

Convolutional Neural Networks

Instructor: Alan Ritter

Slides Adapted from Andrej Karpathy

Neural Networks

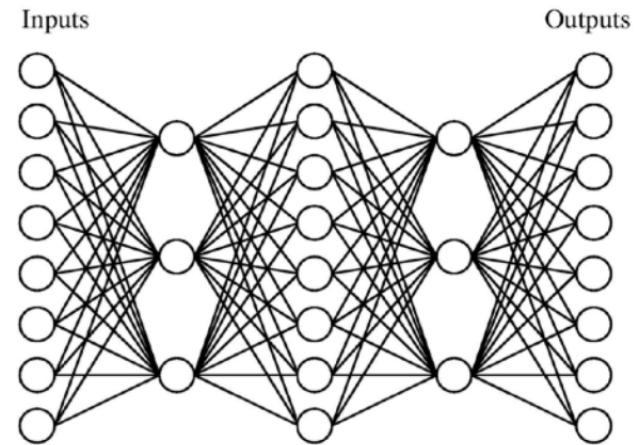
$$f(x) = f^{(3)}(f^{(2)}(f^{(1)}(x)))$$

Third Layer

Second Layer

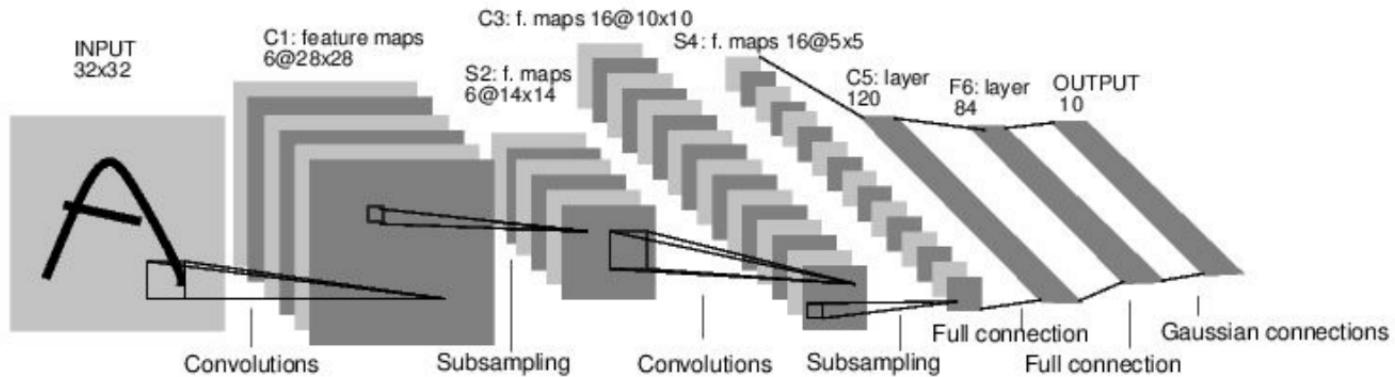
First Layer

Depth=3 in this case



Depth=4 in this case

Convolutional Neural Networks



[LeNet-5, LeCun 1980]

A bit of history:

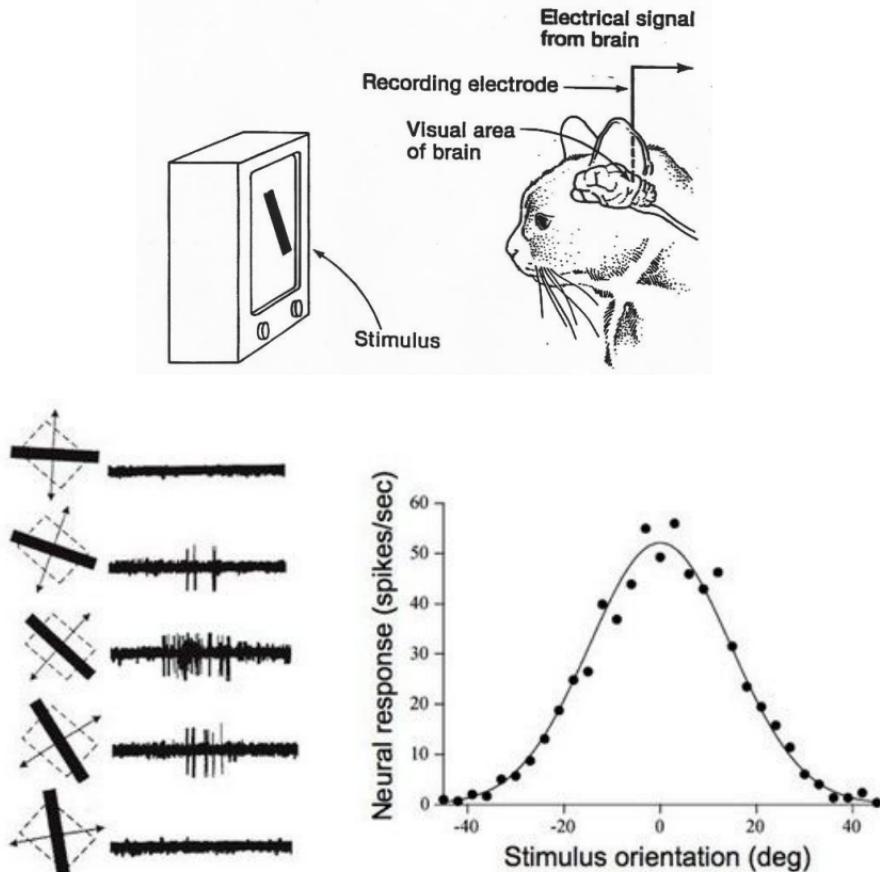
Hubel & Wiesel, 1959

RECEPTIVE FIELDS OF SINGLE
NEURONES IN
THE CAT'S STRIATE CORTEX

1962

RECEPTIVE FIELDS, BINOCULAR
INTERACTION
AND FUNCTIONAL ARCHITECTURE IN
THE CAT'S VISUAL CORTEX

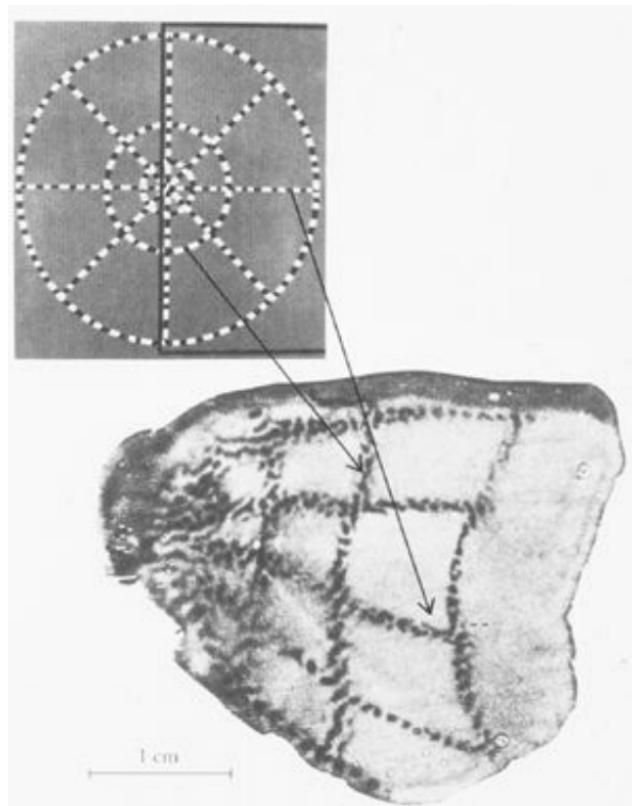
1968...



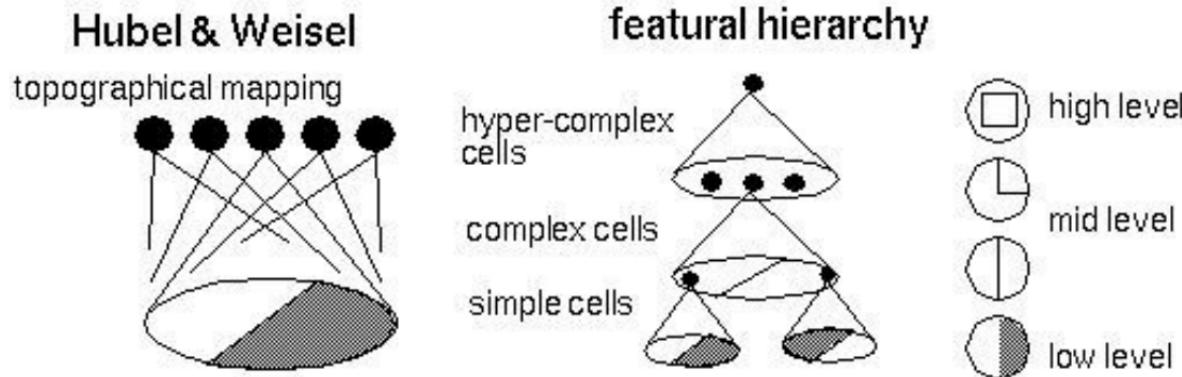
<https://www.youtube.com/watch?v=8VdFf3egwfg>

A bit of history

Topographical mapping in the cortex:
nearby cells in cortex represented
nearby regions in the visual field

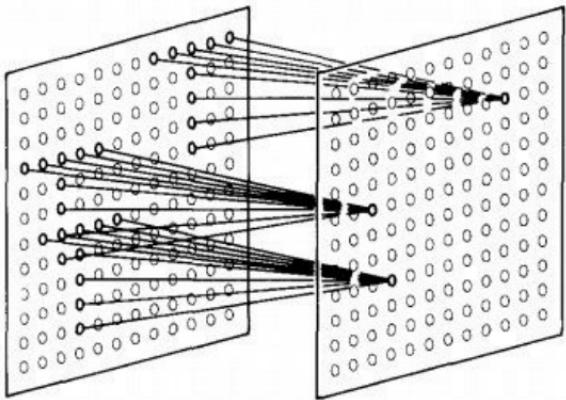


Hierarchical organization

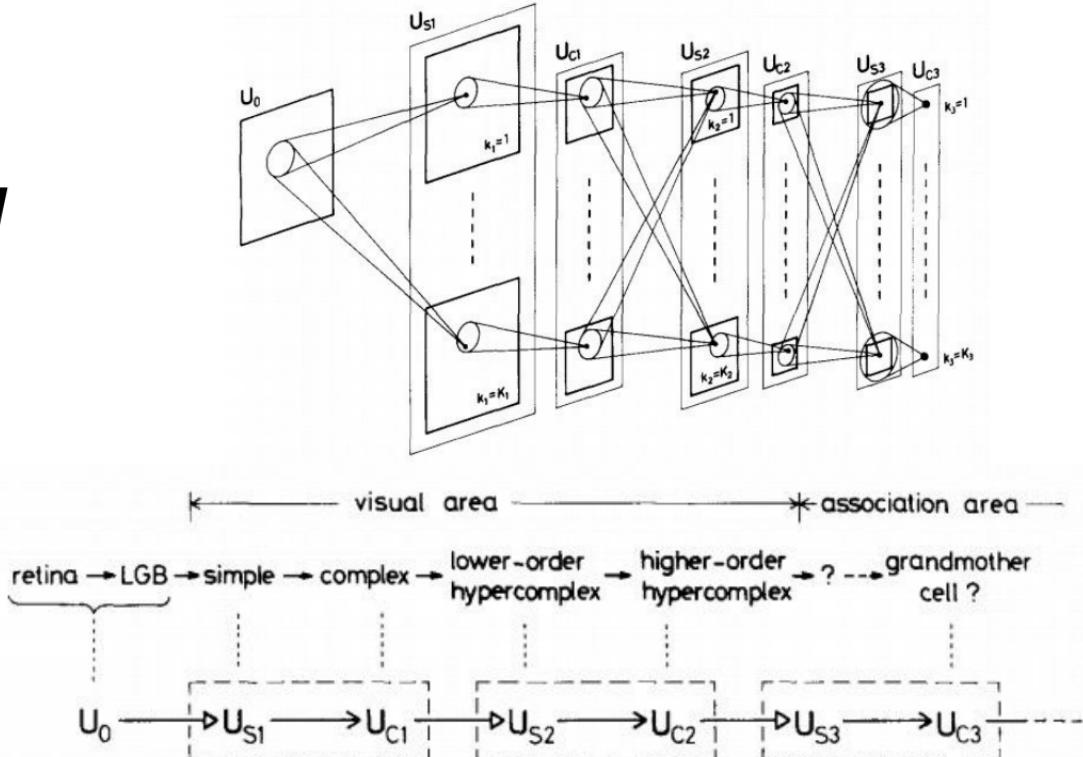


A bit of history:

Neurocognitron [Fukushima 1980]

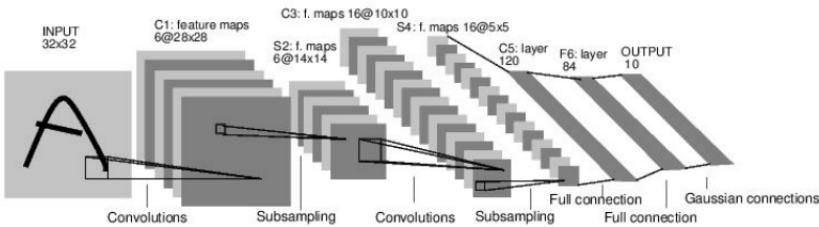


“sandwich” architecture (SCSCSC...)
simple cells: modifiable parameters
complex cells: perform pooling

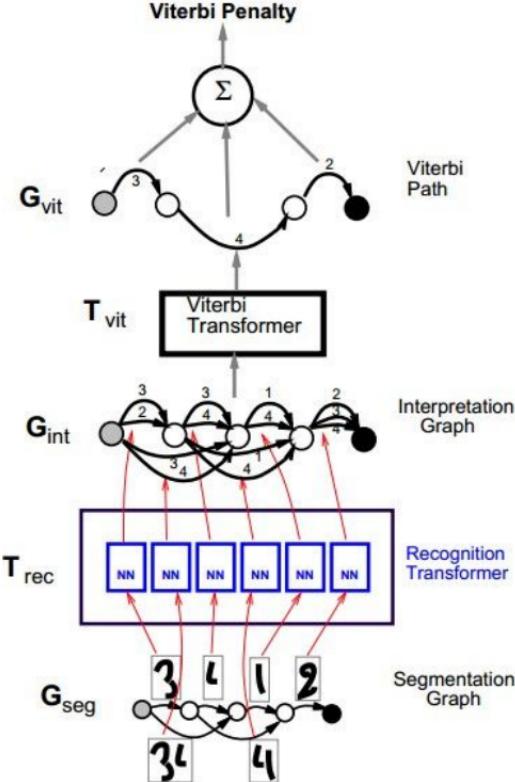


A bit of history: Gradient-based learning applied to document recognition

[LeCun, Bottou, Bengio, Haffner
1998]



