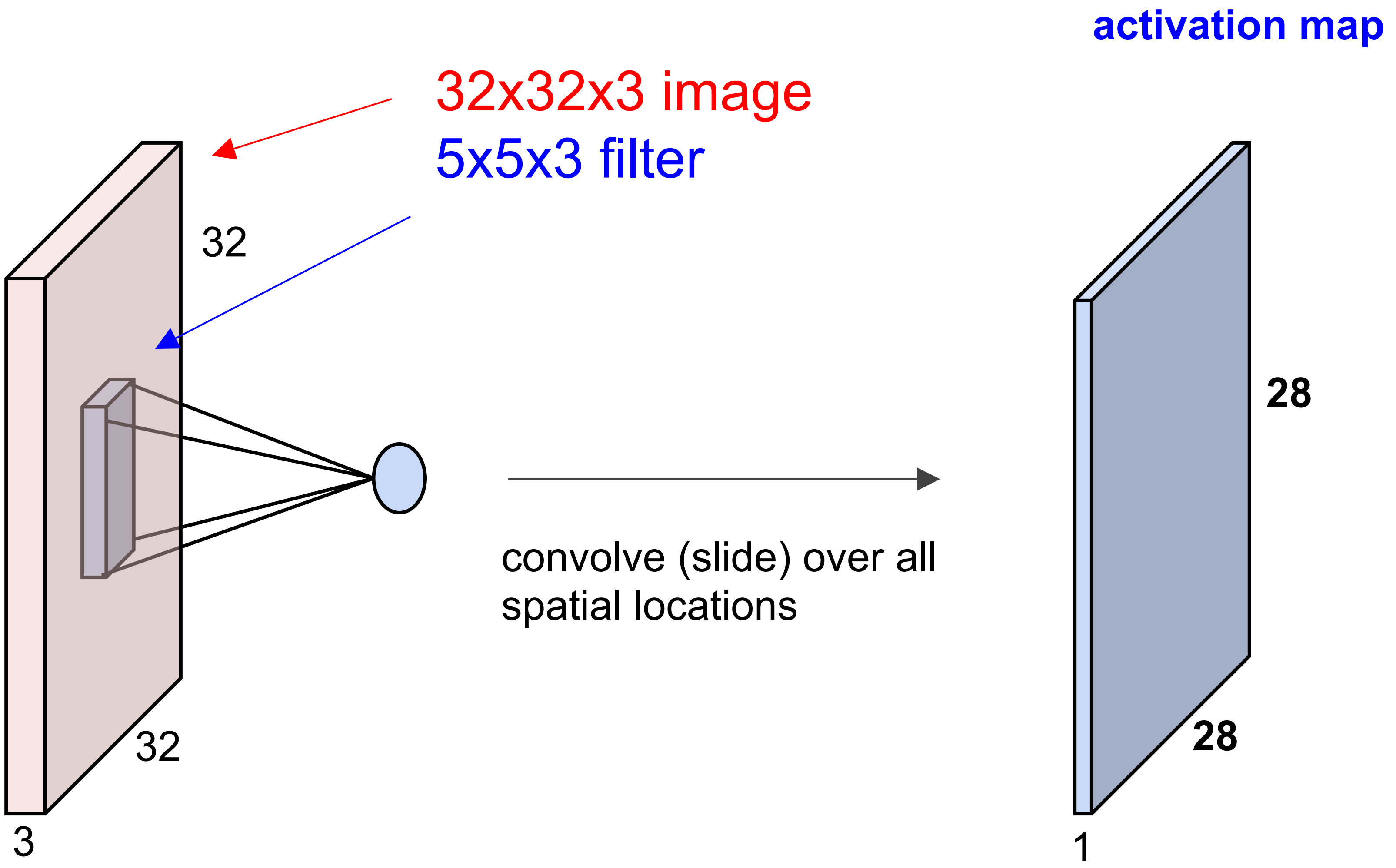



e.g. input 7x7
**3x3** filter, applied with **stride 1**
**pad with 1 pixel** border => what is the output?

**7x7 output!**
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)

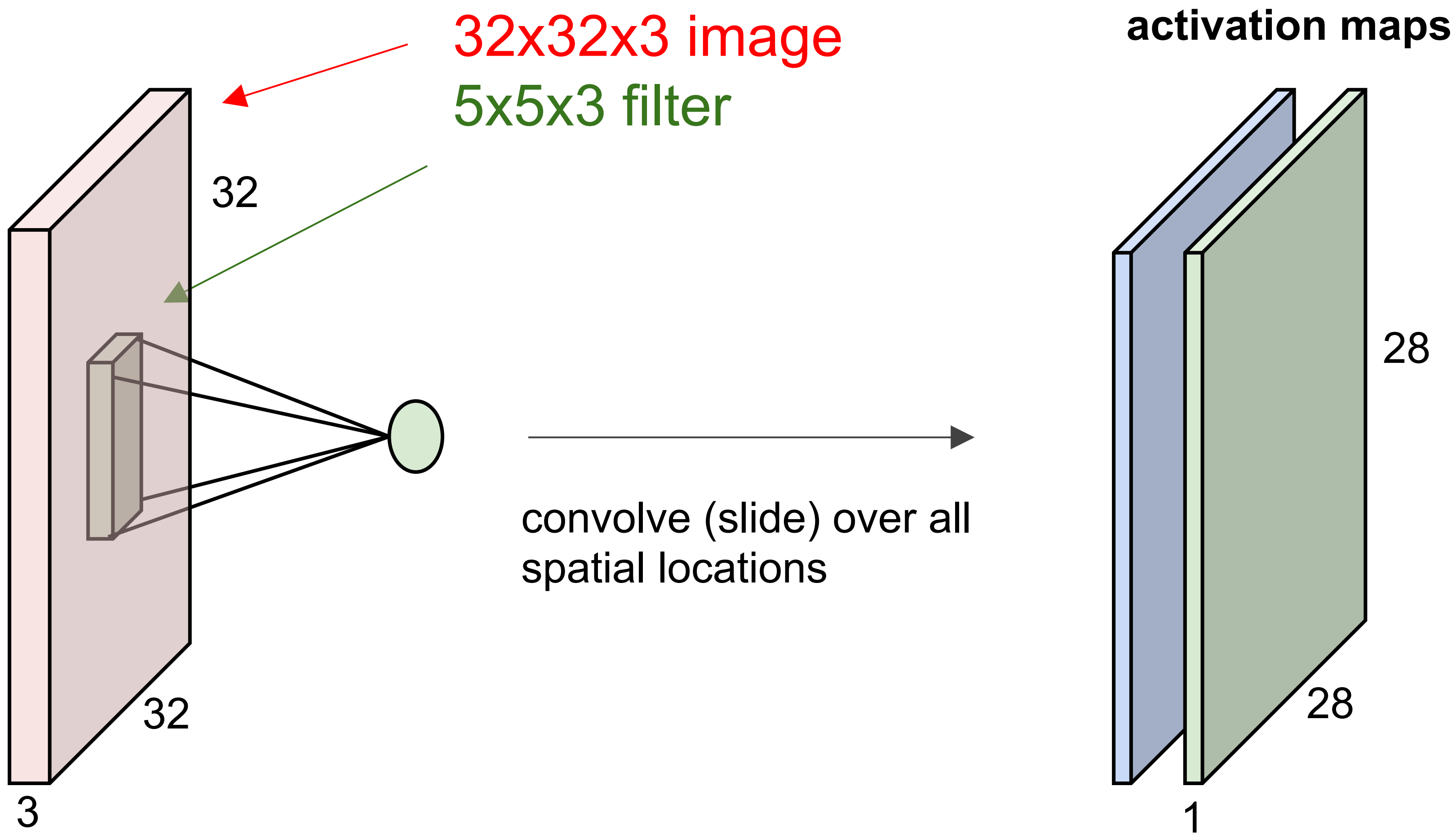
e.g. F = 3 => zero pad with 1
F = 5 => zero pad with 2
F = 7 => zero pad with 3

A closer look at spatial dimensions:

