

BBM406

Fundamentals of Machine Learning

Lecture 14:
Deep Convolutional Networks

Announcement

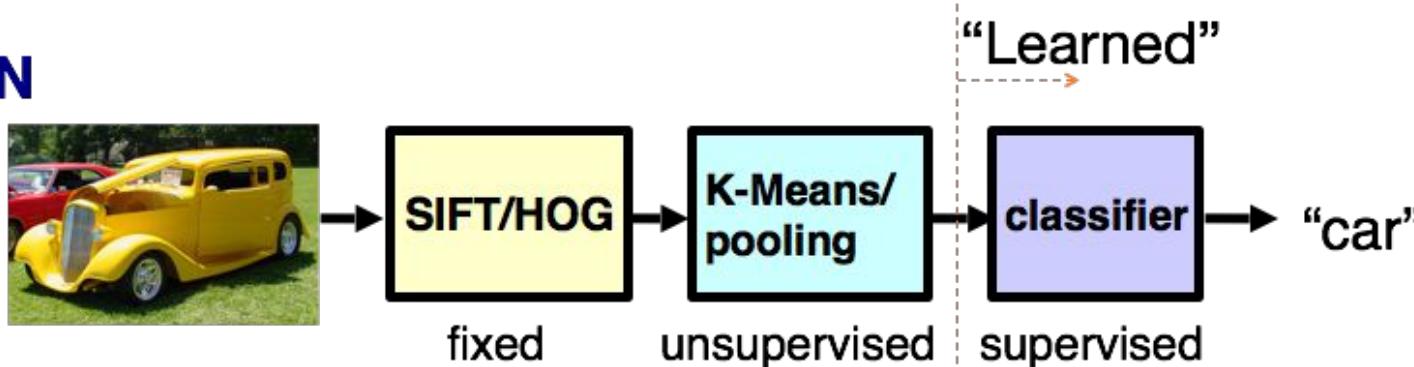
- Midterm exam on Nov 29, 2019 at 09.00 in rooms D3 & D4
- More info in Piazza
- No class next Wednesday! Extra office hour.

Last time... Three key ideas

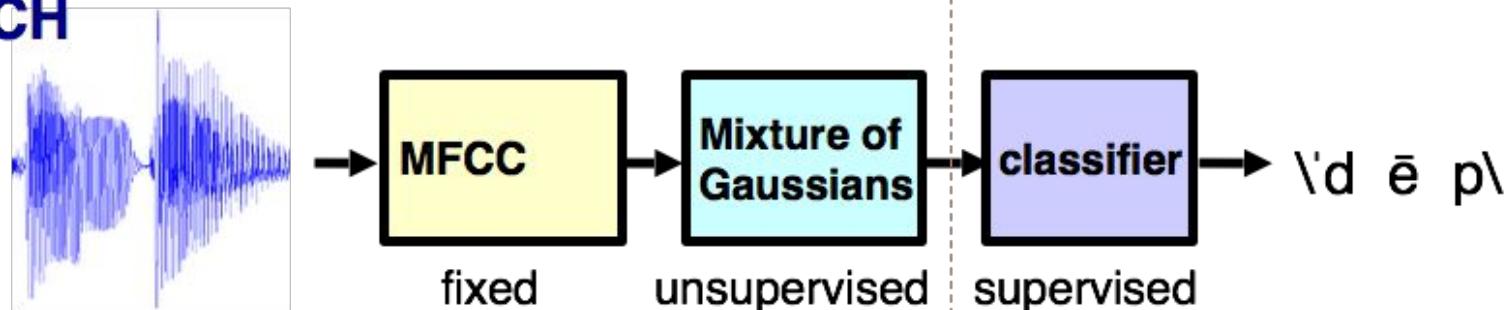
- (Hierarchical) Compositionality
 - Cascade of non-linear transformations
 - Multiple layers of representations
- End-to-End Learning
 - Learning (goal-driven) representations
 - Learning to feature extract
- Distributed Representations
 - No single neuron “encodes” everything
 - Groups of neurons work together

Last time... Intro. to Deep Learning

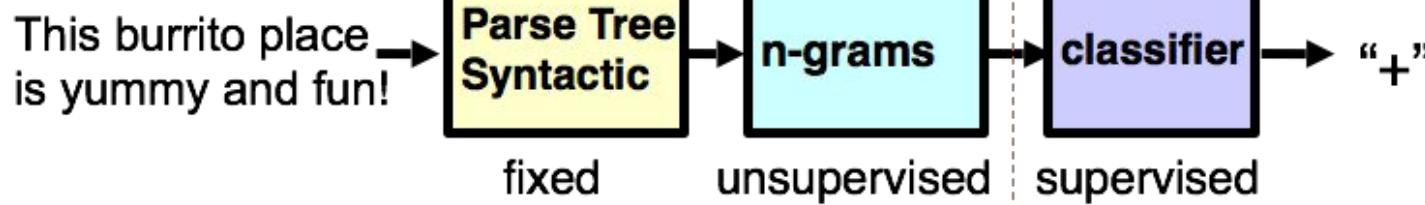
VISION



SPEECH

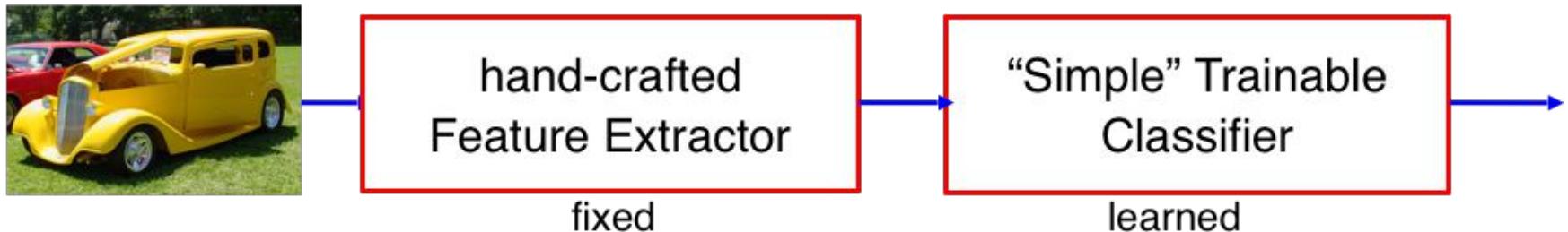


NLP

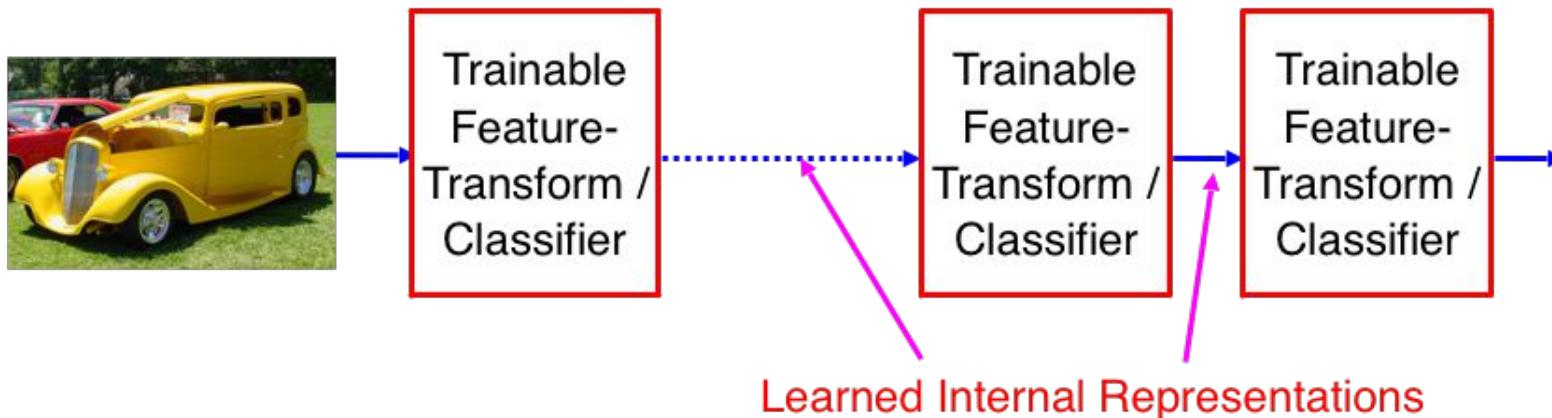


Last time... Intro. to Deep Learning

- “Shallow” models



- Deep models



Deep Convolutional Neural Networks

Convolutions

- Images typically have invariant patterns
 - E.g., directional gradients are translational invariant:



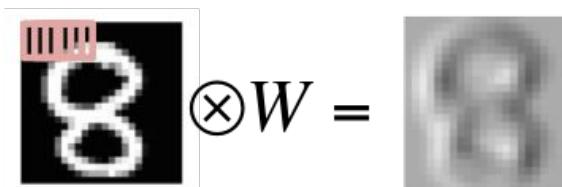
- Apply convolution to local sliding windows

Convolution Filters

- Applies to an image patch x
 - Converts local window into single value
 - Slide across image

$$x \otimes W = \sum_{ij} W_{ij} x_{ij}$$

↑
Local Image Patch



Left-to-Right
Edge Detector

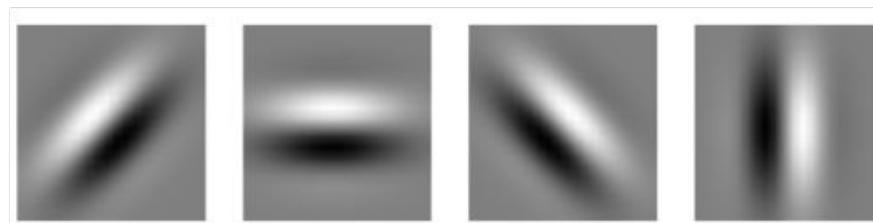
-1	0	+1
-1	0	+1
-1	0	+1

W

Gabor Filters

- Most common low-level convolutions for computer vision

Example W:



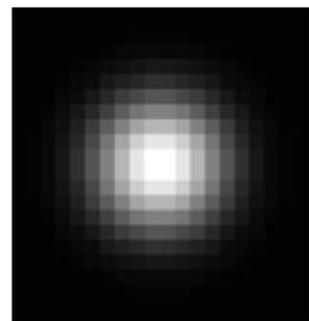
-1	0	+1
-1	0	+1
-1	0	+1

W

http://en.wikipedia.org/wiki/Gabor_filter

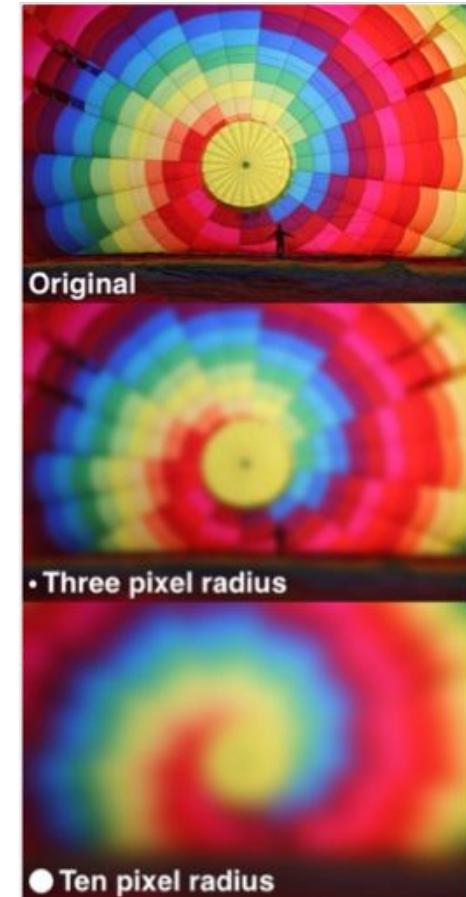
Gaussian Blur Filters

- Weights decay according to Gaussian Distribution
 - Variance term controls radius



Example W:
Apply per RGB Channel

- Black = 0
- White = Positive

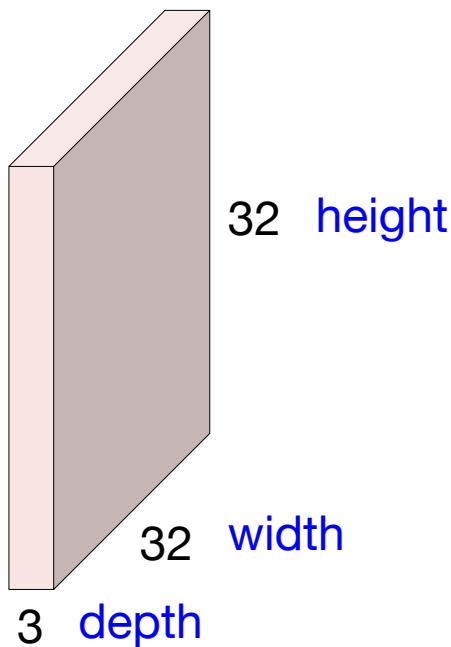


http://en.wikipedia.org/wiki/Gaussian_blur

Convolutional Neural Networks

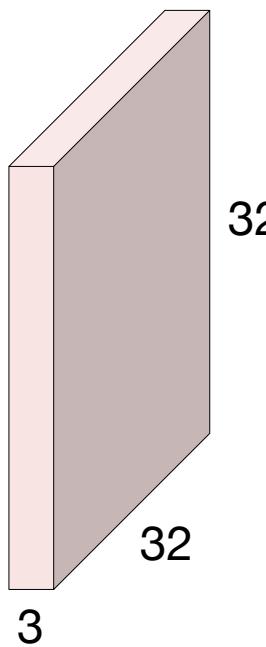
Convolution Layer

32x32x3 image

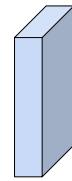


Convolution Layer

32x32x3 image



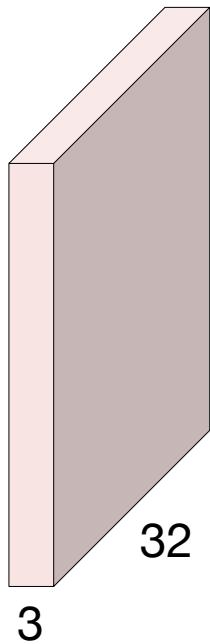
5x5x3 filter



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

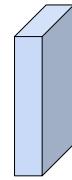
Convolution Layer

32x32x3 image



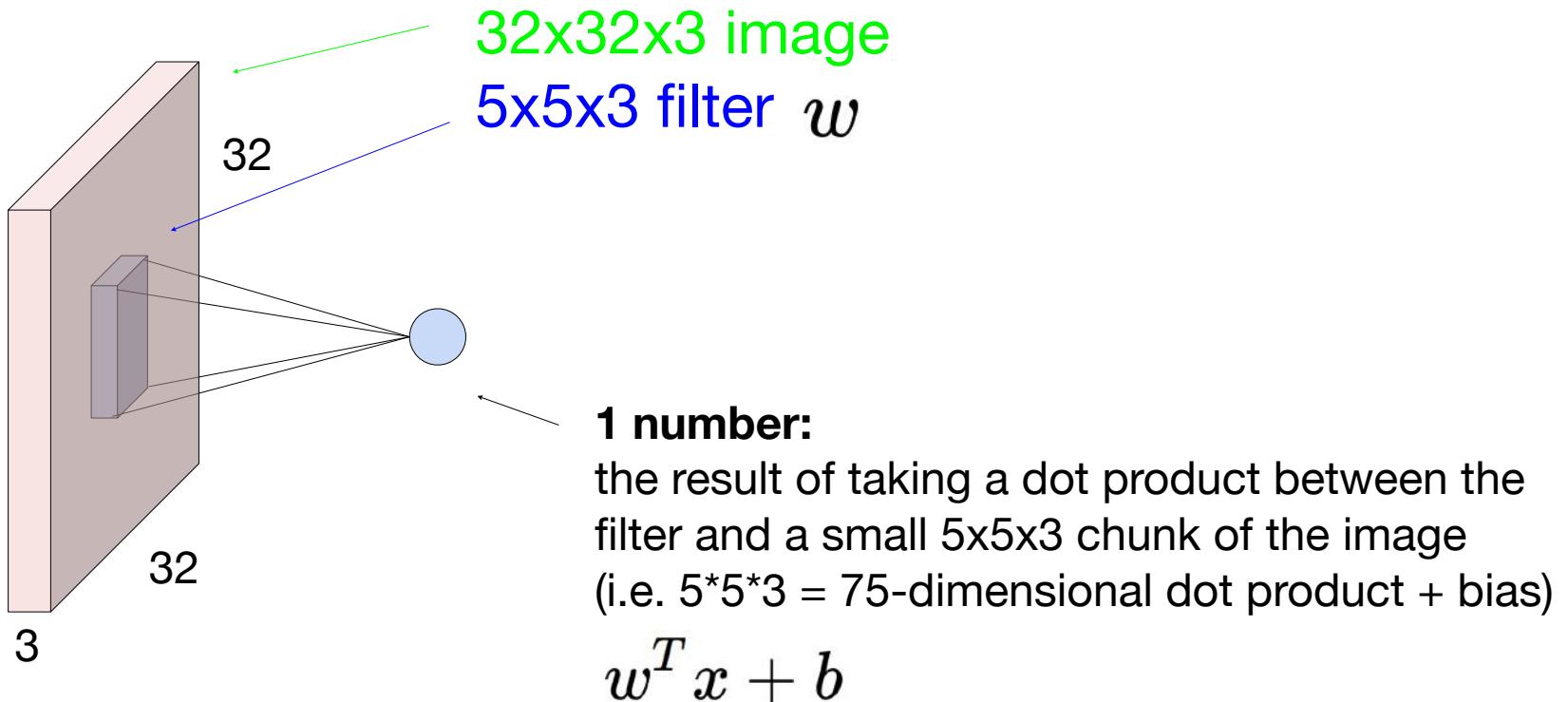
Filters always extend the full depth of the input volume

5x5x3 filter



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

Convolution Layer

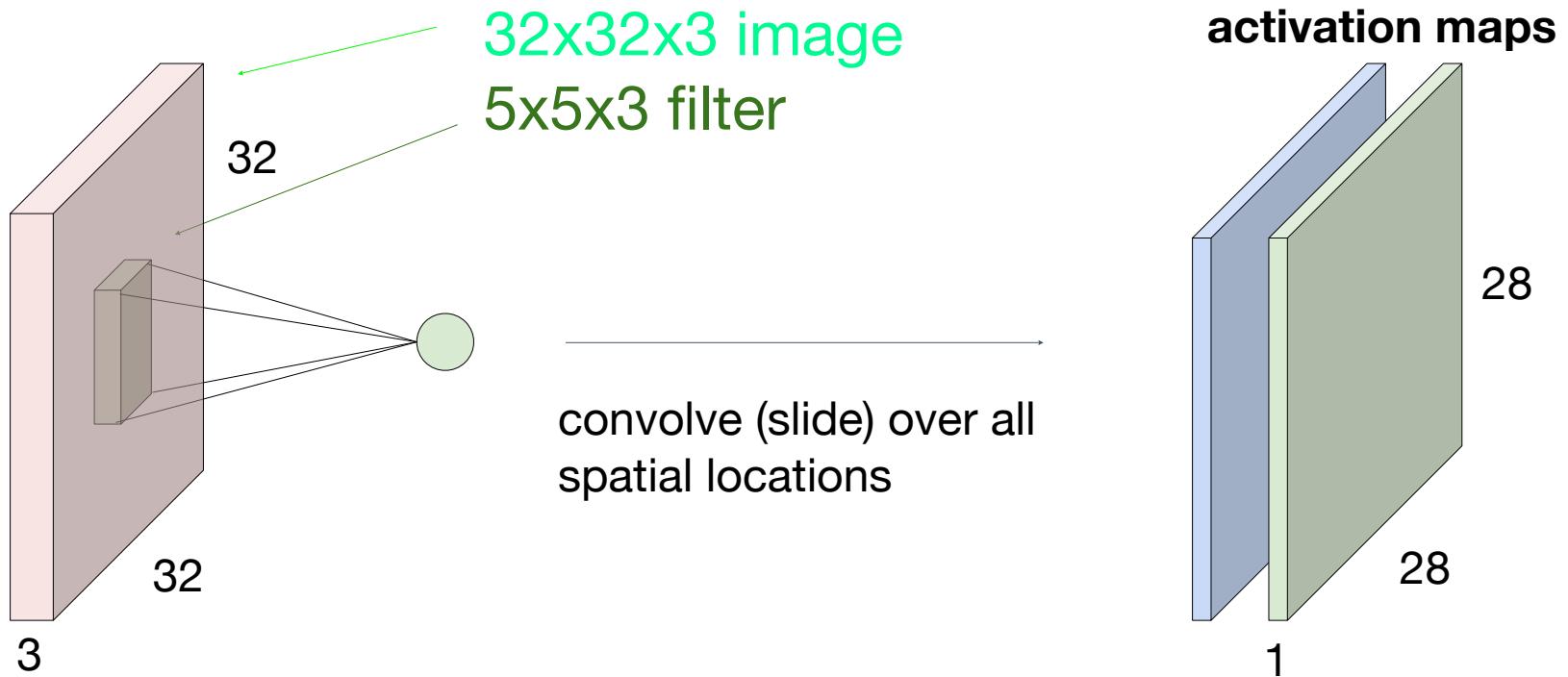


Convolution Layer

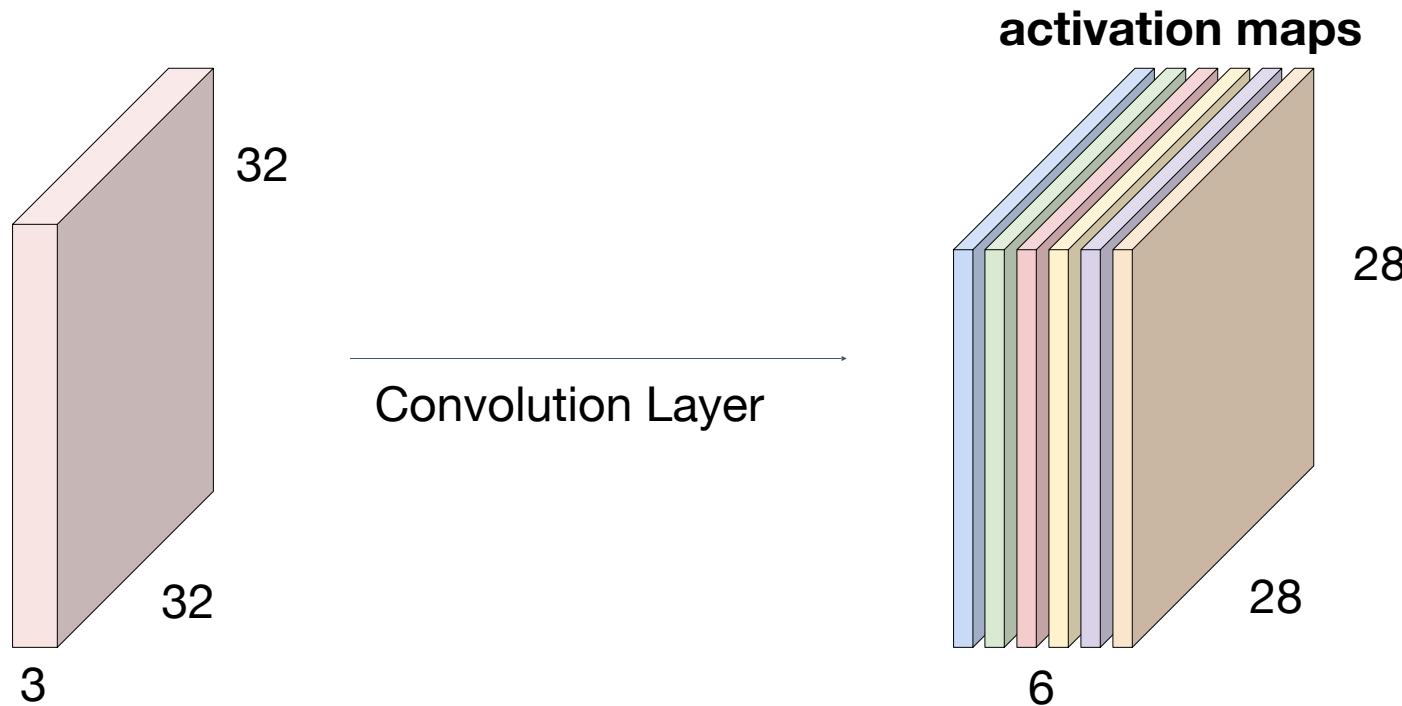


Convolution Layer

consider a second, green filter

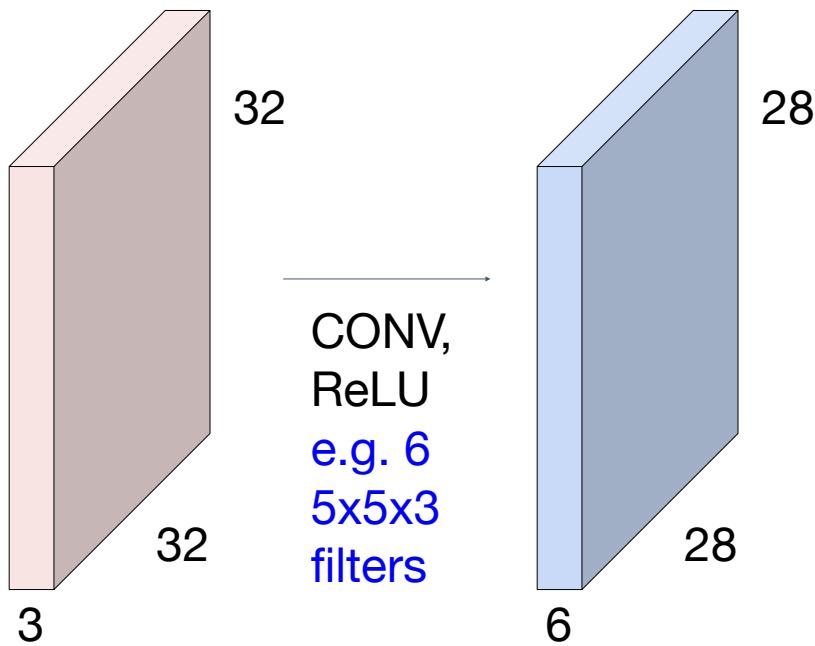


For example, if we had 6 5×5 filters, we'll get 6 separate activation maps:

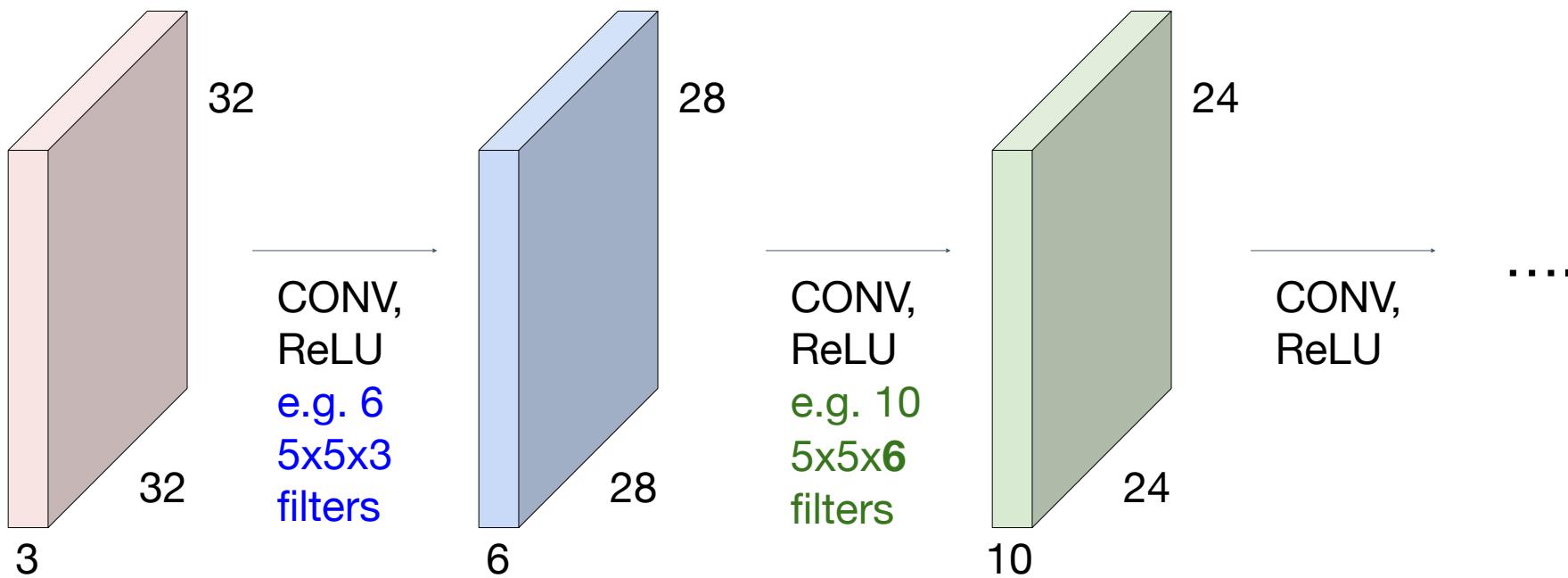


We stack these up to get a “new image” of size $28 \times 28 \times 6$!

