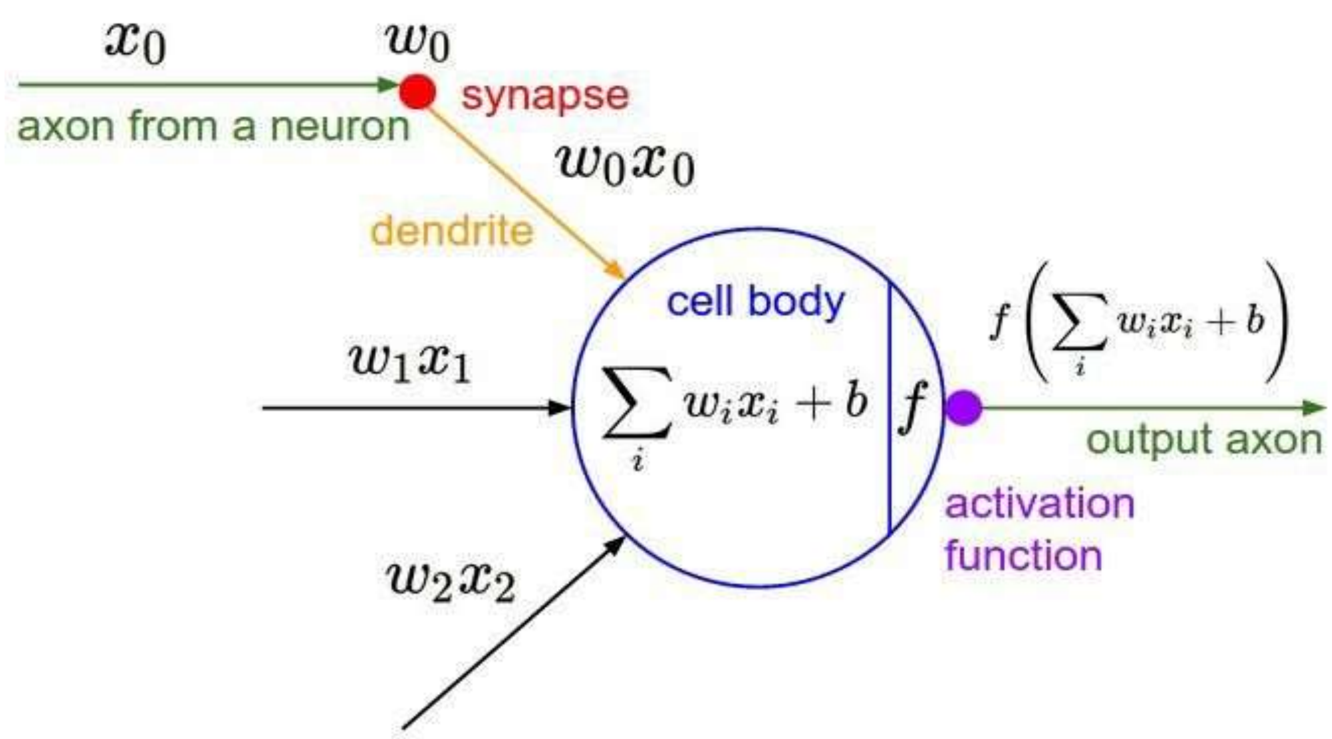
Machine Learning

CNN

Dr. Shuang LIANG

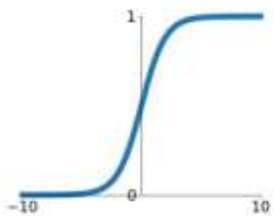
Recall: Neuron



Recall: Activation function

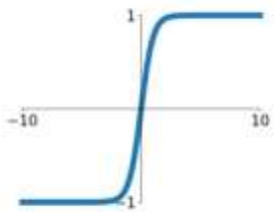
Sigmoid

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



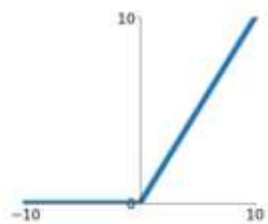
tanh

$\tanh(x)$



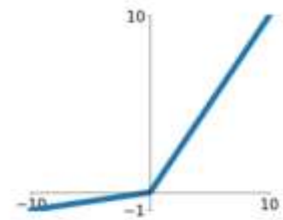
ReLU

$\max(0, x)$



Leaky ReLU

$\max(0.1x, x)$

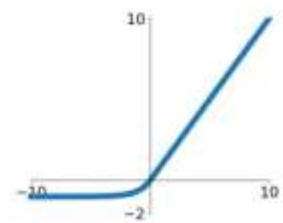


Maxout

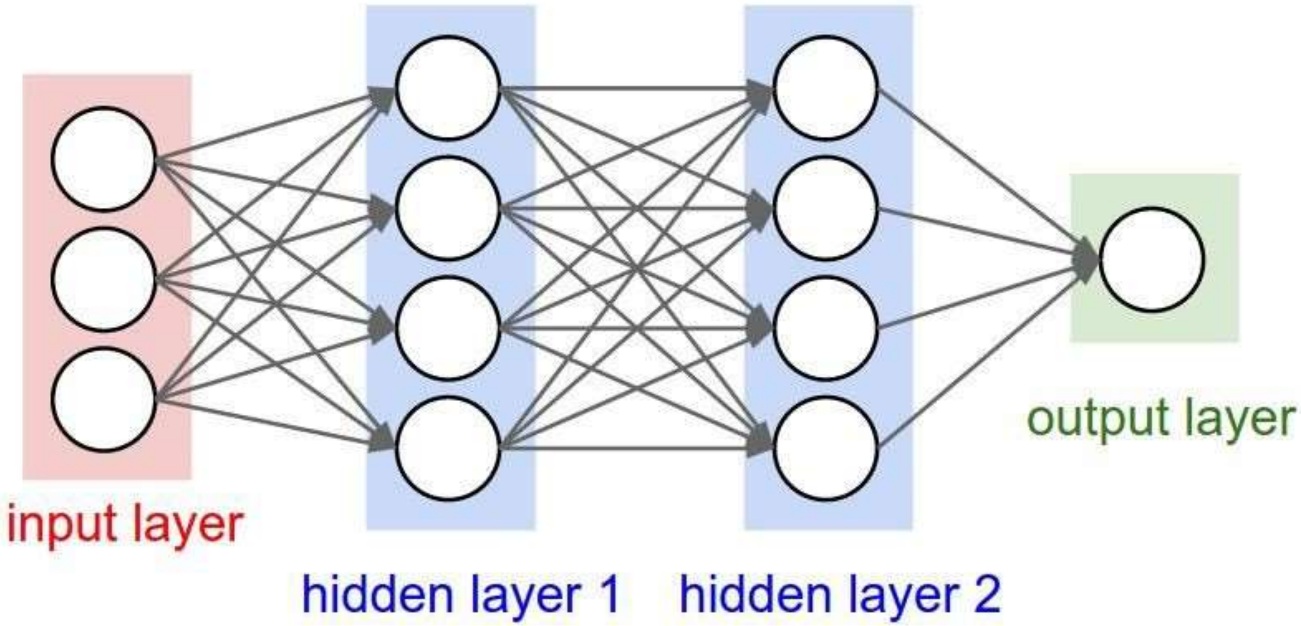
$\max(w_1^T x + b_1, w_2^T x + b_2)$

ELU

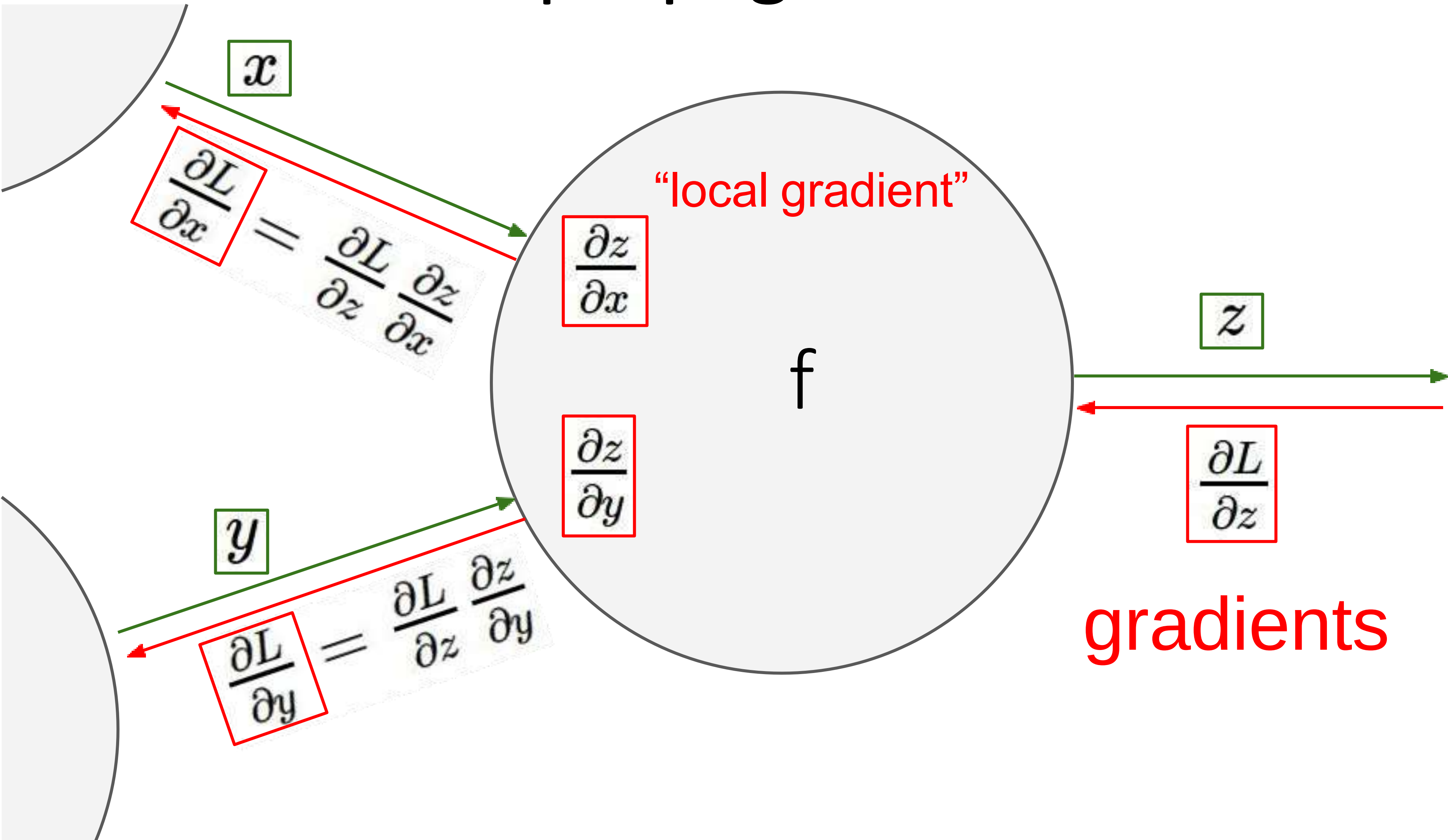
$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



Recall: Neural Network



Recall: Backpropagation



Today's Topics

- CNN Development
- CNN Layer
- CNN Architecture

Today's Topics

- ***CNN Development***
- CNN Layer
- CNN Architecture

A bit of history

Hubel & Wiesel,

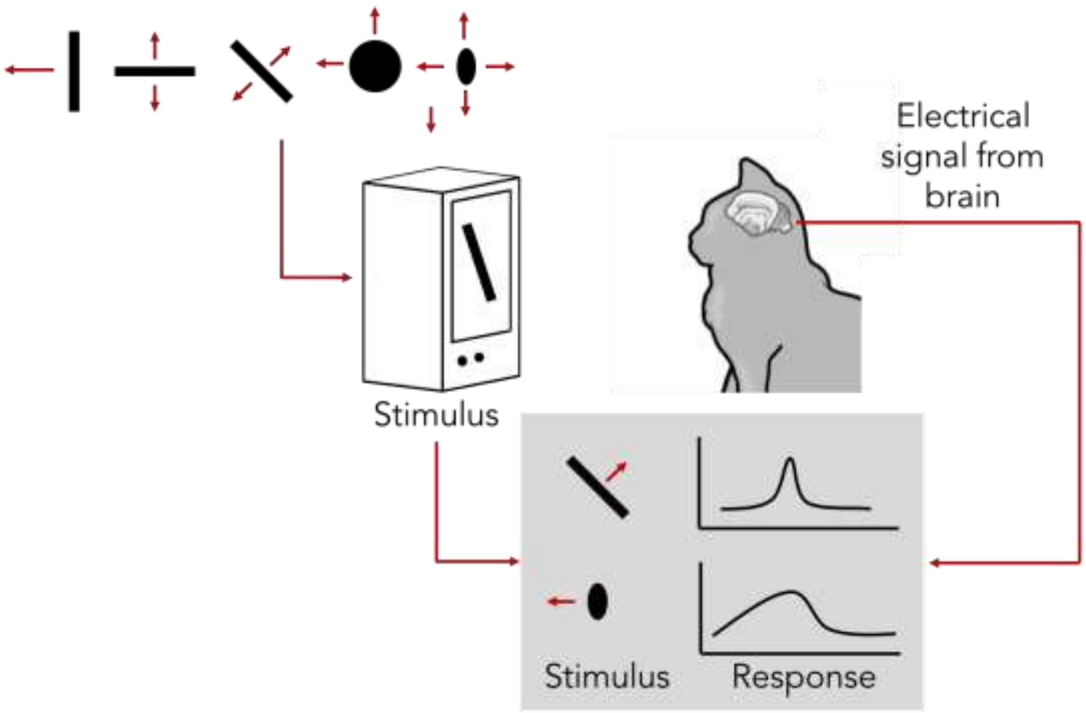
1959

Receptive fields of single neurones in the cat's striate cortex

1962

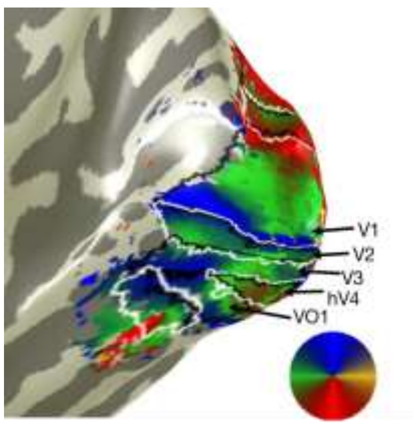
Receptive fields, binocular interaction and functional architecture in the cat's visual cortex

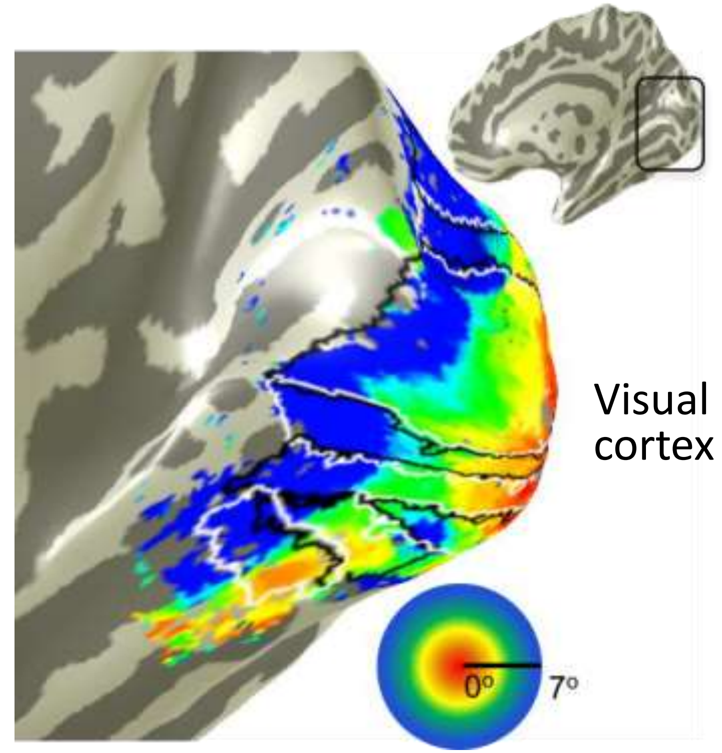
1968...



