

Convolutional Neural Networks

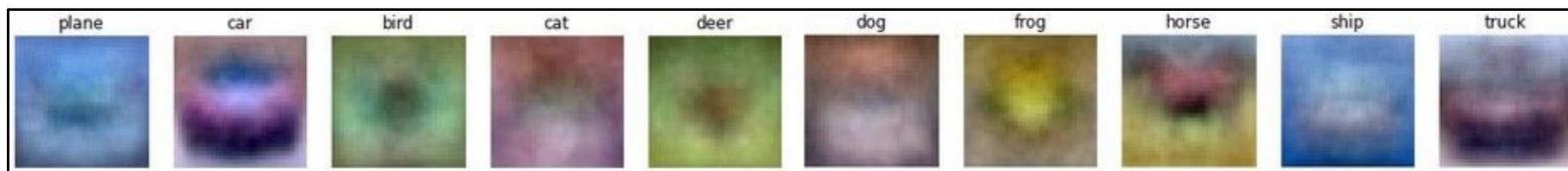
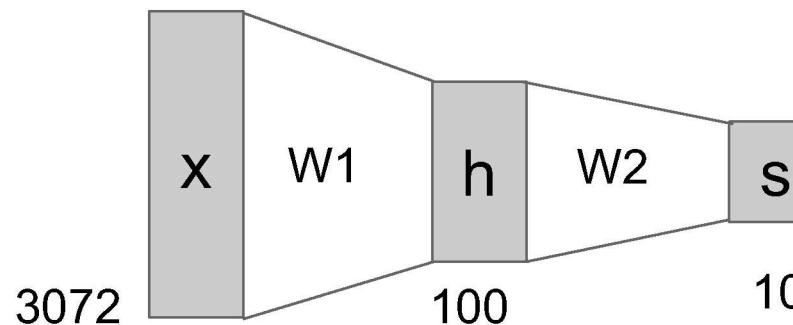
Neural Networks

Linear score function:

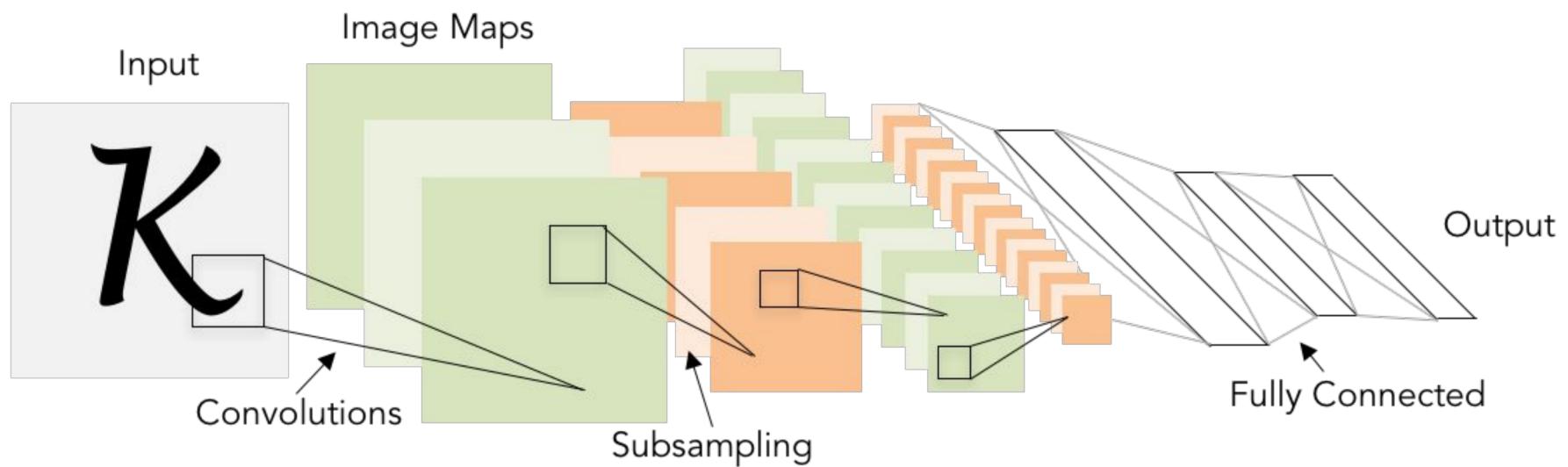
$$f = Wx$$

2-layer Neural Network

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



Next: Convolutional Neural Networks



Fast-forward to today: ConvNets are everywhere

Classification



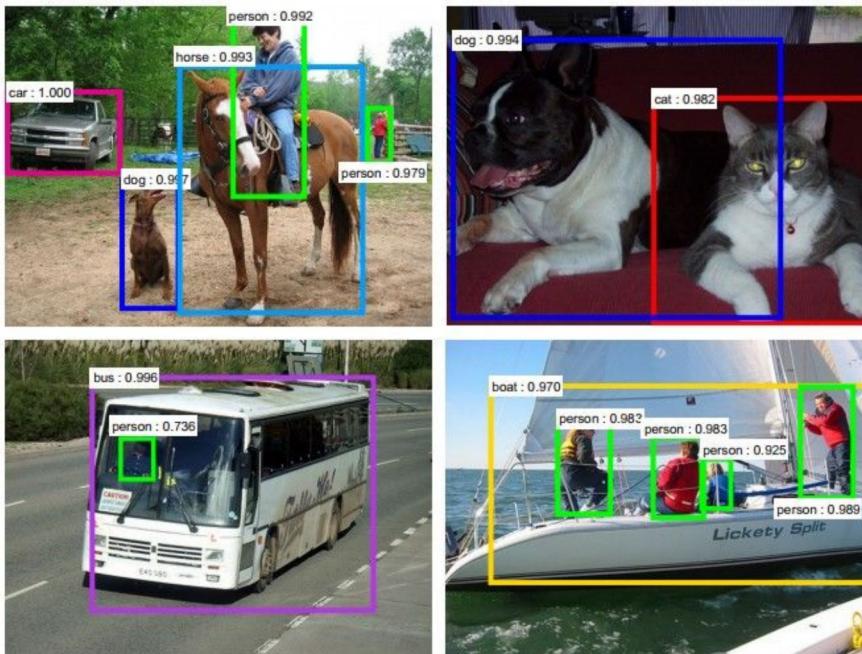
Retrieval



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

Fast-forward to today: ConvNets are everywhere

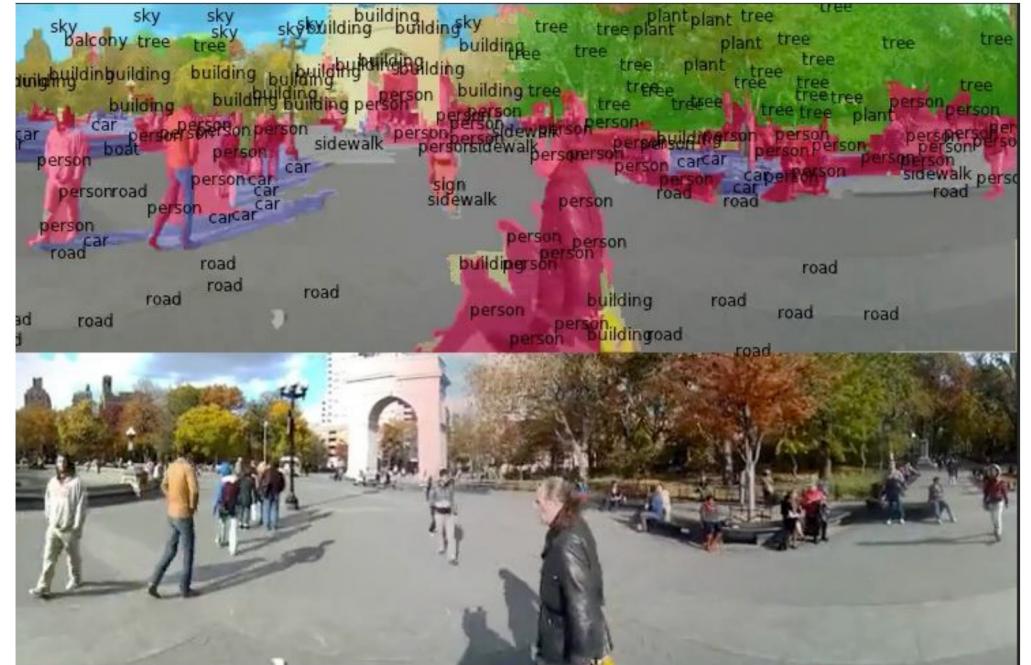
Detection



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

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

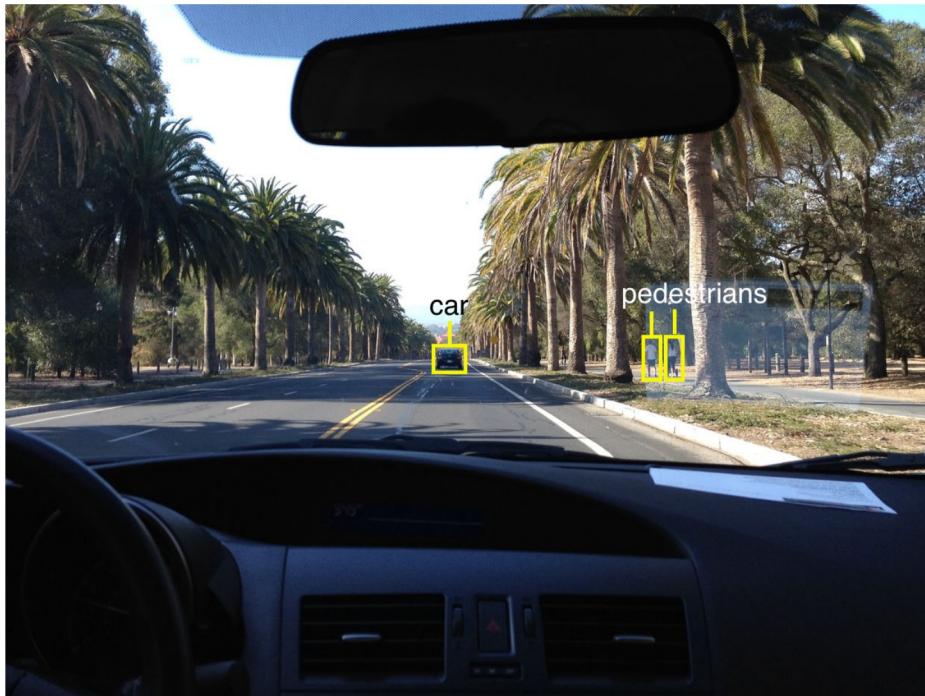
Segmentation



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.