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

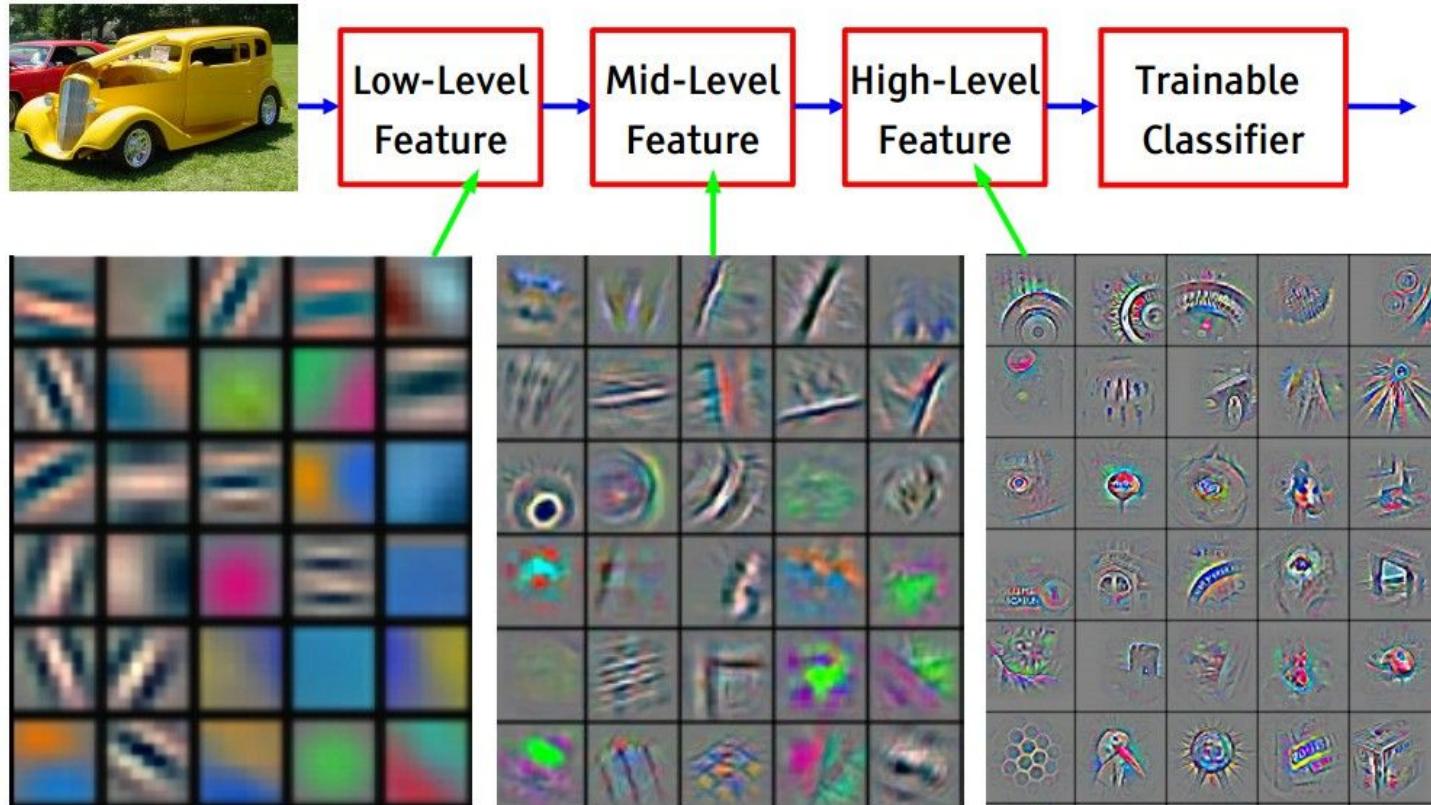


Preview: ConvNet is a sequence of Convolutional Layers, interspersed with activation functions



Preview

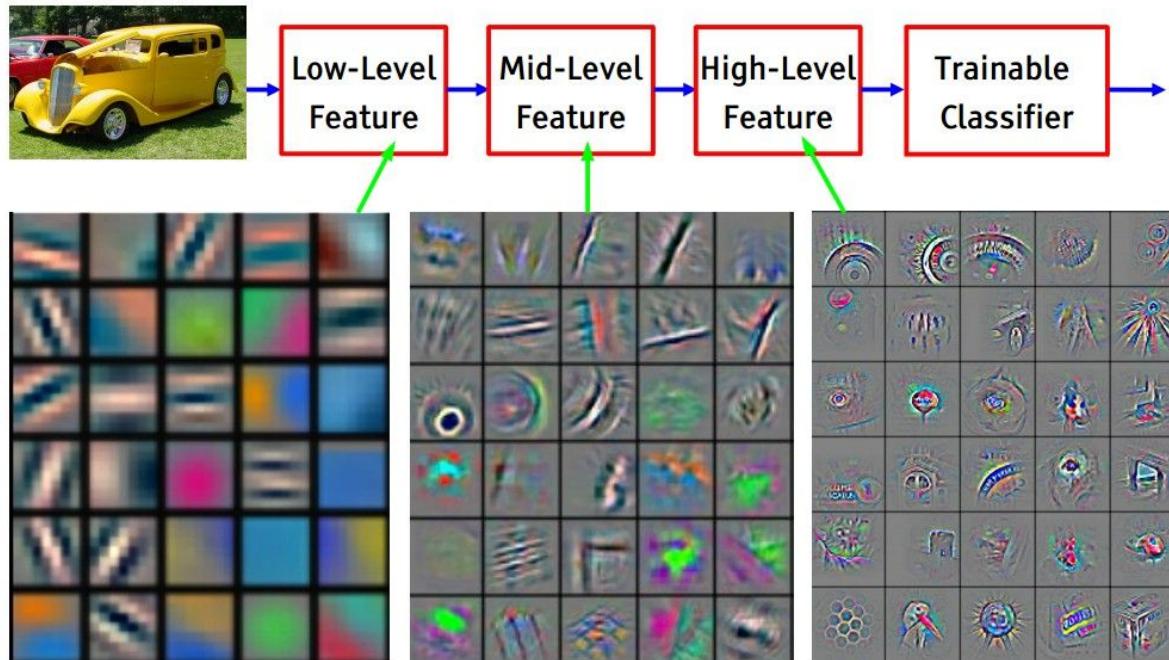
[From recent Yann LeCun slides]



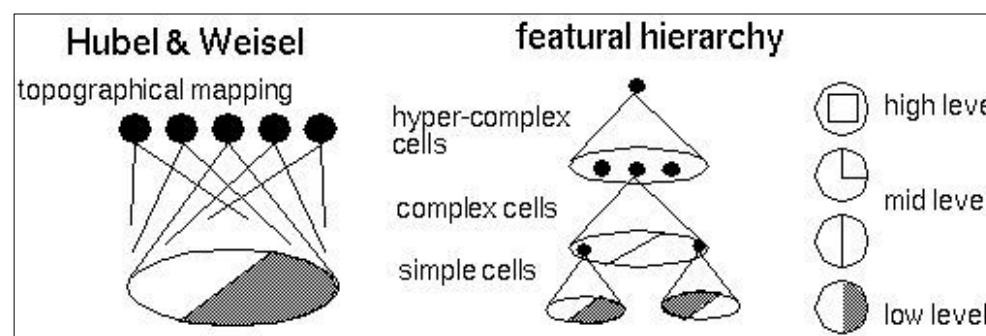
Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

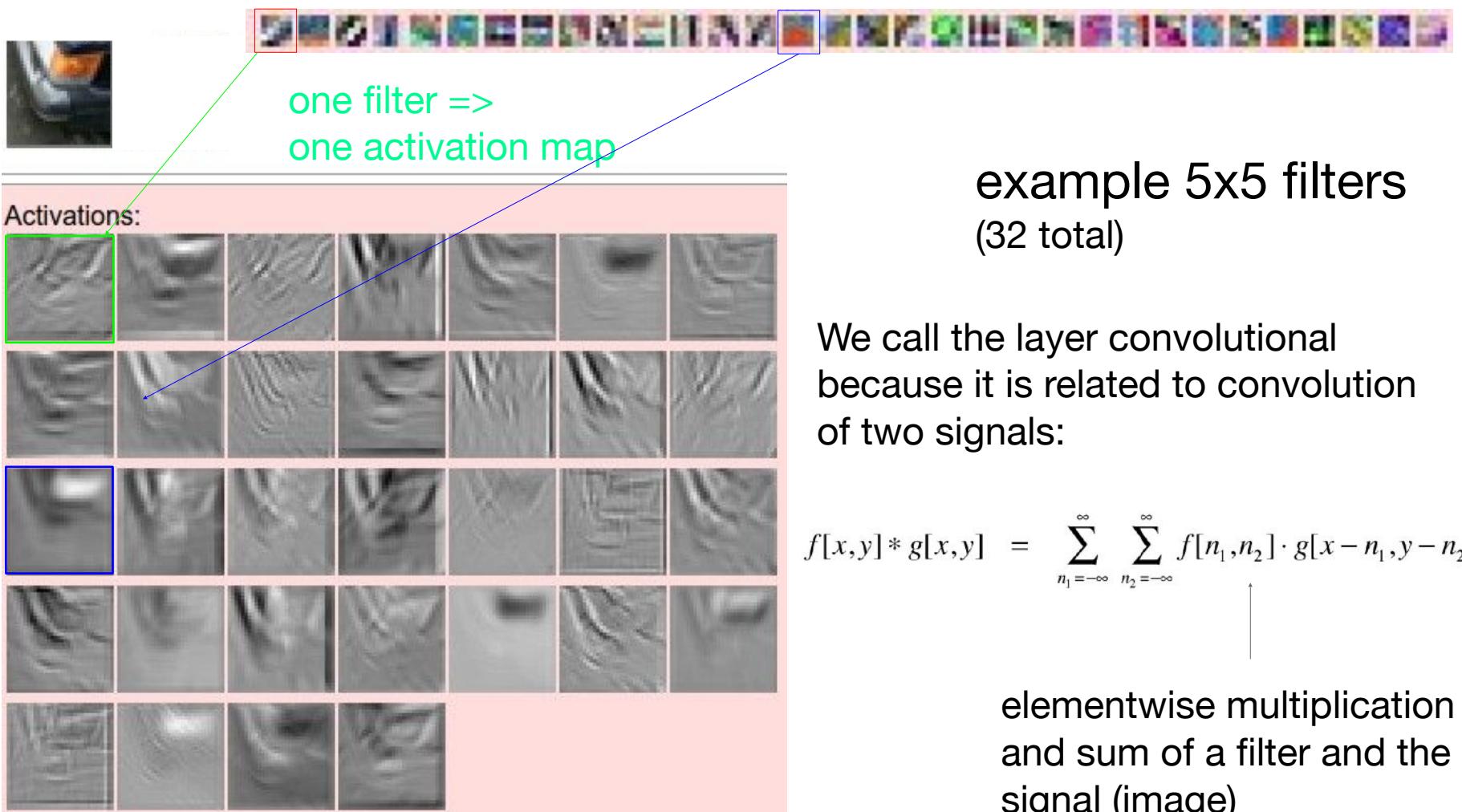
Preview

[From recent Yann LeCun slides]



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





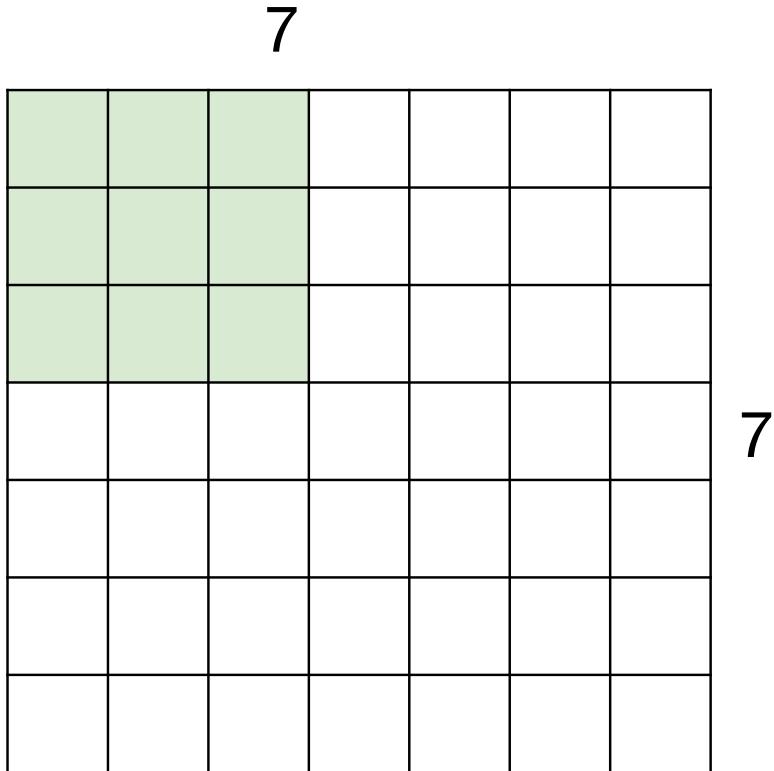
Preview



A closer look at spatial dimensions:

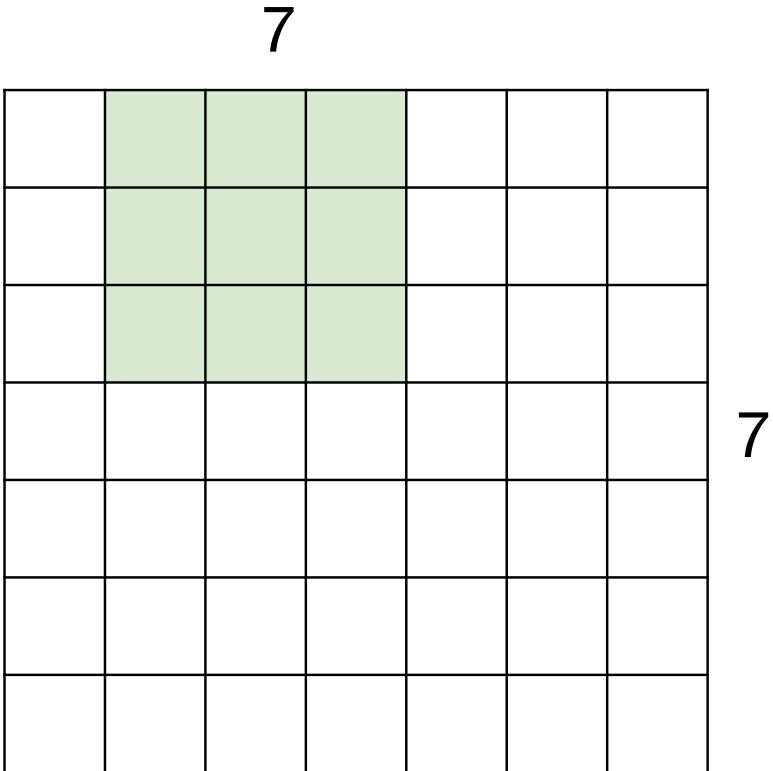


A closer look at spatial dimensions:



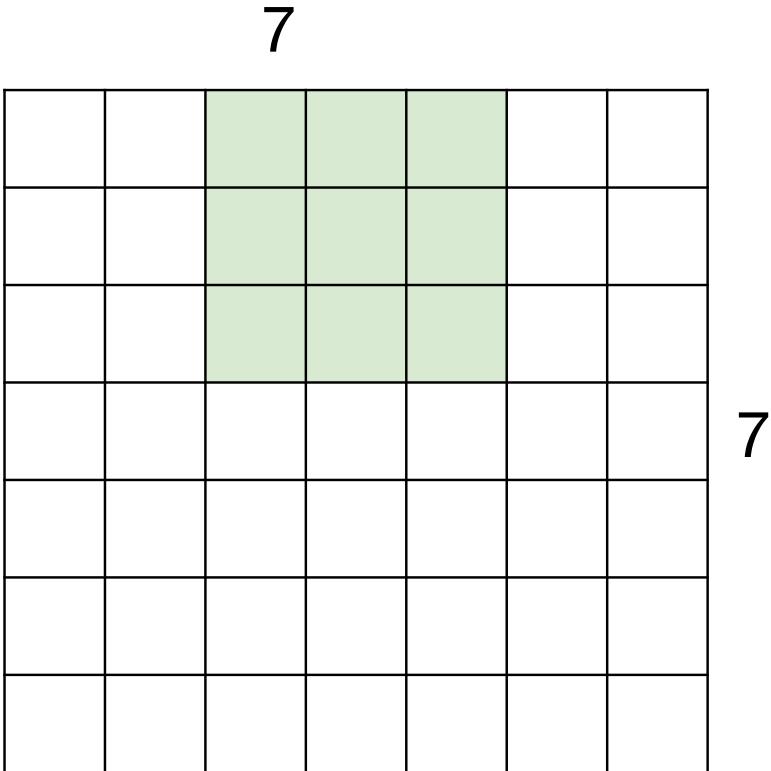
7x7 input (spatially)
assume 3x3 filter

A closer look at spatial dimensions:



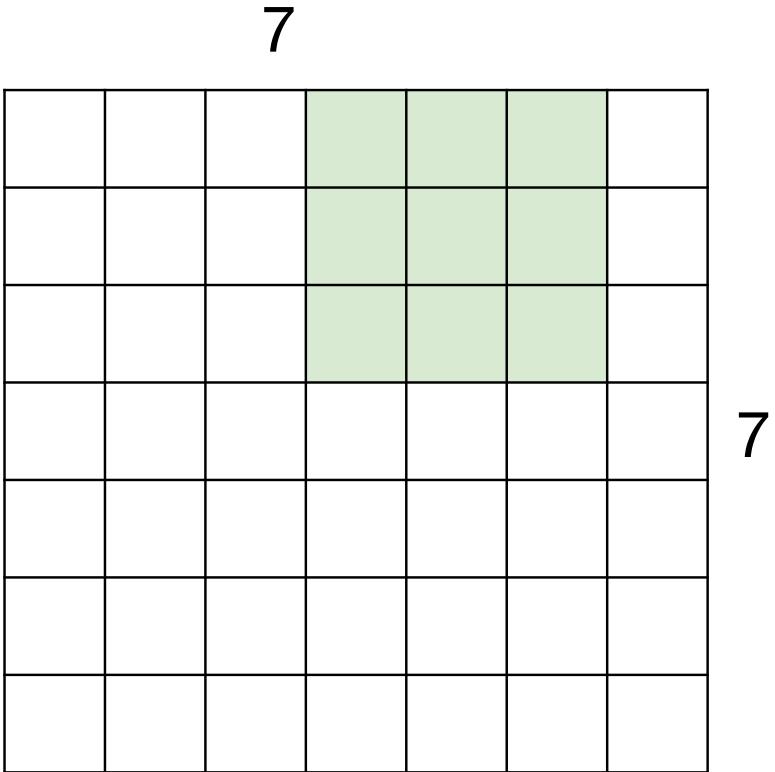
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A closer look at spatial dimensions:



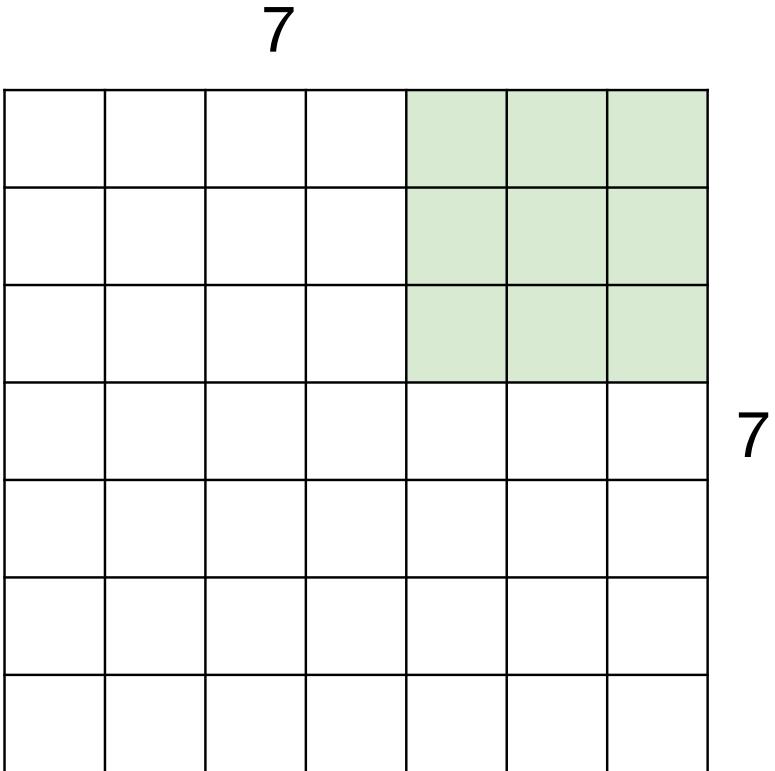
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A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter

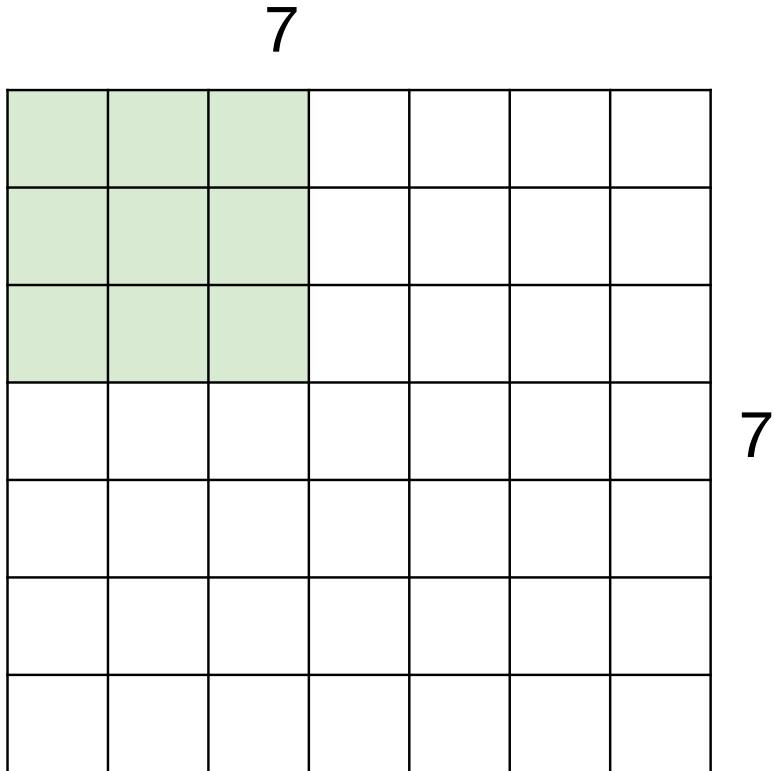
A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter

