

# Lecture 5: Convolutional Neural Networks

# Administrative

**Assignment 1 due Thursday April 20, 11:59pm on Canvas**

**Assignment 2 will be released Thursday**

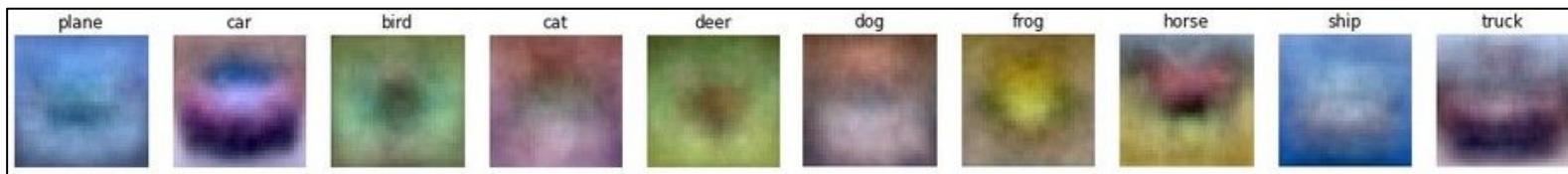
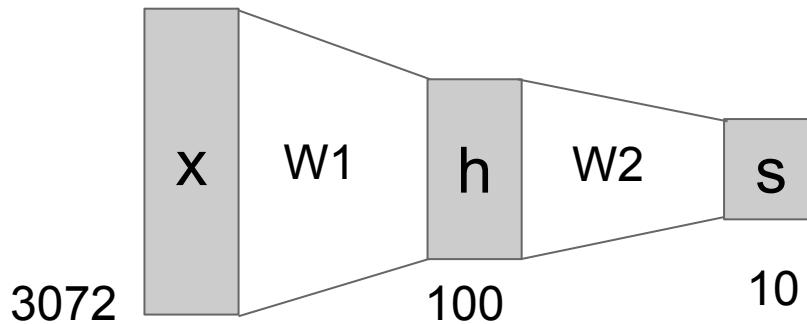
# Last time: Neural Networks

Linear score function:

$$f = Wx$$

2-layer Neural Network

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



# Next: Convolutional Neural Networks

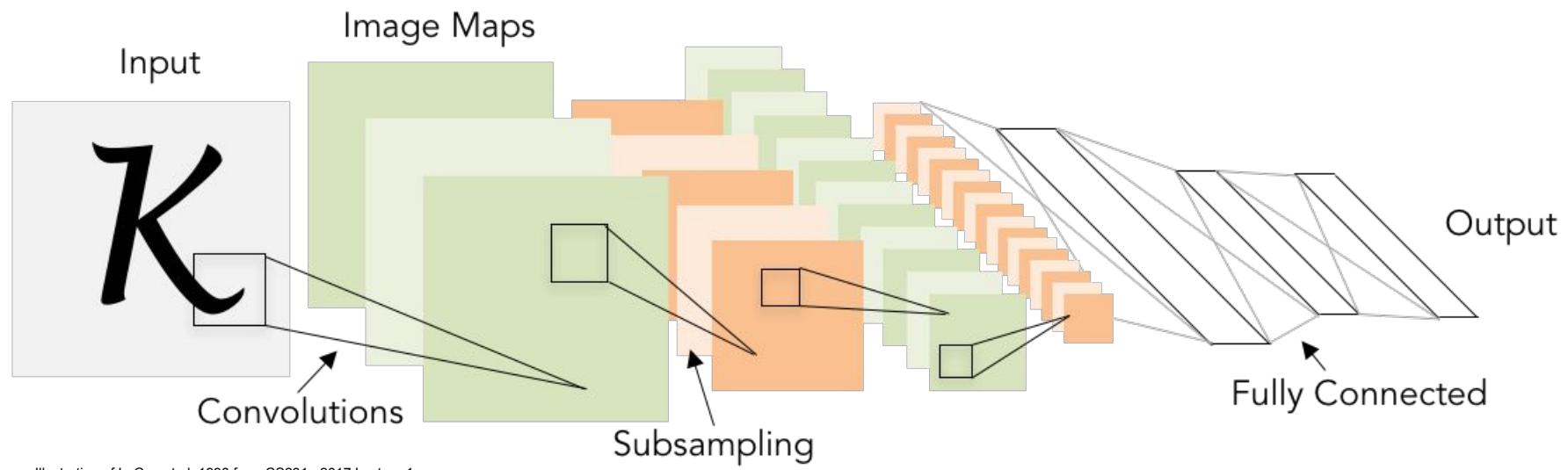


Illustration of LeCun et al. 1998 from CS231n 2017 Lecture 1

# A bit of history...

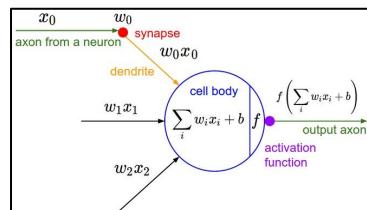
The **Mark I Perceptron** machine was the first implementation of the perceptron algorithm.

The machine was connected to a camera that used  $20 \times 20$  cadmium sulfide photocells to produce a 400-pixel image.

recognized  
letters of the alphabet

update rule:

$$w_i(t+1) = w_i(t) + \alpha(d_j - y_j(t))x_{j,i}$$

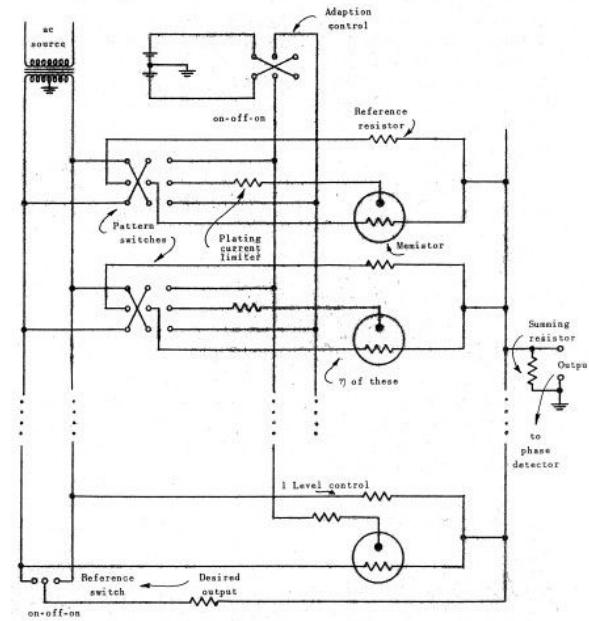
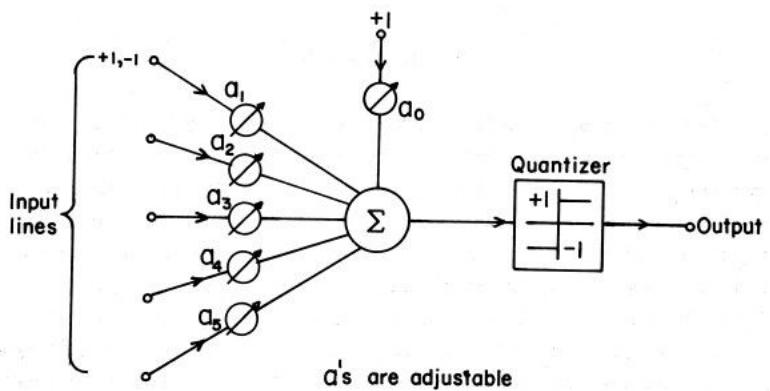


Frank Rosenblatt, ~1957: Perceptron



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# A bit of history...

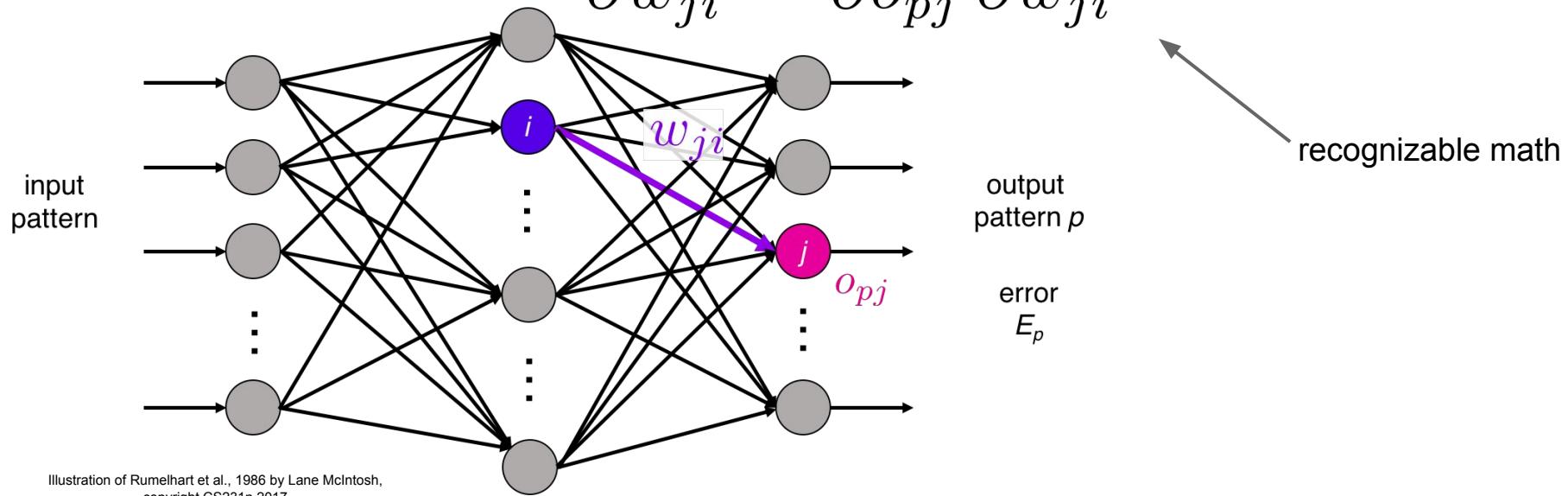


Widrow and Hoff, ~1960: Adaline/Madaline

These figures are reproduced from [Widrow 1960, Stanford Electronics Laboratories Technical Report](#) with permission from [Stanford University Special Collections](#).

# A bit of history...

$$\frac{\partial E_p}{\partial w_{ji}} = \frac{\partial E_p}{\partial o_{pj}} \frac{\partial o_{pj}}{\partial w_{ji}}$$



Rumelhart et al., 1986: First time back-propagation became popular

# A bit of history...

[Hinton and Salakhutdinov 2006]

Reinvigorated research in  
Deep Learning

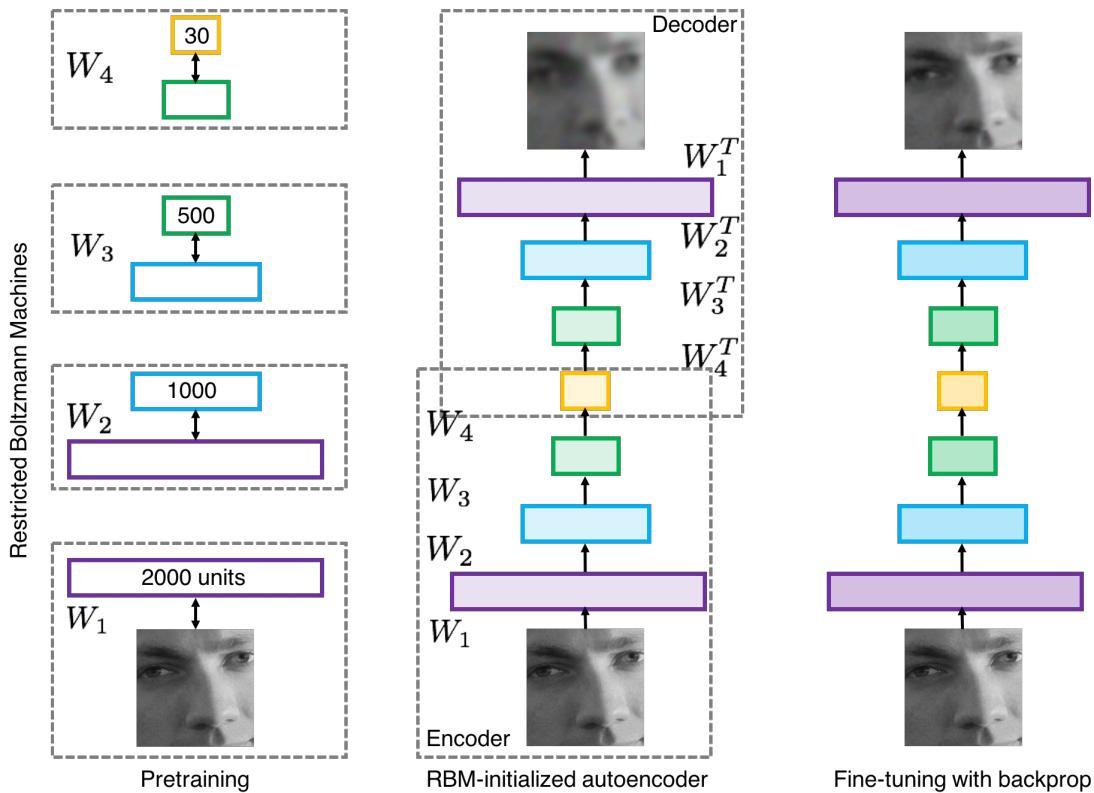


Illustration of Hinton and Salakhutdinov 2006 by Lane McIntosh, copyright CS231n 2017

# First strong results

## **Acoustic Modeling using Deep Belief Networks**

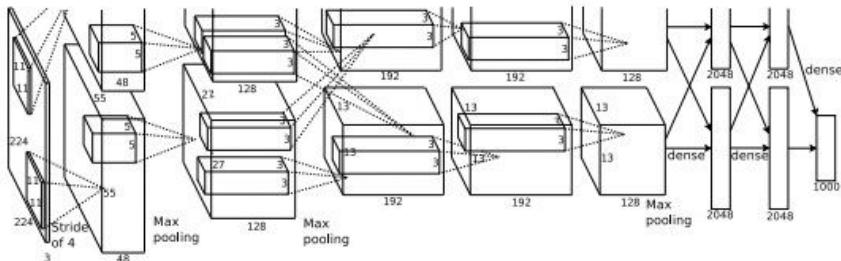
Abdel-rahman Mohamed, George Dahl, Geoffrey Hinton, 2010