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

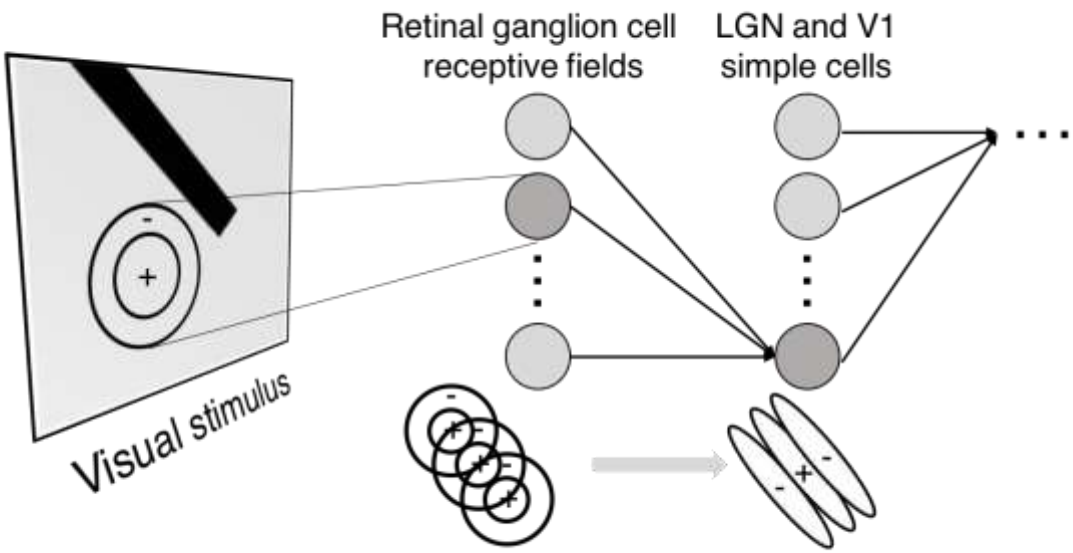
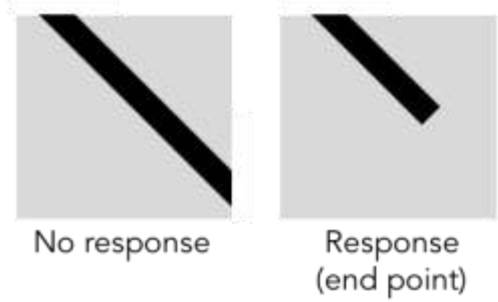


Illustration of hierarchical organization in early visual pathways by Lane McIntosh, copyright CS231n 2017

Simple cells:
Response to light orientation

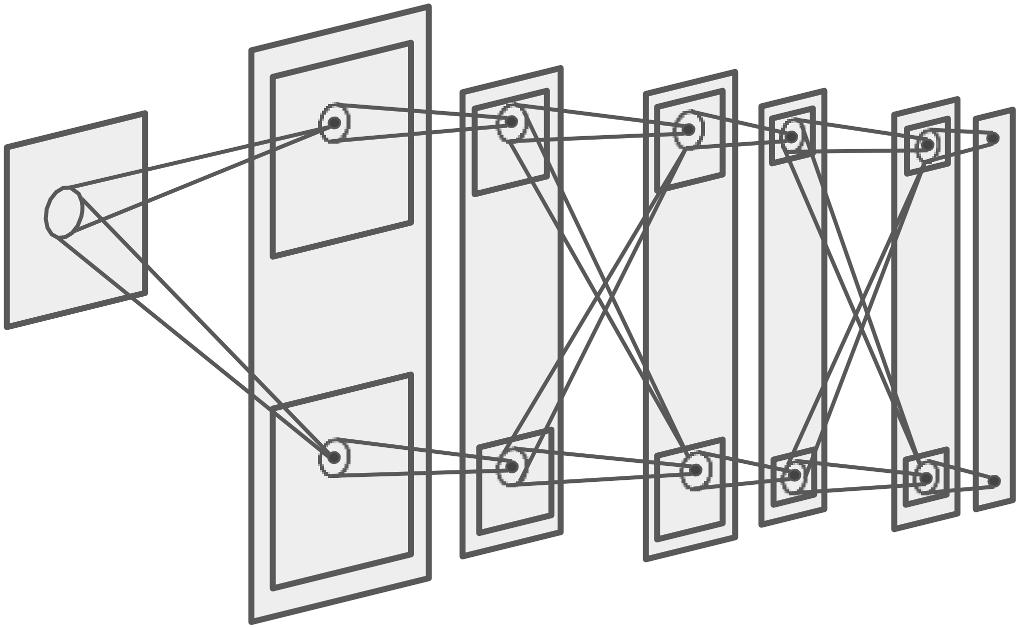
Complex cells:
Response to light orientation and movement

Hypercomplex cells:
response to movement with an end point



A bit of history

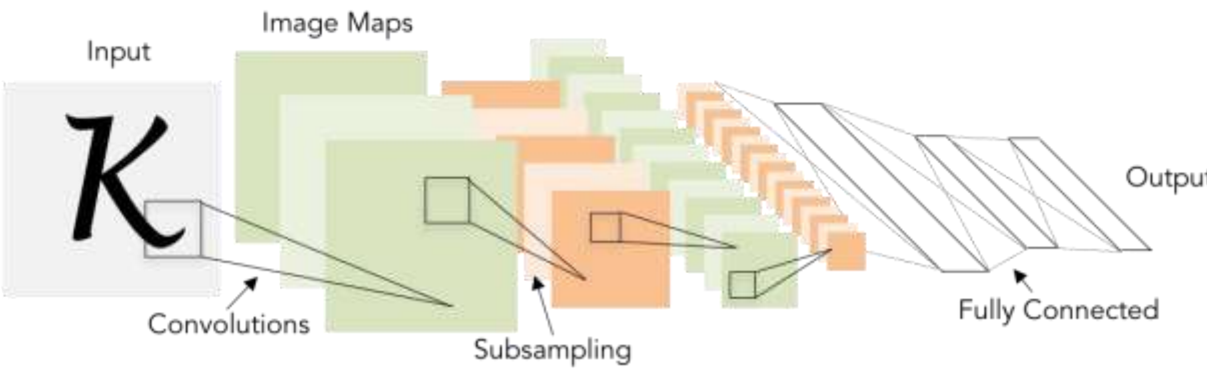
Neocognitron
[Fukushima 1980]



"sandwich" architecture (SCSCSC…)
simple cells: modifiable parameters
complex cells: perform pooling

A bit of history

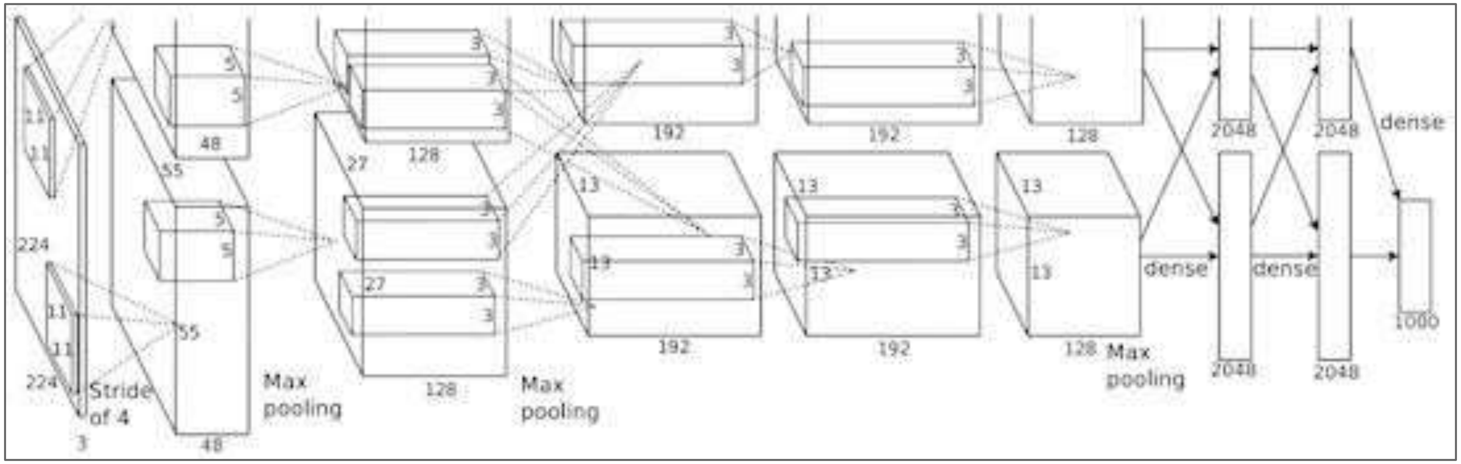
Gradient-based learning applied to document recognition
[LeCun, Bottou, Bengio, Haffner 1998]



LeNet-5

A bit of history

ImageNet Classification with Deep Convolutional Neural Networks
[Krizhevsky, Sutskever, Hinton, 2012]



"AlexNet"

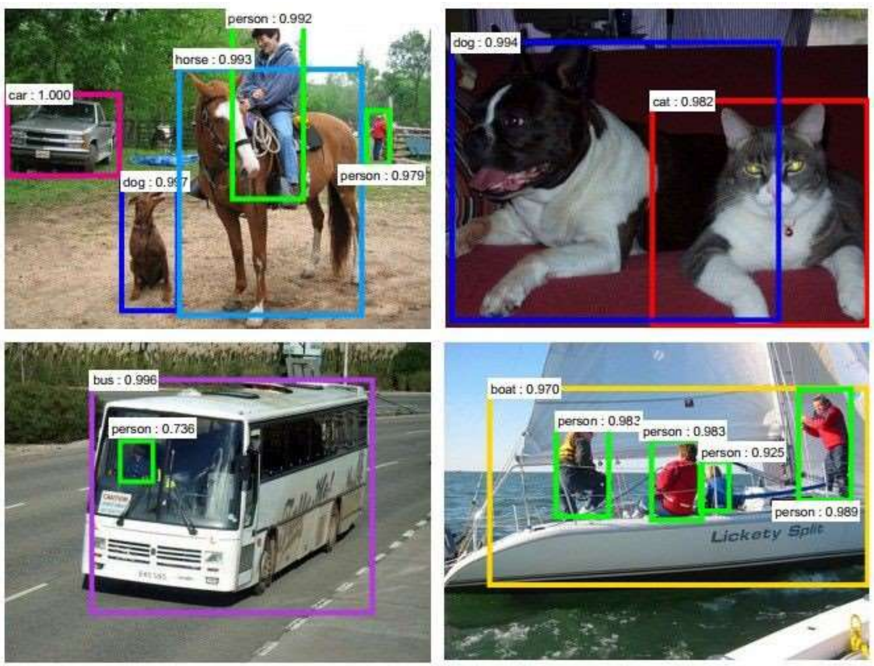
Fast-forward to today: ConvNets are everywhere

Classification

Retrieval

Fast-forward to today: ConvNets are everywhere

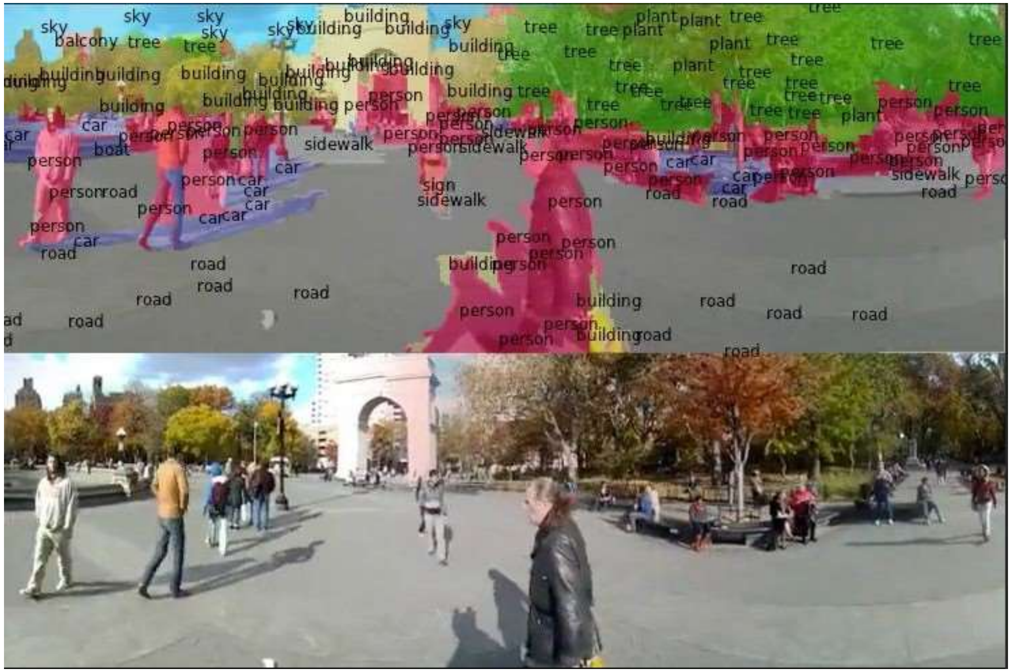
Detection



Figures copyright Shaoqing Ren, Kaiming He, Ross Girschick, 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

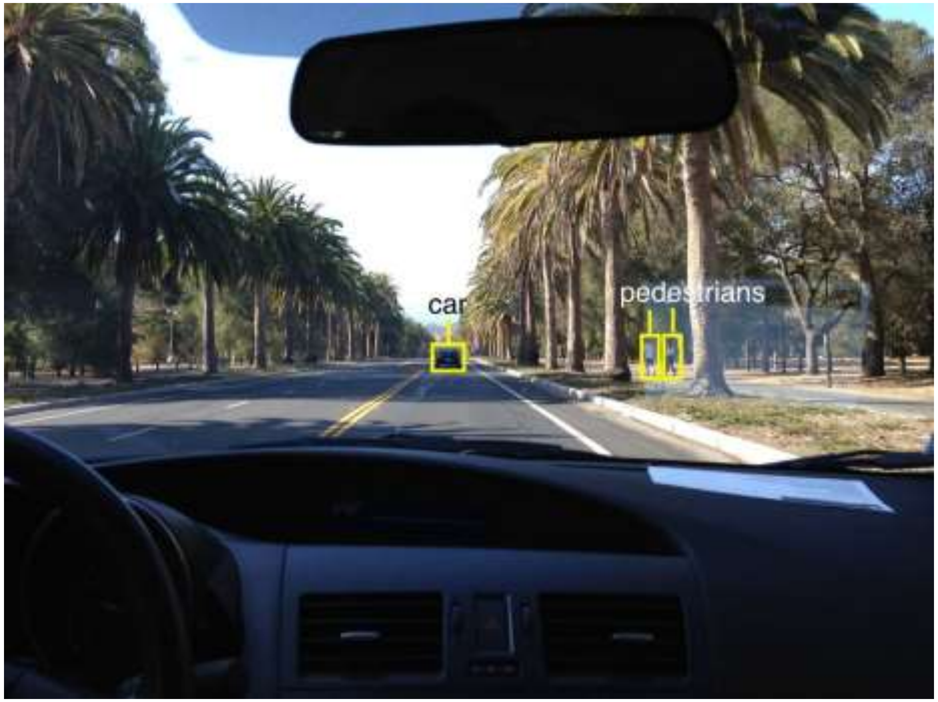


Photo by Lane McIntosh. Copyright CS231n 2017.