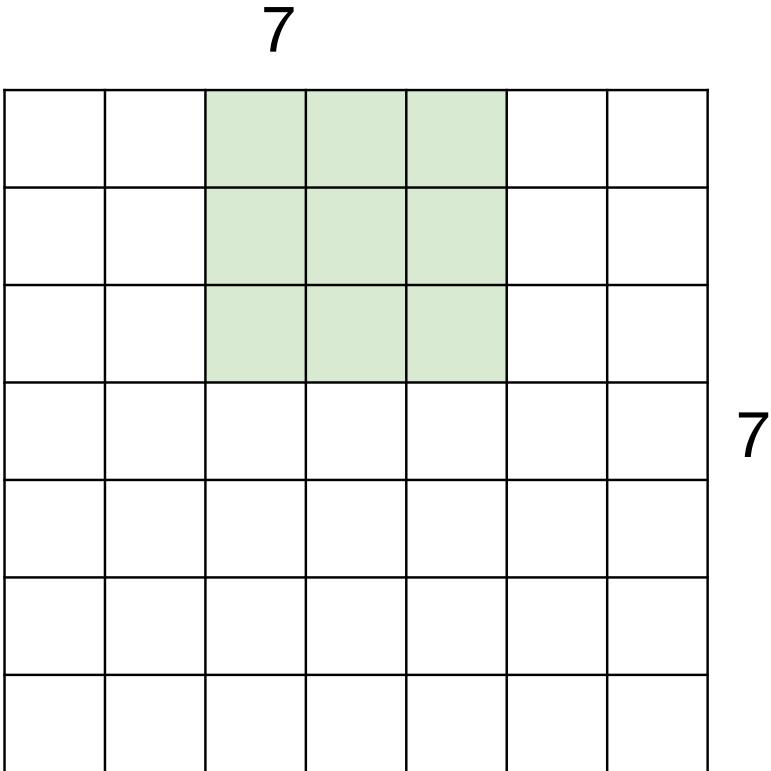
=> **5x5 output**

A closer look at spatial dimensions:



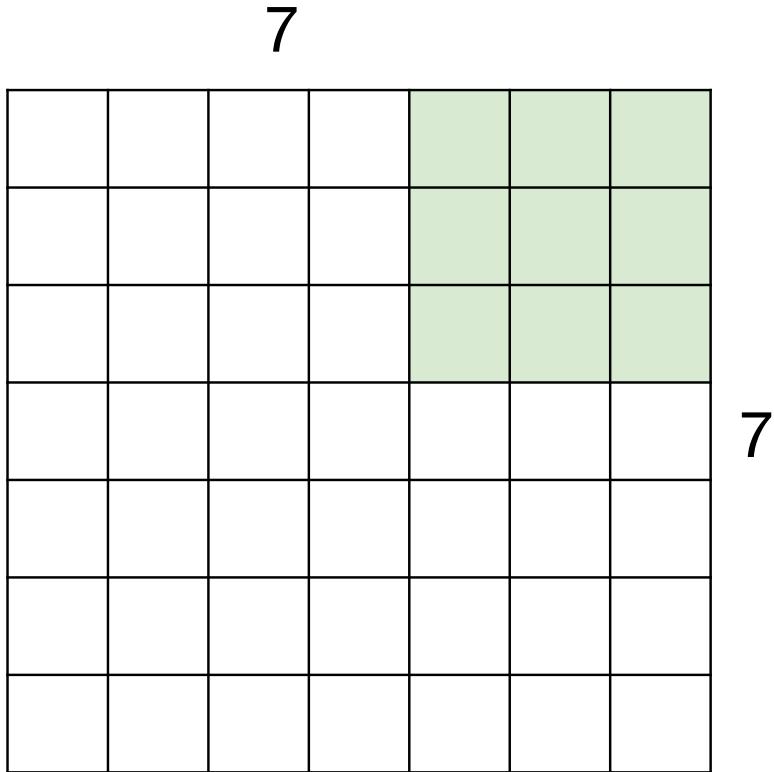
7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**

A closer look at spatial dimensions:



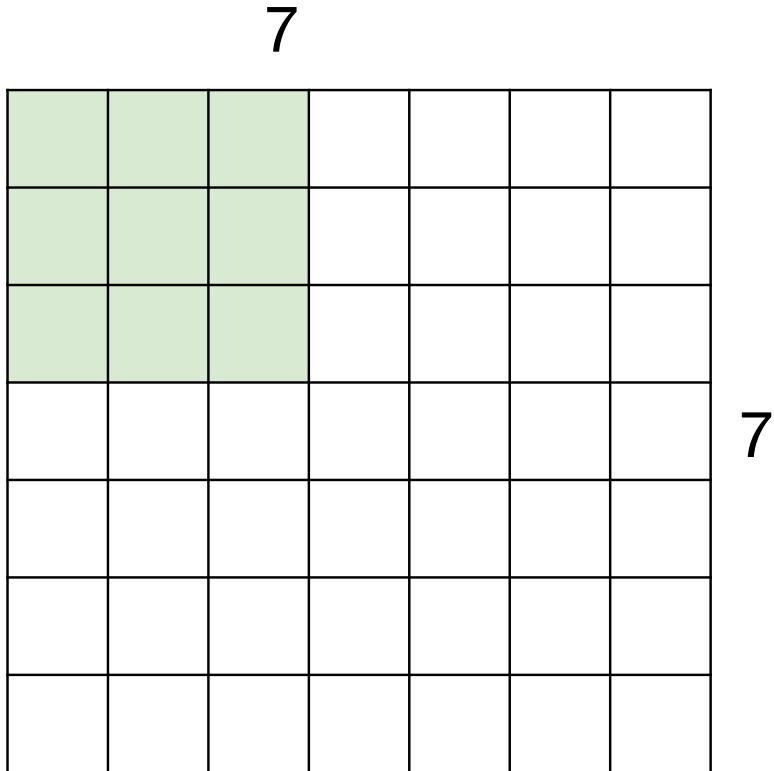
7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**

A closer look at spatial dimensions:



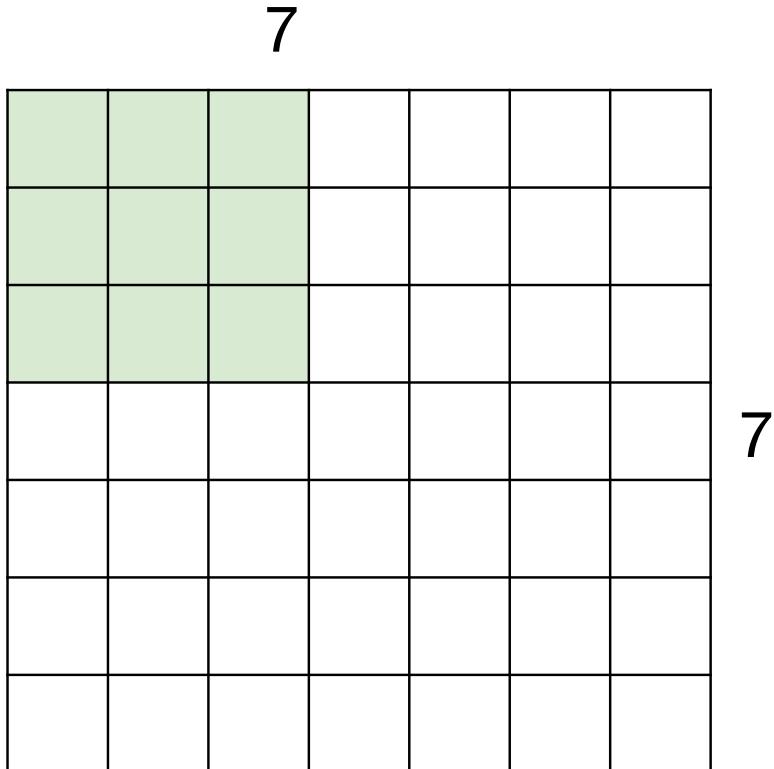
7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**
=> 3x3 output!

A closer look at spatial dimensions:



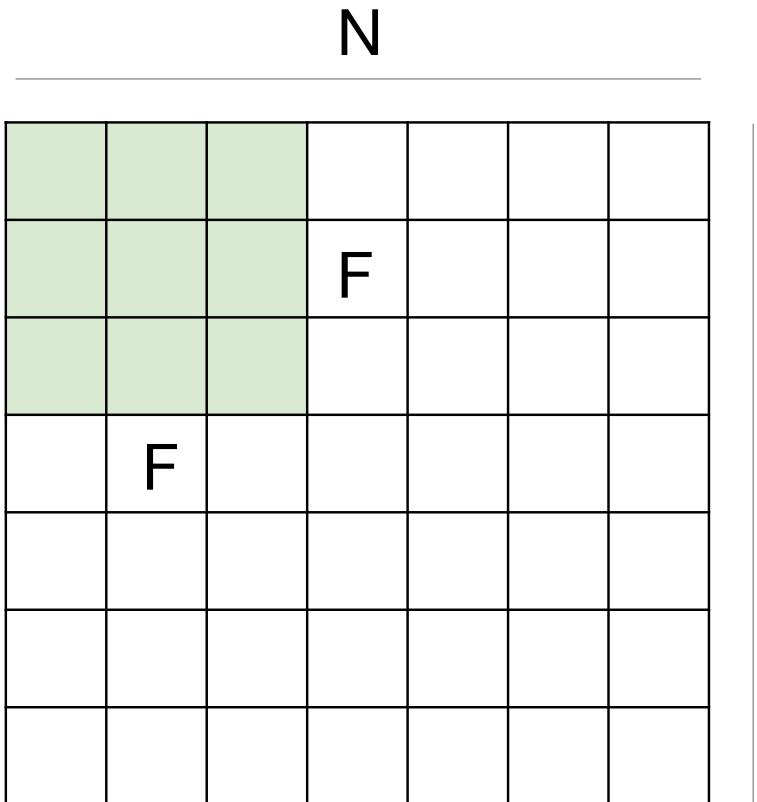
7x7 input (spatially)
assume 3x3 filter
applied **with stride 3?**

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 => $(7 - 3)/3 + 1 = 2.33 : \backslash$

In practice: Common to zero pad the border

0	0	0	0	0	0		
0							
0							
0							
0							

e.g. input 7x7

3x3 filter, applied with stride 1

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

(recall:)

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

In practice: Common to zero pad the border

0	0	0	0	0	0		
0							
0							
0							
0							

e.g. input 7x7

3x3 filter, applied with stride 1

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

7x7 output!

In practice: Common to zero pad the border

0	0	0	0	0	0		
0							
0							
0							
0							

e.g. input 7x7

3x3 filter, applied with stride 1

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

7x7 output!

in general, common to see CONV layers with stride 1, filters of size FxF, and zero-padding with $(F-1)/2$. (will preserve size spatially)

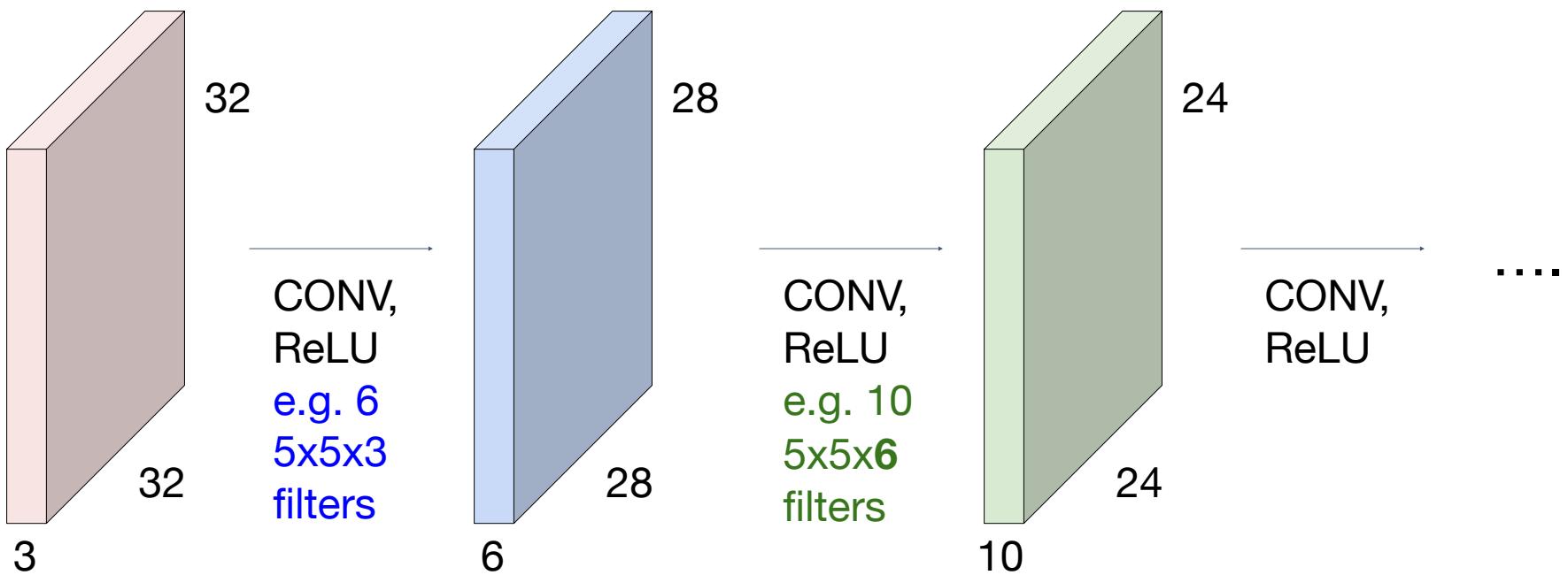
e.g. $F = 3 \Rightarrow$ zero pad with 1

$F = 5 \Rightarrow$ zero pad with 2

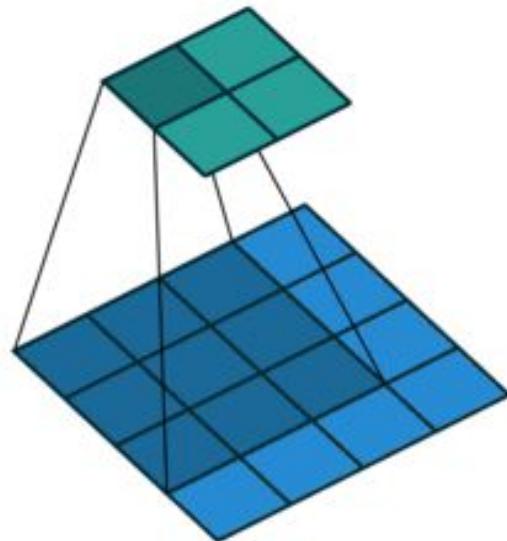
$F = 7 \Rightarrow$ zero pad with 3

Remember back to...

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



Recap: Convolution Layer



$$f = Wx$$

$$W =$$

$$\begin{pmatrix} w_{0,0} & w_{0,1} & w_{0,2} & 0 & w_{1,0} & w_{1,1} & w_{1,2} & 0 & w_{2,0} & w_{2,1} & w_{2,2} & 0 & 0 & 0 & 0 & 0 \\ 0 & w_{0,0} & w_{0,1} & w_{0,2} & 0 & w_{1,0} & w_{1,1} & w_{1,2} & 0 & w_{2,0} & w_{2,1} & w_{2,2} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & w_{0,0} & w_{0,1} & w_{0,2} & 0 & w_{1,0} & w_{1,1} & w_{1,2} & 0 & w_{2,0} & w_{2,1} & w_{2,2} & 0 \\ 0 & 0 & 0 & 0 & 0 & w_{0,0} & w_{0,1} & w_{0,2} & 0 & w_{1,0} & w_{1,1} & w_{1,2} & 0 & w_{2,0} & w_{2,1} & w_{2,2} \end{pmatrix}$$

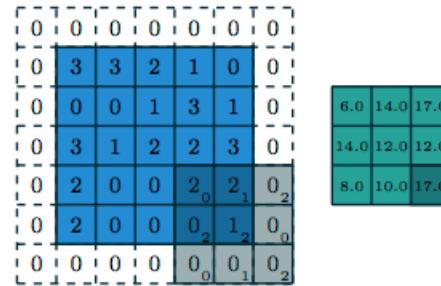
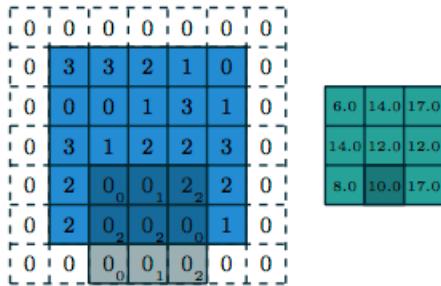
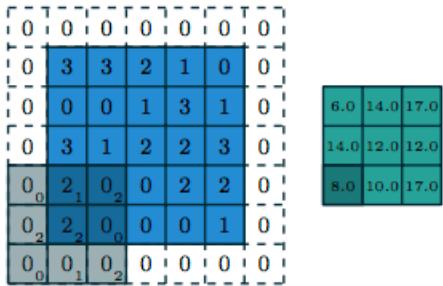
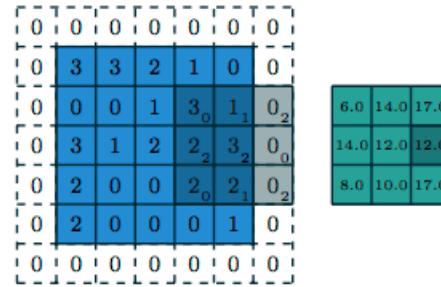
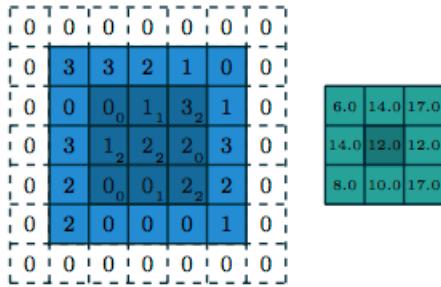
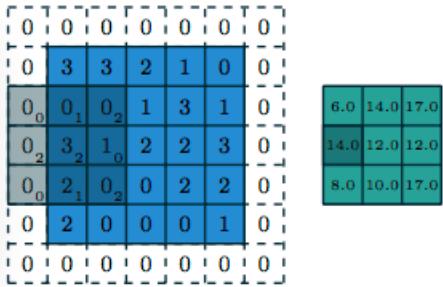
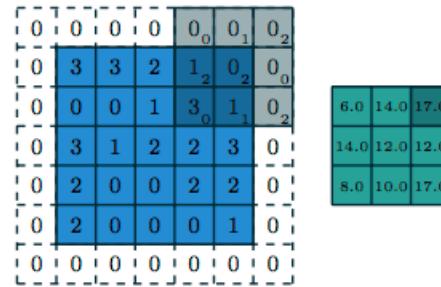
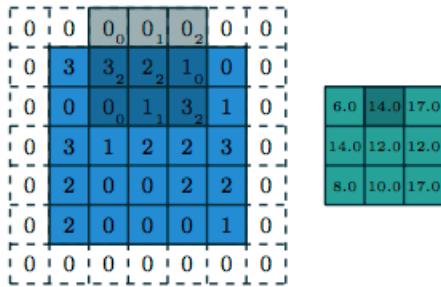
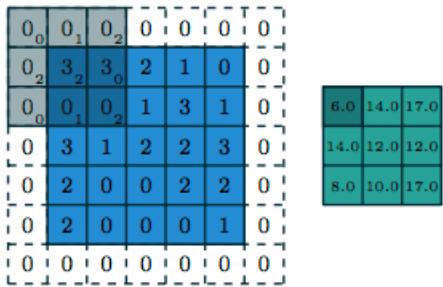
(No padding, no strides)

Convolving a 3×3 kernel over a 4×4 input using unit strides
(i.e., $i = 4$, $k = 3$, $s = 1$ and $p = 0$).

Computing the output values of a 2D discrete convolution

$i_1 = i_2 = 5$, $k_1 = k_2 = 3$, $s_1 = s_2 = 2$, and $p_1 = p_2 = 1$

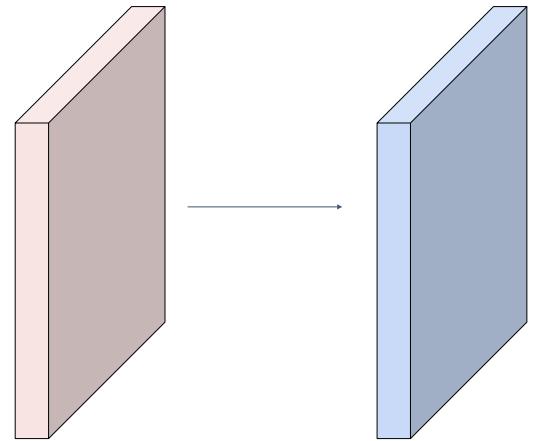
0	1	2
2	2	0
0	1	2



Examples time:

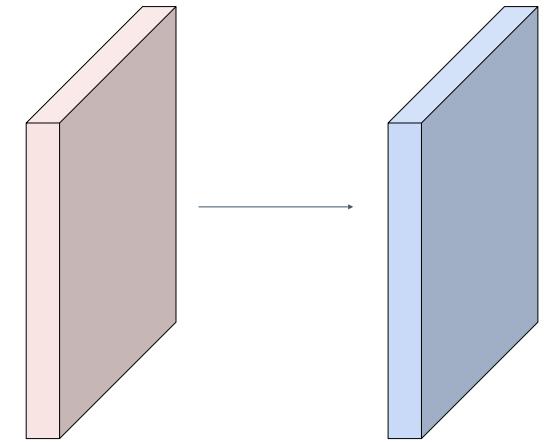
Input volume: **32x32x3**
10 5x5 filters with stride 1, pad 2

Output volume size: ?



Examples time:

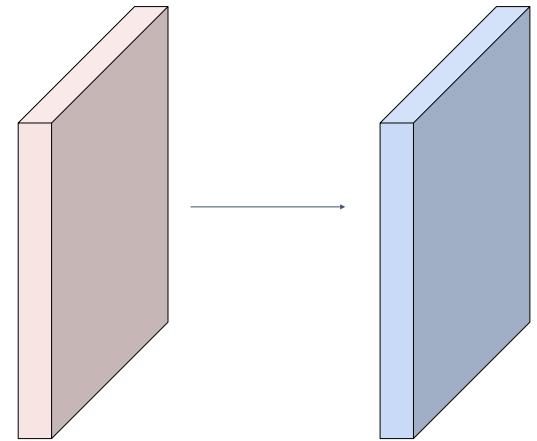
Input volume: **32x32x3**
10 5x5 filters with stride **1**, pad **2**



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

Examples time:

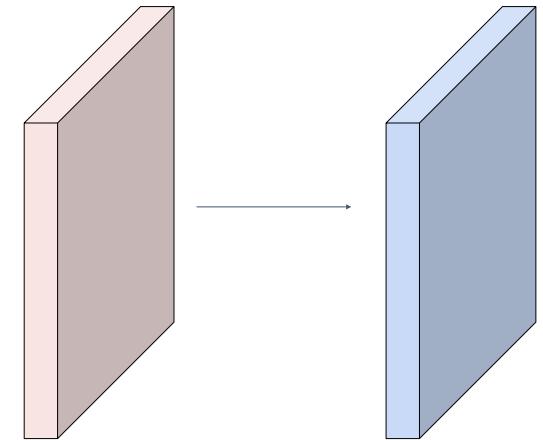
Input volume: **32x32x3**
10 5x5 filters with stride 1, pad 2



Number of parameters in this layer?

Examples

time:



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

Number of parameters in this layer?
each filter has $5^*5^*3 + 1 = 76$ params (+1 for bias)
 $=> 76^*10 = 760$

Summary. To summarize, the Conv Layer:

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

Common settings:

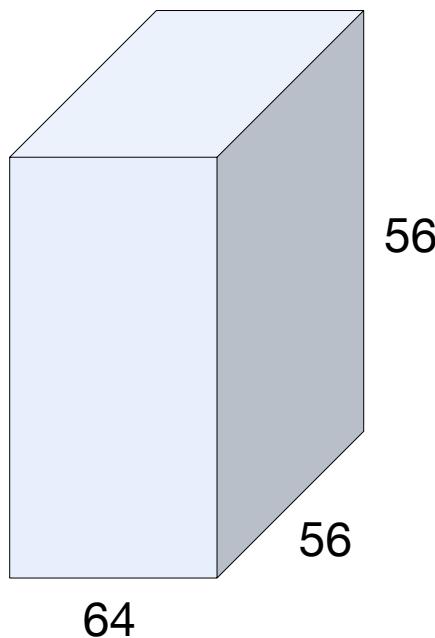
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$K = (\text{powers of } 2, \text{ e.g. } 32, 64, 128, 512)$

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

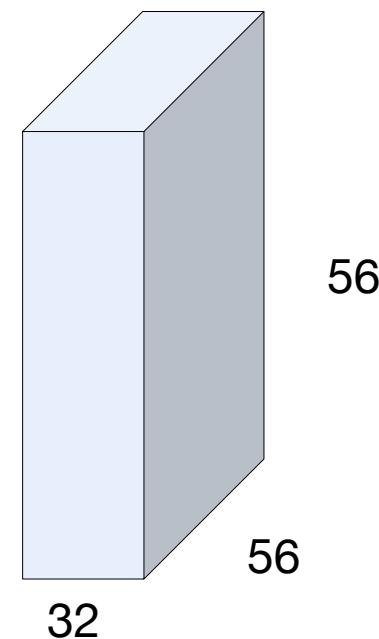
(btw, 1x1 convolution layers make perfect sense)



1x1 CONV
with 32 filters

→

(each filter has size
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`.

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 .