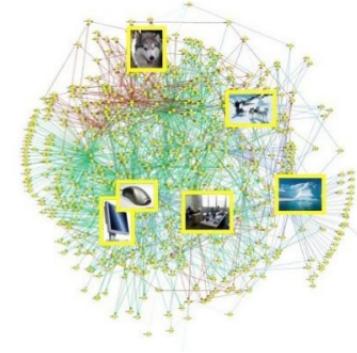
LeNet-5



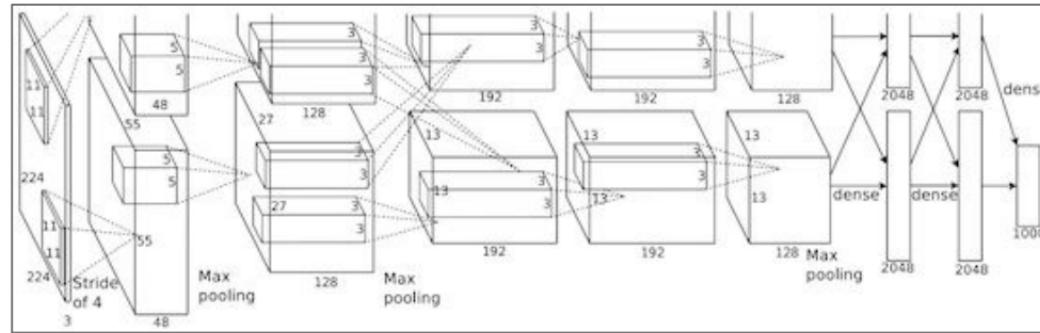
A bit of history:

ImageNet Classification with Deep Convolutional Neural Networks

[Krizhevsky, Sutskever, Hinton, 2012]



IMAGENET



“AlexNet”

Fast-forward to today: ConvNets are everywhere

Classification



Retrieval



[Krizhevsky 2012]

Fast-forward to today: ConvNets are everywhere



[Toshev, Szegedy 2014]



[Mnih 2013]



Whale recognition, Kaggle Challenge

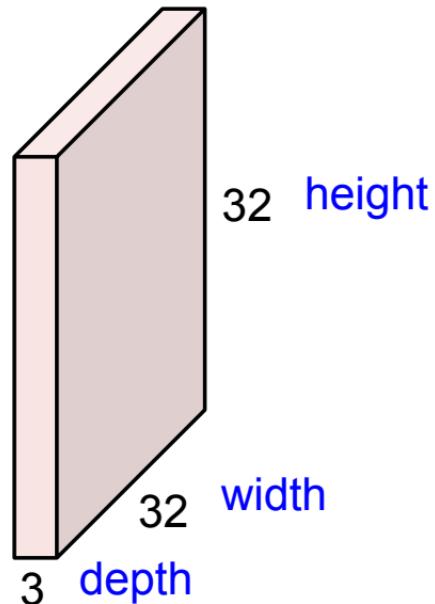


Mnih and Hinton, 2010

Convolutional Neural Networks

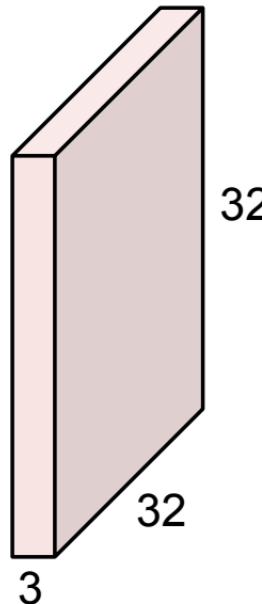
Convolution Layer

32x32x3 image



Convolution Layer

32x32x3 image



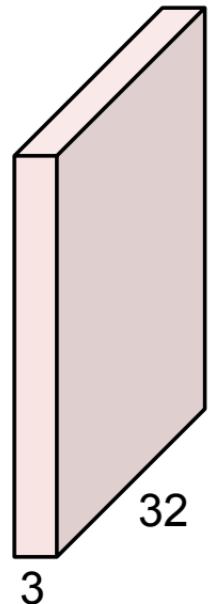
5x5x3 filter



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

Convolution Layer

32x32x3 image



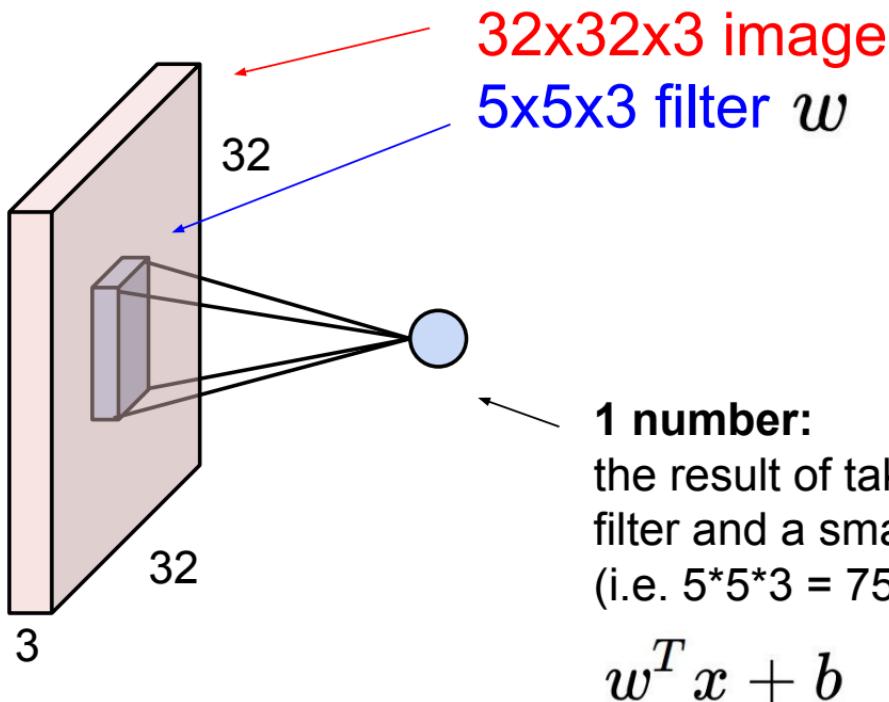
5x5x3 filter



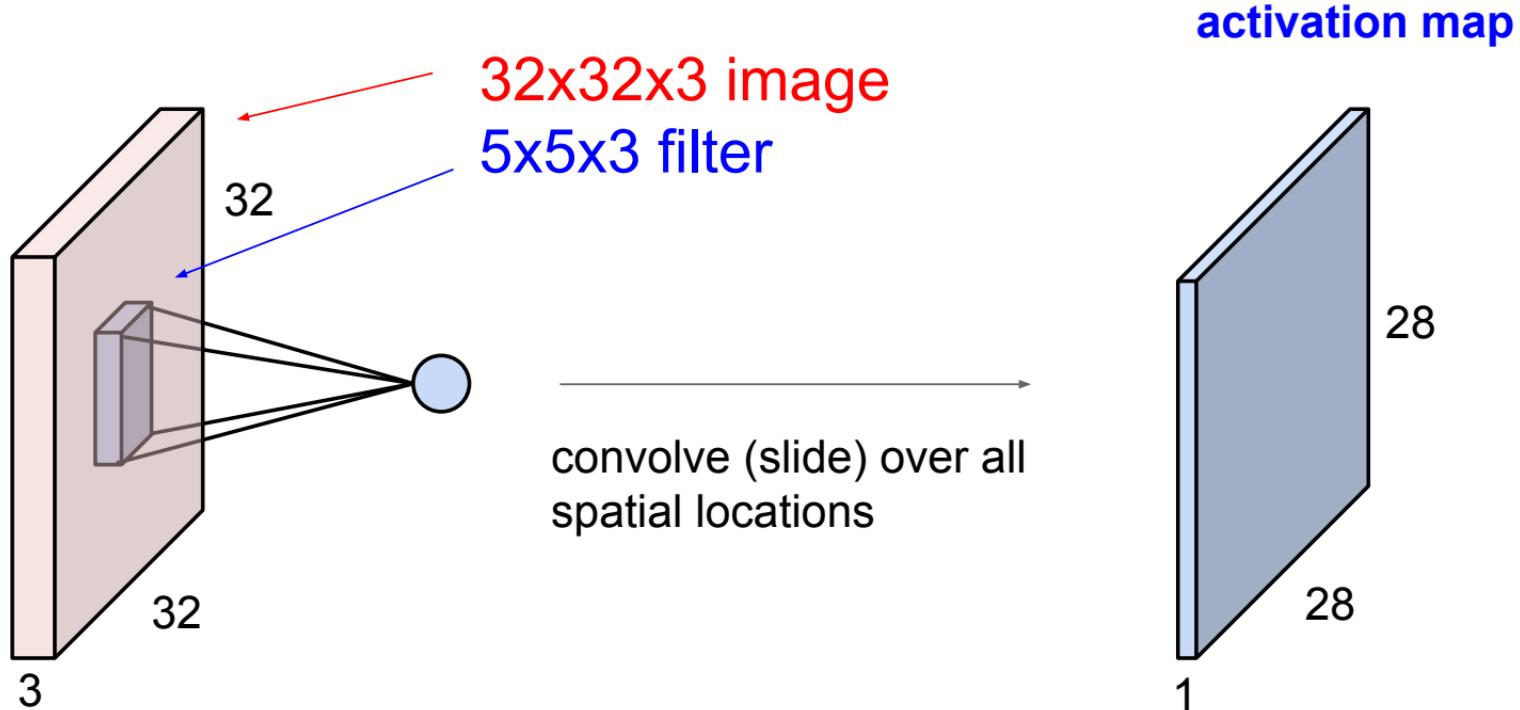
Filters always extend the full depth of the input volume

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

Convolution Layer

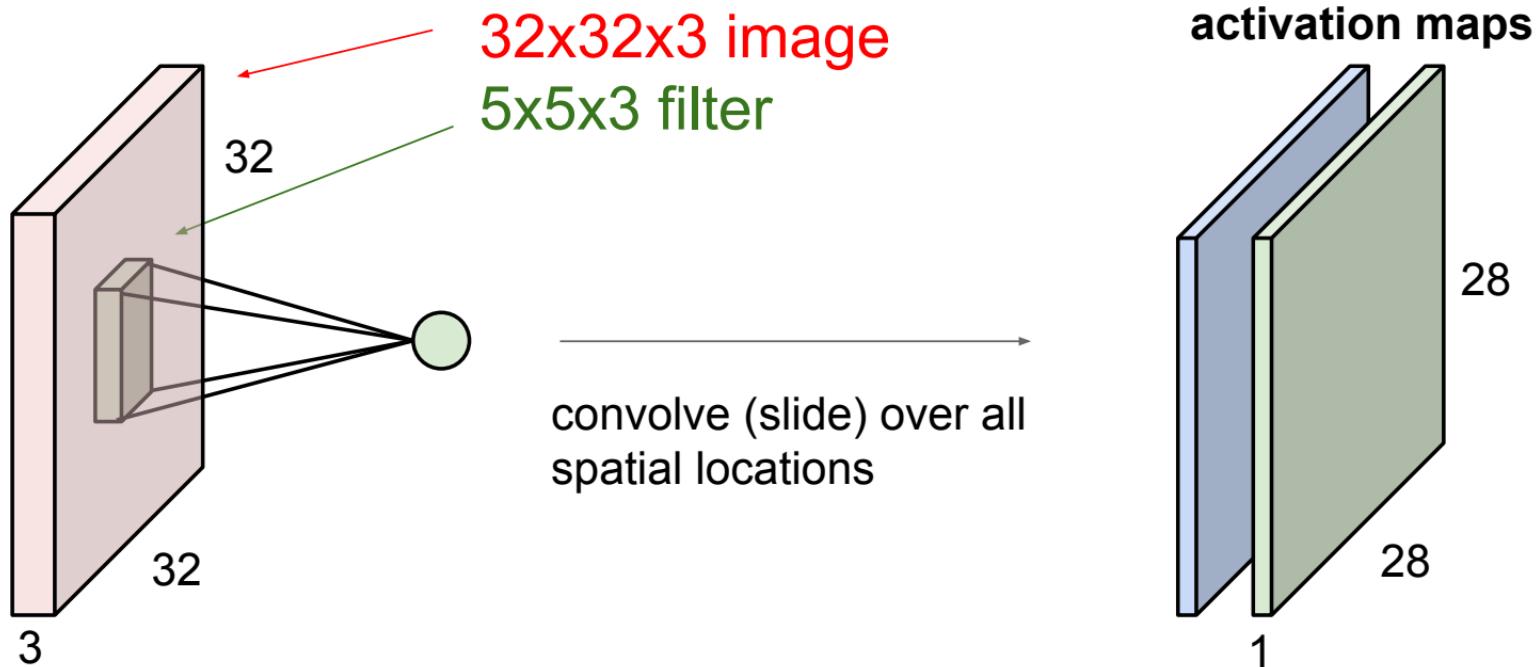


Convolution Layer

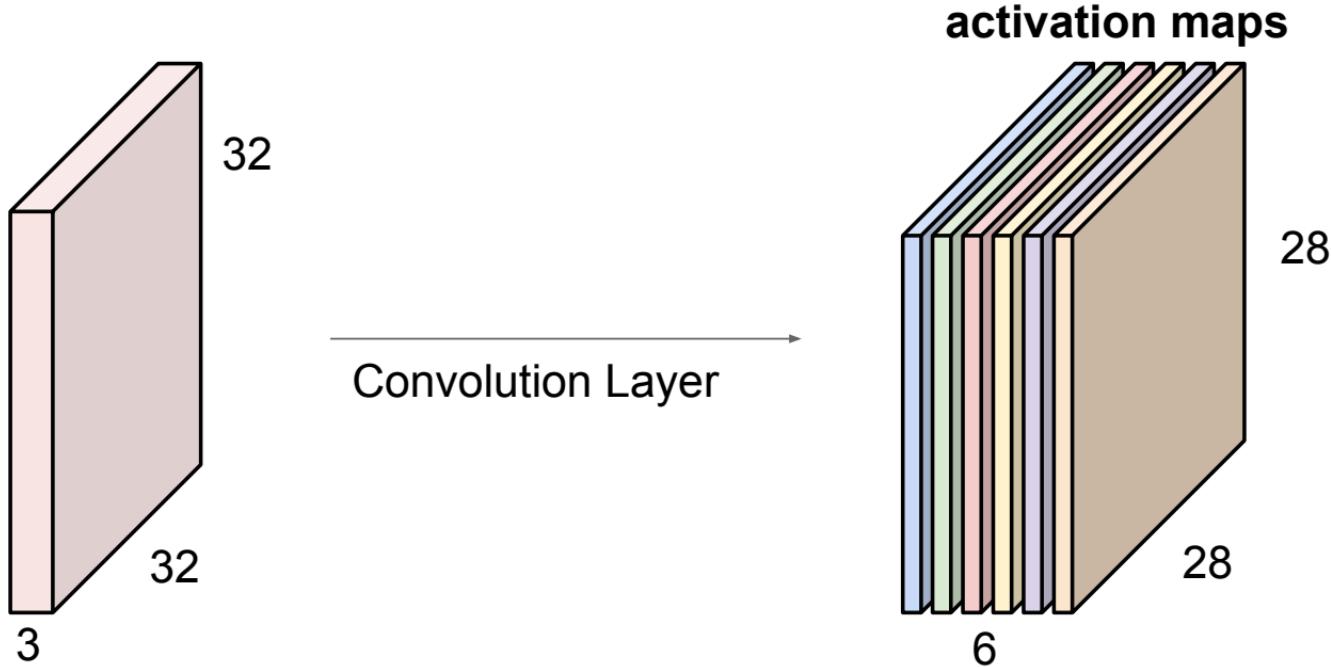


Convolution Layer

consider a second, green filter

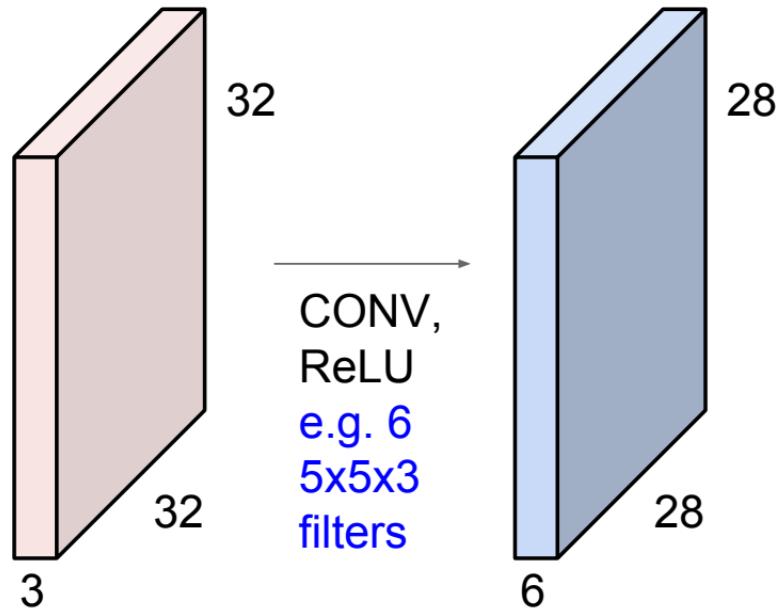


For example, if we had 6 5x5 filters, we'll get 6 separate activation maps:

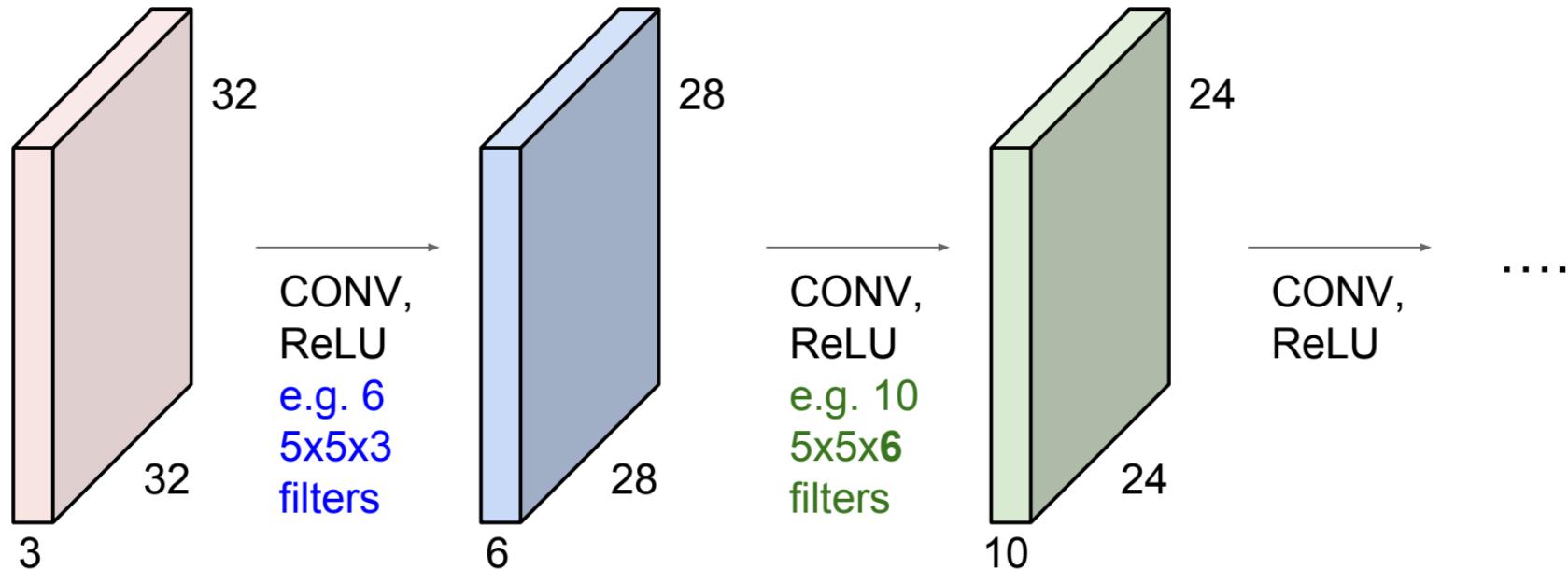


We stack these up to get a “new image” of size $28 \times 28 \times 6$!

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

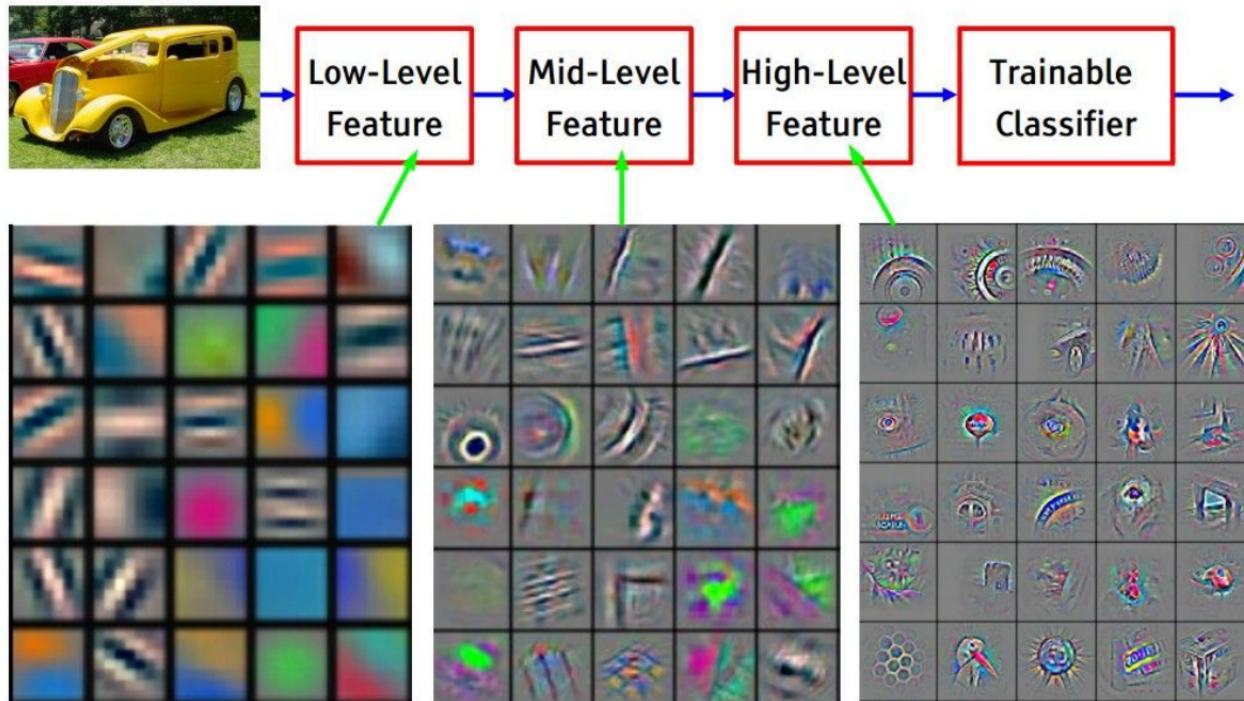


Preview: ConvNet is a sequence of Convolutional Layers, interspersed with activation functions



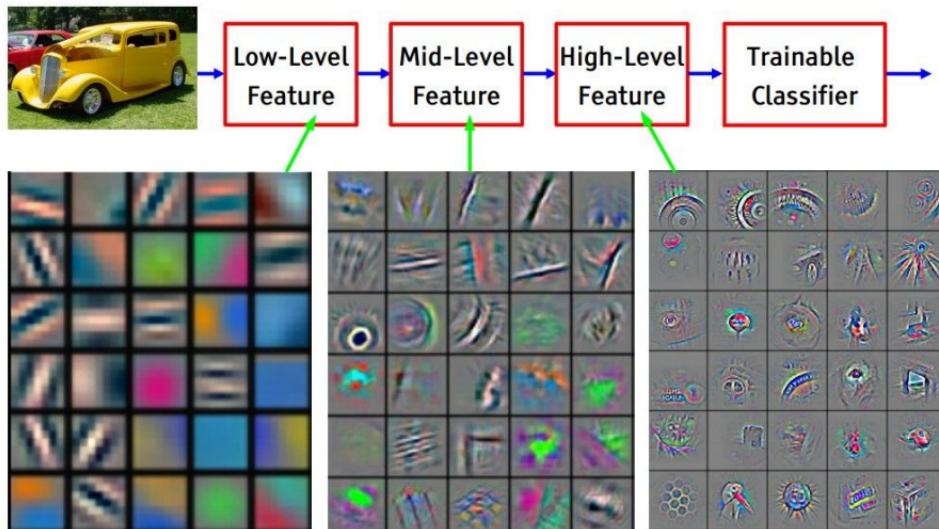
Preview

[From recent Yann LeCun slides]



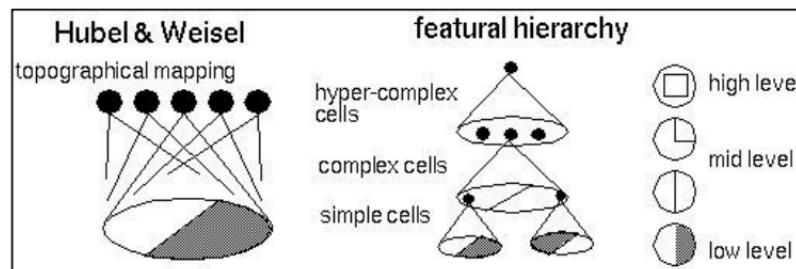
Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

Preview



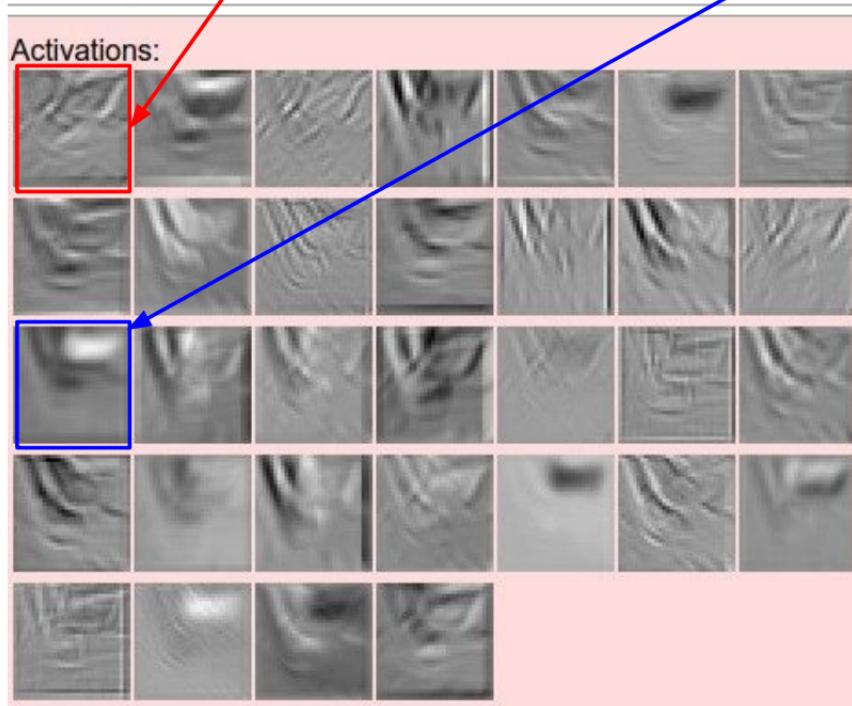
[From recent Yann LeCun slides]

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





one filter =>
one activation map



example 5x5 filters
(32 total)

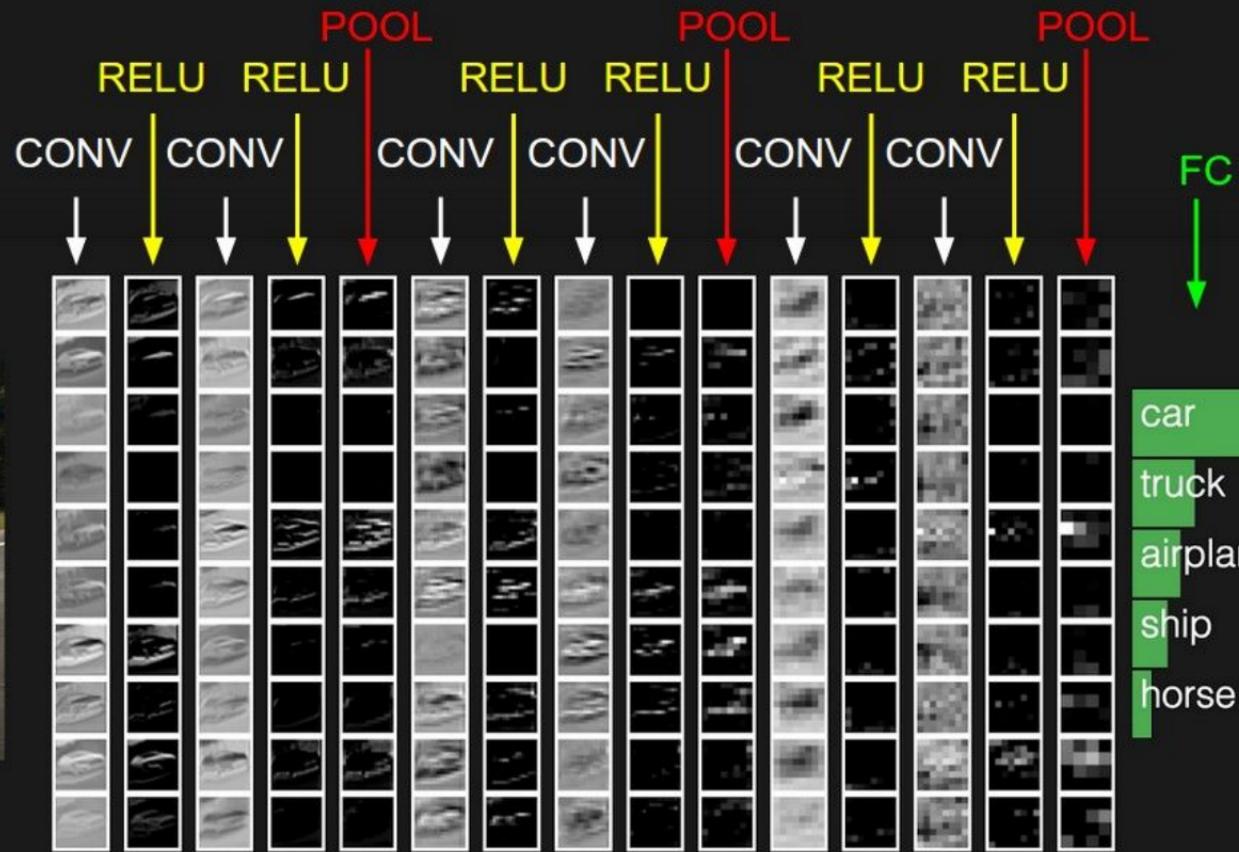
We call the layer convolutional
because it is related to convolution
of two signals:

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

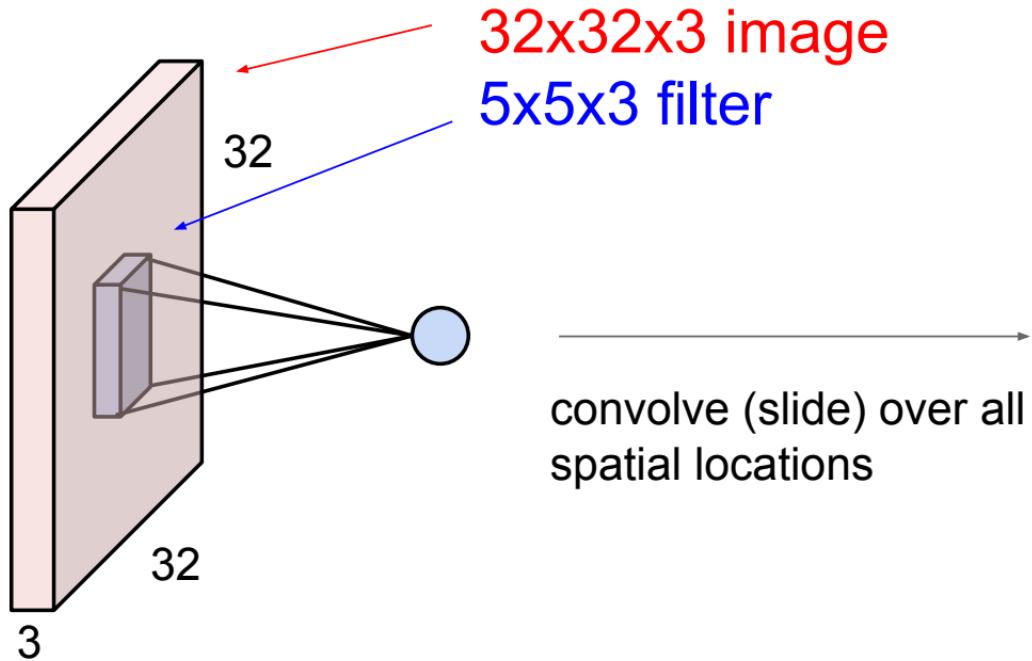


elementwise multiplication and sum of
a filter and the signal (image)

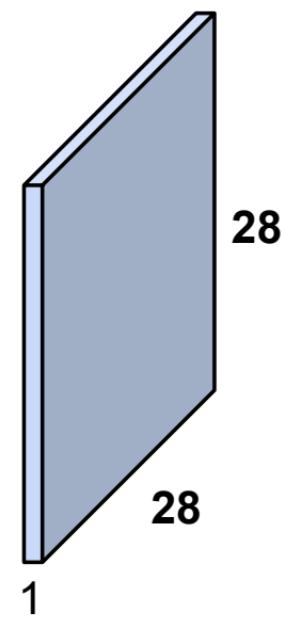
preview:



A closer look at spatial dimensions:

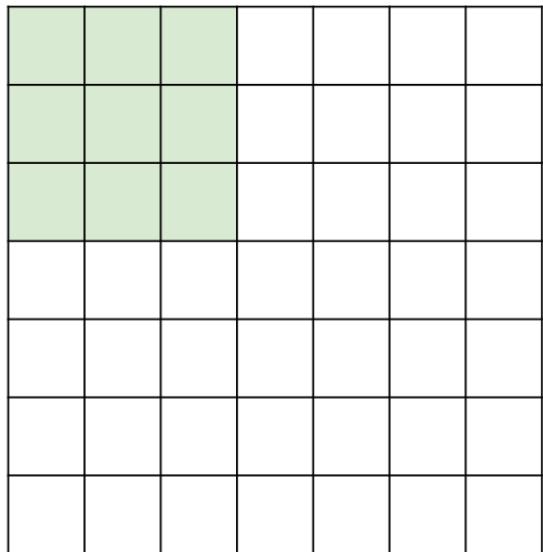


activation map



A closer look at spatial dimensions:

7

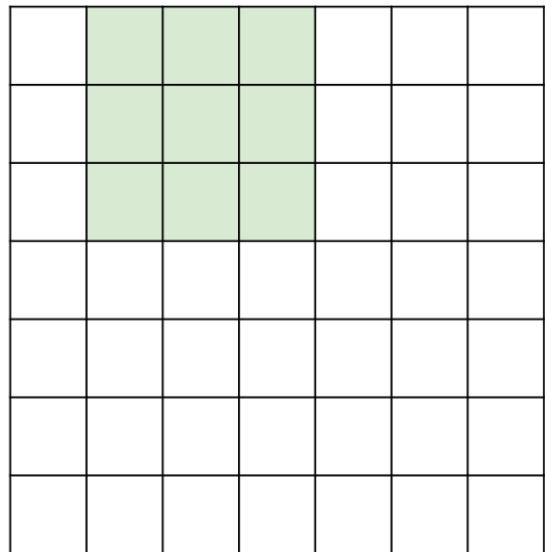


7x7 input (spatially)
assume 3x3 filter

7

A closer look at spatial dimensions:

7

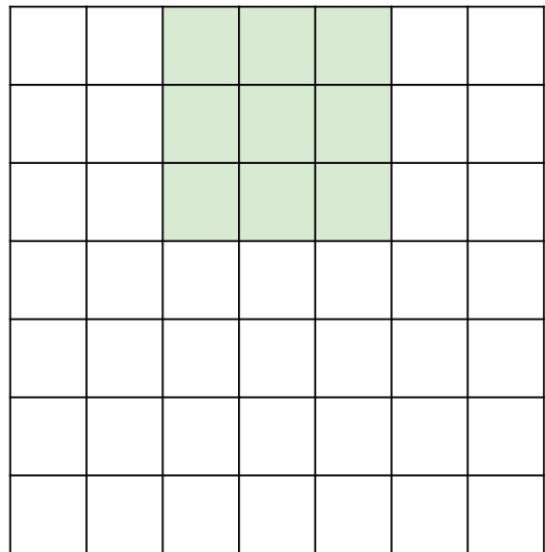


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A closer look at spatial dimensions:

7

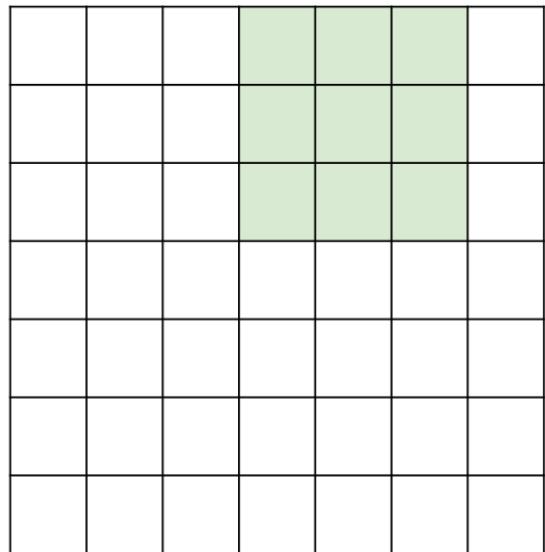


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A closer look at spatial dimensions:

7

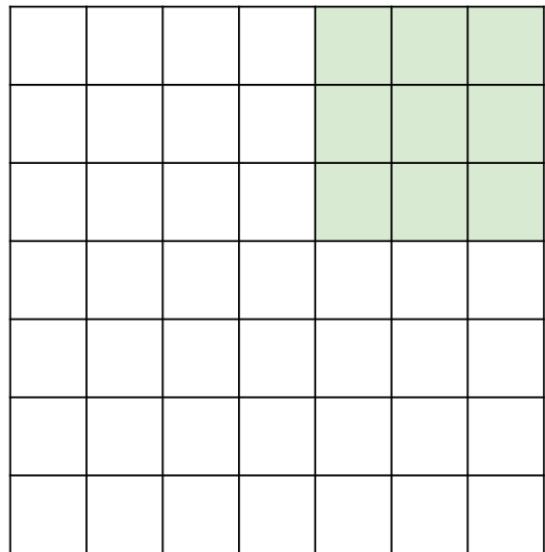


7x7 input (spatially)
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A closer look at spatial dimensions:

7



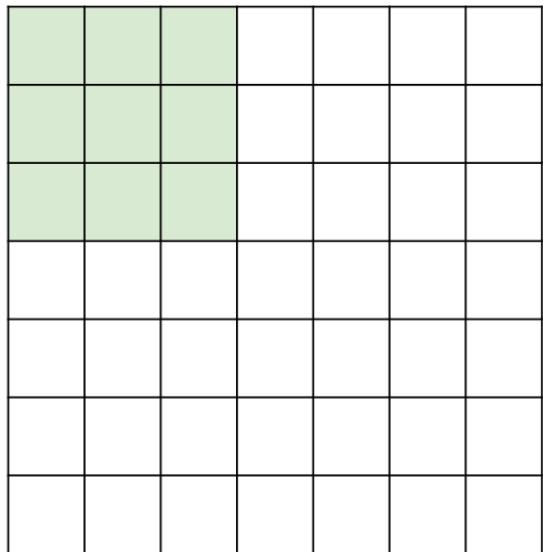
7x7 input (spatially)
assume 3x3 filter

=> 5x5 output

7

A closer look at spatial dimensions:

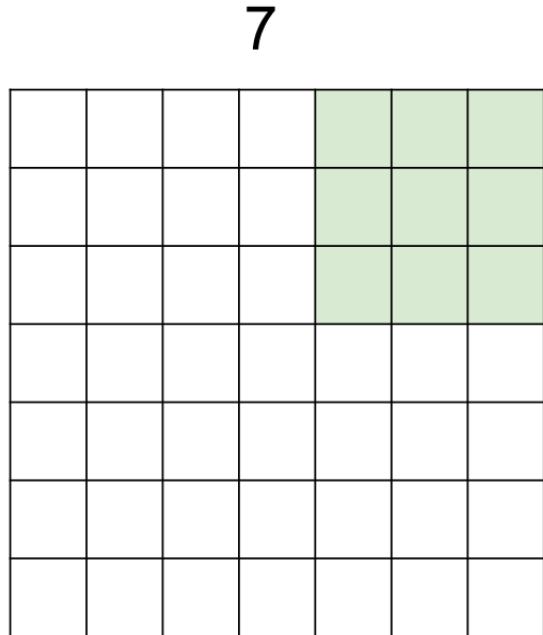
7



7

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

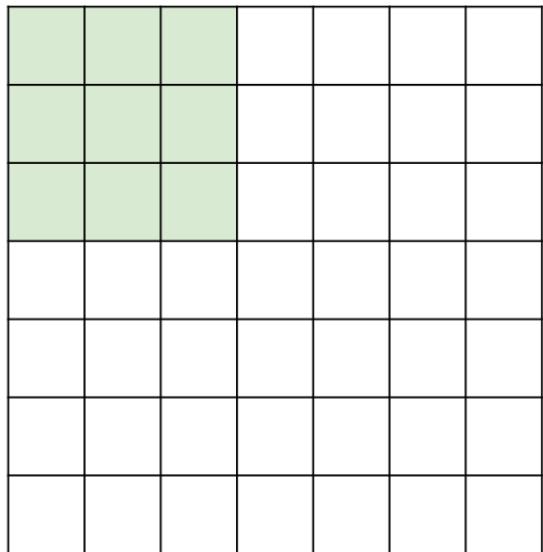
A closer look at spatial dimensions:



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

A closer look at spatial dimensions:

7

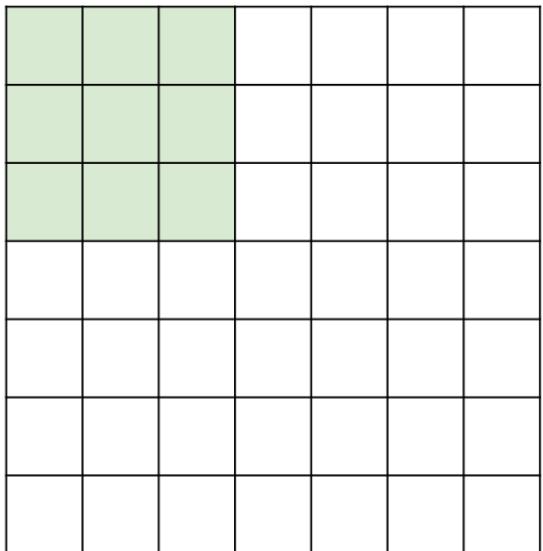


7

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

A closer look at spatial dimensions:

7

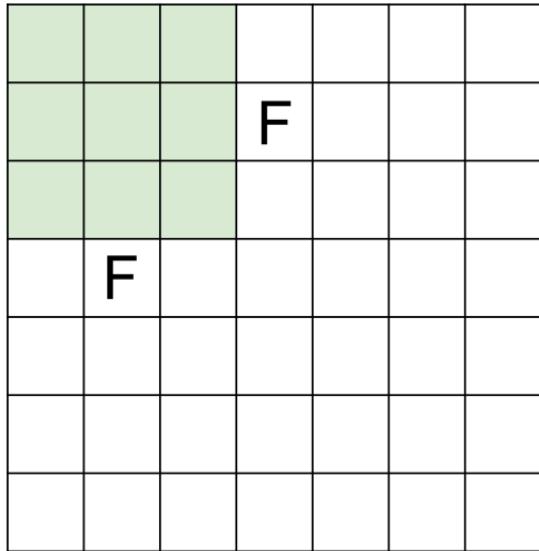


7

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

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

N



N

Output size:
 $(N - F) / \text{stride} + 1$

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

$$\text{stride } 1 \Rightarrow (7 - 3)/1 + 1 = 5$$

$$\text{stride } 2 \Rightarrow (7 - 3)/2 + 1 = 3$$

$$\text{stride } 3 \Rightarrow (7 - 3)/3 + 1 = 2.33 :\backslash$$

In practice: Common to zero pad the border

0	0	0	0	0	0		
0							
0							
0							
0							

e.g. input 7x7

3x3 filter, applied with stride 1

pad with 1 pixel border => what is the output?

(recall:)

$$(N - F) / \text{stride} + 1$$

In practice: Common to zero pad the border

0	0	0	0	0	0		
0							
0							
0							
0							

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

0	0	0	0	0	0		
0							
0							
0							
0							

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)

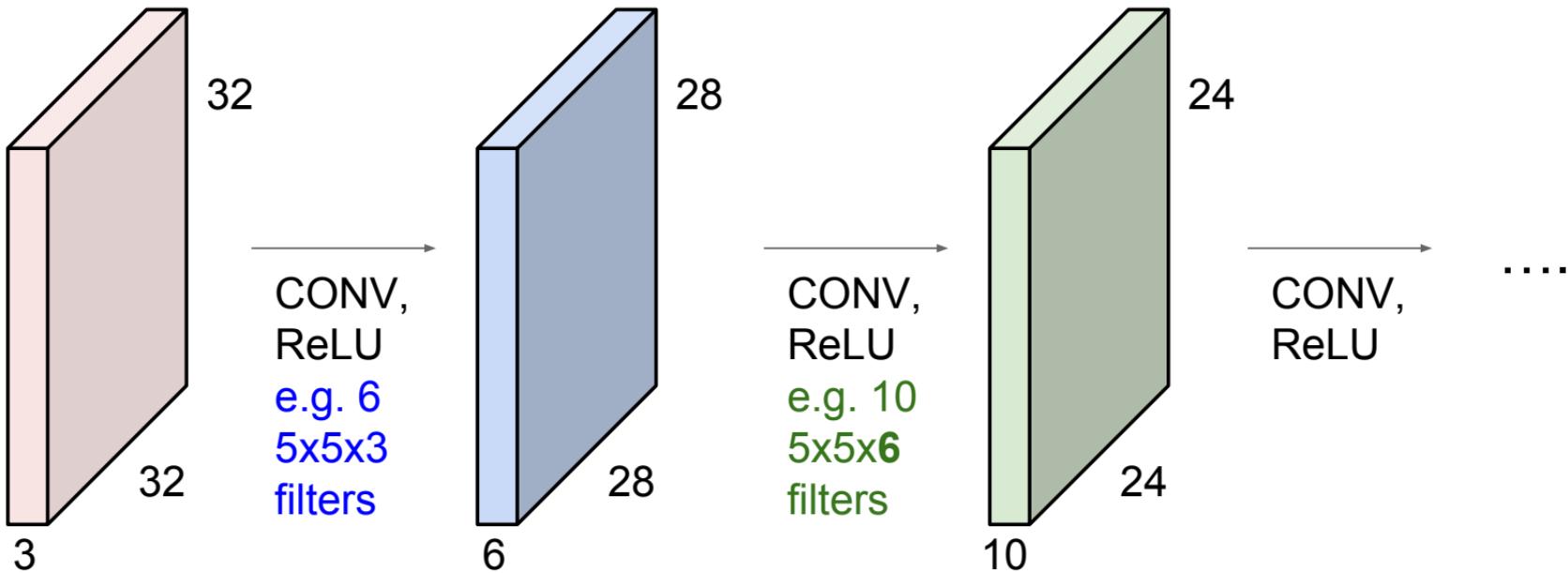
e.g. $F = 3 \Rightarrow$ zero pad with 1

$F = 5 \Rightarrow$ zero pad with 2

$F = 7 \Rightarrow$ zero pad with 3

Remember back to...