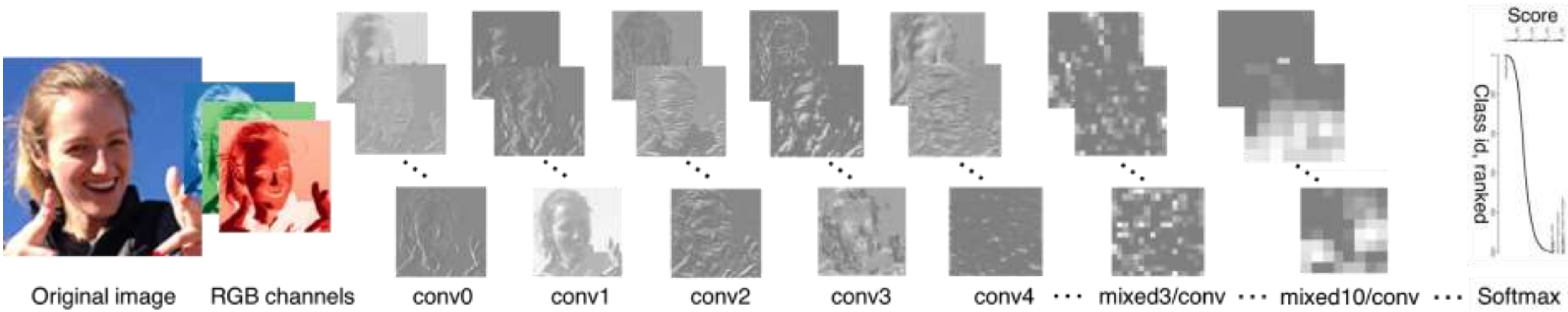
self-driving cars

NVIDIA Tesla line

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

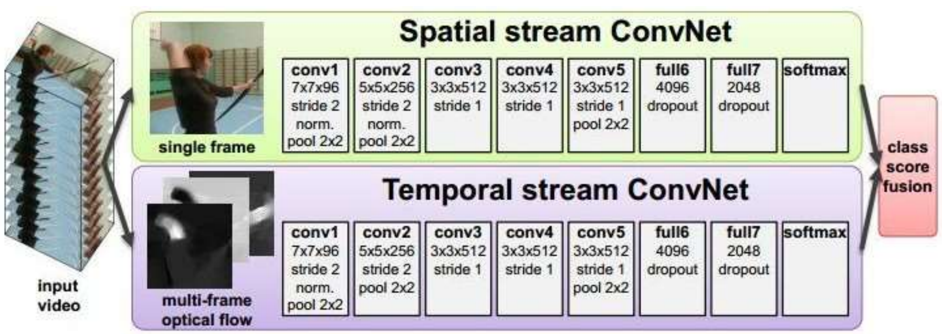
Note that for embedded systems a typical setup would involve NVIDIA Tegras, with integrated GPU and ARM-based CPU cores.

Fast-forward to today: ConvNets are everywhere



[Taigman et al. 2014]

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]

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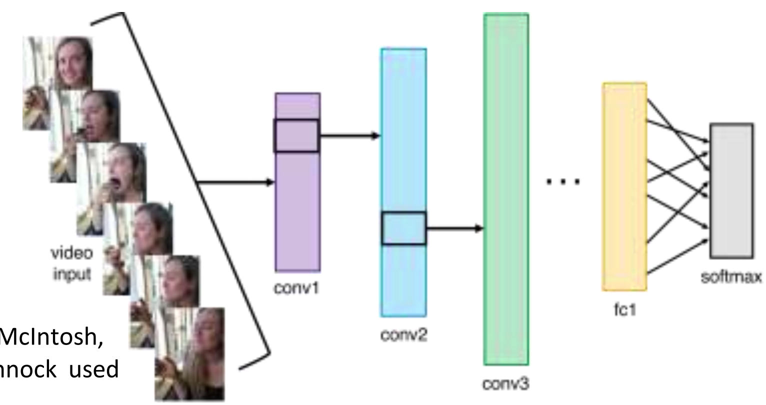


Illustration by Lane McIntosh, photos of Katie Cumnock used with permission.

Fast-forward to today: ConvNets are everywhere

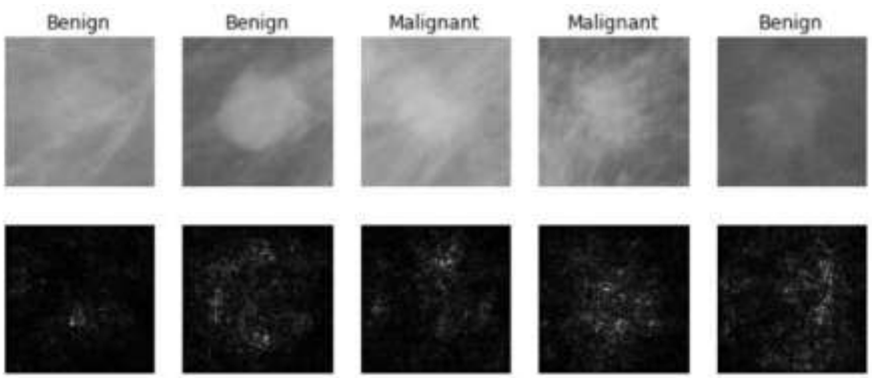
[Toshev, Szegedy 2014]

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

[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]

[Dieleman et al. 2014]

[Sermanet et al. 2011]
[Ciresan et al.]

Fast-forward to today: ConvNets are everywhere

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

Fast-forward to today: ConvNets are everywhere

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

Image Captioning

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

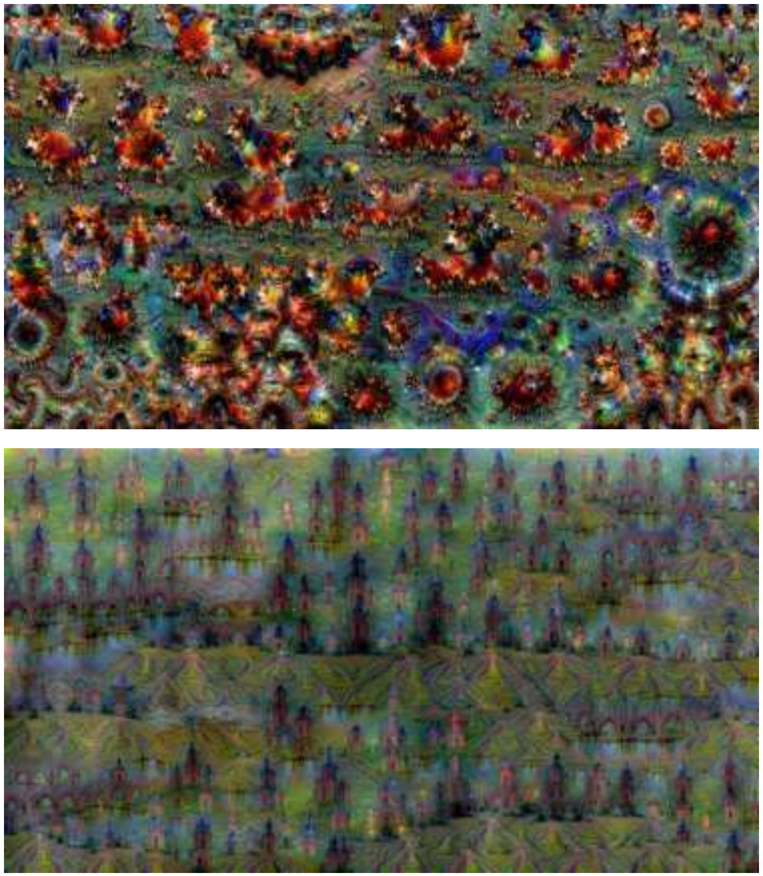
A man riding a wave on top of a surfboard

A cat sitting on a suitcase on the floor

A woman standing on a beach holding a surfboard

Captions generated by Justin Johnson using Neuraltalk2

Fast-forward to today: ConvNets are everywhere



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

Today's Topics

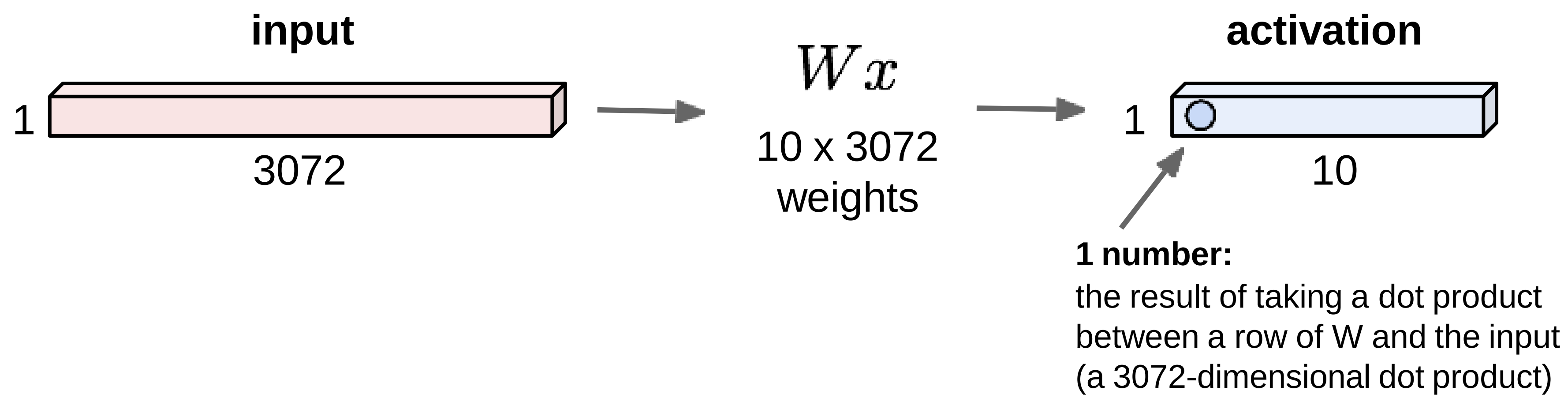
- CNN Development
- ***CNN Layer***
- CNN Architecture

CNN Layer

- ***Fully Connected Layer***
- Convolution Layer
- Pooling Layer

Fully Connected Layer

32x32x3 image -> stretch to 3072 x 1

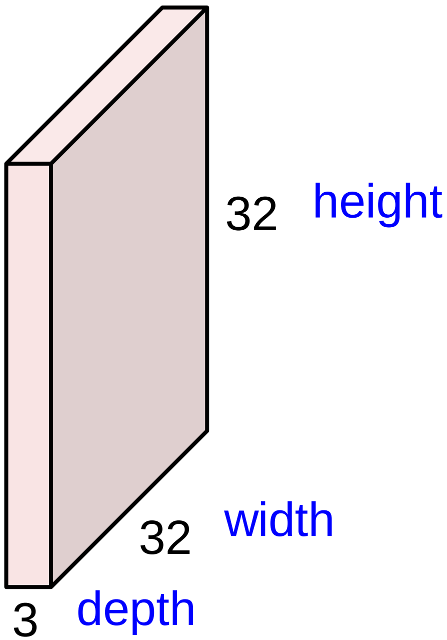


CNN Layer

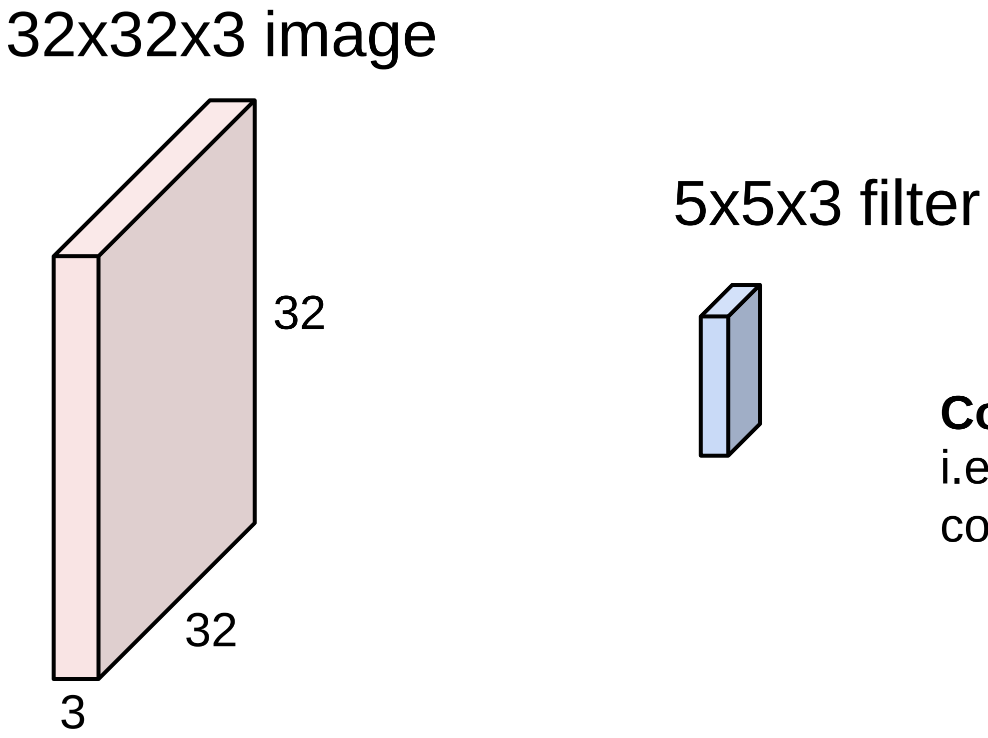
- Fully Connected Layer
- ***Convolution Layer***
- Pooling Layer

Convolution Layer

32x32x3 image -> preserve spatial structure



Convolution Layer

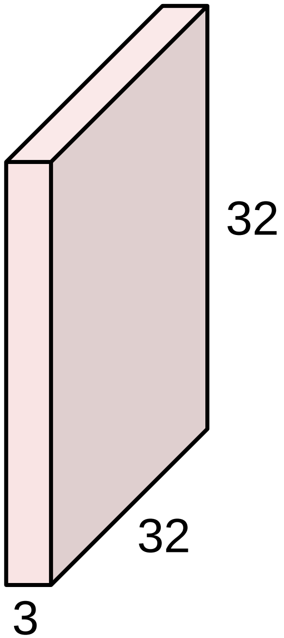


Convolve the filter with the image
i.e. “slide over the image spatially,
computing dot products”

