

CS 1699: Deep Learning

Convolutional Neural Networks

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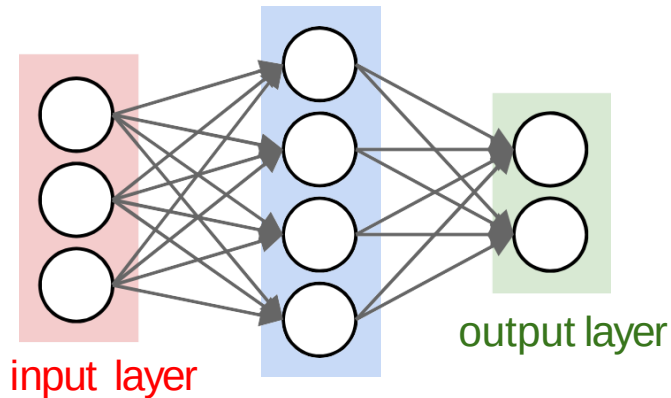
Plan for this lecture

- Motivation: Scanning for patterns
- Convolutional network operations
- Common architectures
- Visualizing convolutional networks
- Applications in computer vision

Neural networks so far

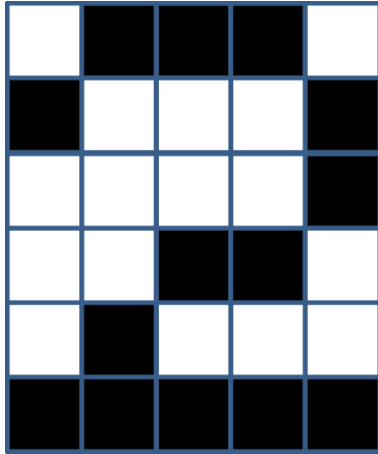


Or, more generally
a vector input

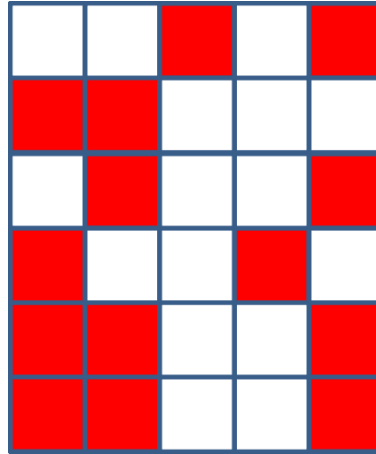


- Can recognize patterns in data (e.g. digits)

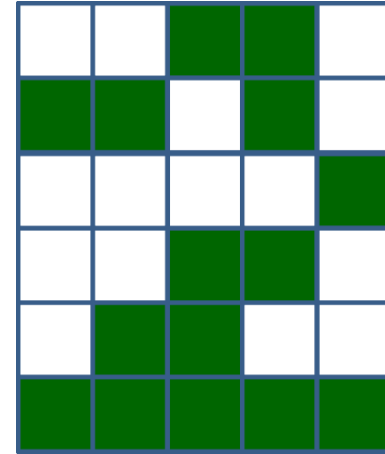
The weights look for patterns



$$y = \begin{cases} 1 & \text{if } \sum w_i x_i \geq T \\ 0 & \text{else} \end{cases}$$



Correlation = 0.57

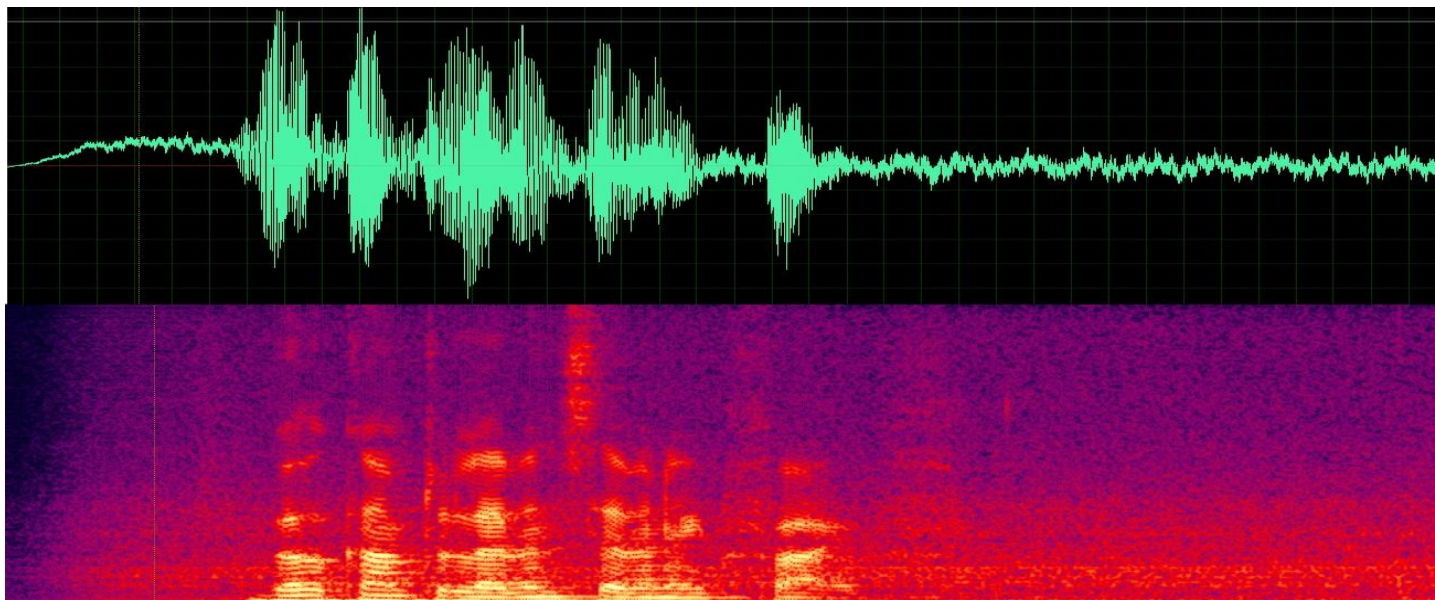


Correlation = 0.82



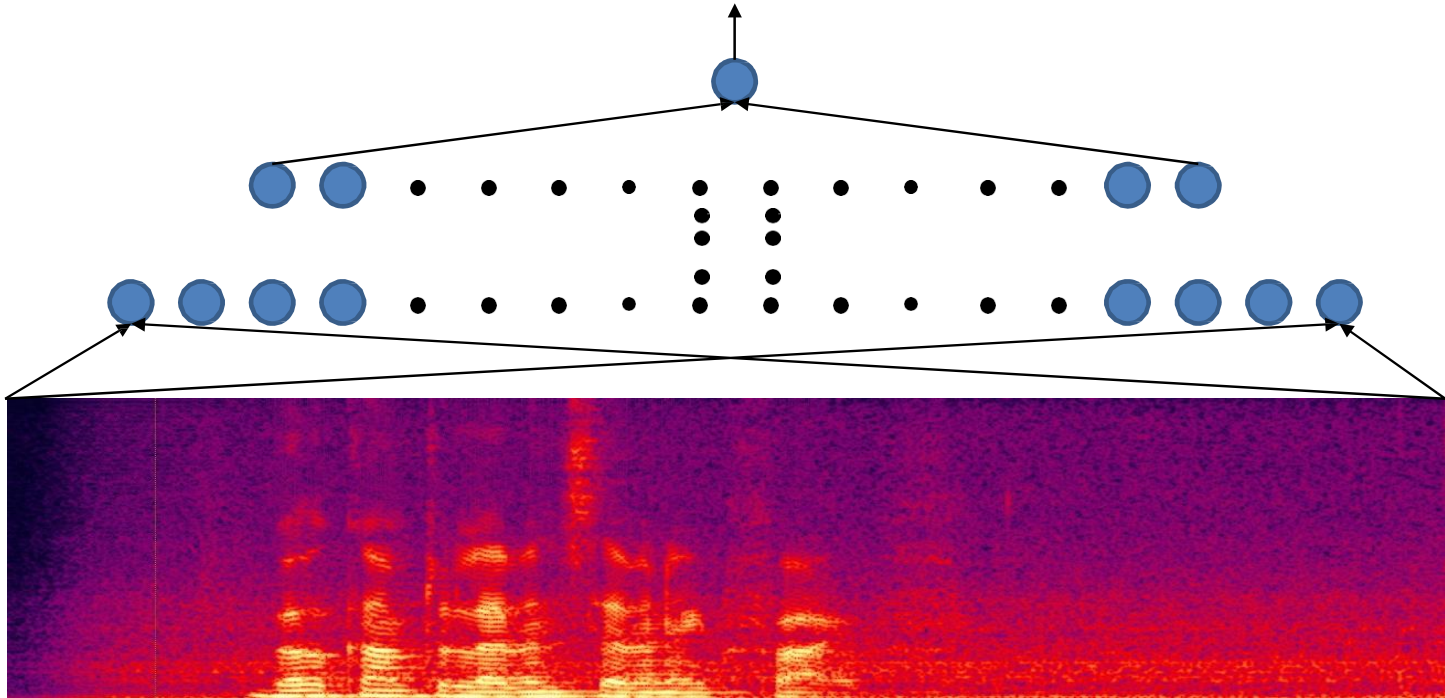
- The green pattern looks more like the weights pattern (black) than the red pattern
 - The green pattern is more *correlated* with the weights

A problem



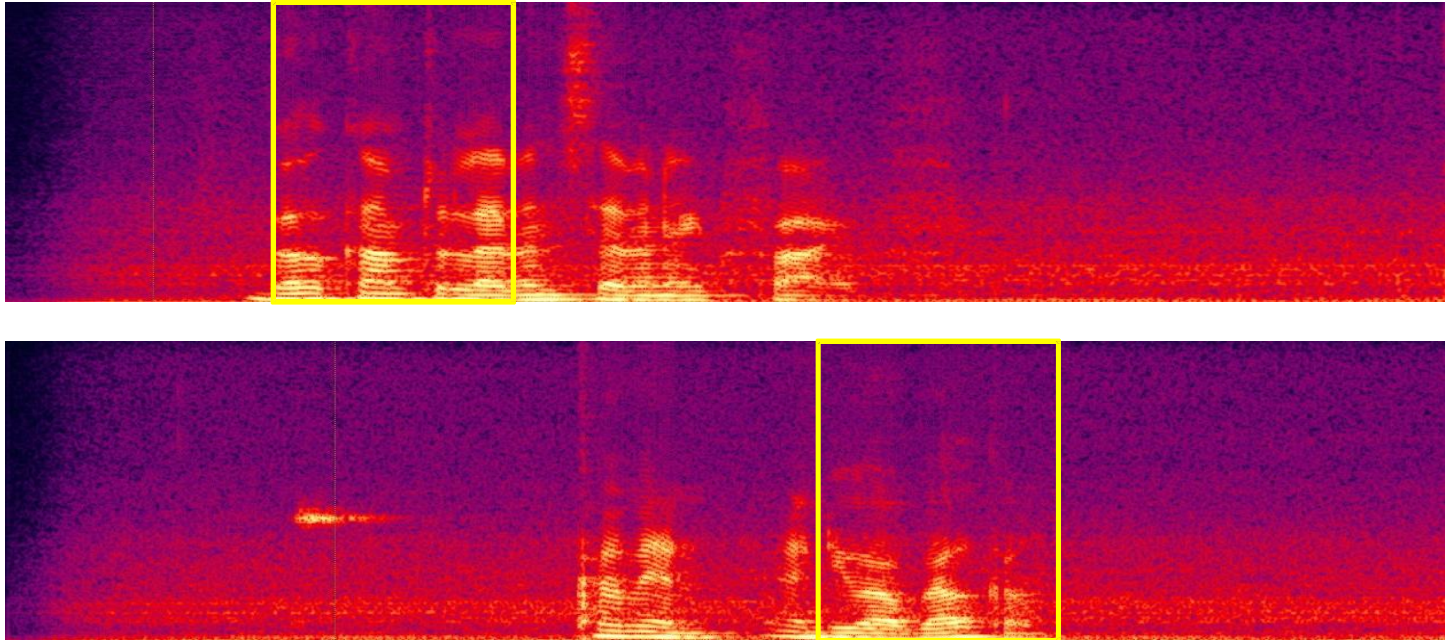
- Does this signal contain the word “Welcome”?
- Compose a NN for this problem
 - Assuming all recordings are exactly the same length