E.g. 32x32 input convolved repeatedly with 5x5 filters shrinks volumes spatially!
(32 -> 28 -> 24 ...). Shrinking too fast is not good, doesn't work well.

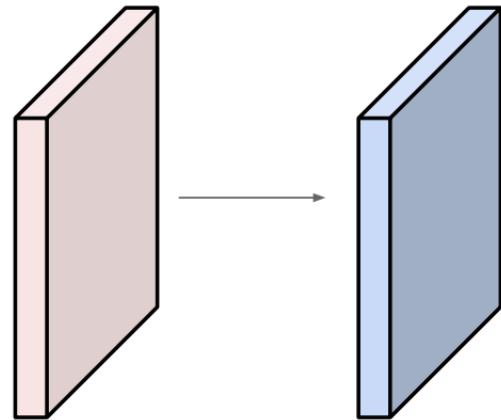


Examples time:

Input volume: **32x32x3**

10 5x5 filters with stride 1, pad 2

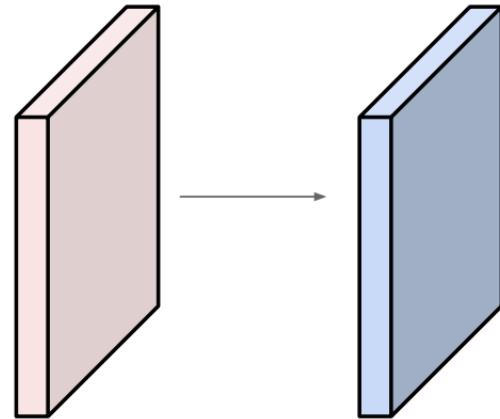
Output volume size: ?



Examples time:

Input volume: **32x32x3**

10 **5x5** filters with stride **1**, pad **2**



Output volume size:

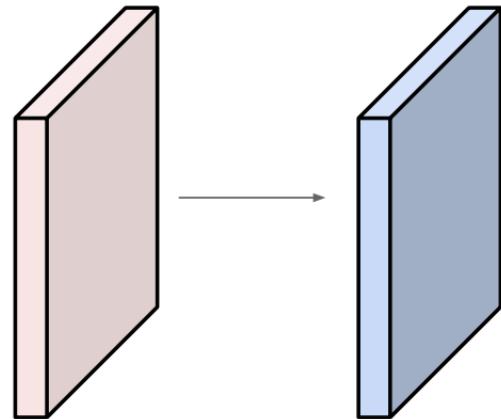
$(32+2*2-5)/1+1 = 32$ spatially, so

32x32x10

Examples time:

Input volume: **32x32x3**

10 5x5 filters with stride 1, pad 2

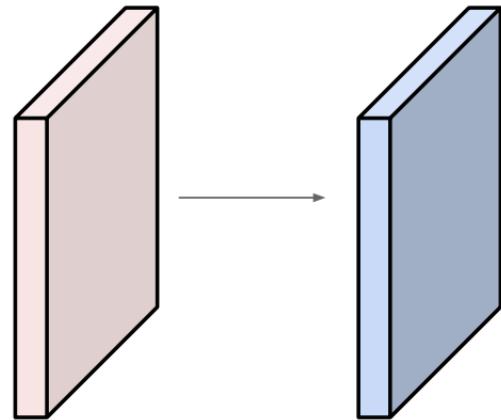


Number of parameters in this layer?

Examples time:

Input volume: **32x32x3**

10 **5x5** filters with stride 1, pad 2



Number of parameters in this layer?

each filter has **5*5*3 + 1 = 76** params (+1 for bias)
=> **76*10 = 760**

Summary. To summarize, the Conv Layer:

- Accepts a volume of size $W_1 \times H_1 \times D_1$
- Requires four hyperparameters:
 - Number of filters K ,
 - their spatial extent F ,
 - the stride S ,
 - the amount of zero padding P .
- Produces a volume of size $W_2 \times H_2 \times D_2$ where:
 - $W_2 = (W_1 - F + 2P)/S + 1$
 - $H_2 = (H_1 - F + 2P)/S + 1$ (i.e. width and height are computed equally by symmetry)
 - $D_2 = K$
- With parameter sharing, it introduces $F \cdot F \cdot D_1$ weights per filter, for a total of $(F \cdot F \cdot D_1) \cdot K$ weights and K biases.
- In the output volume, the d -th depth slice (of size $W_2 \times H_2$) is the result of performing a valid convolution of the d -th filter over the input volume with a stride of S , and then offset by d -th bias.

Common settings:

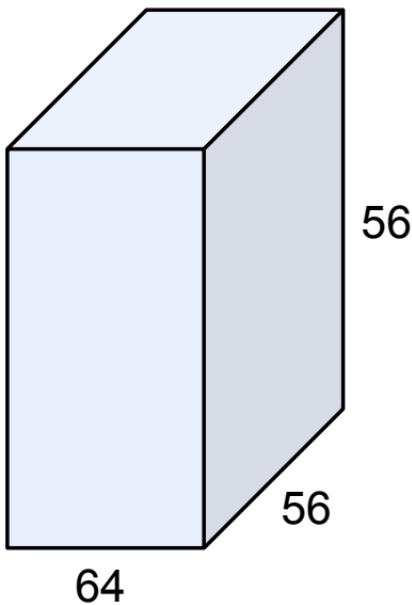
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$K = (\text{powers of 2, e.g. } 32, 64, 128, 512)$

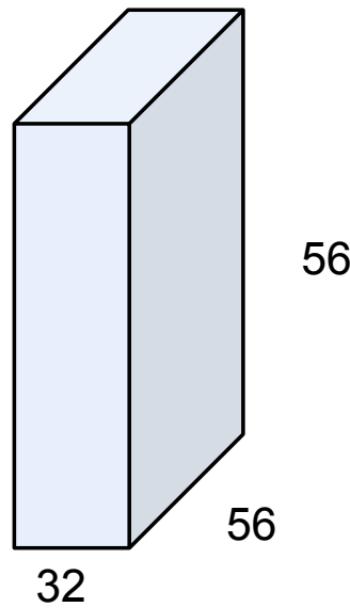
- $F = 3, S = 1, P = 1$
- $F = 5, S = 1, P = 2$
- $F = 5, S = 2, P = ?$ (whatever fits)
- $F = 1, S = 1, P = 0$

(btw, 1x1 convolution layers make perfect sense)



1x1 CONV
with 32 filters

→
(each filter has size
 $1 \times 1 \times 64$, and performs a
64-dimensional dot
product)



PyTorch

Summary. To summarize, the Conv Layer:

- Accepts a volume of size $W_1 \times H_1 \times D_1$
- Requires four hyperparameters:
 - Number of filters K ,
 - their spatial extent F ,
 - the stride S ,
 - the amount of zero padding P .

```
class torch.nn.Conv2d(in_channels, out_channels, kernel_size, stride=1, padding=0, dilation=1, groups=1, bias=True) [source]
```

Applies a 2D convolution over an input signal composed of several input planes.

In the simplest case, the output value of the layer with input size (N, C_{in}, H, W) and output $(N, C_{out}, H_{out}, W_{out})$ can be precisely described as:

$$\text{out}(N_i, C_{out_j}) = \text{bias}(C_{out_j}) + \sum_{k=0}^{C_{in}-1} \text{weight}(C_{out_j}, k) \star \text{input}(N_i, k),$$

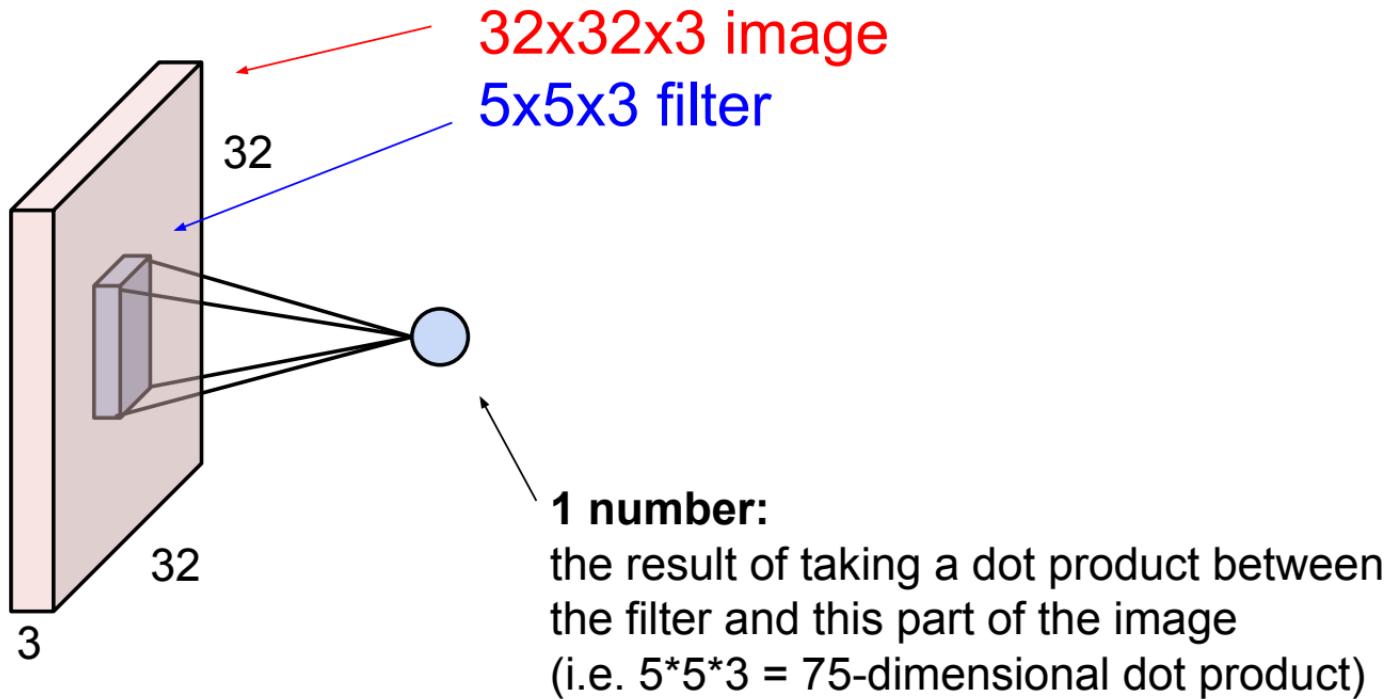
where \star is the valid 2D cross-correlation operator, N is a batch size, C denotes a number of channels, H is a height of input planes in pixels, and W is width in pixels.

- `stride` controls the stride for the cross-correlation, a single number or a tuple.
- `padding` controls the amount of implicit zero-paddings on both sides for `padding` number of points for each dimension.
- `dilation` controls the spacing between the kernel points; also known as the à trous algorithm. It is harder to describe, but this [link](#) has a nice visualization of what `dilation` does.
- `groups` controls the connections between inputs and outputs. `in_channels` and `out_channels` must both be divisible by `groups`. For example,
 - At `groups=1`, all inputs are convolved to all outputs.
 - At `groups=2`, the operation becomes equivalent to having two conv layers side by side, each seeing half the input channels, and producing half the output channels, and both subsequently concatenated.
 - At `groups=[in_channels]`, each input channel is convolved with its own set of filters (of size $\lceil \frac{\text{out_channels}}{\text{in_channels}} \rceil$).

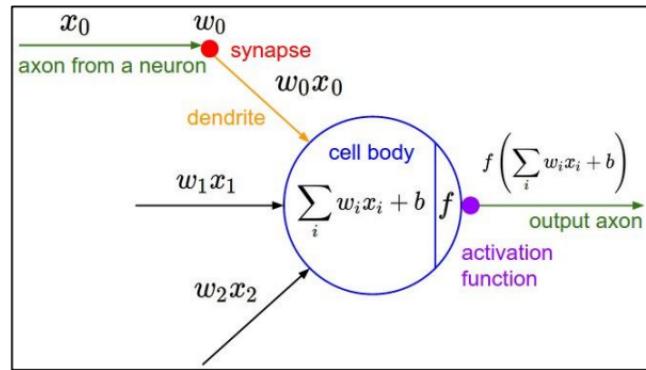
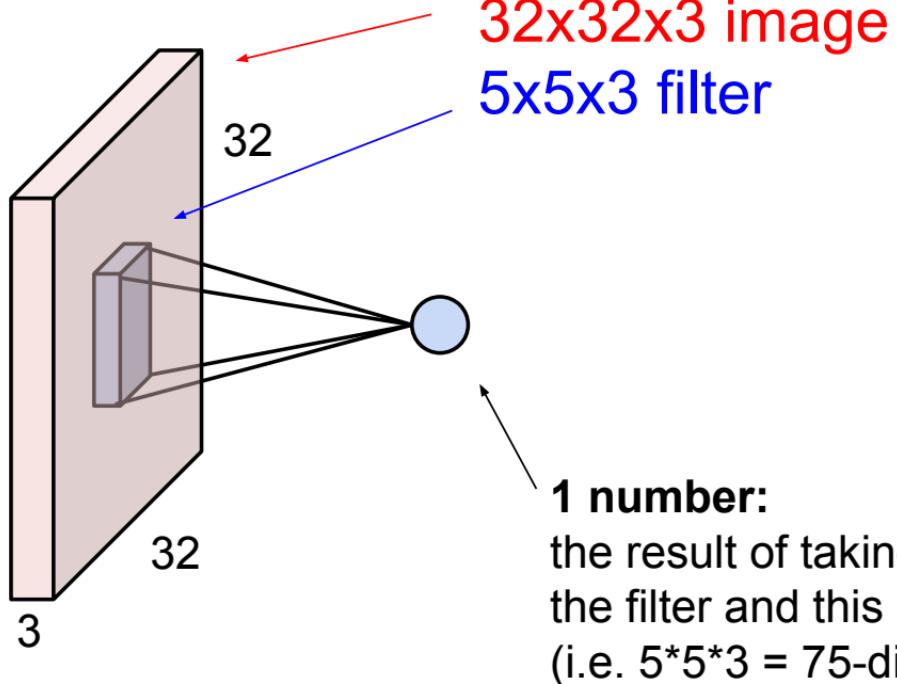
The parameters `kernel_size`, `stride`, `padding`, `dilation` can either be:

- a single `int` – in which case the same value is used for the height and width dimension

The brain/neuron view of CONV Layer

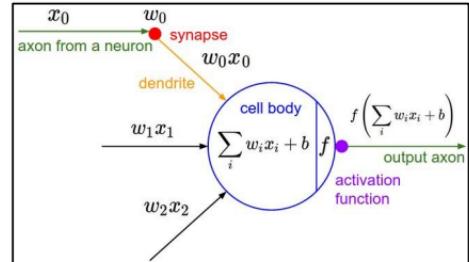
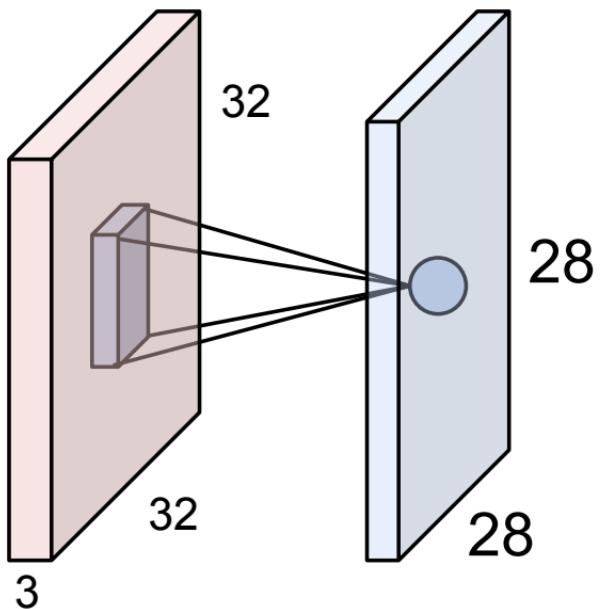


The brain/neuron view of CONV Layer



It's just a neuron with local connectivity...