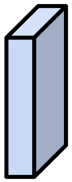
Convolution Layer

Filters always extend the full depth of the input volume

32x32x3 image

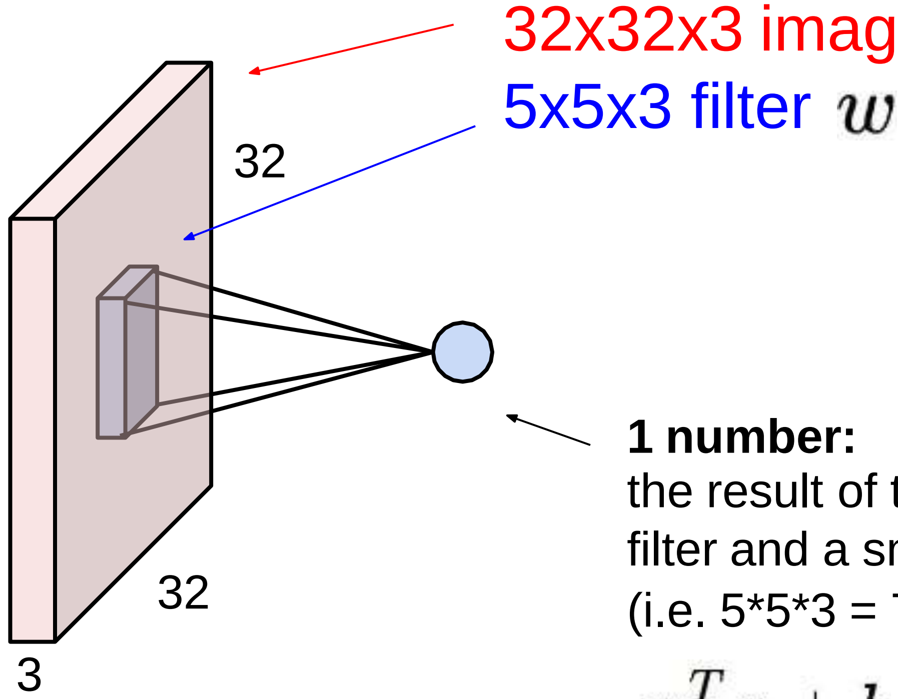


5x5x3 filter



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

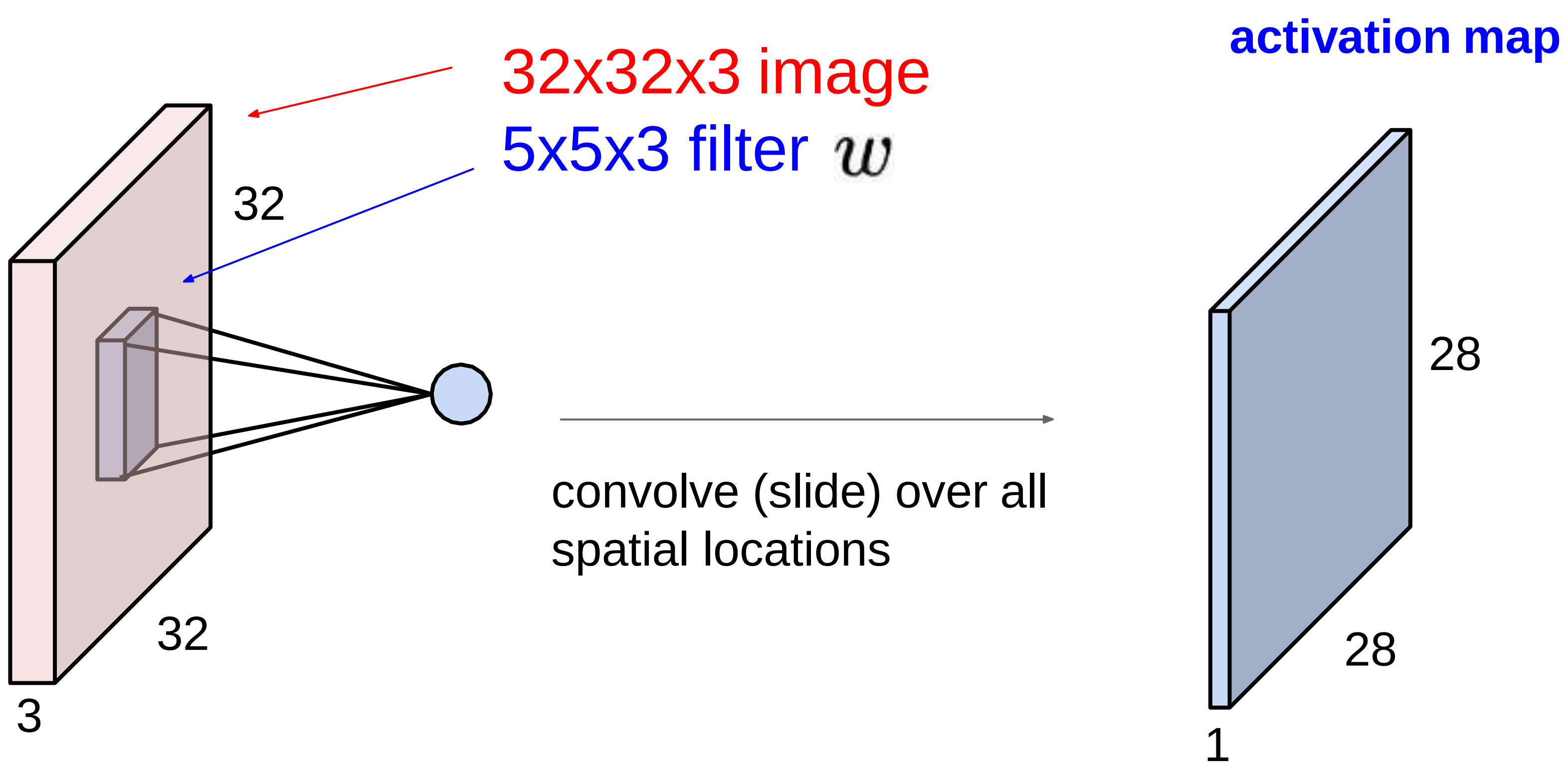
Convolution Layer



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

$$w^T x + b$$

Convolution Layer

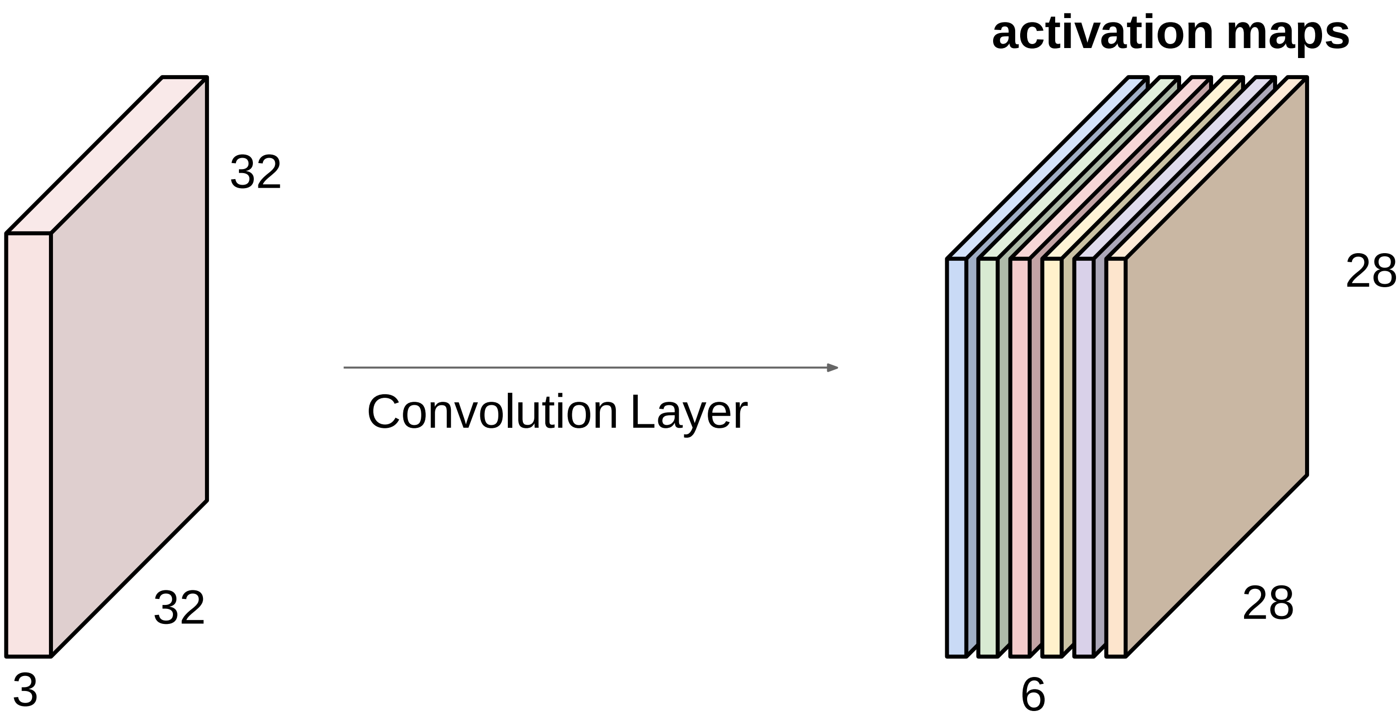


Convolution Layer

consider a second, green filter

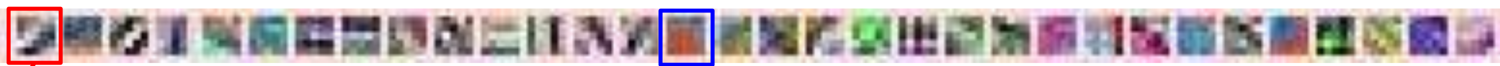
Convolution Layer

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!

Convolution Layer



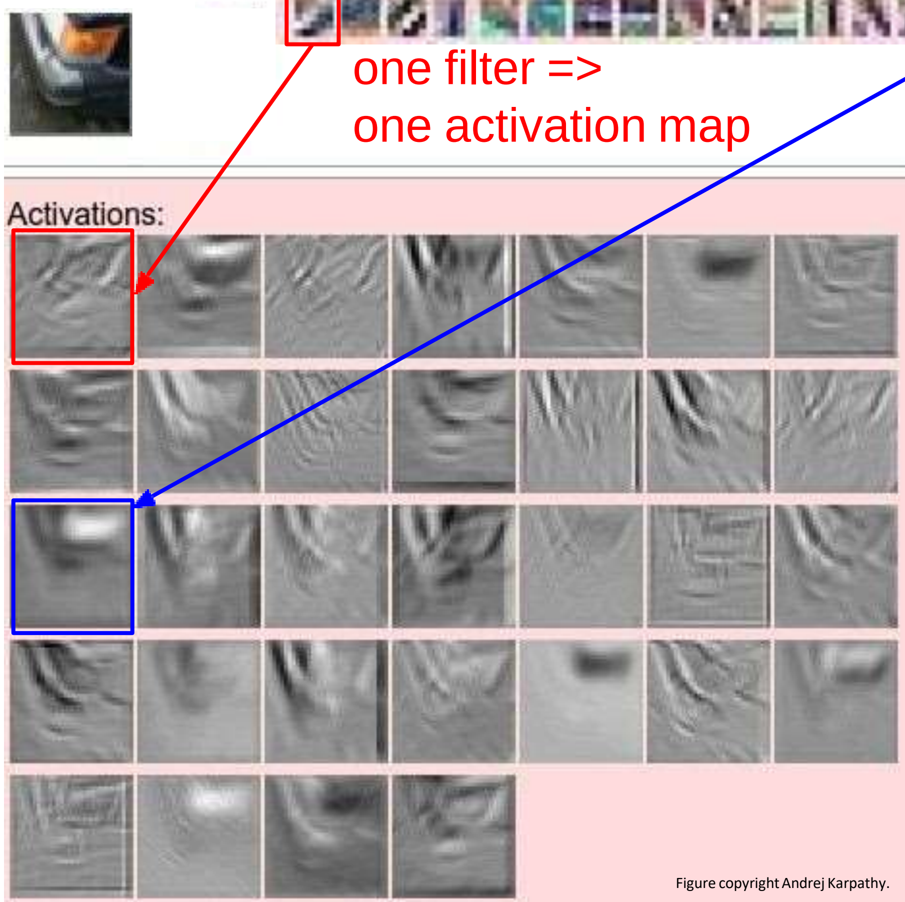


Figure copyright Andrej Karpathy.

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)