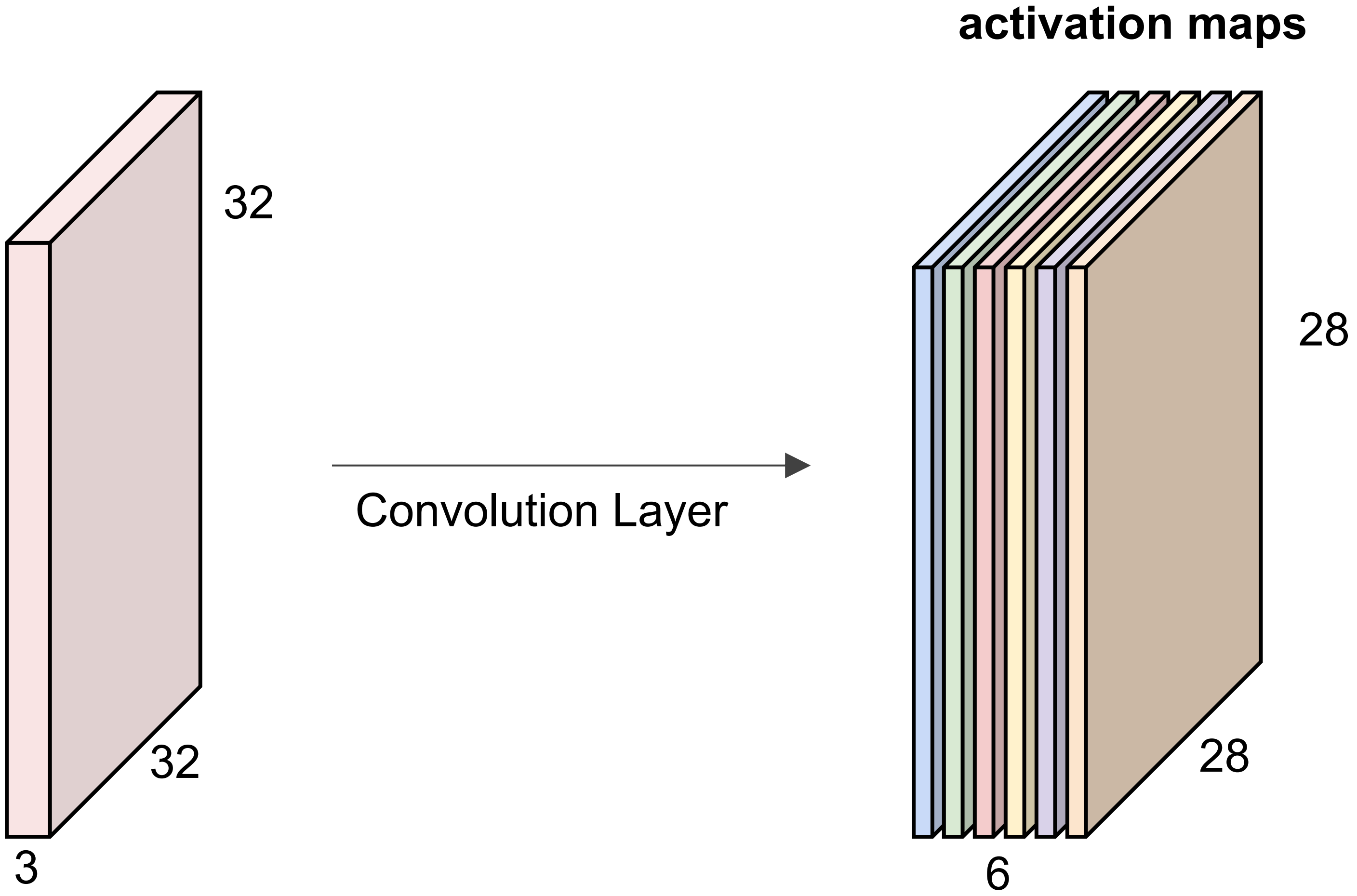


# Convolutional Layer

consider a second, green filter

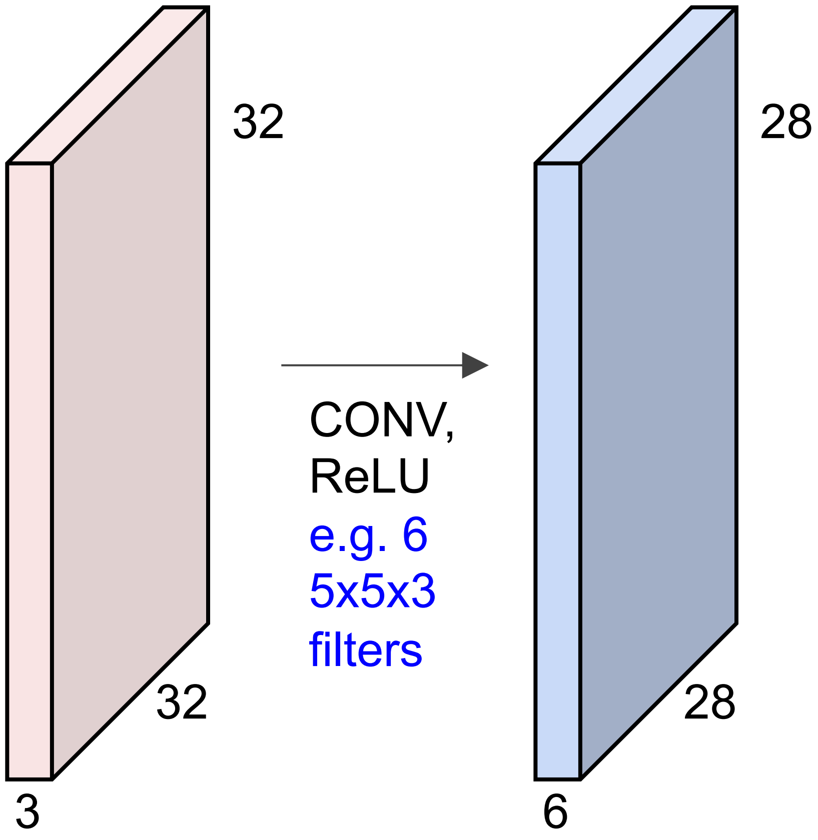


For example, if we had 6 5x5 filters, we'll get 6 separate activation maps:

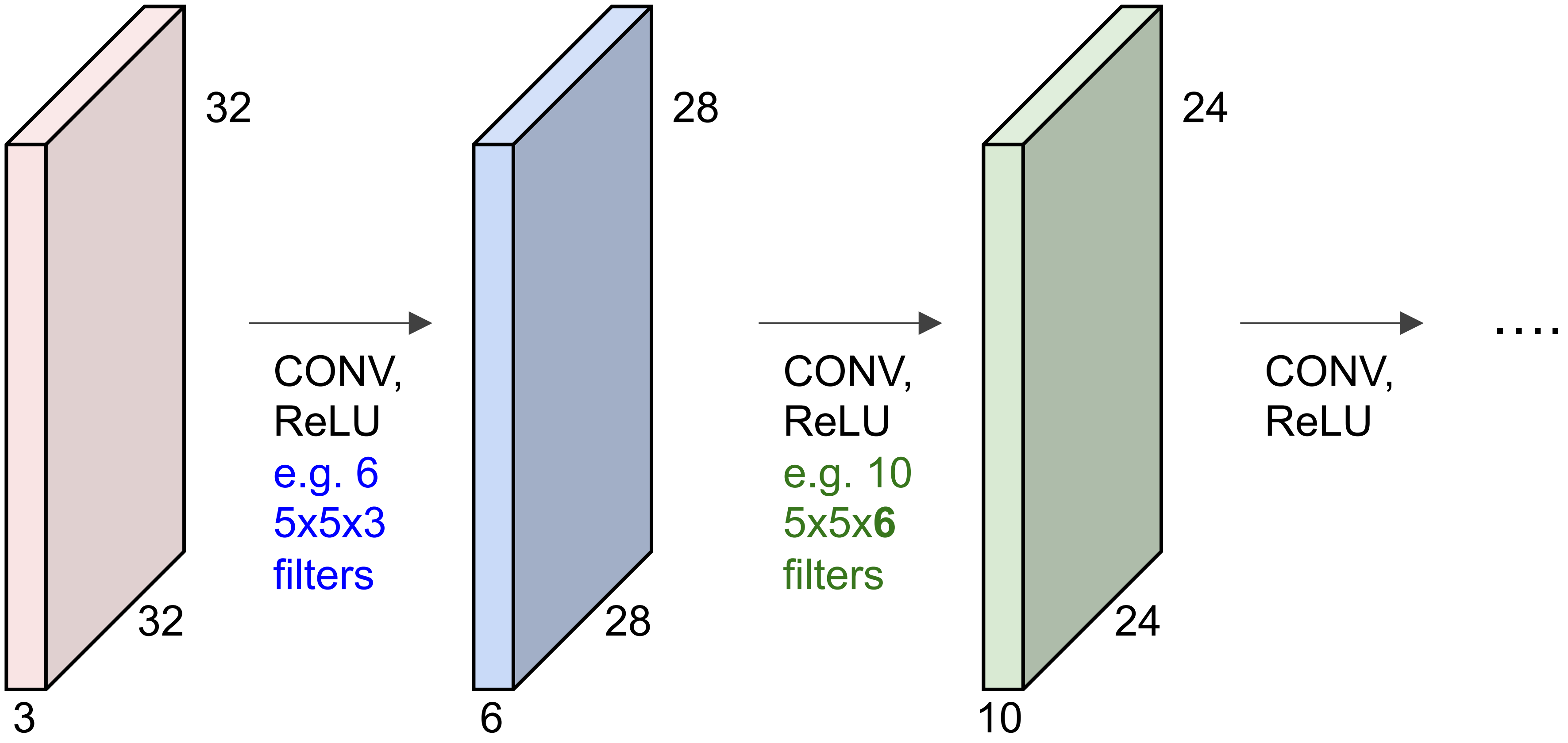



We stack these up to get a "new image" of size 28x28x6!

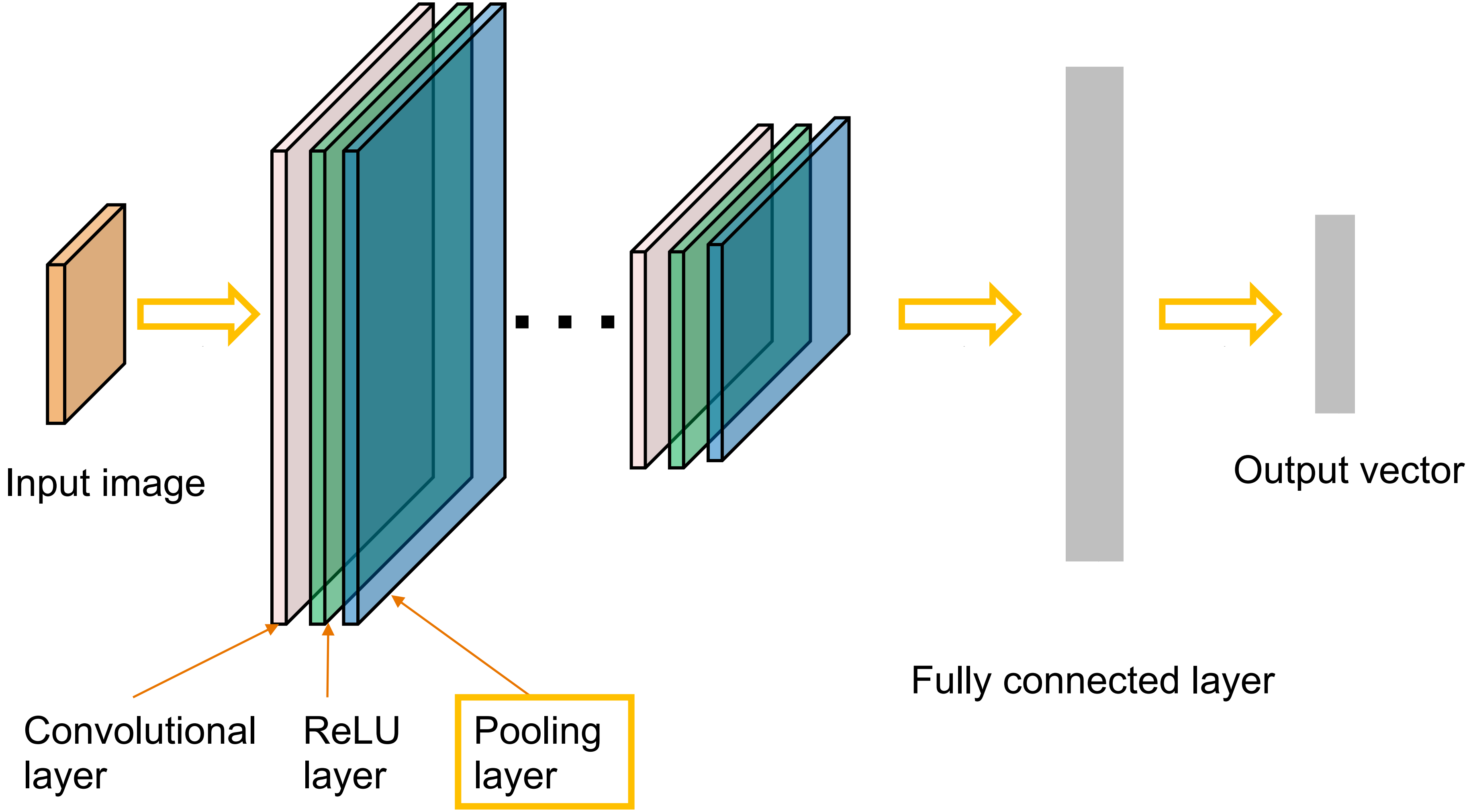
**Preview:** ConvNet is a sequence of Convolution Layers, interspersed with activation functions