Finding a Welcome



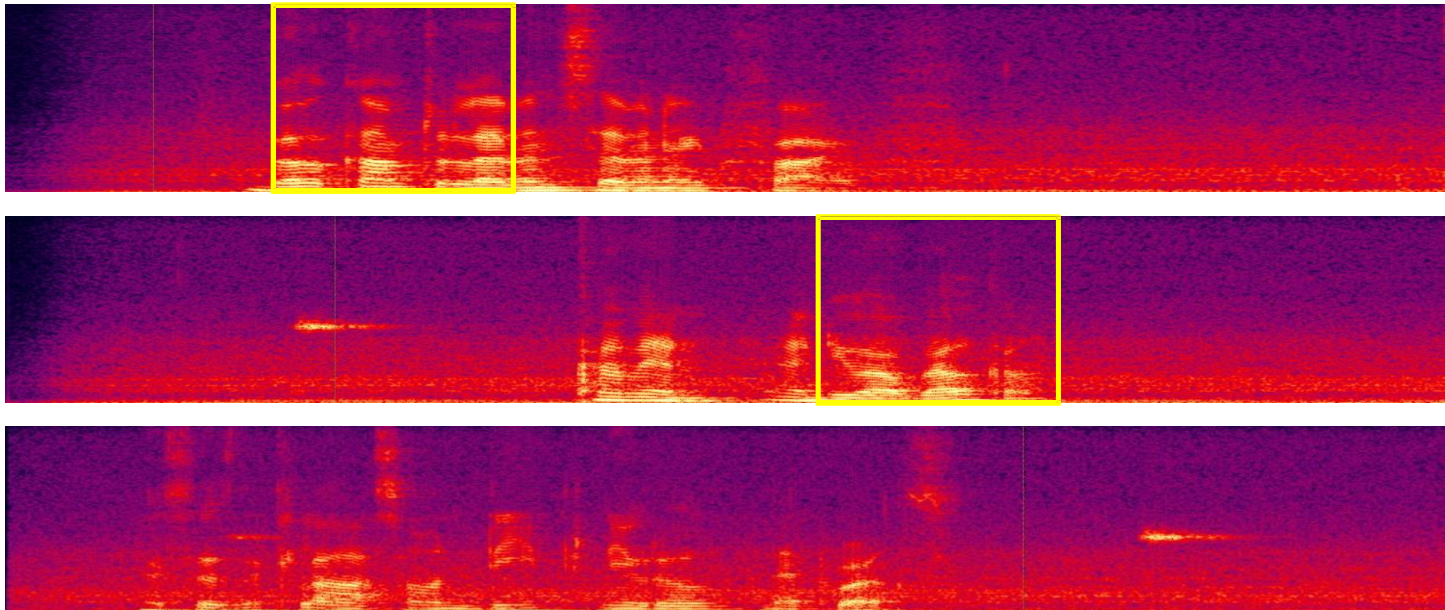
- Trivial solution: Train a NN for the entire recording

Finding a Welcome



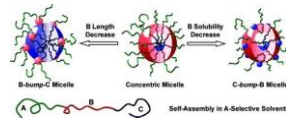
- Problem with trivial solution: Network that finds a “welcome” in the top recording will not find it in the lower one
 - Unless trained with both
 - Will require a very large network and a large amount of training data to cover every case

Finding a Welcome



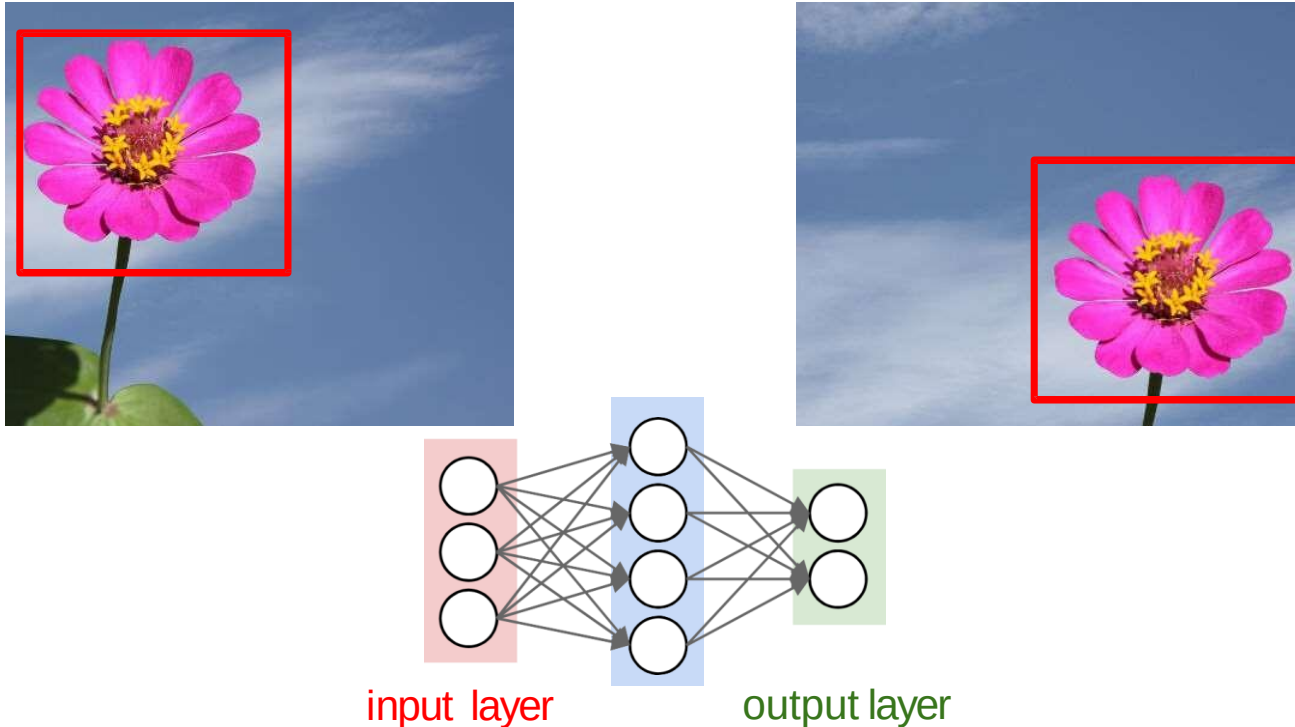
- Need a *simple* network that will fire regardless of the location of “Welcome”
 - and not fire when there is none

Flowers



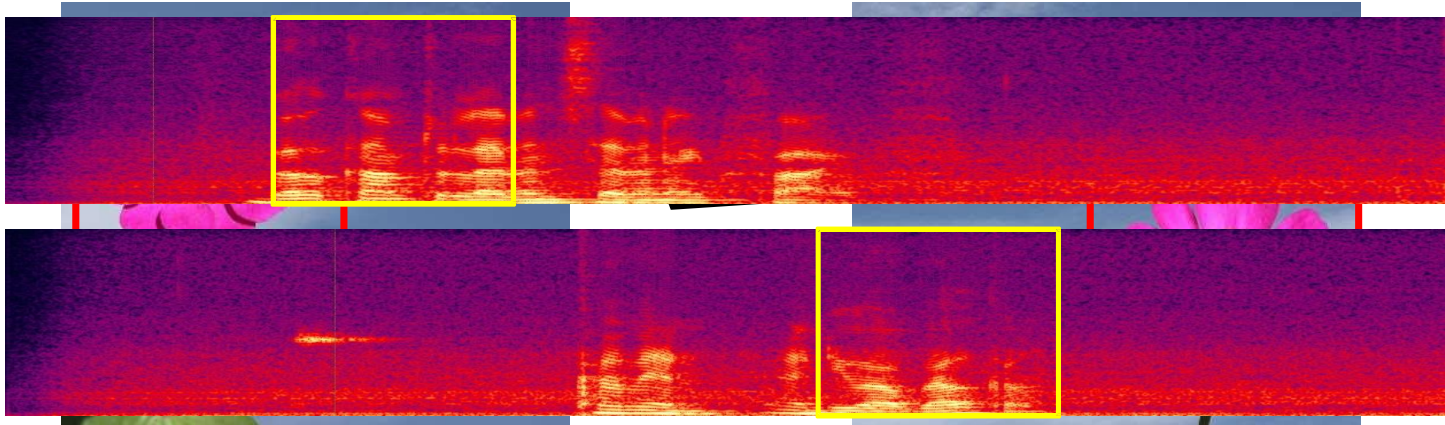
- Is there a flower in any of these images?

A problem



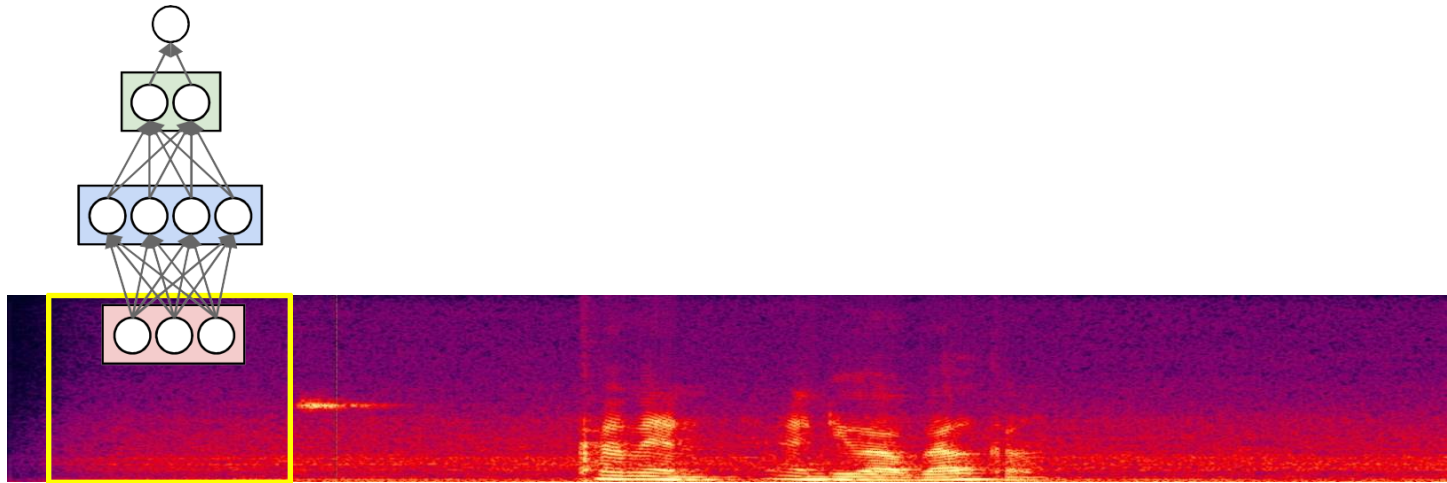
- Will a NN that recognizes the left image as a flower also recognize the one on the right as a flower?
- Need a network that will “fire” regardless of the precise location of the target object