Convolution

stride=1

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 x 6 image

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

3 -1

Convolution

If stride=2

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 x 6 image

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

3 -3

We set stride=1 below

Convolution

stride=1

1	-1	-1
-1	1	-1
-1	-1	1

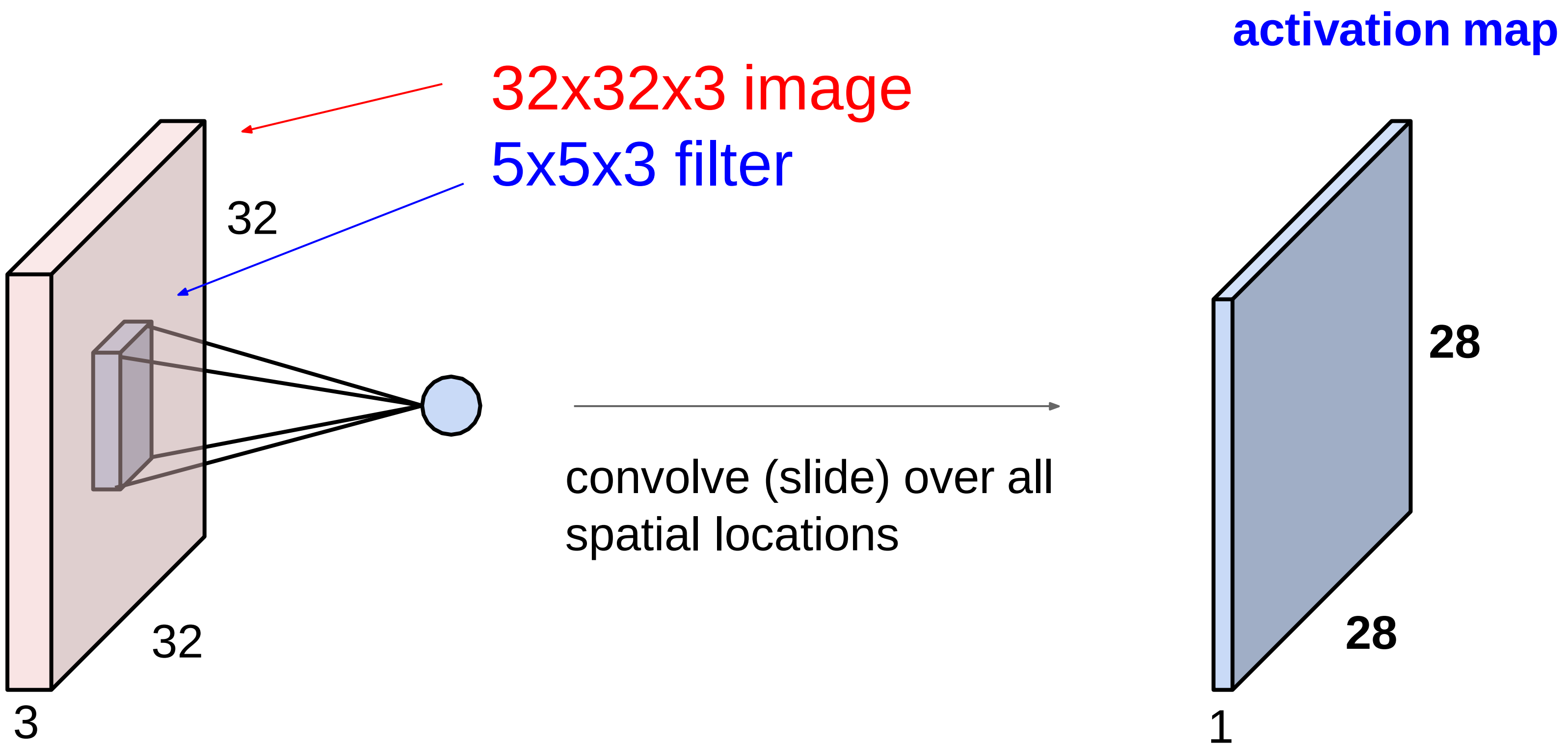
Filter 1

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

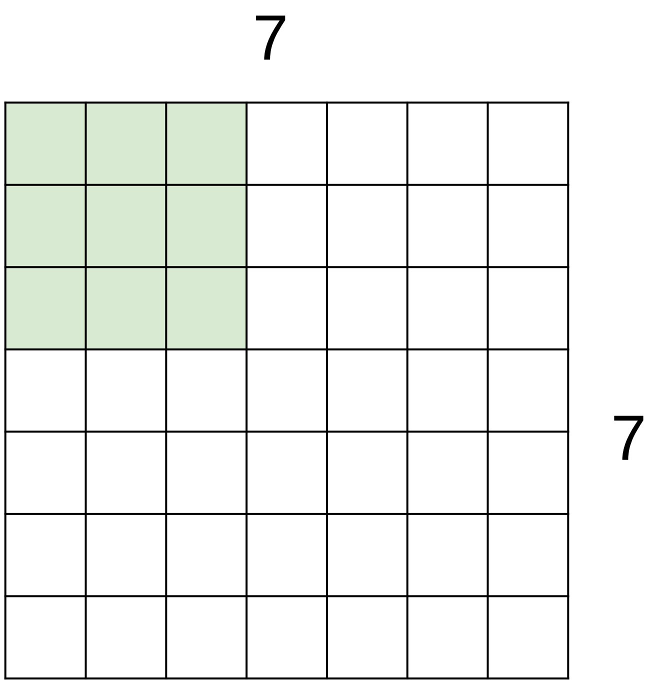
6 x 6 image

3	-1	-3	-1
-3	1	0	-3
-3	-3	0	1
3	-2	-2	-1

A closer look at spatial dimensions

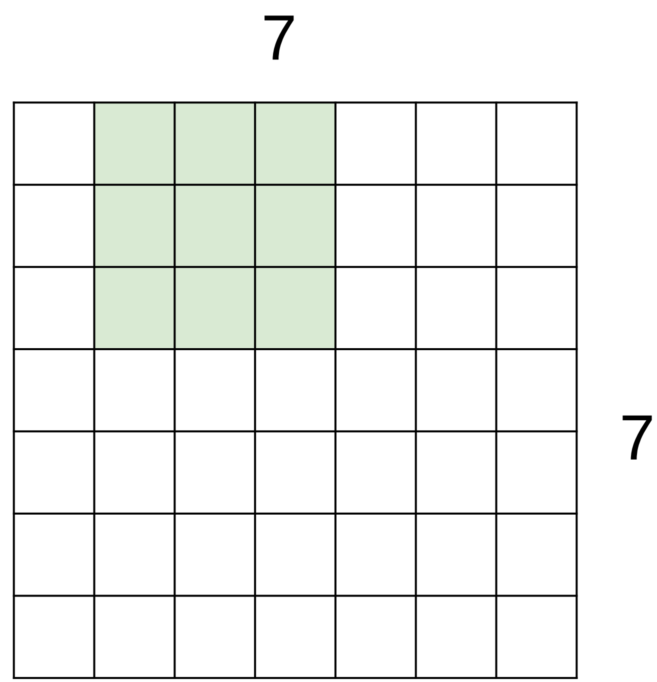


A closer look at spatial dimensions



7x7 input (spatially)
assume 3x3 filter

A closer look at spatial dimensions



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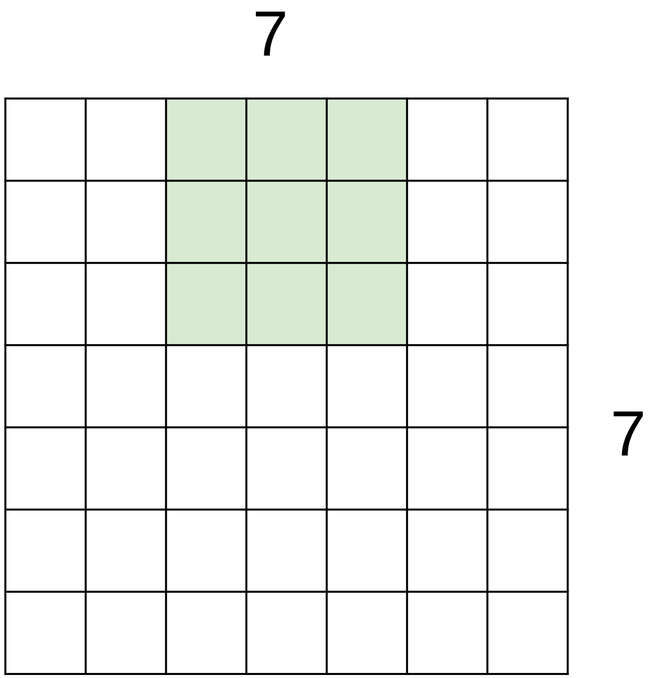
A closer look at spatial dimensions



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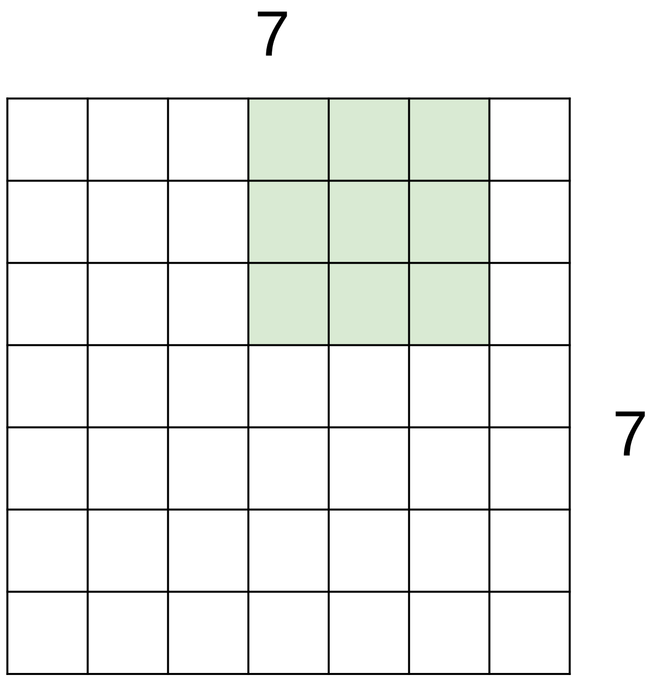
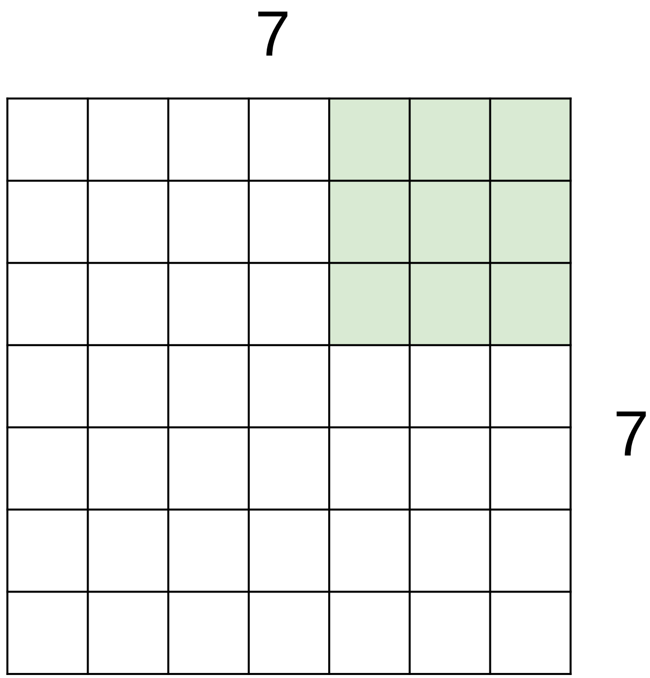
A closer look at spatial dimensions



7x7 input (spatially)
assume 3x3 filter

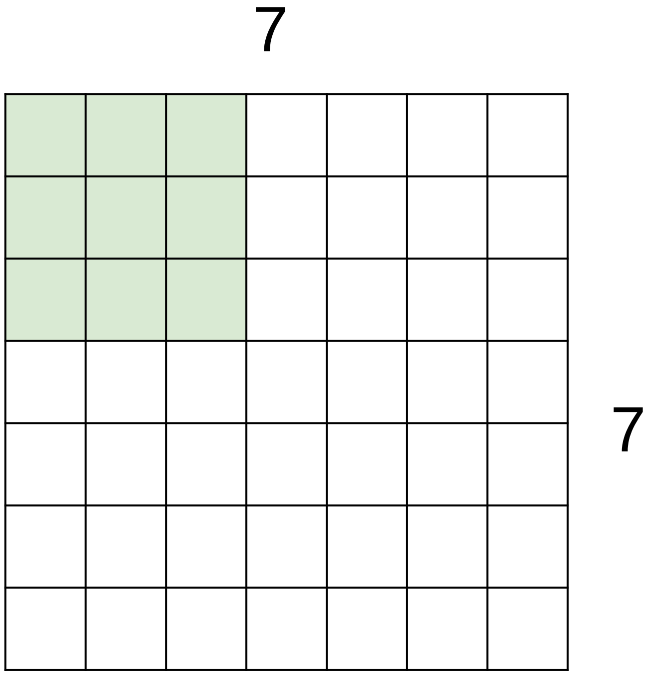
A closer look at spatial dimensions



7x7 input (spatially)
assume 3x3 filter

=> 5x5 output

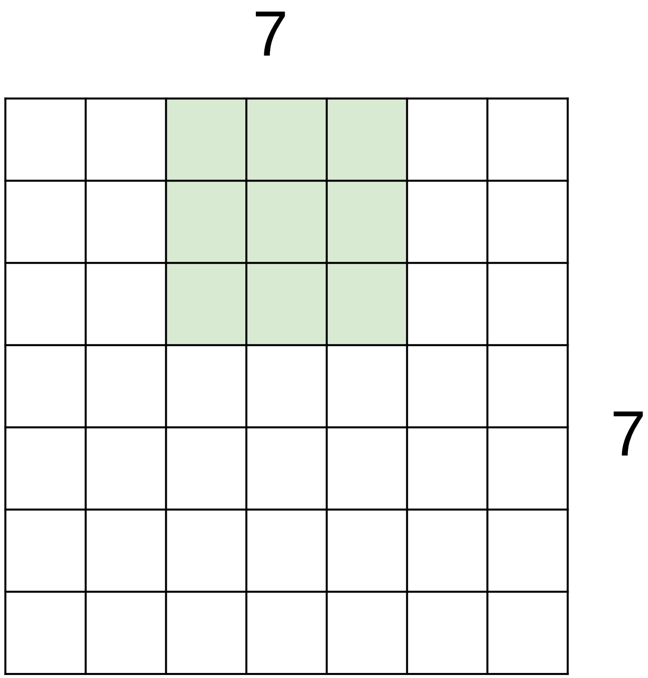
A closer look at spatial dimensions



7x7 input (spatially)
assume 3x3 filter

Applied **with stride 2**

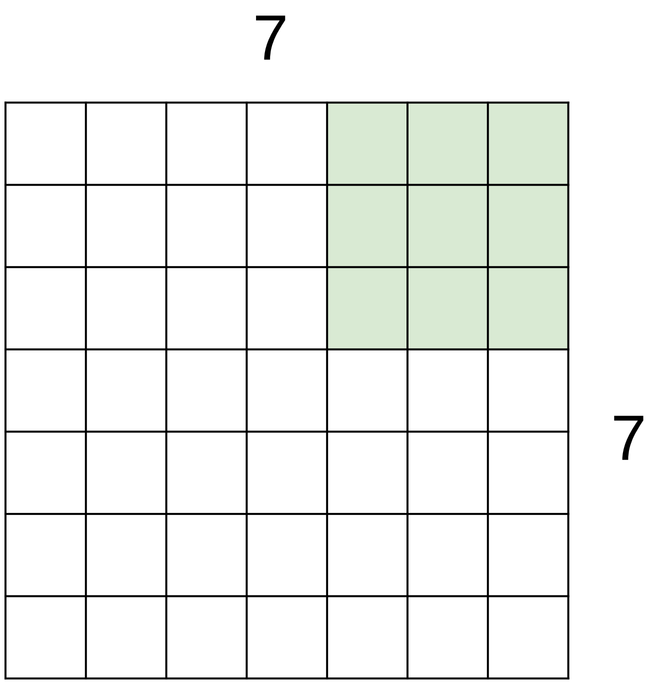
A closer look at spatial dimensions



7x7 input (spatially)
assume 3x3 filter

Applied **with stride 2**

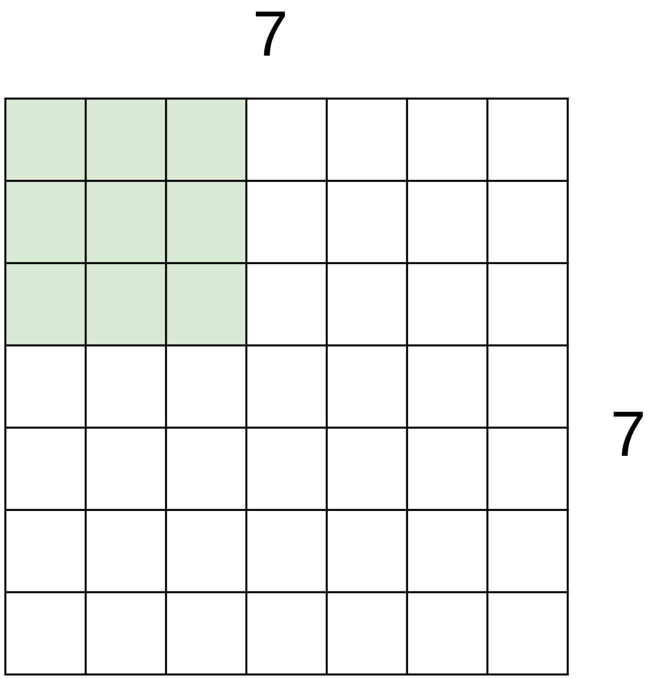
A closer look at spatial dimensions



7x7 input (spatially)
assume 3x3 filter

Applied **with stride 2**
=> 3x3 output!

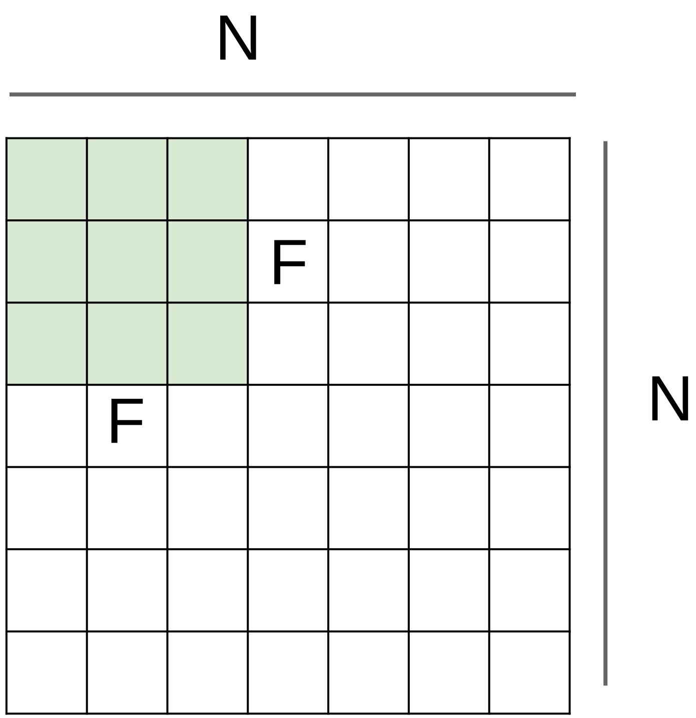
A closer look at spatial dimensions



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

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

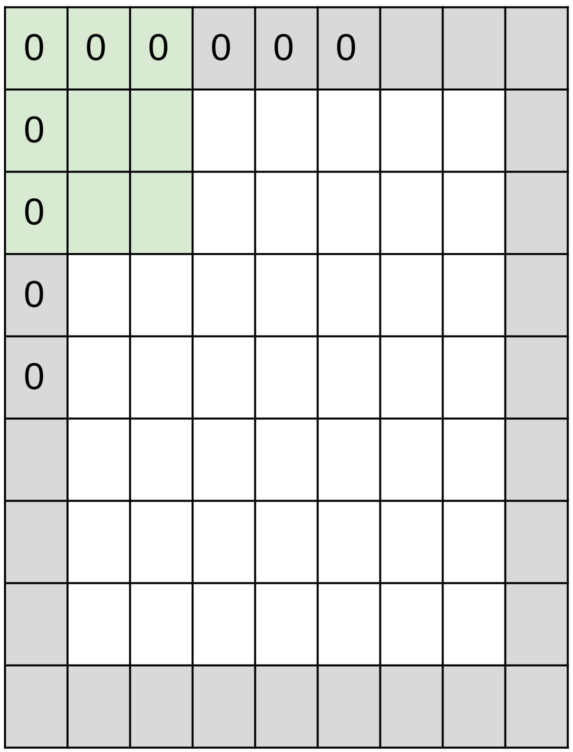
Convolution Layer



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

e.g. N = 7, F = 3:
stride 1 => (7 - 3)/1 + 1 = 5
stride 2 => (7 - 3)/2 + 1 = 3
stride 3 => (7 - 3)/3 + 1 = 2.33 :\