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

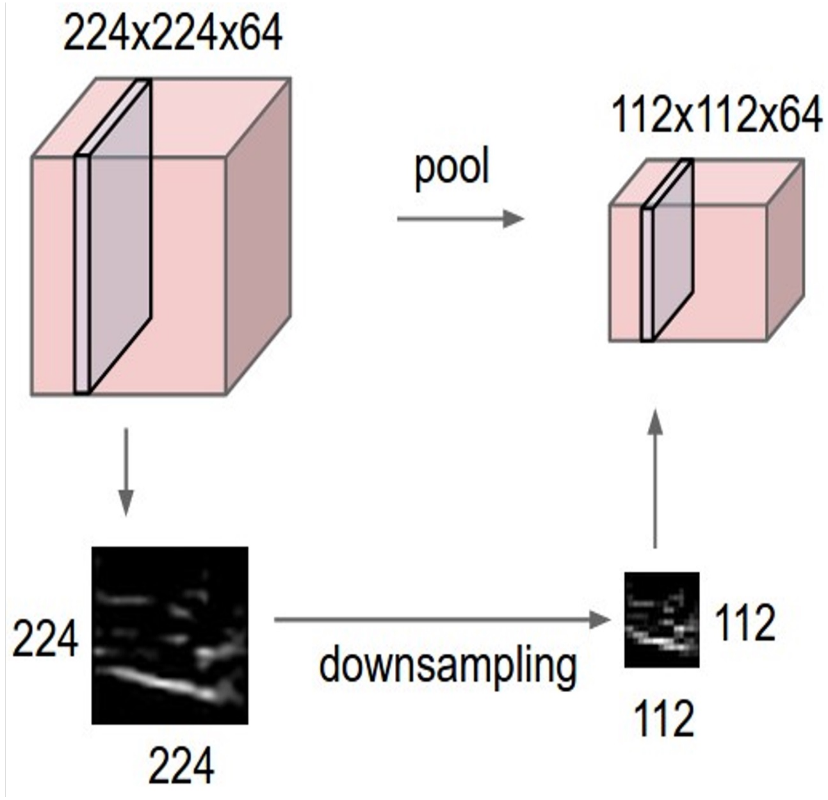


# Convolutional Neural Networks

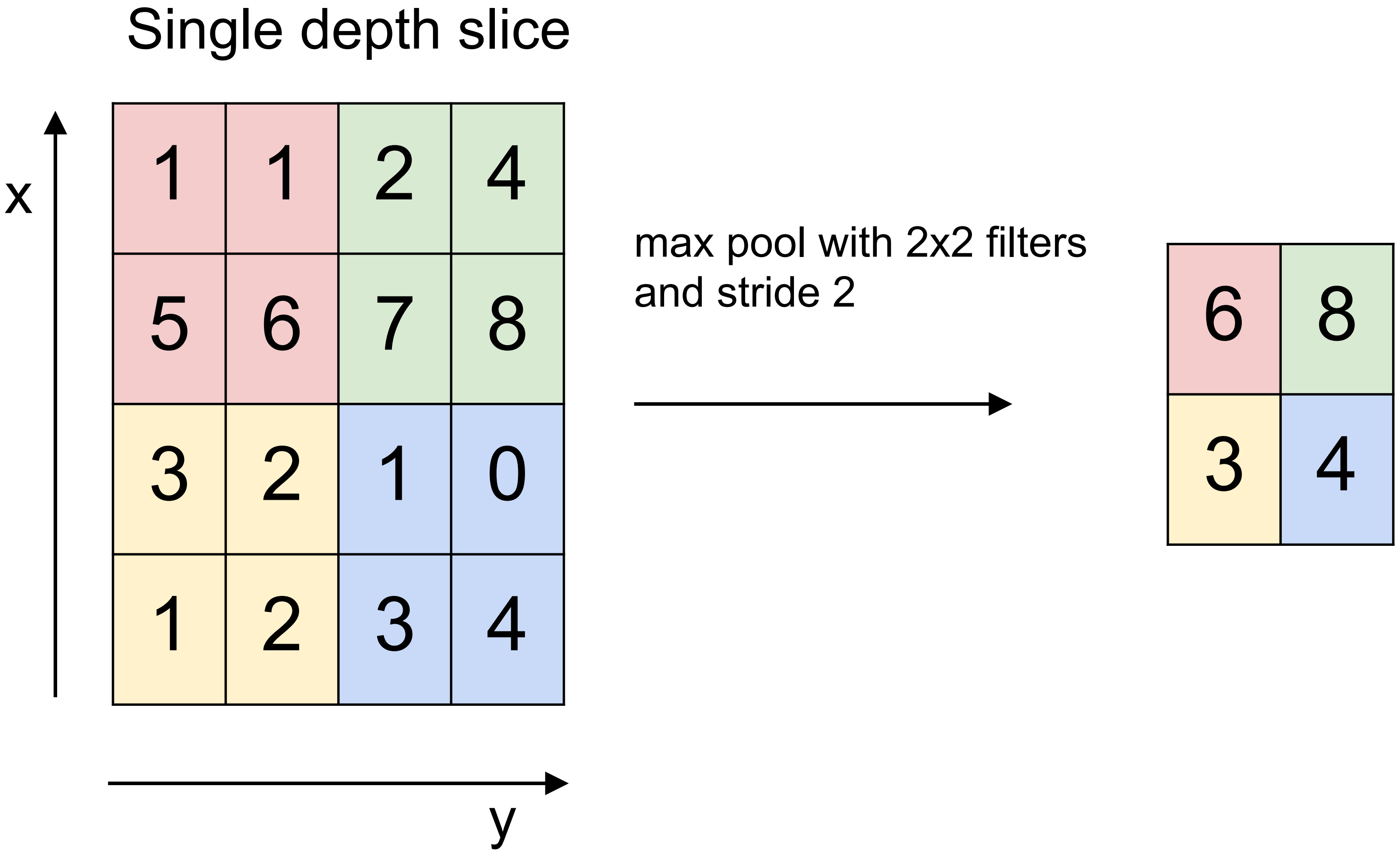


# Pooling layer

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

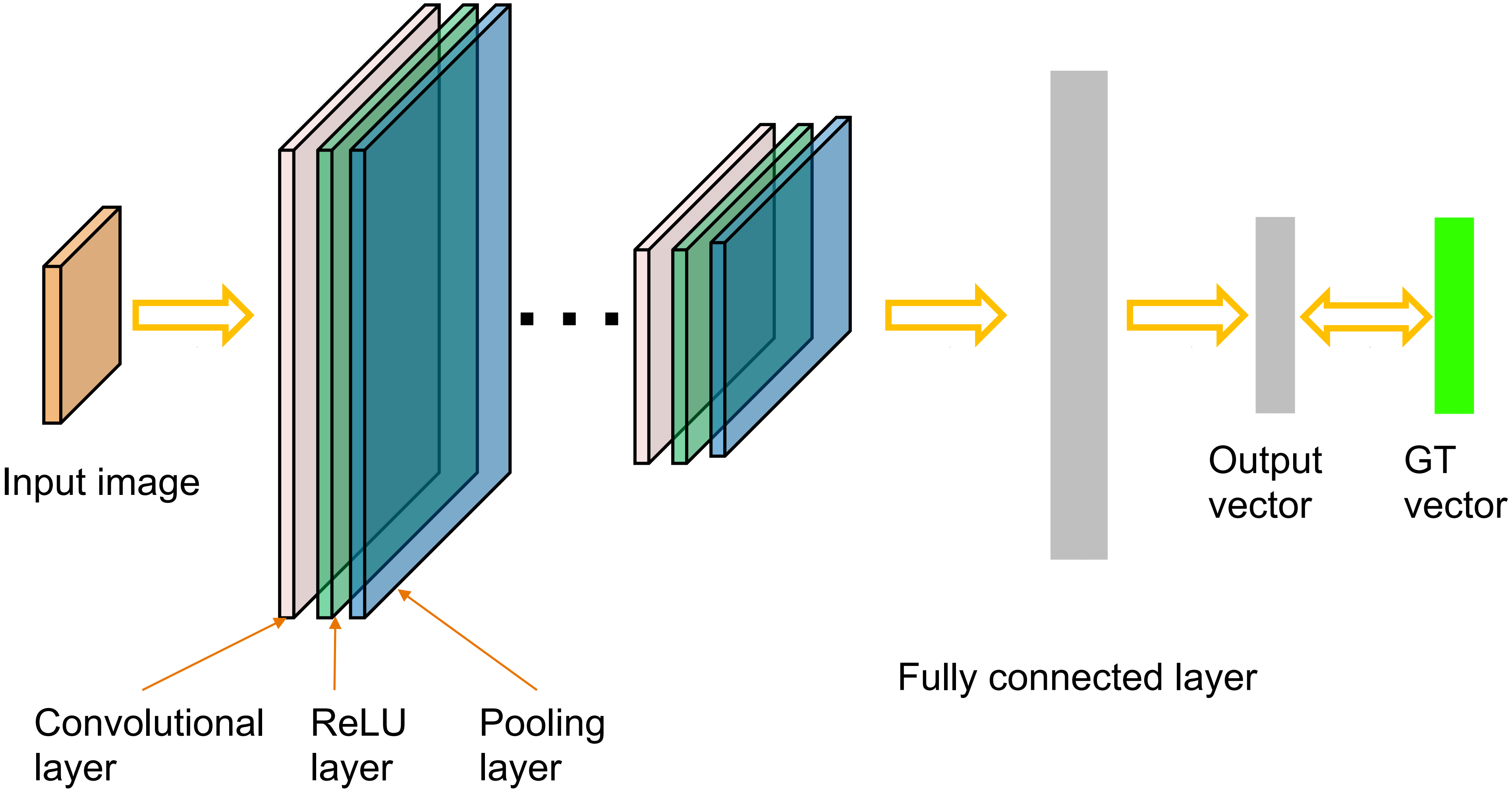


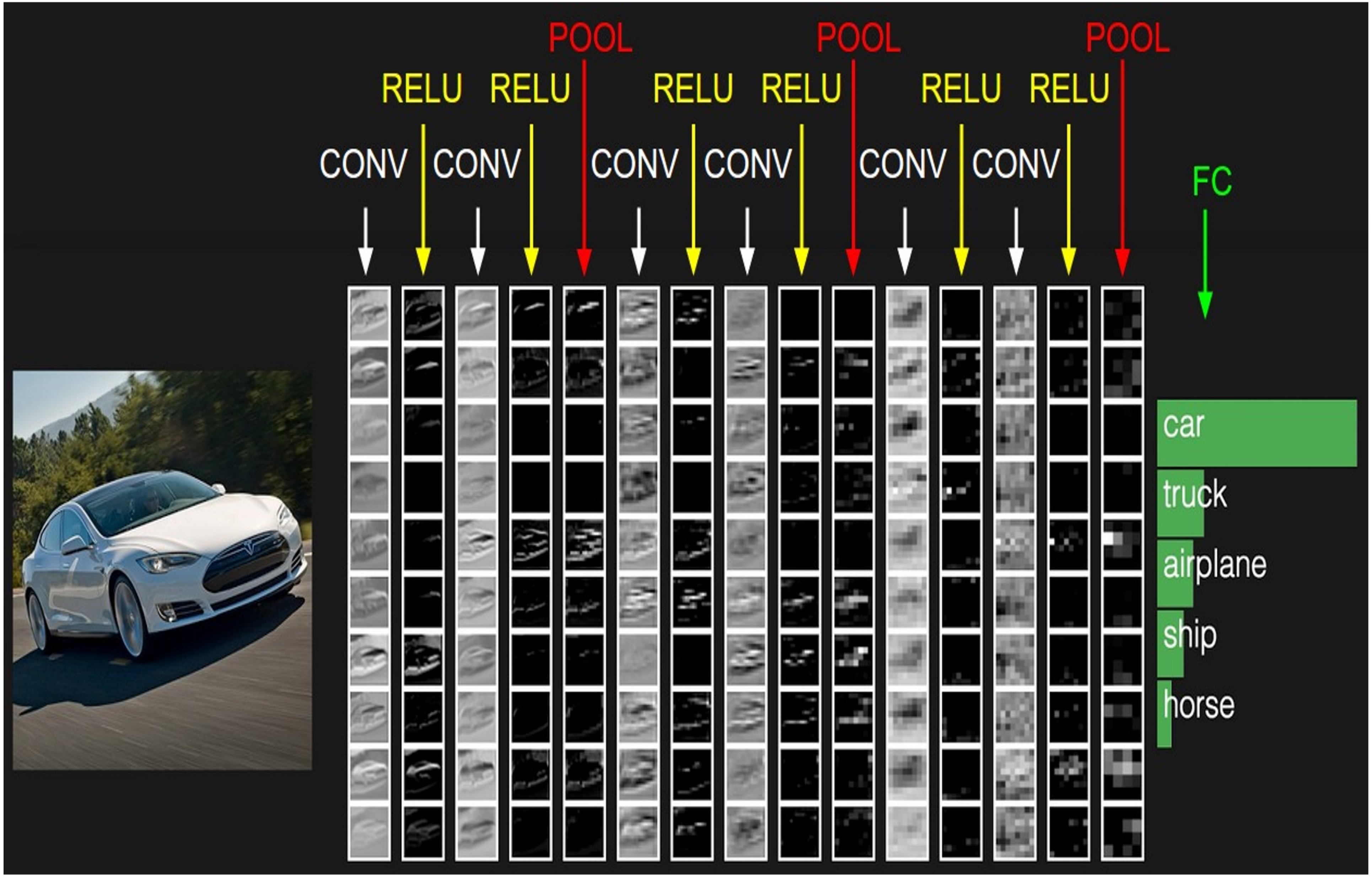