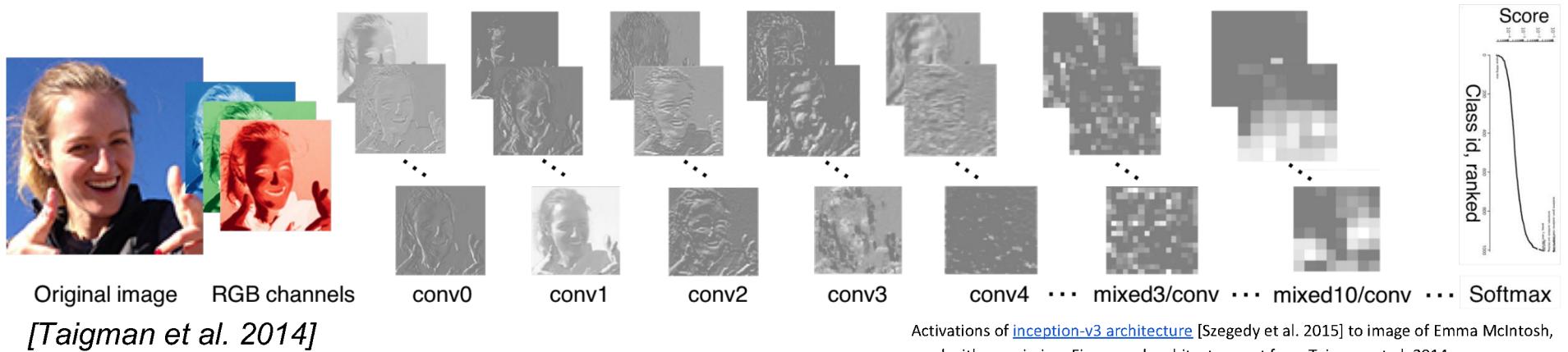
[This image](#) by GBPublic_PR is licensed under [CC-BY 2.0](#)

NVIDIA Tesla line

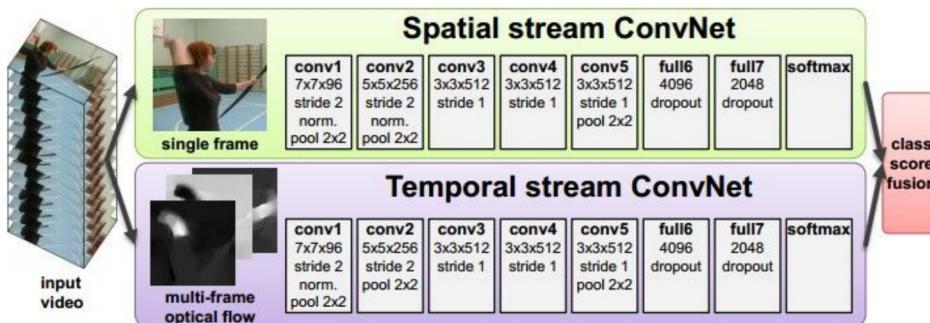
(these are the GPUs on rye01.stanford.edu)

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

Fast-forward to today: ConvNets are everywhere



Activations of [Inception-v3 architecture](#) [Szegedy et al. 2015] to image of Emma McIntosh, used with permission. Figure and architecture not from Taigman et al. 2014.



[Simonyan et al. 2014]

Figures copyright Simonyan et al., 2014.
Reproduced with permission.

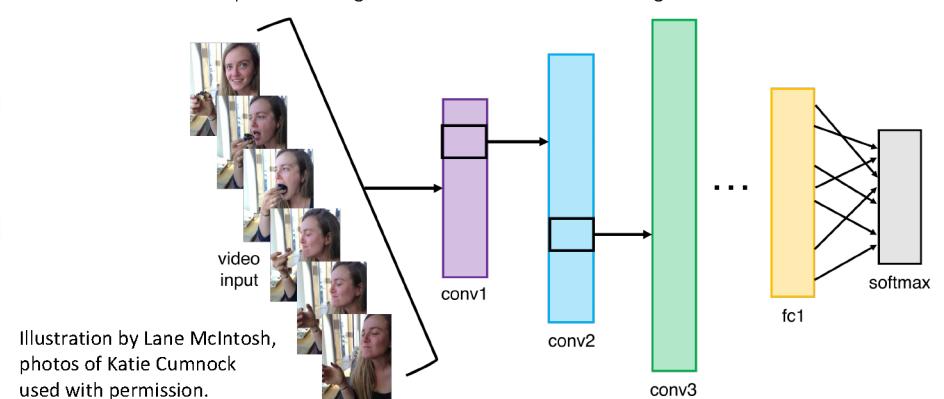


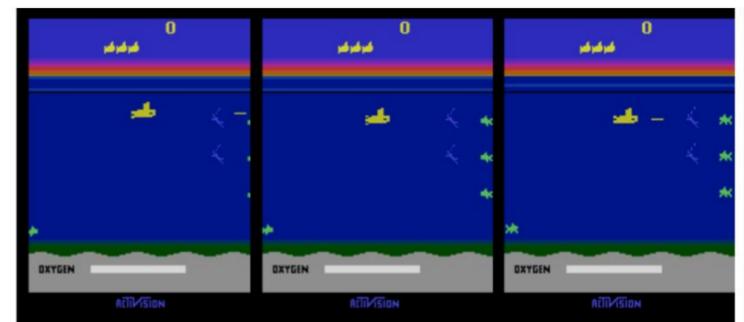
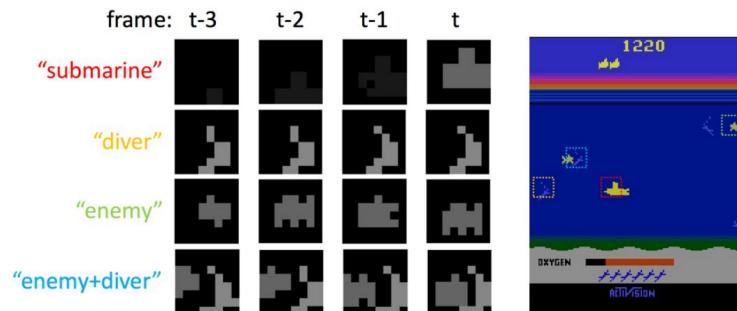
Illustration by Lane McIntosh,
photos of Katie Cumnock
used with permission.

Fast-forward to today: ConvNets are everywhere



Images are examples of pose estimation, not actually from Toshev & Szegedy 2014. Copyright Lane McIntosh.

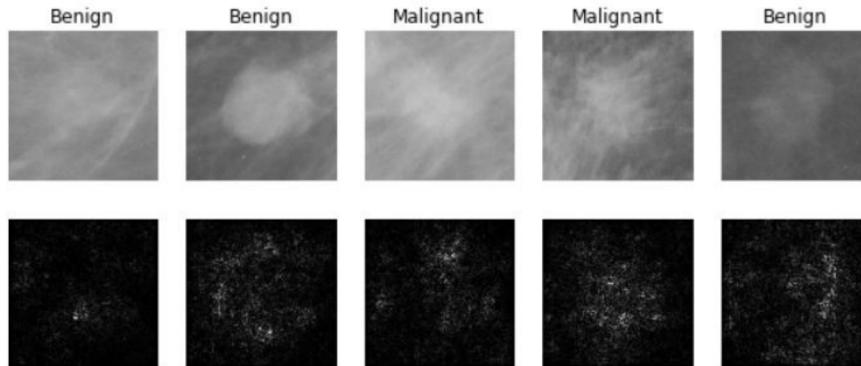
[Toshev, Szegedy 2014]



[Guo et al. 2014]

Figures copyright Xiaoxiao Guo, Satinder Singh, Honglak Lee, Richard Lewis, and Xiaoshi Wang, 2014. Reproduced with permission.

Fast-forward to today: ConvNets are everywhere



[Levy et al. 2016]

Figure copyright Levy et al. 2016.
Reproduced with permission.



[Dieleman et al. 2014]

From left to right: [public domain by NASA](#), usage [permitted](#) by
ESA/Hubble, [public domain by NASA](#), and [public domain](#).



[Sermanet et al. 2011]

[Ciresan et al.]

Photos by Lane McIntosh.
Copyright CS231n 2017.

[This image](#) by Christin Khan is in the public domain and originally came from the U.S. NOAA.



Whale recognition, Kaggle Challenge

Photo and figure by Lane McIntosh; not actual example from Mnih and Hinton, 2010 paper.



Mnih and Hinton, 2010

Image Captioning

[Vinyals et al., 2015]
[Karpathy and Fei-Fei,
2015]

No errors



A white teddy bear sitting in the grass

Minor errors



A man in a baseball uniform throwing a ball

Somewhat related



A woman is holding a cat in her hand



A man riding a wave on top of a surfboard



A cat sitting on a suitcase on the floor

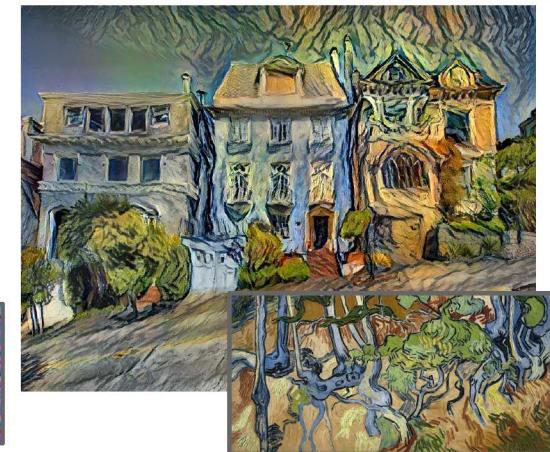
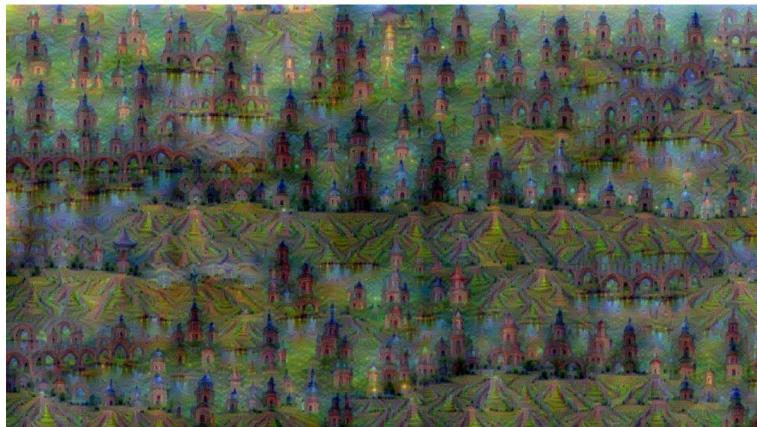
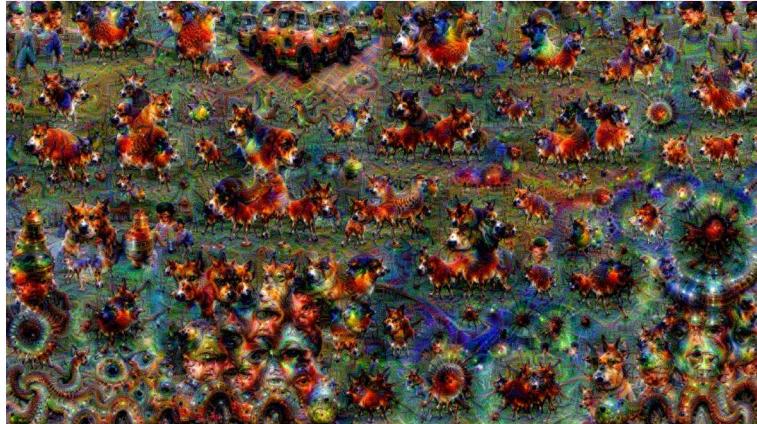


A woman standing on a beach holding a surfboard

All images are CC0 Public domain:

<https://pixabay.com/en/luggage-antique-cat-1643010/>
<https://pixabay.com/en/teddy-plush-bears-cute-teddy-bear-1623436/>
<https://pixabay.com/en/surf-wave-summer-sport-litoral-1668716/>
<https://pixabay.com/en/woman-female-model-portrait-adult-983967/>
<https://pixabay.com/en/handstand-lake-meditation-496008/>
<https://pixabay.com/en/baseball-player-shortstop-infield-1045263/>

Captions generated by Justin Johnson using [Neuraltalk2](#)



Figures copyright Justin Johnson, 2015. Reproduced with permission. Generated using the Inceptionism approach from a [blog post](#) by Google Research.

