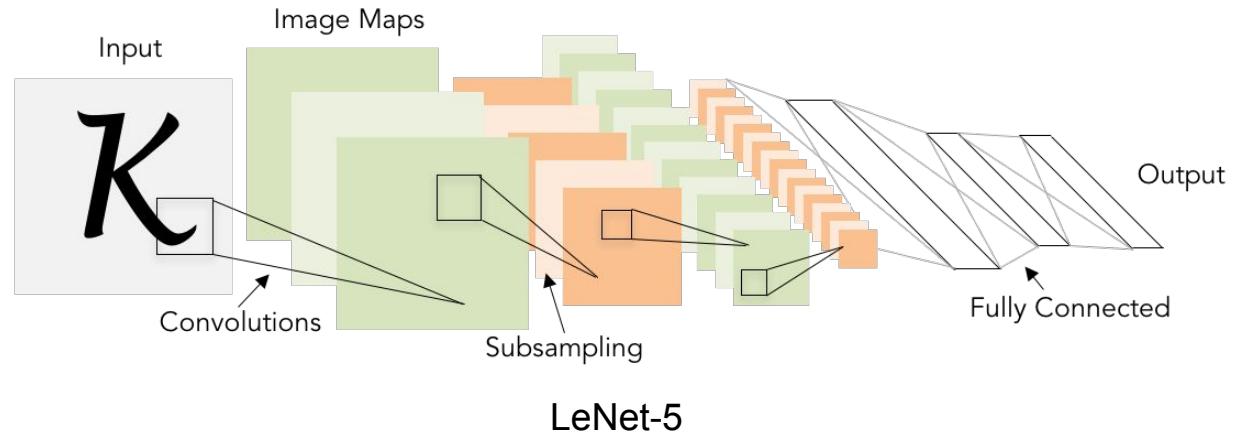




Lecture 5: Convolutional Neural Networks

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

[LeCun, Bottou, Bengio, Haffner 1998]



A bit of history: ImageNet Classification with Deep Convolutional Neural Networks *[Krizhevsky, Sutskever, Hinton, 2012]*

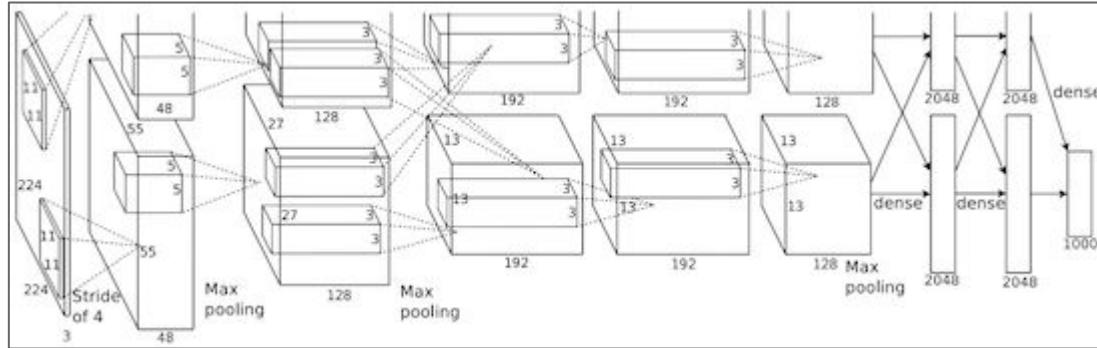


Figure copyright Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, 2012. Reproduced with permission.

“AlexNet”

Fast-forward to today: ConvNets are everywhere

Classification



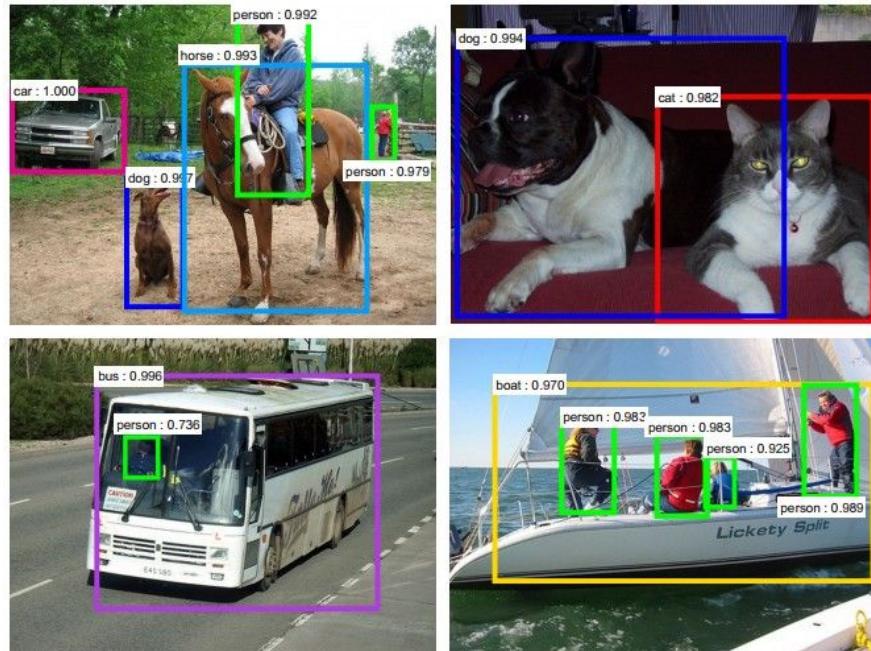
Retrieval



Figures copyright Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, 2012. Reproduced with permission.

Fast-forward to today: ConvNets are everywhere

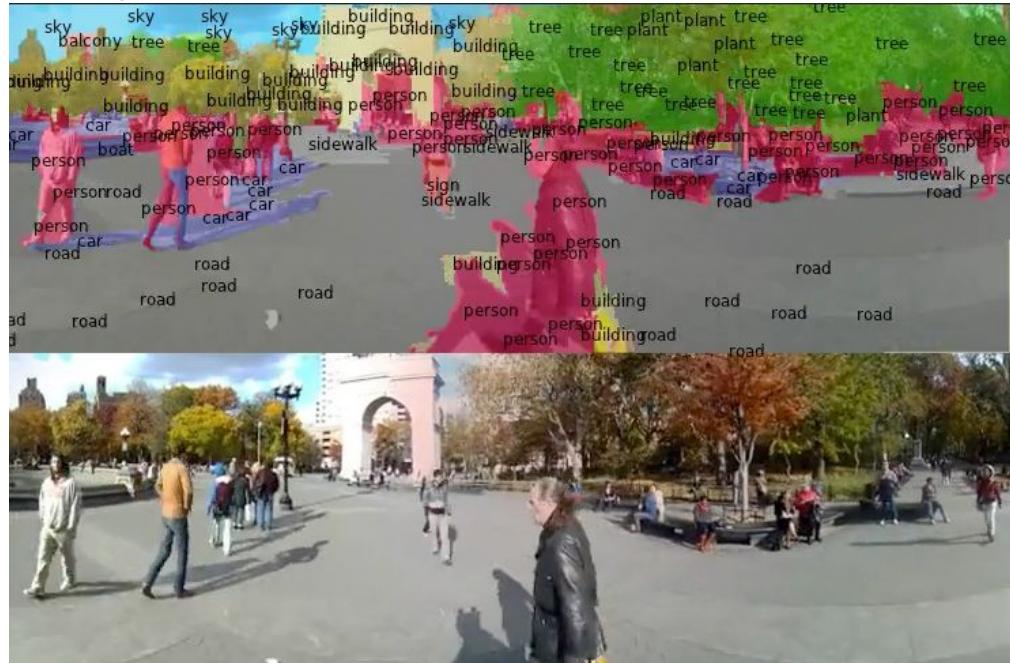
Detection



Figures copyright Shaoqing Ren, Kaiming He, Ross Girshick, Jian Sun, 2015. Reproduced with permission.

[*Faster R-CNN: Ren, He, Girshick, Sun 2015*]

Segmentation



Figures copyright Clement Farabet, 2012.
Reproduced with permission.

[*Farabet et al., 2012*]

Fast-forward to today: ConvNets are everywhere



self-driving cars

Photo by Lane McIntosh. Copyright CS231n 2017.



[This image](#) by GBPublic_PR is licensed under [CC-BY 2.0](#)

NVIDIA Tesla line

(these are the GPUs on rye01.stanford.edu)

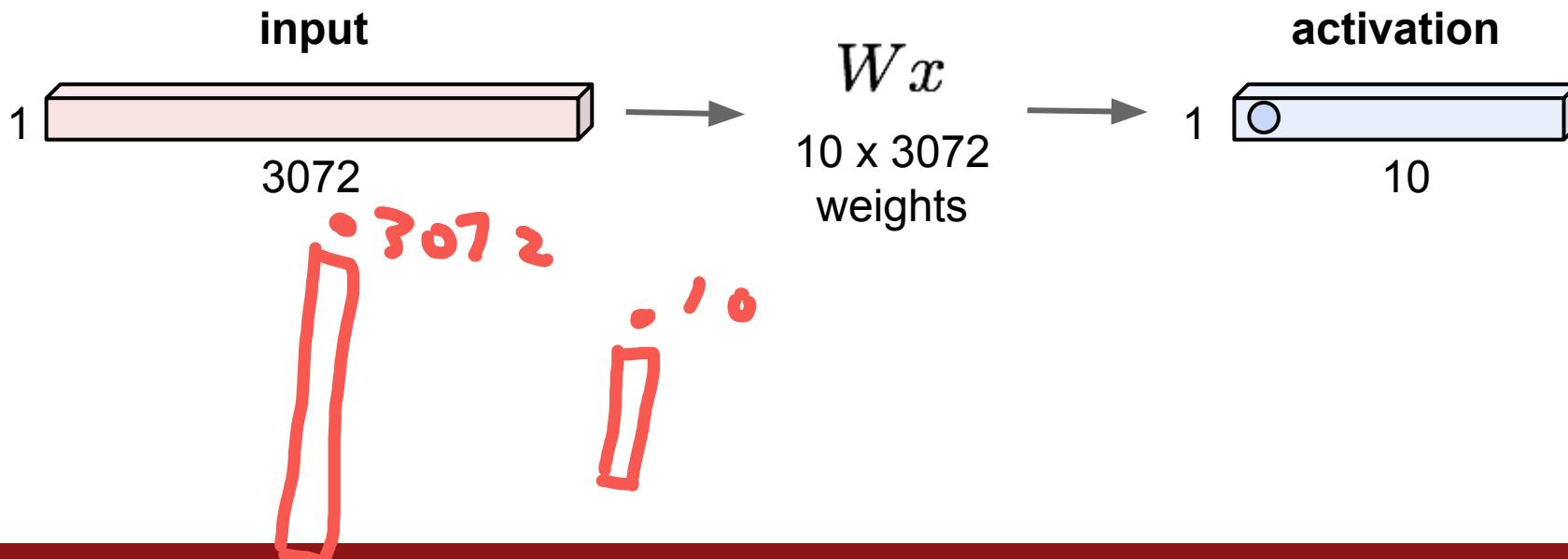
Note that for embedded systems a typical setup would involve NVIDIA Tegras, with integrated GPU and ARM-based CPU cores.