# MAX POOLING



Single depth slice
x
y
1 1 2 4
5 6 7 8
3 2 1 0
1 2 3 4
max pool with 2x2 filters
and stride 2
6 8
3 4

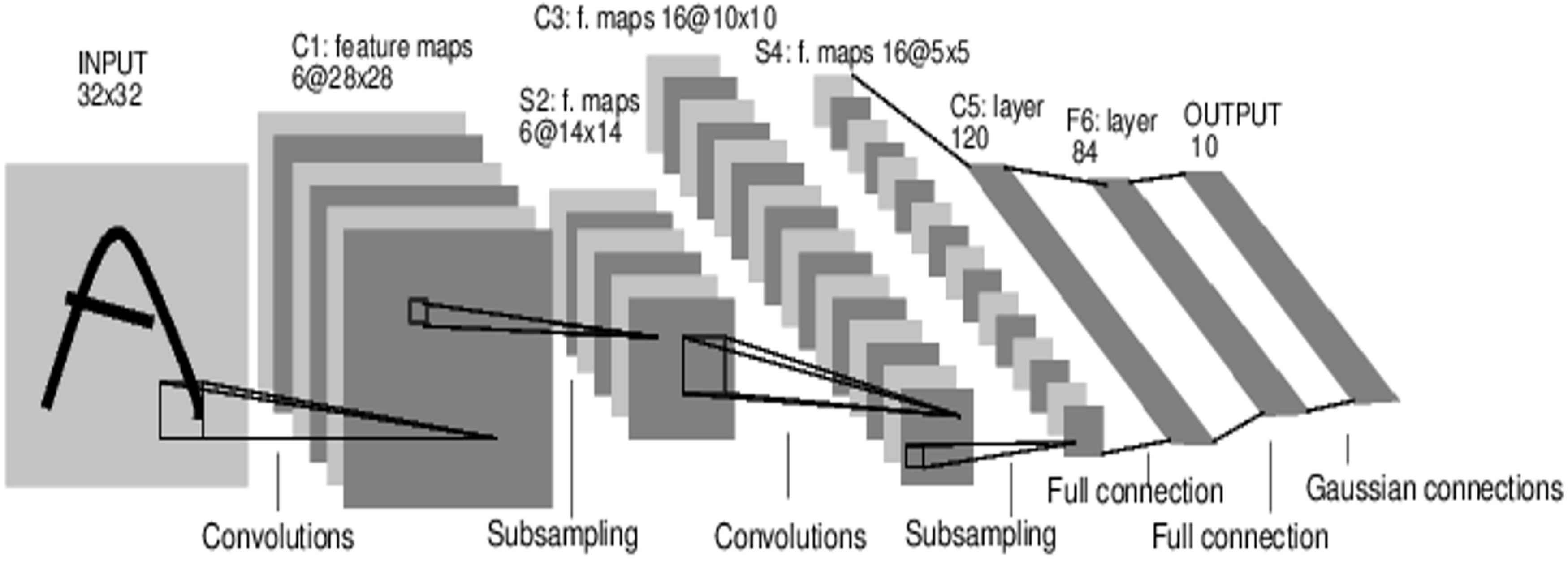
# Training: back-propotate errors




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

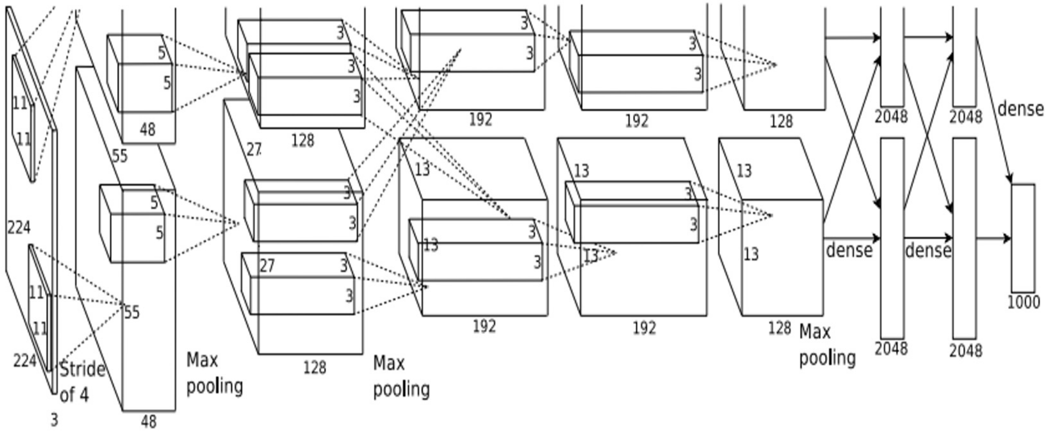
[LeCun et al., 1998]