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 owidht` where

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

Example: CONV layer in Caffe

```
layer {
  name: "conv1"
  type: "Convolution"
  bottom: "data"
  top: "conv1"
  # 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 .

Example: CONV layer in Lasagne

Summary. To summarize, the Conv Layer:

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

```
class lasagne.layers.Conv2DLayer(incoming, num_filters, filter_size, stride=(1, 1), pad=0,
unite_biases=False, W=lasagne.init.GlorotUniform(), b=lasagne.init.Constant(0.),
nonlinearity=lasagne.nonlinearities.rectify, flip_filters=True, convolution=theano.tensor.nnet.conv2d,
**kwargs) [source]
```

2D convolutional layer

Performs a 2D convolution on its input and optionally adds a bias and applies an elementwise nonlinearity.

Parameters: incoming : a `Layer` instance or a tuple

The layer feeding into this layer, or the expected input shape. The output of this layer should be a 4D tensor, with shape
`(batch_size, num_input_channels, input_rows, input_columns)`.

`num_filters` : int

The number of learnable convolutional filters this layer has.

`filter_size` : int or iterable of int

An integer or a 2-element tuple specifying the size of the filters.

`stride` : int or iterable of int

An integer or a 2-element tuple specifying the stride of the convolution operation.

`pad` : int, iterable of int, 'full', 'same' or 'valid' (default: 0)

By default, the convolution is only computed where the input and the filter fully overlap (a valid convolution). When `stride=1`, this yields an output that is smaller than the input by `filter_size - 1`. The `pad` argument allows you to implicitly pad the input with zeros, extending the output size.

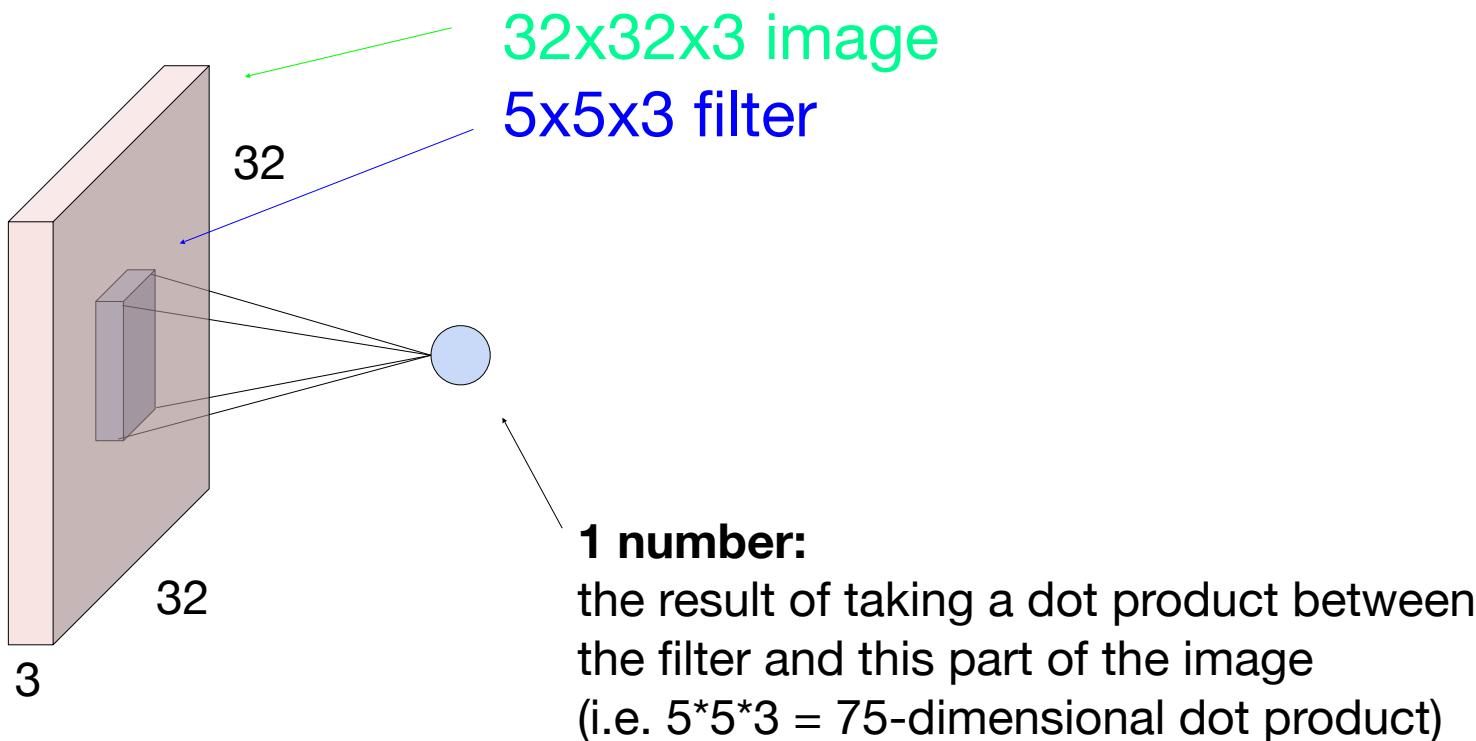
A single integer results in symmetric zero-padding of the given size on all borders, a tuple of two integers allows different symmetric padding per dimension.

'`full`' pads with one less than the filter size on both sides. This is equivalent to computing the convolution wherever the input and the filter overlap by at least one position.

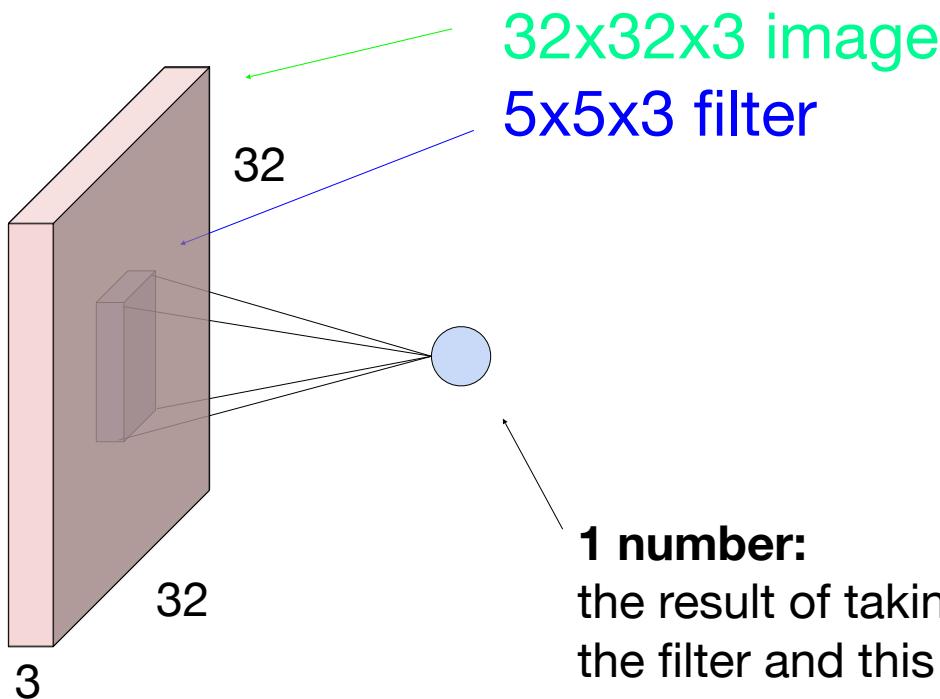
'`same`' pads with half the filter size (rounded down) on both sides. When `stride=1` this results in an output size equal to the input size. Even filter size is not supported.

'`valid`' is an alias for `0` (no padding / a valid convolution).

The brain/neuron view of CONV Layer

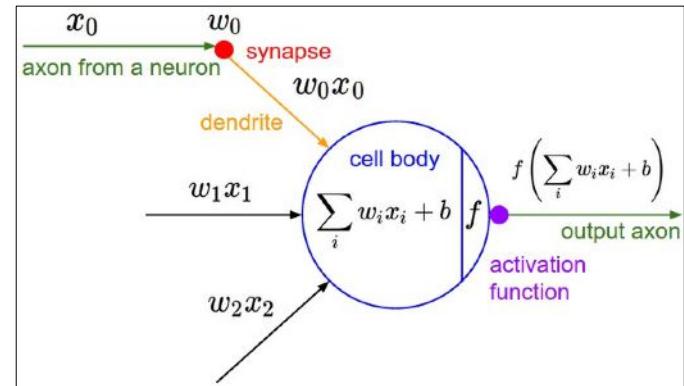


The brain/neuron view of CONV Layer



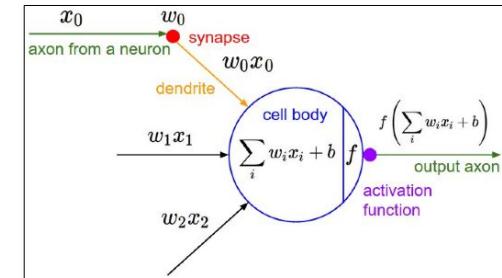
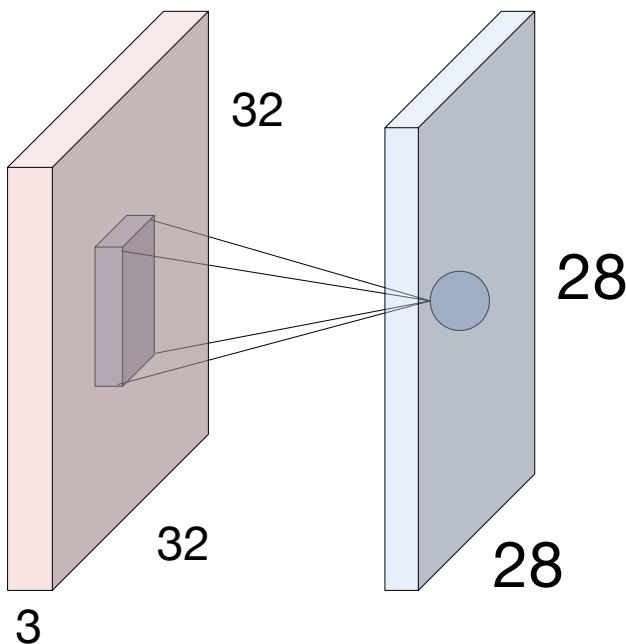
1 number:

the result of taking a dot product between
the filter and this part of the image
(i.e. $5 \times 5 \times 3 = 75$ -dimensional dot product)



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

The brain/neuron view of CONV Layer

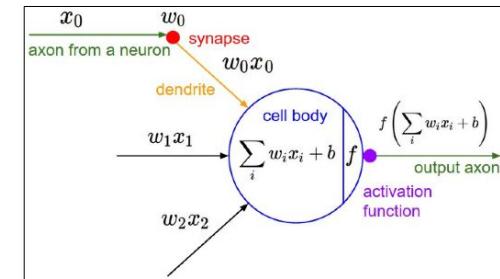
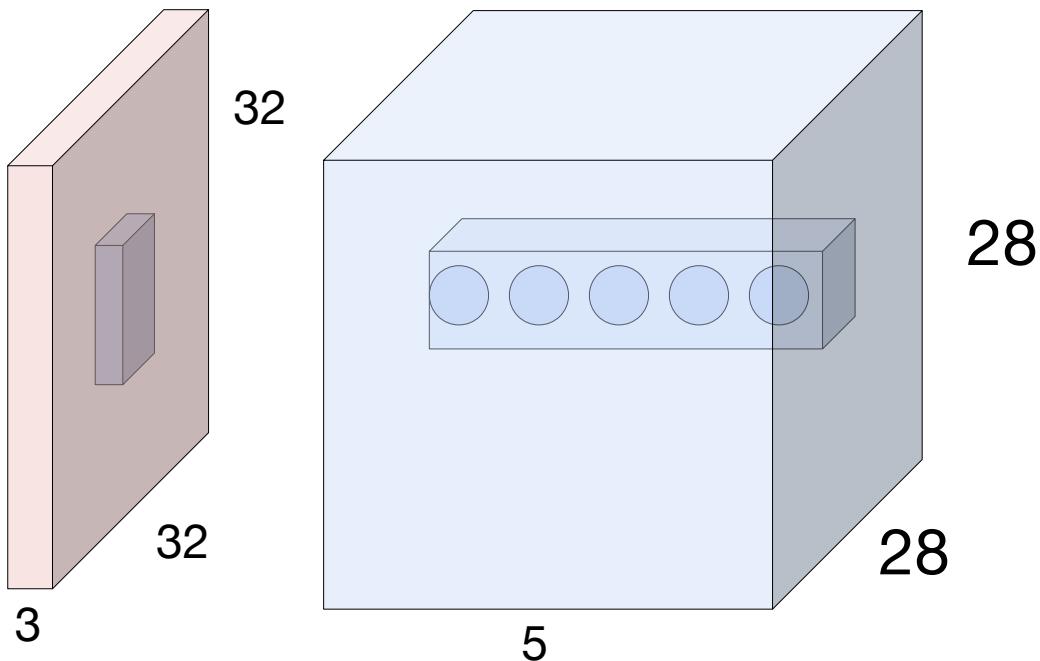


An activation map is a 28x28 sheet of neuron outputs:

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”

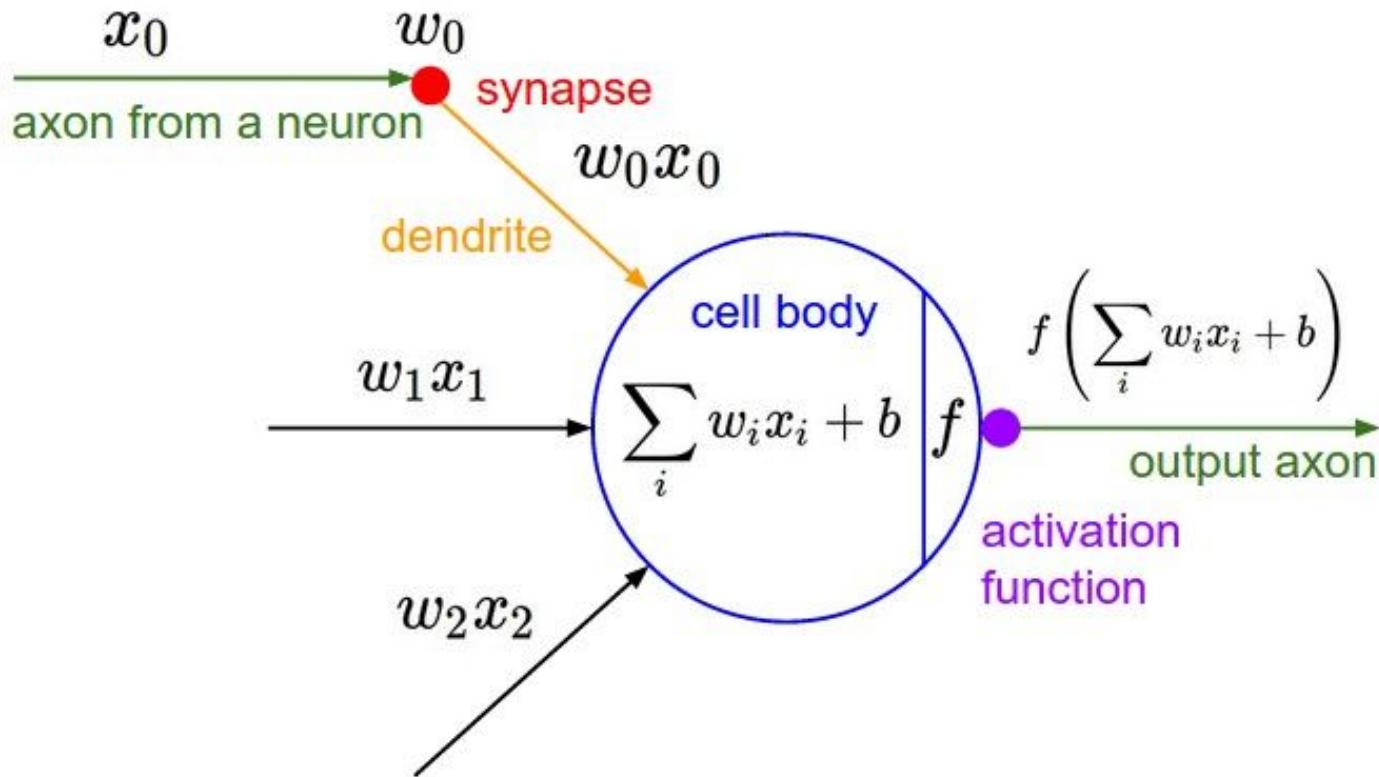
The brain/neuron view of CONV Layer



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

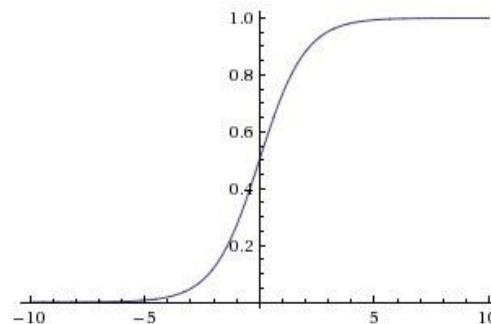
Activation Functions



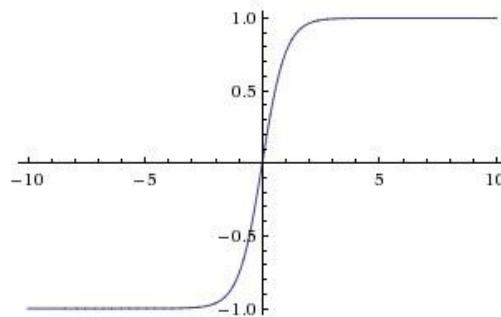
Activation Functions

Sigmoid

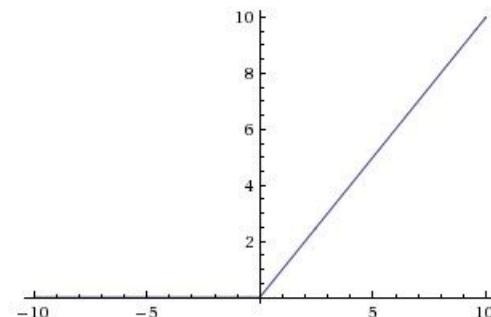
$$\sigma(x) = 1/(1 + e^{-x})$$



$$\tanh \quad \tanh(x)$$

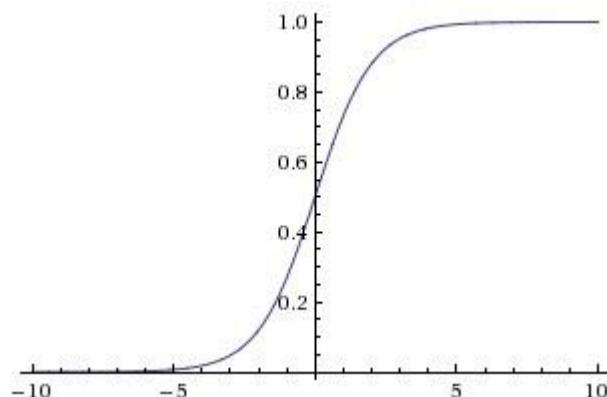


$$\text{ReLU} \quad \max(0, x)$$



Activation Functions

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



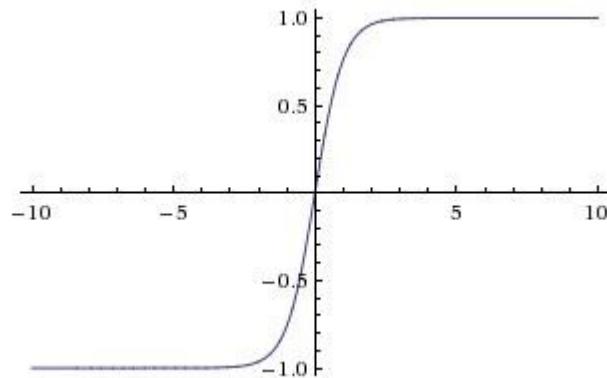
Sigmoid

- Squashes numbers to range [0,1]
- Historically popular since they have nice interpretation as a saturating “firing rate” of a neuron

3 problems:

1. Saturated neurons “kill” the gradients
2. Sigmoid outputs are not zero-centered
3. $\exp()$ is a bit compute expensive

Activation Functions



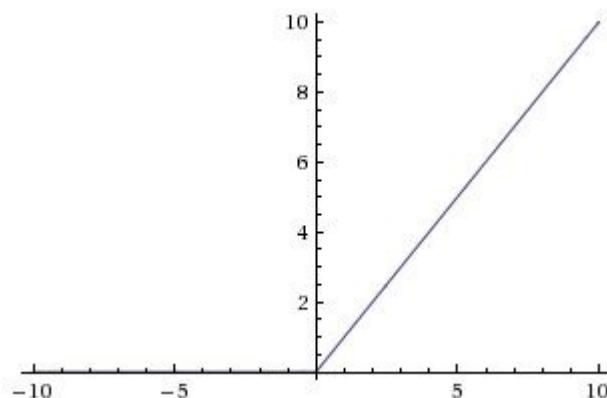
tanh(x)

- Squashes numbers to range [-1,1]
- zero centered (nice)
- still kills gradients when saturated :(

[LeCun et al., 1991]

Activation Functions

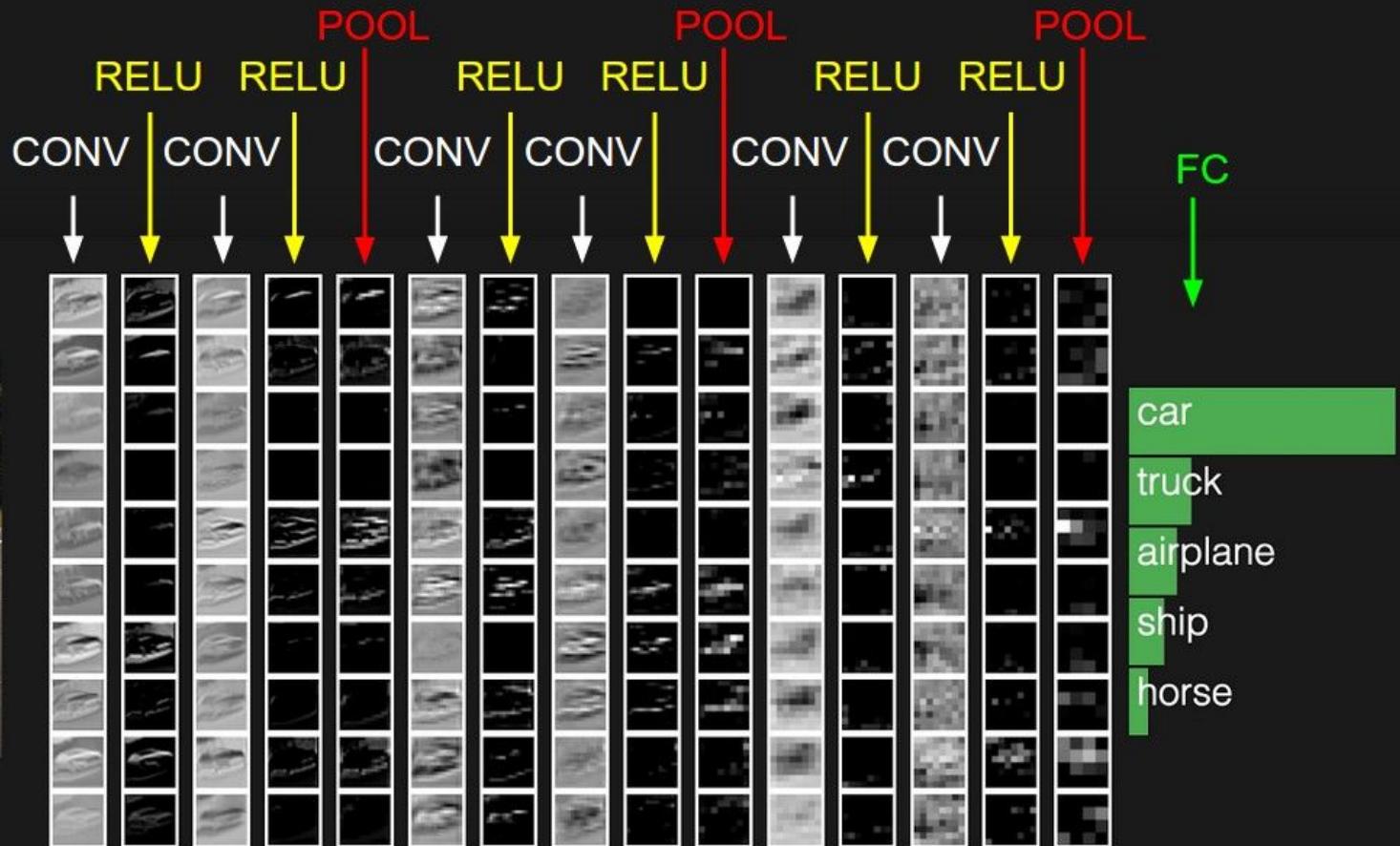
- Computes $f(x) = \max(0, x)$
- Does not saturate (in +region)
- Very computationally efficient
- Converges much faster than sigmoid/tanh in practice (e.g. 6x)



ReLU
(Rectified Linear Unit)

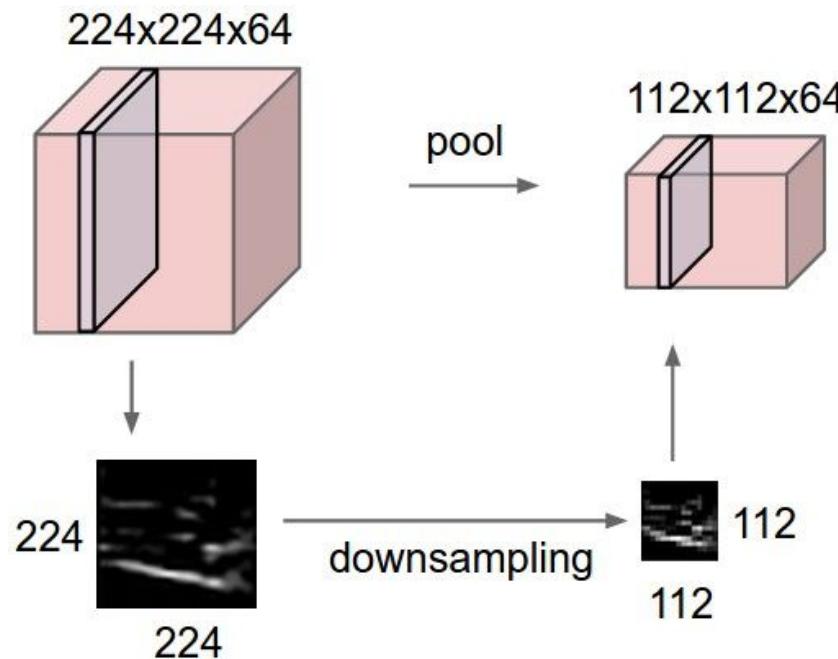
[Krizhevsky et al., 2012]

two more layers to go: POOL/FC



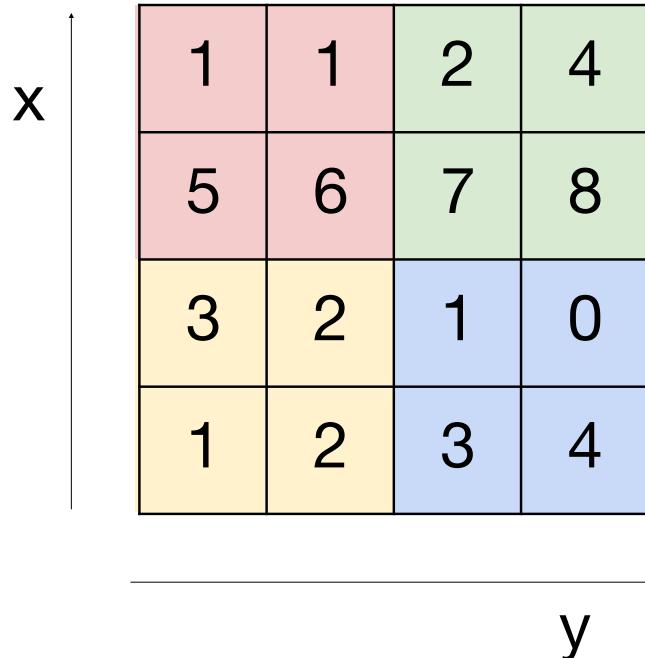
Pooling layer

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



Max Pooling

Single depth slice



max pool with 2x2 filters
and stride 2

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

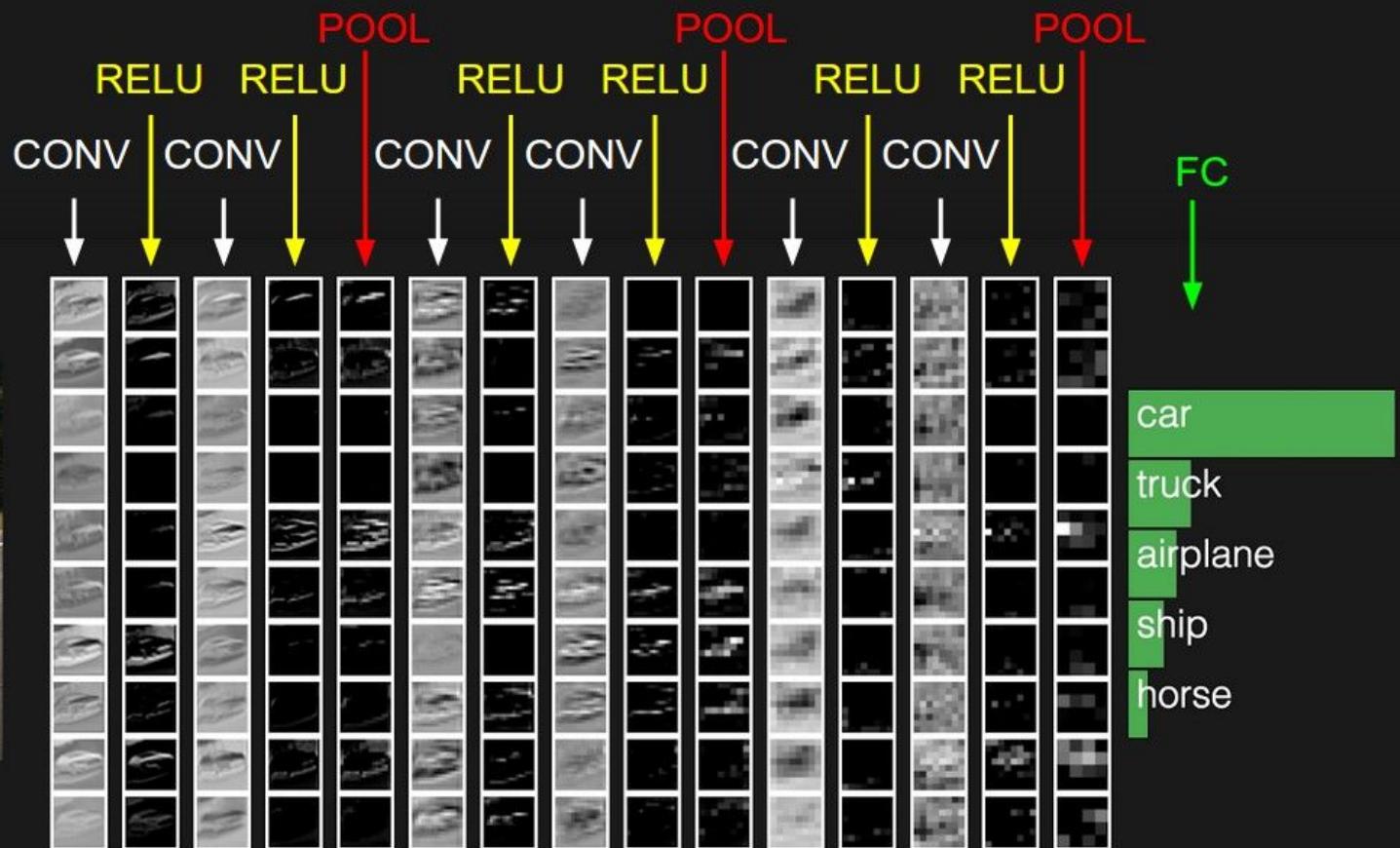
Common settings:

- 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

$$\begin{aligned}F &= 2, S = 2 \\F &= 3, S = 2\end{aligned}$$

Fully Connected Layer (FC layer)

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

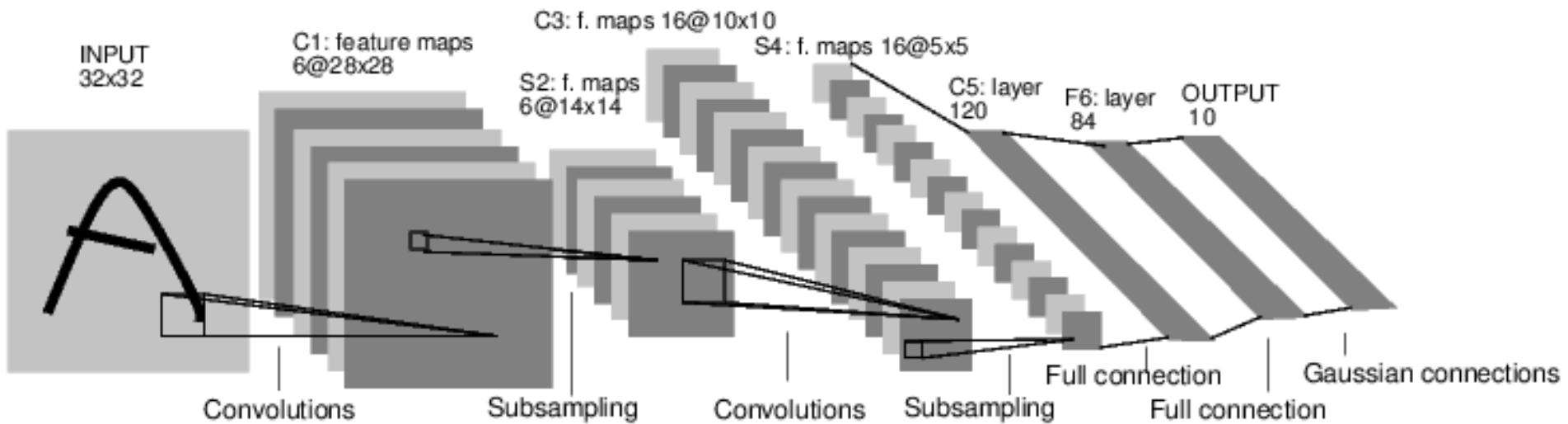


[ConvNetJS demo: training on CIFAR-10]

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

Case studies

Case Study: LeNet-5 [LeCun et al., 1998]

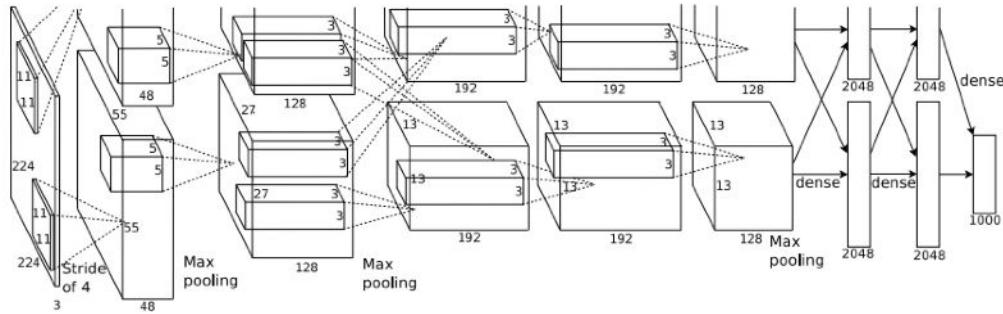


Conv filters were 5x5, applied at stride 1

Subsampling (Pooling) layers were 2x2 applied at stride 2
i.e. architecture is [CONV-POOL-CONV-POOL-CONV-FC]

Case Study: AlexNet

[Krizhevsky et al. 2012]



Input: 227x227x3 images

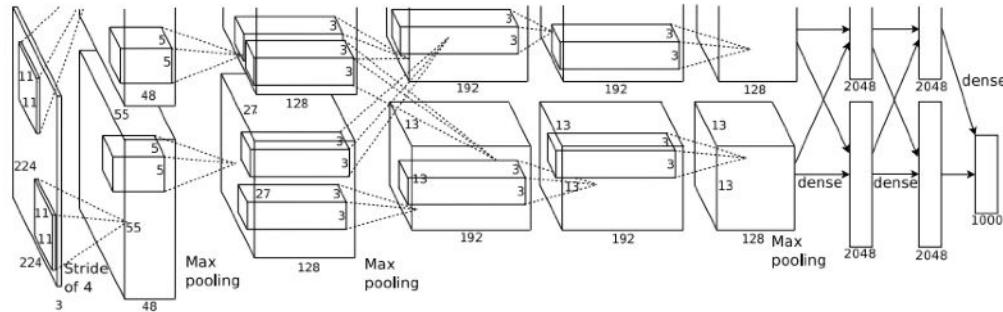
First layer (CONV1): 96 11x11 filters applied at stride 4

=>

Q: what is the output volume size? Hint: $(227-11)/4+1 = 55$

Case Study: AlexNet

[Krizhevsky et al. 2012]



Input: 227x227x3 images