Convolutional Neural Networks

(First without the brain stuff)

Fully Connected Layer

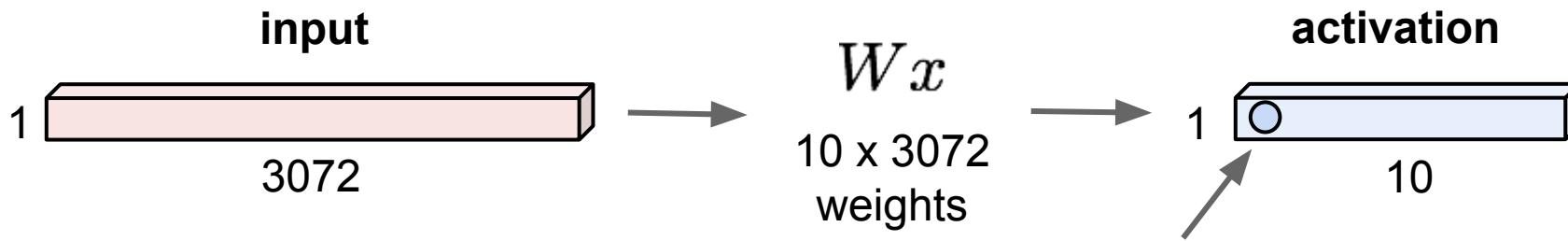
32x32x3 image -> stretch to 3072 x 1



Fully Connected Layer

32x32x3 image -> stretch to 3072 x 1

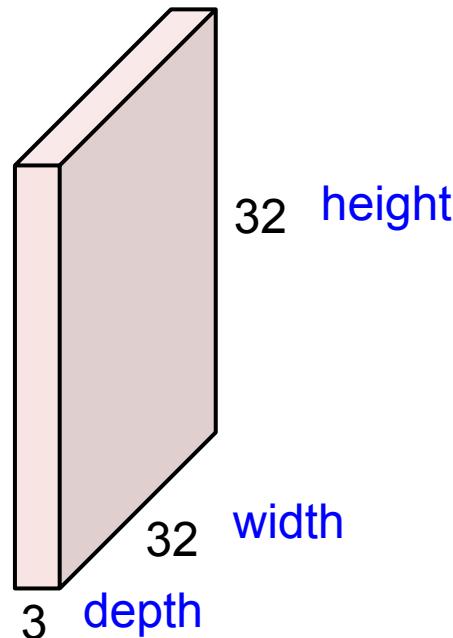
1. Why only 10 W?
2. Why we need activation?
3. Why Relu



1 number:
the result of taking a dot product
between a row of W and the input
(a 3072-dimensional dot product)

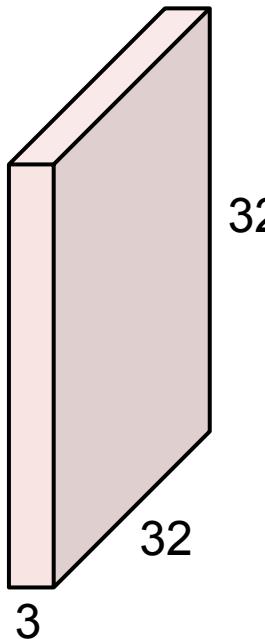
Convolution Layer

32x32x3 image -> preserve spatial structure



Convolution Layer

32x32x3 image



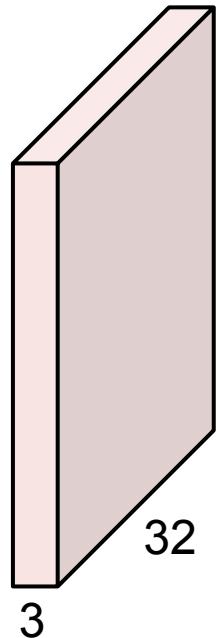
5x5x3 filter



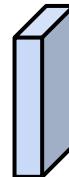
Convolve the filter with the image
i.e. “slide over the image spatially,
computing dot products”