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

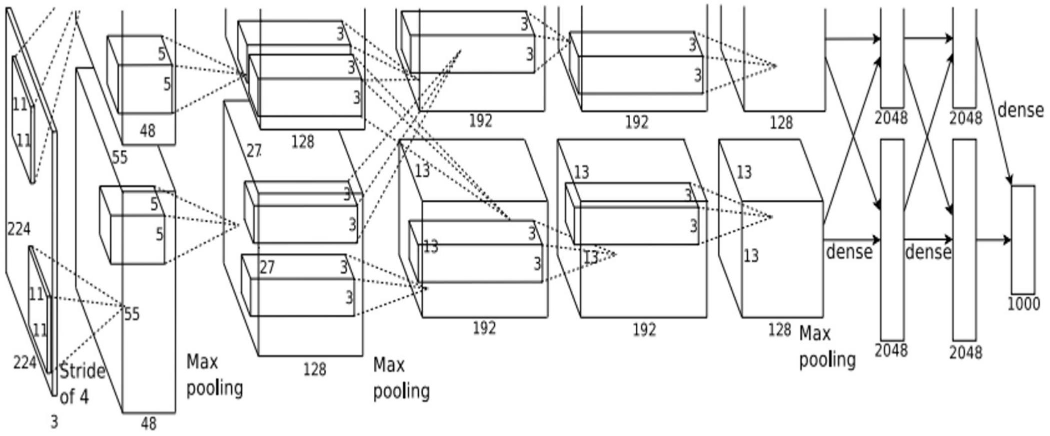
**First layer** (CONV1): 96 11x11 filters applied at stride 4