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

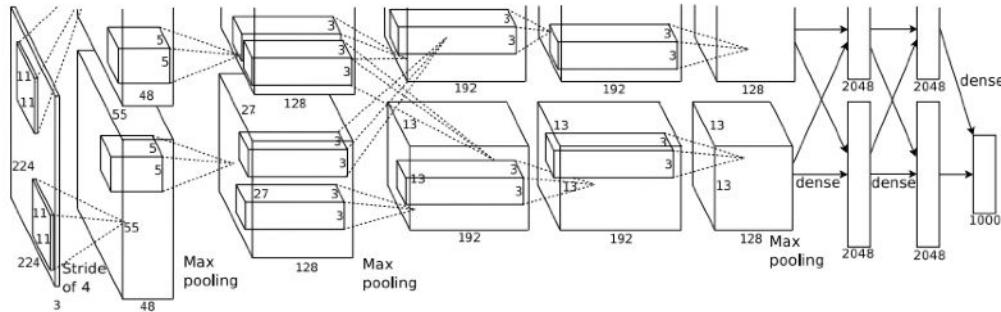
=>

Output volume **[55x55x96]**

Q: What is the total number of parameters in this layer?

Case Study: AlexNet

[Krizhevsky et al. 2012]



Input: 227x227x3 images

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

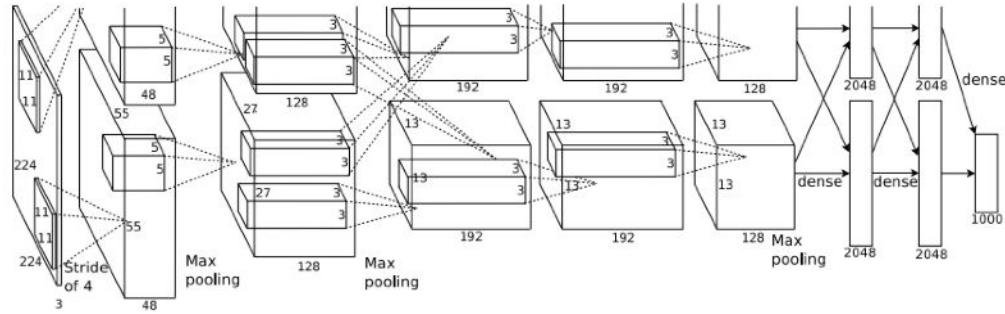
=>

Output volume **[55x55x96]**

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

Case Study: AlexNet

[Krizhevsky et al. 2012]



Input: 227x227x3 images

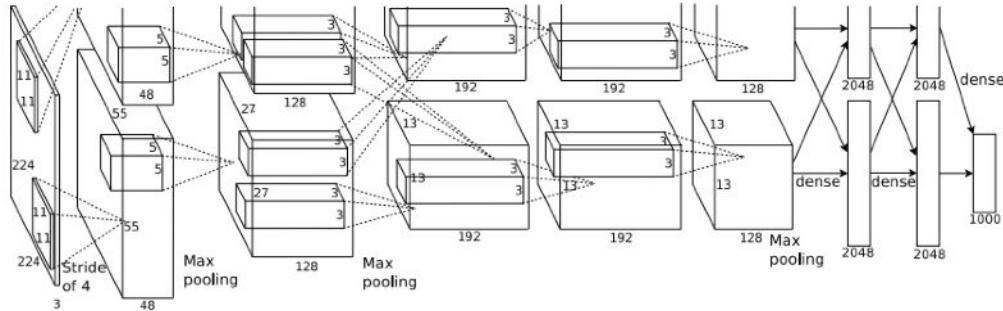
After CONV1: 55x55x96

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

Q: what is the output volume size? Hint: $(55-3)/2+1 = 27$

Case Study: AlexNet

[Krizhevsky et al. 2012]



Input: 227x227x3 images

After CONV1: 55x55x96

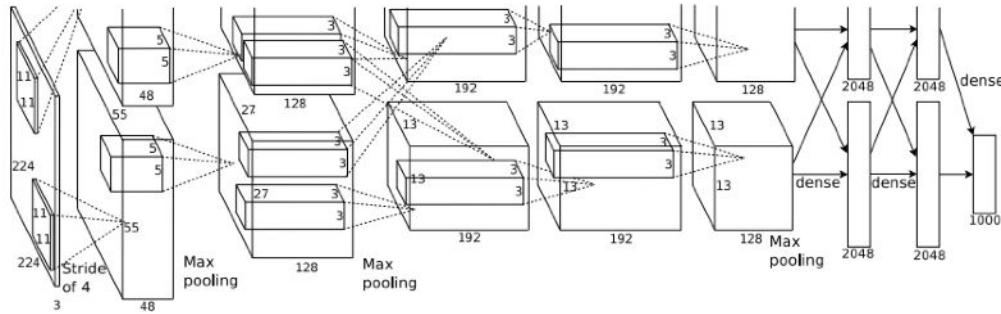
Second layer (POOL1): 3x3 filters applied at stride 2

Output volume: 27x27x96

Q: what is the number of parameters in this layer?

Case Study: AlexNet

[Krizhevsky et al. 2012]



Input: 227x227x3 images

After CONV1: 55x55x96

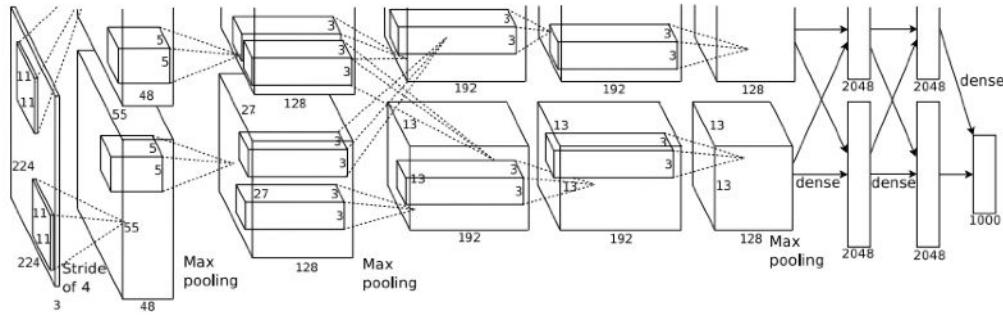
Second layer (POOL1): 3x3 filters applied at stride 2

Output volume: 27x27x96

Parameters: 0!

Case Study: AlexNet

[Krizhevsky et al. 2012]



Input: 227x227x3 images

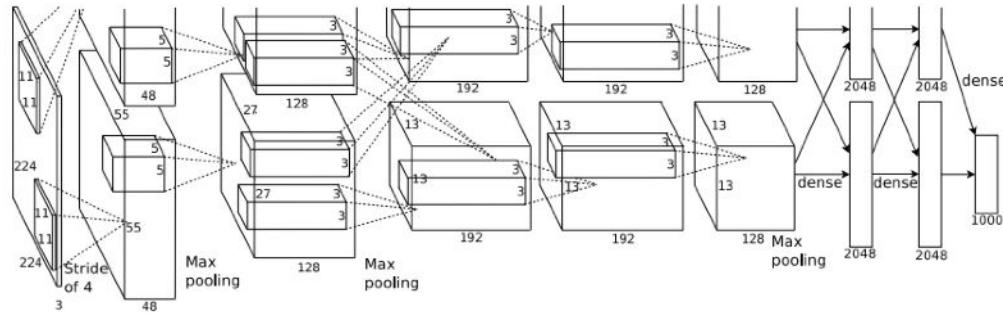
After CONV1: 55x55x96

After POOL1: 27x27x96

...

Case Study: AlexNet

[Krizhevsky et al. 2012]



Full (simplified) AlexNet architecture:

[227x227x3] INPUT

[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0

[27x27x96] MAX POOL1: 3x3 filters at stride 2

[27x27x96] NORM1: Normalization layer

[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2

[13x13x256] MAX POOL2: 3x3 filters at stride 2

[13x13x256] NORM2: Normalization layer

[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1

[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1

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

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

[4096] FC6: 4096 neurons

[4096] FC7: 4096 neurons

[1000] FC8: 1000 neurons (class scores)

Case Study: AlexNet

[Krizhevsky et al. 2012]

Full (simplified) AlexNet architecture:

[227x227x3] INPUT

[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0

[27x27x96] MAX POOL1: 3x3 filters at stride 2

[27x27x96] NORM1: Normalization layer

[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2

[13x13x256] MAX POOL2: 3x3 filters at stride 2

[13x13x256] NORM2: Normalization layer

[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1

[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1

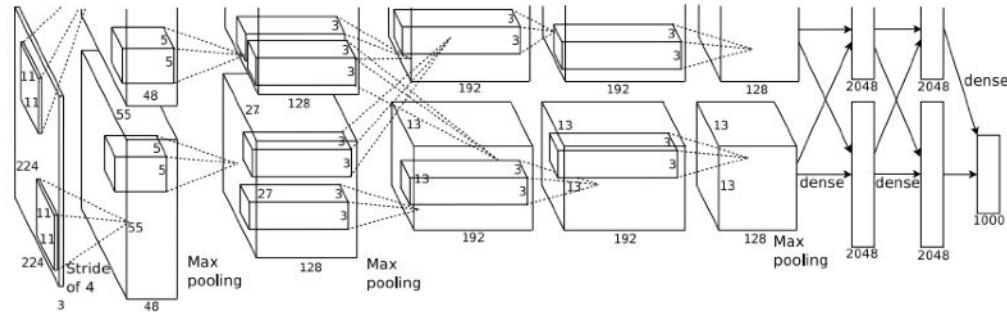
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1

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

[4096] FC6: 4096 neurons

[4096] FC7: 4096 neurons

[1000] FC8: 1000 neurons (class scores)

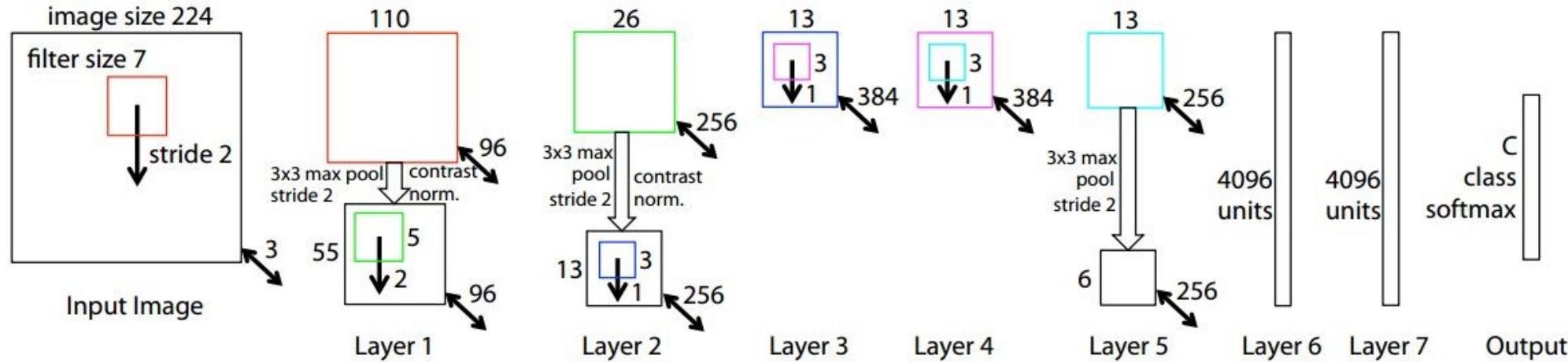


Details/Retrospectives:

- first use of ReLU
- used Norm layers (not common anymore)
- heavy data augmentation
- dropout 0.5
- batch size 128
- SGD Momentum 0.9
- Learning rate 1e-2, reduced by 10 manually when val accuracy plateaus
- L2 weight decay 5e-4
- 7 CNN ensemble: 18.2% -> 15.4%

Case Study: ZFNet

[Zeiler and Fergus, 2013]



AlexNet but:

CONV1: change from (11x11 stride 4) to (7x7 stride 2)

CONV3,4,5: instead of 384, 384, 256 filters use 512, 1024, 512

ImageNet top 5 error: 15.4% -> 14.8%

Case Study: VGGNet

[Simonyan and Zisserman, 2014]

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

best model

11.2% top 5 error in ILSVRC 2013

->

7.3% top 5 error

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 LRN	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 conv1-256	conv3-256 conv3-256 conv3-256 conv3-256
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 conv1-512	conv3-512 conv3-512 conv3-512	conv3-512 conv3-512 conv3-512 conv3-512
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 conv1-512	conv3-512 conv3-512 conv3-512	conv3-512 conv3-512 conv3-512 conv3-512
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

Table 2: Number of parameters (in millions).

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

(not counting biases)

INPUT: [224x224x3] memory: $224 \times 224 \times 3 = 150K$ params: 0

CONV3-64: [224x224x64] memory: $224 \times 224 \times 64 = 3.2M$ params: $(3 \times 3 \times 3) \times 64 = 1,728$

CONV3-64: [224x224x64] memory: $224 \times 224 \times 64 = 3.2M$ params: $(3 \times 3 \times 64) \times 64 = 36,864$

POOL2: [112x112x64] memory: $112 \times 112 \times 64 = 800K$ params: 0

CONV3-128: [112x112x128] memory: $112 \times 112 \times 128 = 1.6M$ params: $(3 \times 3 \times 64) \times 128 = 73,728$

CONV3-128: [112x112x128] memory: $112 \times 112 \times 128 = 1.6M$ params: $(3 \times 3 \times 128) \times 128 = 147,456$

POOL2: [56x56x128] memory: $56 \times 56 \times 128 = 400K$ params: 0

CONV3-256: [56x56x256] memory: $56 \times 56 \times 256 = 800K$ params: $(3 \times 3 \times 128) \times 256 = 294,912$

CONV3-256: [56x56x256] memory: $56 \times 56 \times 256 = 800K$ params: $(3 \times 3 \times 256) \times 256 = 589,824$

CONV3-256: [56x56x256] memory: $56 \times 56 \times 256 = 800K$ params: $(3 \times 3 \times 256) \times 256 = 589,824$

POOL2: [28x28x256] memory: $28 \times 28 \times 256 = 200K$ params: 0

CONV3-512: [28x28x512] memory: $28 \times 28 \times 512 = 400K$ params: $(3 \times 3 \times 256) \times 512 = 1,179,648$

CONV3-512: [28x28x512] memory: $28 \times 28 \times 512 = 400K$ params: $(3 \times 3 \times 512) \times 512 = 2,359,296$

CONV3-512: [28x28x512] memory: $28 \times 28 \times 512 = 400K$ params: $(3 \times 3 \times 512) \times 512 = 2,359,296$

POOL2: [14x14x512] memory: $14 \times 14 \times 512 = 100K$ params: 0