## **Context-Dependent Pre-trained Deep Neural Networks for Large Vocabulary Speech Recognition**

George Dahl, Dong Yu, Li Deng, Alex Acero, 2012

## **Imagenet classification with deep convolutional neural networks**

Alex Krizhevsky, Ilya Sutskever, Geoffrey E Hinton, 2012



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

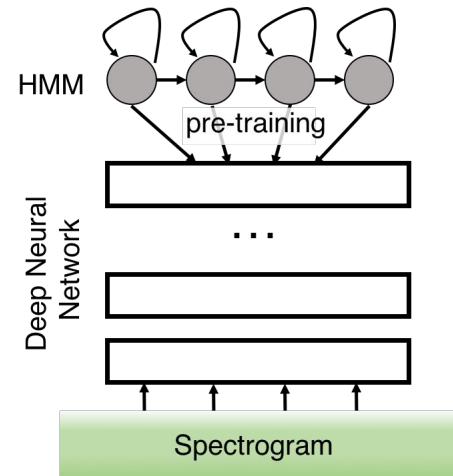


Illustration of Dahl et al. 2012 by Lane McIntosh, copyright CS231n 2017

# A bit of history:

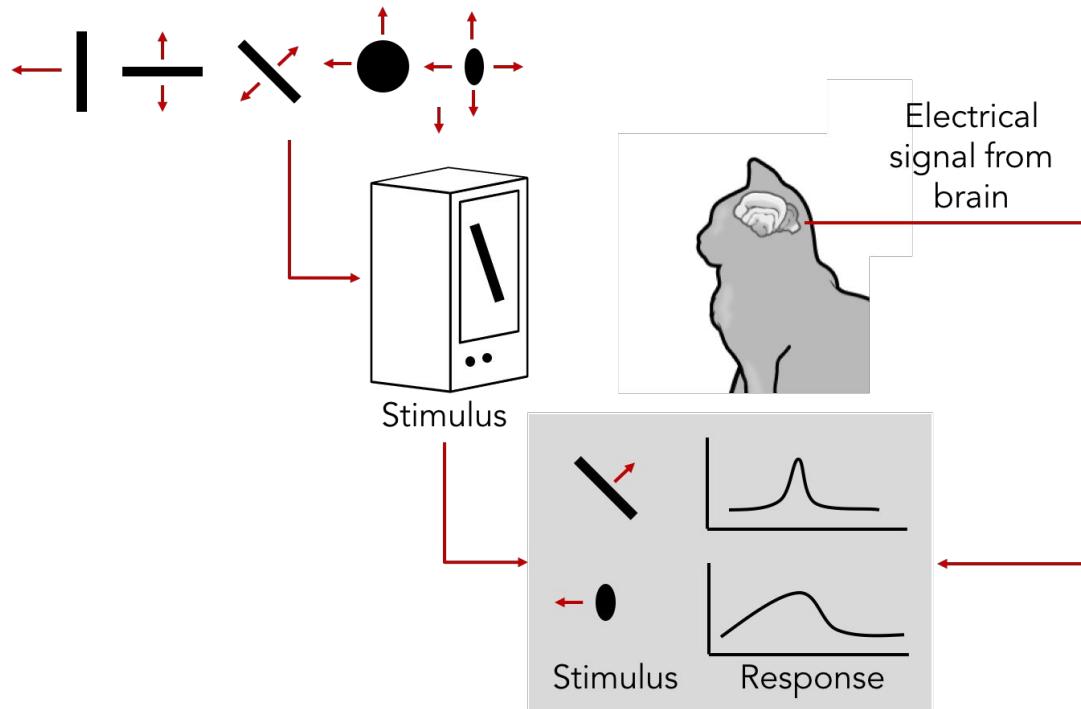
**Hubel & Wiesel,  
1959**

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

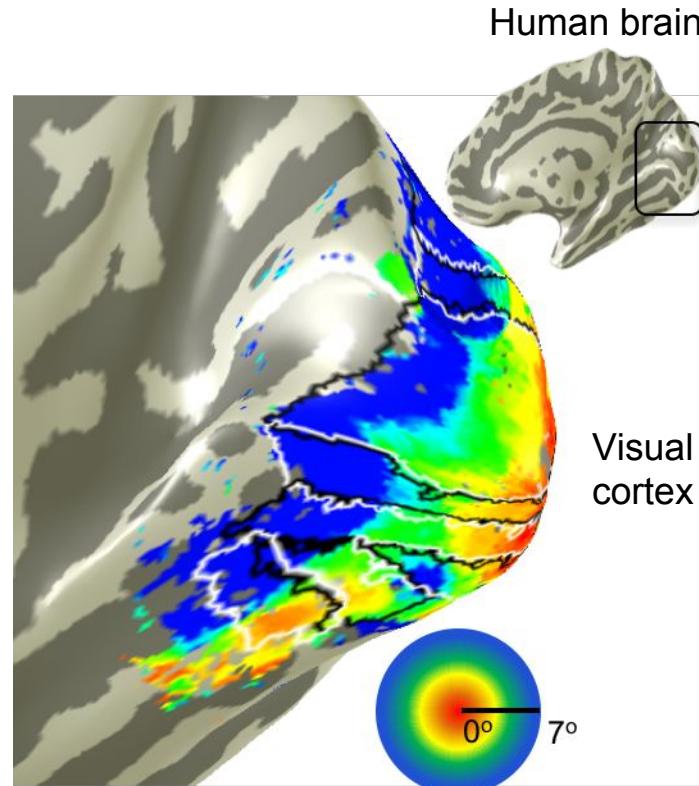
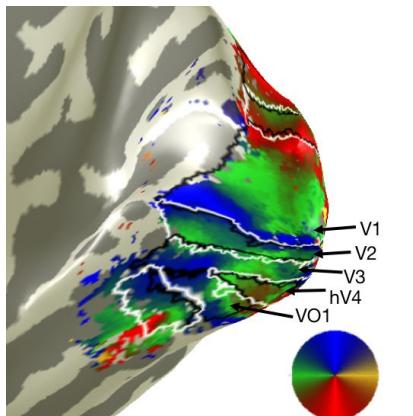
**1968...**



[Cat image](#) by CNX OpenStax is licensed  
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# A bit of history

**Topographical mapping in the cortex:**  
nearby cells in cortex represent  
nearby regions in the visual field



Retinotopy images courtesy of Jesse Gomez in the Stanford Vision & Perception Neuroscience Lab.

# Hierarchical organization

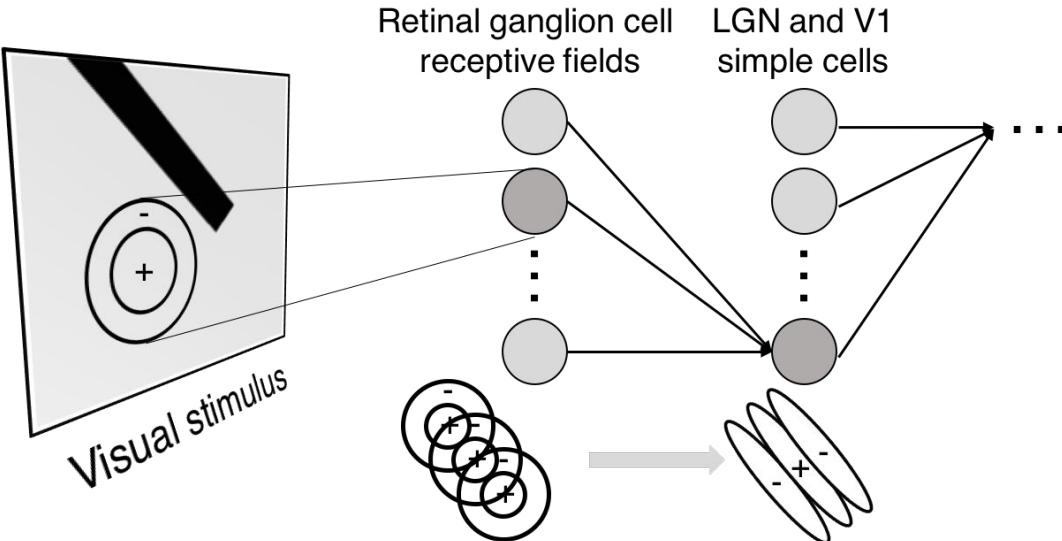
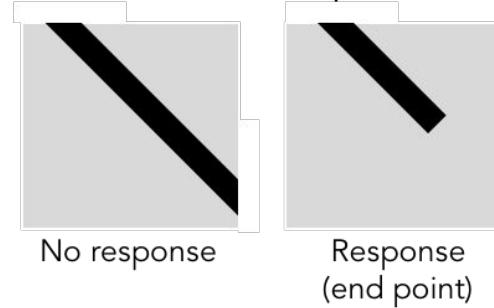


Illustration of hierarchical organization in early visual pathways by Lane McIntosh, copyright CS231n 2017

**Simple cells:**  
Response to light orientation

**Complex cells:**  
Response to light orientation and movement

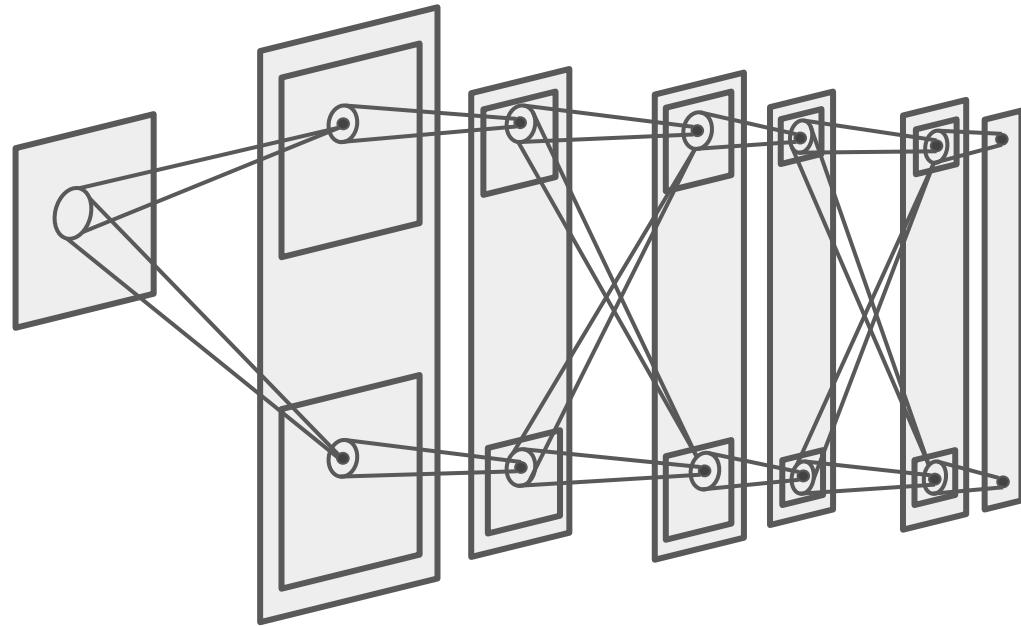
**Hypercomplex cells:**  
response to movement with an end point



# A bit of history:

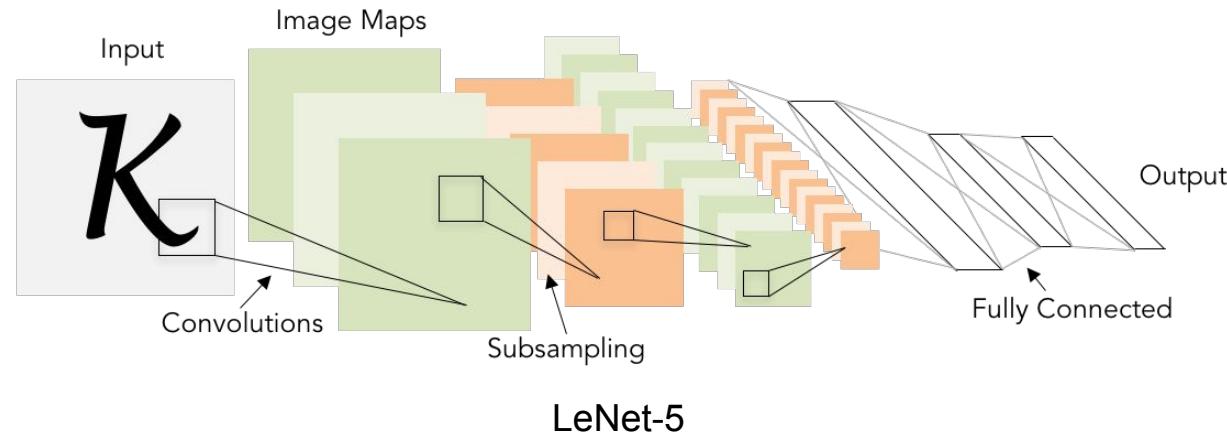
## Neocognitron [Fukushima 1980]

“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]



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

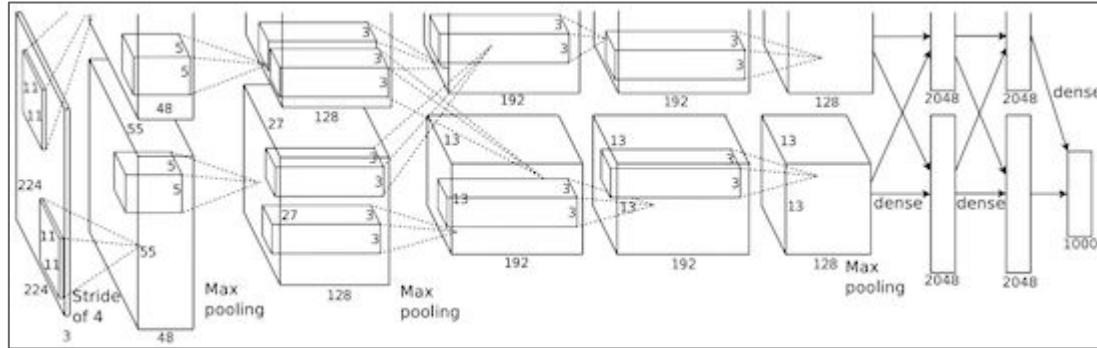
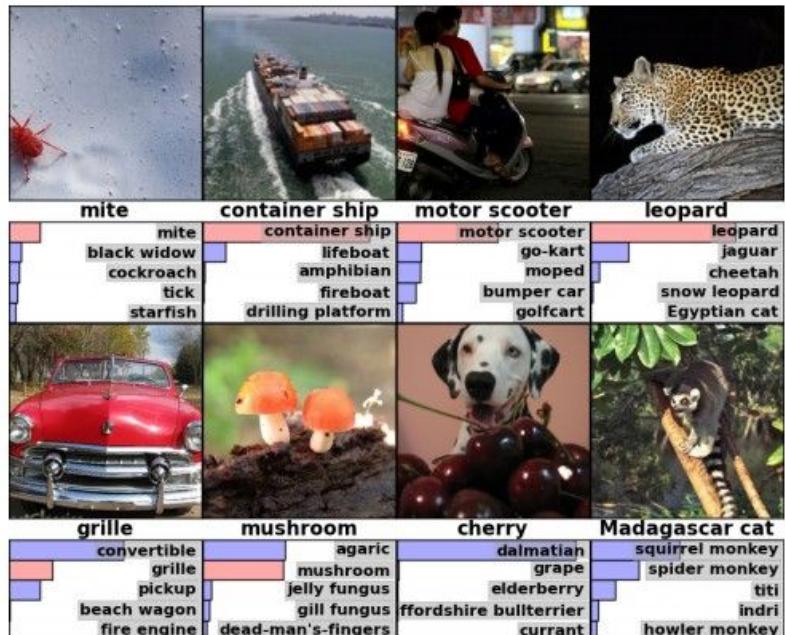


Figure copyright Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, 2012. Reproduced with permission.

“AlexNet”

# Fast-forward to today: ConvNets are everywhere

Classification



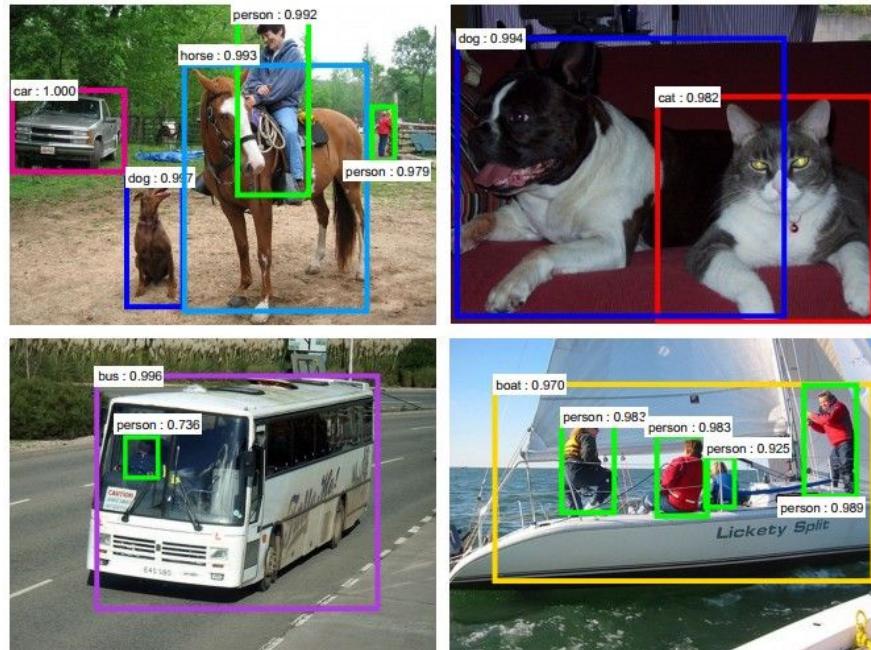
Retrieval



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# Fast-forward to today: ConvNets are everywhere

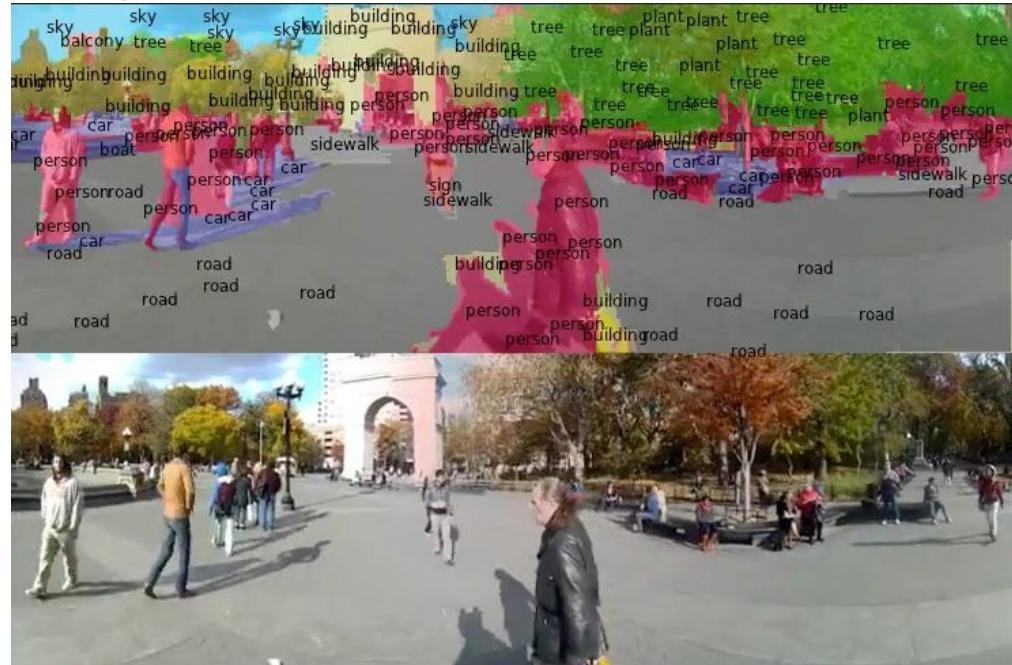
## Detection



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

## Segmentation



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[*Farabet et al., 2012*]

# Fast-forward to today: ConvNets are everywhere



self-driving cars

Photo by Lane McIntosh. Copyright CS231n 2017.