=>

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

# Case Study: AlexNet

*[Krizhevsky et al. 2012]*



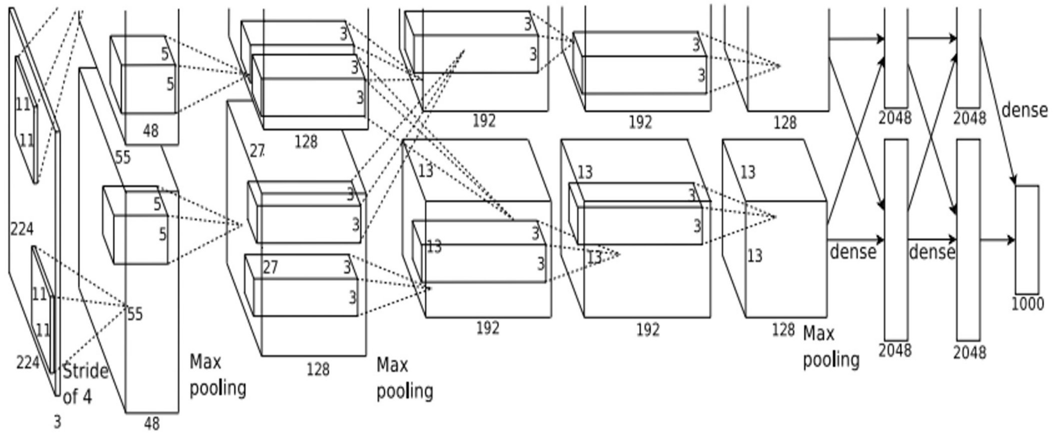

Input: 227x227x3 images

**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]*

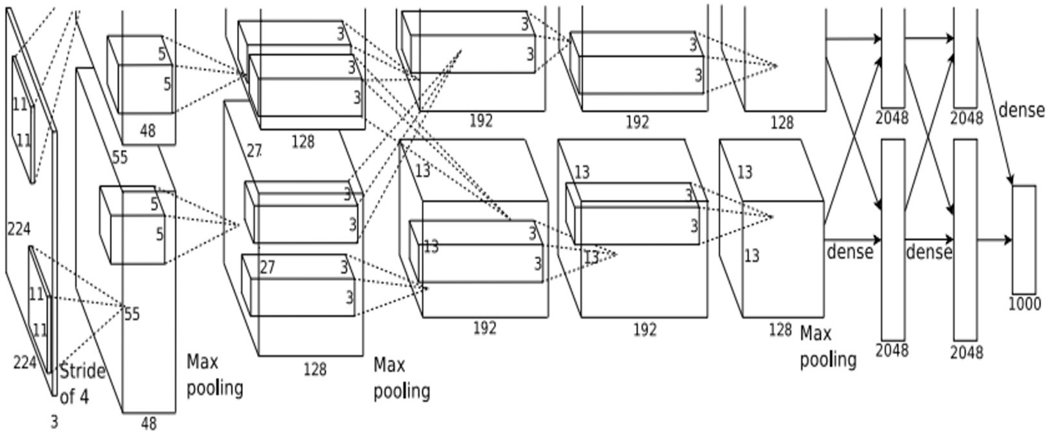



Input: 227x227x3 images

**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]*



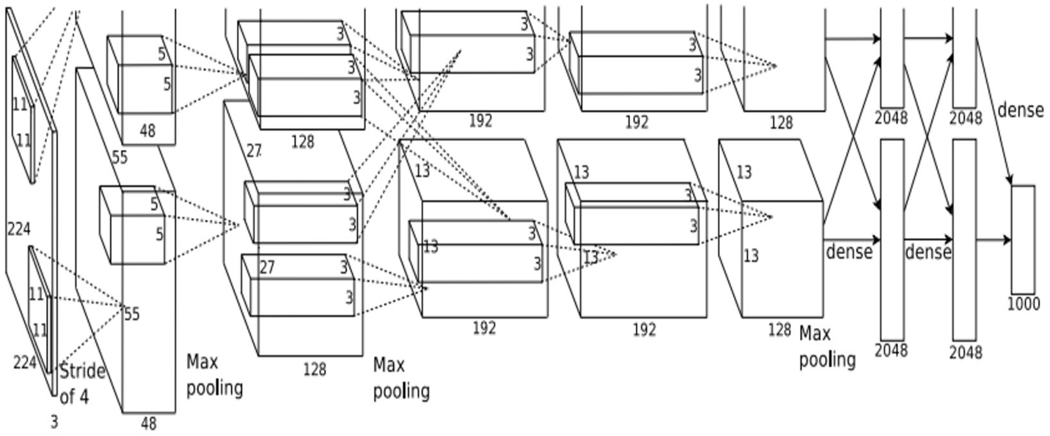

Input: 227x227x3 images
After CONV1: 55x55x96

**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]*



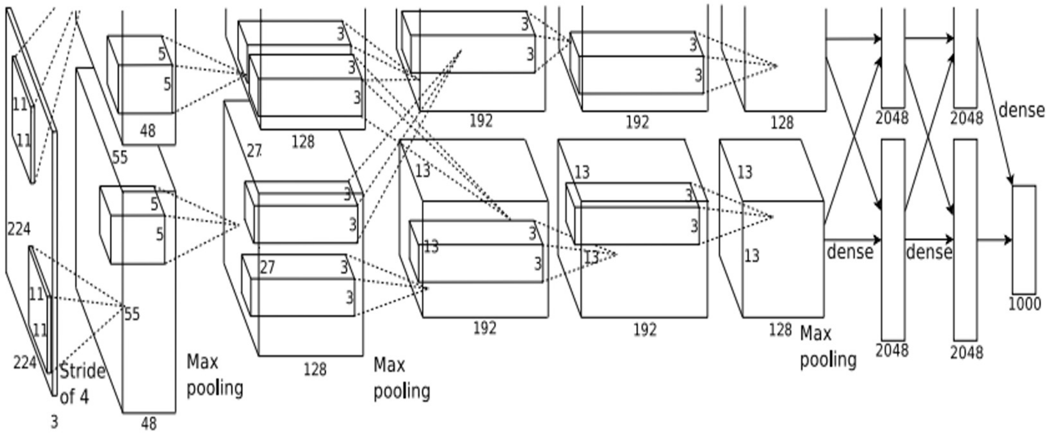

Input: 227x227x3 images
After CONV1: 55x55x96

**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]*

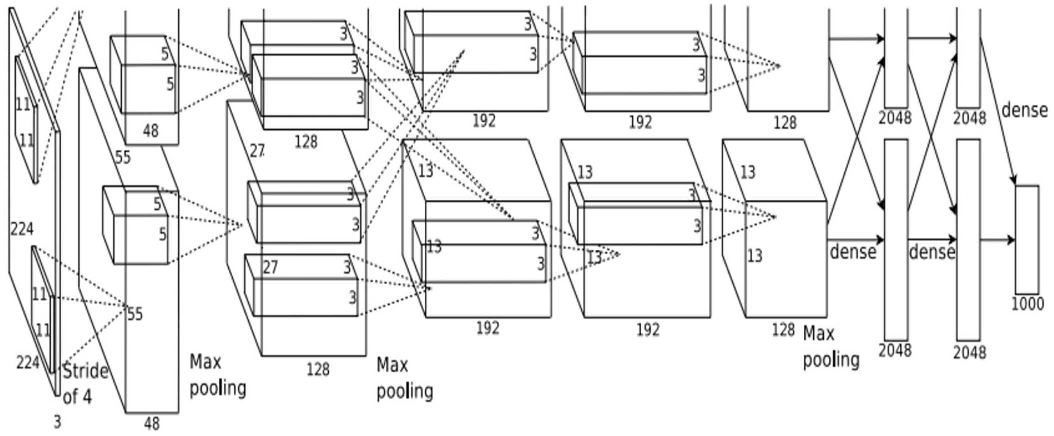



Input: 227x227x3 images
After CONV1: 55x55x96

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

# Case Study: AlexNet

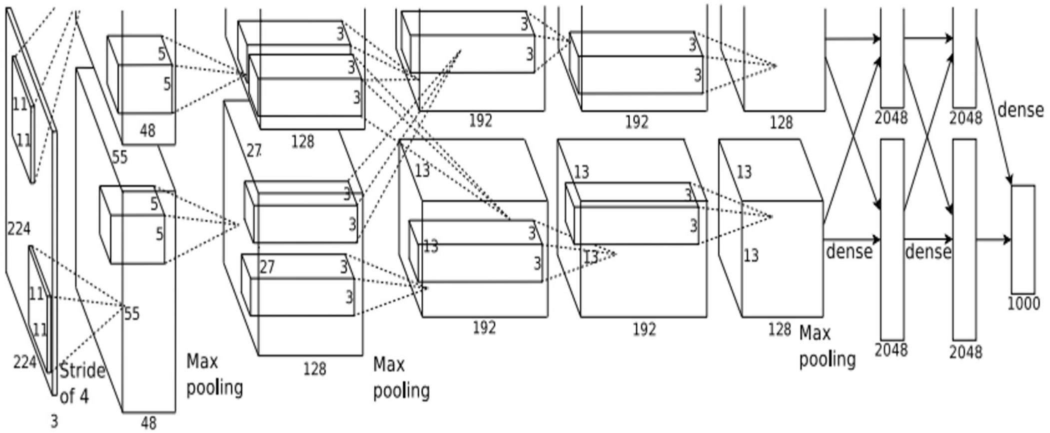
*[Krizhevsky et al. 2012]*




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

# Case Study: AlexNet

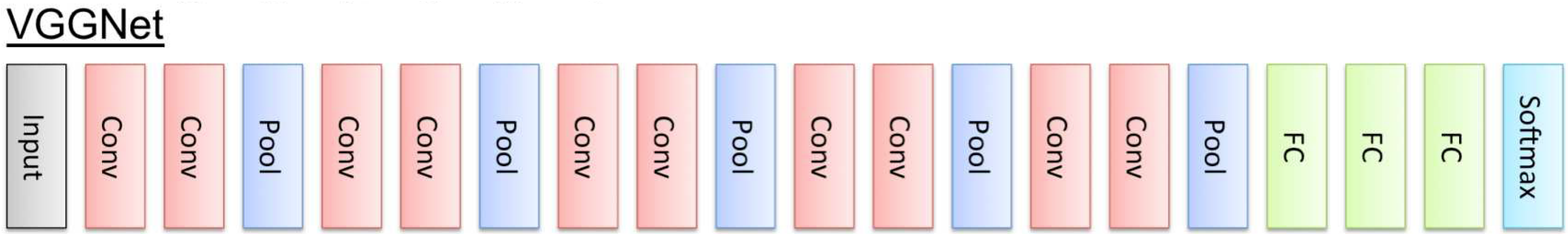
*[Krizhevsky et al. 2012]*




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

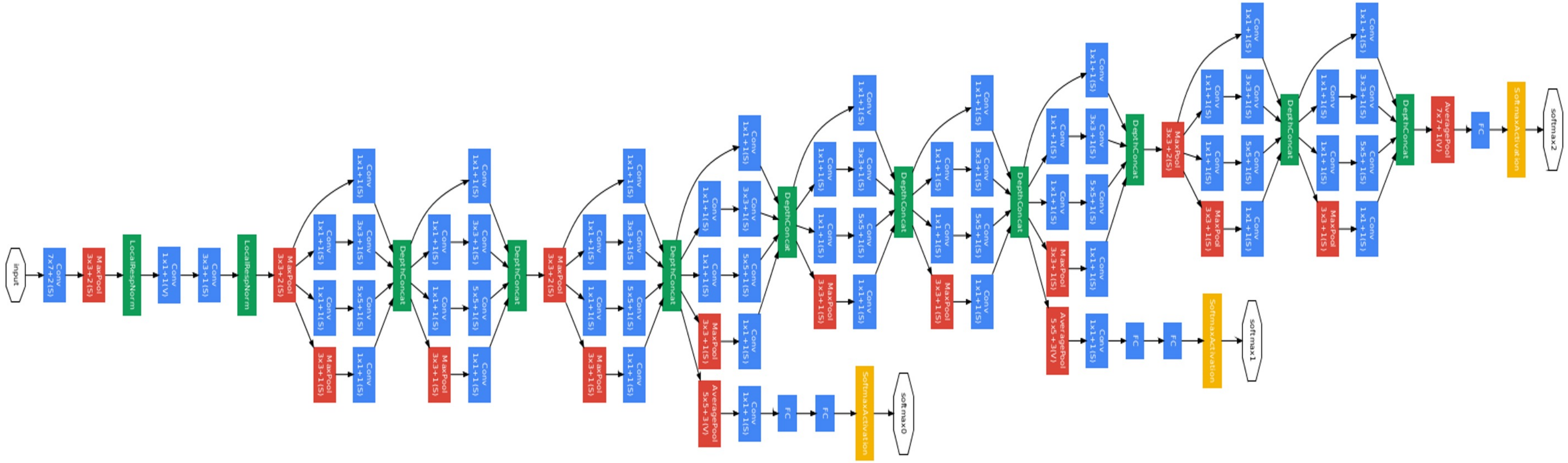
11.2% top 5 error in ILSVRC 2013
->
7.3% top 5 error

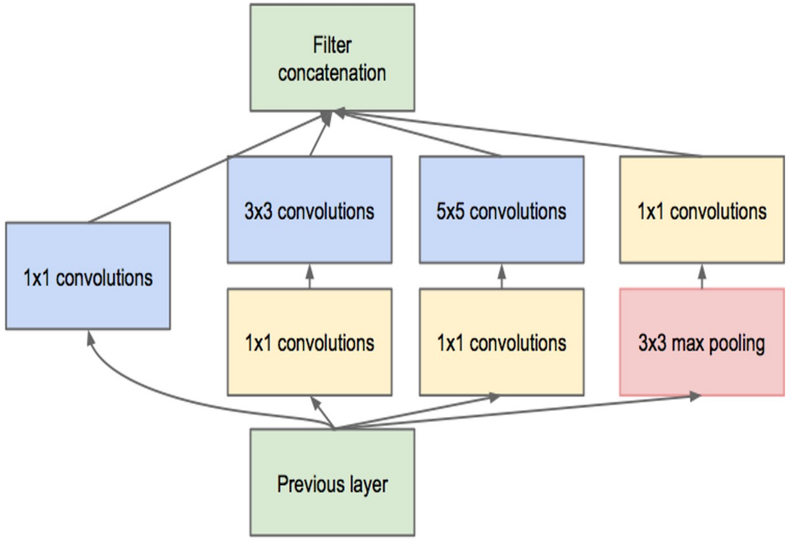
# Case Study: VGGNet *[Simonyan and Zisserman, 2014]*