CONV3-512: [14x14x512] memory: $14 \times 14 \times 512 = 100K$ params: $(3 \times 3 \times 512) \times 512 = 2,359,296$

CONV3-512: [14x14x512] memory: $14 \times 14 \times 512 = 100K$ params: $(3 \times 3 \times 512) \times 512 = 2,359,296$

CONV3-512: [14x14x512] memory: $14 \times 14 \times 512 = 100K$ params: $(3 \times 3 \times 512) \times 512 = 2,359,296$

POOL2: [7x7x512] memory: $7 \times 7 \times 512 = 25K$ params: 0

FC: [1x1x4096] memory: 4096 params: $7 \times 7 \times 512 \times 4096 = 102,760,448$

FC: [1x1x4096] memory: 4096 params: $4096 \times 4096 = 16,777,216$

FC: [1x1x1000] memory: 1000 params: $4096 \times 1000 = 4,096,000$

ConvNet Configuration			
B	C	D	E
13 weight layers	16 weight layers	16 weight layers	19 weight layers
put (224 × 224 RGB image)			
conv3-64	conv3-64	conv3-64	conv3-64
conv3-64	conv3-64	conv3-64	conv3-64
maxpool			
conv3-128	conv3-128	conv3-128	conv3-128
conv3-128	conv3-128	conv3-128	conv3-128
maxpool			
conv3-256	conv3-256	conv3-256	conv3-256
conv3-256	conv3-256	conv3-256	conv3-256
conv1-256		conv3-256	conv3-256
maxpool			
conv3-512	conv3-512	conv3-512	conv3-512
conv3-512	conv3-512	conv3-512	conv3-512
conv1-512		conv3-512	conv3-512
maxpool			
conv3-512	conv3-512	conv3-512	conv3-512
conv3-512	conv3-512	conv3-512	conv3-512
conv1-512		conv3-512	conv3-512
maxpool			
FC-4096			
FC-4096			
FC-1000			
soft-max			

(not counting biases)

INPUT: [224x224x3] memory: $224 \times 224 \times 3 = 150K$ params: 0

CONV3-64: [224x224x64] memory: $224 \times 224 \times 64 = 3.2M$ params: $(3 \times 3 \times 3) \times 64 = 1,728$

CONV3-64: [224x224x64] memory: $224 \times 224 \times 64 = 3.2M$ params: $(3 \times 3 \times 64) \times 64 = 36,864$

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CONV3-512: [28x28x512] memory: $28 \times 28 \times 512 = 400K$ params: $(3 \times 3 \times 512) \times 512 = 2,359,296$

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POOL2: [14x14x512] memory: $14 \times 14 \times 512 = 100K$ params: 0

CONV3-512: [14x14x512] memory: $14 \times 14 \times 512 = 100K$ params: $(3 \times 3 \times 512) \times 512 = 2,359,296$

CONV3-512: [14x14x512] memory: $14 \times 14 \times 512 = 100K$ params: $(3 \times 3 \times 512) \times 512 = 2,359,296$

CONV3-512: [14x14x512] memory: $14 \times 14 \times 512 = 100K$ params: $(3 \times 3 \times 512) \times 512 = 2,359,296$

POOL2: [7x7x512] memory: $7 \times 7 \times 512 = 25K$ params: 0

FC: [1x1x4096] memory: 4096 params: $7 \times 7 \times 512 \times 4096 = 102,760,448$

FC: [1x1x4096] memory: 4096 params: $4096 \times 4096 = 16,777,216$

FC: [1x1x1000] memory: 1000 params: $4096 \times 1000 = 4,096,000$

ConvNet Configuration			
B	C	D	E
13 weight layers	16 weight layers	16 weight layers	19 weight layers
put (224 × 224 RGB image)			
conv3-64	conv3-64	conv3-64	conv3-64
conv3-64	conv3-64	conv3-64	conv3-64
		maxpool	
conv3-128	conv3-128	conv3-128	conv3-128
conv3-128	conv3-128	conv3-128	conv3-128
		maxpool	
conv3-256	conv3-256	conv3-256	conv3-256
conv3-256	conv3-256	conv3-256	conv3-256
conv1-256			conv3-256
		maxpool	
conv3-512	conv3-512	conv3-512	conv3-512
conv3-512	conv3-512	conv3-512	conv3-512
conv1-512			conv3-512
		maxpool	
conv3-512	conv3-512	conv3-512	conv3-512
conv3-512	conv3-512	conv3-512	conv3-512
conv1-512			conv3-512
		maxpool	
FC-4096			
FC-4096			
FC-1000			
soft-max			

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

TOTAL params: 138M parameters

INPUT: [224x224x3] memory: $224 \times 224 \times 3 = 150K$ params: 0
 CONV3-64: [224x224x64] memory: $224 \times 224 \times 64 = 3.2M$ params: $(3 \times 3 \times 3) \times 64 = 1,728$
 CONV3-64: [224x224x64] memory: $224 \times 224 \times 64 = 3.2M$ params: $(3 \times 3 \times 64) \times 64 = 36,864$
 POOL2: [112x112x64] memory: $112 \times 112 \times 64 = 800K$ params: 0
 CONV3-128: [112x112x128] memory: $112 \times 112 \times 128 = 1.6M$ params: $(3 \times 3 \times 64) \times 128 = 73,728$
 CONV3-128: [112x112x128] memory: $112 \times 112 \times 128 = 1.6M$ params: $(3 \times 3 \times 128) \times 128 = 147,456$
 POOL2: [56x56x128] memory: $56 \times 56 \times 128 = 400K$ params: 0
 CONV3-256: [56x56x256] memory: $56 \times 56 \times 256 = 800K$ params: $(3 \times 3 \times 128) \times 256 = 294,912$
 CONV3-256: [56x56x256] memory: $56 \times 56 \times 256 = 800K$ params: $(3 \times 3 \times 256) \times 256 = 589,824$
 CONV3-256: [56x56x256] memory: $56 \times 56 \times 256 = 800K$ params: $(3 \times 3 \times 256) \times 256 = 589,824$
 POOL2: [28x28x256] memory: $28 \times 28 \times 256 = 200K$ params: 0
 CONV3-512: [28x28x512] memory: $28 \times 28 \times 512 = 400K$ params: $(3 \times 3 \times 256) \times 512 = 1,179,648$
 CONV3-512: [28x28x512] memory: $28 \times 28 \times 512 = 400K$ params: $(3 \times 3 \times 512) \times 512 = 2,359,296$
 CONV3-512: [28x28x512] memory: $28 \times 28 \times 512 = 400K$ params: $(3 \times 3 \times 512) \times 512 = 2,359,296$
 POOL2: [14x14x512] memory: $14 \times 14 \times 512 = 100K$ params: 0
 CONV3-512: [14x14x512] memory: $14 \times 14 \times 512 = 100K$ params: $(3 \times 3 \times 512) \times 512 = 2,359,296$
 CONV3-512: [14x14x512] memory: $14 \times 14 \times 512 = 100K$ params: $(3 \times 3 \times 512) \times 512 = 2,359,296$
 CONV3-512: [14x14x512] memory: $14 \times 14 \times 512 = 100K$ params: $(3 \times 3 \times 512) \times 512 = 2,359,296$
 POOL2: [7x7x512] memory: $7 \times 7 \times 512 = 25K$ params: 0
 FC: [1x1x4096] memory: 4096 params: $7 \times 7 \times 512 \times 4096 = 102,760,448$
 FC: [1x1x4096] memory: 4096 params: $4096 \times 4096 = 16,777,216$
 FC: [1x1x1000] memory: 1000 params: $4096 \times 1000 = 4,096,000$

(not counting biases)

Note:

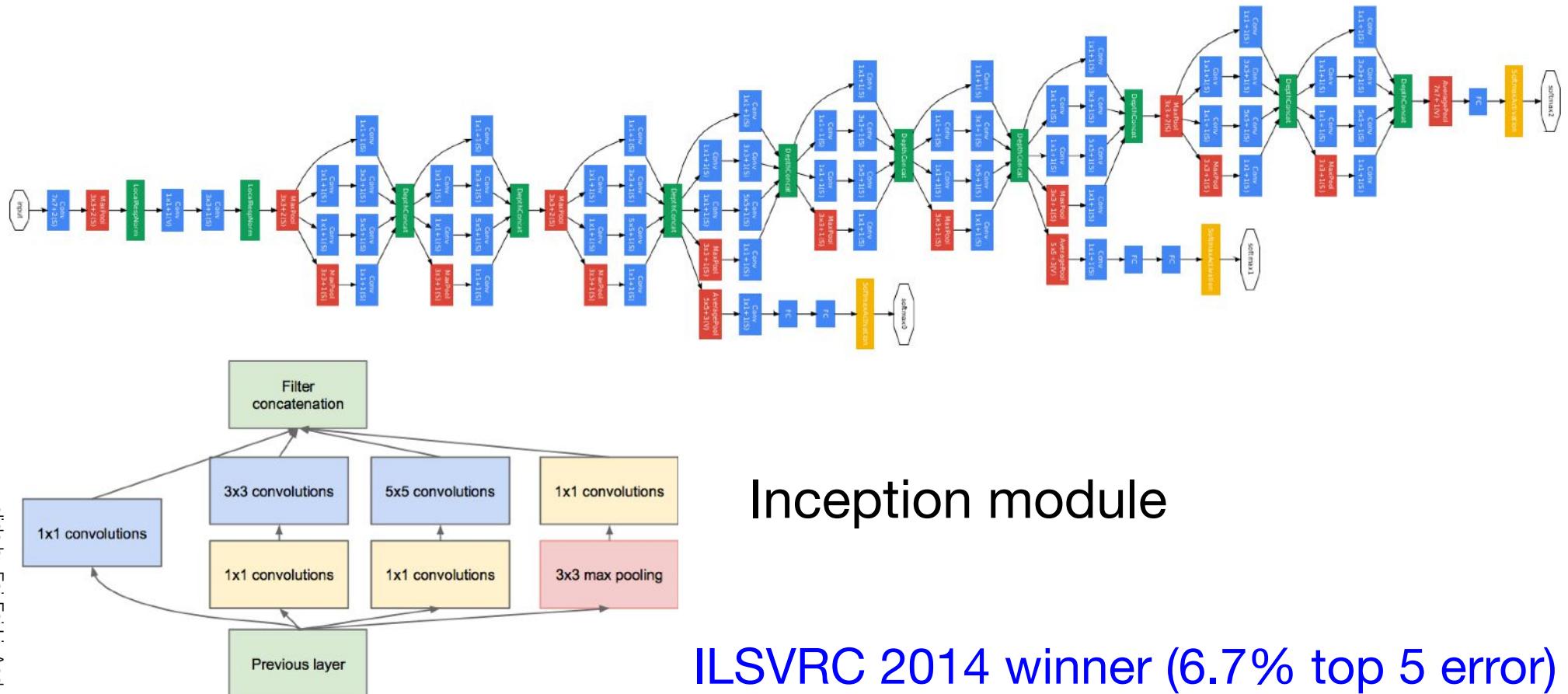
Most memory is in early CONV