The need for *shift invariance*



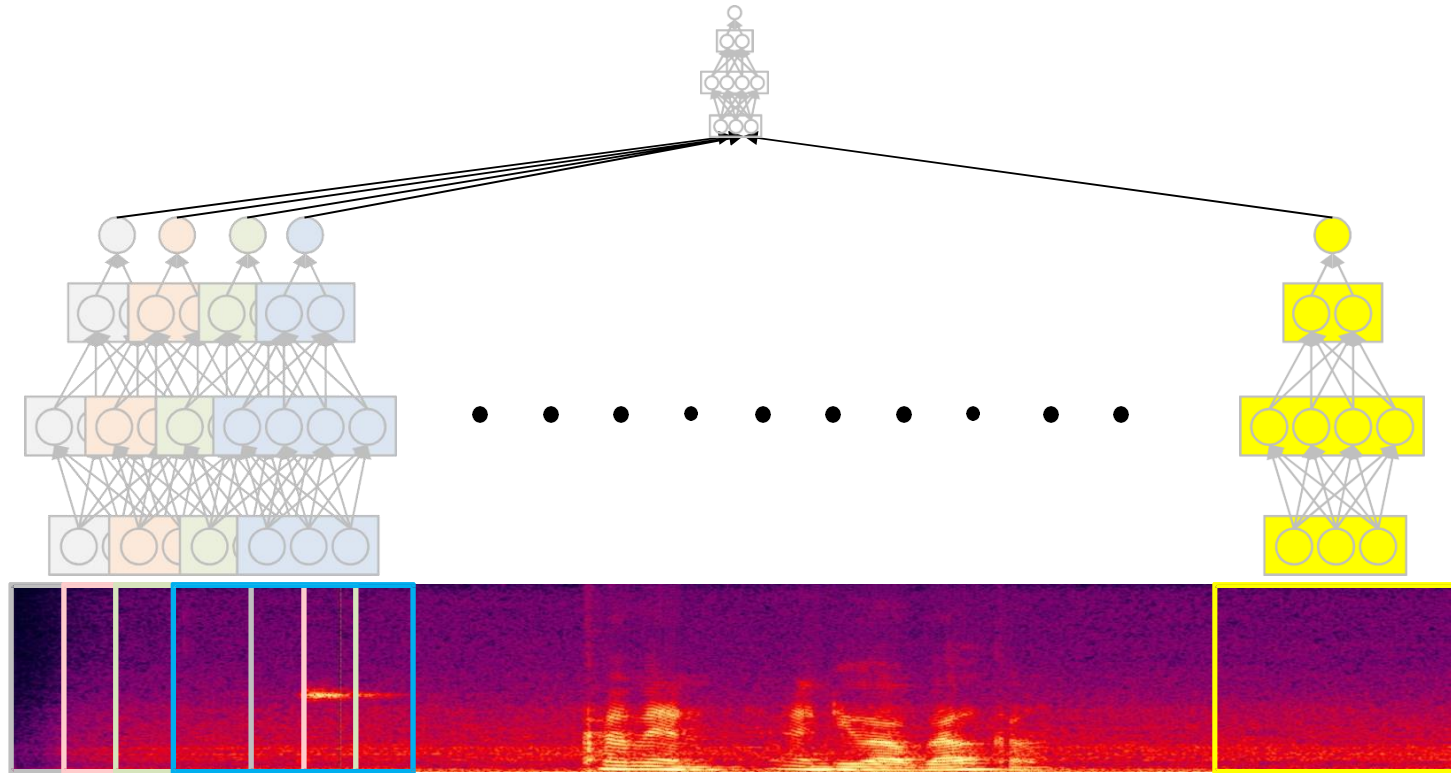
- In many problems the *location* of a pattern is not important
 - Only the presence of the pattern is important
- Conventional NNs are sensitive to location of pattern
 - Moving it by one component results in an entirely different input that the NN won't recognize
- Requirement: Network must be *shift invariant*

Solution: Scan



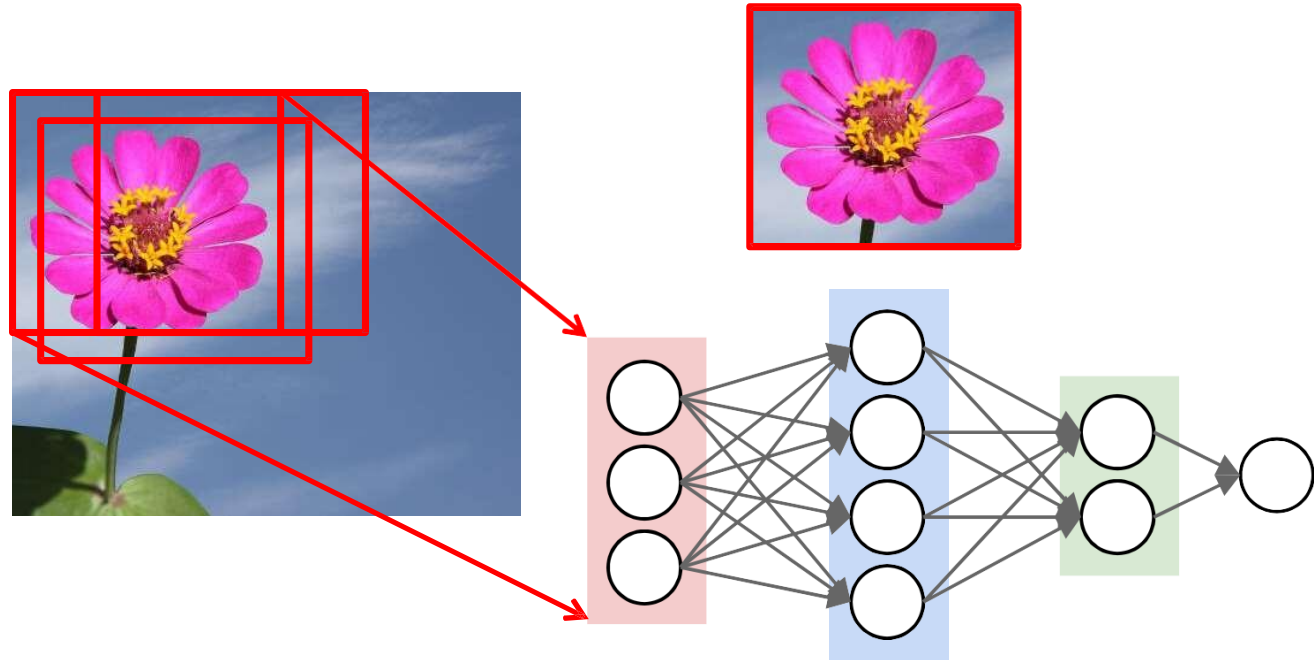
- Scan for the target word
 - The audio signals in a “window” are input to a “welcome-detector” NN

Solution: Scan



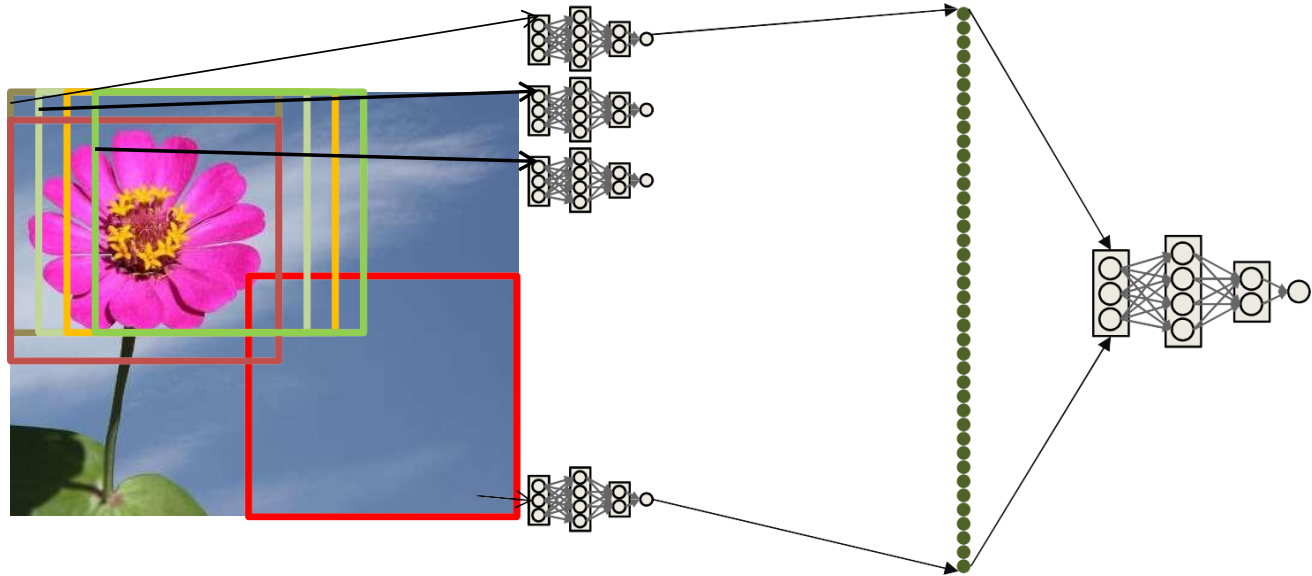
- “Does welcome occur in this recording?”
 - Maximum of all the outputs (Equivalent of Boolean OR)

2-d analogue: Does this picture have a flower?



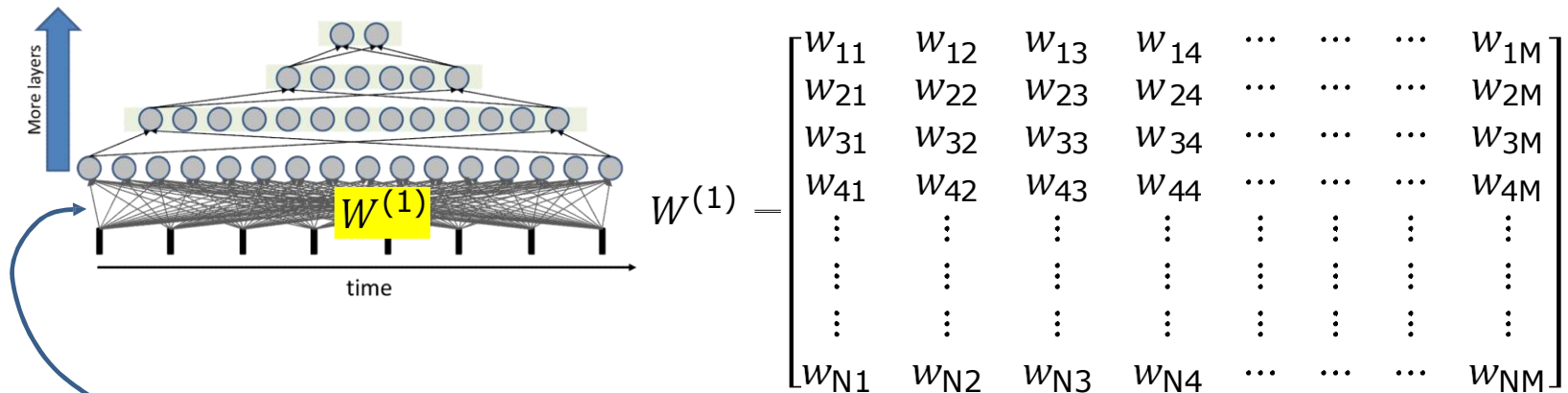
- *Scan* for the desired object
 - “Look” for the target object at each position
 - At each location, entire region is sent through NN