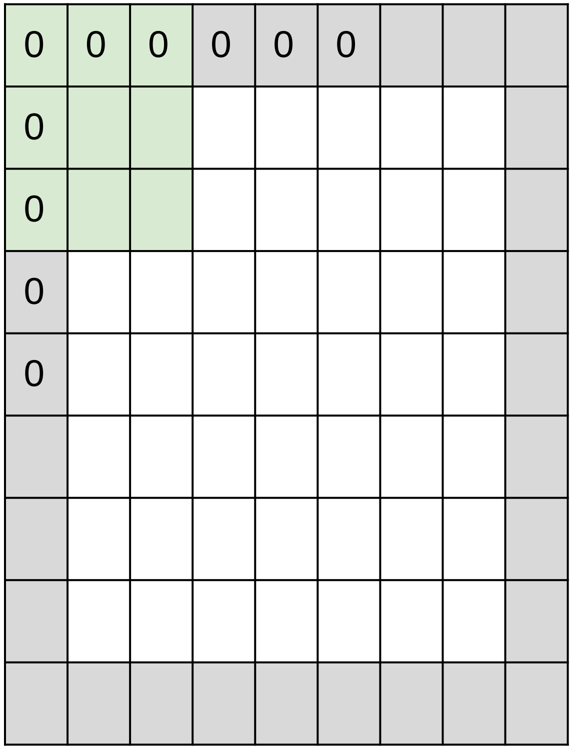
In practice:
Common to zero pad the border



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

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

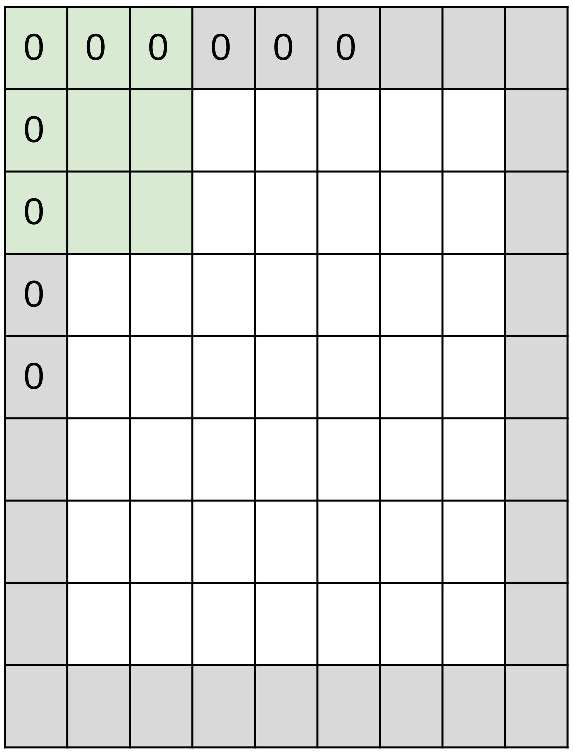
In practice:
Common to zero pad the border



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

7x7 output!

In practice:
Common to zero pad the border

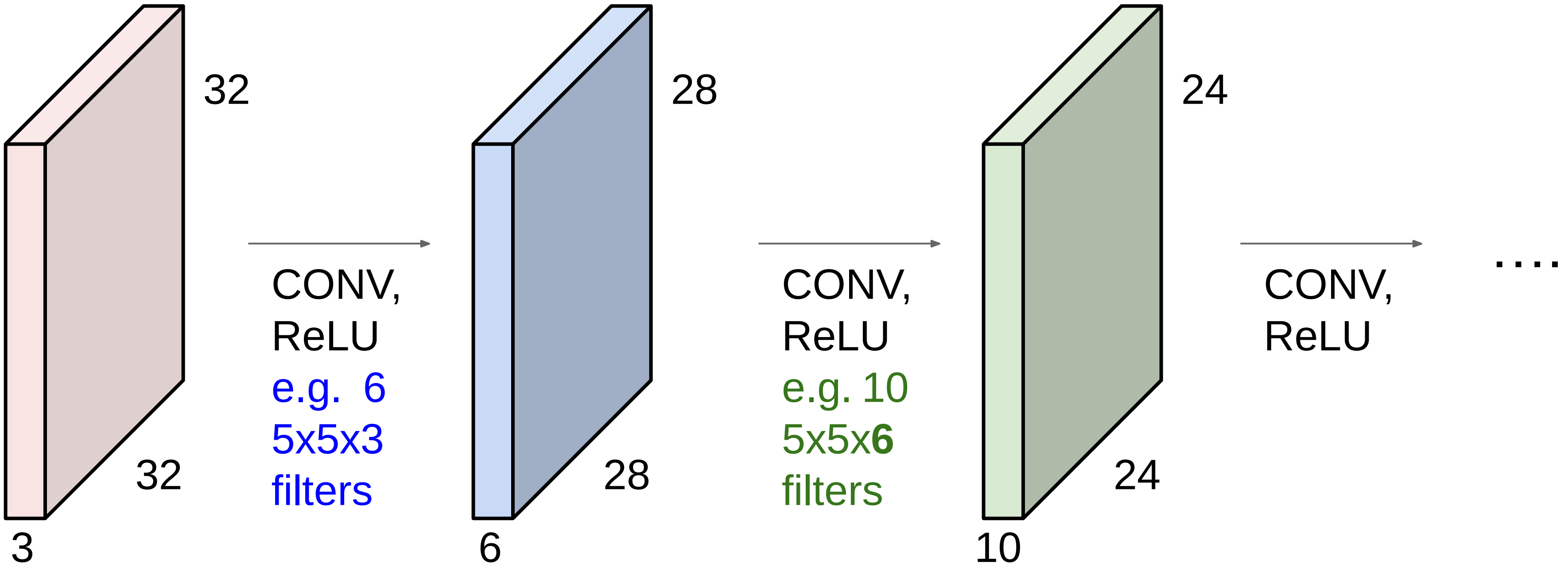


e.g. input 7x7
3x3 filter, applied with **stride 1**
pad with 1 pixel border => what is the output?

7x7 output!
in general, common to see CONV layers with stride 1, filters of size FxF, and zero-padding with (F-1)/2. (will preserve size spatially)
e.g. F = 3 => zero pad with 1
F = 5 => zero pad with 2
F = 7 => zero pad with 3

Convolution Layer: Example

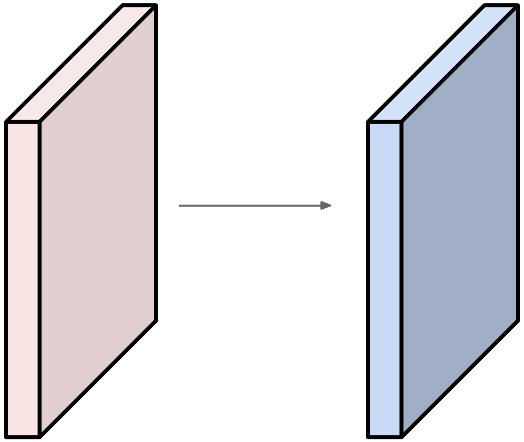
32x32 input convolved repeatedly with 5x5 filters shrinks volumes spatially! (32 -> 28 -> 24 ...). Shrinking too fast is not good, doesn’t work well.



Convolution Layer: Example

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

Output volume size:?



Convolution Layer: Example

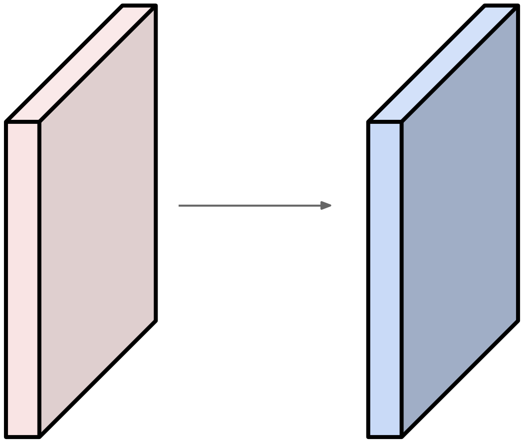
Input volume: **32x32x3**

10 5x5 filters with stride 1, pad 2

Output volume size:

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

32x32x10



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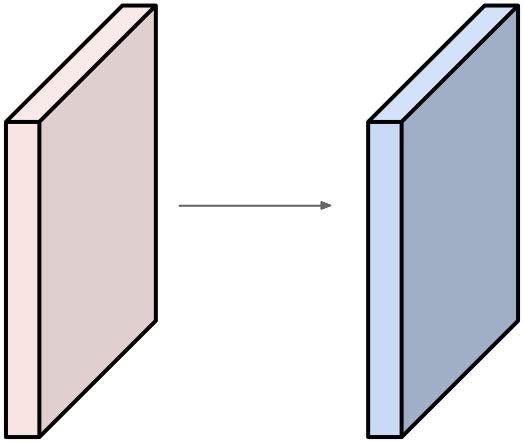
Number of parameters in this layer?



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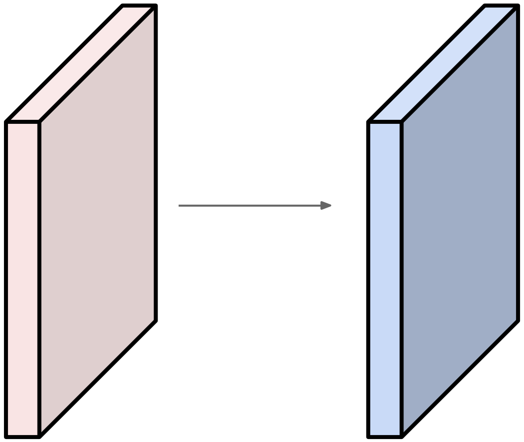


Number of parameters in this layer?

each filter has 5*5*3 + 1 = 76 params

=> 76*10 = **760** (+1 for bias)

Convolution Layer: Summary

- Accepts a volume of size $W_1 \times H_1 \times D_1$
- Requires 4 hyperparameters:
  - Numbers of filters K
  - Their spatial extent F
  - The stride S
  - The amount of zero padding P

Common settings:

K = (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

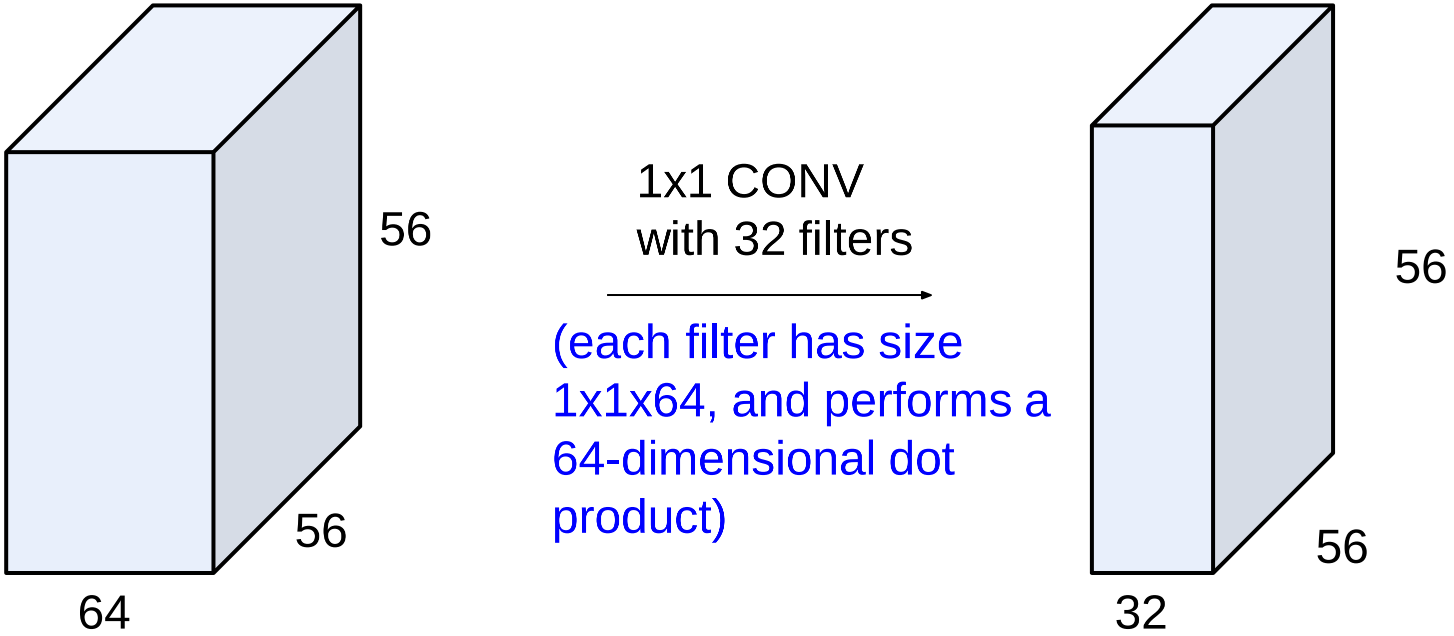
- Produces a volume of size $W_2 \times H_2 \times D_2$ where:
  - $W_2 = \frac{W_1 - F + 2P}{S} + 1$
  - $H_2 = \frac{H_1 - F + 2P}{S} + 1$(i.e. width and height are computed equally by symmetry)
  - $D_2 = K$

Convolution Layer: Summary

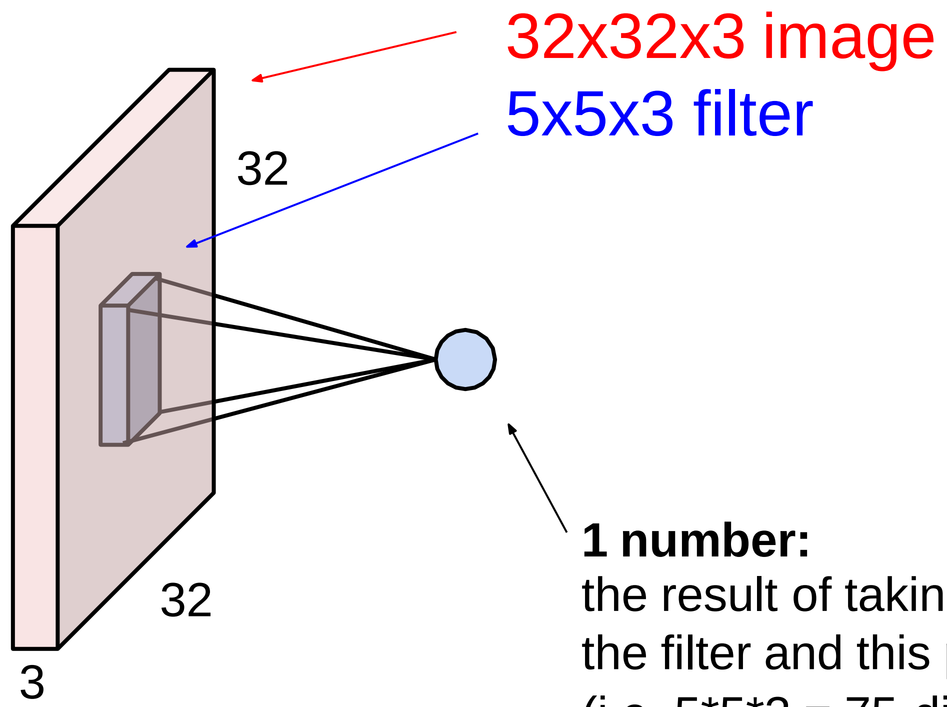
- With parameter sharing, it introduces $F \cdot F \cdot D_1$ weights per filter, for a total of $(F \cdot F \cdot D_1) \cdot K$ weights and K biases
- In the output volume, the *d*-th depth slice (of size $W_2 \times H_2$) is the result of performing a valid convolution of the *d*-th filter over the input volume with a stride of S, and the offset by *d*-th bias.