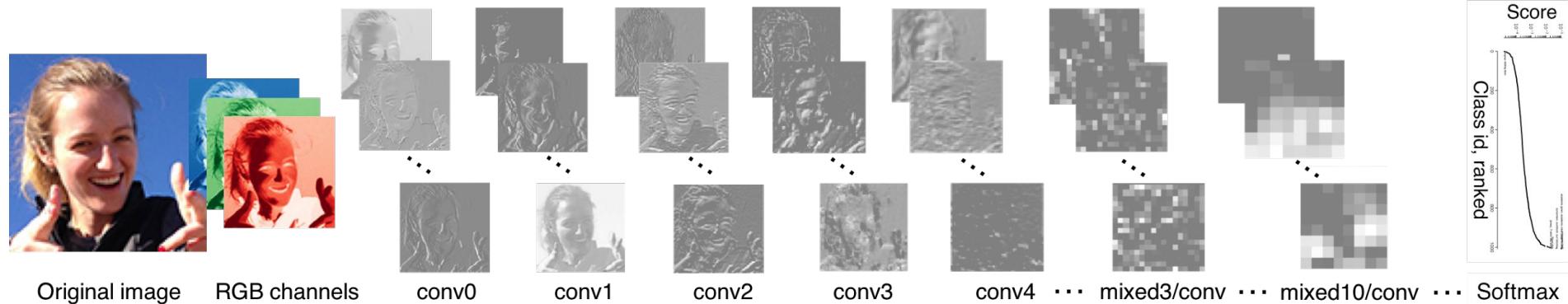
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## NVIDIA Tesla line

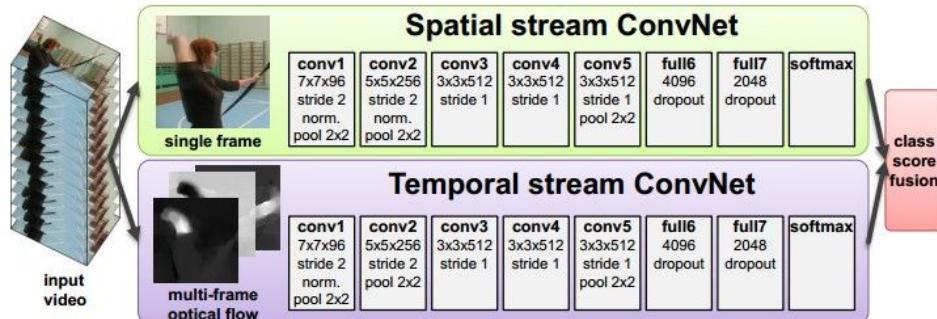
(these are the GPUs on rye01.stanford.edu)

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



[Taigman et al. 2014]



[Simonyan et al. 2014]

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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.

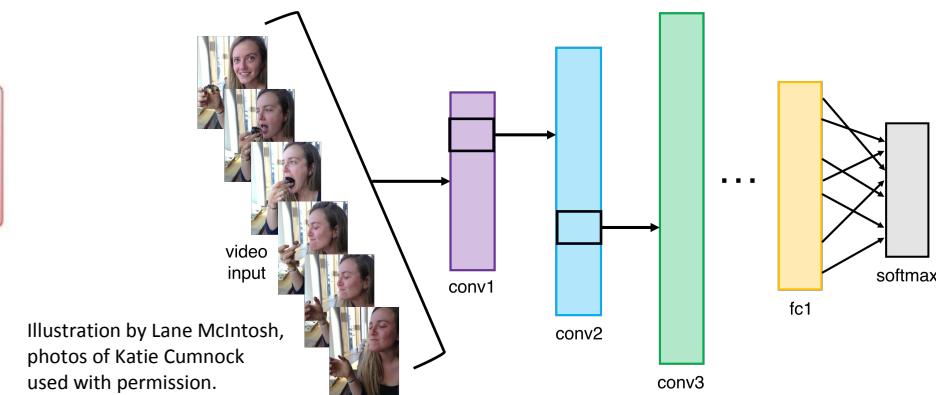


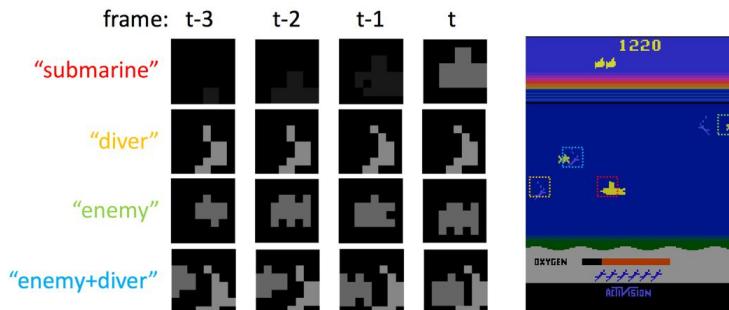
Illustration by Lane McIntosh,  
photos of Katie Cumnock  
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# Fast-forward to today: ConvNets are everywhere



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

[Toshev, Szegedy 2014]

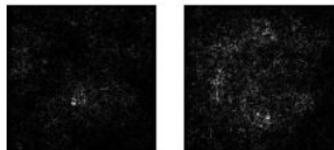
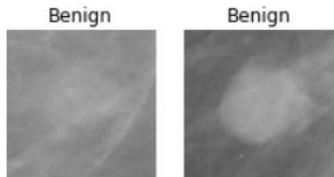


[Guo et al. 2014]



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.  
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[Dieleman et al. 2014]

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ESA/Hubble, [public domain by NASA](#), and [public domain](#).



Photos by Lane McIntosh.  
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[Sermanet et al. 2011]  
[Ciresan et al.]

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*Whale recognition, Kaggle Challenge*

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



*Mnih and Hinton, 2010*

No errors



*A white teddy bear sitting in the grass*



*A man riding a wave on top of a surfboard*

Minor errors



*A man in a baseball uniform throwing a ball*



*A cat sitting on a suitcase on the floor*

Somewhat related



*A woman is holding a cat in her hand*



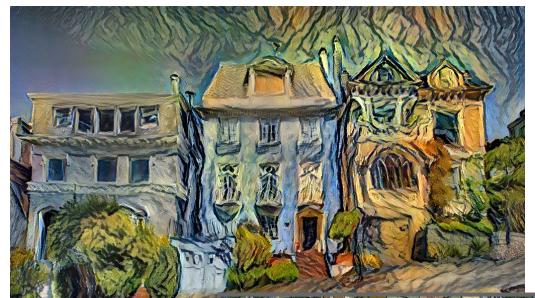
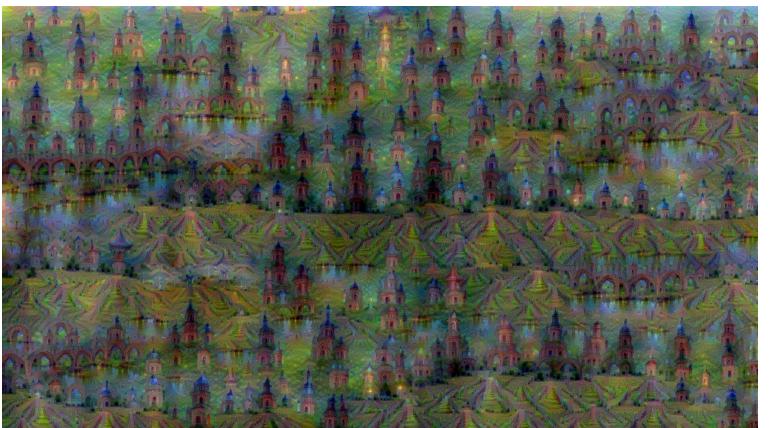
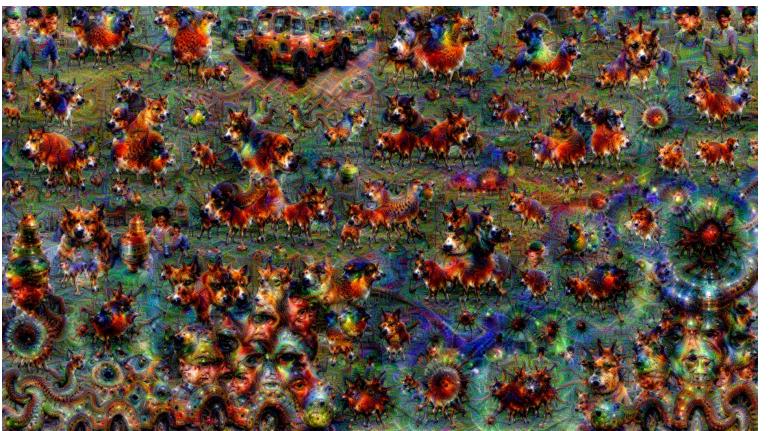
*A woman standing on a beach holding a surfboard*

# Image Captioning

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

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



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

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

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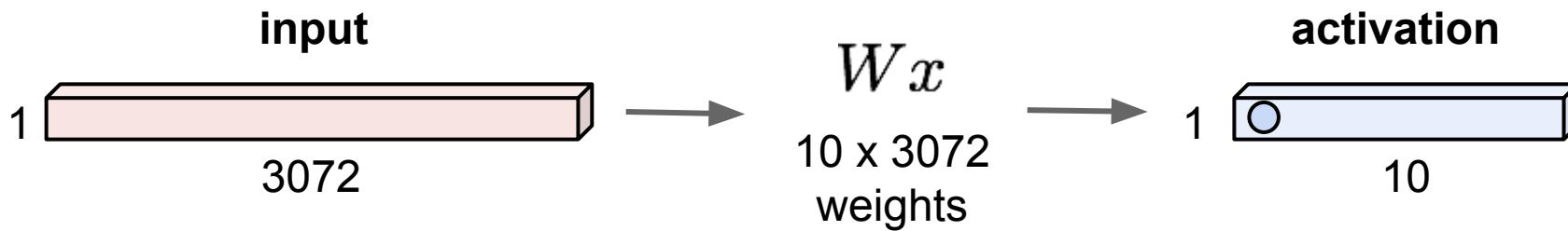
Gatys et al, "Image Style Transfer using Convolutional Neural Networks", CVPR 2016  
Gatys et al, "Controlling Perceptual Factors in Neural Style Transfer", CVPR 2017

# Convolutional Neural Networks

(First without the brain stuff)