A giant net with common identical subnets



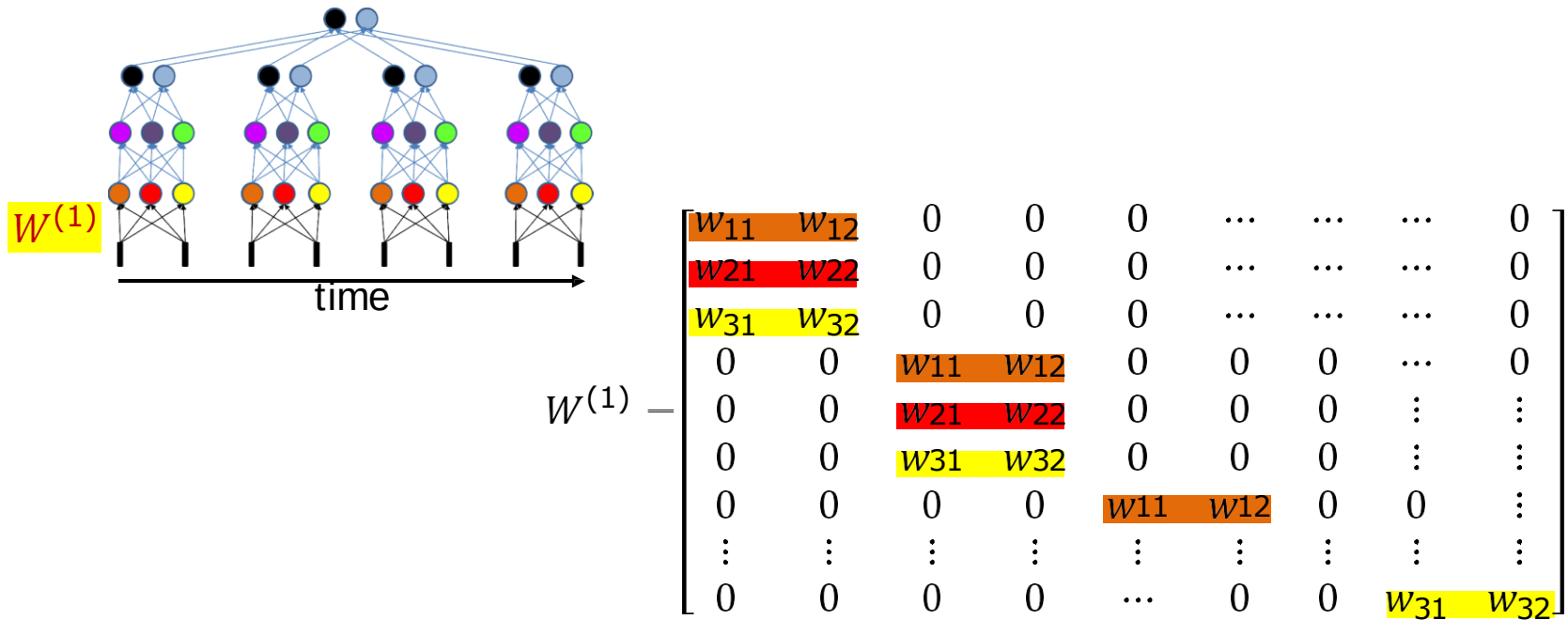
- Determine if any of the locations had a flower
 - Each dot in the right represents the output of the NN when it classifies one location in the input figure
 - Look at the maximum value
 - Or pass it through a softmax or even another NN

Regular network



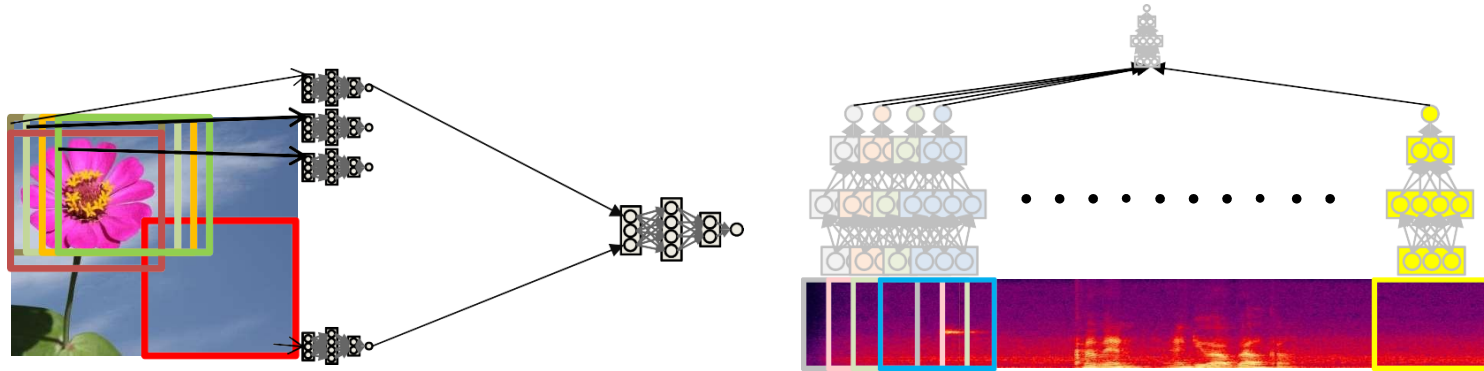
- Consider the first layer
 - Assume N inputs and M outputs
- The weights matrix is a full $N \times M$ matrix
 - Requiring $N \times M$ unique parameters

Scanning networks



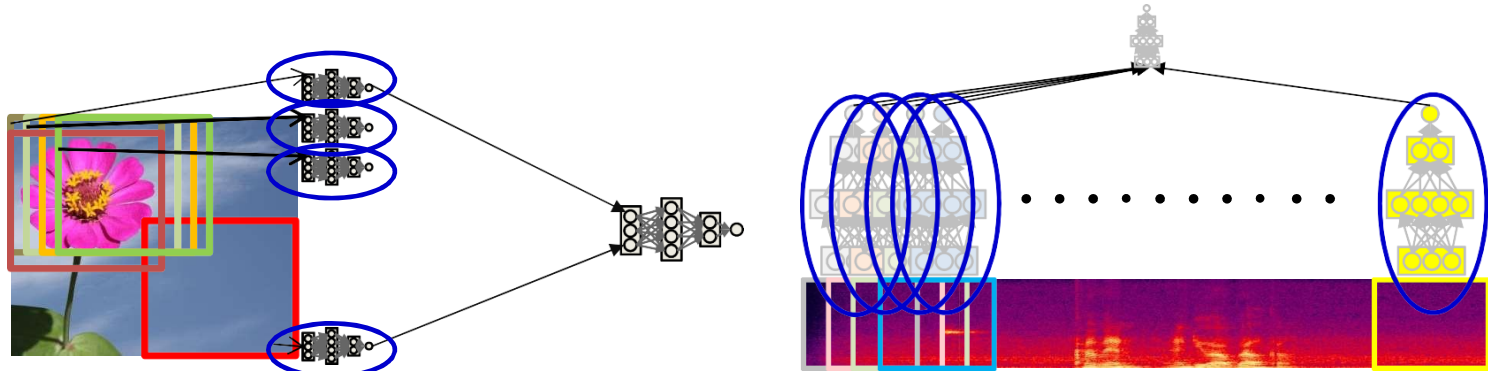
- In a **scanning NN** each neuron is connected to a subset of neurons in the previous layer
 - The weights matrix is sparse
 - The weights matrix is block structured **with identical blocks**
 - **The network is a shared parameter model**

Training the network



- These are really just large networks
- Can just use conventional backpropagation to learn the parameters
- Backprop learns a network that maps the training inputs to the target binary outputs

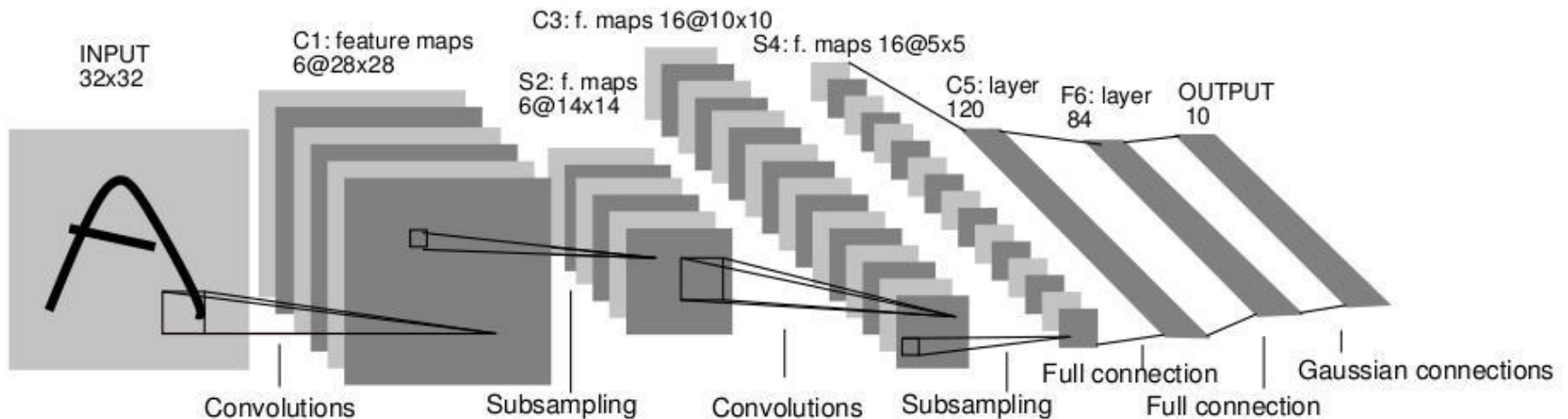
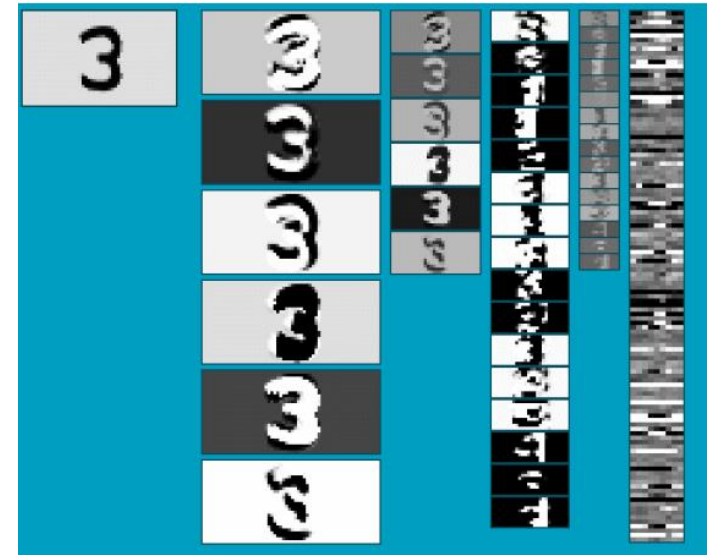
Training the network: constraint



- These are *shared parameter* networks
 - All lower-level subnets are identical
 - Are all searching for the same pattern
 - Any update of the parameters of one copy of the subnet must equally update *all* copies

Convolutional Neural Networks (CNN)

- Neural network with specialized connectivity structure
- Stack multiple stages of feature extractors
- Higher stages compute more global, more invariant, *more abstract* features
- Classification layer at the end