Most params are in late FC

TOTAL memory: $24M \times 4 \text{ bytes} \approx 93\text{MB} / \text{image}$ (only forward! ~ 2 for bwd)
 TOTAL params: 138M parameters

Case Study: GoogLeNet

[Szegedy et al., 2014]



Case Study: ResNet

[He et al., 2015]

ILSVRC 2015 winner
(3.6% top 5 error)

Microsoft
Research

MSRA @ ILSVRC & COCO 2015 Competitions

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

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

*improvements are relative numbers



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

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

Case Study: ResNet

[He et al., 2015]

ILSVRC 2015 winner
(3.6% top 5 error)

Revolution of Depth

AlexNet, 8 layers
(ILSVRC 2012)



VGG, 19 layers
(ILSVRC 2014)



ResNet, 152 layers
(ILSVRC 2015)



2-3 weeks of training
on 8 GPU machine

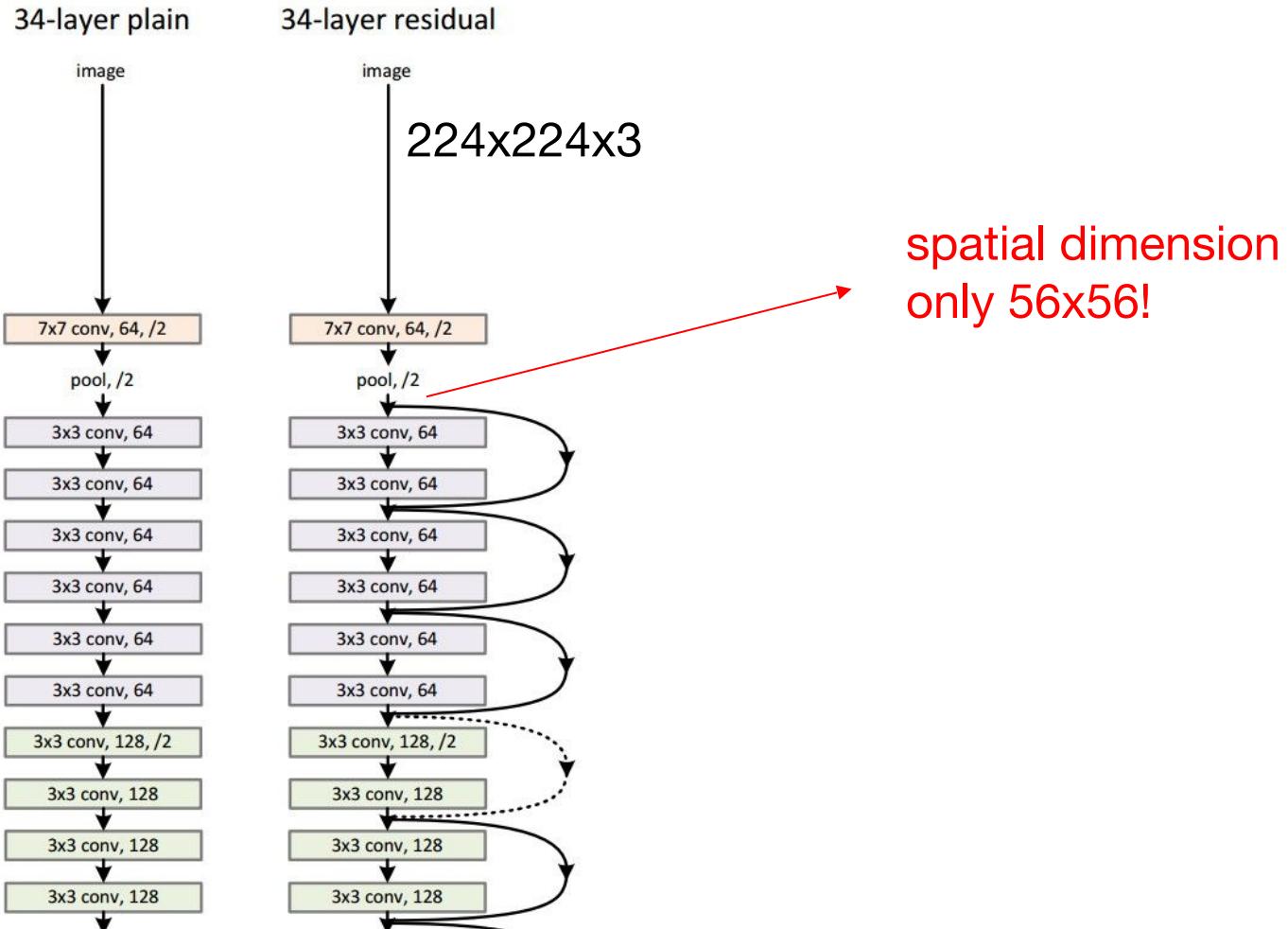
at runtime: faster
than a VGGNet! (even
though it has 8x
more layers)



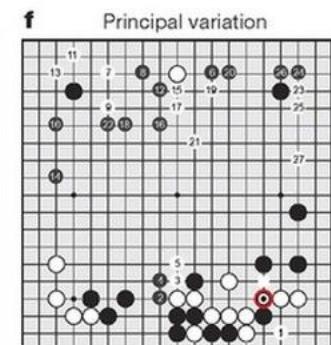
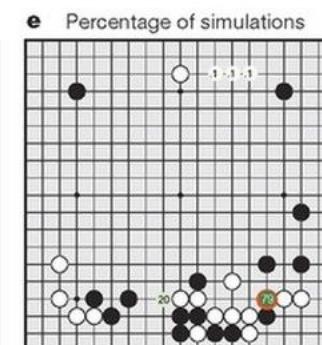
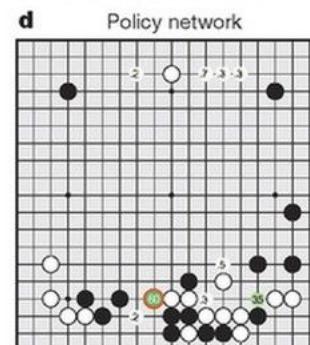
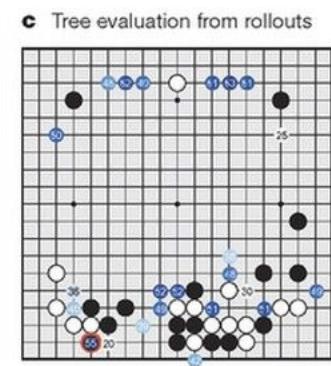
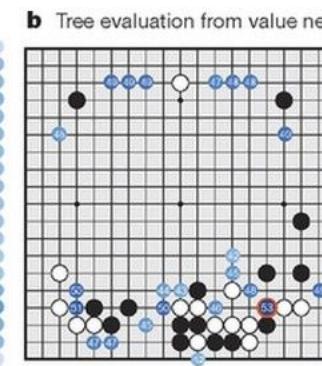
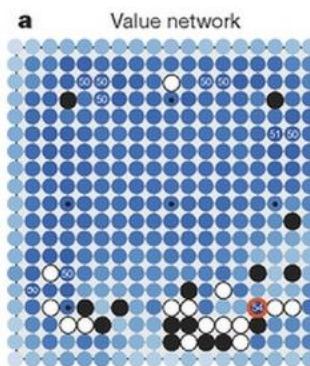
Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". arXiv 2015.

(slide from Kaiming He's recent presentation)

Case Study: ResNet [He et al., 2015]



Case Study Bonus: DeepMind's AlphaGo



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

policy network:

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

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

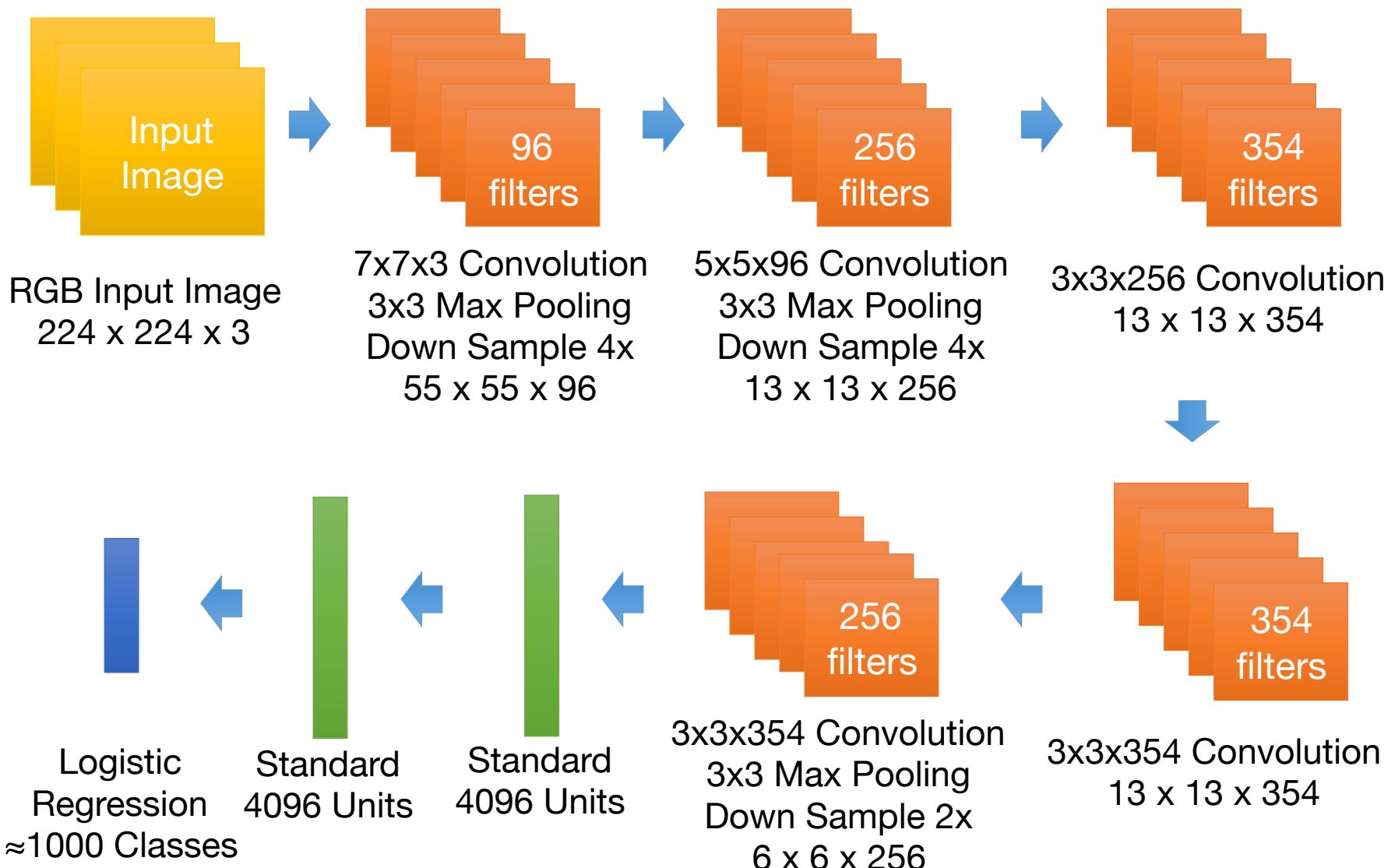
CONV2..12: 192 3×3 filters, stride 1, pad 1 => [$19 \times 19 \times 192$]

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

Summary

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

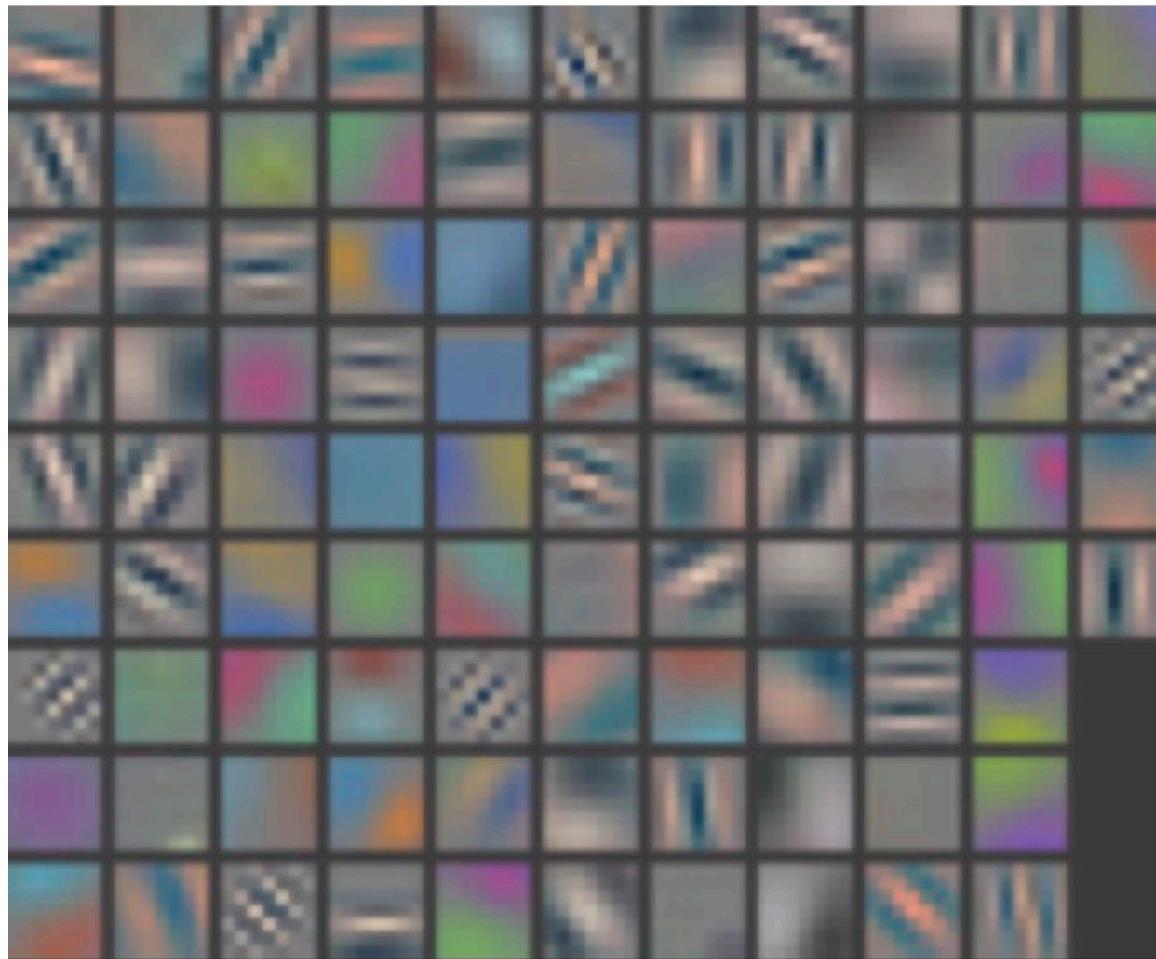
Understanding ConvNets



<http://www.image-net.org/>

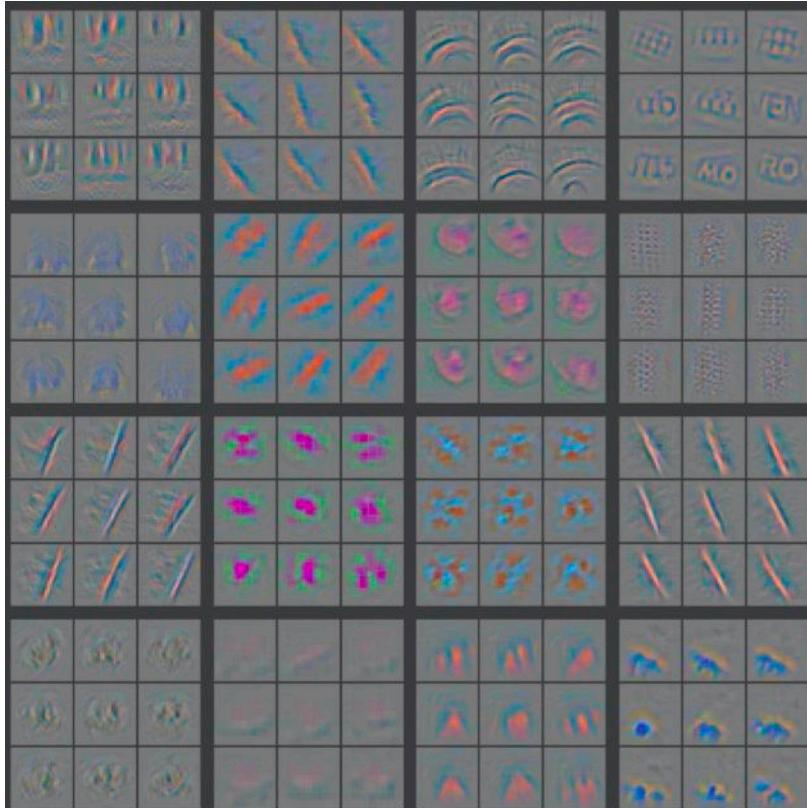
<http://cs.nyu.edu/~fergus/papers/zeilerECCV2014.pdf>
http://cs.nyu.edu/~fergus/presentations/nips2013_final.pdf

Visualizing CNN (Layer 1)

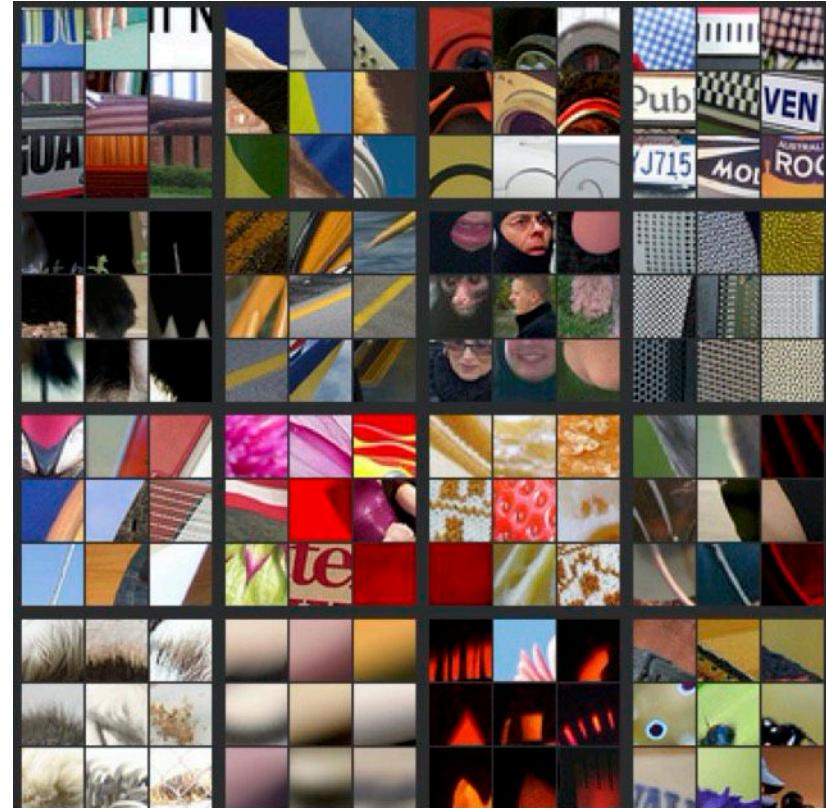


<http://cs.nyu.edu/~fergus/papers/zeilerECCV2014.pdf>
http://cs.nyu.edu/~fergus/presentations/nips2013_final.pdf

Visualizing CNN (Layer 2)



Part that Triggered Filter

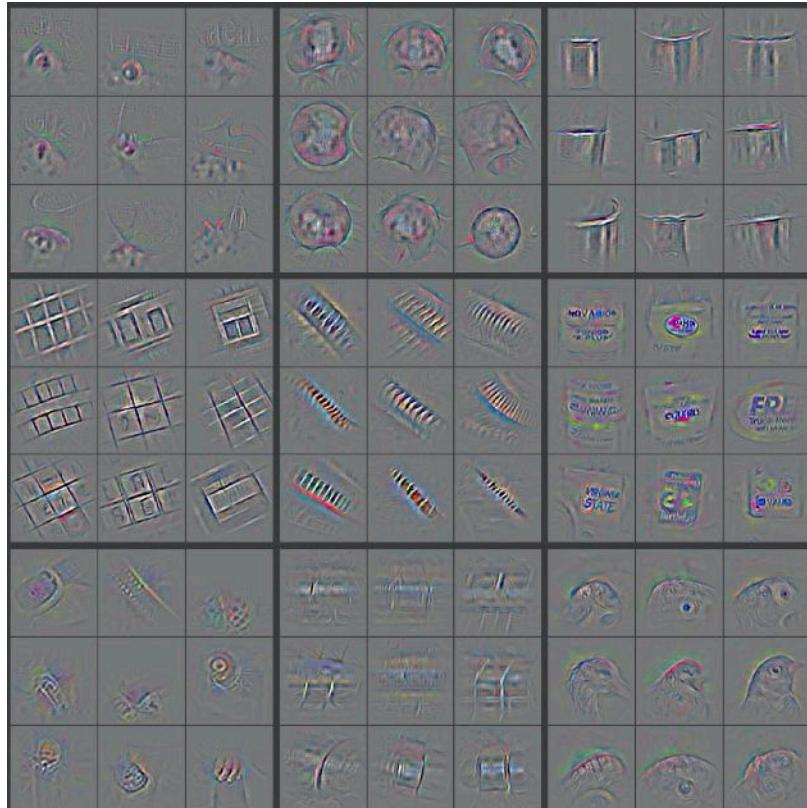


Top Image Patches

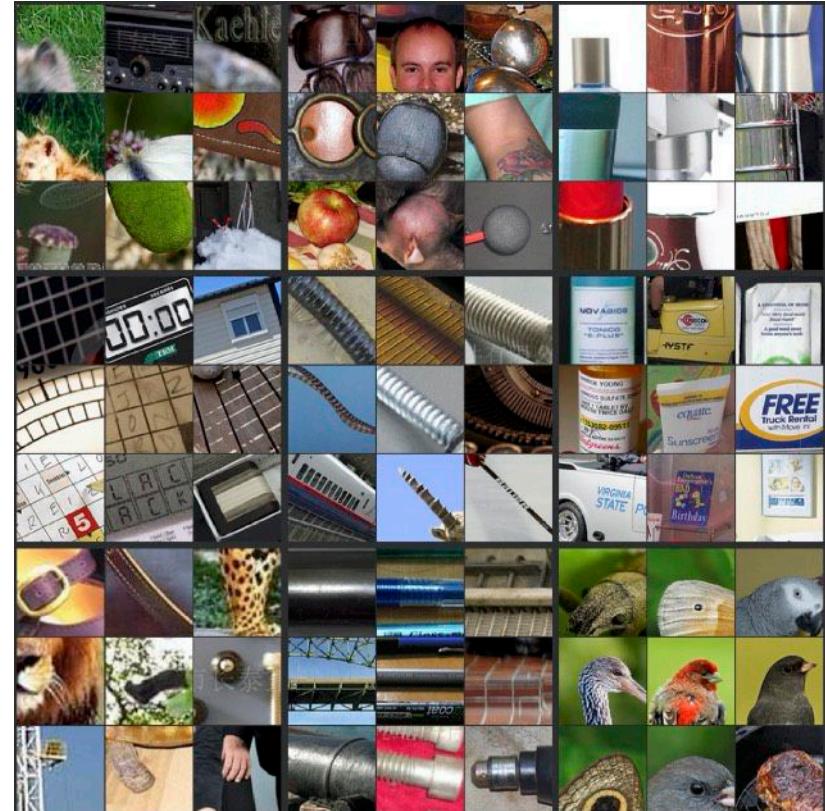
<http://cs.nyu.edu/~fergus/papers/zeilerECCV2014.pdf>

http://cs.nyu.edu/~fergus/presentations/nips2013_final.pdf

Visualizing CNN (Layer 3)



Part that Triggered Filter

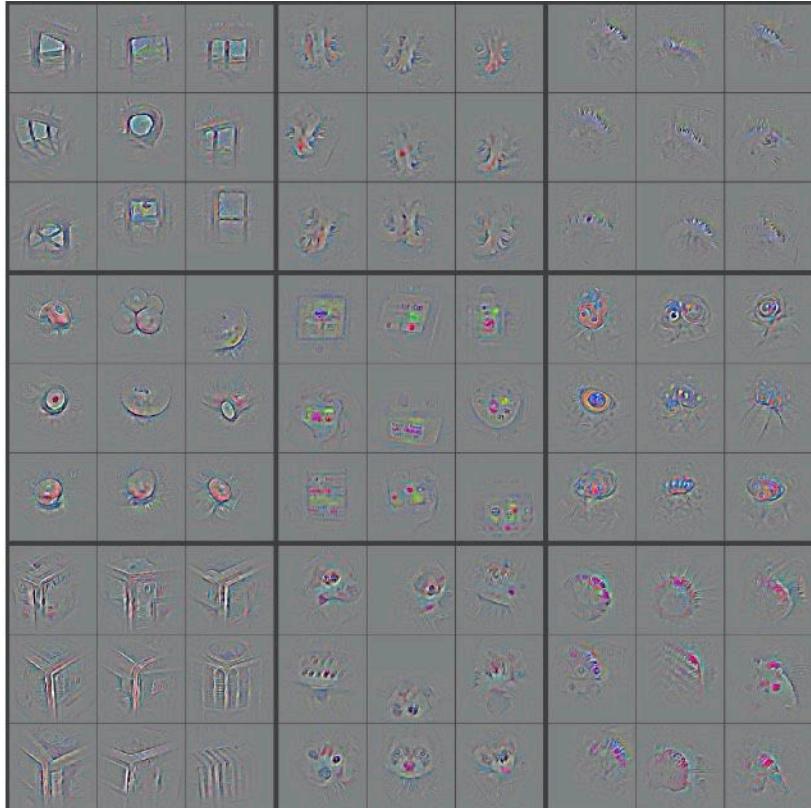


Top Image Patches

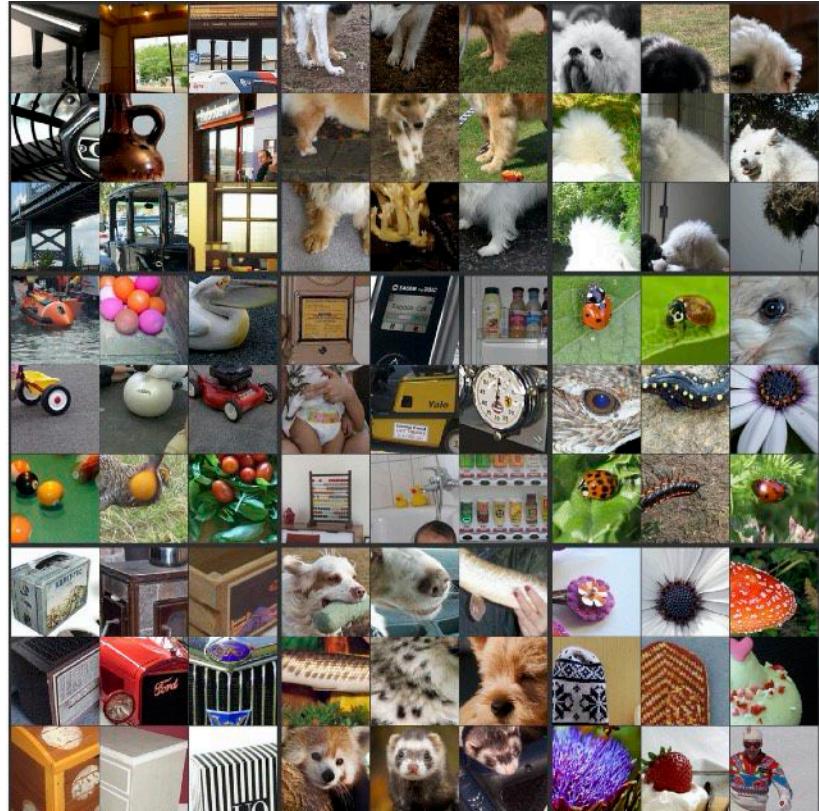
<http://cs.nyu.edu/~fergus/papers/zeilerECCV2014.pdf>

http://cs.nyu.edu/~fergus/presentations/nips2013_final.pdf

Visualizing CNN (Layer 4)



Part that Triggered Filter

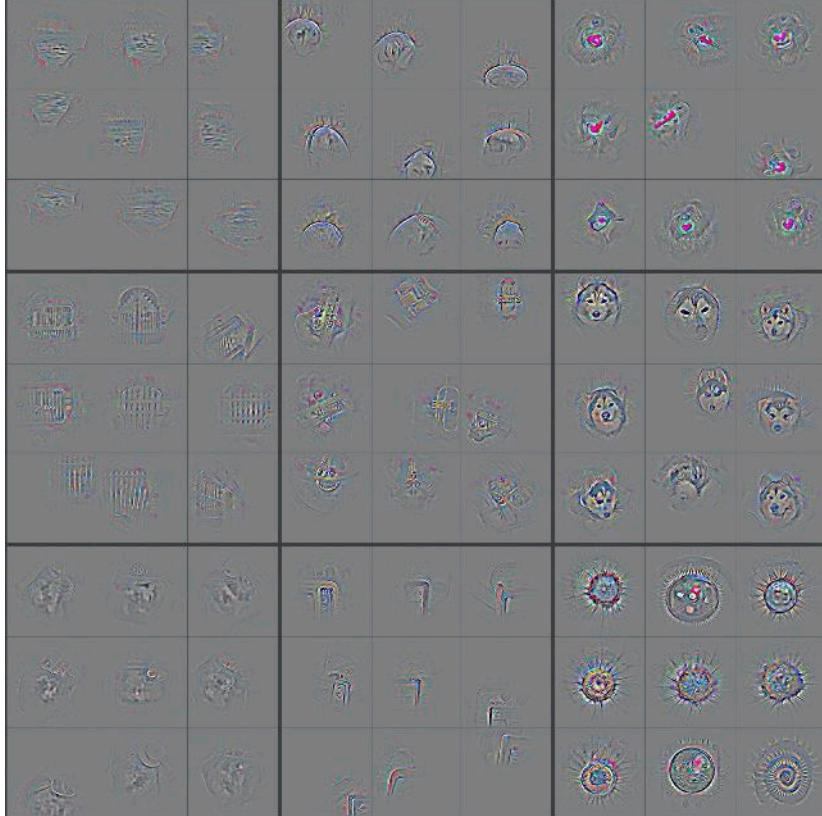


Top Image Patches

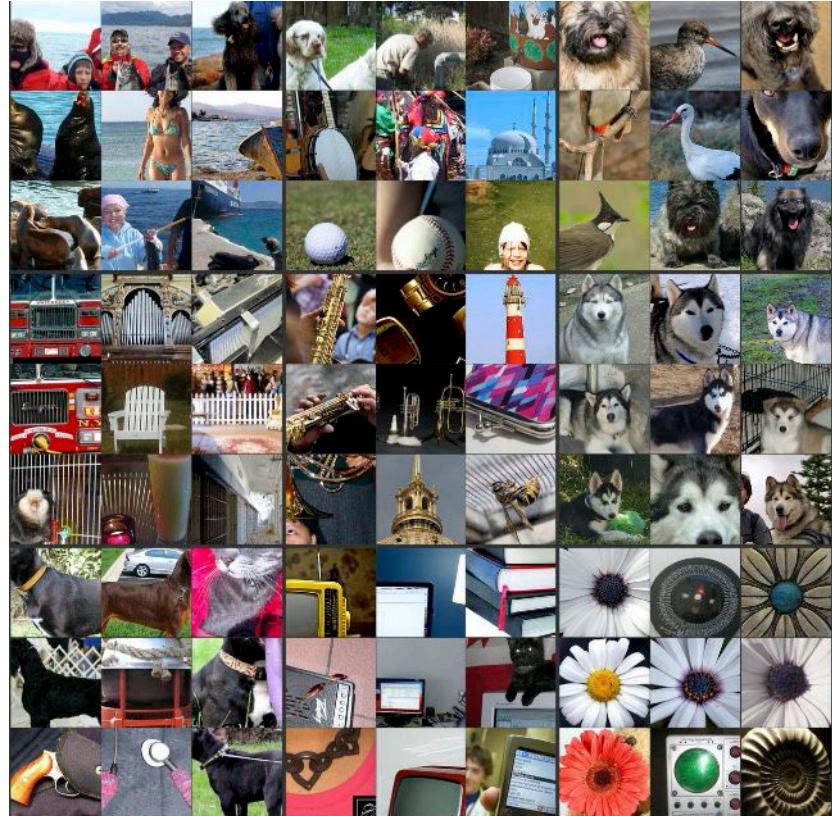
<http://cs.nyu.edu/~fergus/papers/zeilerECCV2014.pdf>

http://cs.nyu.edu/~fergus/presentations/nips2013_final.pdf

Visualizing CNN (Layer 5)



Part that Triggered Filter



Top Image Patches

<http://cs.nyu.edu/~fergus/papers/zeilerECCV2014.pdf>

http://cs.nyu.edu/~fergus/presentations/nips2013_final.pdf

Deep Visualization Toolbox

yosinski.com/deepvis

#deepvis



Jason Yosinski



Jeff Clune



Anh Nguyen



Thomas Fuchs



Hod Lipson



Cornell University

UNIVERSITY
OF WYOMING



Jet Propulsion Laboratory
California Institute of Technology

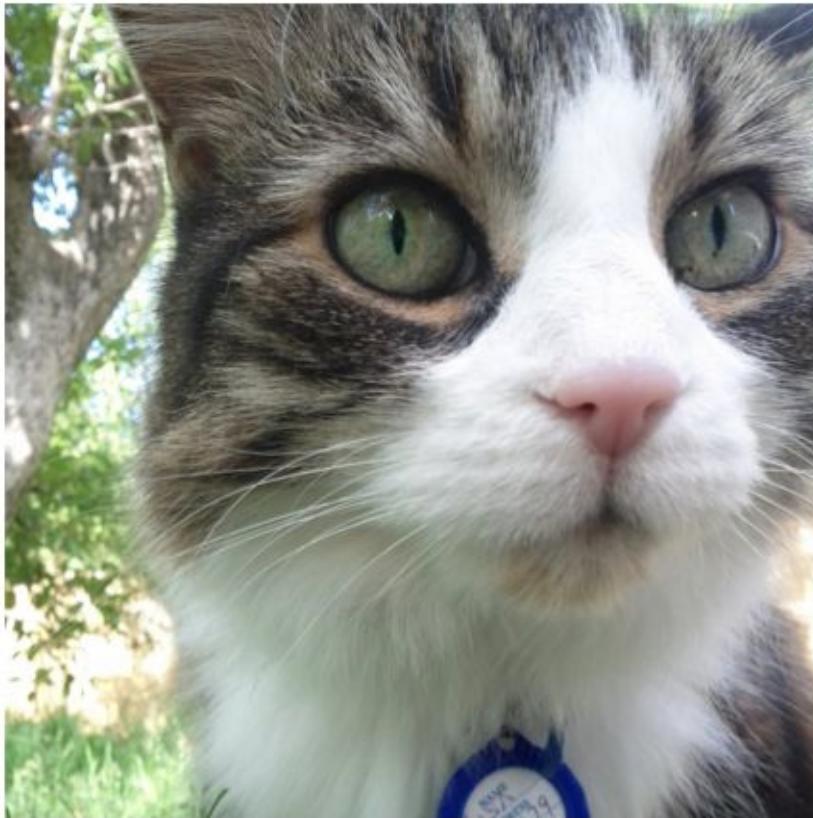
Tips and Tricks

- Shuffle the training samples
- Use Dropout and Batch Normalization for regularization

Input representation

“Given a rectangular image, we first rescaled the image such that the shorter side was of length 256, and then cropped out the central 256×256 patch from the resulting image”

- Centered (0-mean) RGB values.



An input image (256x256)



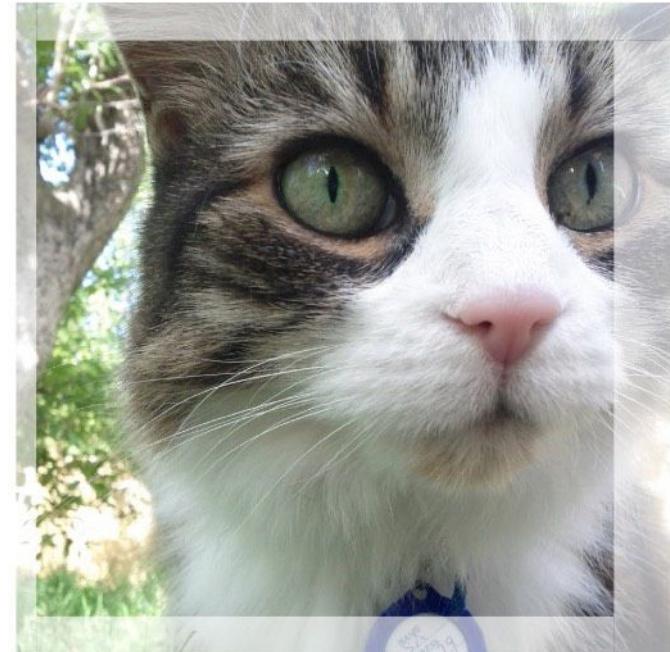
Minus sign



The mean input image

Data Augmentation

- The neural net has 60M real-valued parameters and 650,000 neurons
- It overfits a lot. Therefore, they train on 224x224 patches extracted randomly from 256x256 images, and also their horizontal reflections.



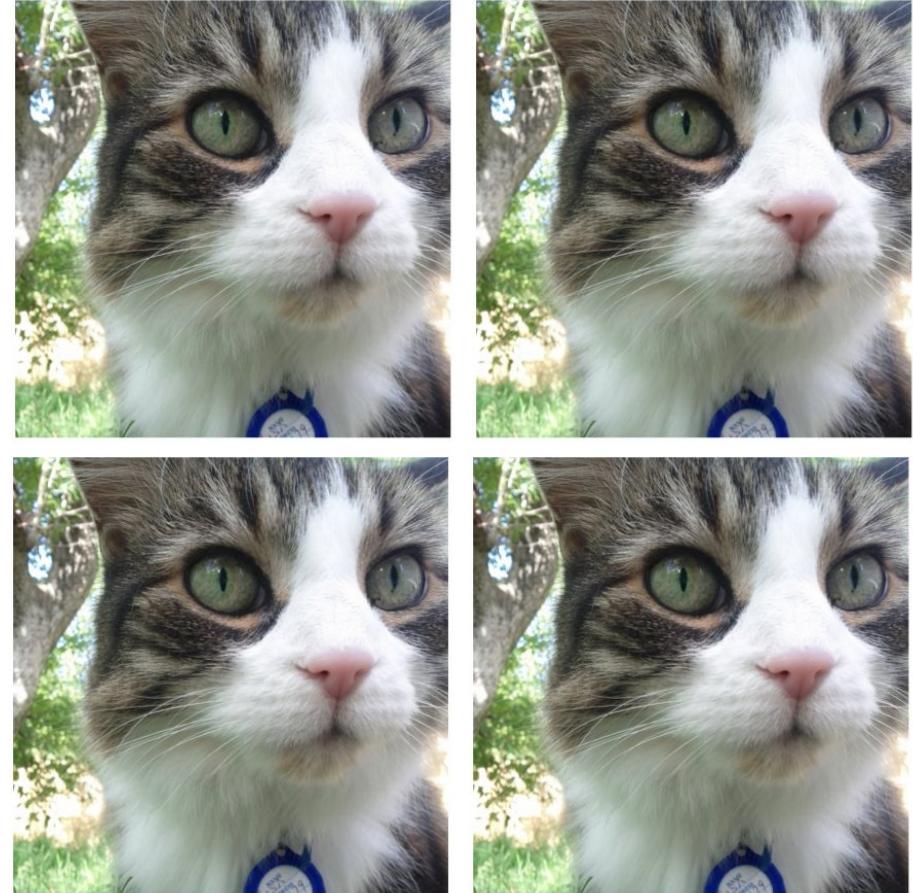
“This increases the size of our training set by a factor of 2048, though the resulting training examples are, of course, highly inter-dependent.”

[Krizhevsky et al. 2012]

Data Augmentation

- Alter the intensities of the RGB channels in training images.

“Specifically, we perform PCA on the set of RGB pixel values throughout the ImageNet training set. To each training image, we add multiples of the found principal components, with magnitudes proportional to the corresponding eigenvalues times a random variable drawn from a Gaussian with mean zero and standard deviation 0.1...This scheme approximately captures an important property of natural images, namely, that object identity is invariant to changes in the intensity and color of the illumination. This scheme reduces the top-1 error rate by over 1%.”



[Krizhevsky et al. 2012]

Data Augmentation

Horizontal flips



Data Augmentation

Get creative!

Random mix/combinations of :

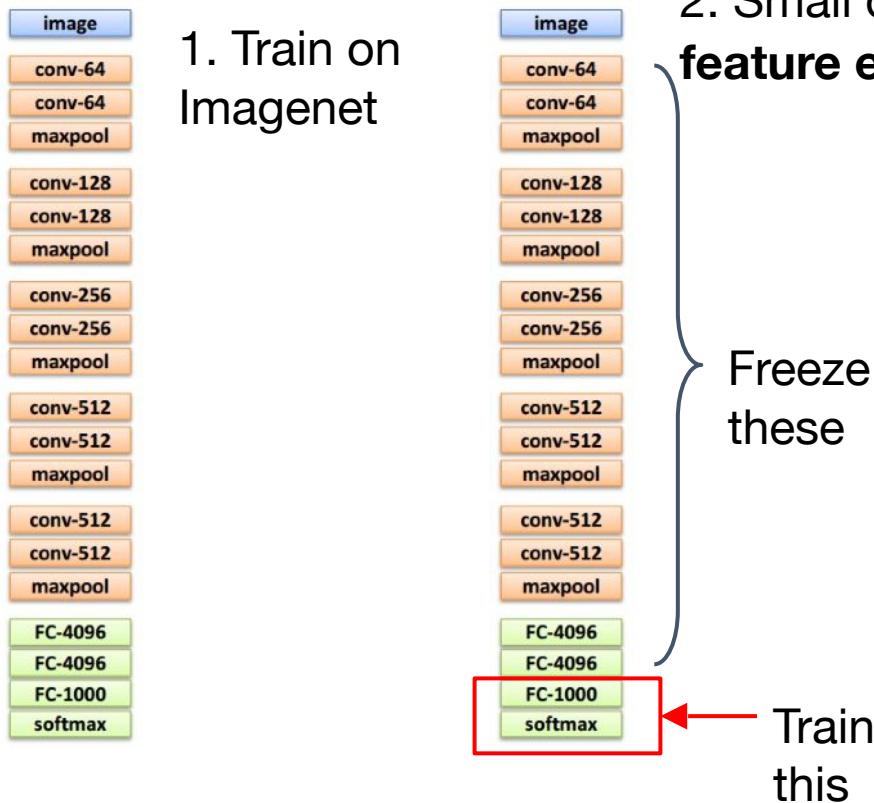
- translation
- rotation
- stretching
- shearing,
- lens distortions, ... (go crazy)

Transfer Learning with ConvNets

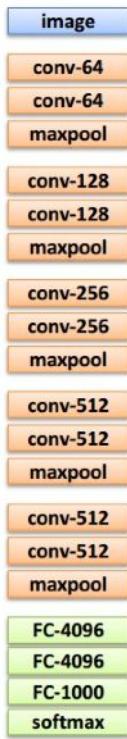


1. Train on
Imagenet

Transfer Learning with ConvNets



Transfer Learning with ConvNets



1. Train on
Imagenet



2. Small dataset:
feature extractor

Freeze
these

Train
this



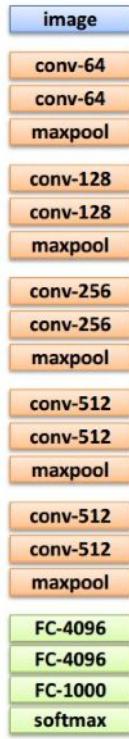
3. Medium dataset:
finetuning

more data = retrain more of
the network (or all of it)

Freeze these