The brain/neuron view of CONV Layer

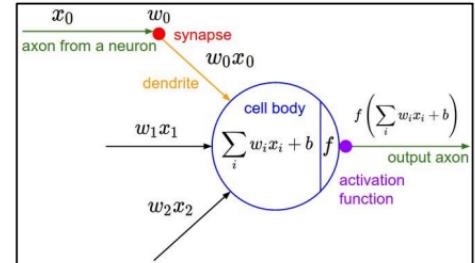
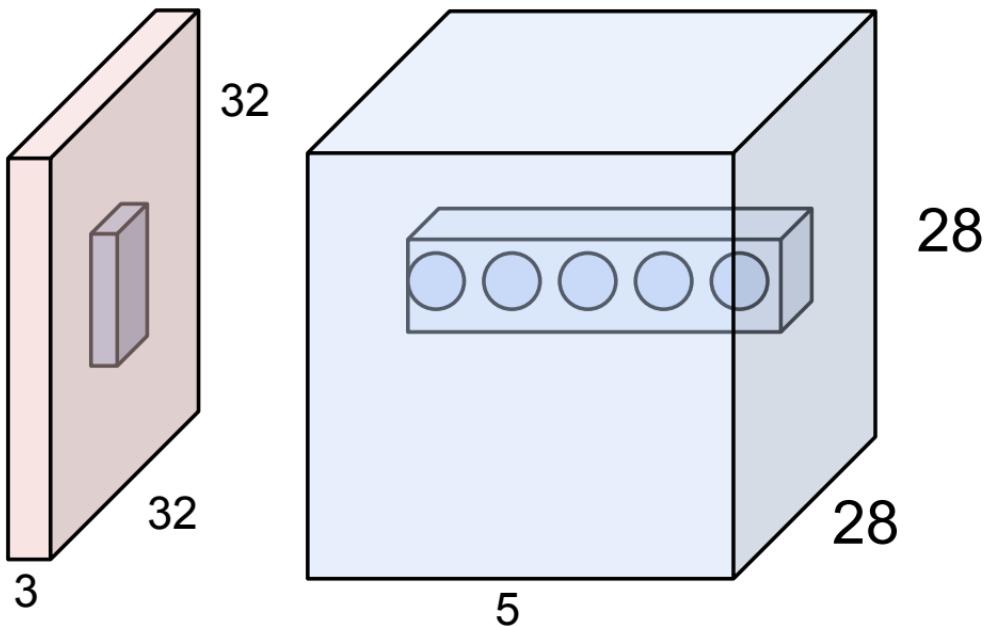


An activation map is a 28×28 sheet of neuron outputs:

1. Each is connected to a small region in the input
2. All of them share parameters

“5x5 filter” -> “5x5 receptive field for each neuron”

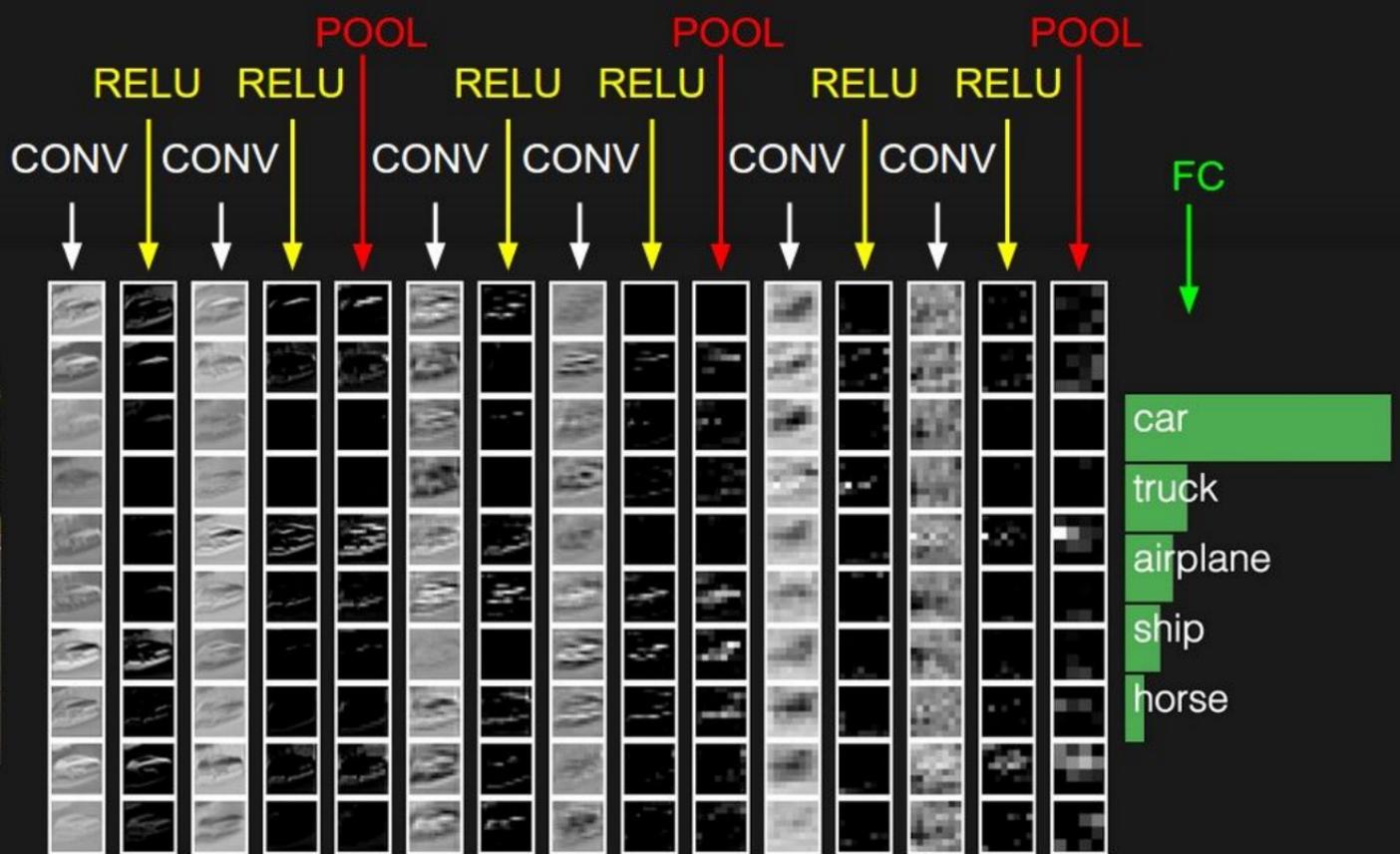
The brain/neuron view of CONV Layer



E.g. with 5 filters,
CONV layer consists of
neurons arranged in a 3D grid
(28x28x5)

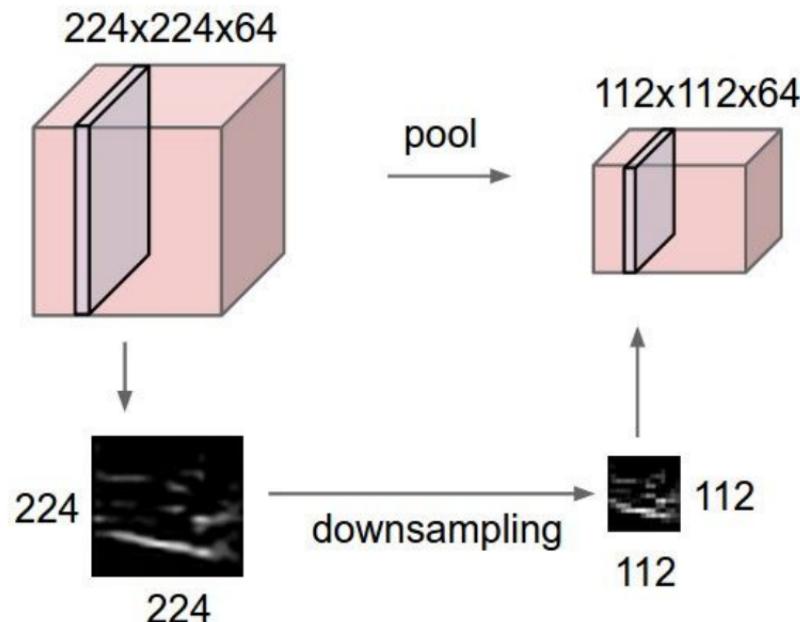
There will be 5 different
neurons all looking at the same
region in the input volume

two more layers to go: POOL/FC



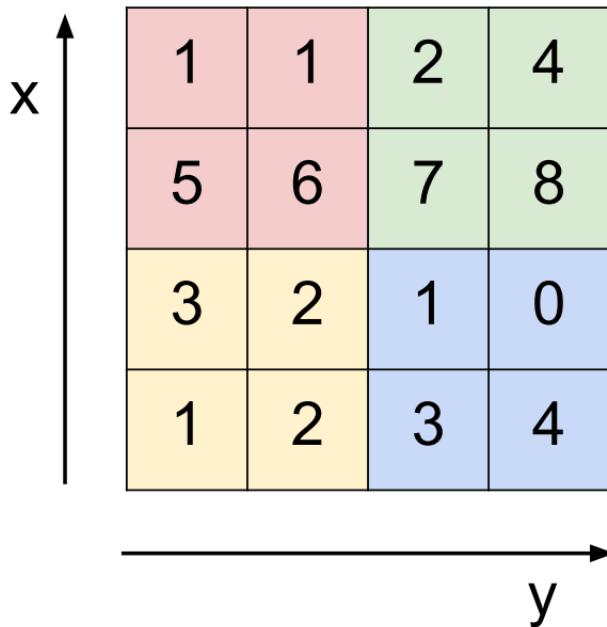
Pooling layer

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

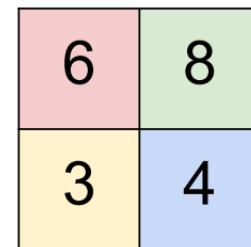


MAX POOLING

Single depth slice



max pool with 2x2 filters
and stride 2



- Accepts a volume of size $W_1 \times H_1 \times D_1$
- Requires three hyperparameters:
 - their spatial extent F ,
 - the stride S ,
- Produces a volume of size $W_2 \times H_2 \times D_2$ where:
 - $W_2 = (W_1 - F)/S + 1$
 - $H_2 = (H_1 - F)/S + 1$
 - $D_2 = D_1$
- Introduces zero parameters since it computes a fixed function of the input
- Note that it is not common to use zero-padding for Pooling layers

Common settings:

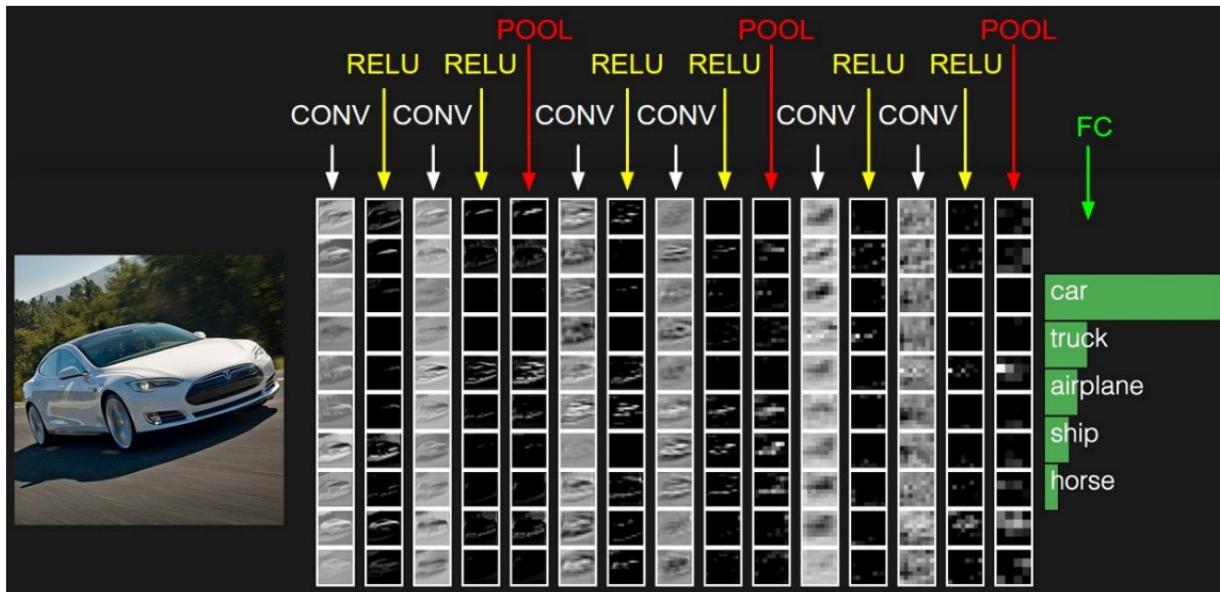
- Accepts a volume of size $W_1 \times H_1 \times D_1$
- Requires three hyperparameters:
 - their spatial extent F ,
 - the stride S ,
- Produces a volume of size $W_2 \times H_2 \times D_2$ where:
 - $W_2 = (W_1 - F)/S + 1$
 - $H_2 = (H_1 - F)/S + 1$
 - $D_2 = D_1$
- Introduces zero parameters since it computes a fixed function of the input
- Note that it is not common to use zero-padding for Pooling layers

$$F = 2, S = 2$$

$$F = 3, S = 2$$

Fully Connected Layer (FC layer)