Convolution Layer

32x32x3 image



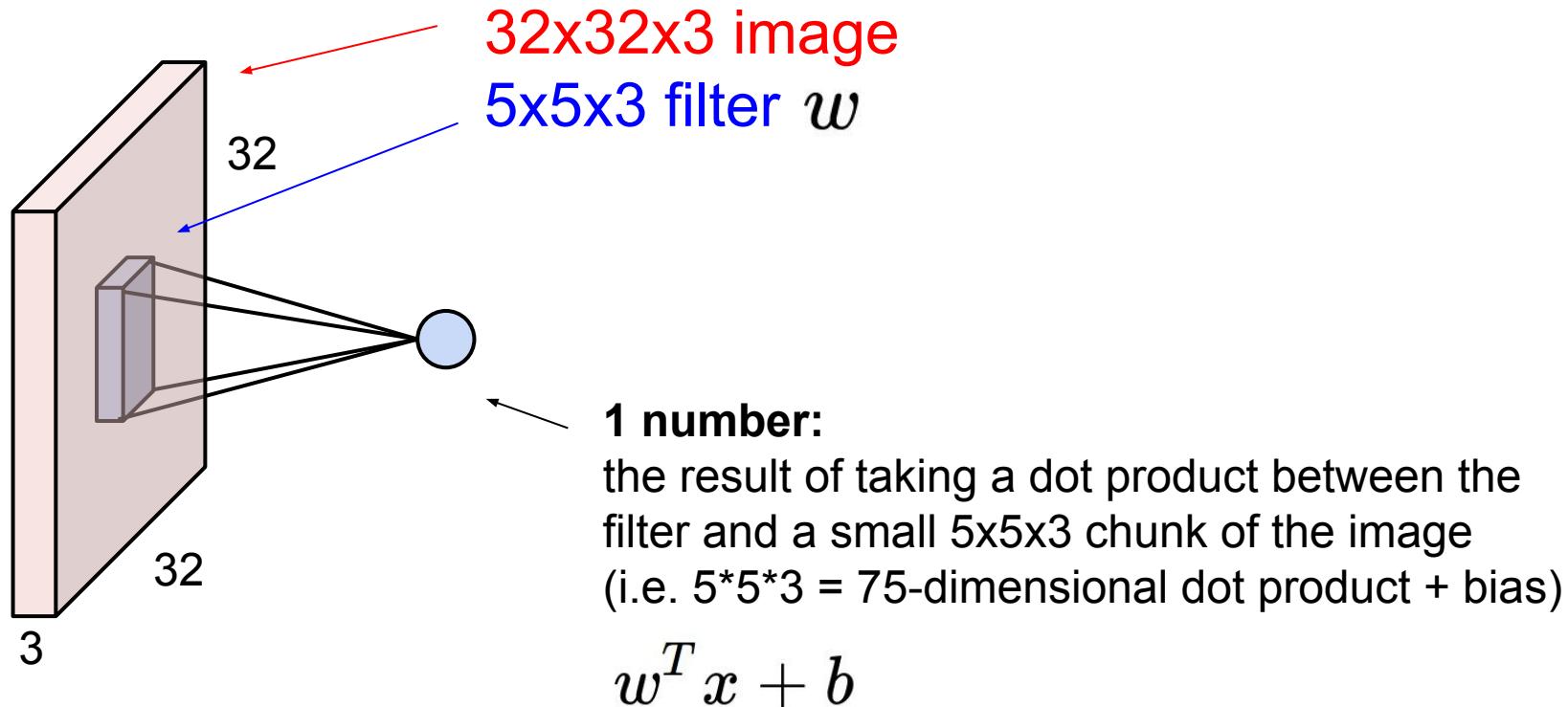
5x5x3 filter



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

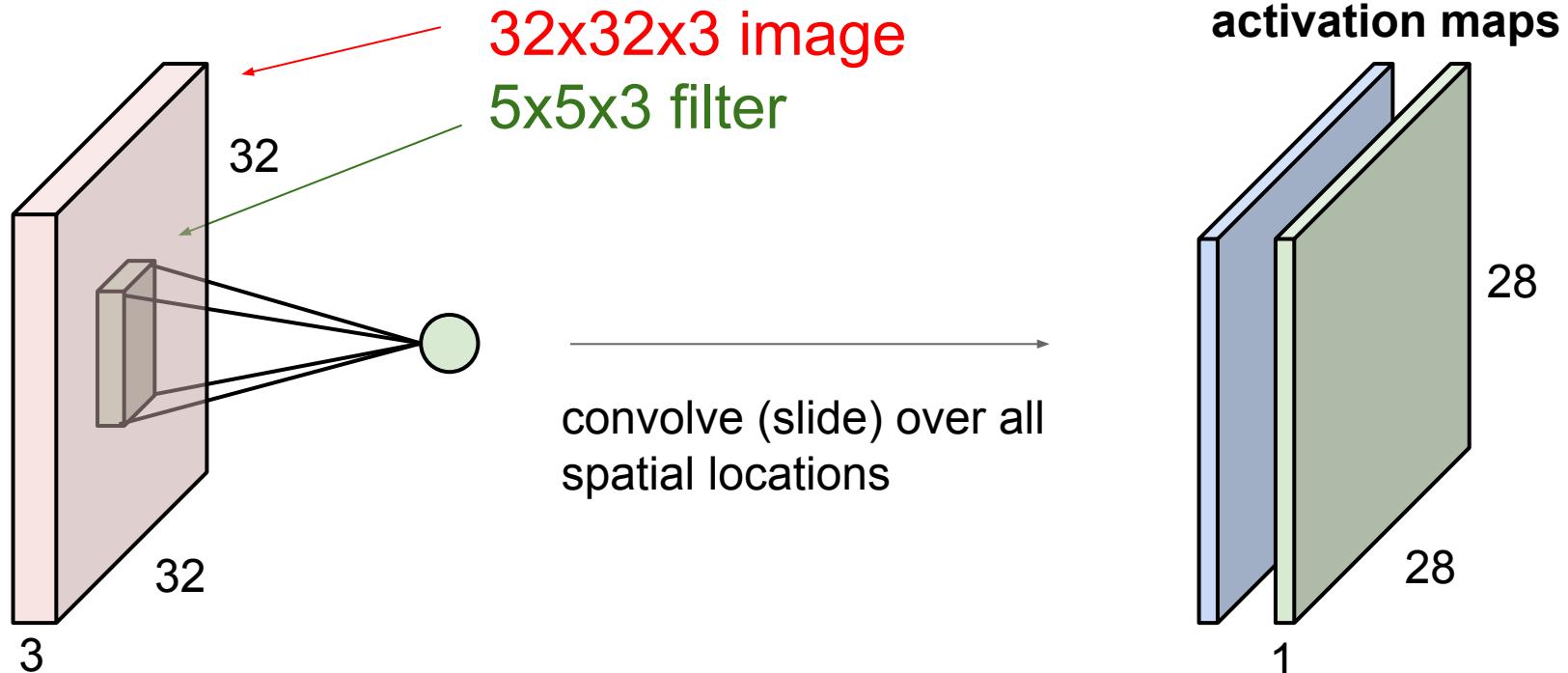


Convolution Layer

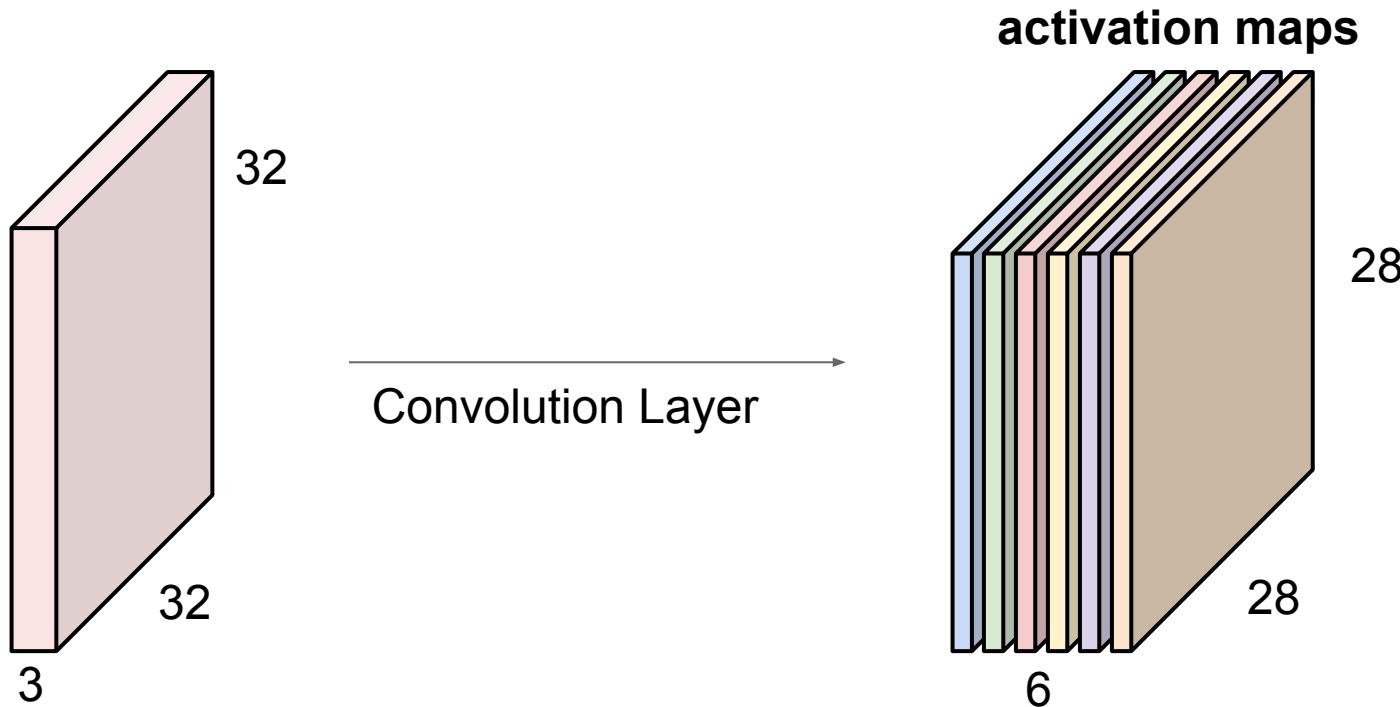


Convolution Layer

consider a second, green filter

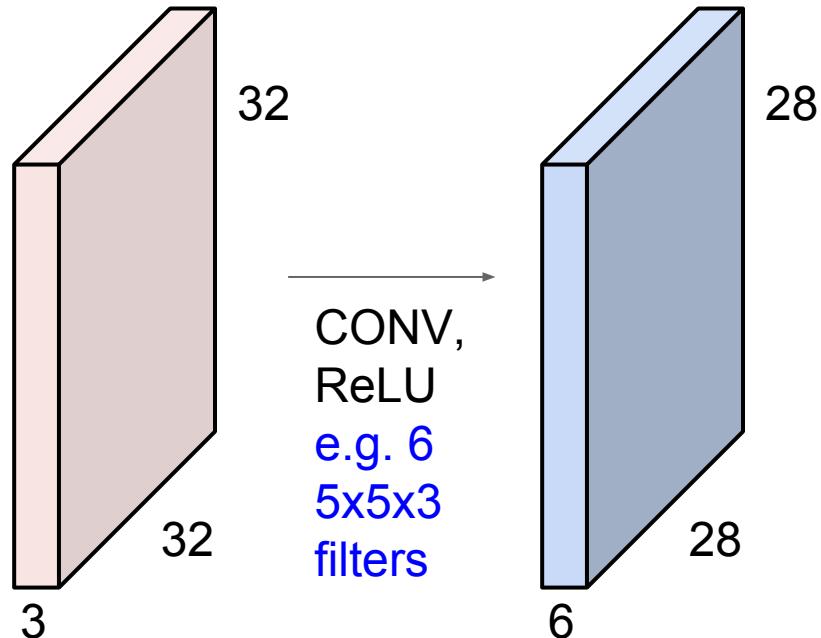


For example, if we had 6 5×5 filters, we'll get 6 separate activation maps:

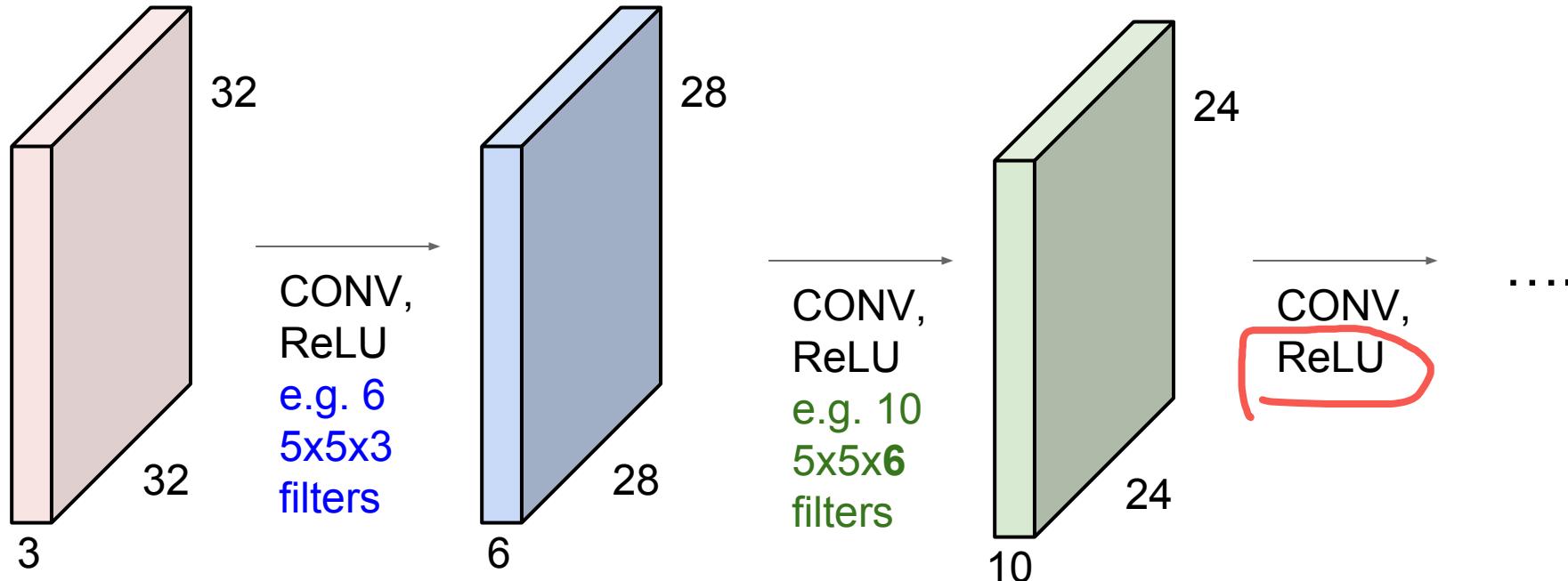


We stack these up to get a “new image” of size $28 \times 28 \times 6$!

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



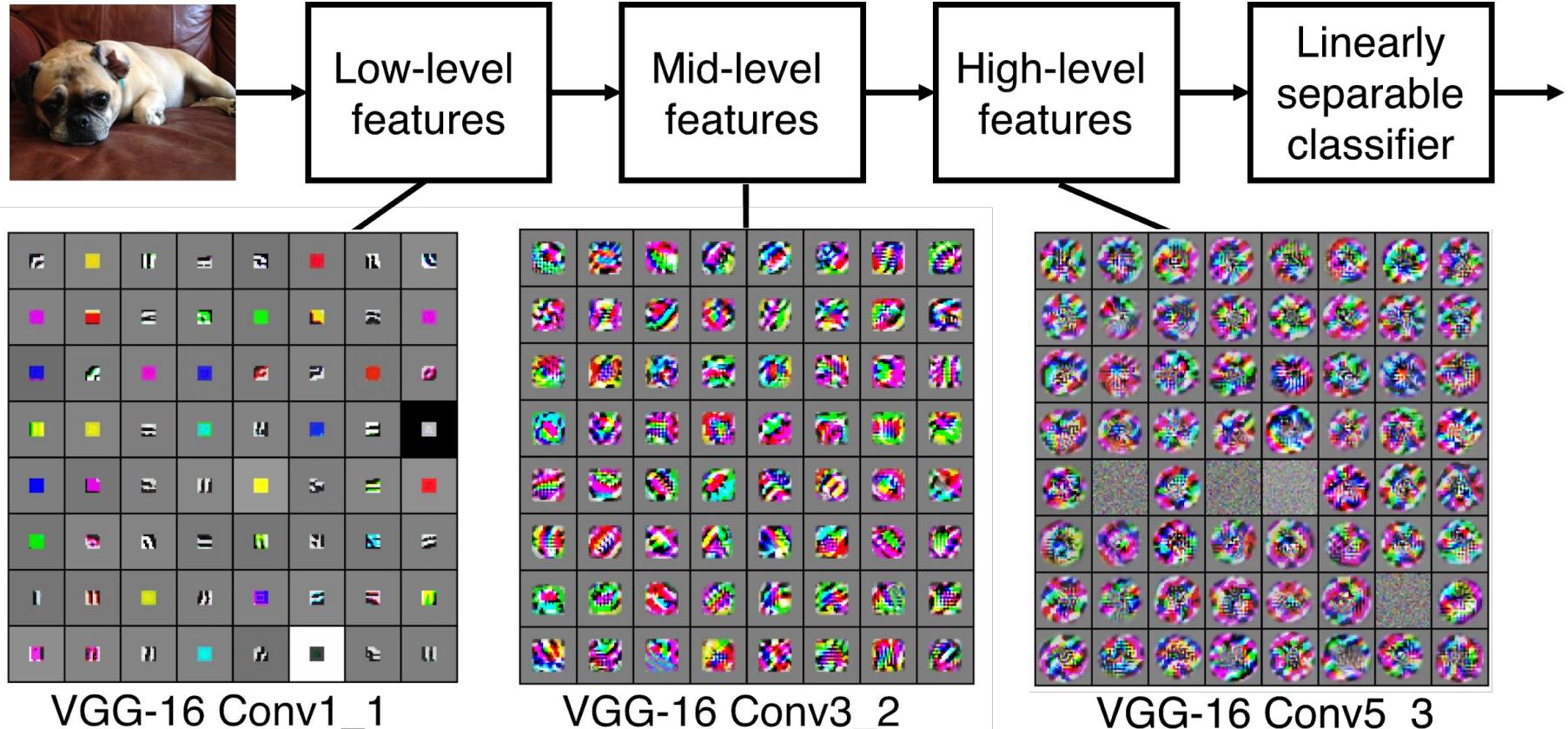
Preview: ConvNet is a sequence of Convolution Layers, interspersed with activation functions



Preview

[Zeiler and Fergus 2013]

Visualization of VGG-16 by Lane McIntosh. VGG-16 architecture from [Simonyan and Zisserman 2014].