[Original image](#) is CC0 public domain

[Starry Night](#) and [Tree Roots](#) by Van Gogh are in the public domain

[Bokeh image](#) is in the public domain

Stylized images copyright Justin Johnson, 2017;
reproduced with permission

Gatys et al, "Image Style Transfer using Convolutional Neural Networks", CVPR 2016
Gatys et al, "Controlling Perceptual Factors in Neural Style Transfer", CVPR 2017

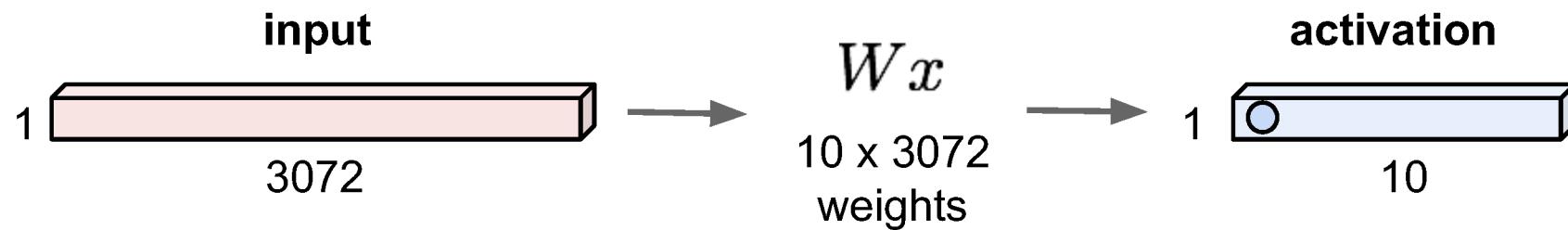
Convolutional Neural Networks

(First without the brain stuff)



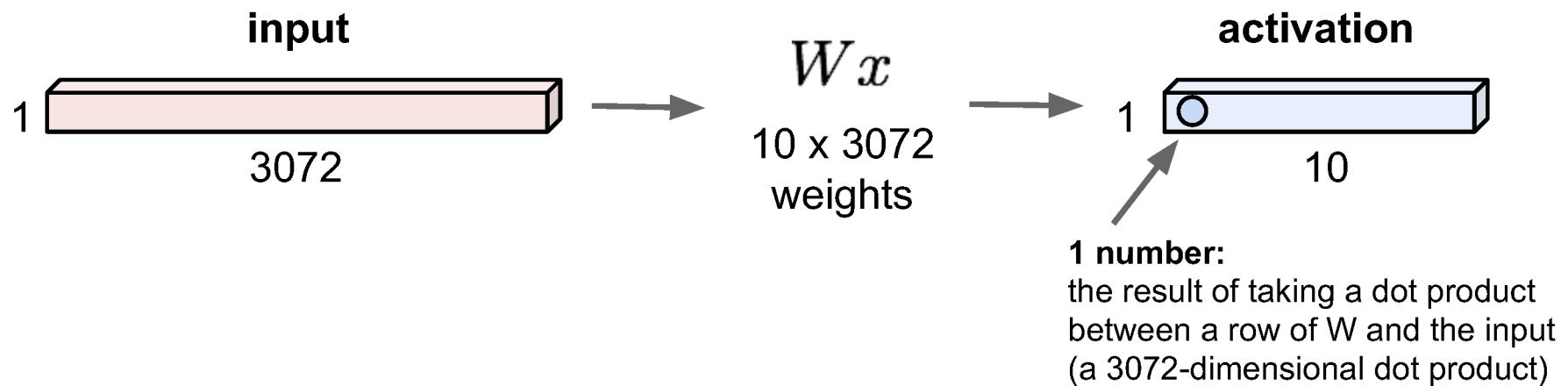
Fully Connected Layer

32x32x3 image -> stretch to 3072 x 1



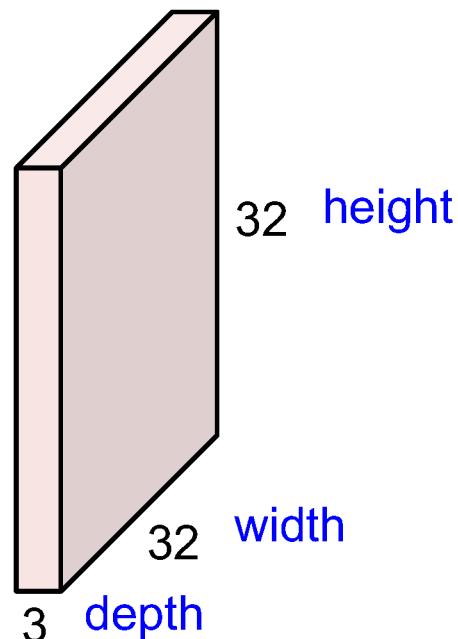
Fully Connected Layer

32x32x3 image -> stretch to 3072 x 1



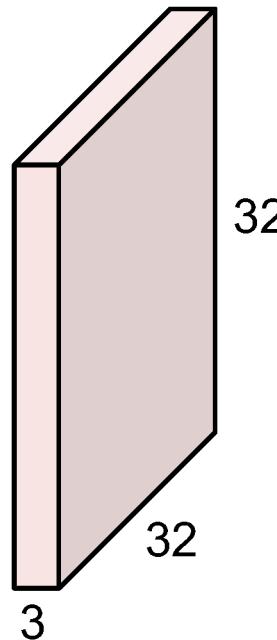
Convolution Layer

32x32x3 image -> preserve spatial structure



Convolution Layer

32x32x3 image



5x5x3 filter

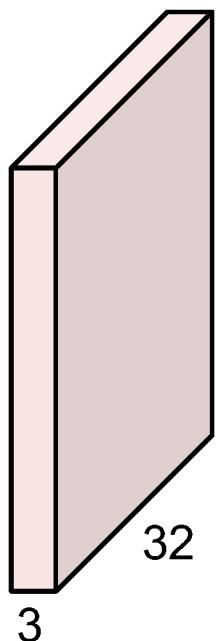


Convolve the filter with the image
i.e. “slide over the image spatially,
computing dot products”



Convolution Layer

32x32x3 image



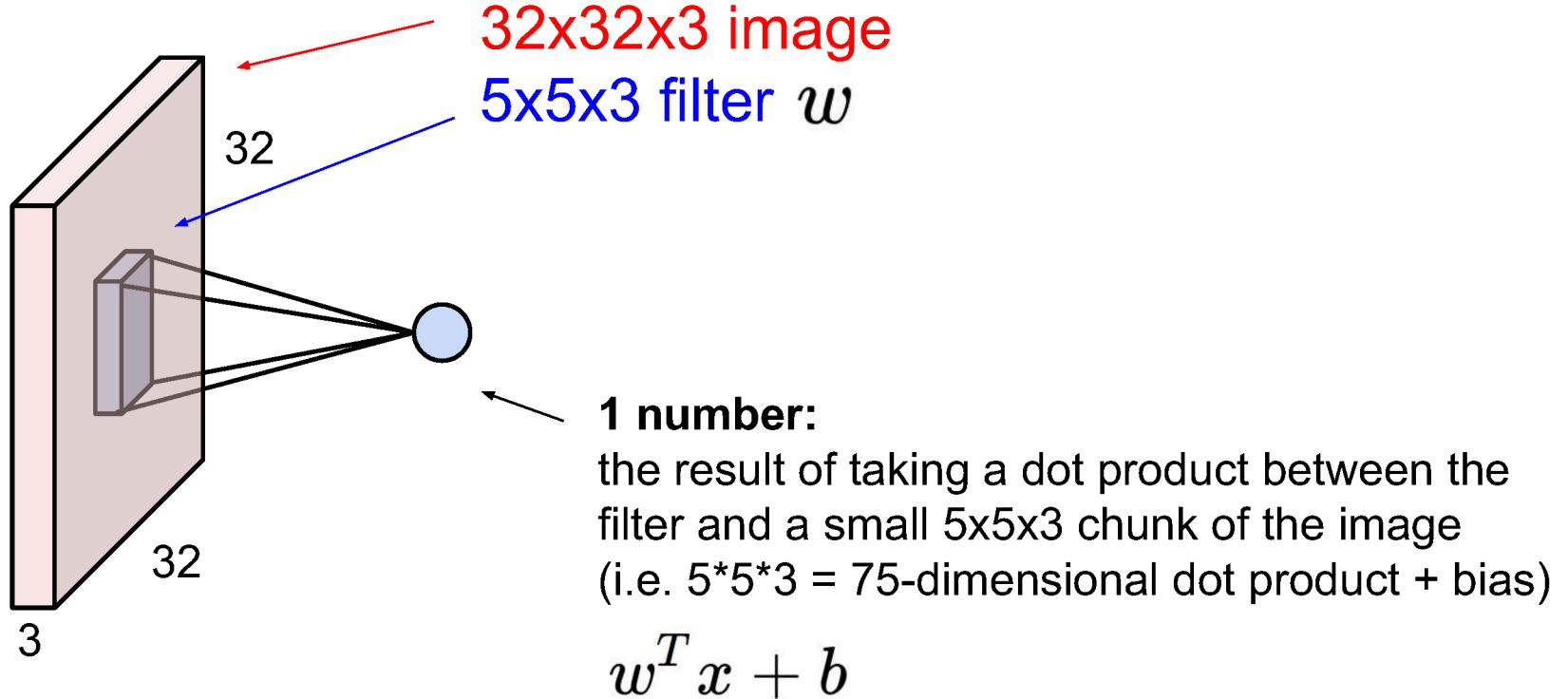
5x5x3 filter



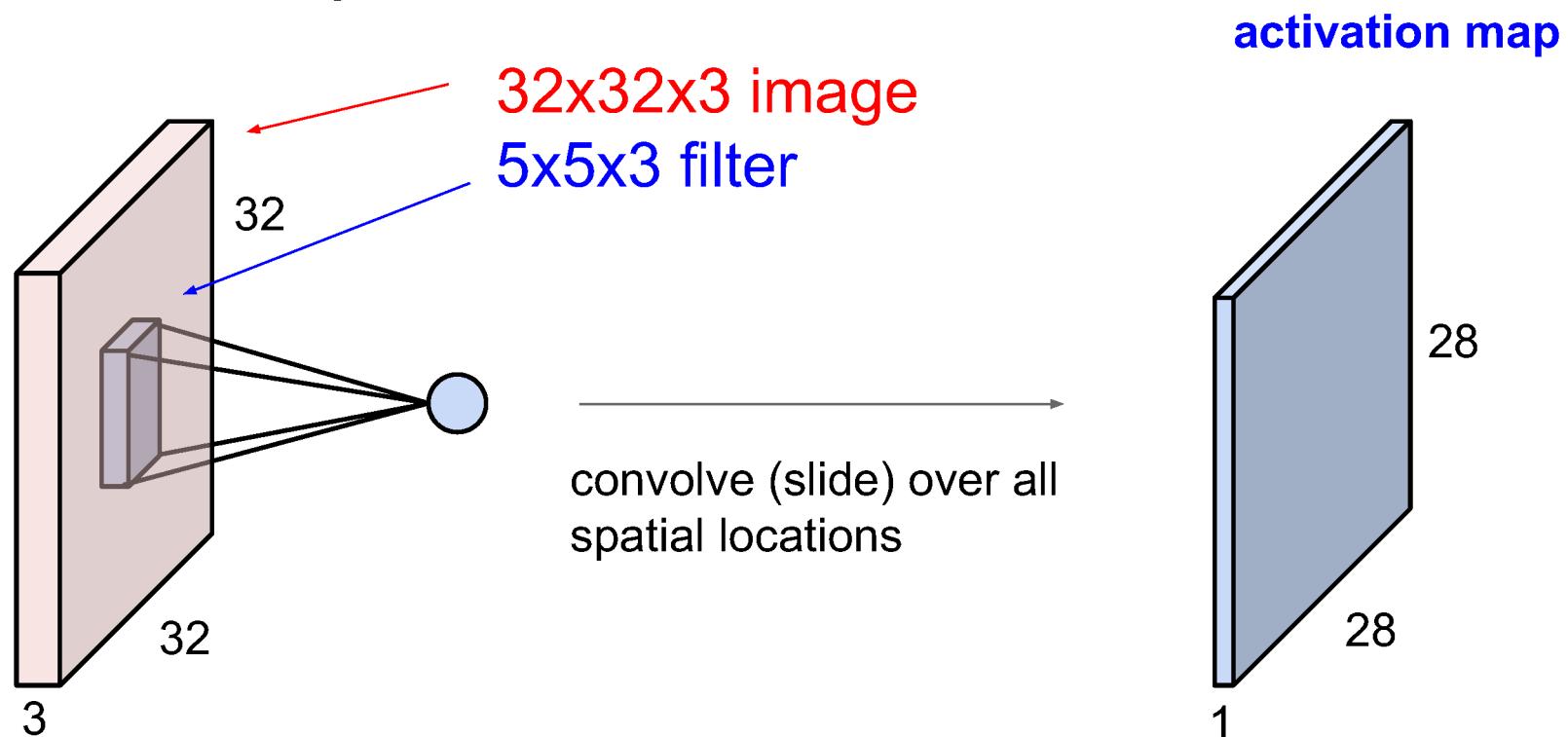
Filters always extend the full depth of the input volume