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

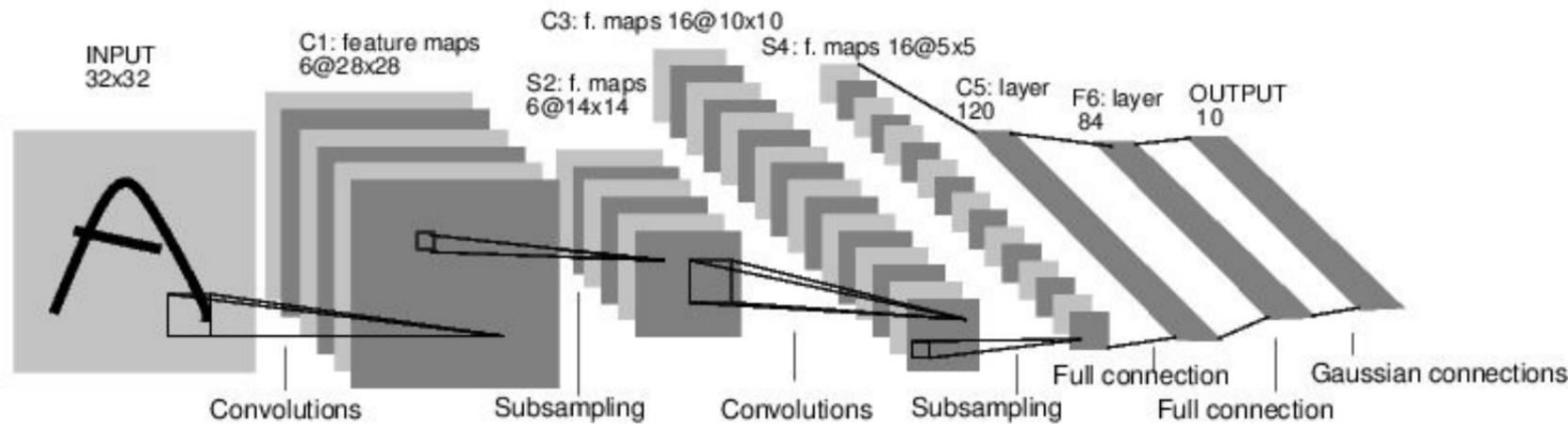


[ConvNetJS demo: training on CIFAR-10]

<http://cs.stanford.edu/people/karpathy/convnetjs/demo/cifar10.html>

Case Study: LeNet-5

[LeCun et al., 1998]

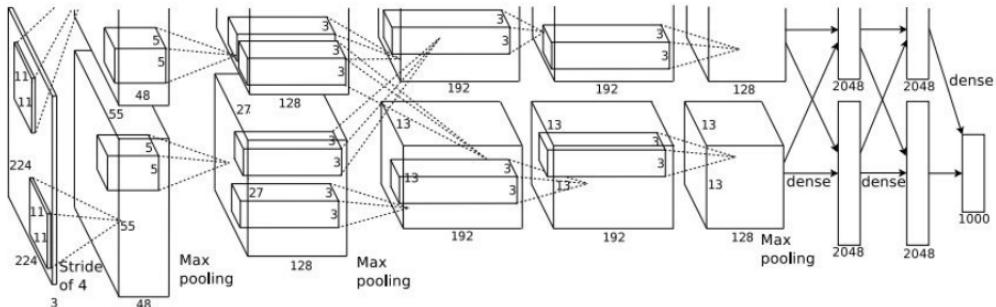


Conv filters were 5x5, applied at stride 1

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

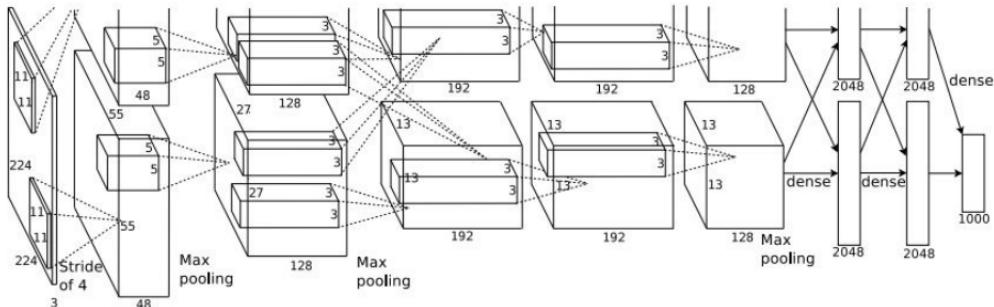
First layer (CONV1): 96 11x11 filters applied at stride 4

=>

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

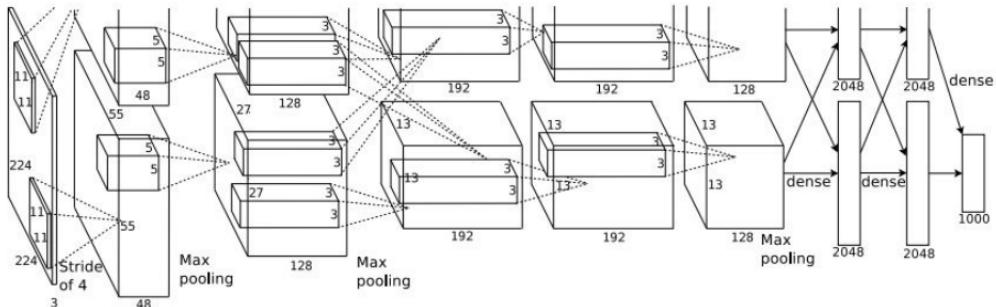
=>

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

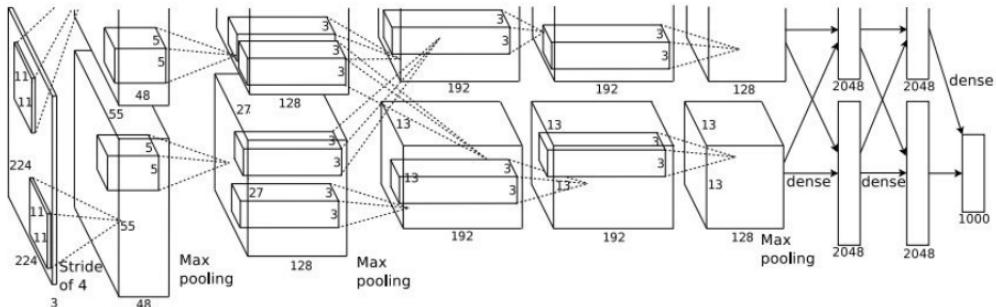
=>

Output volume **[55x55x96]**

Parameters: $(11 \times 11 \times 3) \times 96 = 35K$

Case Study: AlexNet

[Krizhevsky et al. 2012]



Input: 227x227x3 images

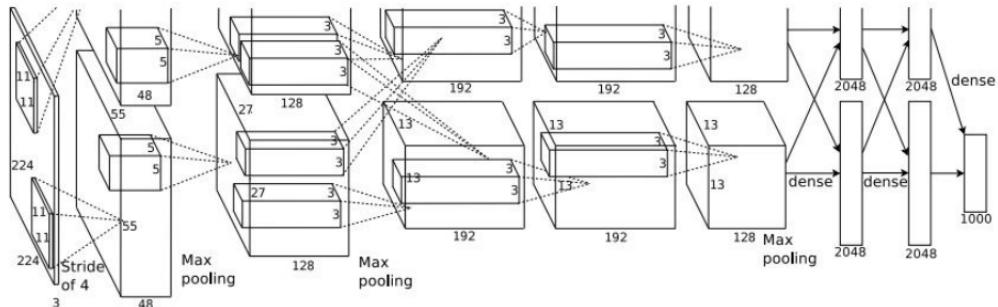
After CONV1: 55x55x96

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

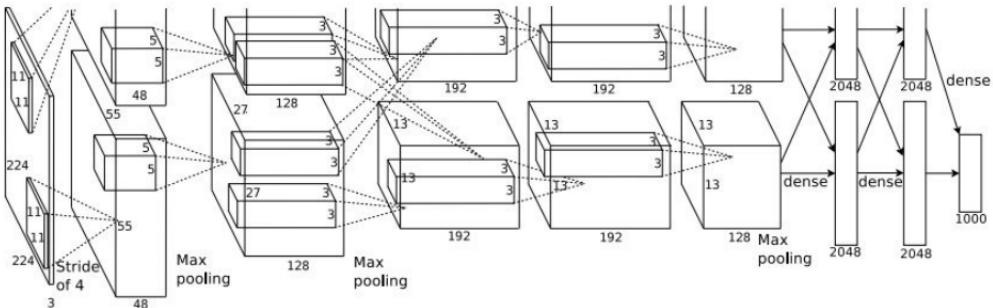
Second layer (POOL1): 3x3 filters applied at stride 2

Output volume: 27x27x96

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

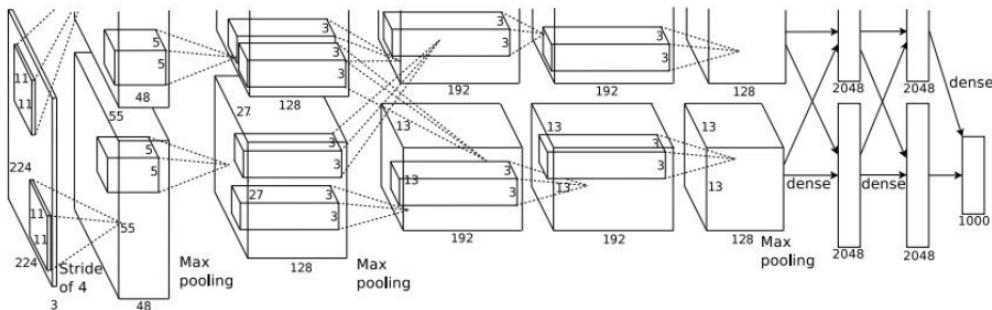
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1

[6x6x256] MAX POOL3: 3x3 filters at stride 2

[4096] FC6: 4096 neurons

[4096] FC7: 4096 neurons

[1000] FC8: 1000 neurons (class scores)



Case Study: 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

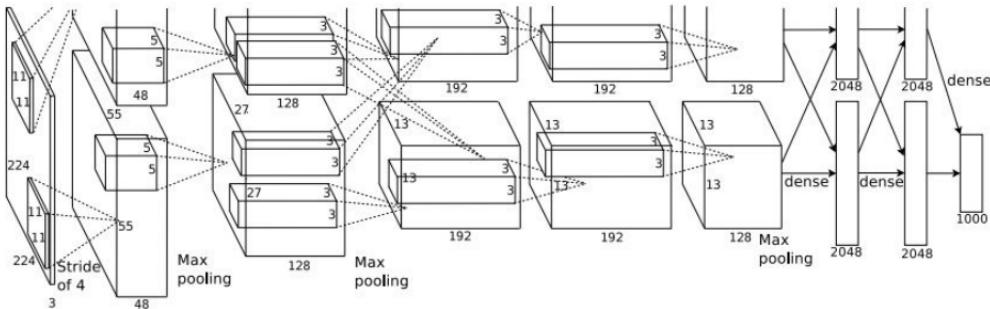
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1

[6x6x256] MAX POOL3: 3x3 filters at stride 2

[4096] FC6: 4096 neurons

[4096] FC7: 4096 neurons

[1000] FC8: 1000 neurons (class scores)

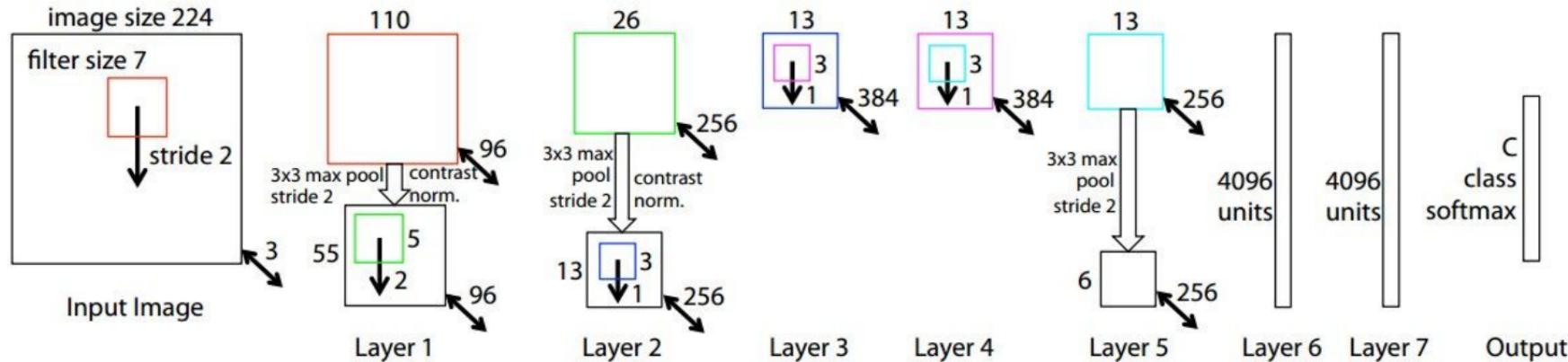


Details/Retrospectives:

- 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%

Case Study: ZFNet

[Zeiler and 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

ImageNet top 5 error: 15.4% -> 14.8%

Case Study: VGGNet

[Simonyan and Zisserman, 2014]

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

best model

11.2% top 5 error in ILSVRC 2013

->

7.3% top 5 error

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 LRN	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 conv3-256 conv3-256
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 conv3-512 conv3-512
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 conv3-512 conv3-512
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

Table 2: Number of parameters (in millions).