1×1 conv

- 1x1 convolution layers make perfect sense



The brain/neuron view of Conv Layer

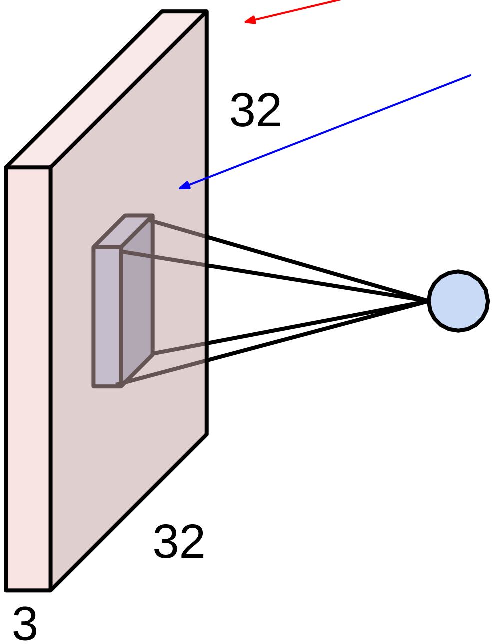


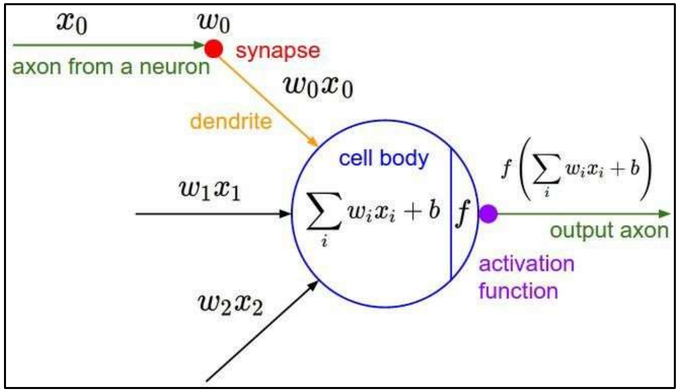
1 number:
the result of taking a dot product between the filter and this part of the image
(i.e. 5*5*3 = 75-dimensional dot product)

The brain/neuron view of Conv Layer

32x32x3 image

5x5x3 filter

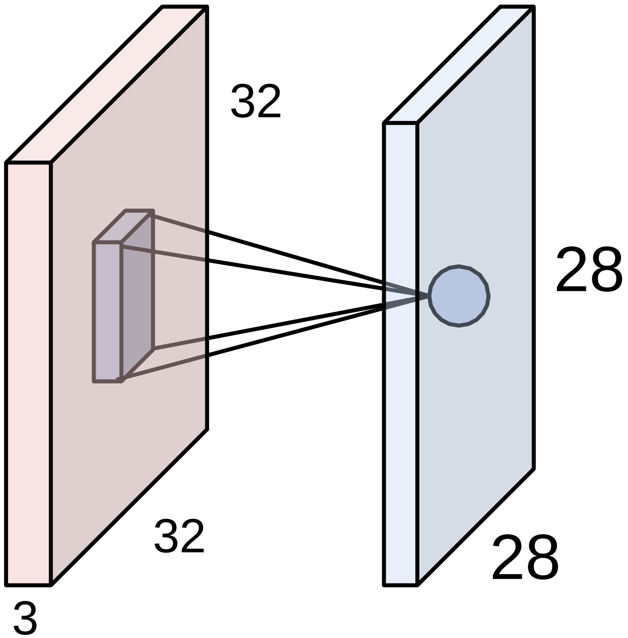


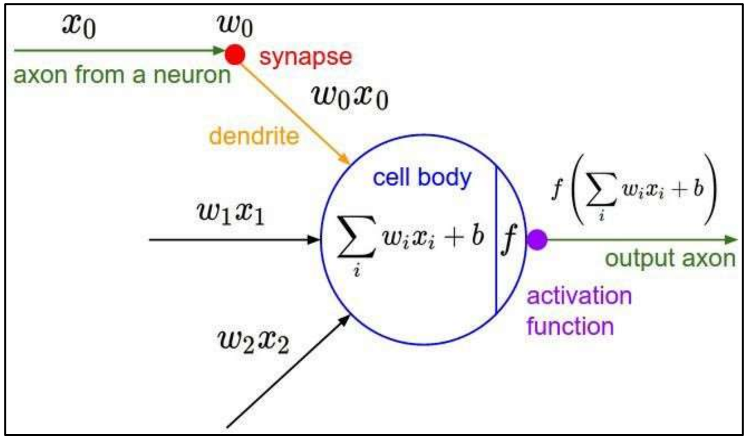


It's just a neuron with local connectivity...

1 number:
the result of taking a dot product between the filter and this part of the image
(i.e. 5*5*3 = 75-dimensional dot product)

The brain/neuron view of Conv Layer



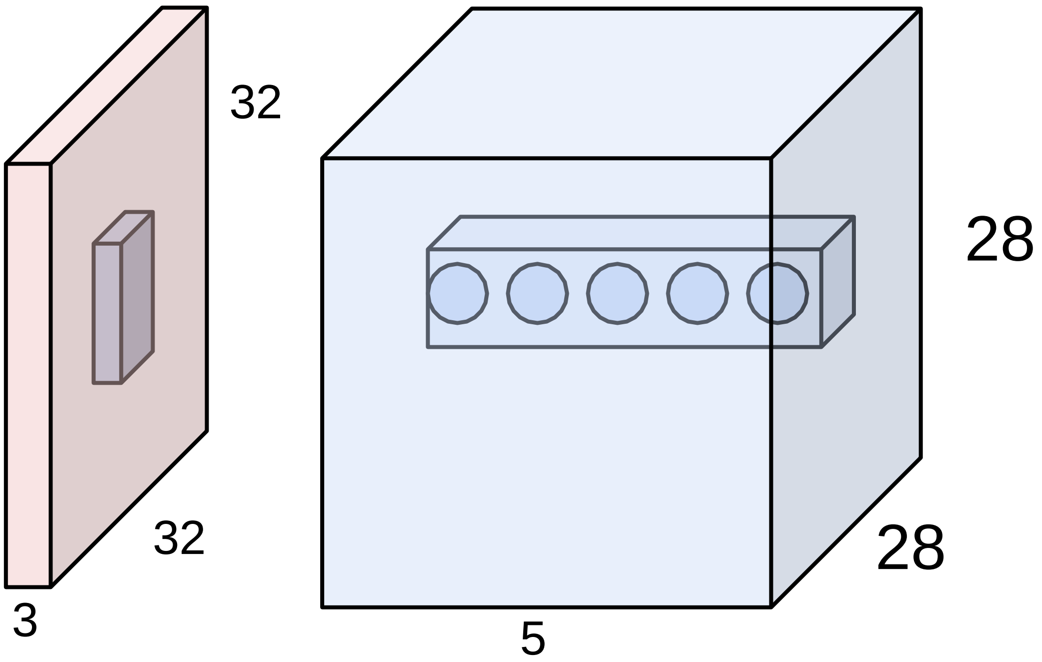


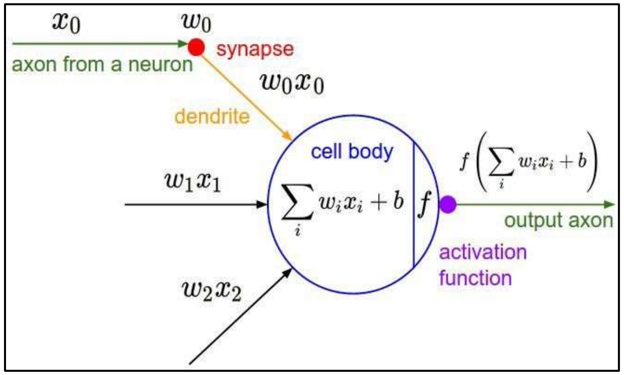
An activation map is a 28x28 sheet of neuron outputs:

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





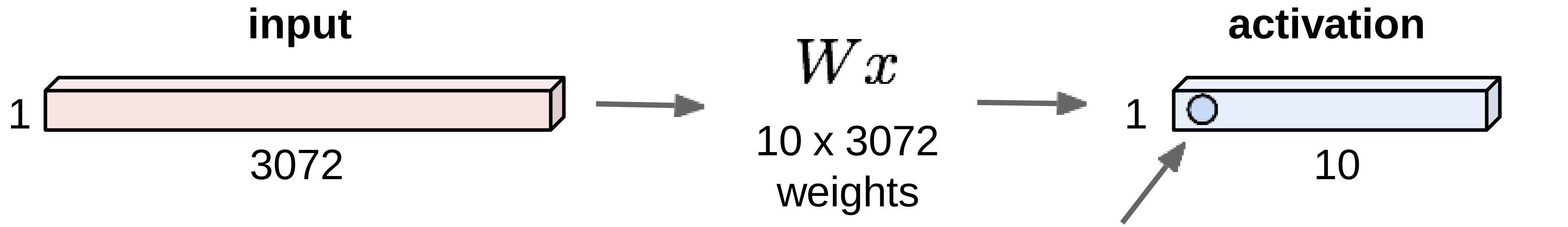
E.g. with 5 filters,
CONV layer consists of neurons arranged in a 3D grid (28x28x5)

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

Reminder: FC Layer

32x32x3 image -> stretch to 3072 x 1

Each neuron looks at the full input volume



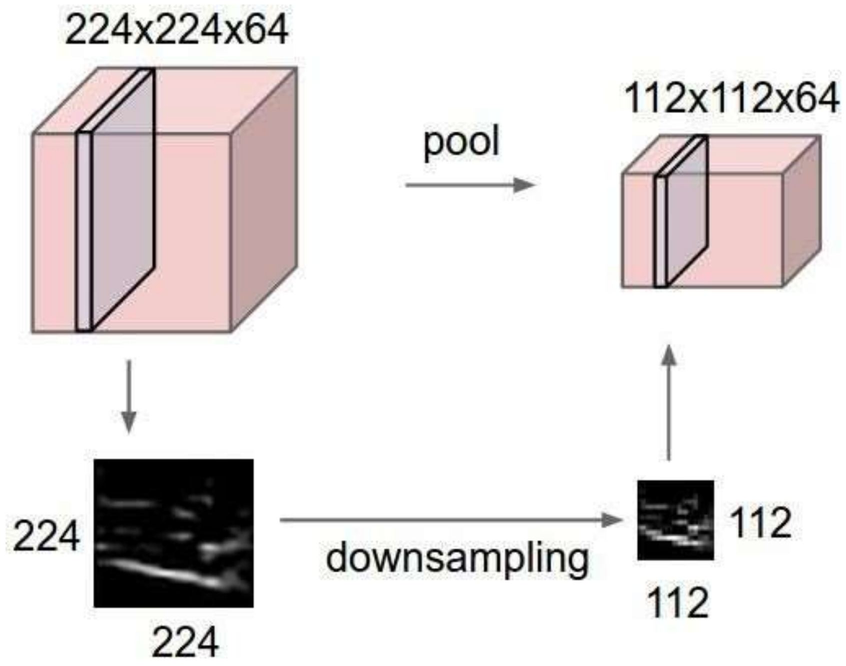
1 number:
the result of taking a dot product between a row of W and the input (a 3072-dimensional dot product)

CNN Layer

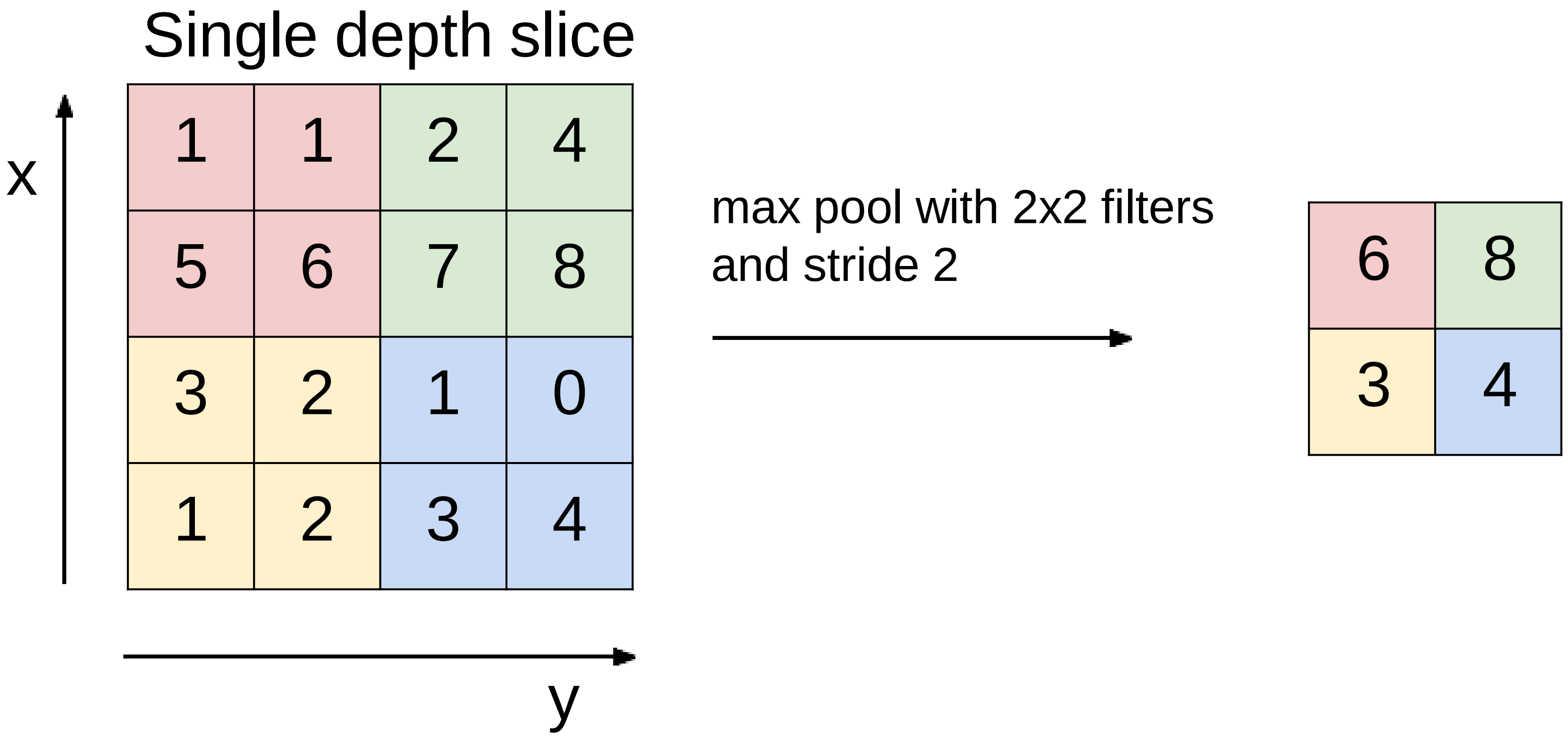
- Fully Connected Layer
- Convolution Layer
- ***Pooling Layer***