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! (Removes FC layers completely)

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

# Case Study: ResNet *[He et al., 2015]*

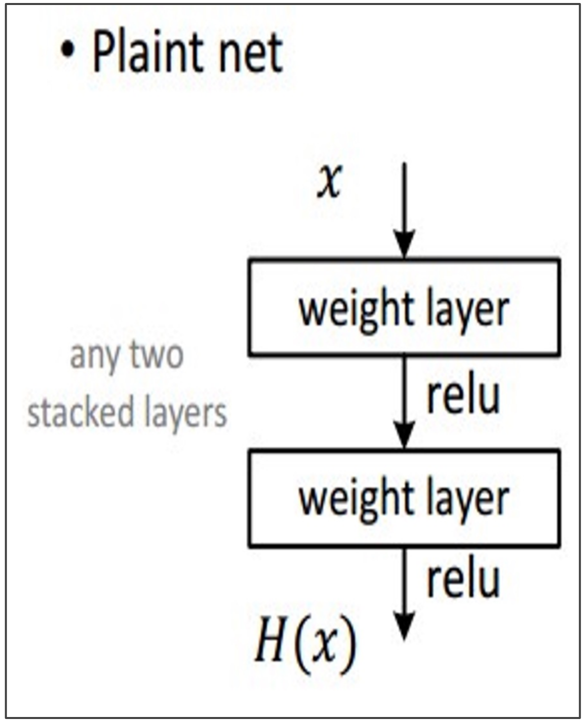
ILSVRC 2015 winner (3.6% top 5 error)

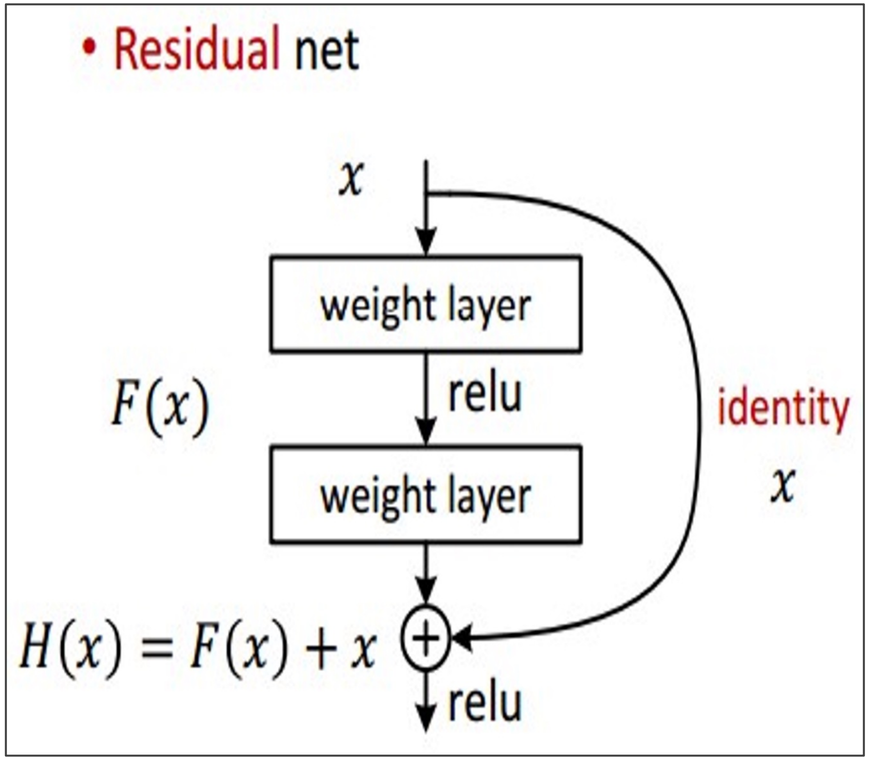
LeNet (5 layers) | AlexNet (8 layers) | VGGNet (19 layers) | GoogleNet | ResNet (152 layers)

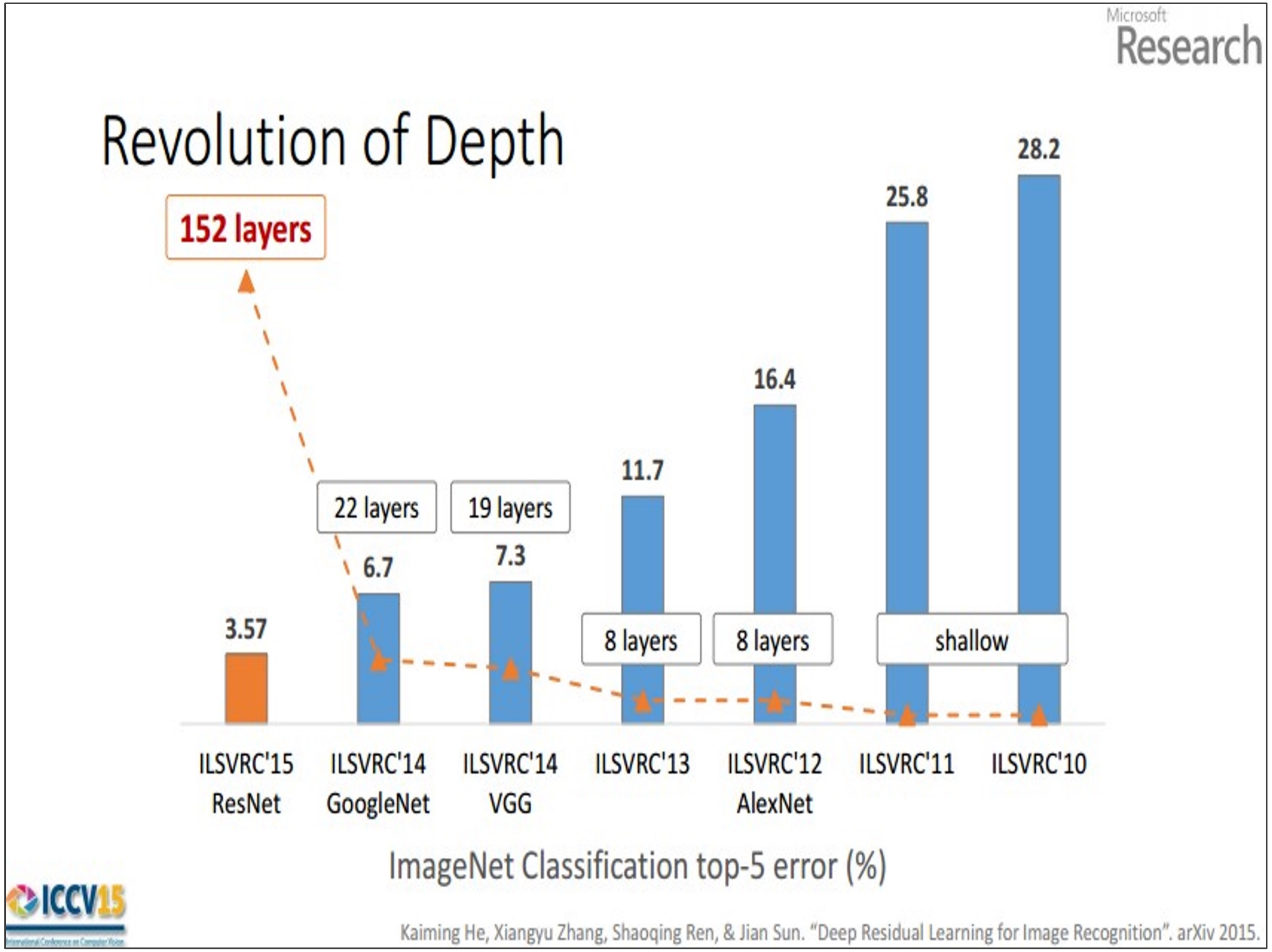
2-3 weeks of training on 8 GPU machine

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