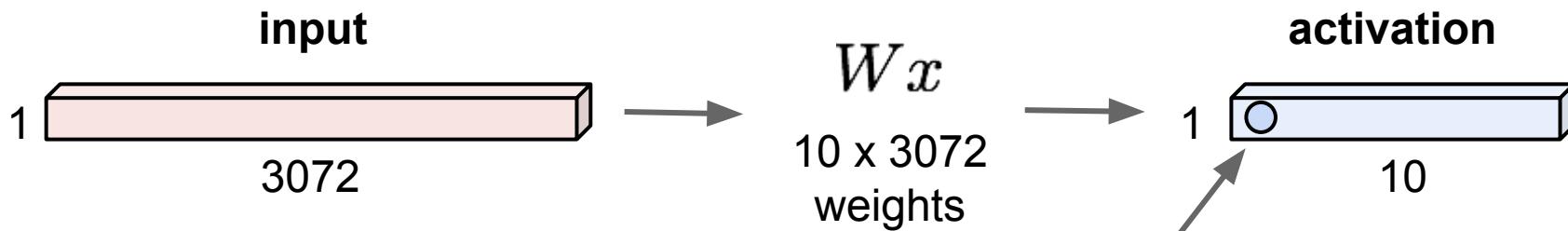
# Fully Connected Layer

32x32x3 image -> stretch to 3072 x 1



# Fully Connected Layer

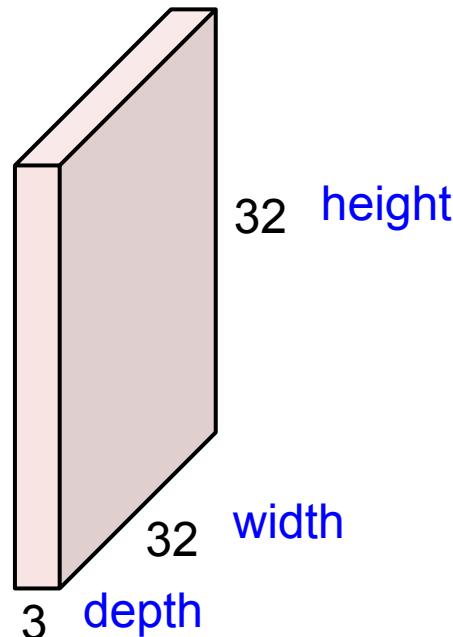
32x32x3 image -> stretch to 3072 x 1



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

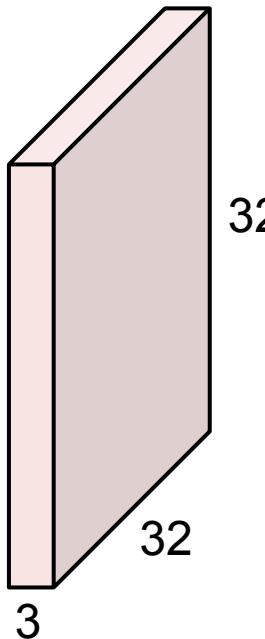
# Convolution Layer

32x32x3 image -> preserve spatial structure

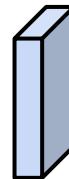


# Convolution Layer

32x32x3 image



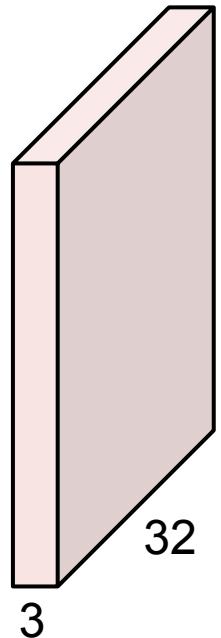
5x5x3 filter



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

# Convolution Layer

32x32x3 image



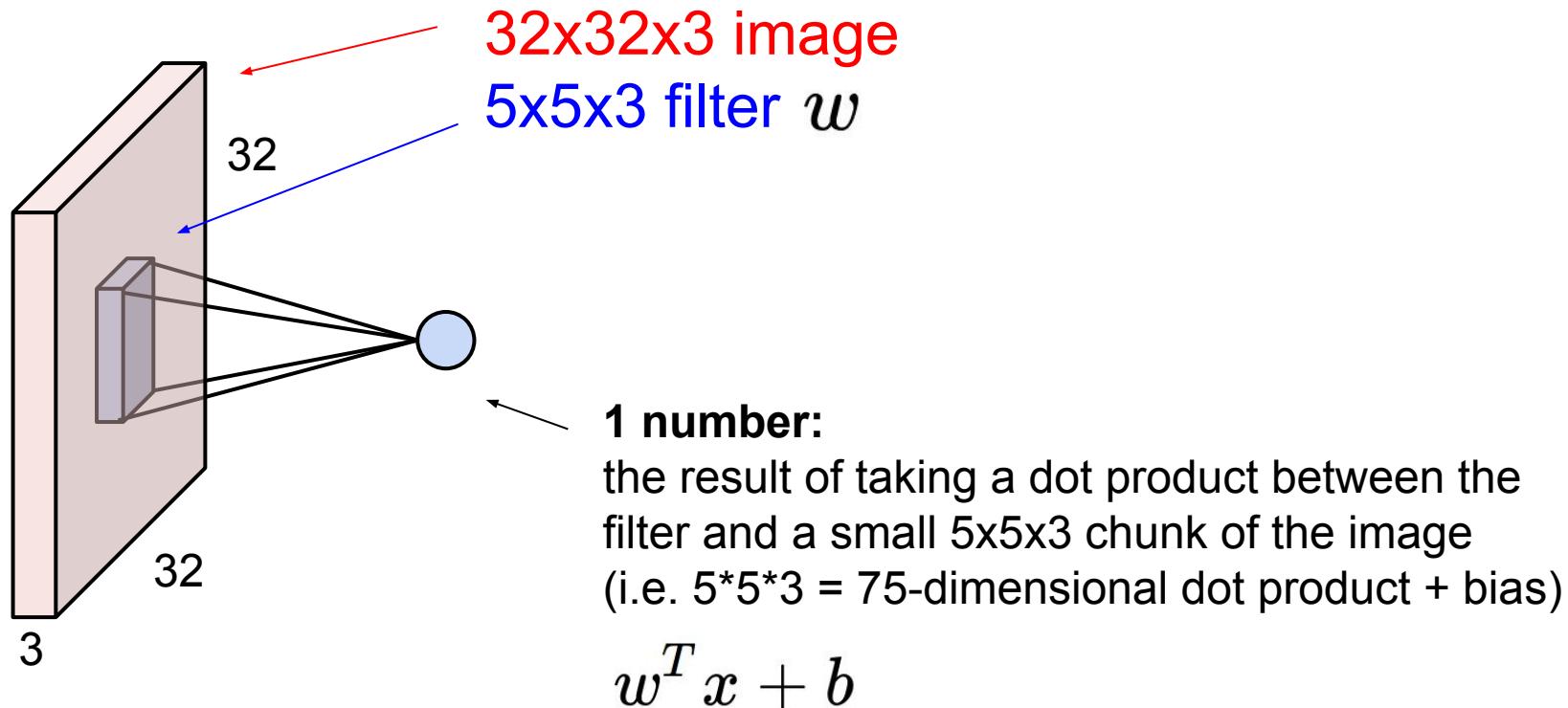
5x5x3 filter



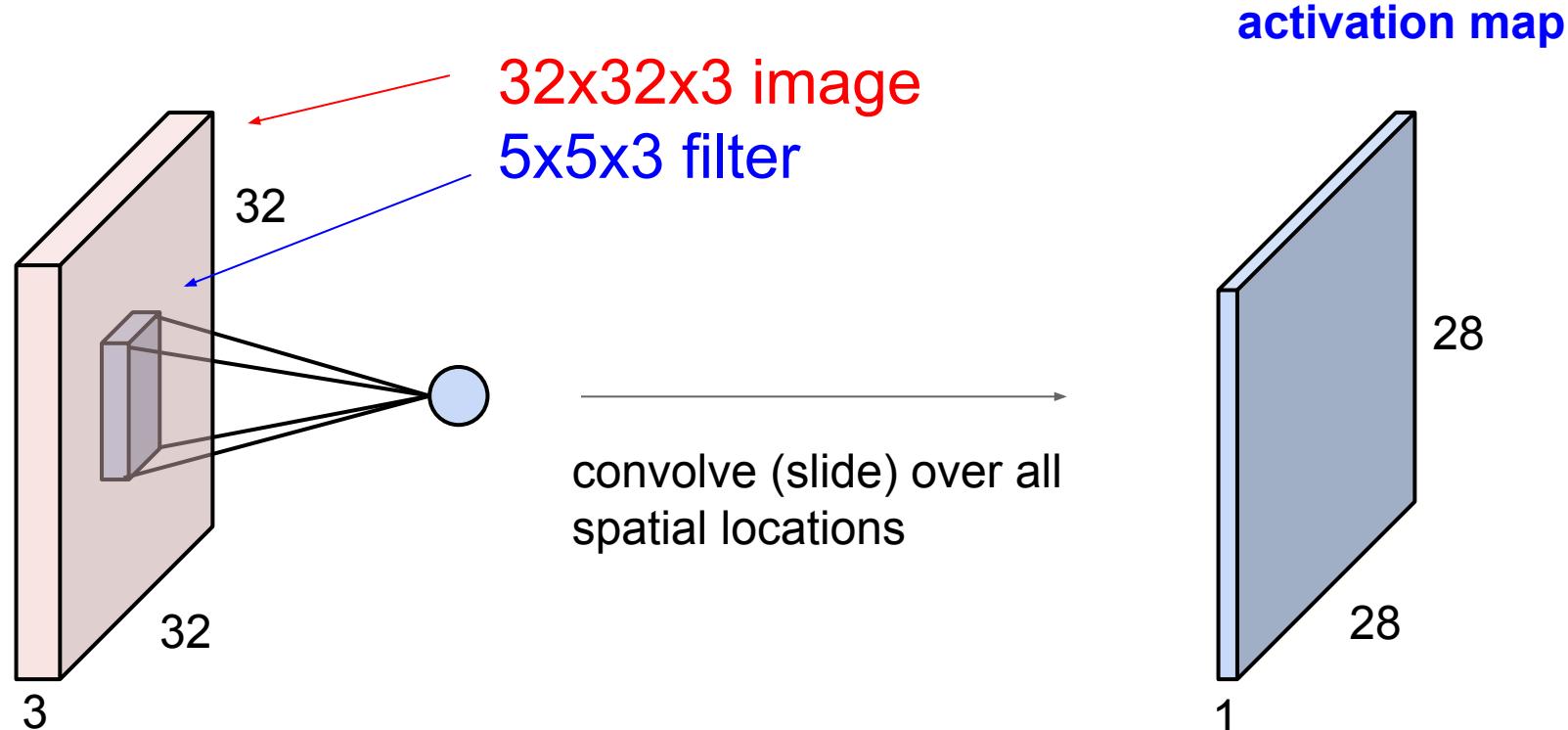
Filters always extend the full depth of the input volume

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

# Convolution Layer

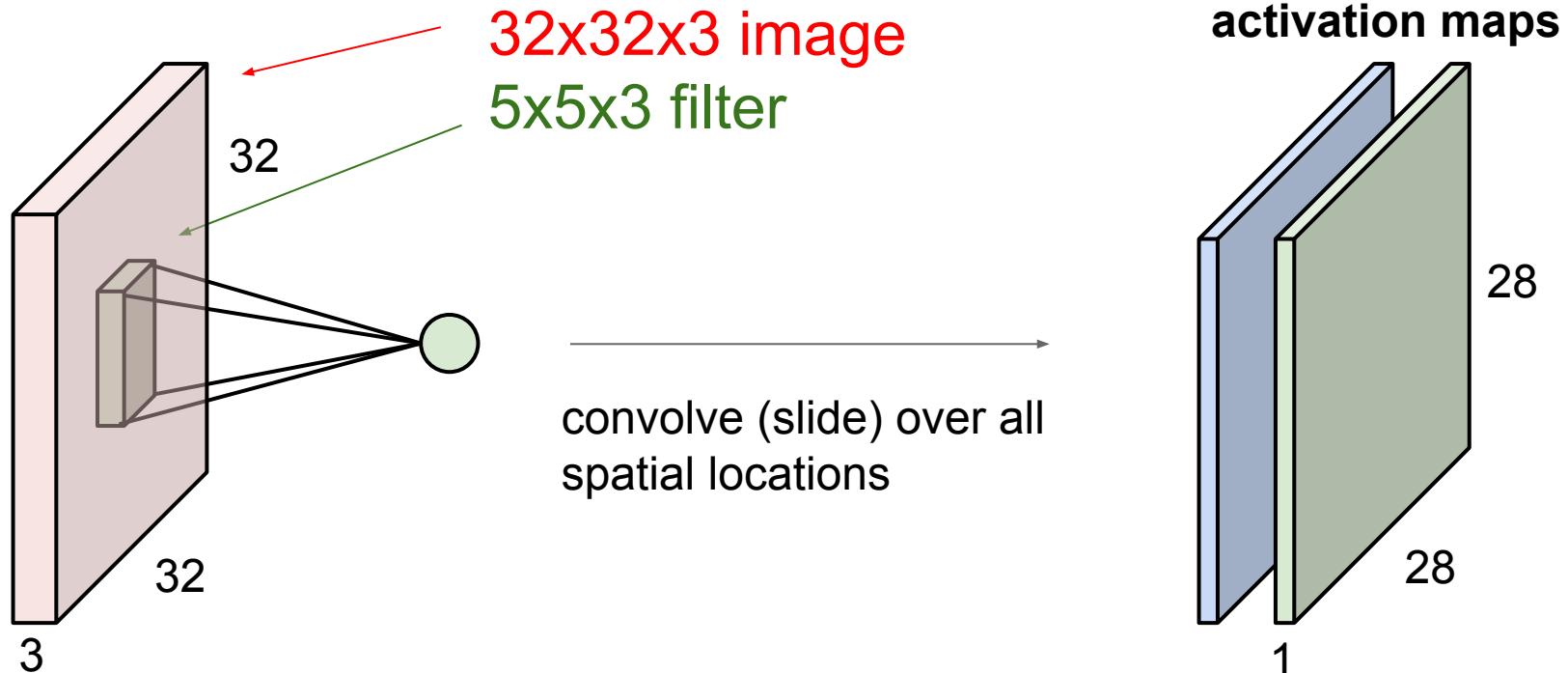


# Convolution Layer

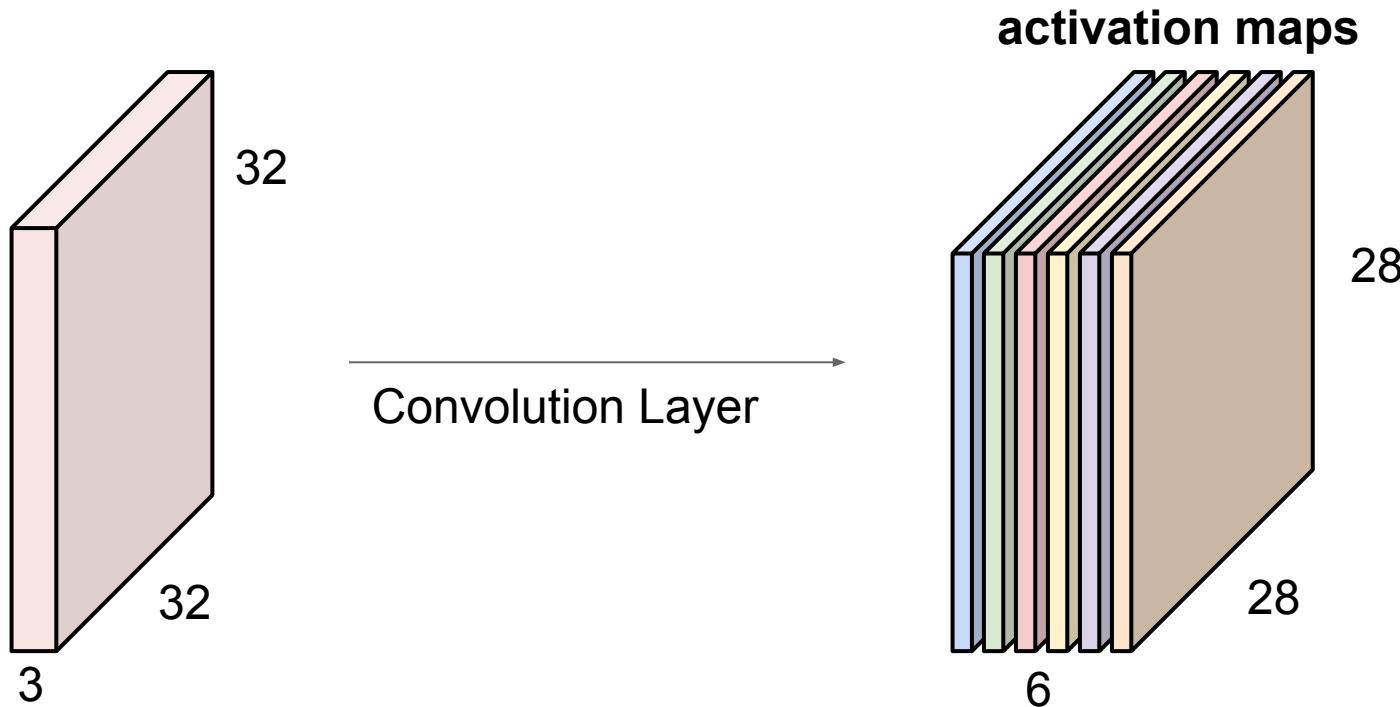


# Convolution Layer

consider a second, green filter

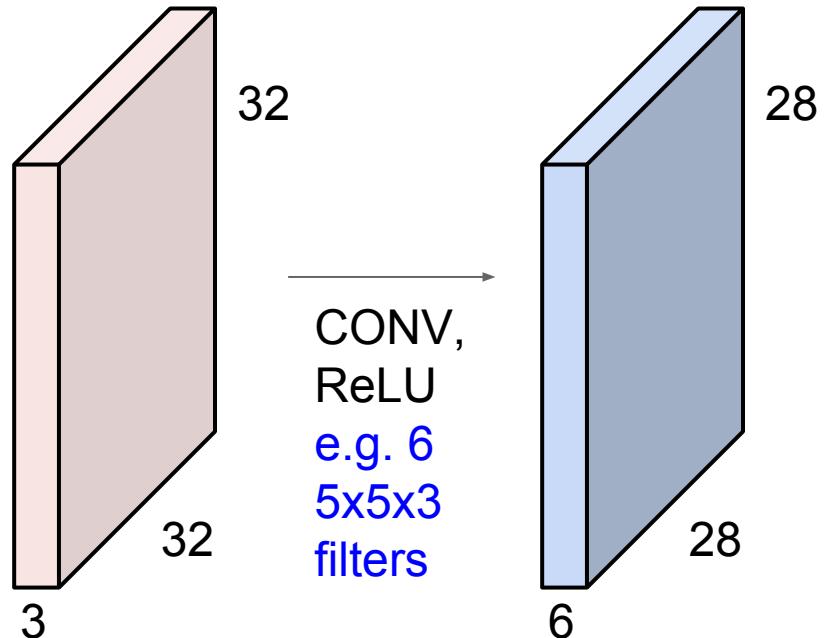


For example, if we had 6  $5 \times 5$  filters, we'll get 6 separate activation maps:

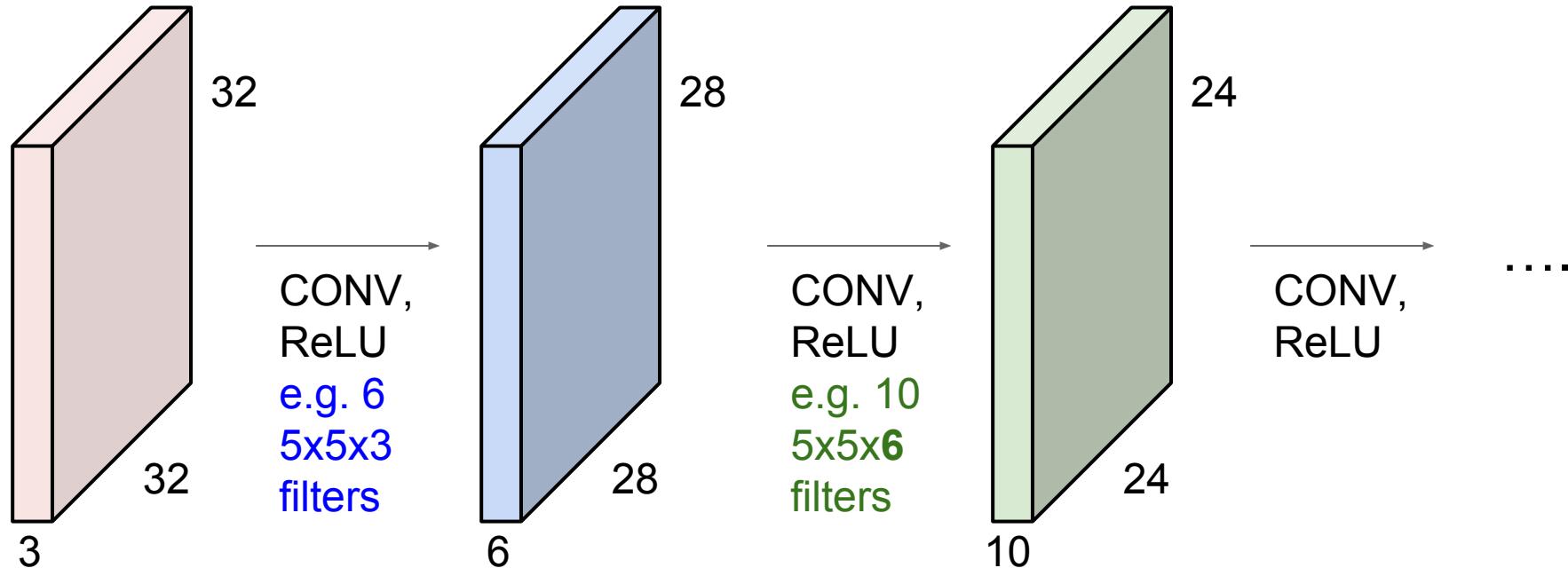


We stack these up to get a “new image” of size  $28 \times 28 \times 6$ !