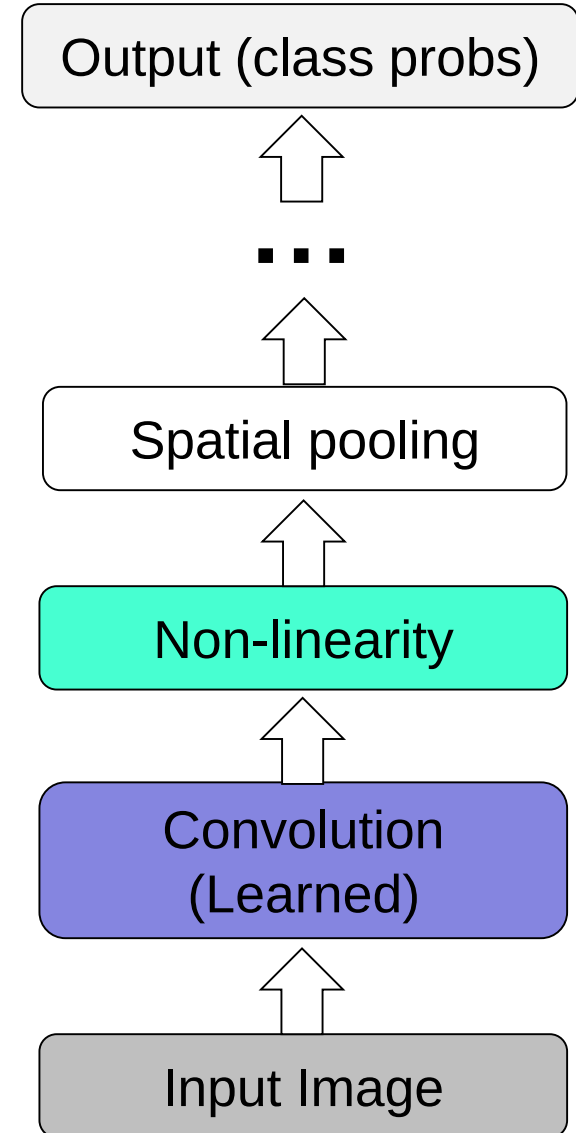


Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, [Gradient-based learning applied to document recognition](#), Proceedings of the IEEE 86(11): 2278–2324, 1998.

Adapted from Rob Fergus

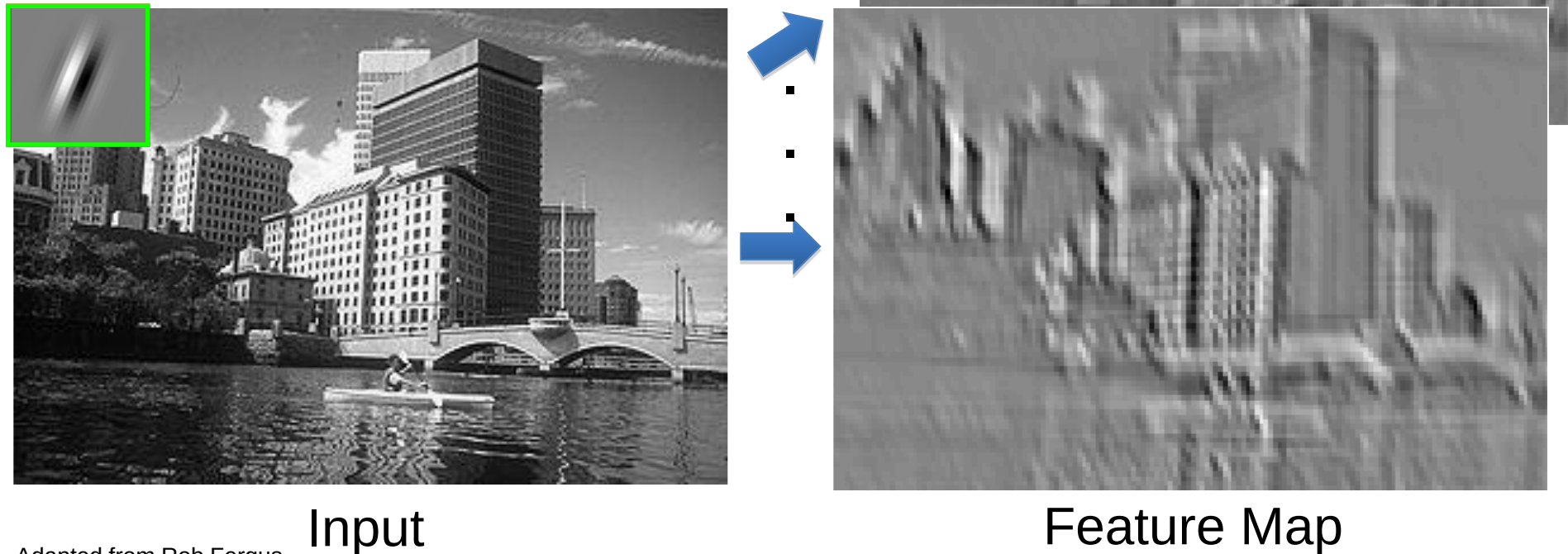
Convolutional Neural Networks (CNN)

- Feed-forward feature extraction:
 1. *Convolve* input with learned filters
 2. Apply non-linearity
 3. Spatial pooling (downsample)
- Recent architectures have additional operations (to be discussed)
- Trained with some loss, backprop



1. Convolution

- Apply learned filter weights
- One feature map per filter
- Stride can be greater than 1 (faster, less memory)



2. Non-Linearity

- Per-element (independent)
- Some options:
 - **Tanh**
 - **Sigmoid**: $1/(1+\exp(-x))$
 - **Rectified linear unit (ReLU)**
 - Avoids saturation issues

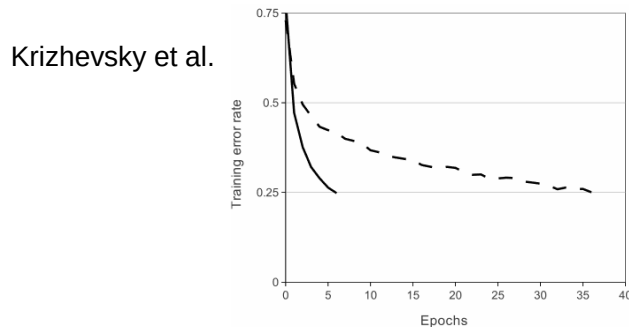
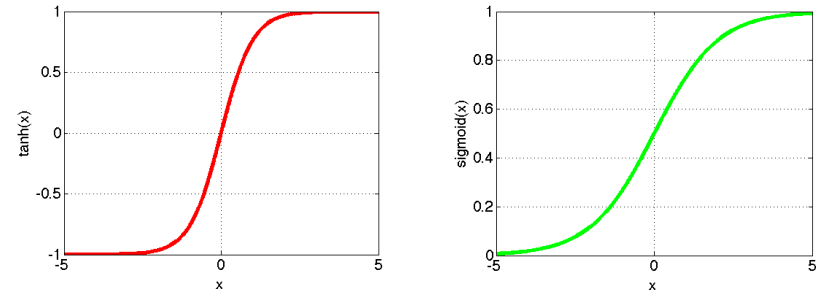
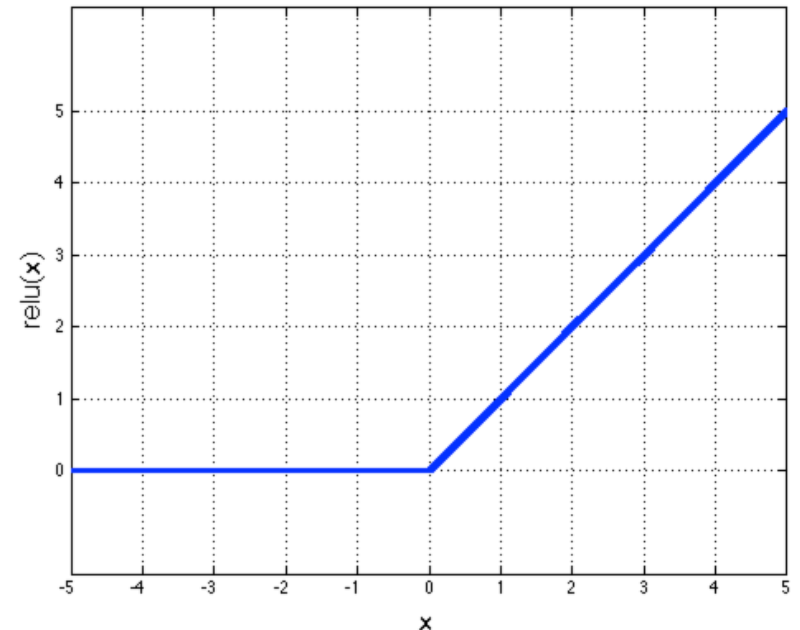
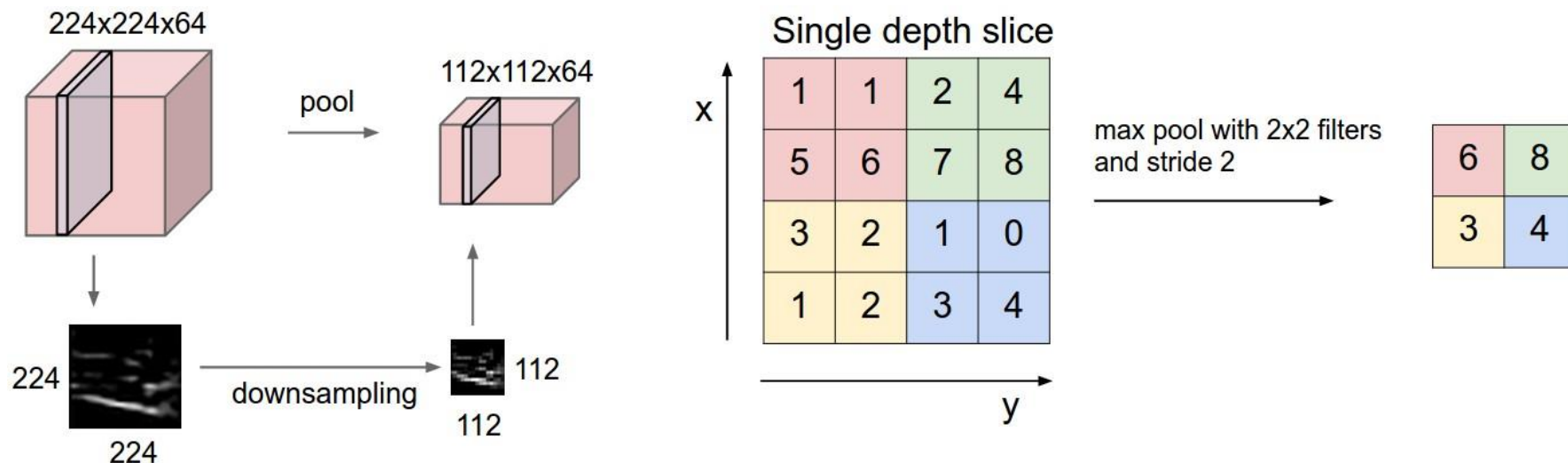


Figure 1: A four-layer convolutional neural network with **ReLU**s (solid line) reaches a 25% training error rate on CIFAR-10 six times faster than an equivalent network with tanh neurons (dashed line). The learning rates for each network were chosen independently to make training as fast as possible. No regularization of any kind was employed. The magnitude of the effect demonstrated here varies with network architecture, but networks with **ReLU**s consistently learn several times faster than equivalents with saturating neurons.