Train this

Transfer Learning with ConvNets



1. Train on
Imagenet



2. Small dataset:
feature extractor

Freeze
these

Train
this



3. Medium dataset:
finetuning

more data = retrain more of
the network (or all of it)

Freeze these

tip: use only ~1/10th of
the original learning rate
in finetuning top layer,
and ~1/100th on
intermediate layers

Train this

Today ConvNets are everywhere

Classification



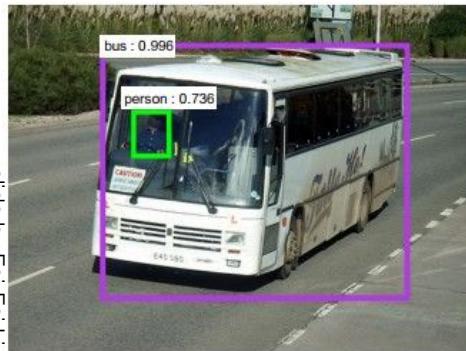
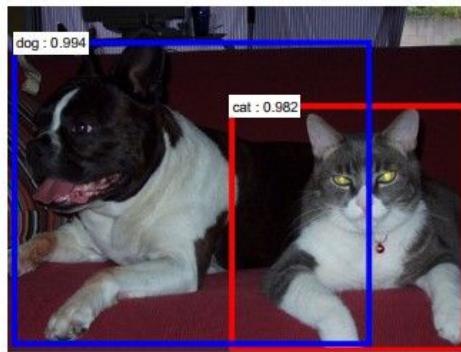
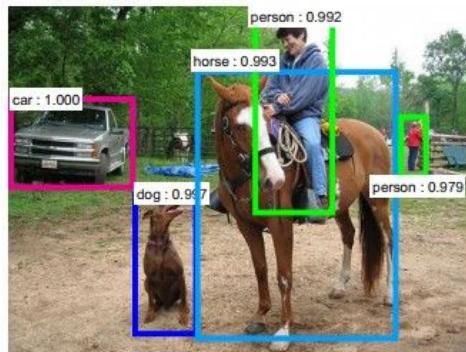
Retrieval



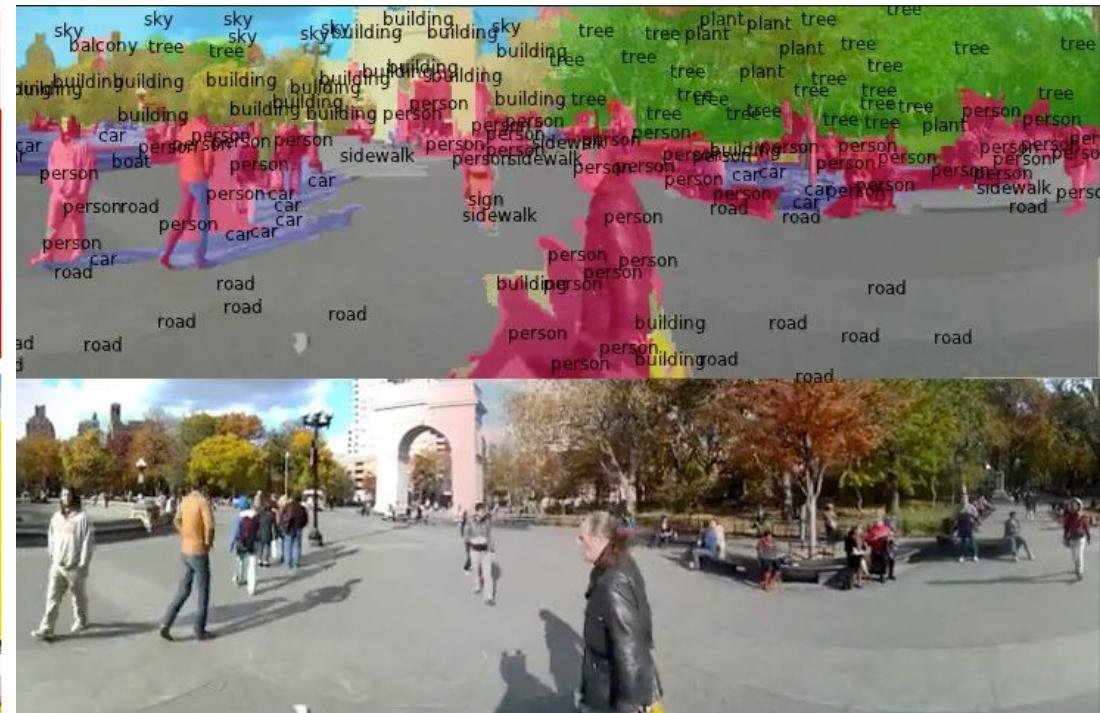
[Krizhevsky 2012]

Today ConvNets are everywhere

Detection



Segmentation



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

[Farabet et al., 2012]

Today ConvNets are everywhere



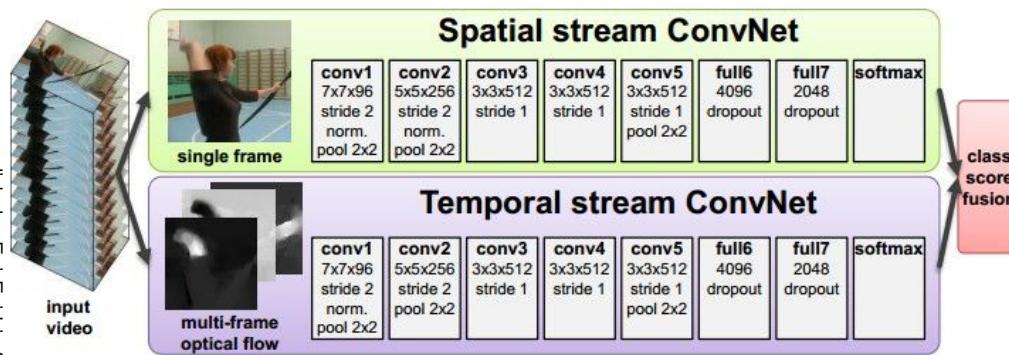
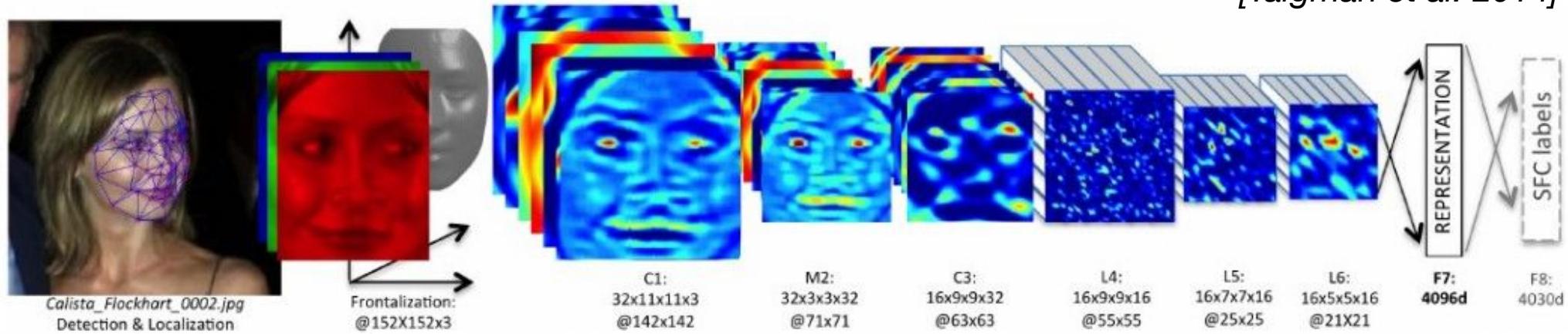
self-driving cars



NVIDIA Tegra X1

Today ConvNets are everywhere

[Taigman et al. 2014]



[Goodfellow 2014]

Today ConvNets are everywhere

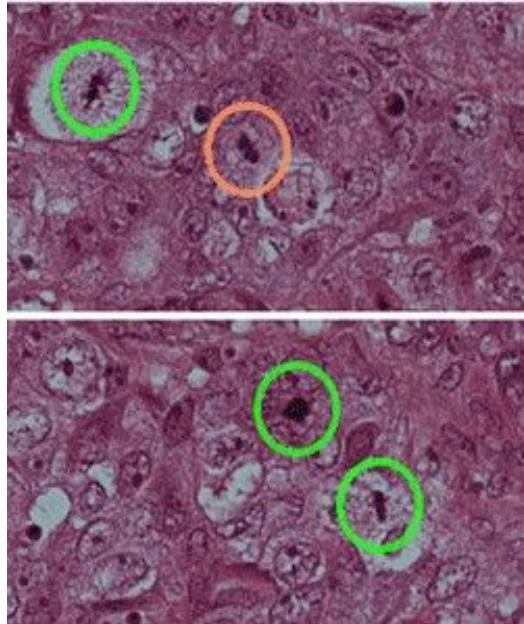


[Toshev, Szegedy 2014]



[Mnih 2013]

Today ConvNets are everywhere



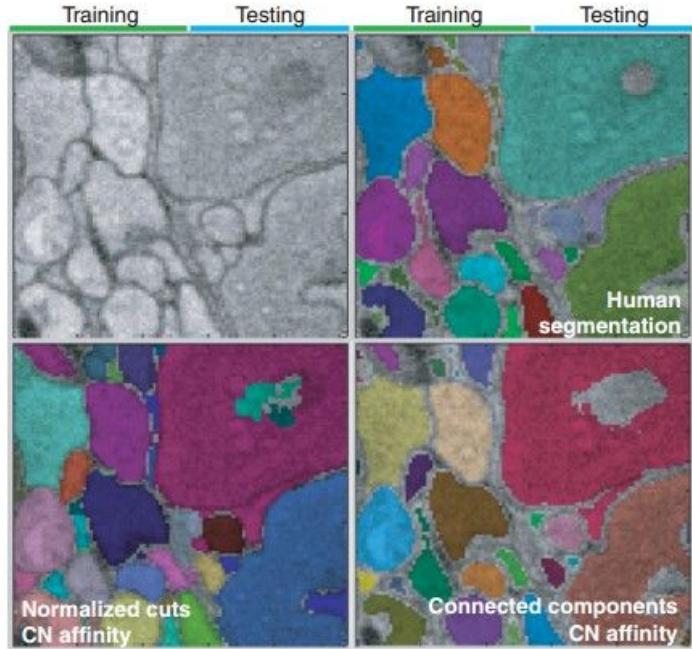
咱攢暫贊莊雕葬遭
擇則澤賊怎增櫓曾
旅摘籌宅窄債寨瞻
湛綻掉章彙漳張尊
囉罩兆摩召遮折哲
針傾枕疚診震振鎮
鄭征艺枝支吱吻知
止趾只旨紙志擎擲

[Ciresan et al. 2013]

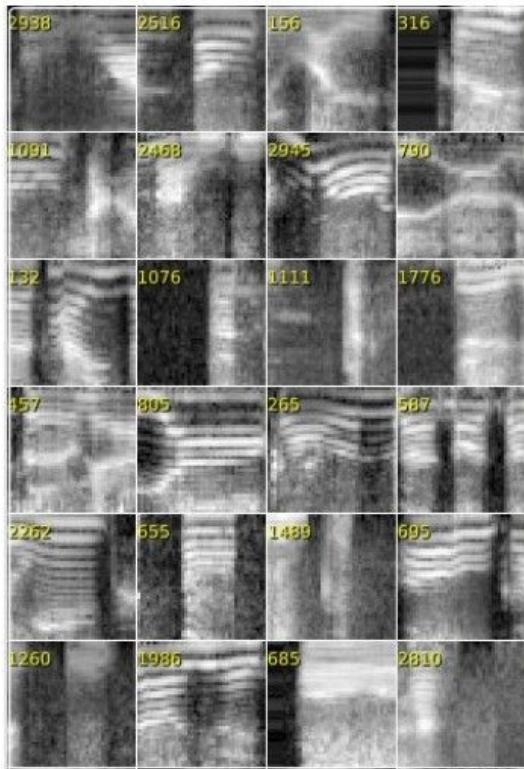


[Sermanet et al. 2011]
[Ciresan et al.]

Today ConvNets are everywhere



[Turaga et al., 2010]



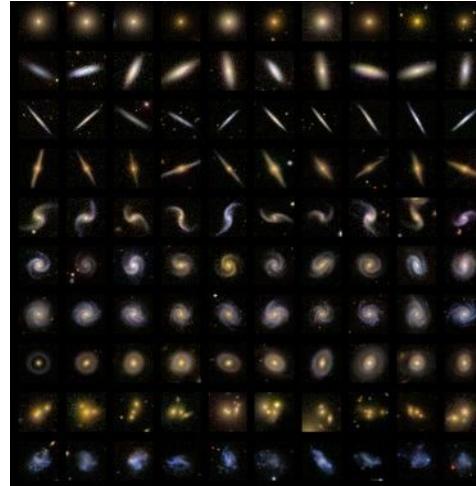
I caught this movie on the Sci-Fi channel recently. It actually turned out to be pretty decent as far as B-list horror/suspense films go. Two guys (one naive and one fond mounted a ***) take a road trip to stop a wedding but have the worst possible luck when a maniac in a freaky, make-shift tank/truck hybrid decides to play cat-and-mouse with them. Things are further complicated when they pick up a ridiculously whorish hitchhiker. What makes this film unique is that the combination of comedy and terror actually work in this movie, unlike so many others. The two guys are likable enough and there are some good chase/suspense scenes. Nice pacing and comic timing make this movie more than passable for the horror/slasher buff. Definitely worth checking out.

I just saw this on a local independent station in the New York City area. The cast showed promise but when I saw the director, George Cosmatos, I became suspicious. And sure enough, it was every bit as bad, every bit as pointless and stupid as every George Cosmatos movie I ever saw. He's like a stupid man's Michael Bay - with all the awfulness that accolade promises. There's no point to the conspiracy, no burning issues that urge the conspirators on. We are left to ourselves to connect the dots from one bit of graffiti on various walls in the film to the next. Thus, the current budget crisis, the war in Iraq, Islamic extremism, fate of social security, 47 million Americans without health care, stagnating wages and the death of the middle class are all subsumed by the sheer terror of graffiti. A truly, stunningly idiotic film.

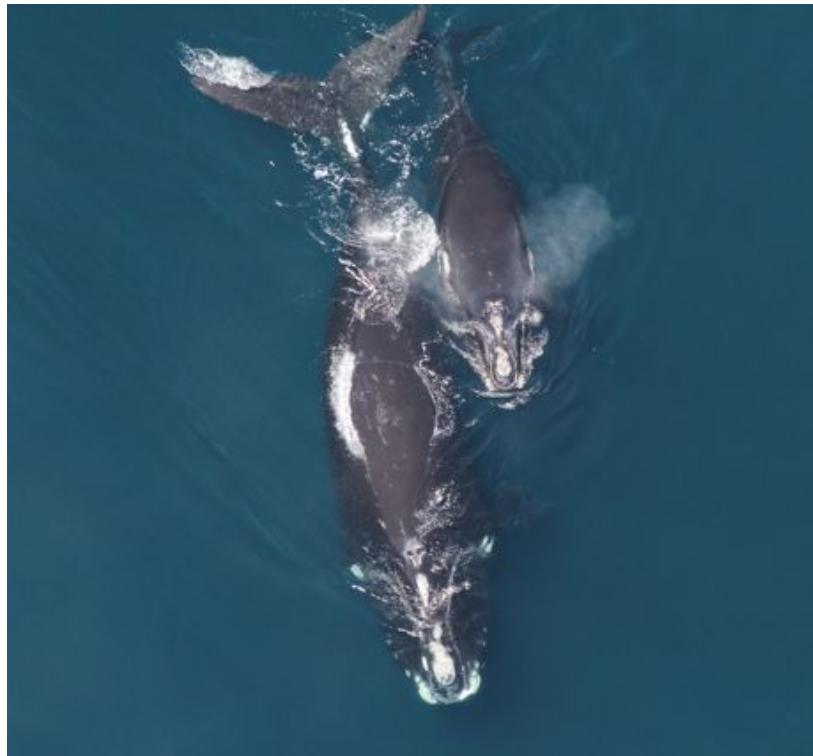
Graphics is far from the best part of the game. This is the number one best TH game in the series. Next to Underworld. It deserves strong love. It is an intense game. There are massive levels, massive unlockable characters... it's just a massive game. Waste your time on this game. This is the kind of money that is wasted properly. And even though graphics suck, that doesn't make a game good. Actually, the graphics were good at the time. Today the graphics are crap. WHO CARES? As they say in Canada. This is the fun game, aye. (You get to go to Canada in THPS3) Well, I don't know if they say that, but they might. Who knows. Well, Canadian people do. Wait a minute, I'm getting off topic. This game rocks. Buy it, play it, enjoy it, love it. It's PURE BRILLIANCE.

The first was good and original. I was a not bad horror/comedy movie. So I heard a second one was made and I had to watch it. What really makes this movie work is Judd Nelson's character and the sometimes clever script. A pretty good script for a person who wrote the Final Destination films and the direction was okay. Sometimes there's scenes where it looks like it was filmed using a home video camera with a grainy - look. Great made - for - TV movie. It was worth the rental and probably worth buying just to get that nice eerie feeling and watch Judd Nelson's Stanley doing what he does best. I suggest newcomers to watch the first one before watching the sequel, just so you'll have an idea what Stanley is like and get a little history background.

[Denil et al. 2014]



Today ConvNets are everywhere



Whale recognition, Kaggle Challenge



Mnih and Hinton, 2010

Today ConvNets are everywhere

Describes without errors



A person riding a motorcycle on a dirt road.

Describes with minor errors



Two dogs play in the grass.

Somewhat related to the image



A skateboarder does a trick on a ramp.

Unrelated to the image



A dog is jumping to catch a frisbee.

Image Captioning



A group of young people playing a game of frisbee.



Two hockey players are fighting over the puck.



A little girl in a pink hat is blowing bubbles.



A refrigerator filled with lots of food and drinks.



A herd of elephants walking across a dry grass field.



A close up of a cat laying on a couch.



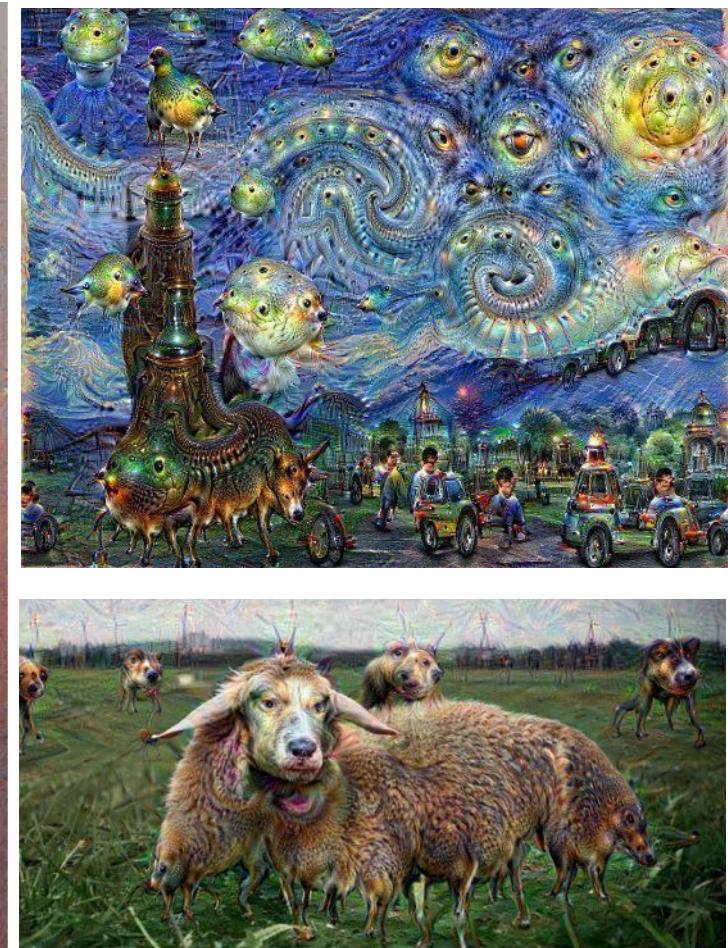
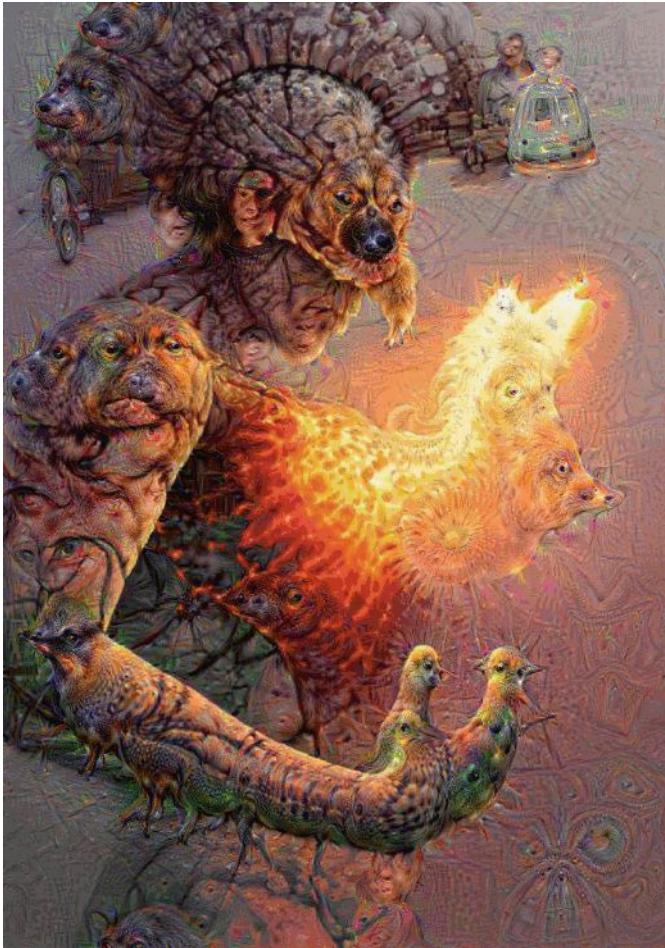
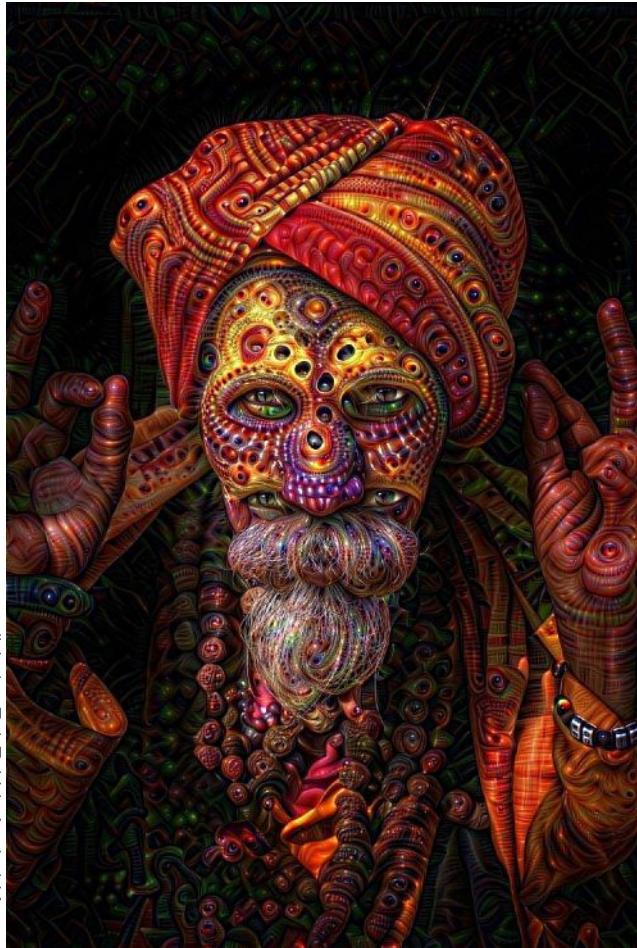
A red motorcycle parked on the side of the road.



A yellow school bus parked in a parking lot.

[Vinyals et al., 2015]

Today ConvNets are everywhere



[reddit.com/r/deepdream](https://www.reddit.com/r/deepdream)

Next Lecture:

Support Vector Machines