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

Convolution Layer

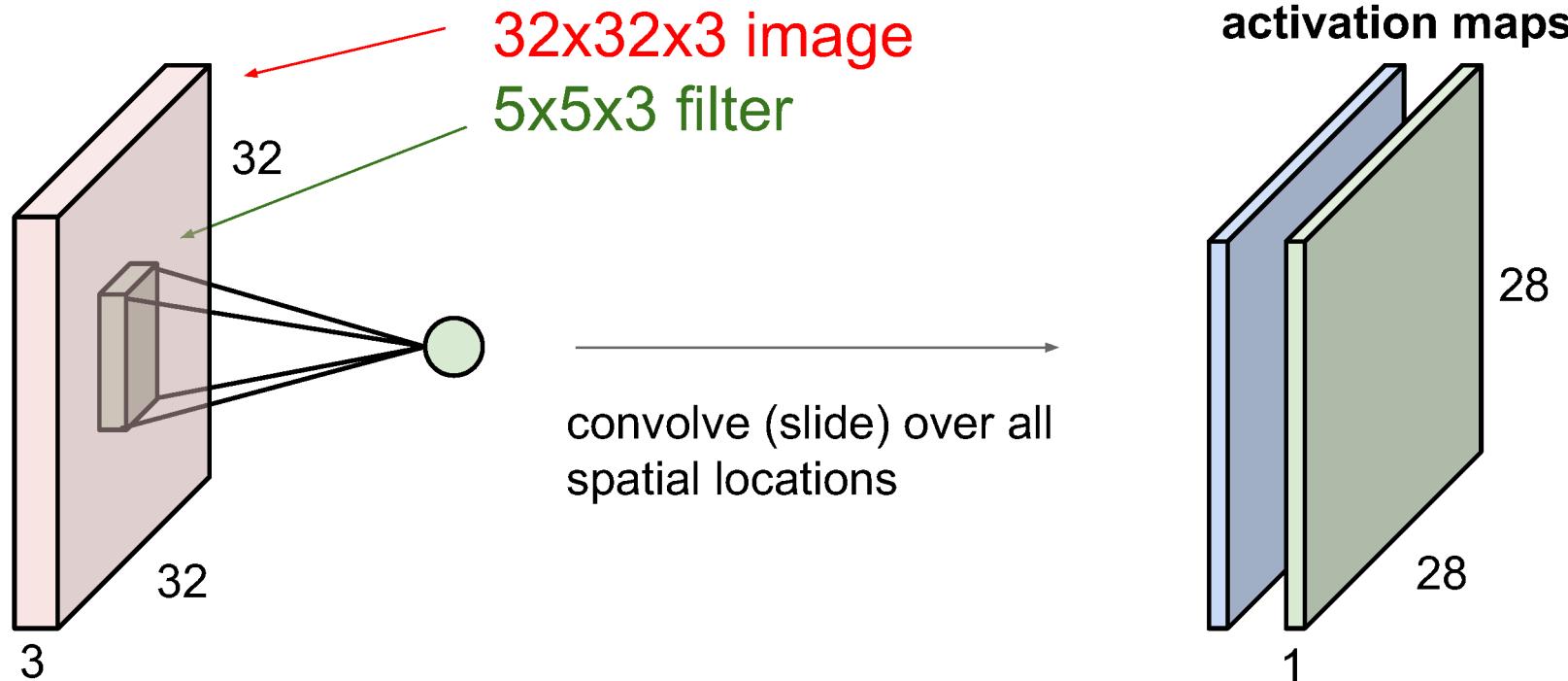


Convolution Layer

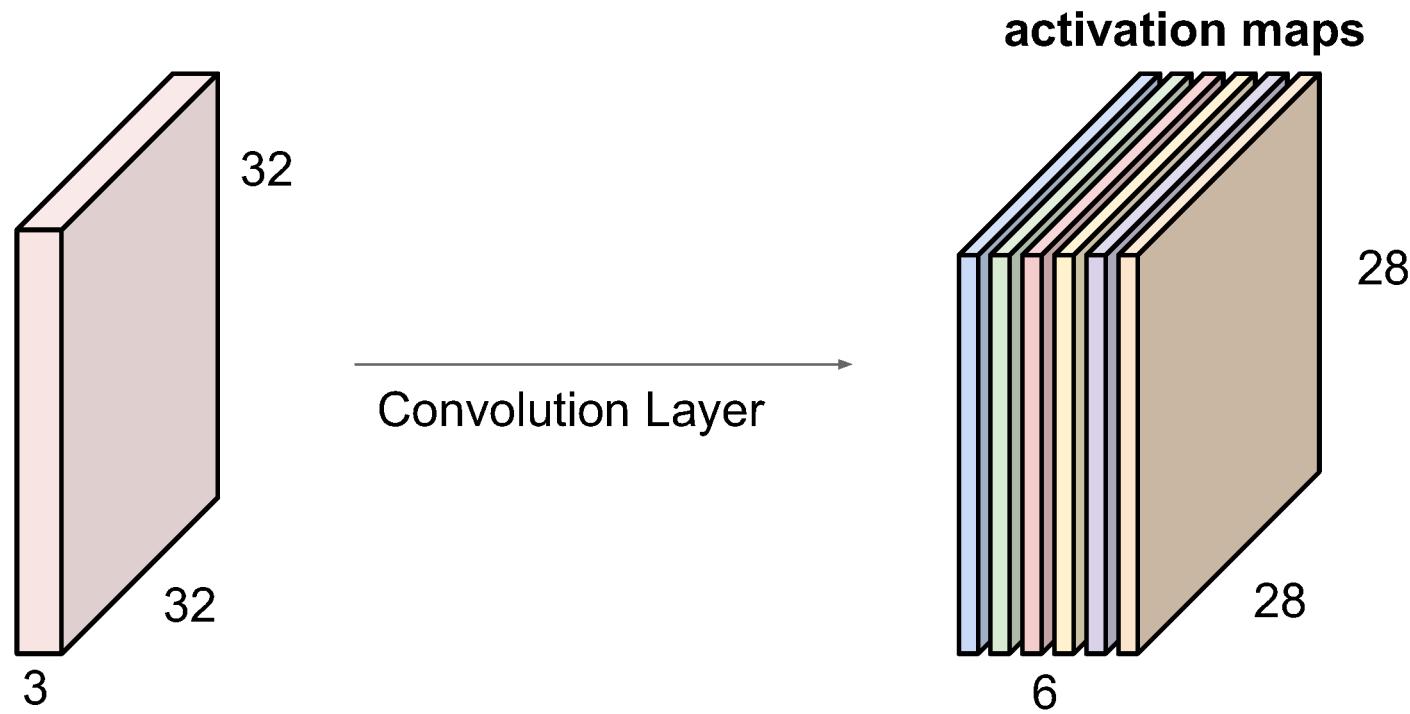


Convolution Layer

consider a second, green filter

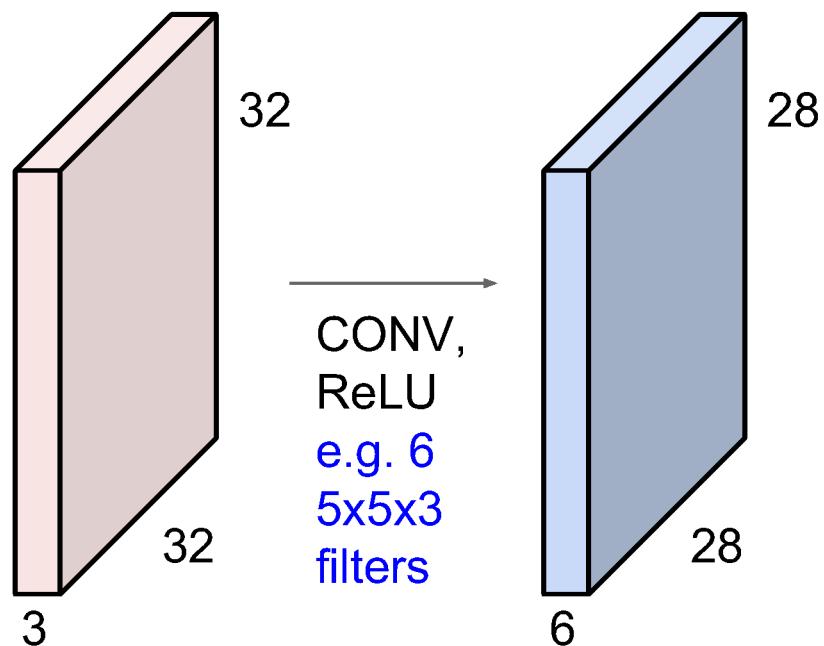


For example, if we had 6 5x5 filters, we'll get 6 separate activation maps:

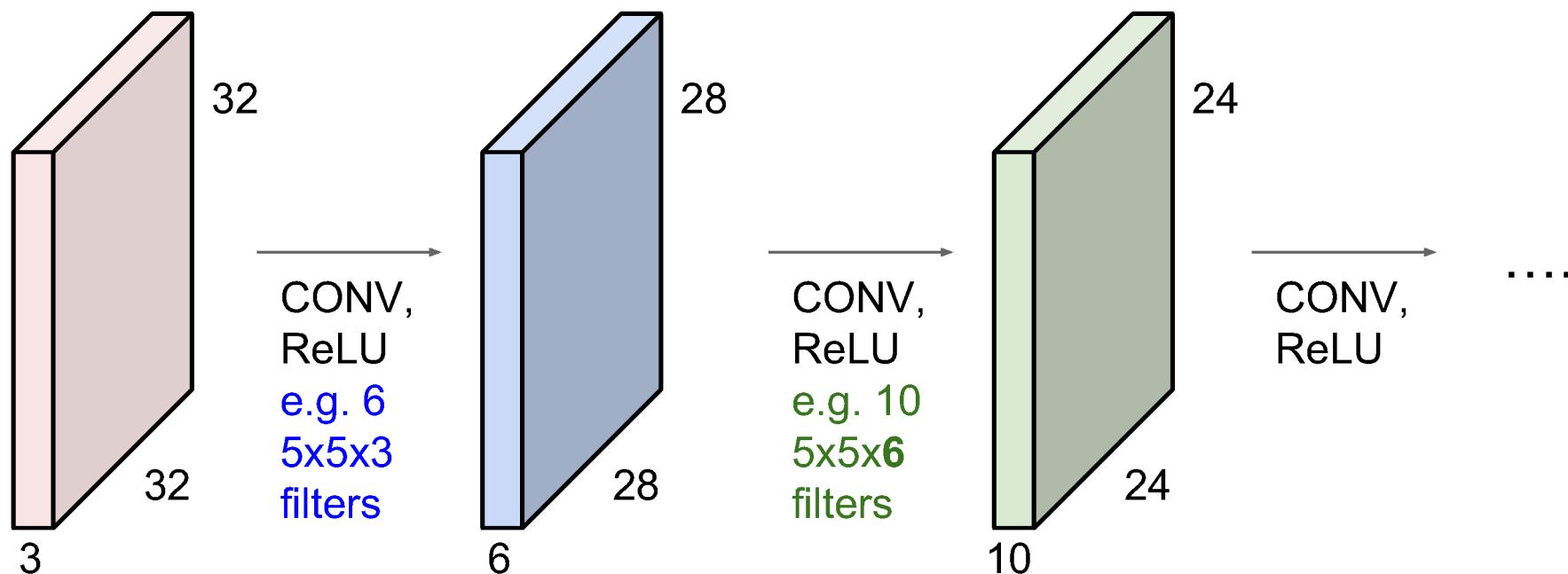


We stack these up to get a “new image” of size 28x28x6!