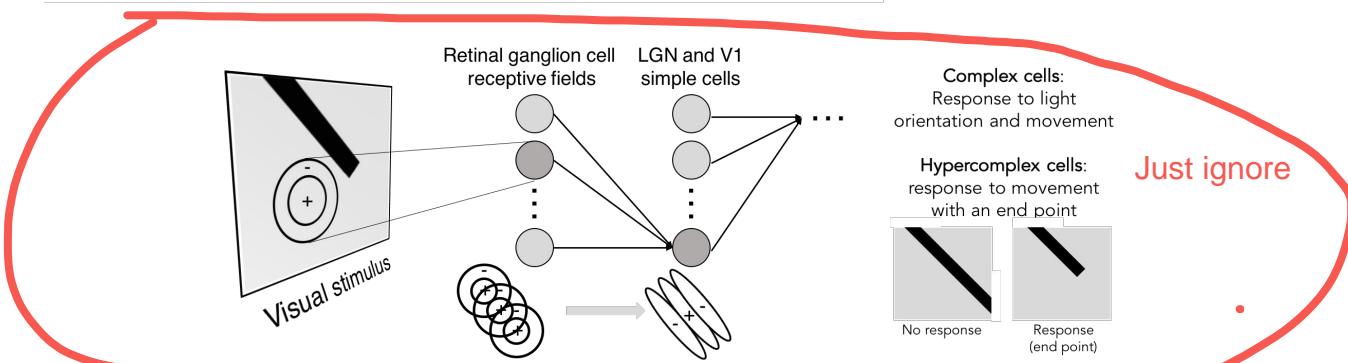
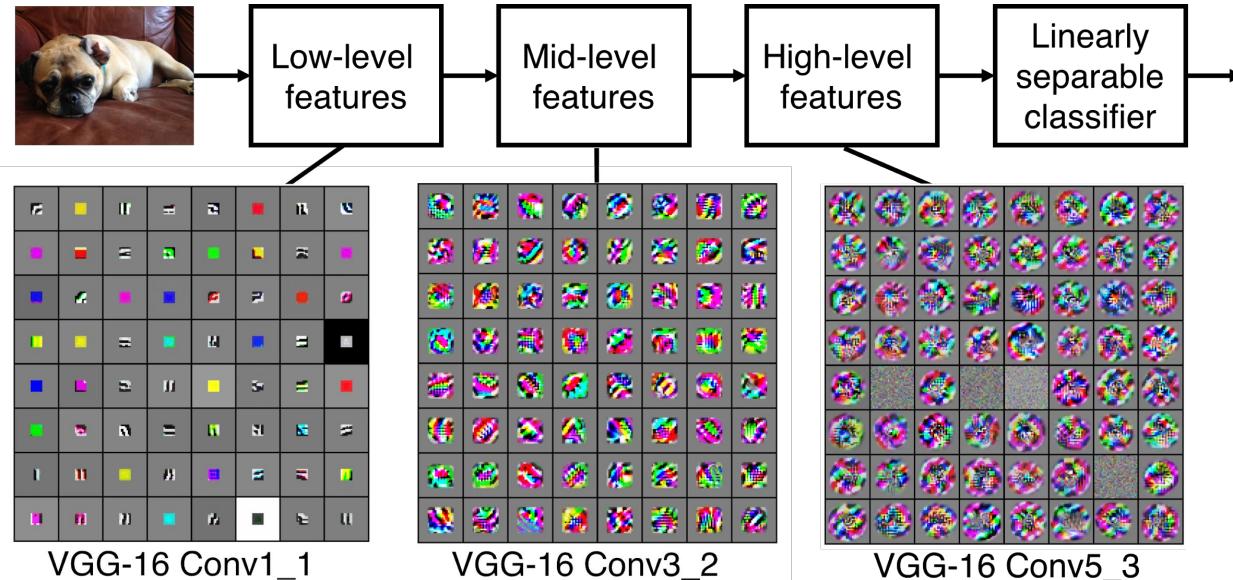


VGG-16 Conv1_1

VGG-16 Conv3_2

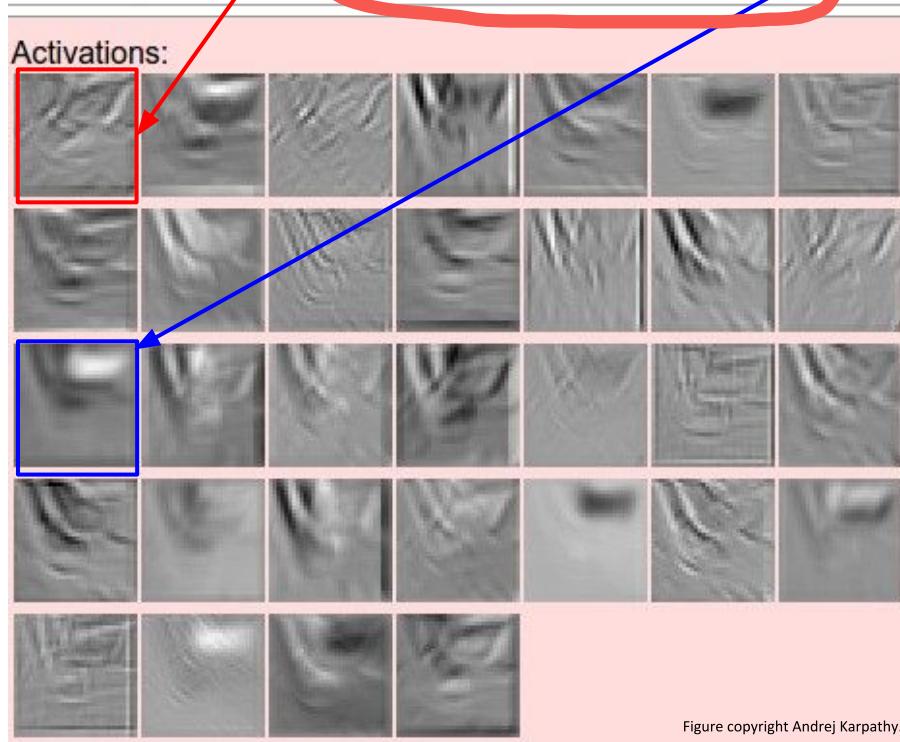
VGG-16 Conv5_3

Preview





one filter =>
one activation map



example 5x5 filters
(32 total)

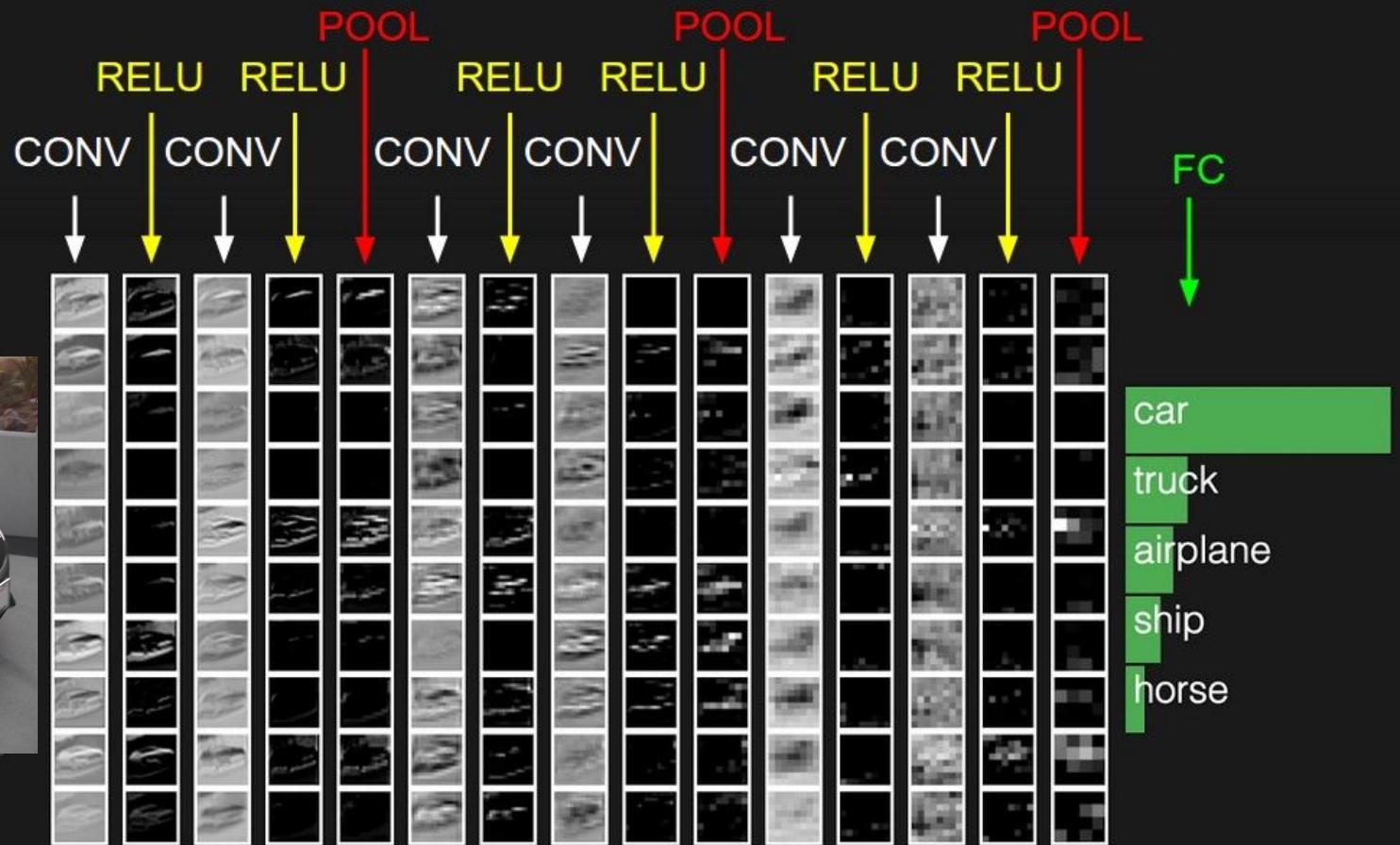
We call the layer convolutional
because it is related to convolution
of two signals:

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

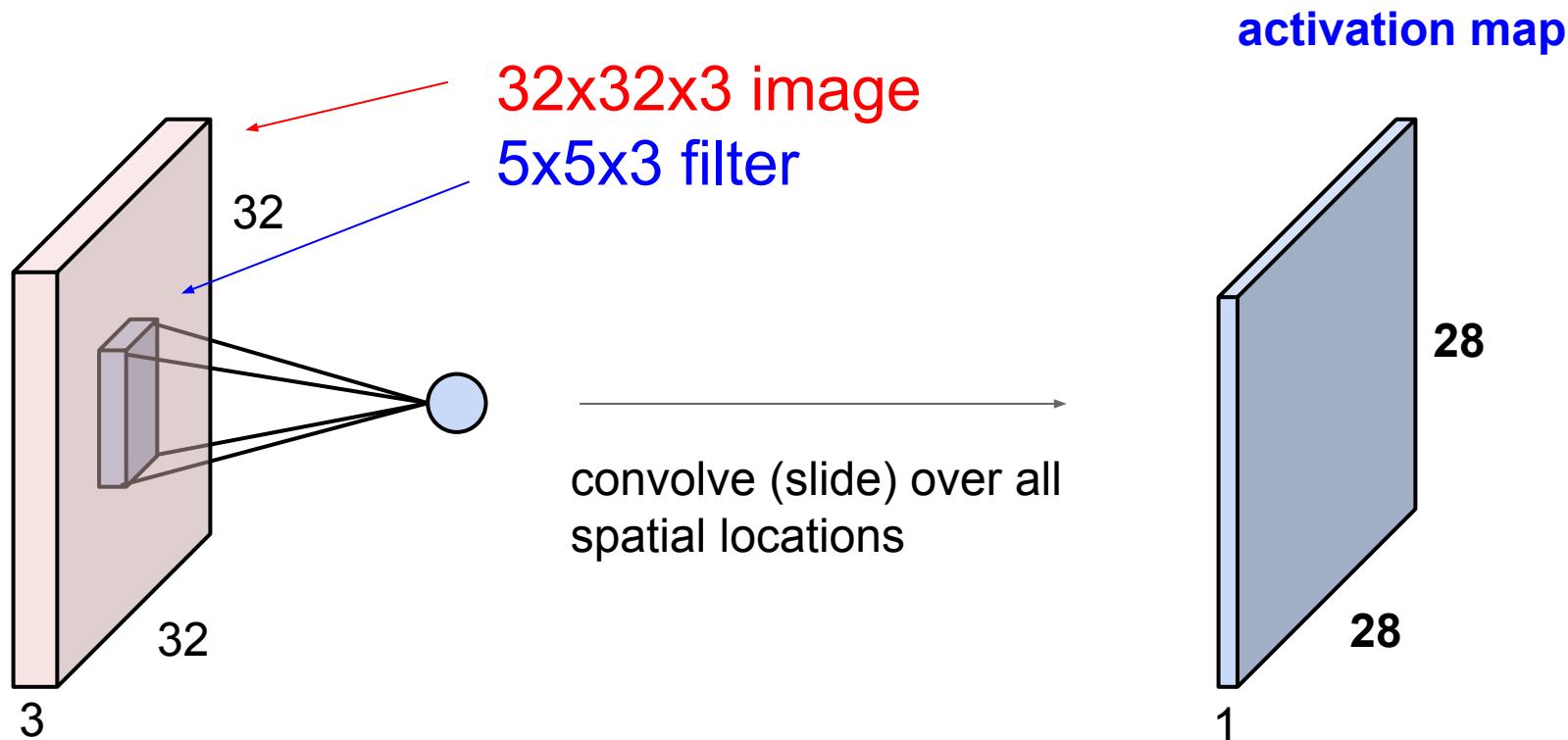
input * filter

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

preview:

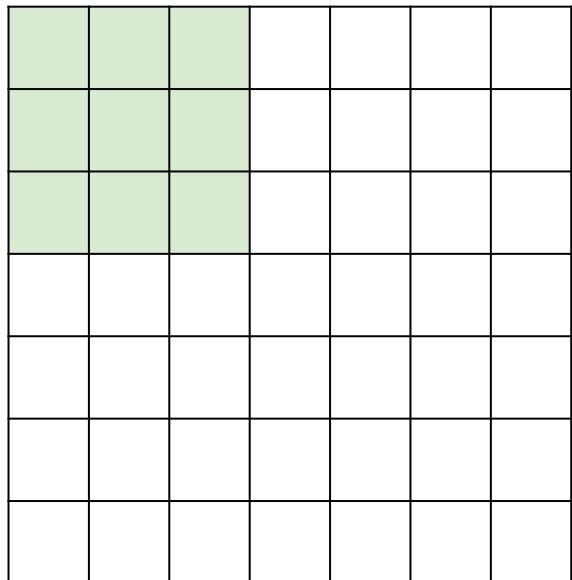


A closer look at spatial dimensions:



A closer look at spatial dimensions:

7

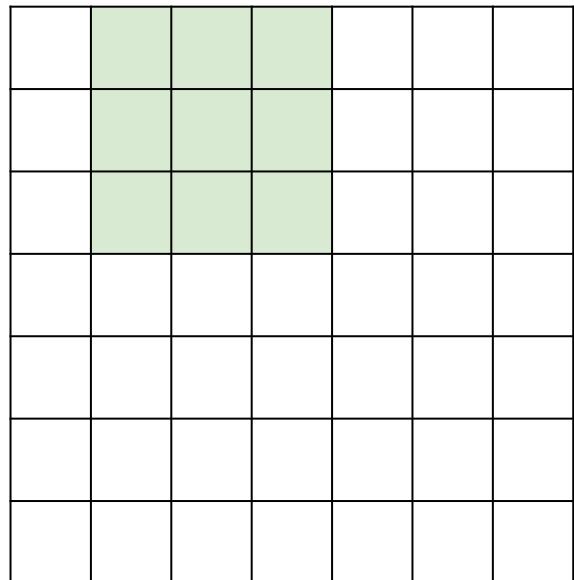


7x7 input (spatially)
assume 3x3 filter

7

A closer look at spatial dimensions:

7

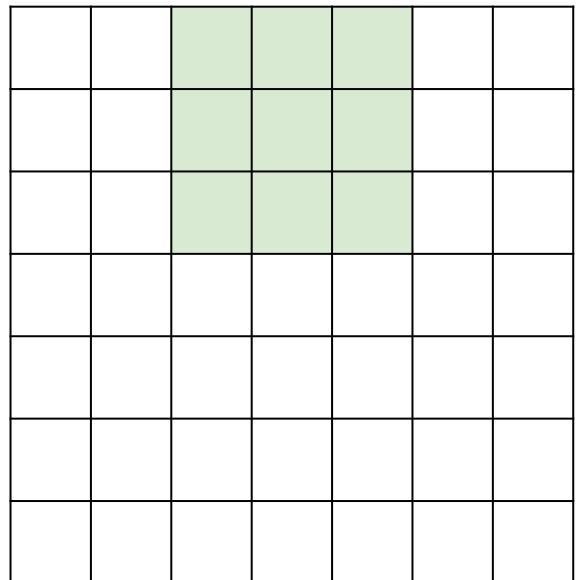


7x7 input (spatially)
assume 3x3 filter

7

A closer look at spatial dimensions:

7

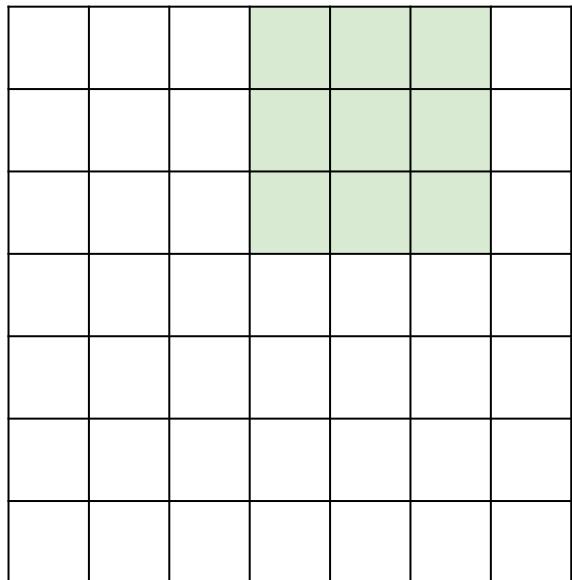


7x7 input (spatially)
assume 3x3 filter

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A closer look at spatial dimensions:

7

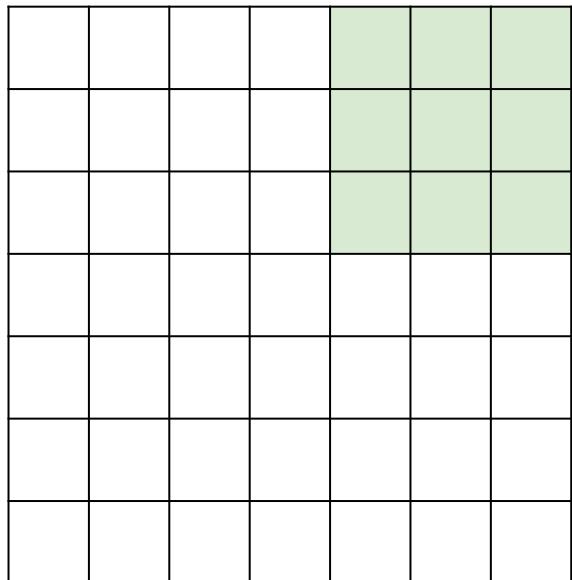


7x7 input (spatially)
assume 3x3 filter

7

A closer look at spatial dimensions:

7

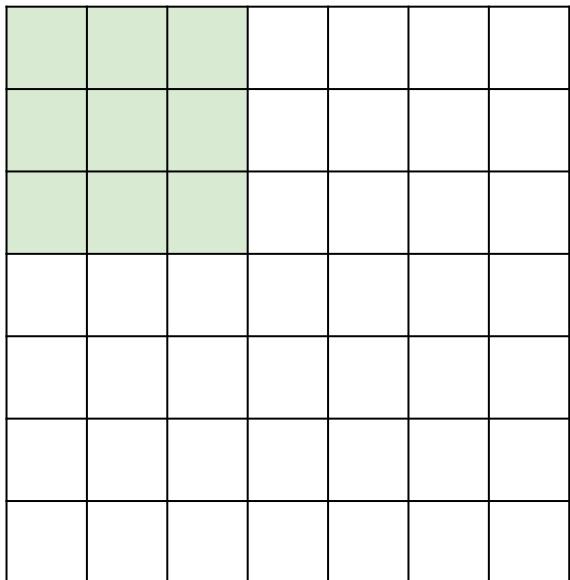


7x7 input (spatially)
assume 3x3 filter

=> 5x5 output

A closer look at spatial dimensions:

7

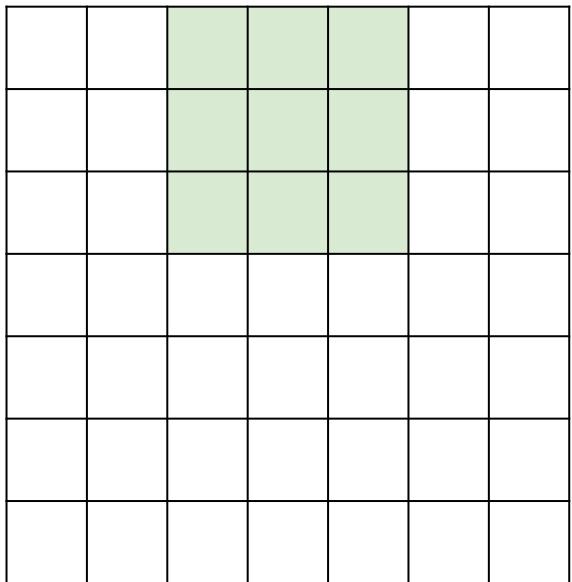


7

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

A closer look at spatial dimensions:

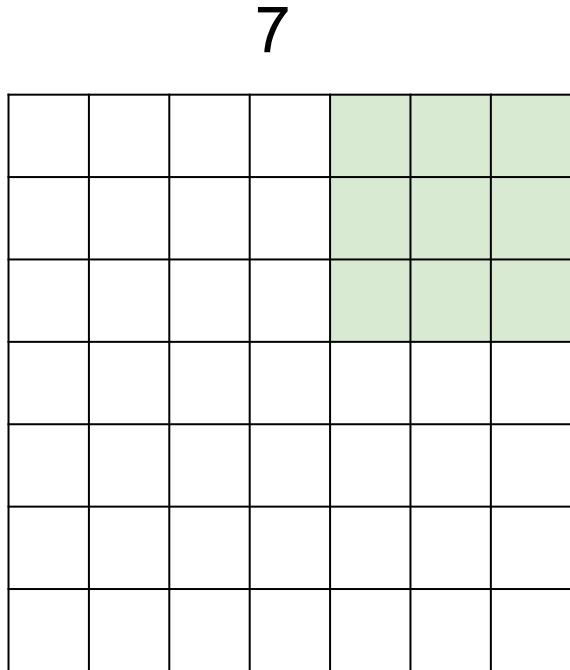
7



7

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

A closer look at spatial dimensions:

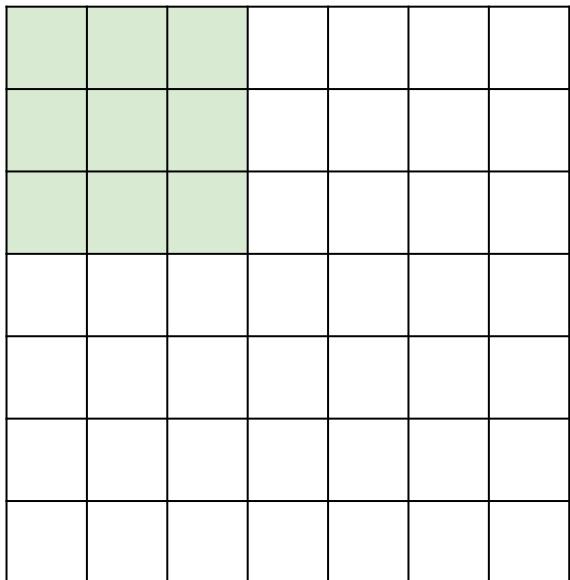


7

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

A closer look at spatial dimensions:

7

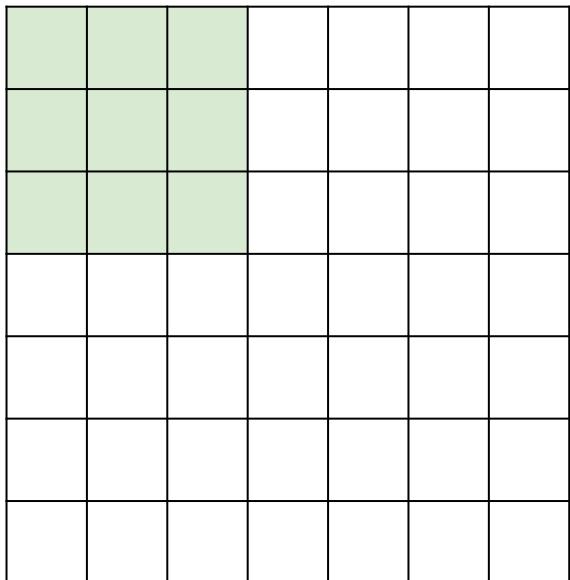


7

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

A closer look at spatial dimensions:

7



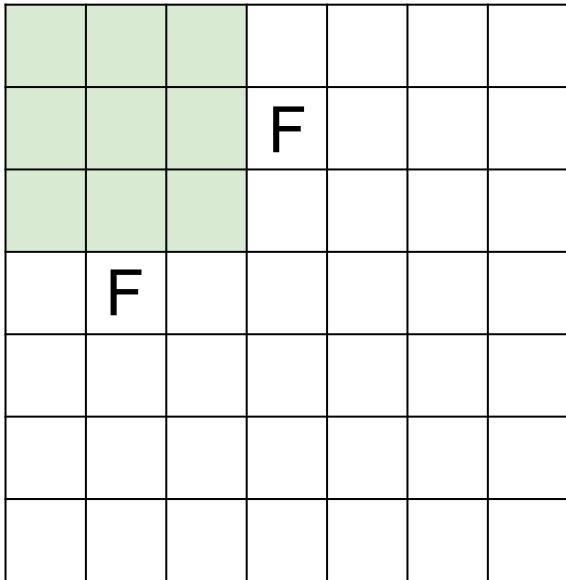
7

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) / 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?

Add 0 to the border



(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

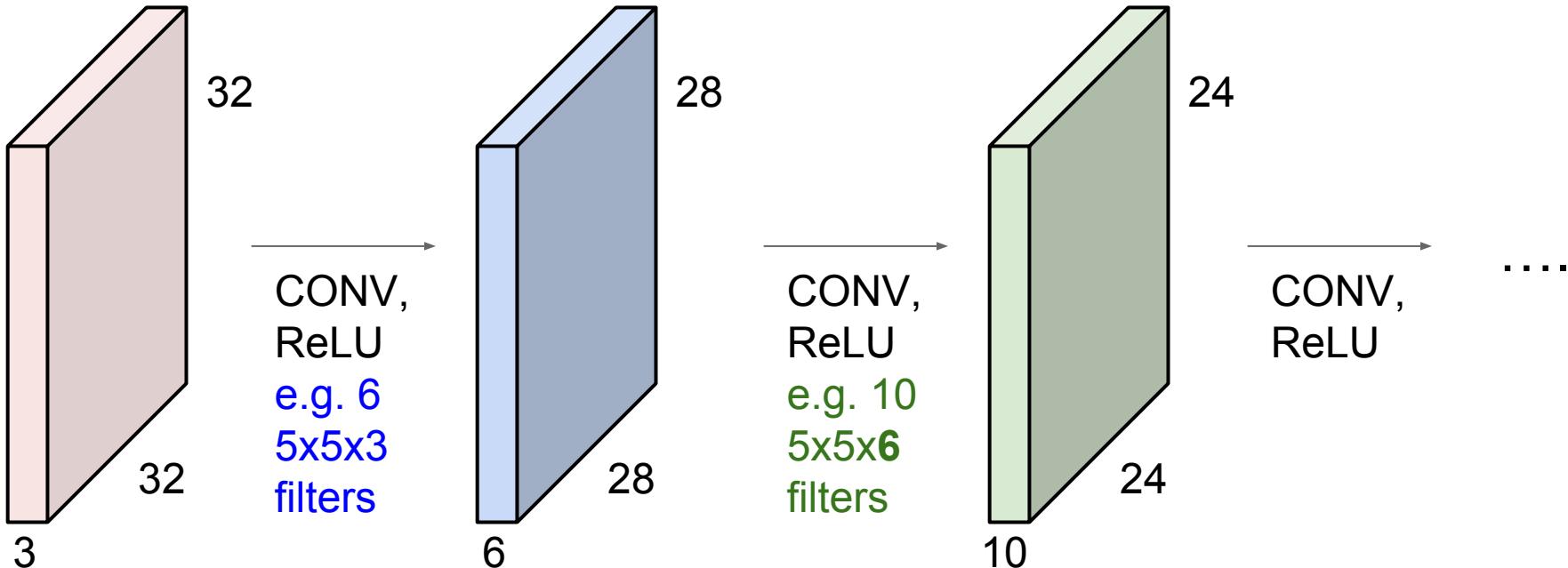
$F = 5 \Rightarrow$ zero pad with 2

$F = 7 \Rightarrow$ 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.

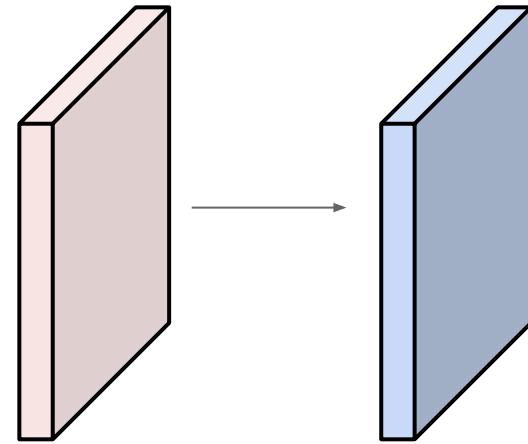


Examples time:

Input volume: **32x32x3**

10 5x5 filters with stride 1, pad 2

Output volume size: ?



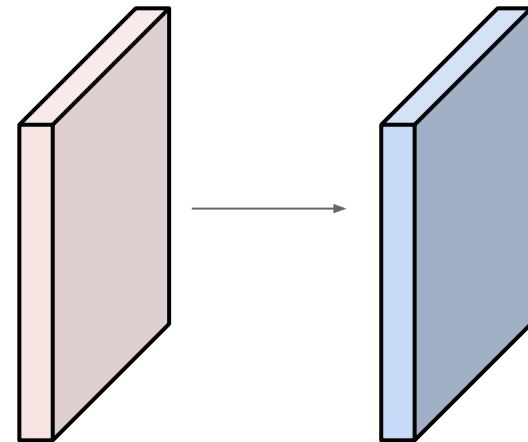
Examples time:

Input volume: **32x32x3**

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

Output volume size:
→ **pad**

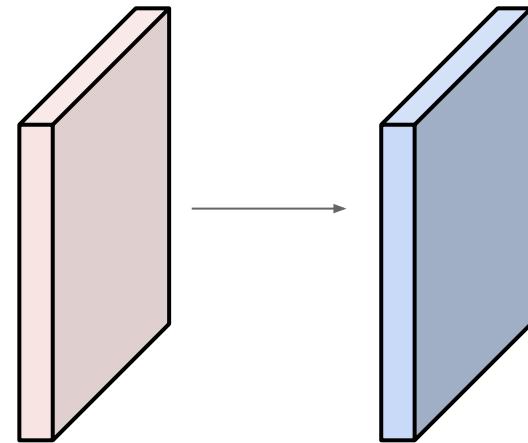
$(32 + 2 * 2 - 5) / 1 + 1 = 32$ spatially, so
32x32x10



Examples time:

Input volume: **32x32x3**

10 5x5 filters with stride 1, pad 2

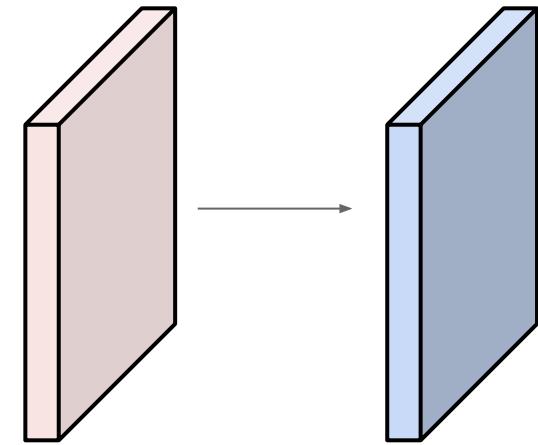


Number of parameters in this layer?

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.