Network	A,A-LRN	B	C	D	E
Number of parameters	133	133	134	138	144

INPUT: [224x224x3] memory: 224*224*3=150K params: 0 (not counting biases)

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: $4096*1000 = 4,096,000$

ConvNet Configuration			
B	C	D	19
13 weight layers	16 weight layers	16 weight layers	
put (224 × 224 RGB image)			
conv3-64	conv3-64	conv3-64	cc
conv3-64	conv3-64	conv3-64	cc
		maxpool	
conv3-128	conv3-128	conv3-128	co
conv3-128	conv3-128	conv3-128	co
		maxpool	
conv3-256	conv3-256	conv3-256	co
conv3-256	conv3-256	conv3-256	co
		maxpool	
conv3-512	conv3-512	conv3-512	co
conv3-512	conv3-512	conv3-512	co
		maxpool	
conv3-512	conv3-512	conv3-512	co
conv3-512	conv3-512	conv3-512	co
		maxpool	
conv3-512	conv3-512	conv3-512	co
conv3-512	conv3-512	conv3-512	co
		maxpool	
FC-4096			
FC-4096			
FC-1000			
soft-max			

INPUT: [224x224x3] memory: 224*224*3=150K params: 0 (not counting biases)

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: $4096*1000 = 4,096,000$

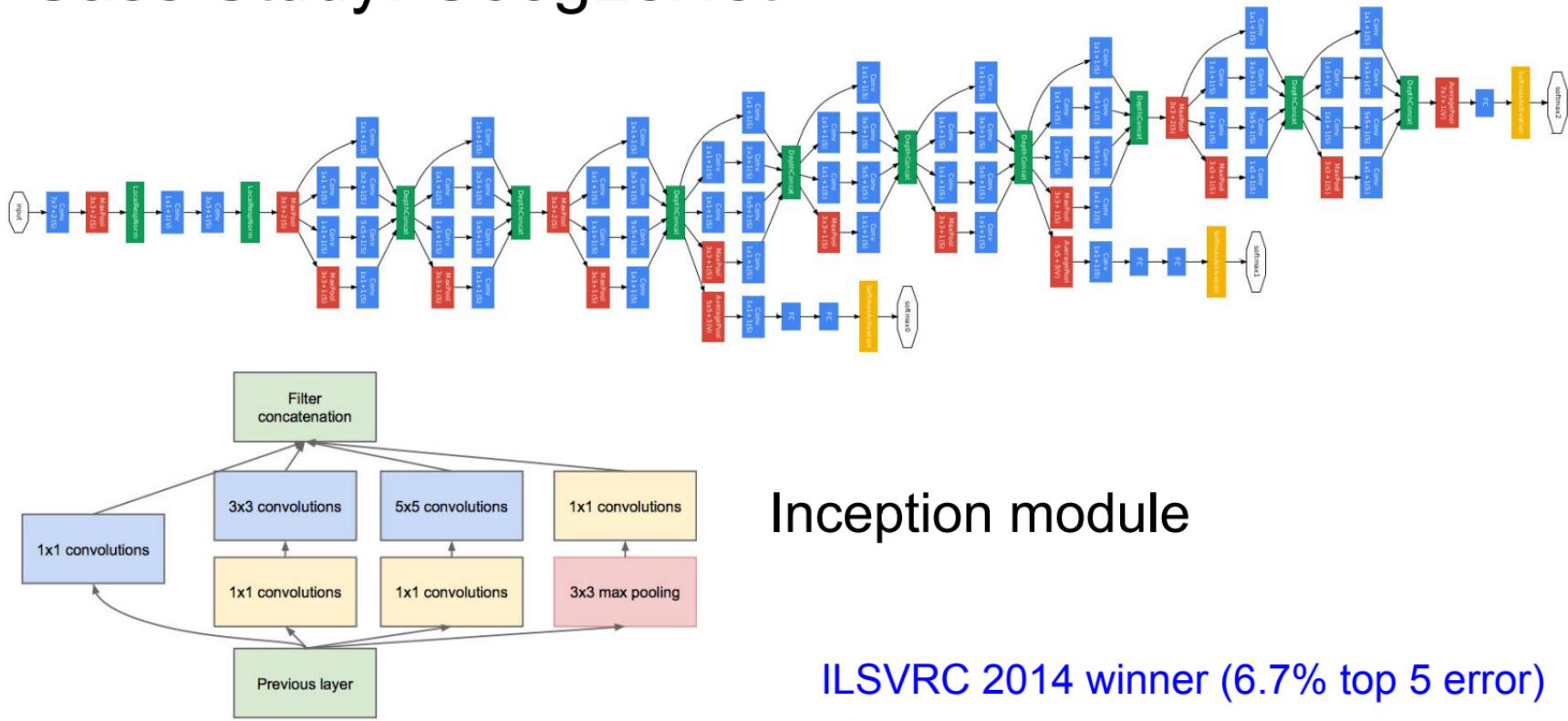
TOTAL memory: 24M * 4 bytes \approx 93MB / image (only forward! ~ 2 for bwd)

TOTAL params: 138M parameters

ConvNet Configuration			
B	C	D	19
13 weight layers	16 weight layers	16 weight layers	
put (224 × 224 RGB image)			
conv3-64	conv3-64	conv3-64	cc
conv3-64	conv3-64	conv3-64	cc
		maxpool	
conv3-128	conv3-128	conv3-128	co
conv3-128	conv3-128	conv3-128	co
		maxpool	
conv3-256	conv3-256	conv3-256	co
conv3-256	conv3-256	conv3-256	co
		conv3-256	co
		maxpool	
conv3-512	conv3-512	conv3-512	co
conv3-512	conv3-512	conv3-512	co
		conv3-512	co
		maxpool	
conv3-512	conv3-512	conv3-512	co
conv3-512	conv3-512	conv3-512	co
		conv3-512	co
		maxpool	
FC-4096			
FC-4096			
FC-1000			
soft-max			

Case Study: GoogLeNet

[Szegedy et al., 2014]



Case Study: ResNet

[He et al., 2015]

ILSVRC 2015 winner (3.6% top 5 error)



MSRA @ ILSVRC & COCO 2015 Competitions

- **1st places** in all five main tracks

- ImageNet Classification: “Ultra-deep” (quote Yann) **152-layer** nets
- ImageNet Detection: **16%** better than 2nd
- ImageNet Localization: **27%** better than 2nd
- COCO Detection: **11%** better than 2nd
- COCO Segmentation: **12%** better than 2nd

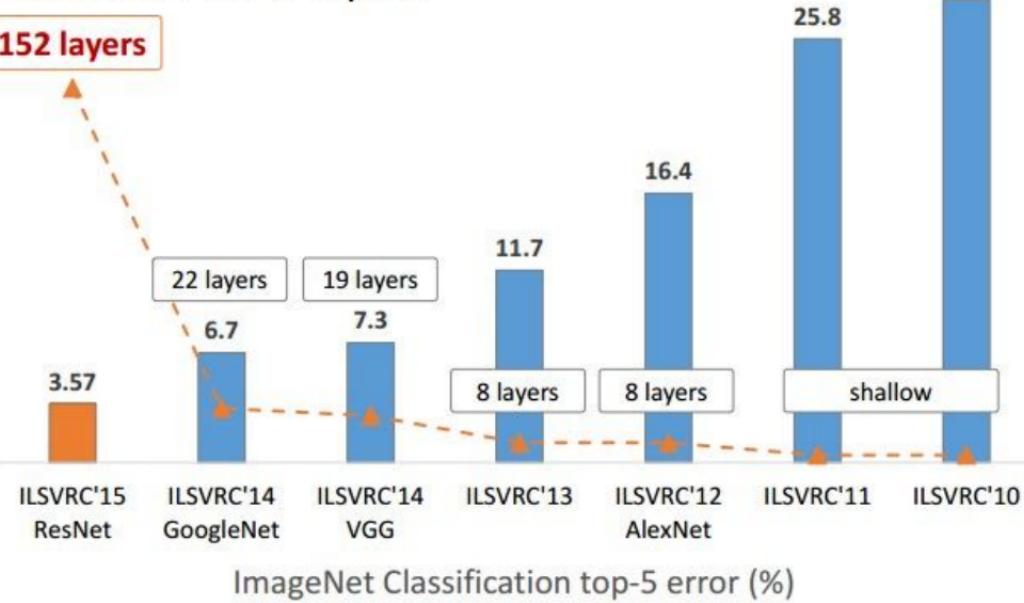
*improvements are relative numbers



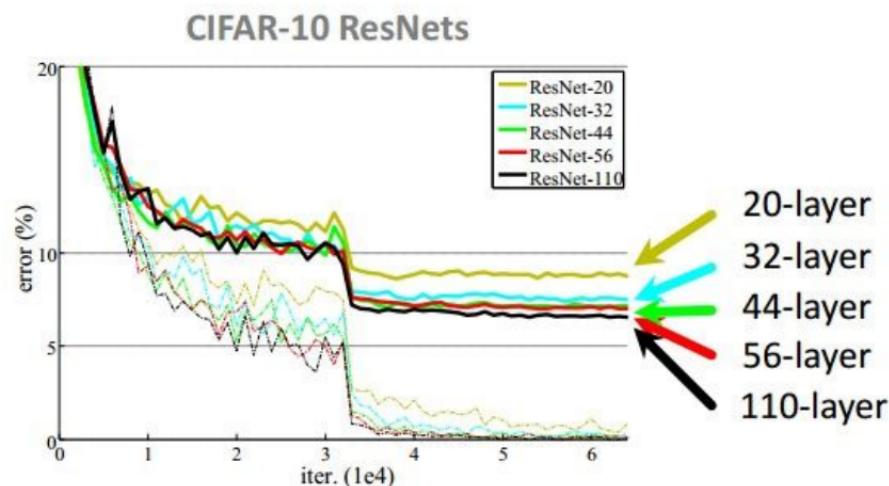
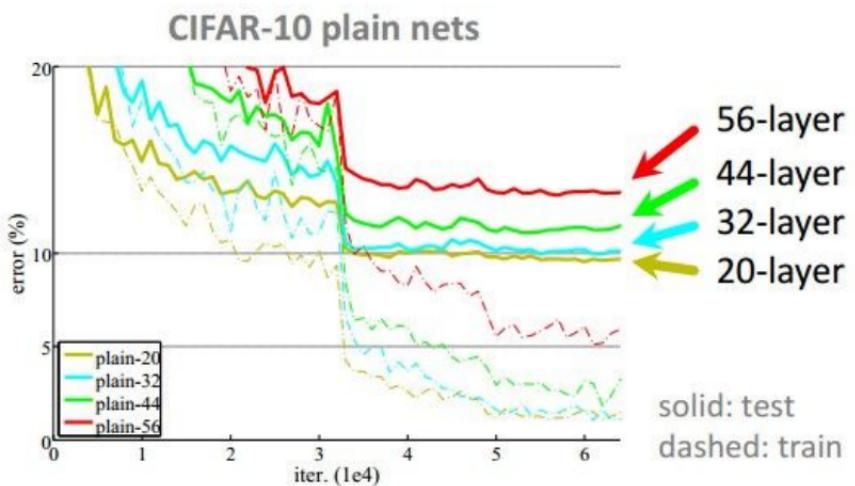
Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". arXiv 2015.

Slide from Kaiming He's recent presentation <https://www.youtube.com/watch?v=1PGLj-uKT1w>

Revolution of Depth



CIFAR-10 experiments



Case Study: ResNet

[He et al., 2015]

ILSVRC 2015 winner (3.6% top 5 error)

Revolution of Depth

AlexNet, 8 layers
(ILSVRC 2012)



VGG, 19 layers
(ILSVRC 2014)



ResNet, 152 layers
(ILSVRC 2015)

Microsoft
Research



2-3 weeks of training
on 8 GPU machine

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

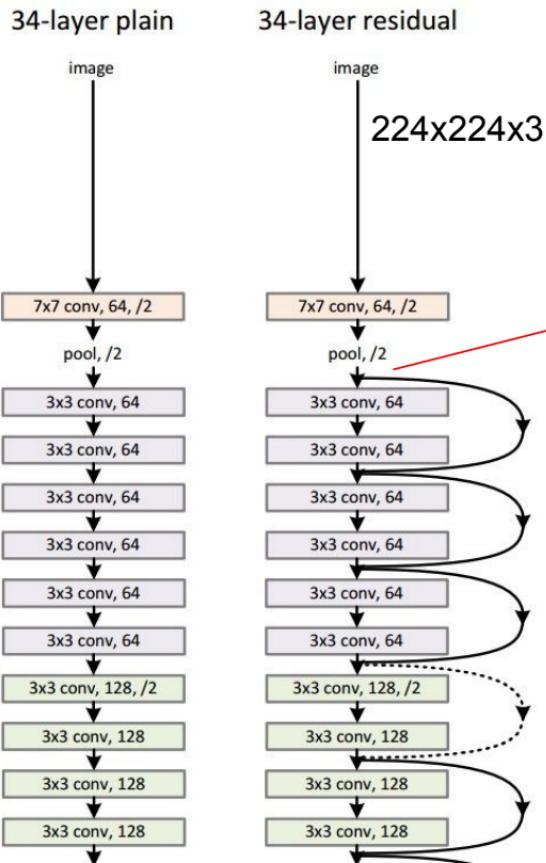


Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". arXiv 2015.

(slide from Kaiming He's recent presentation)

Case Study: ResNet

[He et al., 2015]

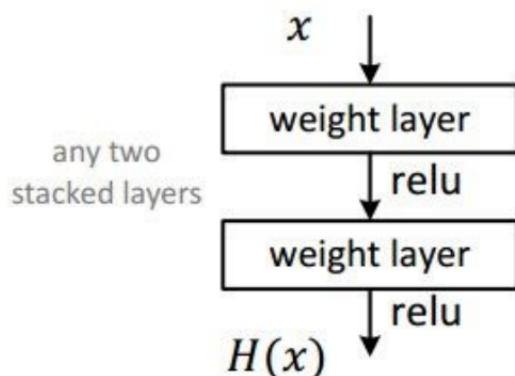


spatial dimension
only 56x56!

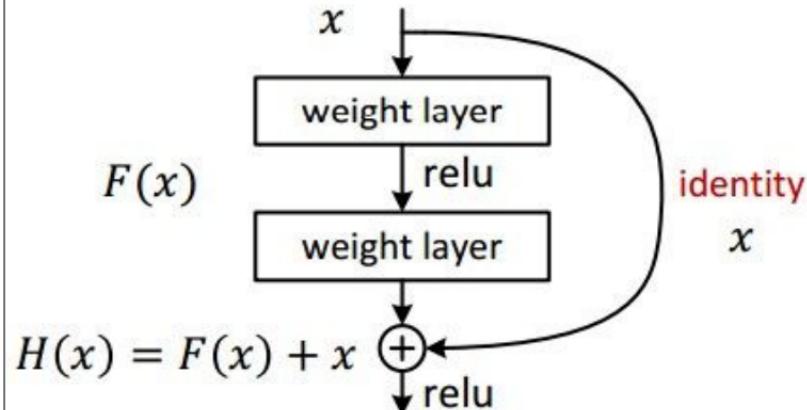
Case Study: ResNet

[He et al., 2015]

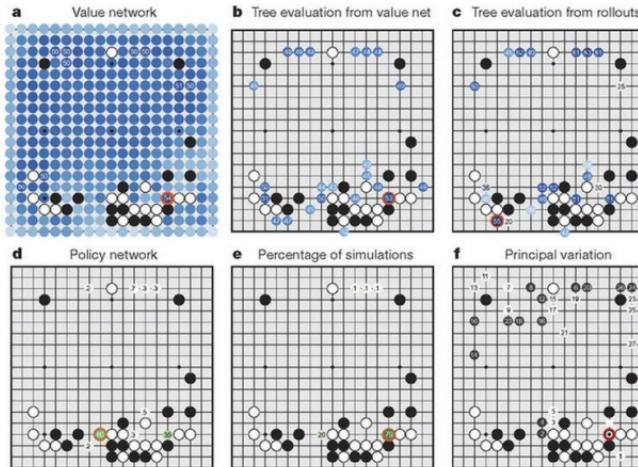
- Plain net



- Residual net



Case Study Bonus: DeepMind's AlphaGo



The input to the policy network is a $19 \times 19 \times 48$ image stack consisting of 48 feature planes. The first hidden layer zero pads the input into a 23×23 image, then convolves k filters of kernel size 5×5 with stride 1 with the input image and applies a rectifier nonlinearity. Each of the subsequent hidden layers 2 to 12 zero pads the respective previous hidden layer into a 21×21 image, then convolves k filters of kernel size 3×3 with stride 1, again followed by a rectifier nonlinearity. The final layer convolves 1 filter of kernel size 1×1 with stride 1, with a different bias for each position, and applies a softmax function. The match version of AlphaGo used $k = 192$ filters; Fig. 2b and [Extended Data Table 3](#) additionally show the results of training with $k = 128, 256$ and 384 filters.

policy network:

[$19 \times 19 \times 48$] Input

CONV1: 192 5×5 filters , stride 1, pad 2 => [$19 \times 19 \times 192$]

CONV2..12: 192 3×3 filters, stride 1, pad 1 => [$19 \times 19 \times 192$]

CONV: 1 1×1 filter, stride 1, pad 0 => [19×19] (*probability map of promising moves*)

Summary

- ConvNets stack CONV,POOL,FC layers
- Trend towards smaller filters and deeper architectures
- Trend towards getting rid of POOL/FC layers (just CONV)
- Typical architectures look like
 $[(\text{CONV-RELU})^*N-\text{POOL?}]^*M-(\text{FC-RELU})^*K,\text{SOFTMAX}$
where N is usually up to ~5, M is large, $0 \leq K \leq 2$.
 - but recent advances such as ResNet/GoogLeNet challenge this paradigm