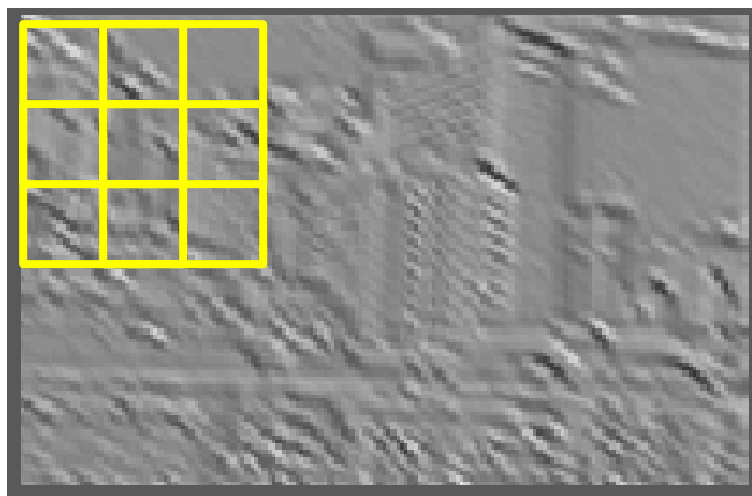
3. Spatial Pooling

- Sum or max over non-overlapping / overlapping regions

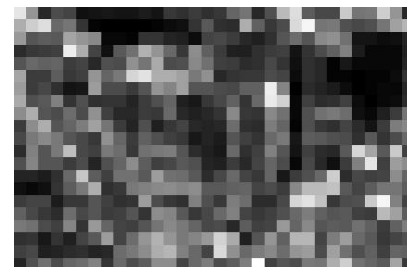


3. Spatial Pooling

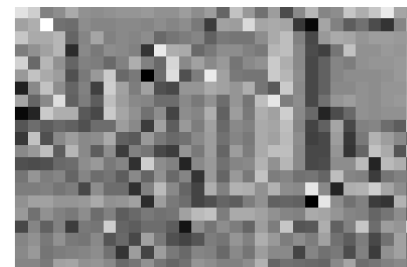
- Sum or max over non-overlapping / overlapping regions
- Role of pooling:
 - Invariance to small transformations
 - Larger receptive fields (neurons see more of input)



Max



Sum



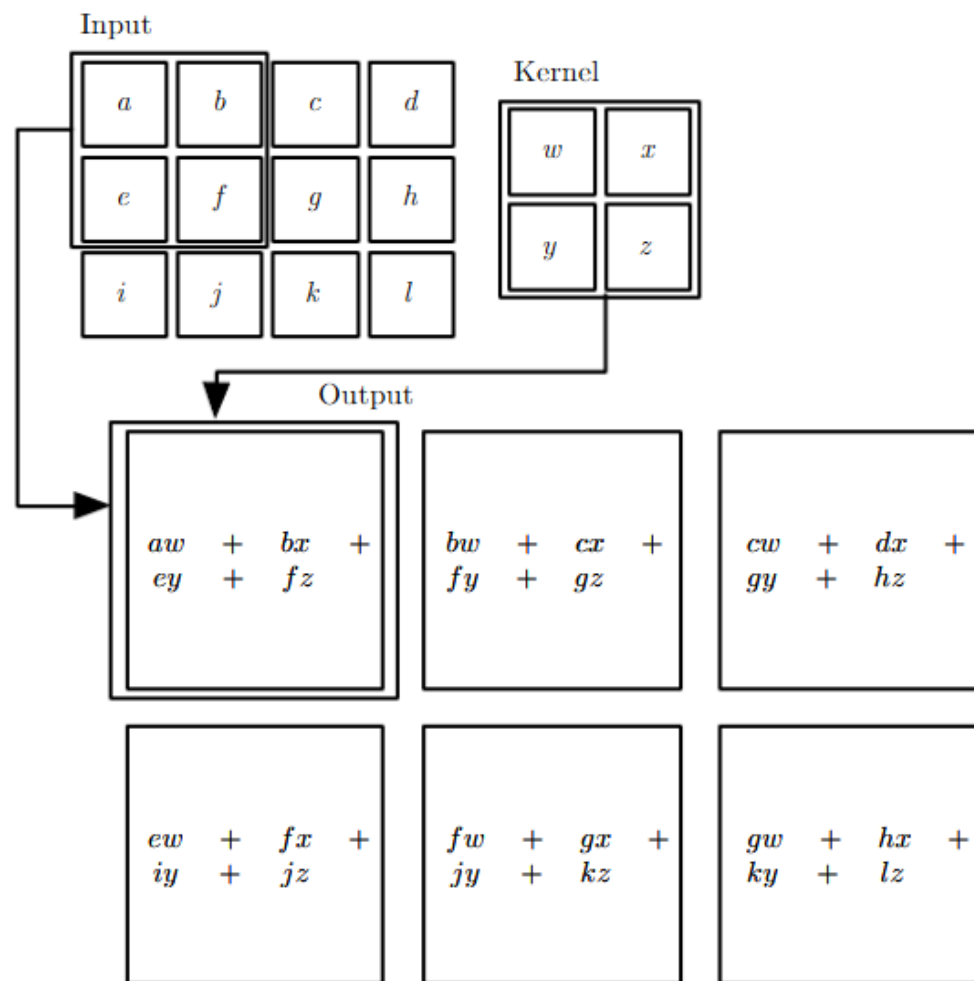


Figure 9.1: An example of 2-D convolution without kernel flipping. We restrict the output to only positions where the kernel lies entirely within the image, called “valid” convolution in some contexts. We draw boxes with arrows to indicate how the upper-left element of the output tensor is formed by applying the kernel to the corresponding upper-left region of the input tensor.

Background: Moving Average In 2D

$$F[x, y]$$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$$G[x, y]$$

	0								

Background: Moving Average In 2D

$$F[x, y]$$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$$G[x, y]$$

	0	10							

Background: Moving Average In 2D

$$F[x, y]$$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$$G[x, y]$$

	0	10	20						

Background: Moving Average In 2D

$$F[x, y]$$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$$G[x, y]$$

	0	10	20	30					

Background: Moving Average In 2D

$$F[x, y]$$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$$G[x, y]$$

	0	10	20	30	30				

Background: Moving Average In 2D

$$F[x, y]$$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$$G[x, y]$$

	0	10	20	30	30	30	20	10	
	0	20	40	60	60	60	40	20	
	0	30	60	90	90	90	60	30	
	0	30	50	80	80	90	60	30	
	0	30	50	80	80	90	60	30	
	0	20	30	50	50	60	40	20	
	10	20	30	30	30	30	20	10	
	10	10	10	0	0	0	0	0	

Image filtering

- Compute a function of the local neighborhood at each pixel in the image
 - Function specified by a “filter” or mask saying how to combine values from neighbors.
 - Element-wise multiplication
- Uses of filtering:
 - Enhance an image (denoise, resize, etc)
 - Extract information (texture, edges, etc)
 - Detect patterns (template matching)

Correlation filtering

Say the averaging window size is $2k+1 \times 2k+1$:

$$G[i, j] = \underbrace{\frac{1}{(2k+1)^2}}_{\text{Attribute uniform weight to each pixel}} \underbrace{\sum_{u=-k}^k \sum_{v=-k}^k F[i+u, j+v]}_{\text{Loop over all pixels in neighborhood around image pixel } F[i,j]}$$

Attribute uniform weight to each pixel

Loop over all pixels in neighborhood around image pixel $F[i,j]$

Now generalize to allow **different weights** depending on neighboring pixel's relative position:

$$G[i, j] = \sum_{u=-k}^k \sum_{v=-k}^k \underbrace{H[u, v]}_{\text{Non-uniform weights}} F[i+u, j+v]$$

Correlation filtering

$$G[i, j] = \sum_{u=-k}^k \sum_{v=-k}^k H[u, v] F[i + u, j + v]$$

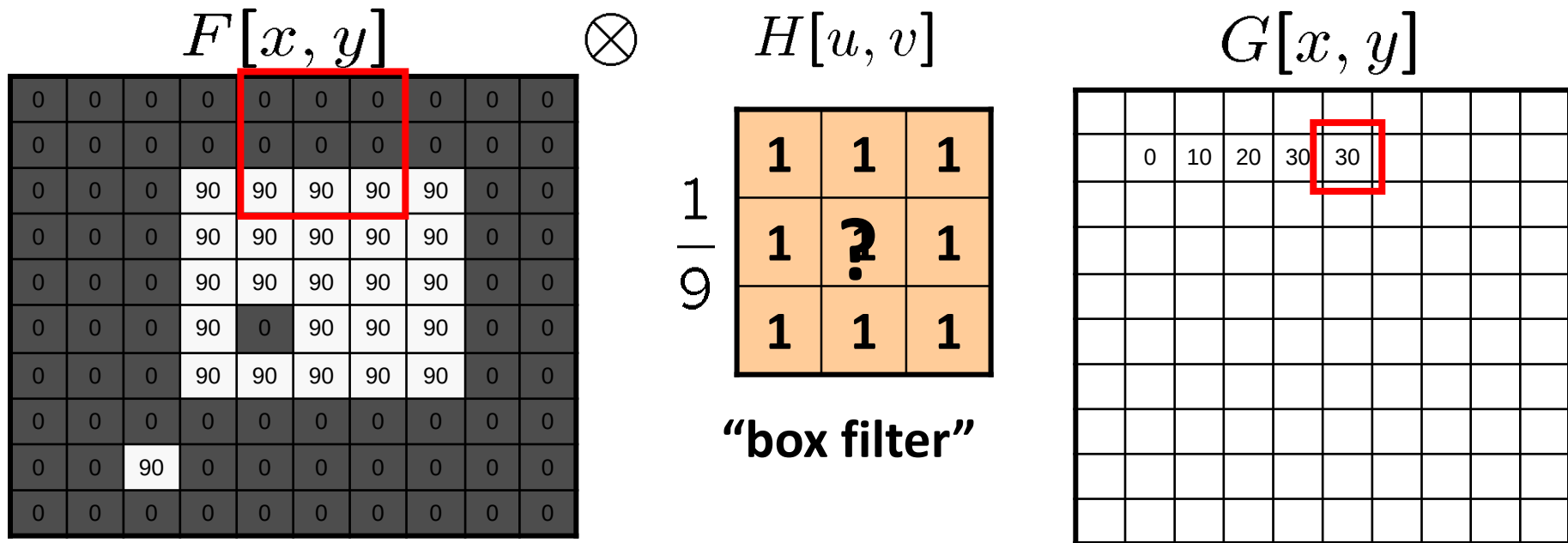
This is called **cross-correlation**, denoted $G = H \otimes F$

Filtering an image: replace each pixel with a linear combination of its neighbors.

The filter a.k.a. kernel a.k.a. mask $H[u, v]$ is the prescription for the weights in the linear combination.

Averaging filter

- What values belong in the kernel H for the moving average example?



$$G = H \otimes F$$

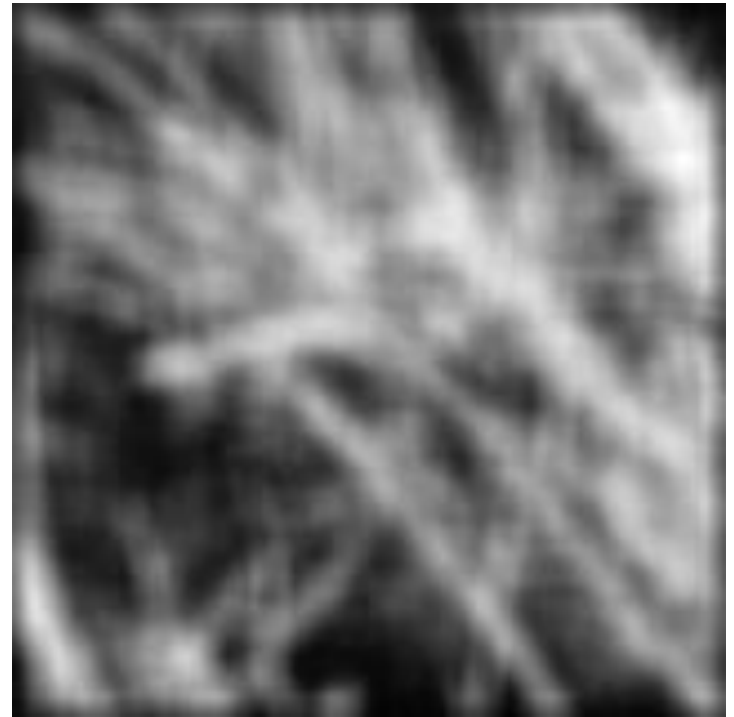
Smoothing by averaging



depicts box filter:
white = high value, black = low value



original



filtered

What if the filter size was 5 x 5 instead of 3 x 3?