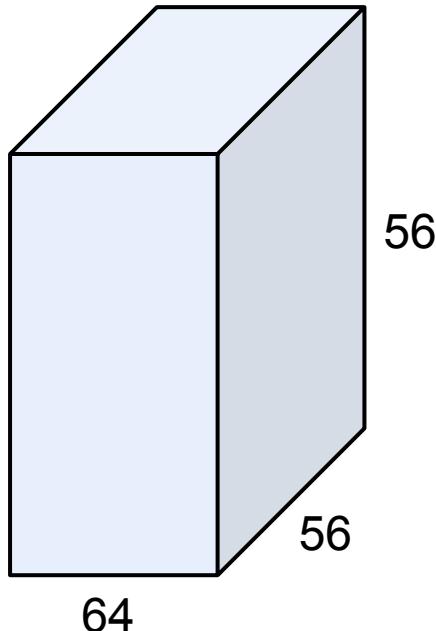
Summary. To summarize, the Conv Layer:

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Common settings:

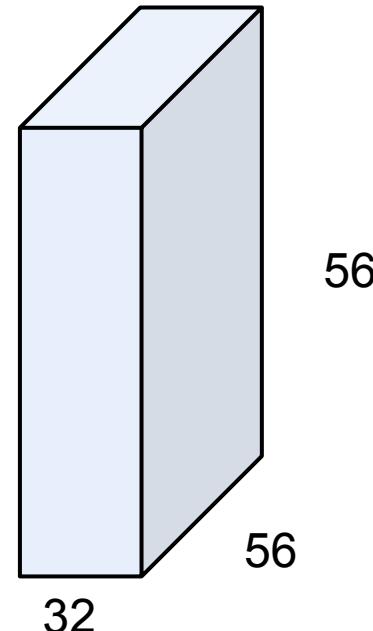
- $K = (\text{powers of 2, e.g. } 32, 64, 128, 512)$
- $F = 3, S = 1, P = 1$
 - $F = 5, S = 1, P = 2$
 - $F = 5, S = 2, P = ? \text{ (whatever fits)}$
 - $F = 1, S = 1, P = 0$

(btw, 1x1 convolution layers make perfect sense)

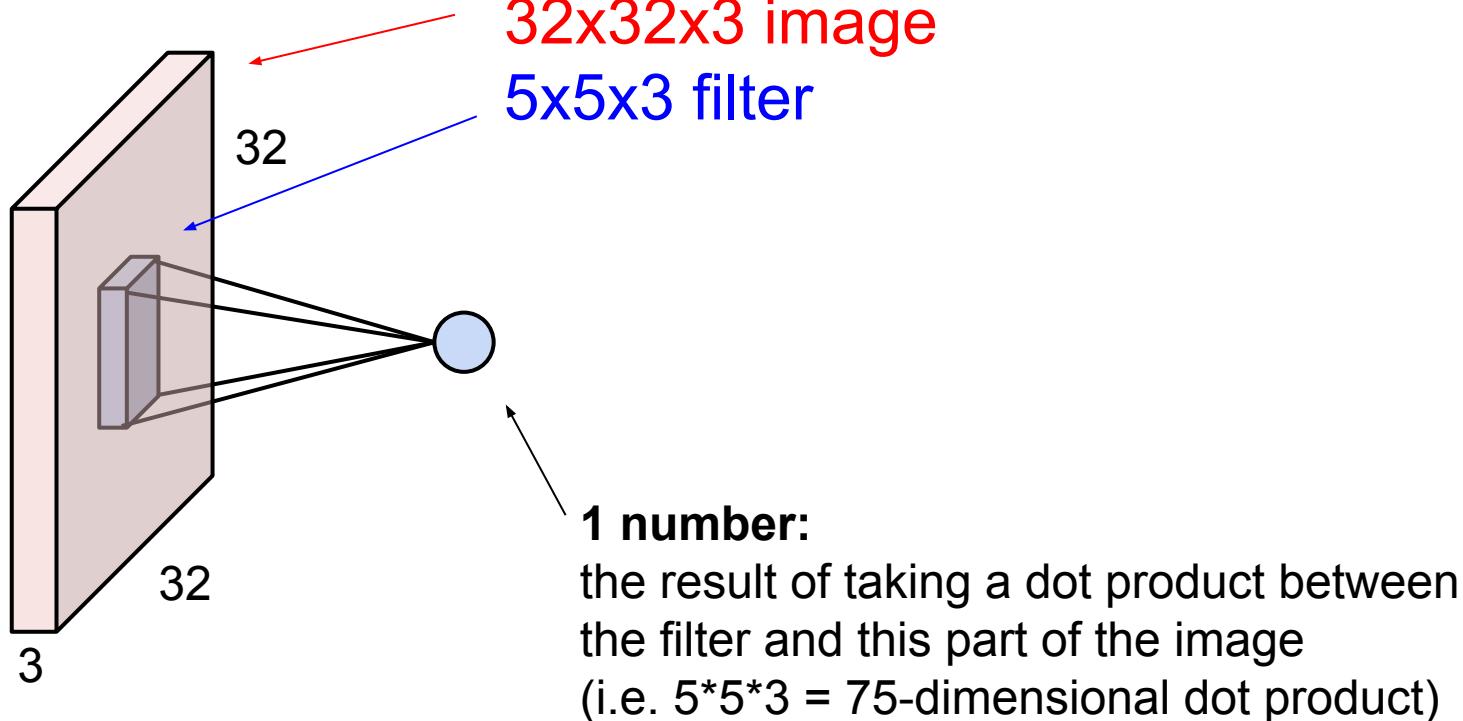


filter
1x1 CONV
with 32 filters

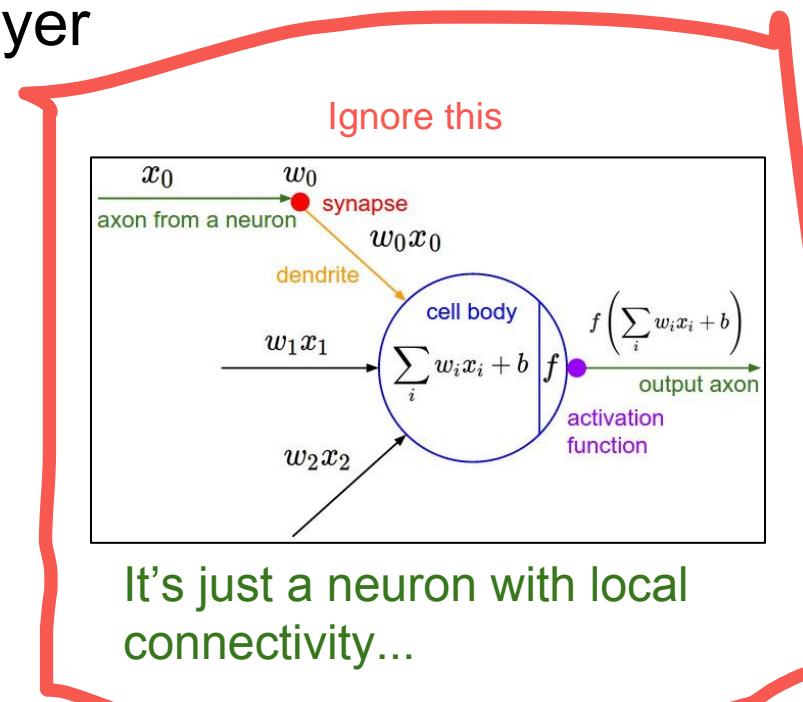
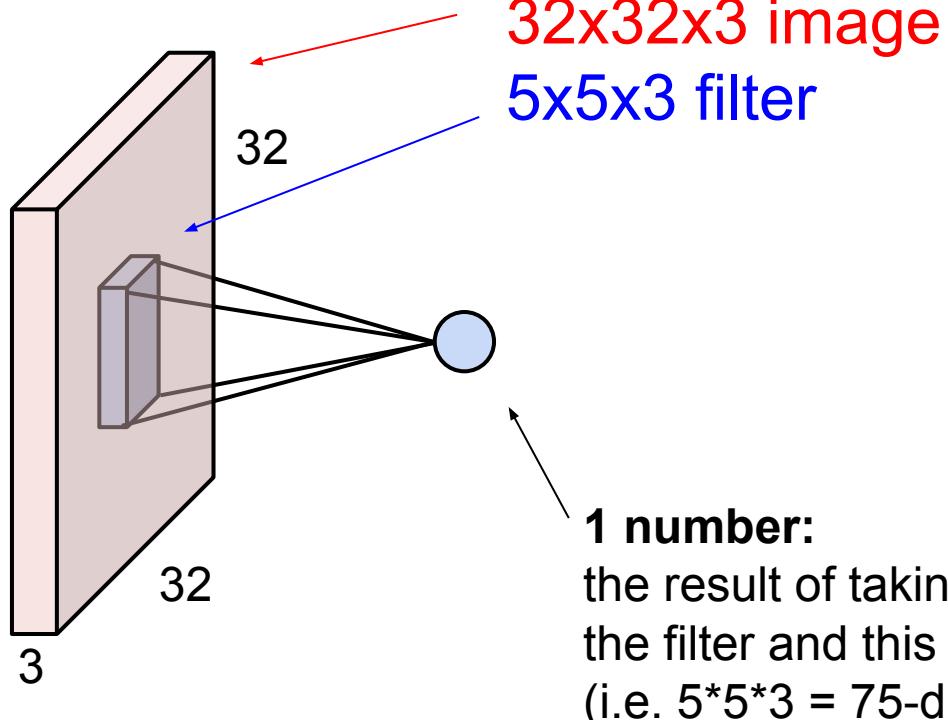
(each filter has size
 $1 \times 1 \times 64$, and performs a
64-dimensional dot
product)



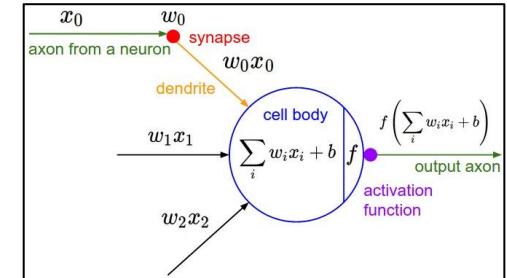
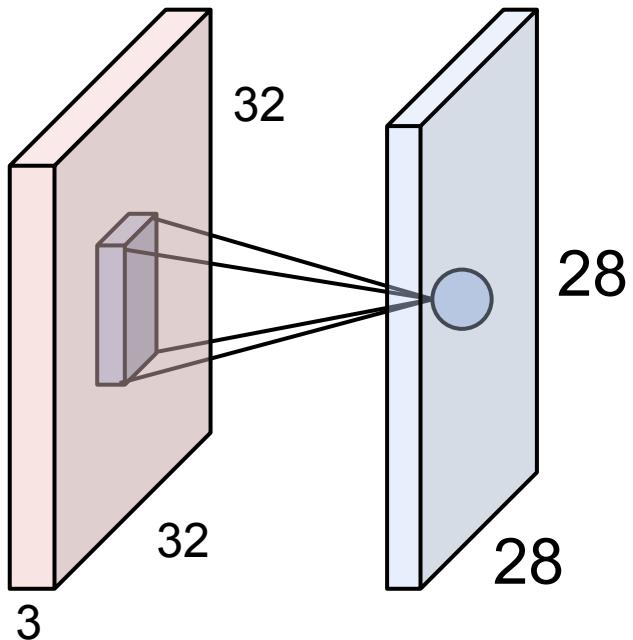
The brain/neuron view of CONV Layer