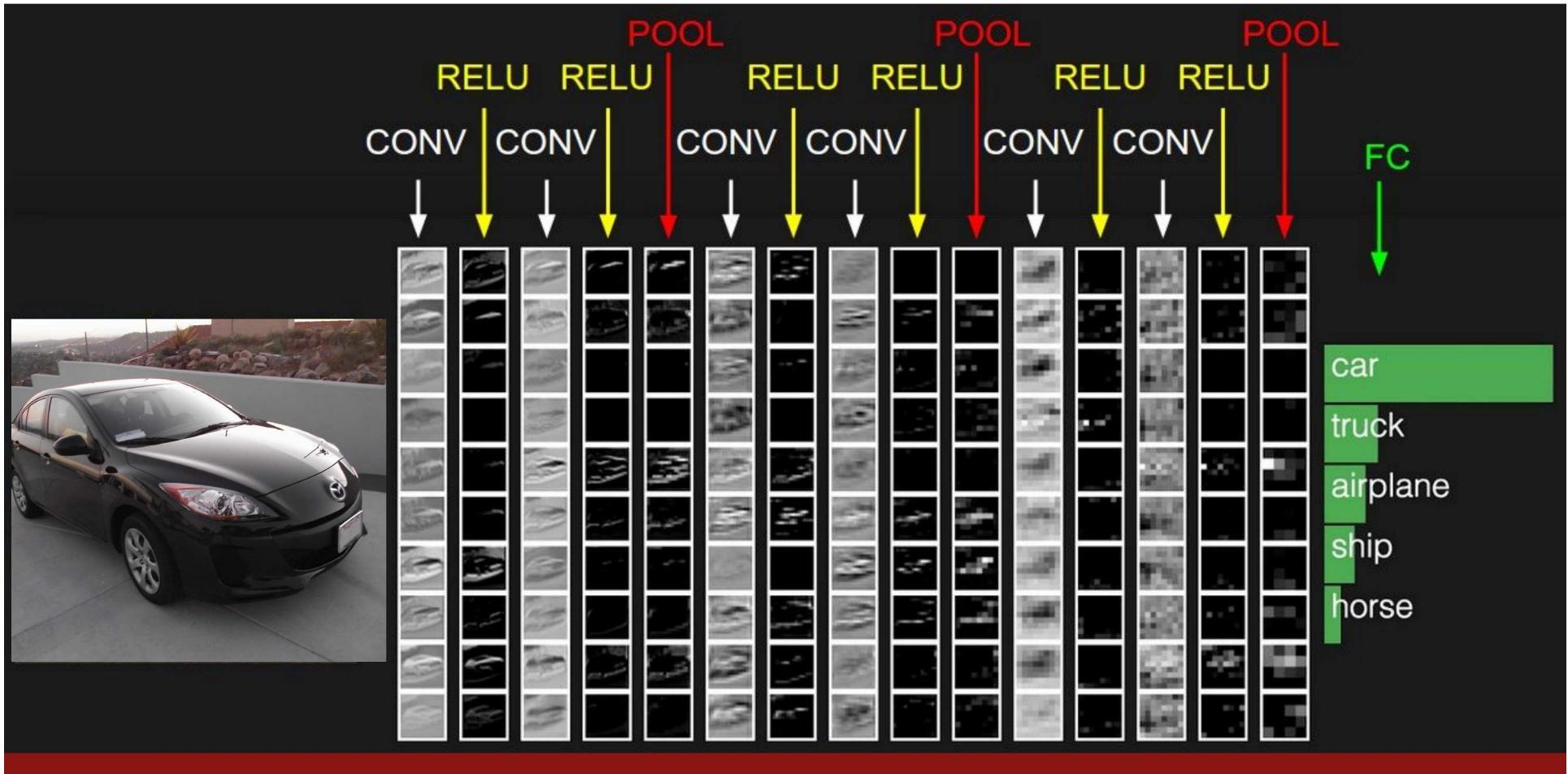
Preview: ConvNet is a sequence of Convolution Layers, interspersed with activation functions



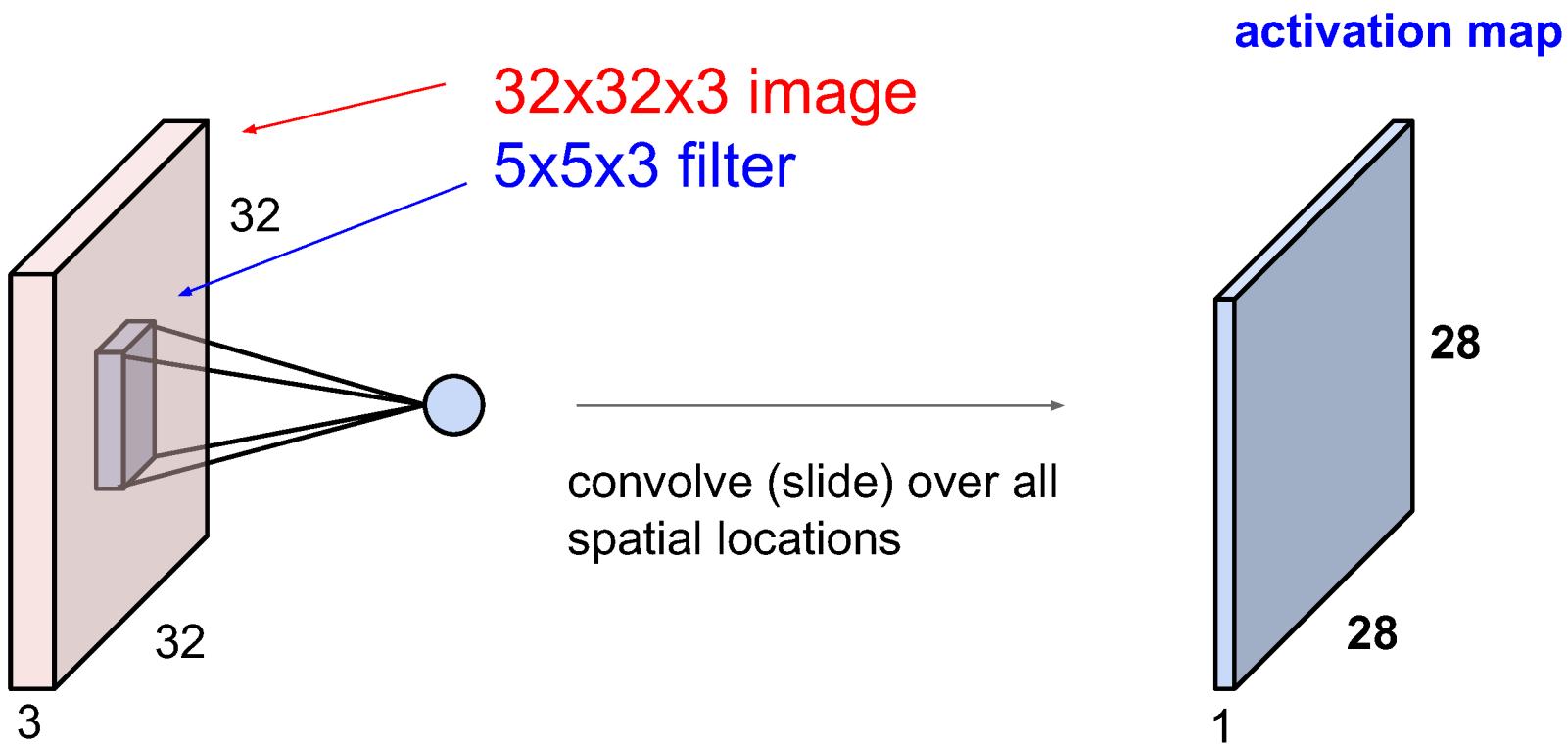
Preview: ConvNet is a sequence of Convolutional Layers, interspersed with activation functions



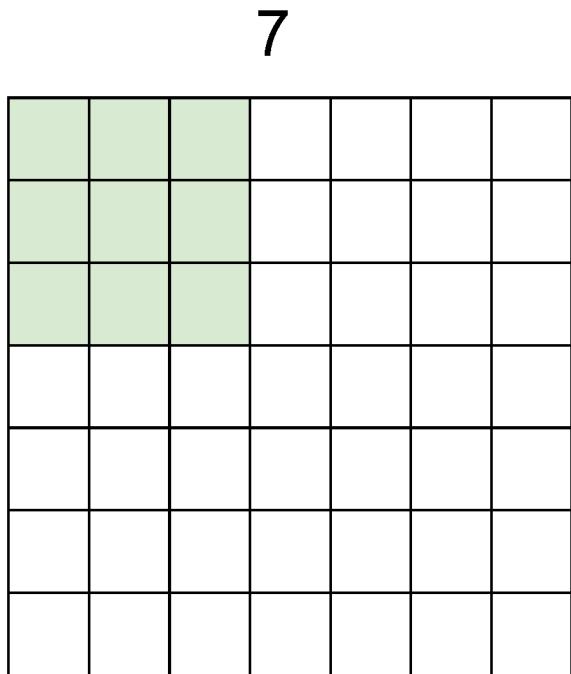
preview:



A closer look at spatial dimensions:

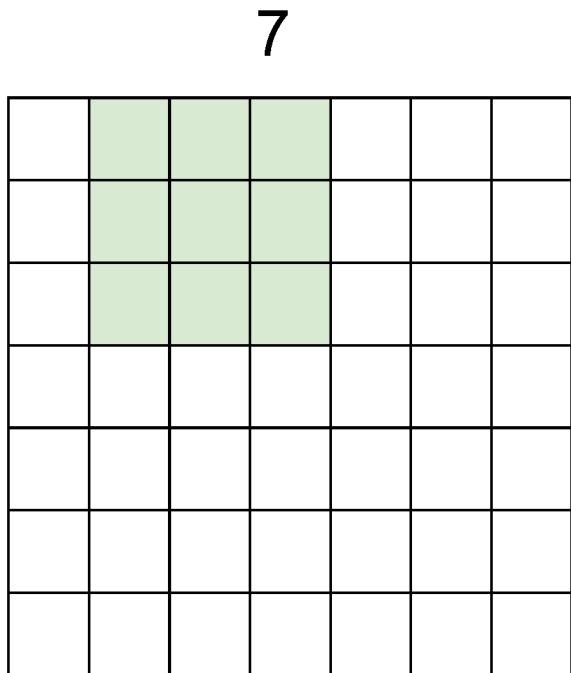


A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter

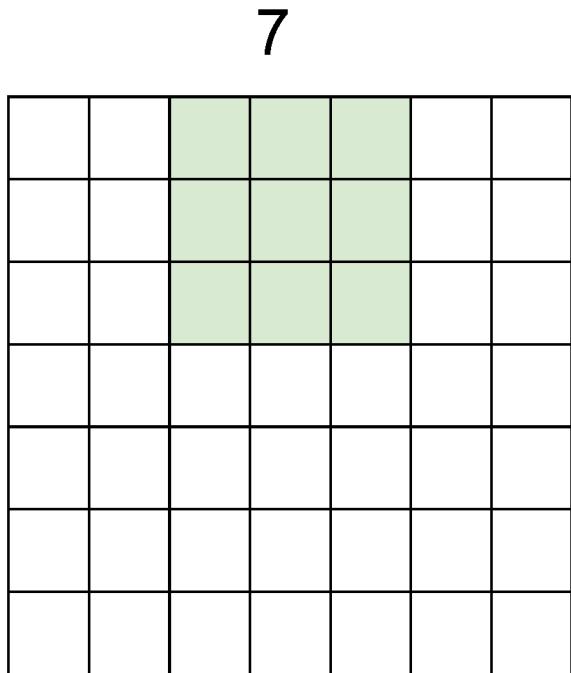
A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter

7

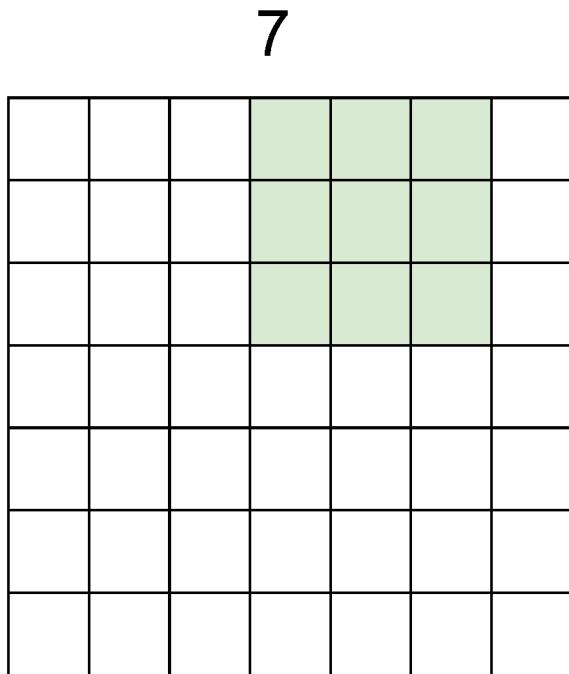
A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter



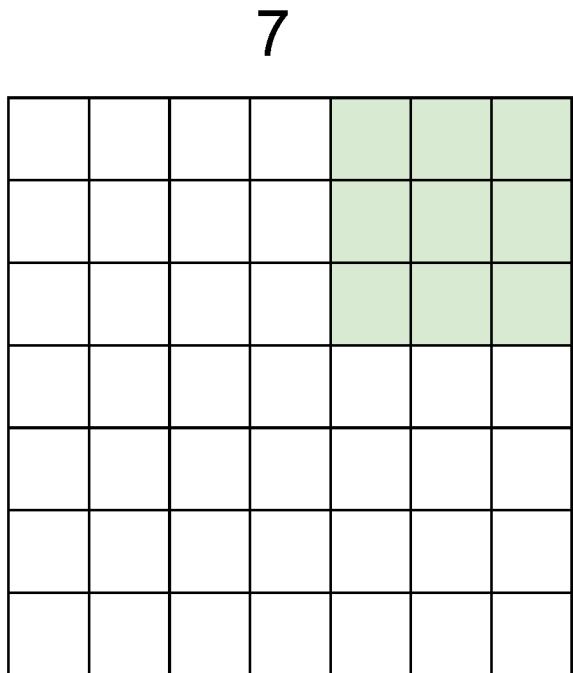
A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter

7

A closer look at spatial dimensions:

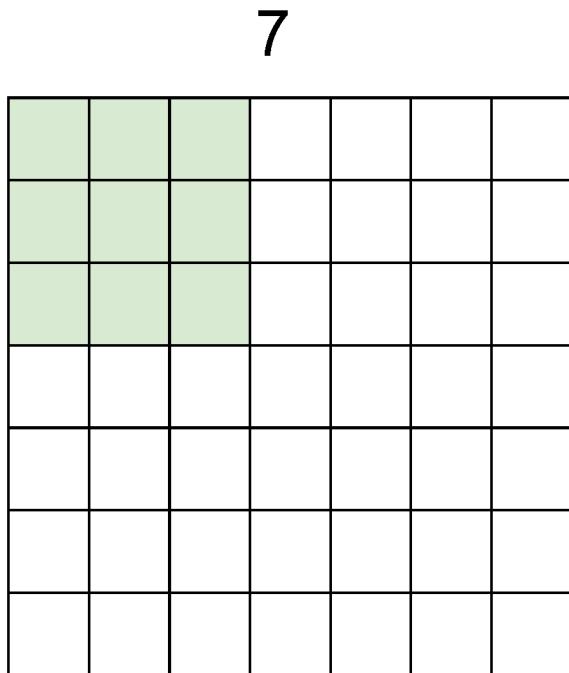


7x7 input (spatially)
assume 3x3 filter

=> 5x5 output

7

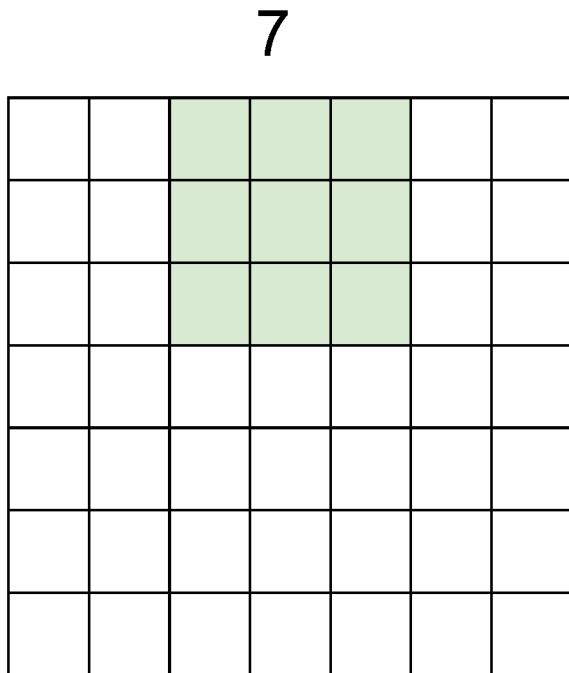
A closer look at spatial dimensions:



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



A closer look at spatial dimensions:

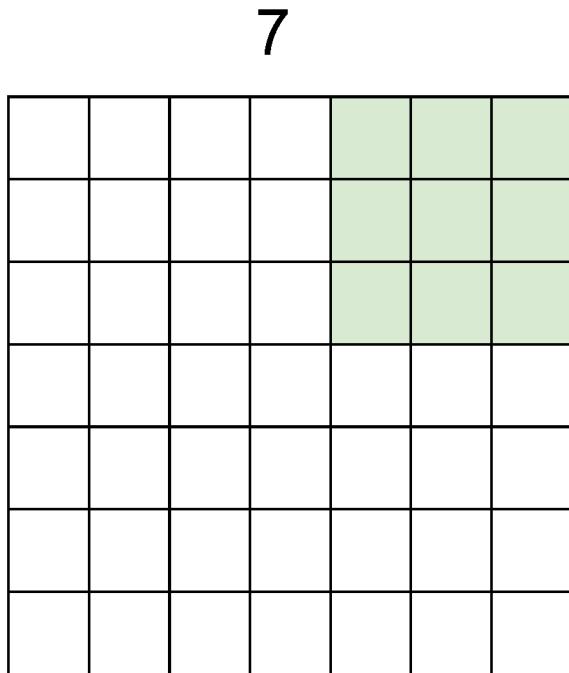


7

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



A closer look at spatial dimensions:

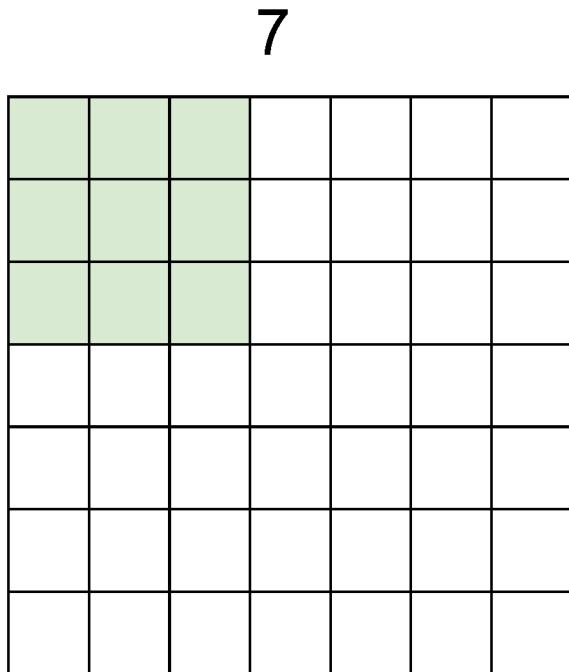


7

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



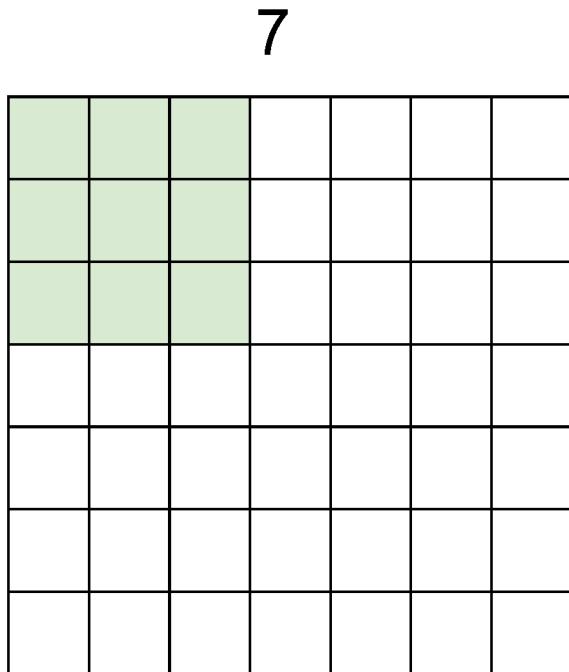
A closer look at spatial dimensions:



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



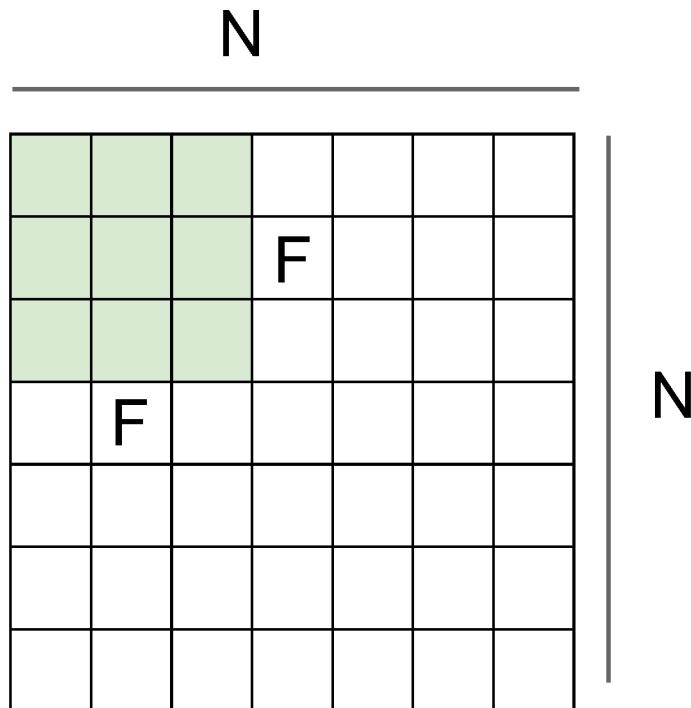
A closer look at spatial dimensions:



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

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

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)

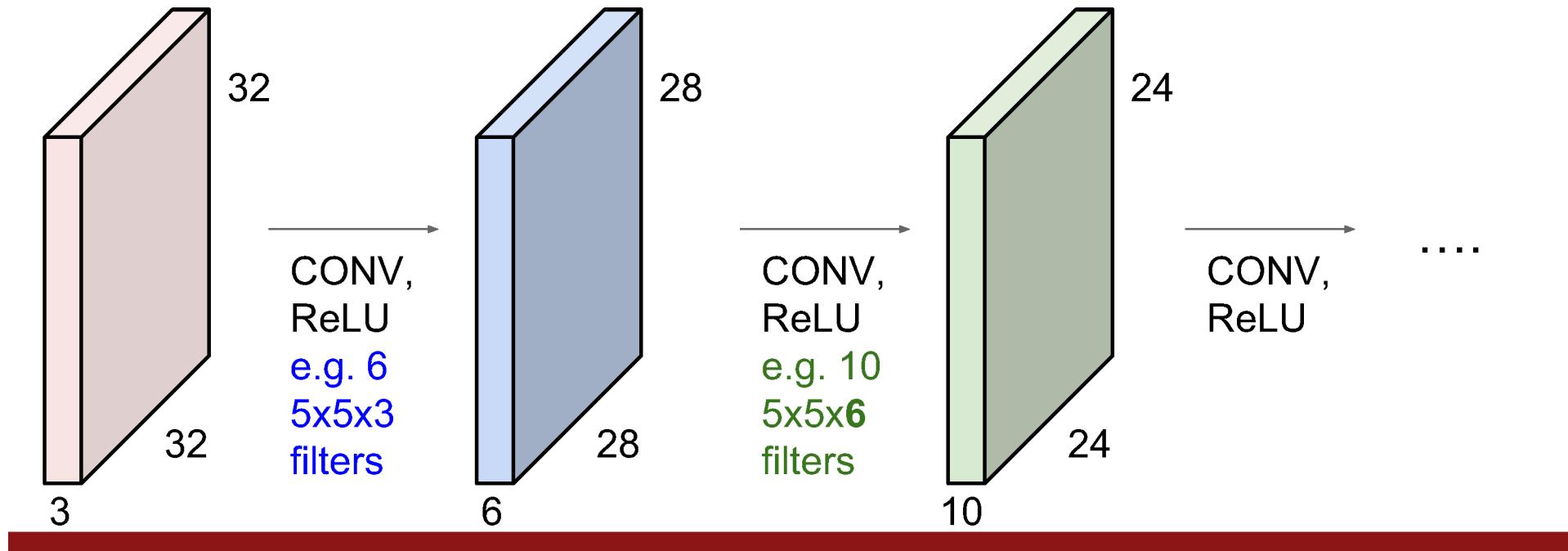
e.g. $F = 3 \Rightarrow$ zero pad with 1

$F = 5 \Rightarrow$ zero pad with 2

$F = 7 \Rightarrow$ zero pad with 3

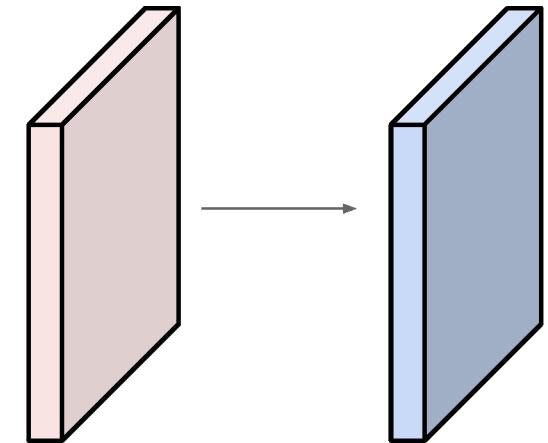
Remember back to...

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



Examples time:

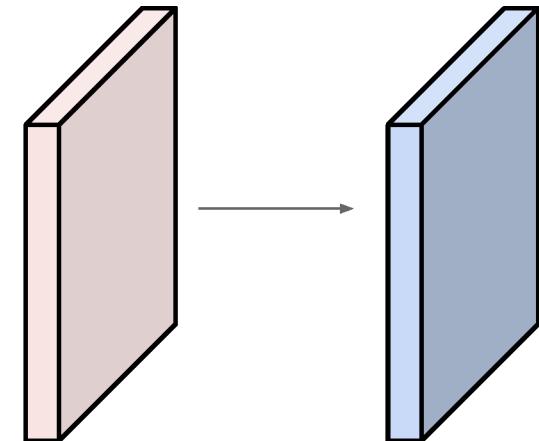
Input volume: **32x32x3**
10 5x5 filters with stride 1, pad 2



Output volume size: ?

Examples time:

Input volume: **32x32x3**
10 5x5 filters with stride **1**, pad **2**

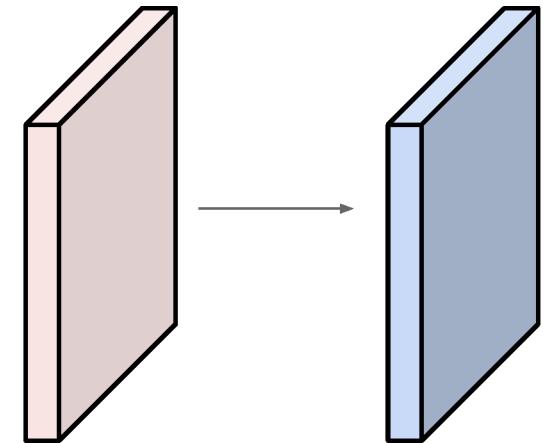


Output volume size:
 $(32+2*2-5)/1+1 = 32$ spatially, so
32x32x10



Examples time:

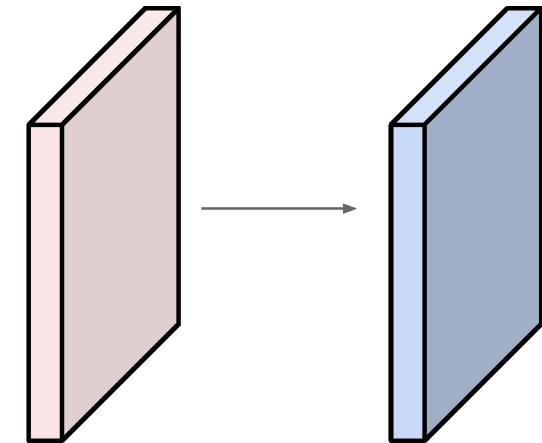
Input volume: **32x32x3**
10 5x5 filters with stride 1, pad 2



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)

$$\Rightarrow 76 * 10 = 760$$



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:

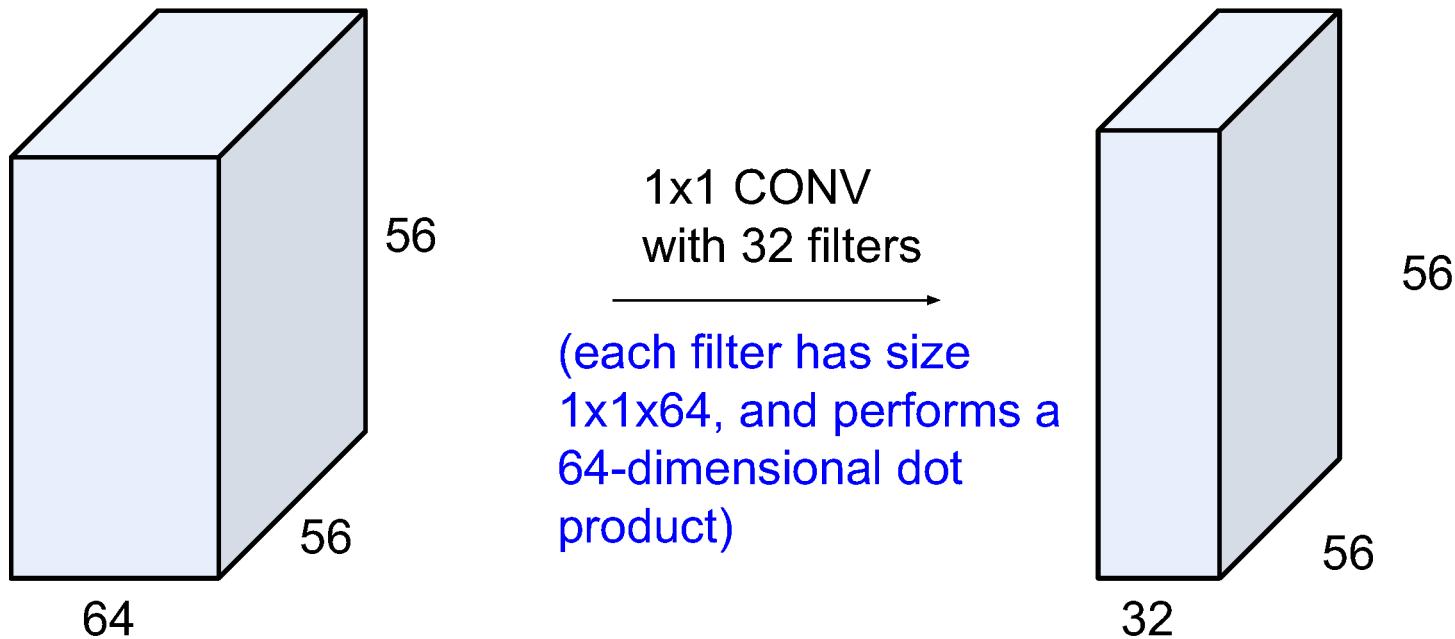
- Accepts a volume of size $W_1 \times H_1 \times D_1$
- Requires four hyperparameters:
 - Number of filters K ,
 - their spatial extent F ,
 - the stride S ,
 - the amount of zero padding P .
- Produces a volume of size $W_2 \times H_2 \times D_2$ where:
 - $W_2 = (W_1 - F + 2P)/S + 1$
 - $H_2 = (H_1 - F + 2P)/S + 1$ (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:

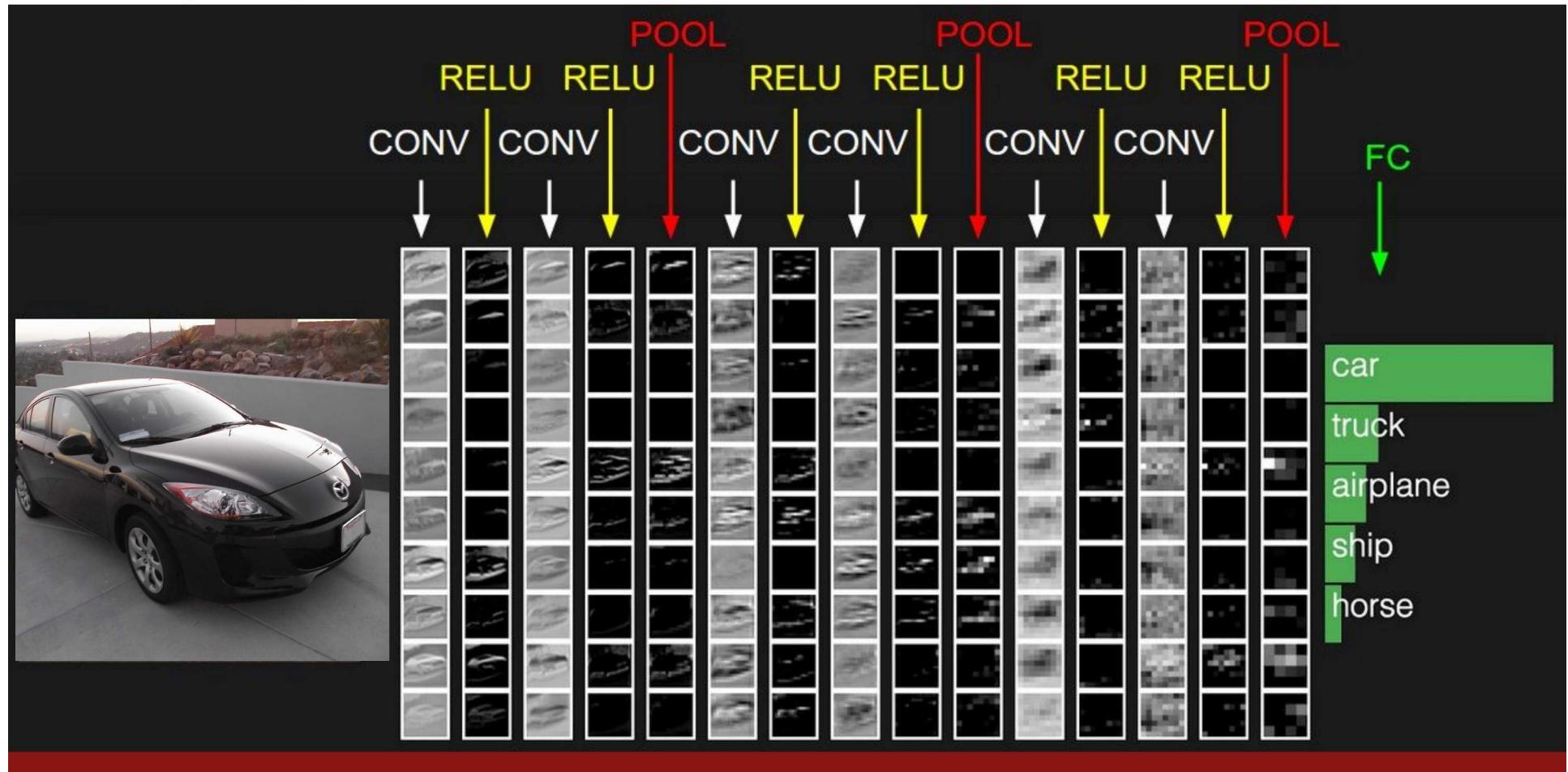
$K = (\text{powers of 2, e.g. } 32, 64, 128, 512)$

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

(btw, 1x1 convolution layers make perfect sense)

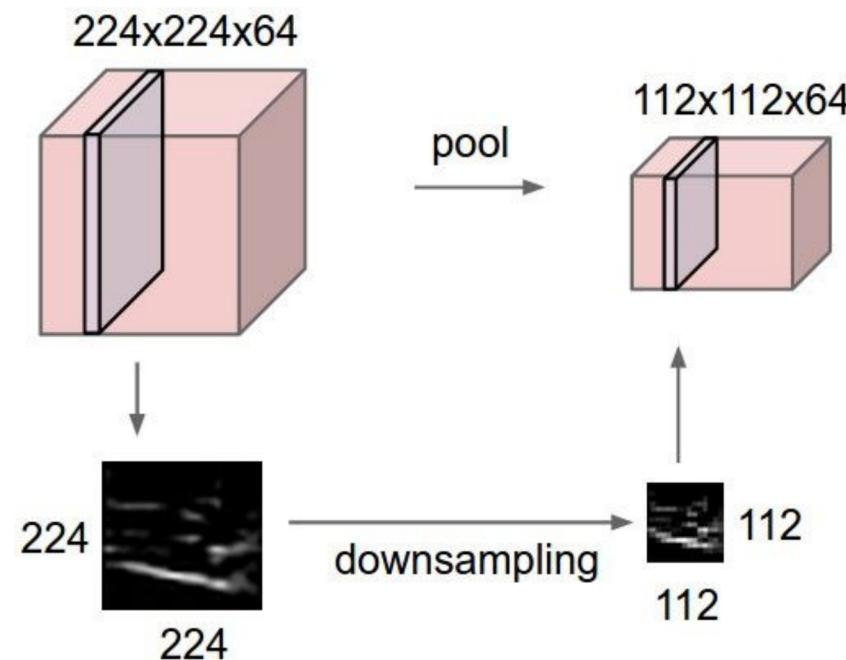


two more layers to go: POOL/FC

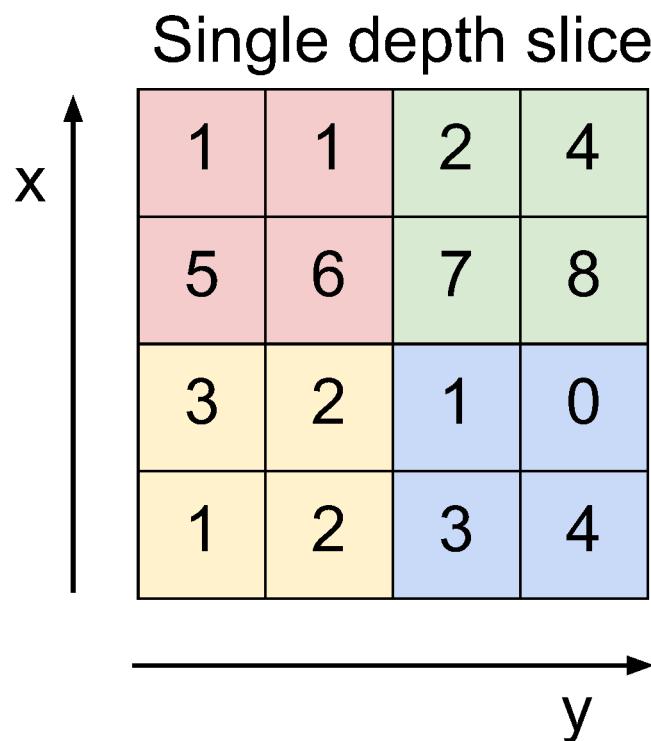


Pooling layer

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



MAX POOLING



max pool with 2x2 filters
and stride 2

6	8
3	4

- 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:

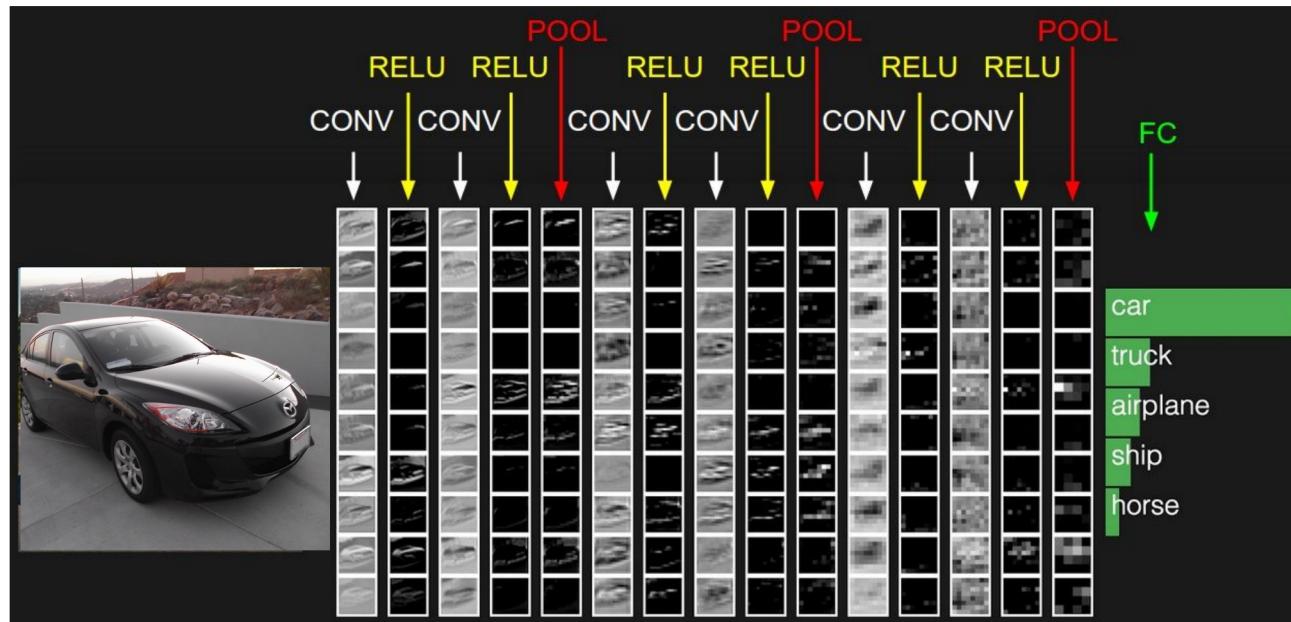
- Accepts a volume of size $W_1 \times H_1 \times D_1$
- Requires three hyperparameters:
 - their spatial extent F ,
 - the stride S ,
- Produces a volume of size $W_2 \times H_2 \times D_2$ where:
 - $W_2 = (W_1 - F)/S + 1$
 - $H_2 = (H_1 - F)/S + 1$
 - $D_2 = D_1$
- Introduces zero parameters since 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)

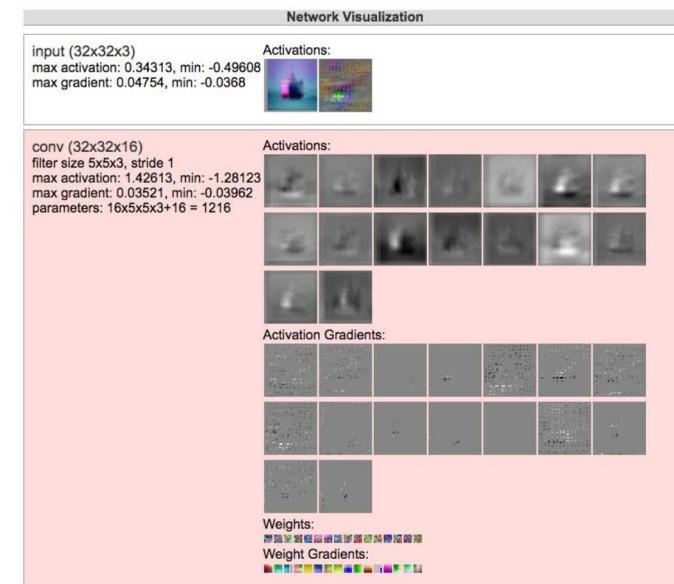
- Contains neurons that connect to the entire input volume, as in ordinary Neural Networks



[ConvNetJS demo: training on CIFAR-10]

[**ConvNetJS CIFAR-10 demo**](#)

Description
This demo trains a Convolutional Neural Network on the CIFAR-10 dataset in your browser, with nothing but Javascript. The state of the art on this dataset is about 90% accuracy and human performance is at about 94% (not perfect as the dataset can be a bit ambiguous). I used this python script to parse the original files (python version) into batches of images that can be easily loaded into page DOM with img tags. This dataset is more difficult and it takes longer to train a network. Data augmentation includes random flipping and random image shifts by up to 2px horizontally and vertically. By default, in this demo we're using Adadelta which is one of per-parameter adaptive step size methods, so we don't have to worry about changing learning rates or momentum over time. However, I still included the text fields for changing these if you'd like to play around with SGD+Momentum trainer. Report questions/bugs/suggestions to @karpathy .



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

Summary

- ConvNets stack CONV,POOL,FC layers
 - Trend towards smaller filters and deeper architectures
 - 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
-