Pooling Layer

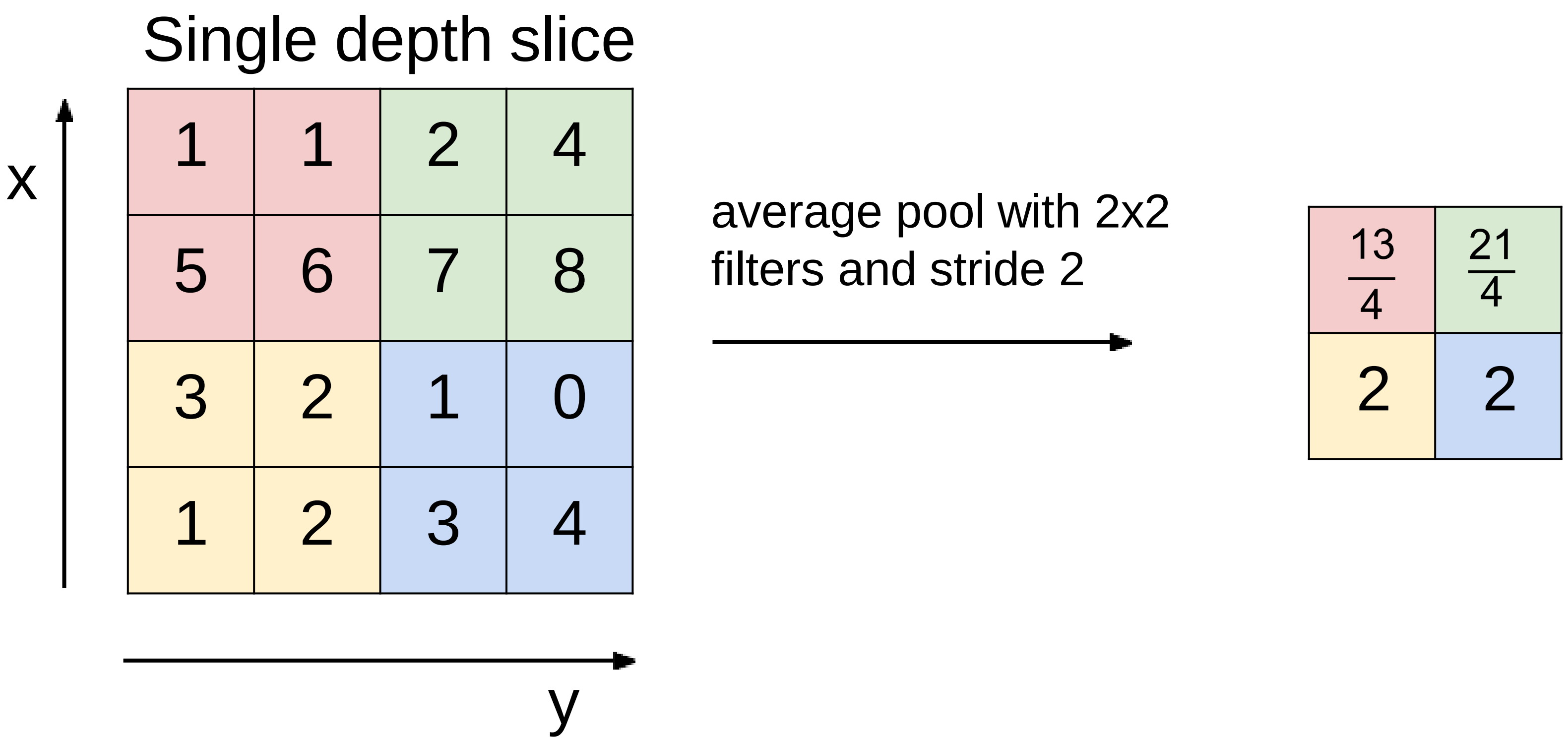
- makes the representations smaller and more manageable
- operates over each activation map independently:



Max Pooling


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

Average Pooling



Pooling Layer: Summary

Common settings:

F = 2, S = 2
F = 3, S = 2

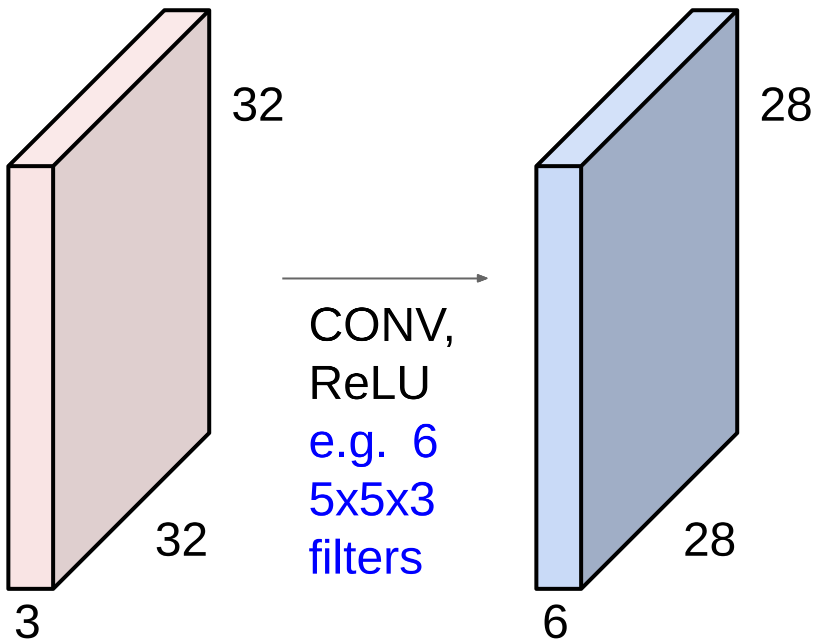
- Accepts a volume of size $W_1 \times H_1 \times D_1$
- Requires 2 hyperparameters:
  - Their spatial extent F
  - The stride S
- Produces a volume of size $W_2 \times H_2 \times D_2$ where:
  - $W_2 = \frac{W_1 - F}{S} + 1$
  - $H_2 = \frac{H_1 - F}{S} + 1$
  - $D_2 = D_1$
- Introduces zero parameters since it computes a fixed function of the input
- Note that it is not common to use zero-padding for Pooling layers

Today's Topics

- CNN Development
- CNN Layer
- ***CNN Architecture***

CNN Architecture

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



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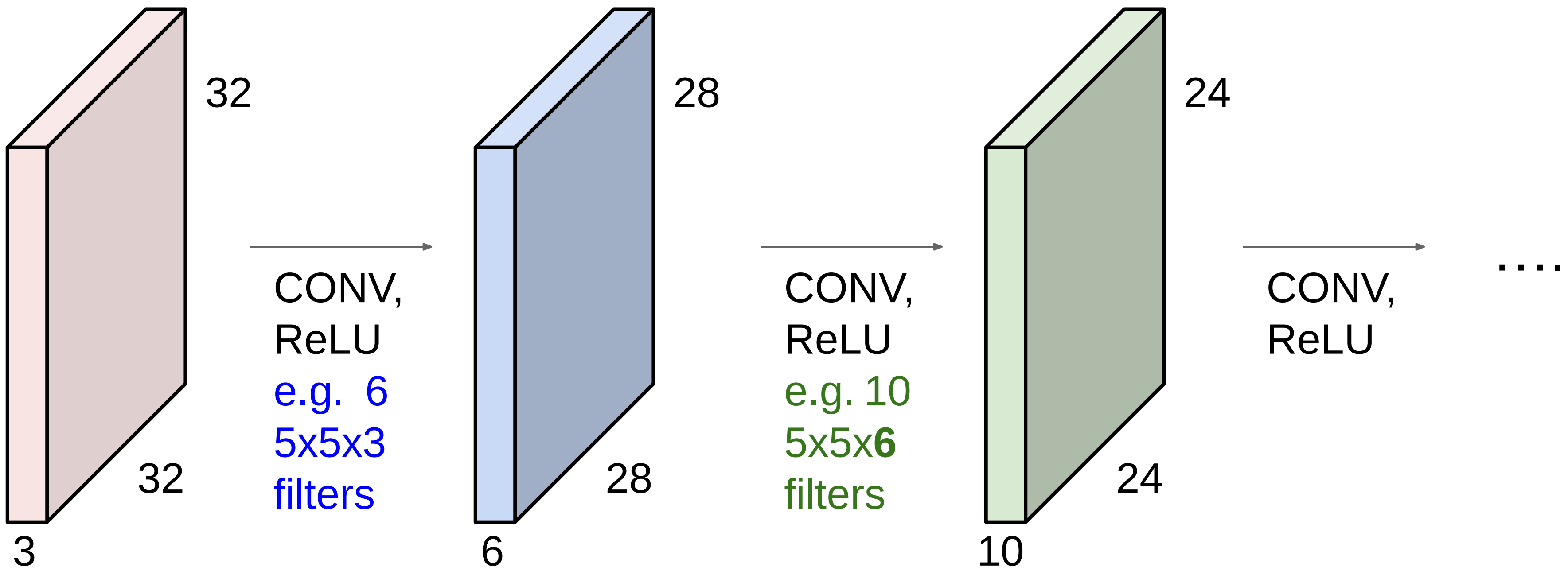

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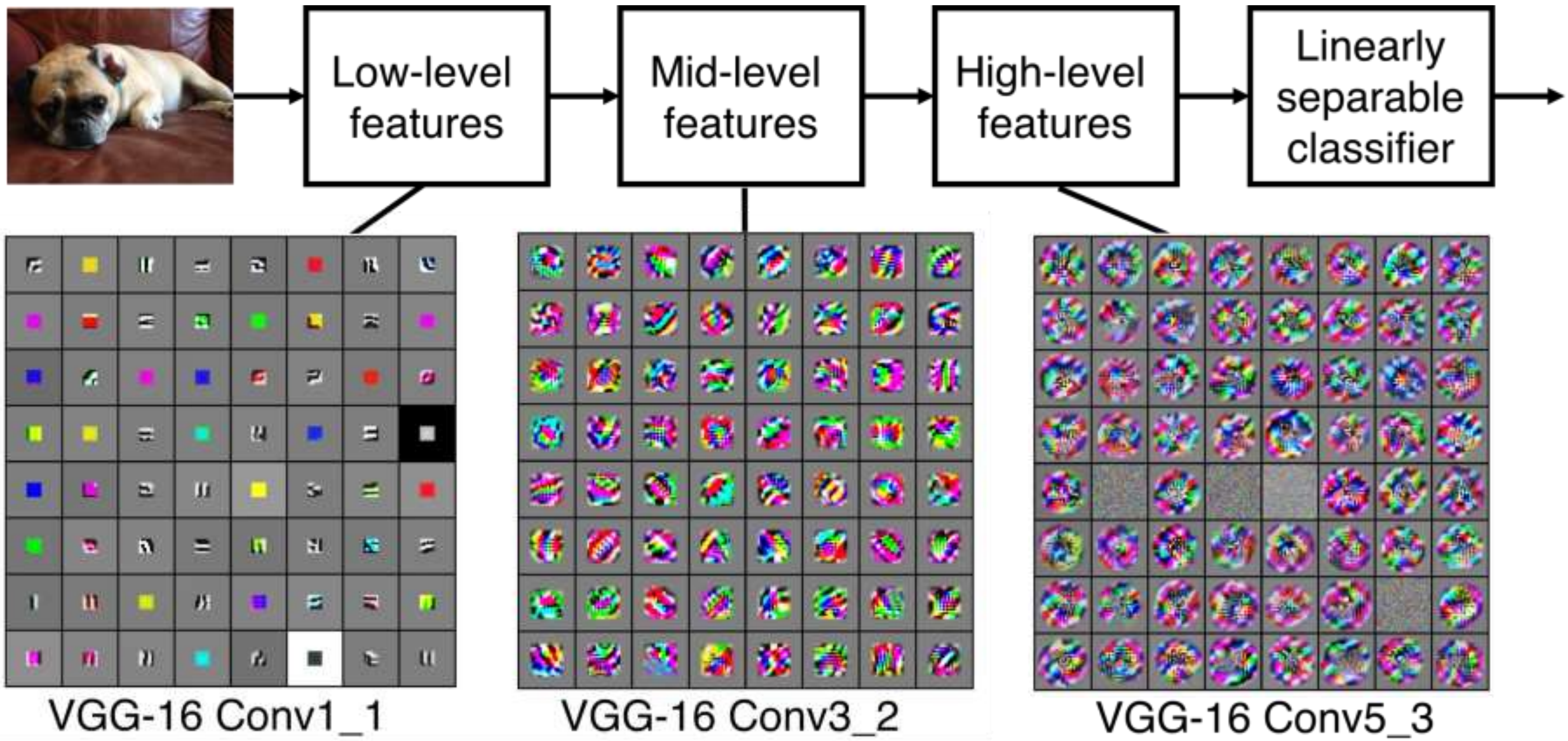

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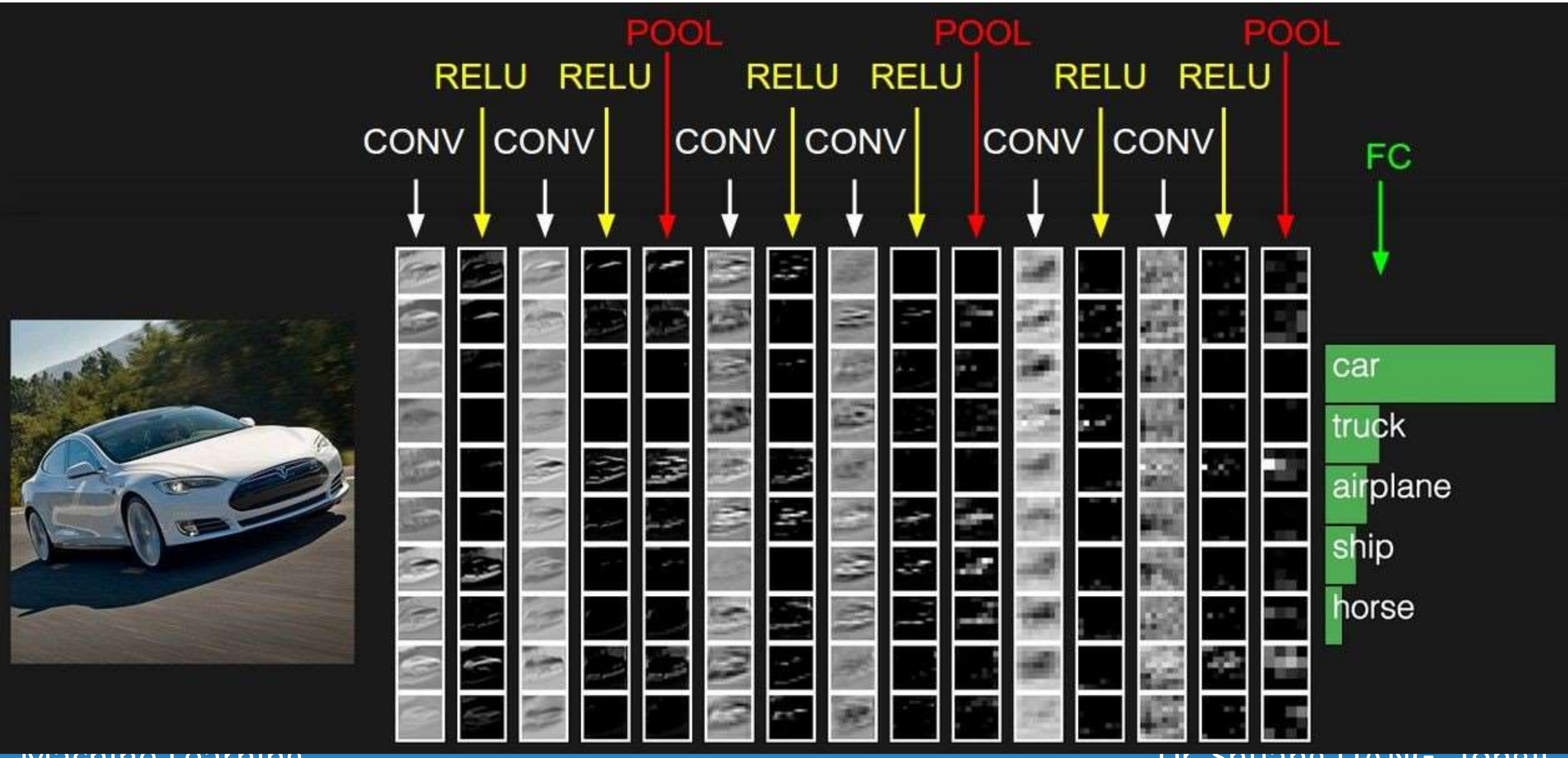

CNN Summary

- 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
  - **[(CONV-RELU)*N-POOL?]*M-(FC-RELU)*K,SOFTMAX**
  - where N is usually up to ~5, M is large, 0 <= K <= 2.
  - but recent advances such as ResNet/GoogLeNet challenge this paradigm

Thinking

- Why do we introduce a max pooling layer instead of using a convolutional layer with a larger stride?
- What are the advantages of convolutional layers over fully connected layers for image classification?