Gaussian filter

- What if we want nearest neighboring pixels to have the most influence on the output?

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$F[x, y]$

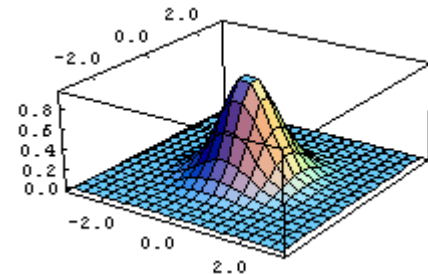
1	2	1
2	4	2
1	2	1

$\frac{1}{16}$

$H[u, v]$

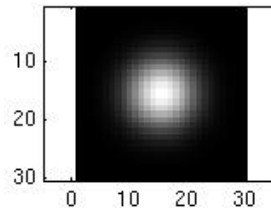
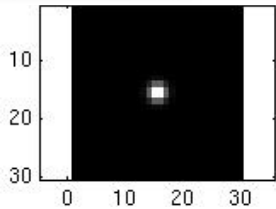
This kernel is an approximation of a 2d Gaussian function:

$$h(u, v) = \frac{1}{2\pi\sigma^2} e^{-\frac{u^2+v^2}{\sigma^2}}$$

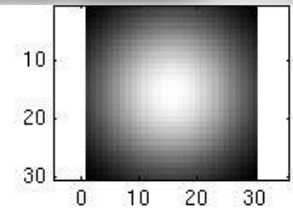


Smoothing with a Gaussian

Parameter σ is the “scale” / “width” / “spread” of the Gaussian kernel, and controls the amount of smoothing.



...



```
for sigma=1:3:10
    h = fspecial('gaussian', fsize, sigma);
    out = imfilter(im, h);
    imshow(out);
    pause;
end
```

Convolution

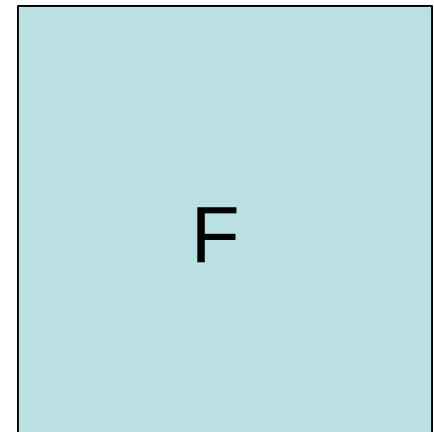
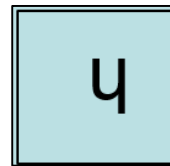
- Convolution:
 - Flip the filter in both dimensions (bottom to top, right to left)
 - Then apply cross-correlation

$$G[i, j] = \sum_{u=-k}^k \sum_{v=-k}^k H[u, v] F[i - u, j - v]$$

$$G = H \star F$$



*Notation for
convolution
operator*



Convolution vs. correlation

Convolution

$$G[i, j] = \sum_{u=-k}^k \sum_{v=-k}^k H[u, v] F[i - u, j - v]$$

$$G = H \star F$$

Cross-correlation

$$G[i, j] = \sum_{u=-k}^k \sum_{v=-k}^k H[u, v] F[i + u, j + v]$$

$$G = H \otimes F$$

For a Gaussian or box filter, how will the outputs differ?

Convolution vs. correlation

Cross-correlation

$$G[i, j] = \sum_{u=-k}^k \sum_{v=-k}^k H[u, v] F[i + u, j + v]$$

$$G = H \otimes F$$

$$u = -1, v = -1$$

F

5	2	5	4	4
5	200	3	200	4
1	5	5	4	4
5	5	1	1	2
200	1	3	5	200
1	200	200	200	1

(i, j)

Convolution

$$G[i, j] = \sum_{u=-k}^k \sum_{v=-k}^k H[u, v] F[i - u, j - v]$$

$$G = H \star F$$

H

.06	.12	.06
.12	.25	.12
.06	.12	.06

(0, 0)

Convolution vs. correlation

Cross-correlation

$$G[i, j] = \sum_{u=-k}^k \sum_{v=-k}^k H[u, v] F[i + u, j + v]$$

$$G = H \otimes F$$

$$\begin{aligned} u &= -1, v = -1 \\ v &= 0 \end{aligned}$$

F

5	2	5	4	4
5	200	3	200	4
1	5	5	4	4
5	5	1	1	2
200	1	3	5	200
1	200	200	200	1

(i, j)

Convolution

$$G[i, j] = \sum_{u=-k}^k \sum_{v=-k}^k H[u, v] F[i - u, j - v]$$

$$G = H \star F$$

H

.06	.12	.06
.12	.25	.12
.06	.12	.06

(0, 0)

Convolution vs. correlation

Cross-correlation

$$G[i, j] = \sum_{u=-k}^k \sum_{v=-k}^k H[u, v] F[i + u, j + v]$$

$$G = H \otimes F$$

$$u = -1, v = -1$$

$$v = 0$$

$$v = +1$$

F

5	2	5	4	4
5	200	3	200	4
1	5	5	4	4
5	5	1	1	2
200	1	3	5	200
1	200	200	200	1

(i, j)

Convolution

$$G[i, j] = \sum_{u=-k}^k \sum_{v=-k}^k H[u, v] F[i - u, j - v]$$

$$G = H \star F$$

H

.06	.12	.06
.12	.25	.12
.06	.12	.06

(0, 0)

Convolution vs. correlation

Cross-correlation

$$G[i, j] = \sum_{u=-k}^k \sum_{v=-k}^k H[u, v] F[i + u, j + v]$$

$$G = H \otimes F$$

$$u = -1, v = -1$$

$$v = 0$$

$$v = +1$$

$$u = 0, v = -1$$

F

5	2	5	4	4
5	200	3	200	4
1	5	5	4	4
5	5	1	1	2
200	1	3	5	200
1	200	200	200	1

(i, j)

Convolution

$$G[i, j] = \sum_{u=-k}^k \sum_{v=-k}^k H[u, v] F[i - u, j - v]$$

$$G = H \star F$$

H

.06	.12	.06
.12	.25	.12
.06	.12	.06

(0, 0)

Convolution vs. correlation

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F

5	2	5	4	4
5	200	3	200	4
1	5	5	4	4
5	5	1	1	2
200	1	3	5	200
1	200	200	200	1

(i, j)

Convolution

$$G[i, j] = \sum_{u=-k}^k \sum_{v=-k}^k H[u, v] F[i - u, j - v]$$

$$G = H \star F$$

H

.06	.12	.06
.12	.25	.12
.06	.12	.06

(0, 0)

Convolution vs. correlation

Cross-correlation

$$G[i, j] = \sum_{u=-k}^k \sum_{v=-k}^k H[u, v] F[i + u, j + v]$$

$$G = H \otimes F$$

$$\begin{aligned} u &= -1, v = -1 \\ v &= 0 \end{aligned}$$

F

5	2	5	4	4
5	200	3	200	4
1	5	5	4	4
5	5	1	1	2
200	1	3	5	200
1	200	200	200	1

(i, j)

Convolution

$$G[i, j] = \sum_{u=-k}^k \sum_{v=-k}^k H[u, v] F[i - u, j - v]$$

$$G = H \star F$$

H

.06	.12	.06
.12	.25	.12
.06	.12	.06

(0, 0)

Convolution vs. correlation

Cross-correlation

$$G[i, j] = \sum_{u=-k}^k \sum_{v=-k}^k H[u, v] F[i + u, j + v]$$

$$G = H \otimes F$$

$$u = -1, v = -1$$

$$v = 0$$

$$v = +1$$

F

5	2	5	4	4
5	200	3	200	4
1	5	5	4	4
5	5	1	1	2
200	1	3	5	200
1	200	200	200	1

(i, j)

Convolution

$$G[i, j] = \sum_{u=-k}^k \sum_{v=-k}^k H[u, v] F[i - u, j - v]$$

$$G = H \star F$$

H

.06	.12	.06
.12	.25	.12
.06	.12	.06

(0, 0)

Convolution vs. correlation

Cross-correlation

$$G[i, j] = \sum_{u=-k}^k \sum_{v=-k}^k H[u, v] F[i + u, j + v]$$

$$G = H \otimes F$$

$$u = -1, v = -1$$

$$v = 0$$

$$v = +1$$

$$u = 0, v = -1$$

F

5	2	5	4	4
5	200	3	200	4
1	5	5	4	4
5	5	1	1	2
200	1	3	5	200
1	200	200	200	1

(i, j)

Convolution

$$G[i, j] = \sum_{u=-k}^k \sum_{v=-k}^k H[u, v] F[i - u, j - v]$$

$$G = H \star F$$

H

.06	.12	.06
.12	.25	.12
.06	.12	.06

(0, 0)

Predict the outputs using correlation filtering


$$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} = ?$$


$$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} = ?$$


$$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 0 \end{bmatrix} - \frac{1}{9} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} = ?$$

Practice with linear filters



Original

0	0	0
0	1	0
0	0	0

?

Practice with linear filters



Original

0	0	0
0	1	0
0	0	0



**Filtered
(no change)**

Practice with linear filters



Original

0	0	0
0	0	1
0	0	0

?

Practice with linear filters



Original

0	0	0
0	0	1
0	0	0



**Shifted left
by 1 pixel
with
correlation**

Practice with linear filters



Original

 $\frac{1}{9}$

1	1	1
1	1	1
1	1	1

?

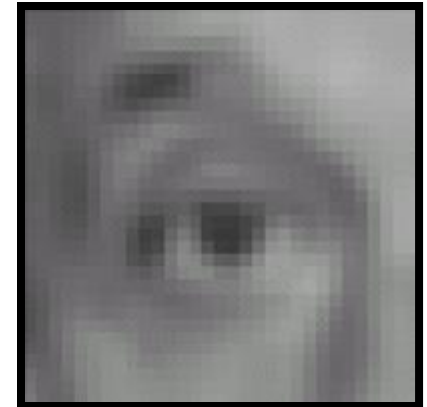
Practice with linear filters



Original

$$\frac{1}{9}$$

1	1	1
1	1	1
1	1	1



**Blur (with a
box filter)**

Practice with linear filters



Original

0	0	0
0	2	0
0	0	0

—

$\frac{1}{9}$

1	1	1
1	1	1
1	1	1

?