The brain/neuron view of CONV Layer



The brain/neuron view of CONV Layer

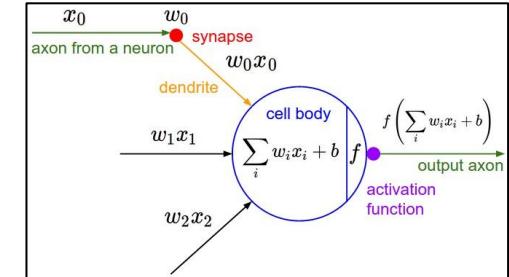
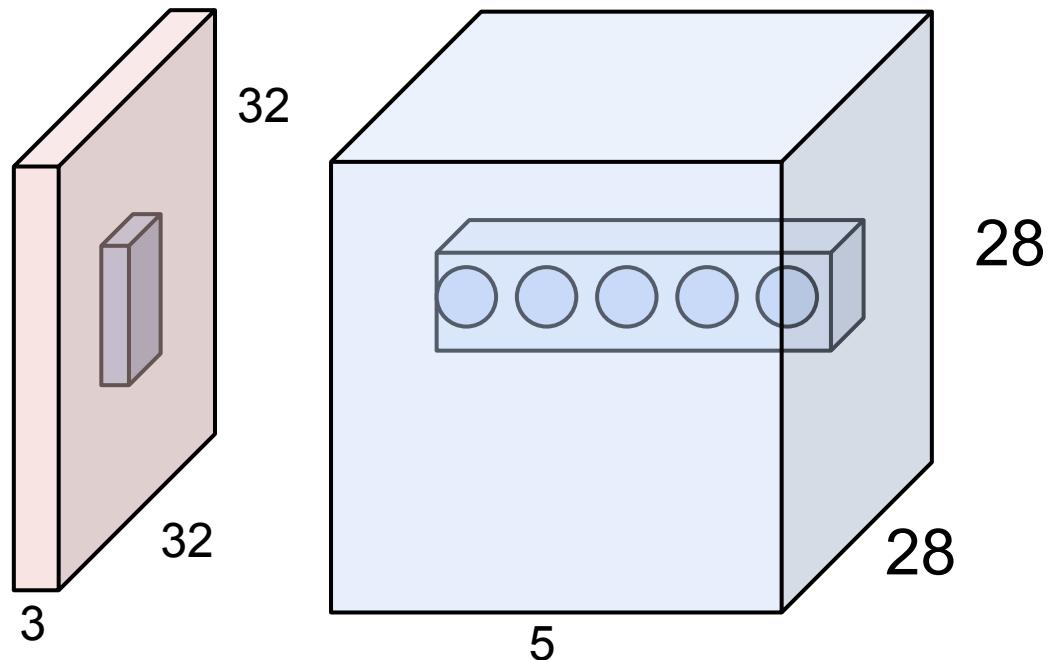


An activation map is a 28x28 sheet of neuron outputs:

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



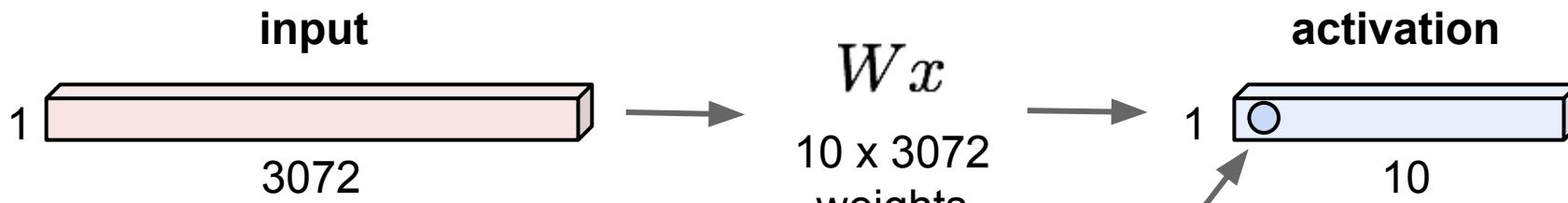
E.g. with 5 filters,
CONV layer consists of
neurons arranged in a 3D grid
($28 \times 28 \times 5$)

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

Reminder: Fully Connected Layer

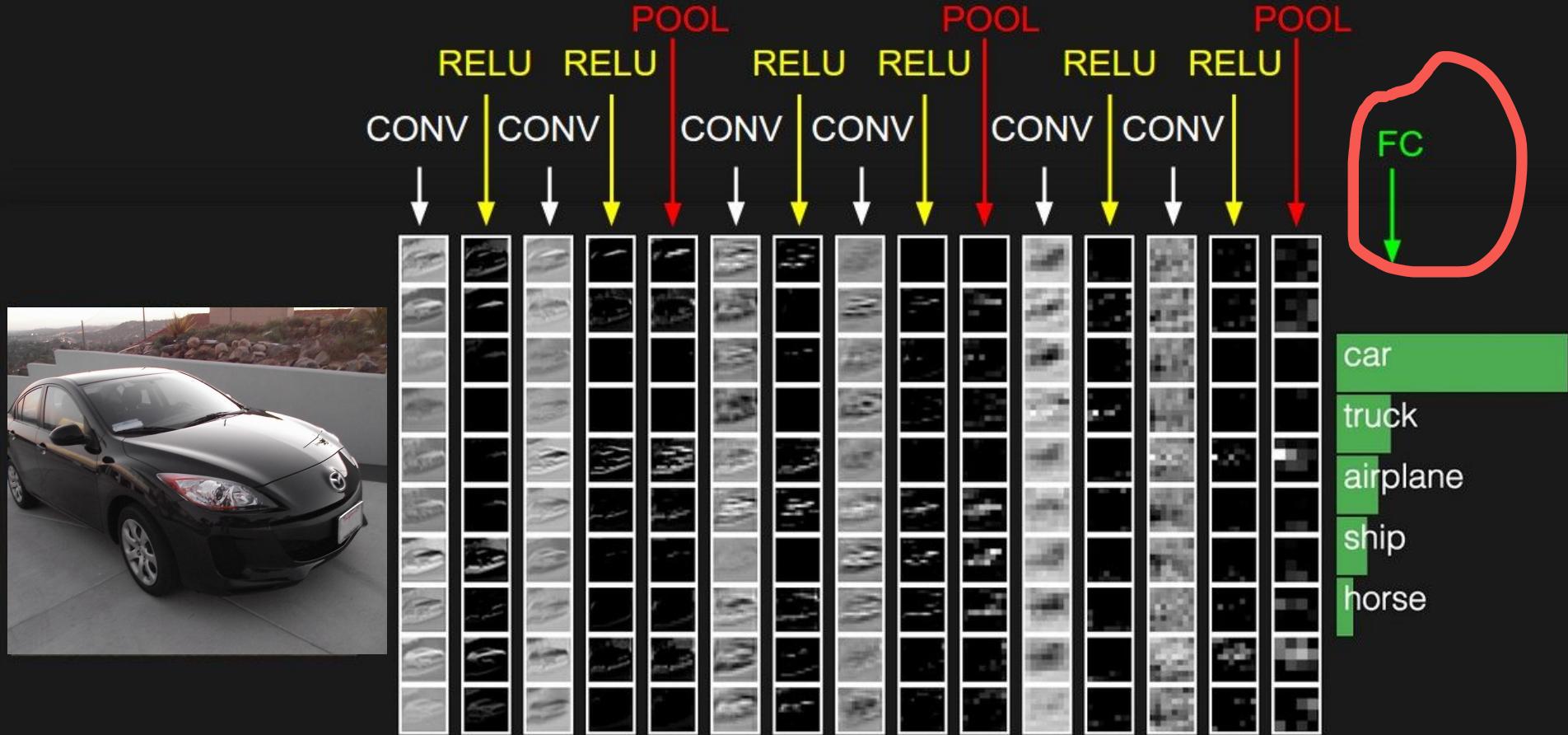
32x32x3 image -> stretch to 3072×1

Each neuron
looks at the full
input volume



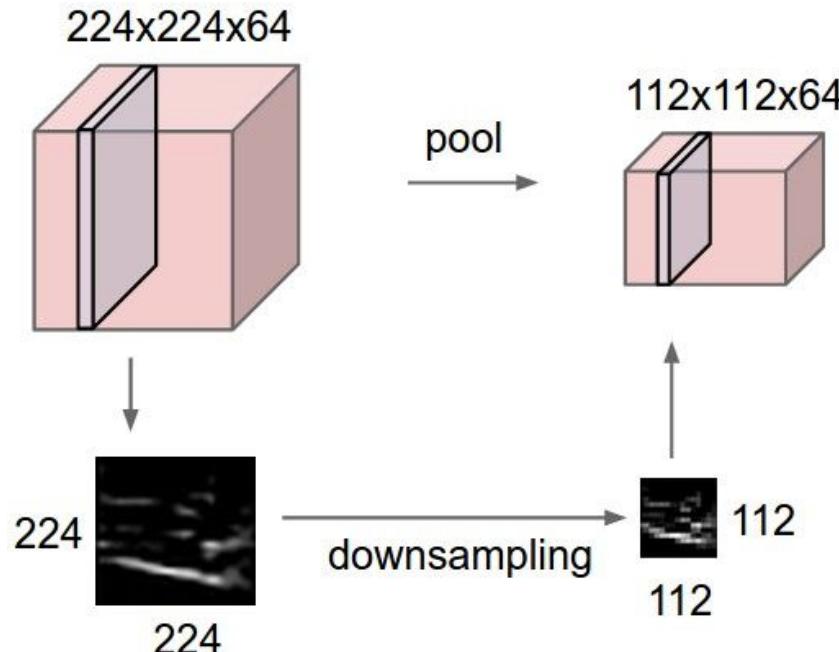
1 number:
the result of taking a dot product
between a row of W and the input
(a 3072-dimensional dot product)

two more layers to go: POOL/FC

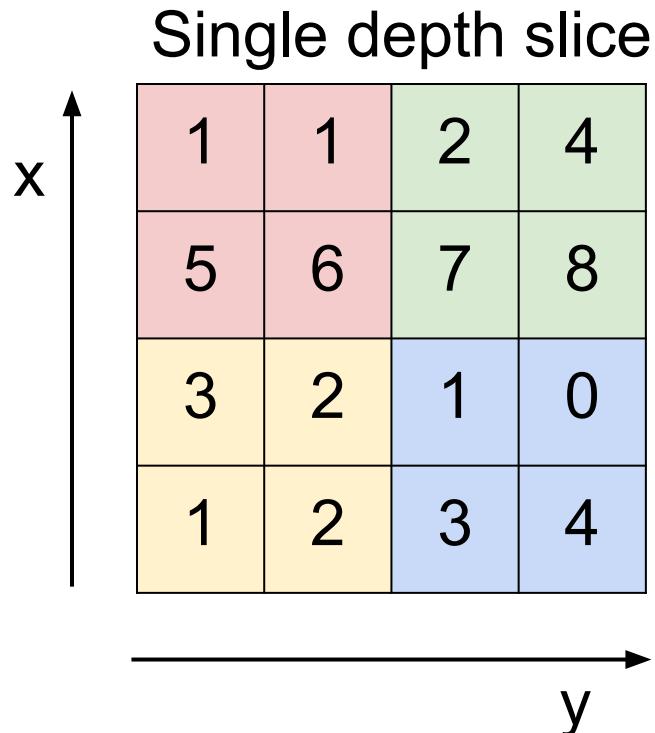


Pooling layer

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



MAX POOLING



- 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:

$F = 2, S = 2$

$F = 3, S = 2$

- 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

Fully Connected Layer (FC layer)

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

How to perform BP in convolution, pooling layers?