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



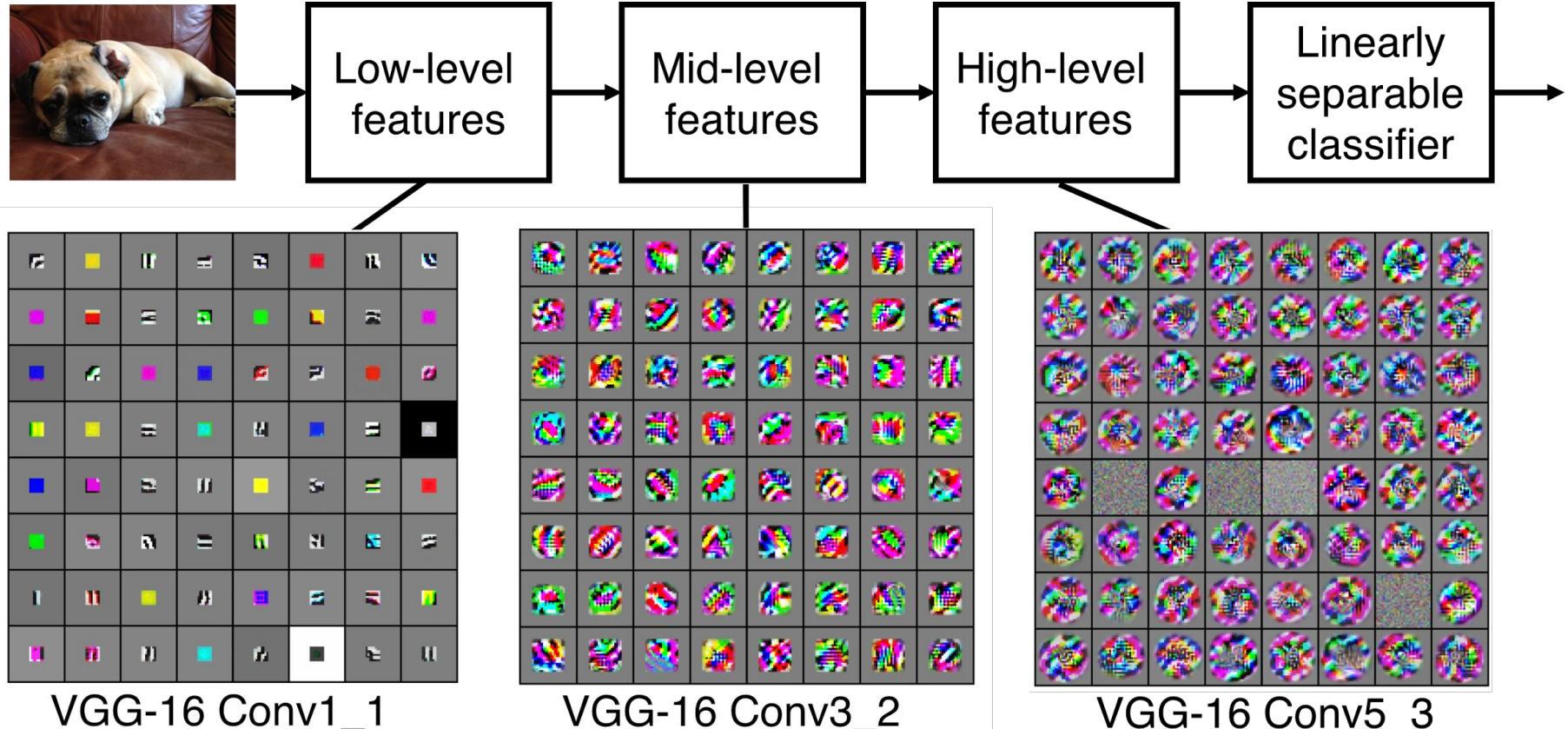
**Preview:** ConvNet is a sequence of Convolutional Layers, interspersed with activation functions



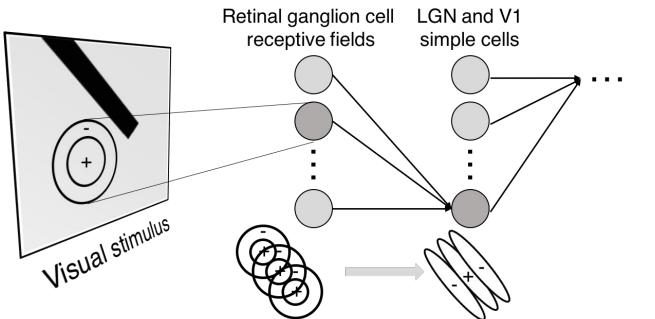
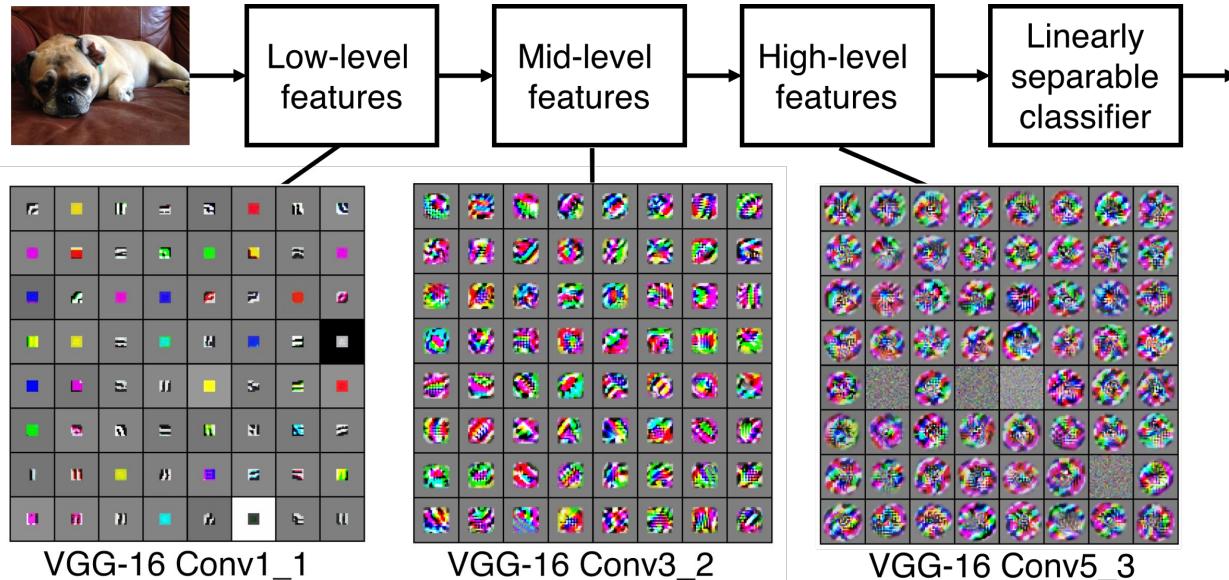
## Preview

[Zeiler and Fergus 2013]

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



# Preview



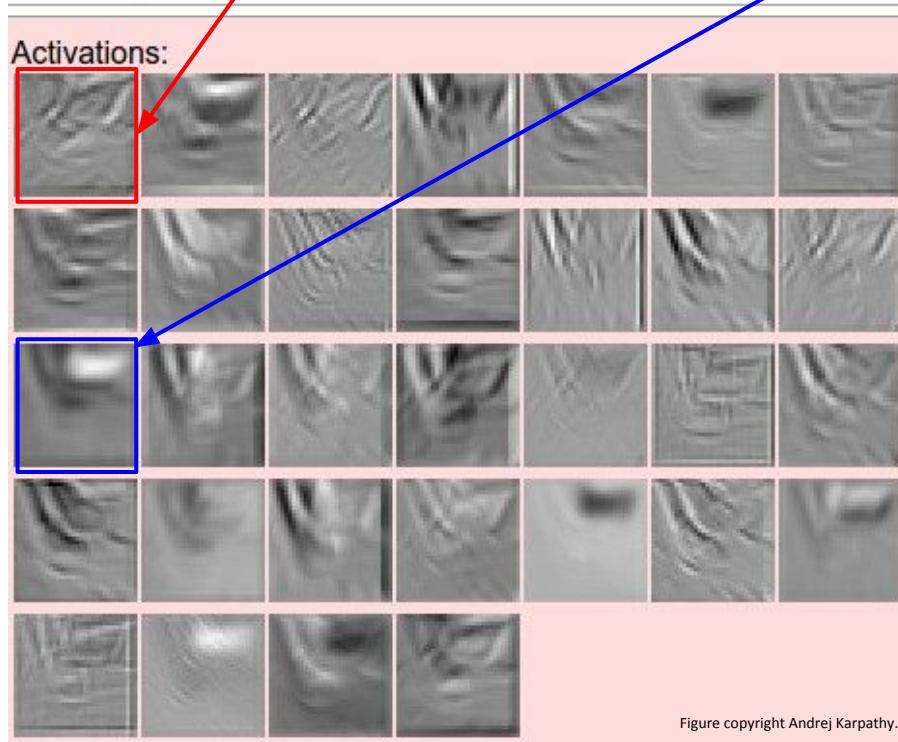
Complex cells:  
Response to light orientation and movement

Hypercomplex cells:  
response to movement with an end point

No response      Response (end point)



one filter =>  
one activation map



example 5x5 filters  
(32 total)

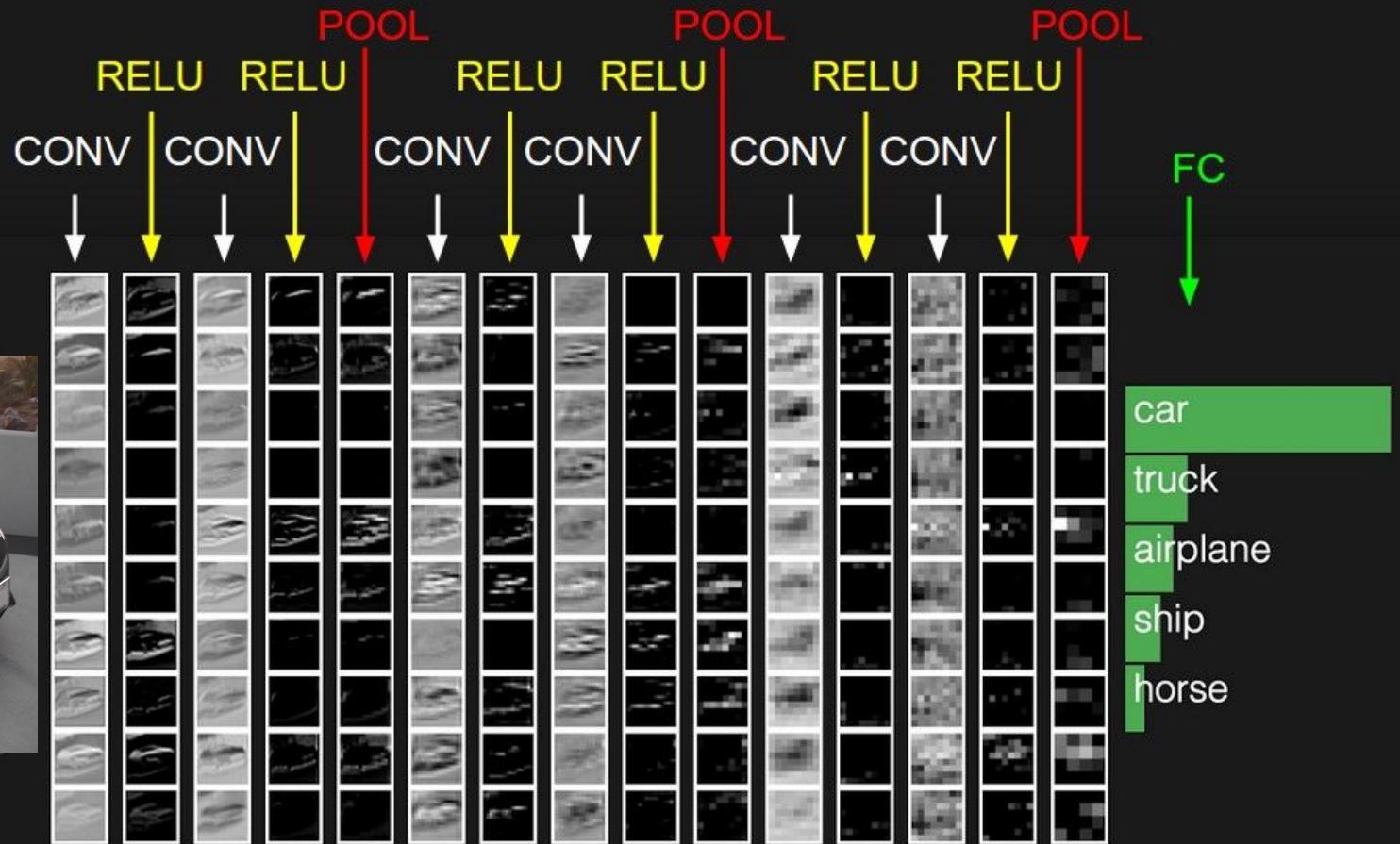
We call the layer convolutional  
because it is related to convolution  
of two signals:

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

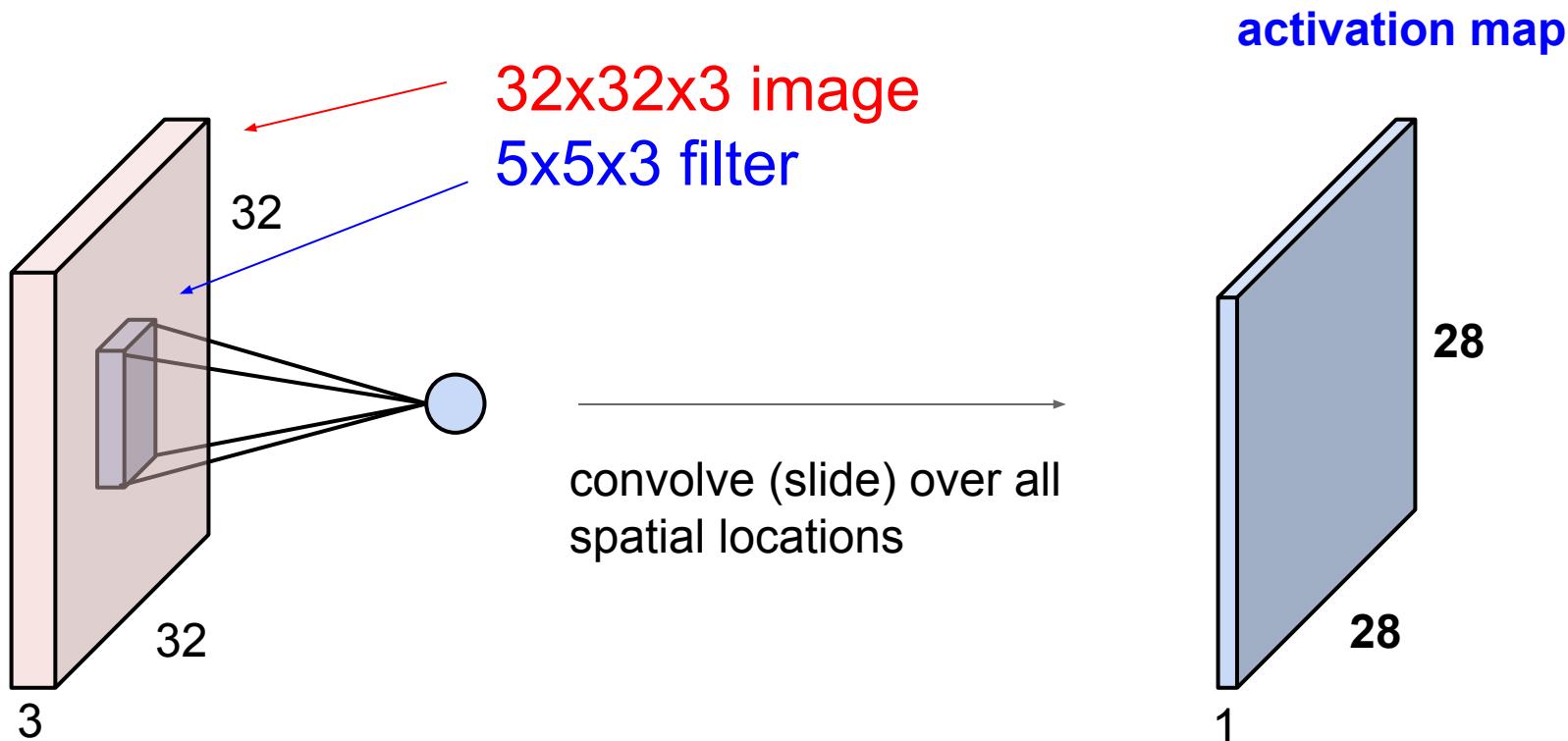


elementwise multiplication and sum of  
a filter and the signal (image)

preview:

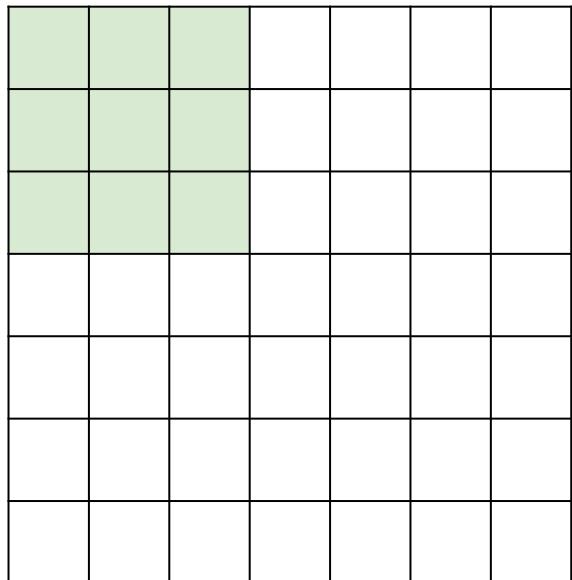


## A closer look at spatial dimensions:



## A closer look at spatial dimensions:

7

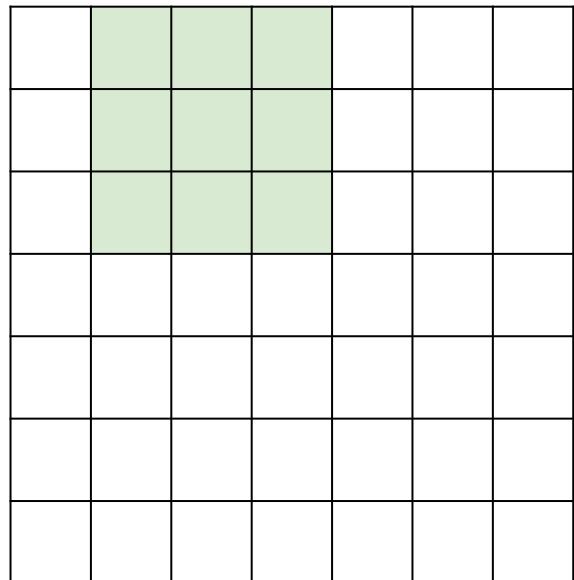


7x7 input (spatially)  
assume 3x3 filter

7

## A closer look at spatial dimensions:

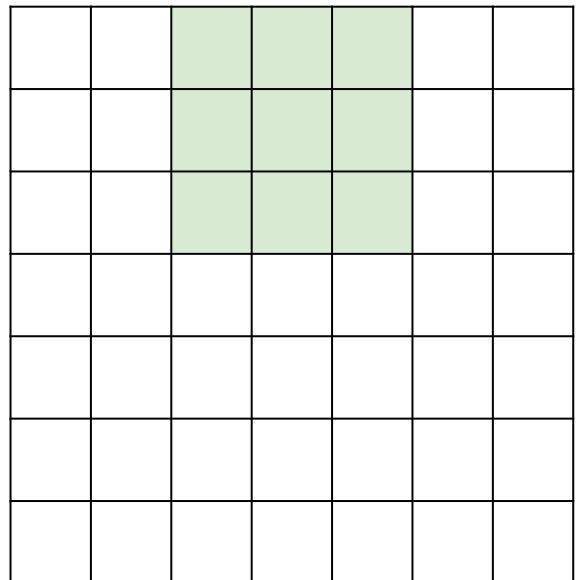
7



7x7 input (spatially)  
assume 3x3 filter

## A closer look at spatial dimensions:

7

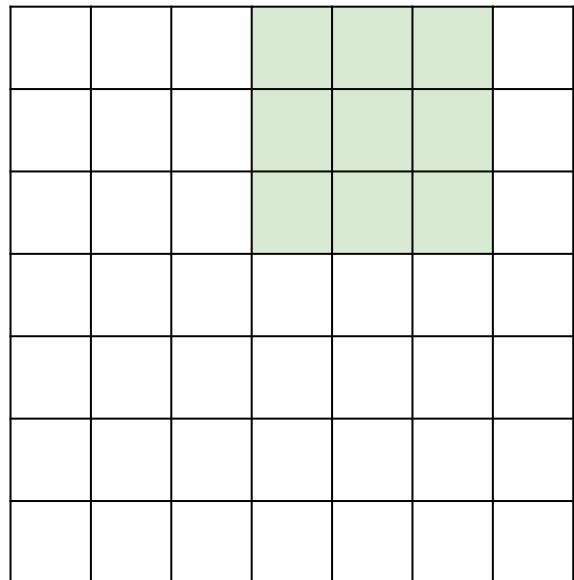


7x7 input (spatially)  
assume 3x3 filter

7

## A closer look at spatial dimensions:

7

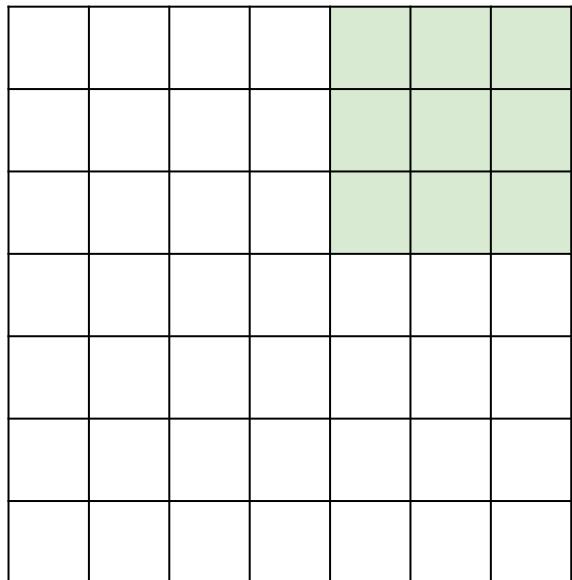


7x7 input (spatially)  
assume 3x3 filter

7

## A closer look at spatial dimensions:

7

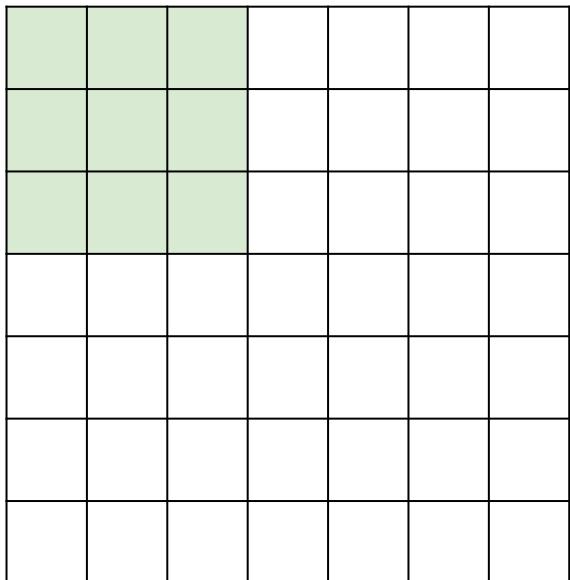


7x7 input (spatially)  
assume 3x3 filter

**=> 5x5 output**

## A closer look at spatial dimensions:

7

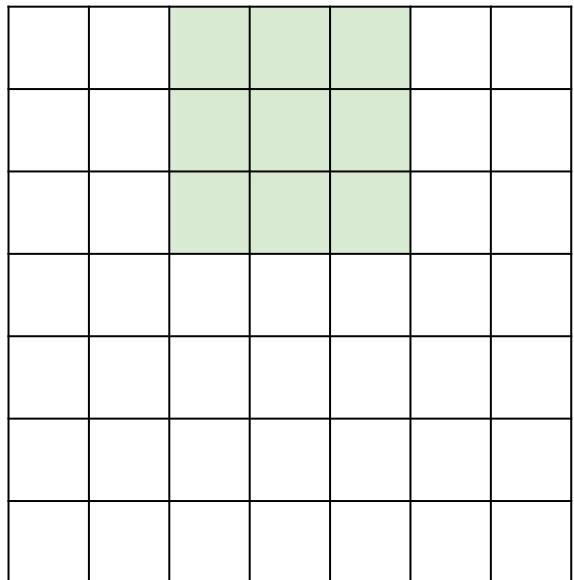


7

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

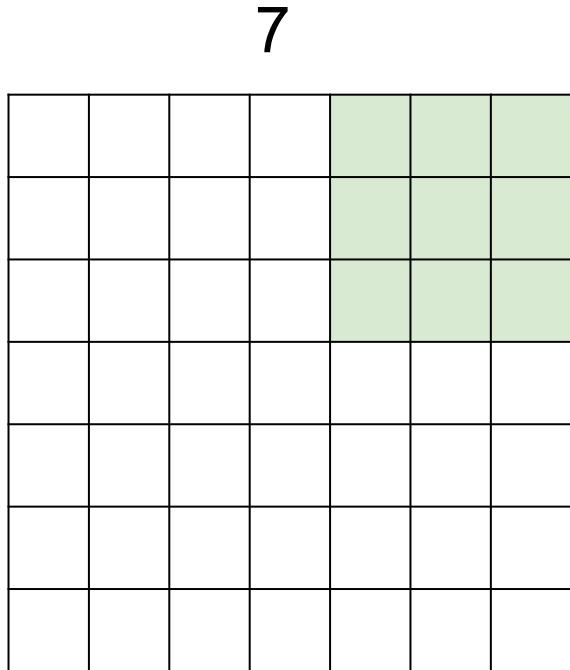
## A closer look at spatial dimensions:

7



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

## A closer look at spatial dimensions:

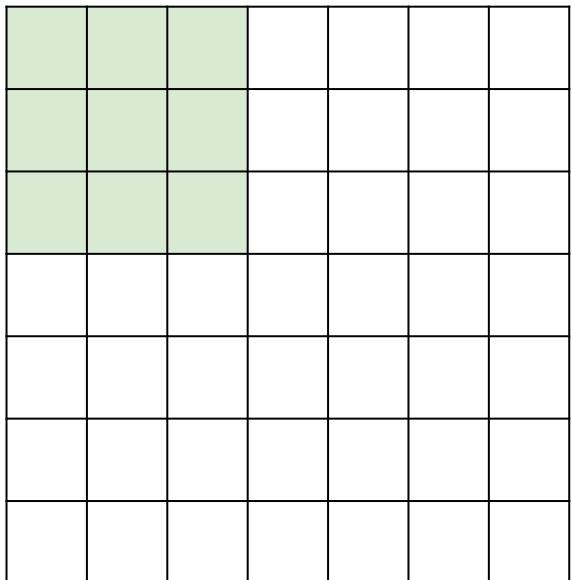


7

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

## A closer look at spatial dimensions:

7

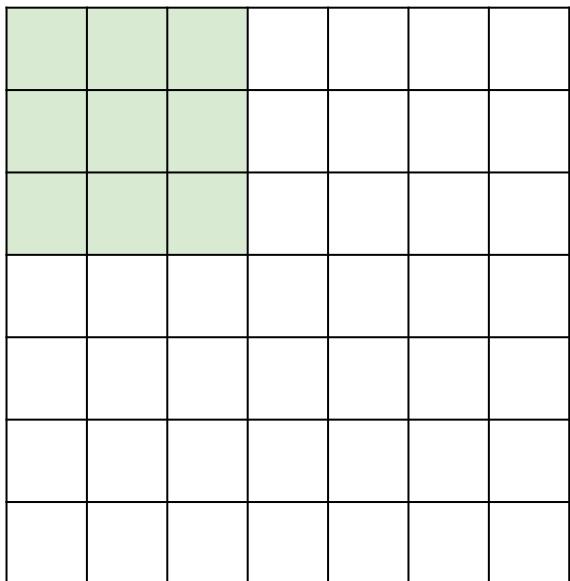


7

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

## A closer look at spatial dimensions:

7



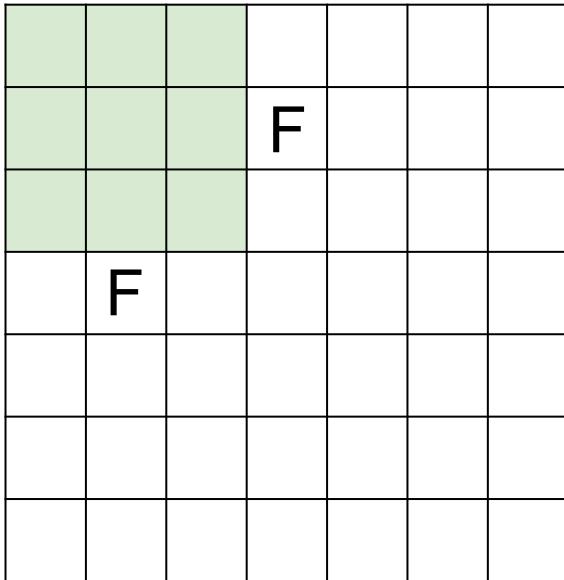
7

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?**

(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  $F \times F$ , and zero-padding with  $(F-1)/2$ . (will preserve size spatially)

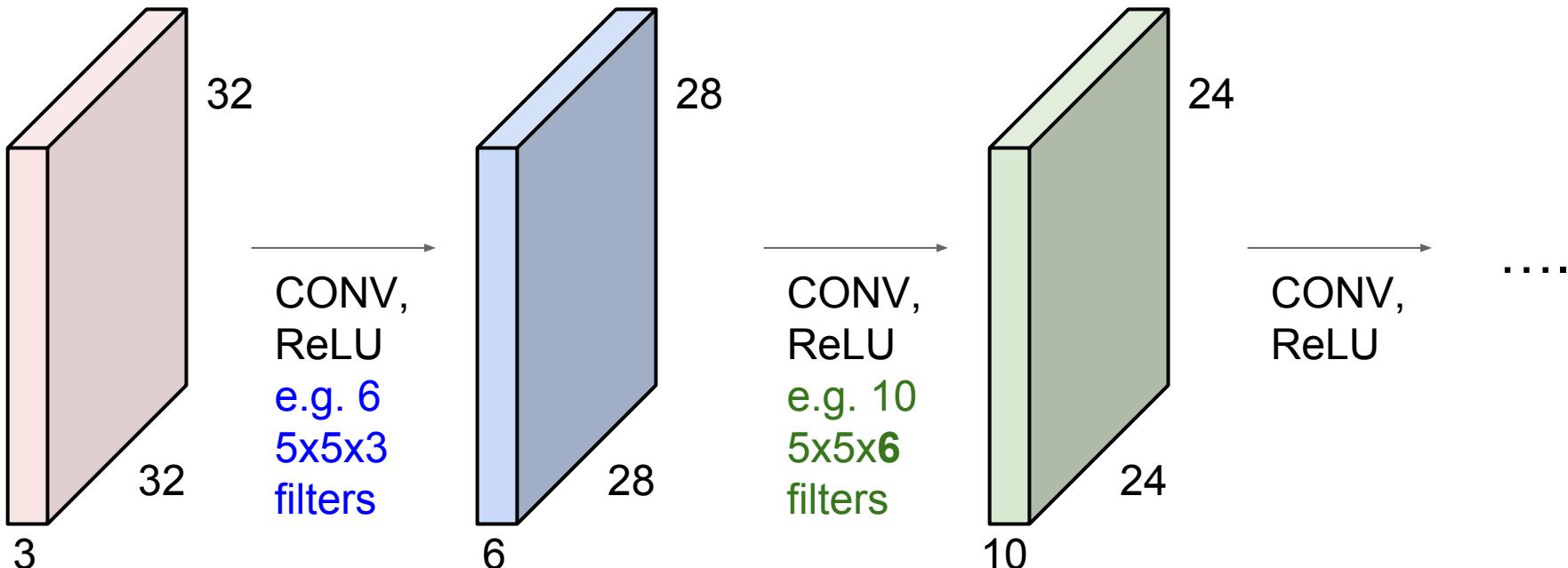
e.g.  $F = 3 \Rightarrow$  zero pad with 1

$F = 5 \Rightarrow$  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.

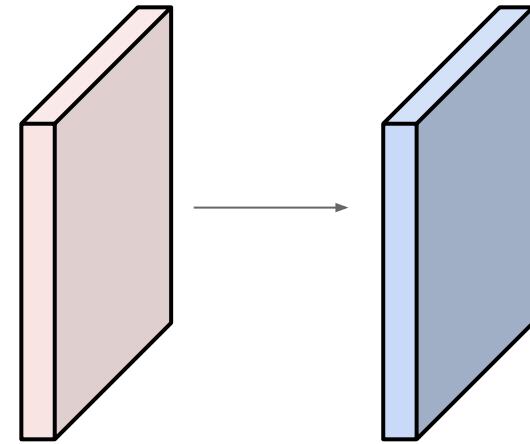


Examples time:

Input volume: **32x32x3**

10 5x5 filters with stride 1, pad 2

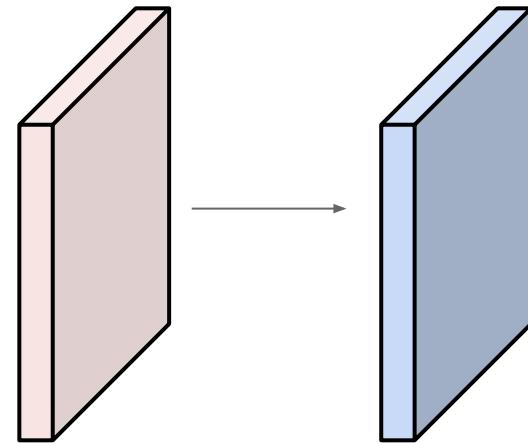
Output volume size: ?



Examples time:

Input volume: **32x32x3**

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



Output volume size:

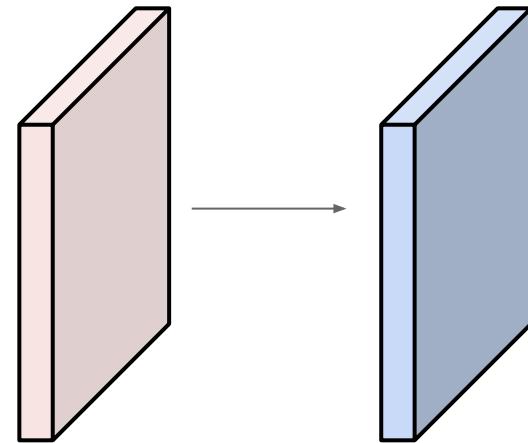
$(32+2*2-5)/1+1 = 32$  spatially, so

**32x32x10**

Examples time:

Input volume: **32x32x3**

10 5x5 filters with stride 1, pad 2

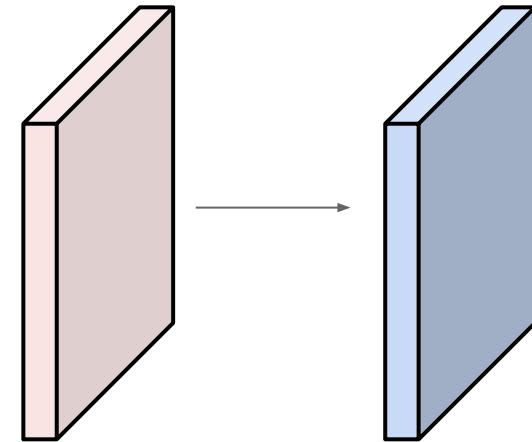


Number of parameters in this layer?

# 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:

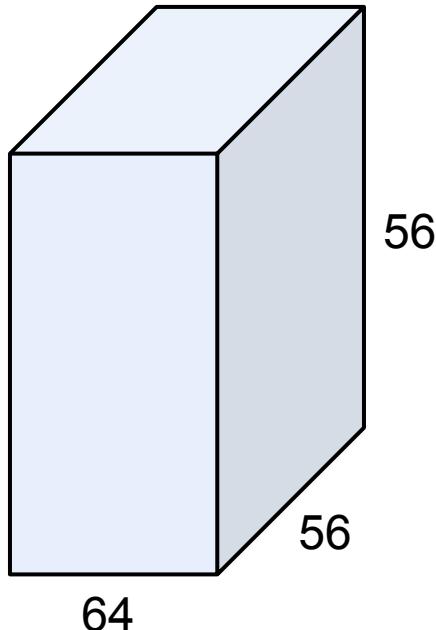
**Summary.** To summarize, the Conv Layer:

- Accepts a volume of size  $W_1 \times H_1 \times D_1$
- Requires four hyperparameters:
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- 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.

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

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

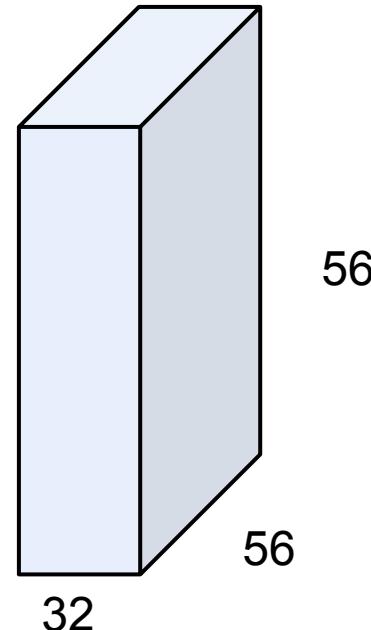
(btw, 1x1 convolution layers make perfect sense)



1x1 CONV  
with 32 filters

---

(each filter has size  
1x1x64, and performs a  
64-dimensional dot  
product)



# Example: CONV layer in Torch

## SpatialConvolution

```
module = nn.SpatialConvolution(nInputPlane, nOutputPlane, kW, KH, [dW], [dH], [padW], [padH])
```

Applies a 2D convolution over an input image composed of several input planes. The `input` tensor in `forward(input)` is expected to be a 3D tensor (`nInputPlane x height x width`).

The parameters are the following:

- `nInputPlane` : The number of expected input planes in the image given into `forward()`.
- `nOutputPlane` : The number of output planes the convolution layer will produce.
- `kW` : The kernel width of the convolution
- `KH` : The kernel height of the convolution
- `dW` : The step of the convolution in the width dimension. Default is `1`.
- `dH` : The step of the convolution in the height dimension. Default is `1`.
- `padW` : The additional zeros added per width to the input planes. Default is `0`, a good number is `(kW-1)/2`.
- `padH` : The additional zeros added per height to the input planes. Default is `padW`, a good number is `(KH-1)/2`.

Note that depending of the size of your kernel, several (of the last) columns or rows of the input image might be lost. It is up to the user to add proper padding in images.

If the input image is a 3D tensor `nInputPlane x height x width`, the output image size will be `nOutputPlane x oheight x owidth` where

```
owidth = floor((width + 2*padW - kW) / dW + 1)
oheight = floor((height + 2*padH - KH) / dH + 1)
```

[Torch](#) is licensed under [BSD 3-clause](#).

# Example: CONV layer in Caffe

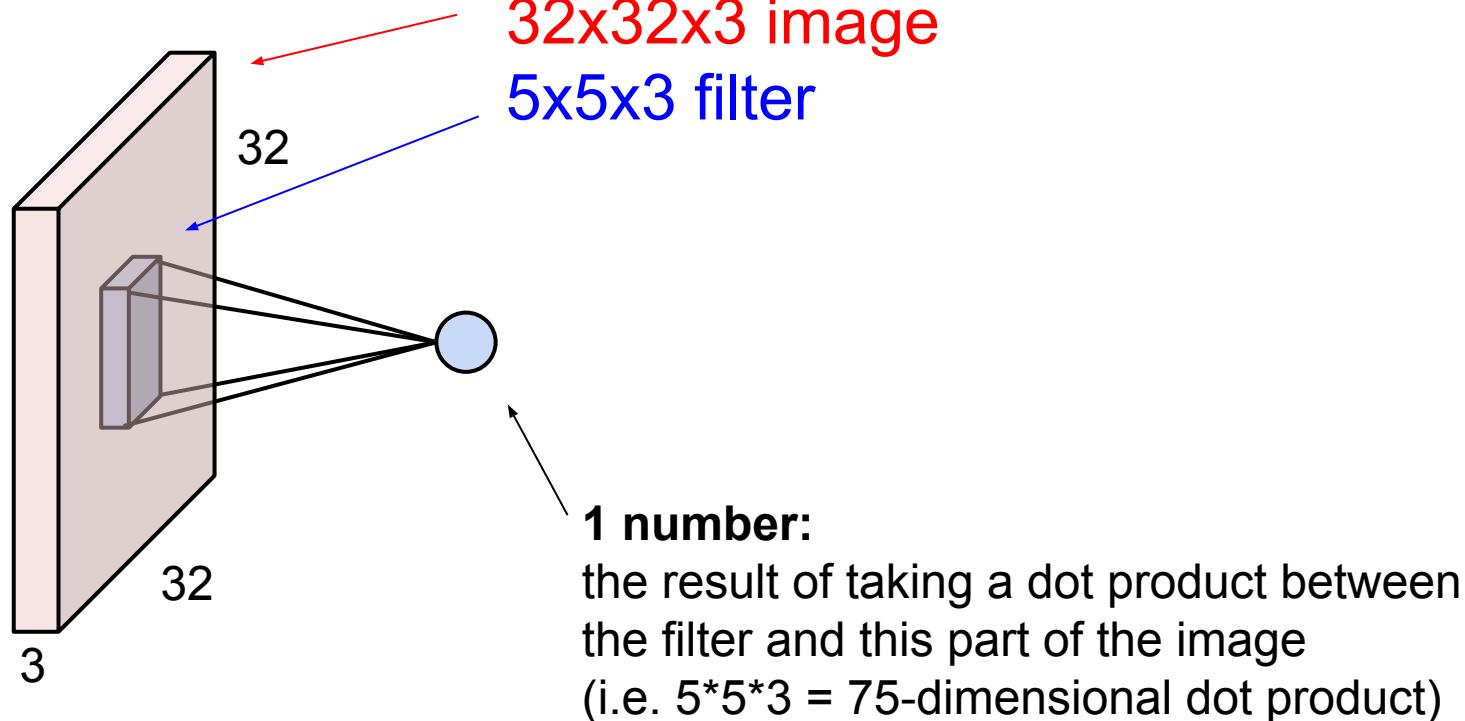
```
layer {
    name: "convl"
    type: "Convolution"
    bottom: "data"
    top: "convl"
    # learning rate and decay multipliers for the filters
    param { lr_mult: 1 decay_mult: 1 }
    # learning rate and decay multipliers for the biases
    param { lr_mult: 2 decay_mult: 0 }
    convolution_param {
        num_output: 96      # learn 96 filters
        kernel_size: 11     # each filter is 11x11
        stride: 4           # step 4 pixels between each filter application
        weight_filler {
            type: "gaussian" # initialize the filters from a Gaussian
            std: 0.01          # distribution with stdev 0.01 (default mean: 0)
        }
        bias_filler {
            type: "constant" # initialize the biases to zero (0)
            value: 0
        }
    }
}
```

**Summary.** To summarize, the Conv Layer:

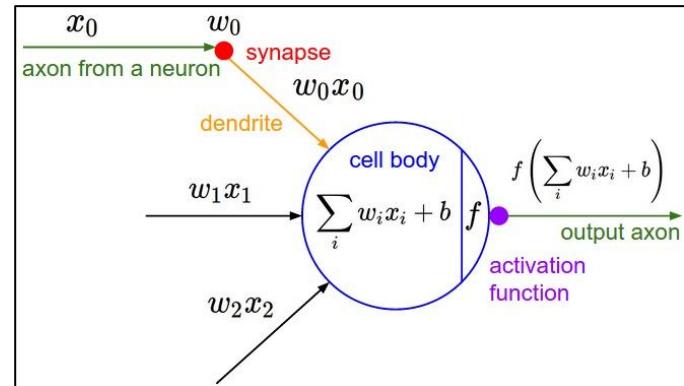
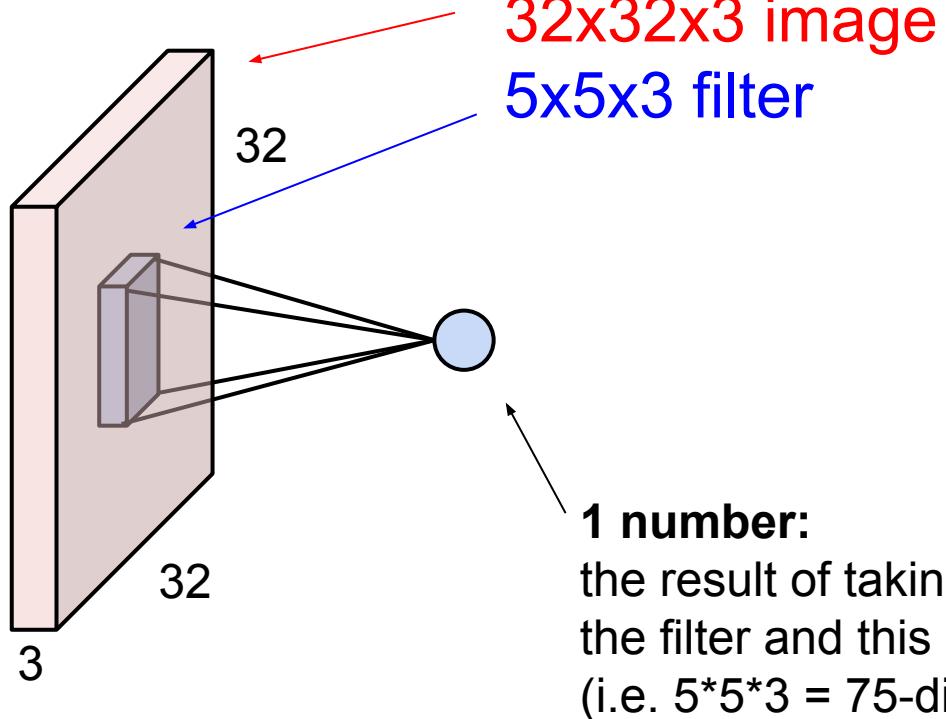
- Accepts a volume of size  $W_1 \times H_1 \times D_1$
- Requires four hyperparameters:
  - Number of filters  $K$ ,
  - their spatial extent  $F$ ,
  - the stride  $S$ ,
  - the amount of zero padding  $P$ .

[Caffe](#) is licensed under [BSD 2-Clause](#).

# The brain/neuron view of CONV Layer

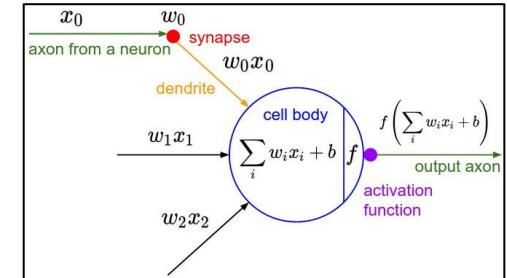
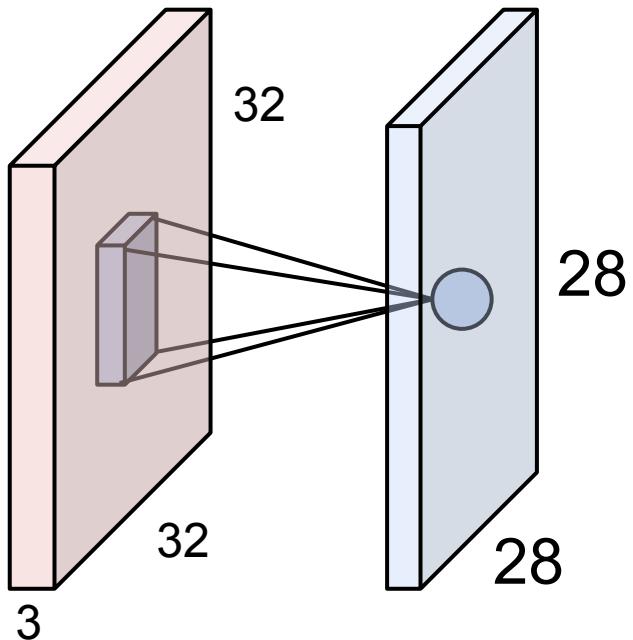


# The brain/neuron view of CONV Layer



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

# The brain/neuron view of CONV Layer

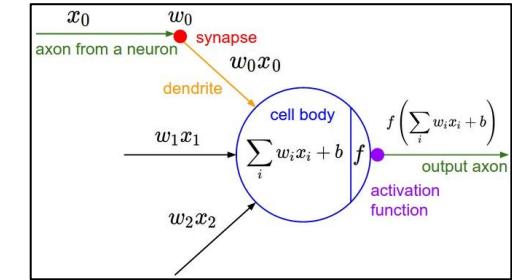
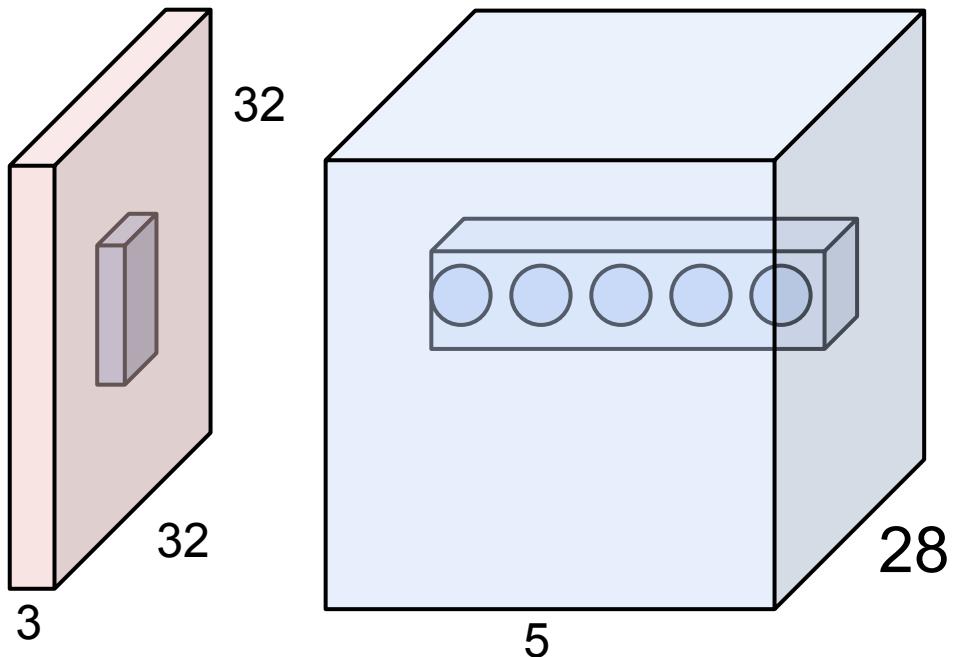


An activation map is a 28x28 sheet of neuron outputs:

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



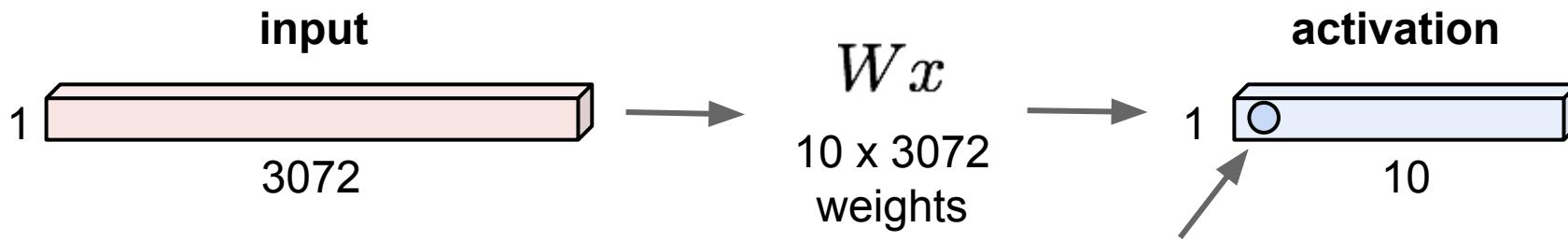
E.g. with 5 filters,  
CONV layer consists of  
neurons arranged in a 3D grid  
( $28 \times 28 \times 5$ )

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

# Reminder: Fully Connected Layer

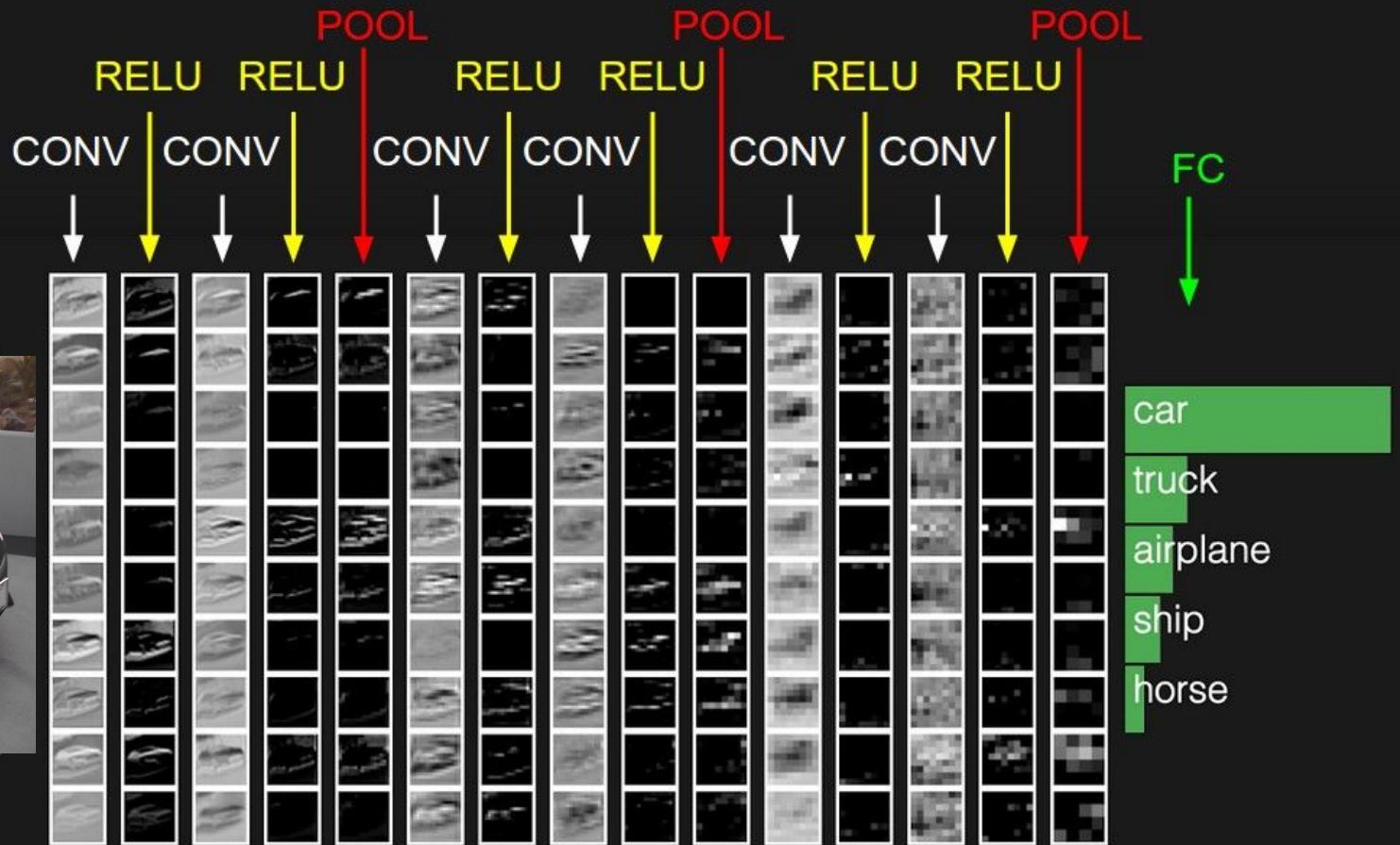
32x32x3 image -> stretch to 3072 x 1

Each neuron  
looks at the full  
input volume



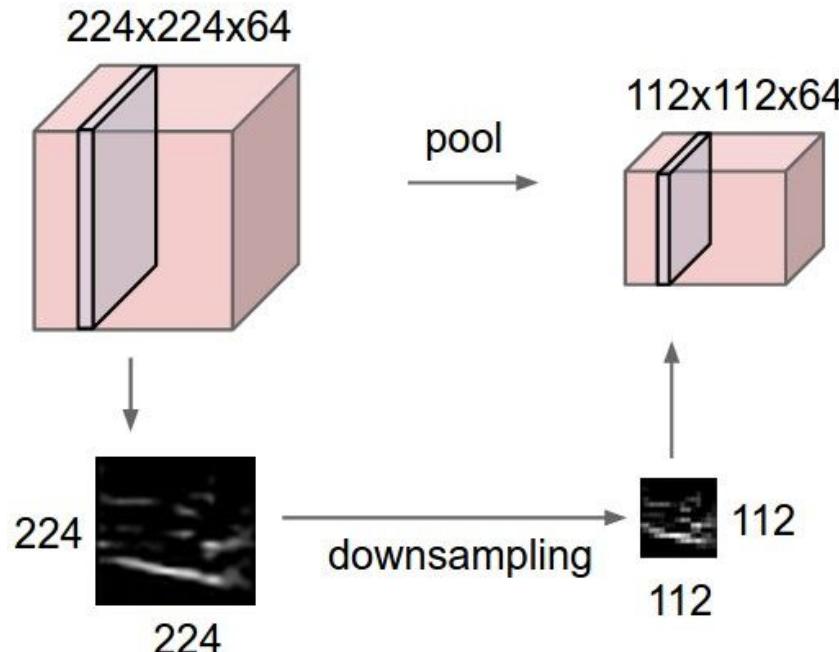
**1 number:**  
the result of taking a dot product  
between a row of  $W$  and the input  
(a 3072-dimensional dot product)

two more layers to go: POOL/FC

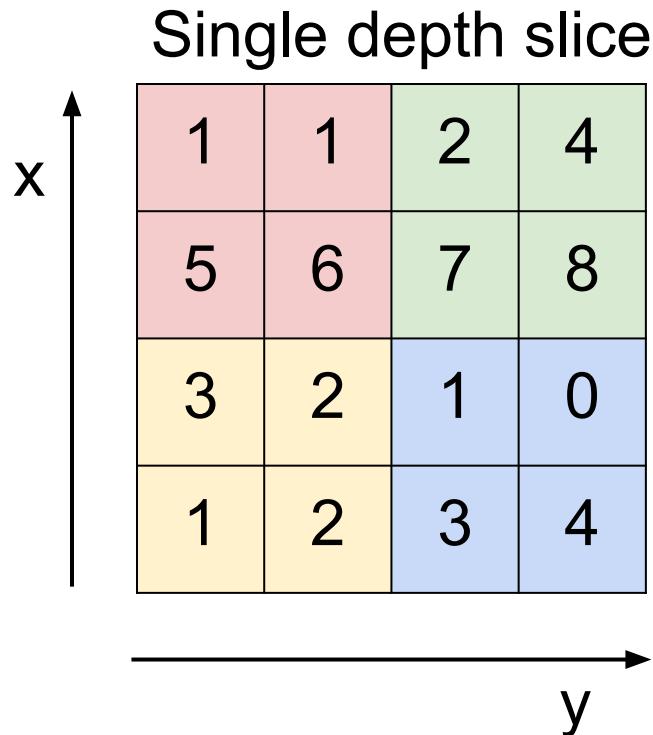


# Pooling layer

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



# MAX POOLING



max pool with 2x2 filters  
and stride 2

The output matrix has two rows and two columns. It contains the maximum values from the 2x2 receptive fields of each unit. The values are:

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:

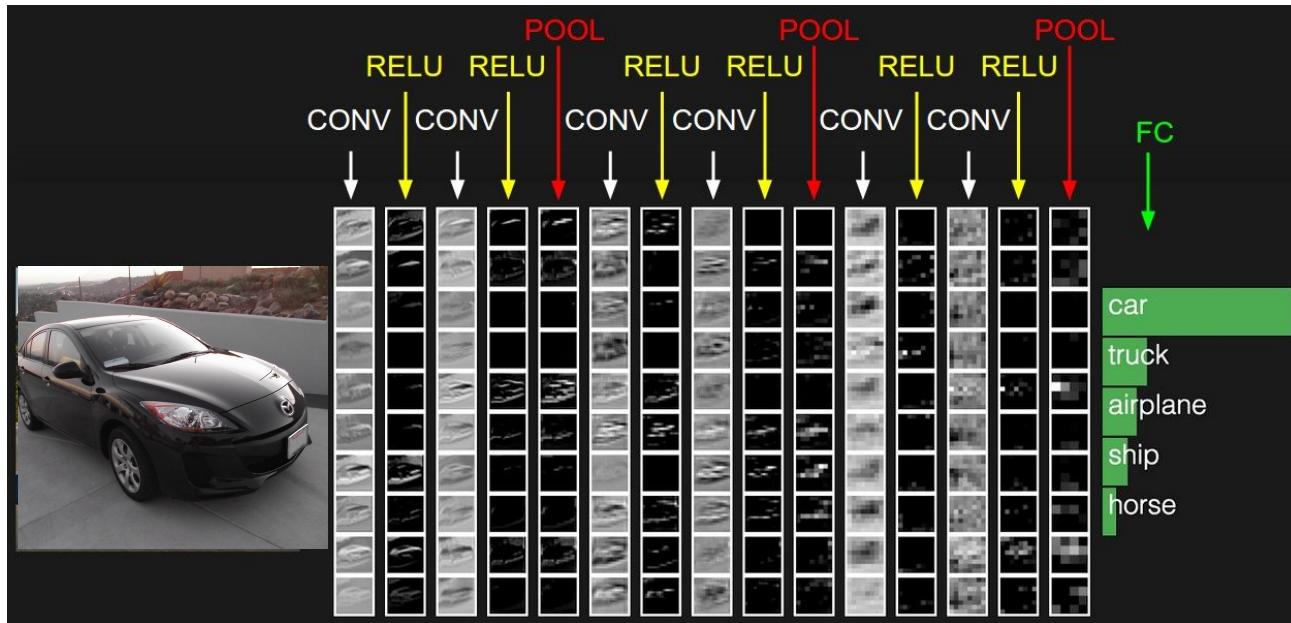
- Accepts a volume of size  $W_1 \times H_1 \times D_1$
- Requires three hyperparameters:
  - their spatial extent  $F$ ,
  - the stride  $S$ ,
- Produces a volume of size  $W_2 \times H_2 \times D_2$  where:
  - $W_2 = (W_1 - F)/S + 1$
  - $H_2 = (H_1 - F)/S + 1$
  - $D_2 = D_1$
- Introduces zero parameters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

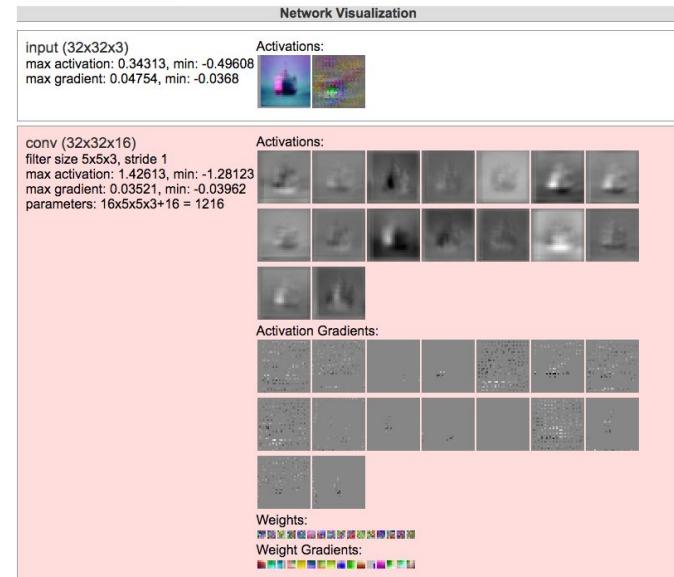
### Description

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
- Trend towards getting rid of POOL/FC layers (just CONV)
- Typical architectures look like  
 **$[(\text{CONV-RELU})^* \text{N-POOL?}]^* \text{M-(FC-RELU)}^* \text{K,SOFTMAX}$**   
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