Practice with linear filters



Original

0	0	0
0	2	0
0	0	0

−

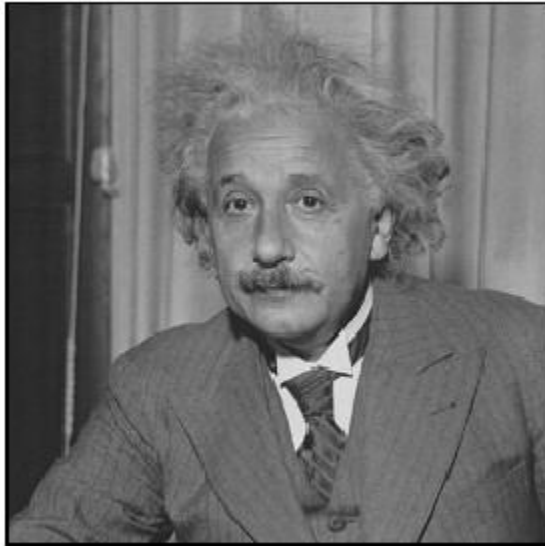
$\frac{1}{9}$

1	1	1
1	1	1
1	1	1

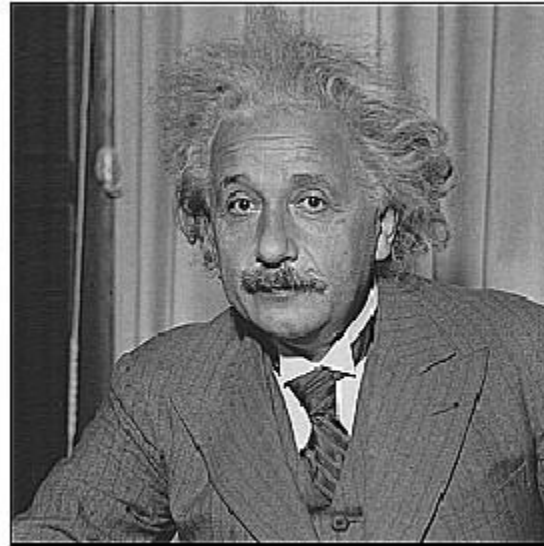


Sharpening filter:
accentuates differences with
local average

Sharpening



before



after

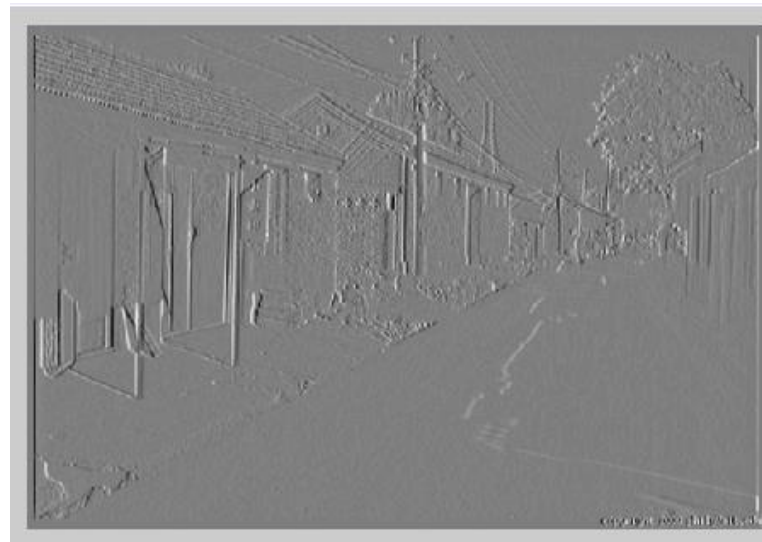
Filters for computing *gradients*

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

intensity image



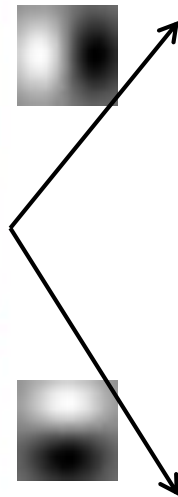
$$* \begin{bmatrix} \text{light gray} & \text{dark gray} \\ \text{white} & \text{black} \end{bmatrix} =$$



Texture representation: example



original image



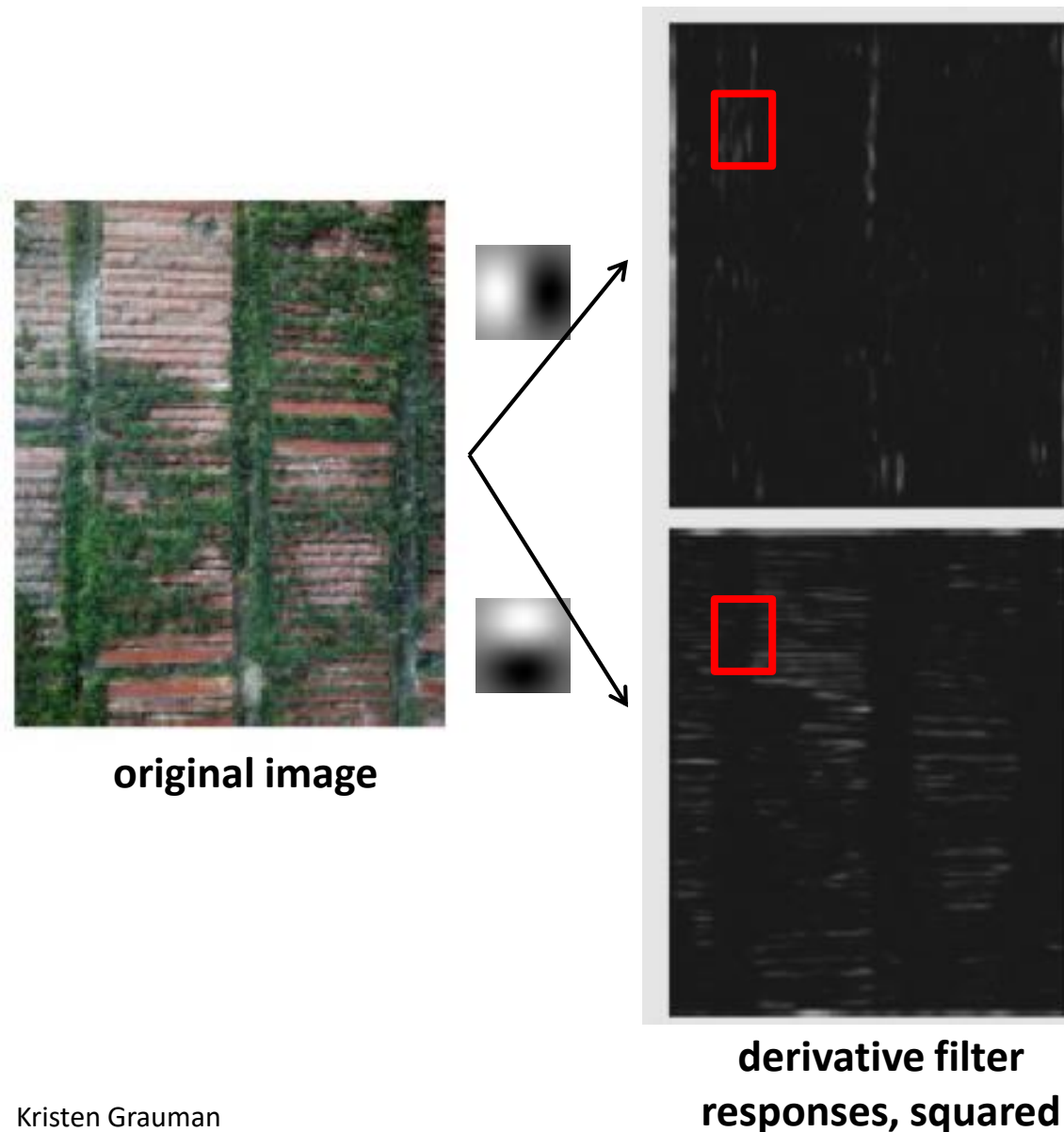
**derivative filter
responses, squared**

	<u>mean</u> <u>d/dx</u> <u>value</u>	<u>mean</u> <u>d/dy</u> <u>value</u>
Win. #1	4	10

⋮

statistics to summarize patterns in small windows

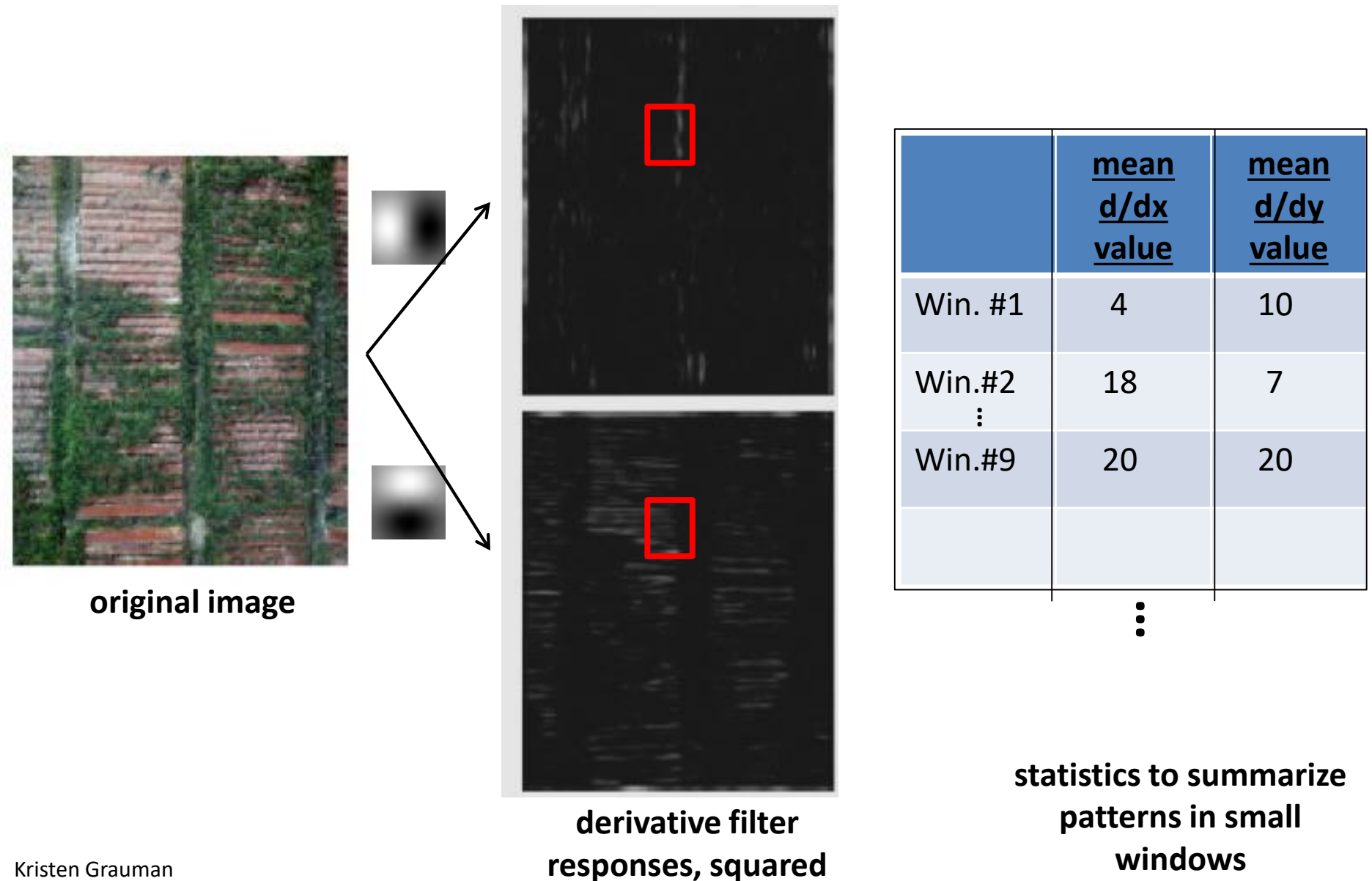
Texture representation: example



	<u>mean d/dx value</u>	<u>mean d/dy value</u>
Win. #1	4	10
Win.#2	18	7
	⋮	

statistics to summarize
patterns in small
windows

Texture representation: example



Vectors of texture responses

To represent pixel, form a “feature vector” from the responses at that pixel.

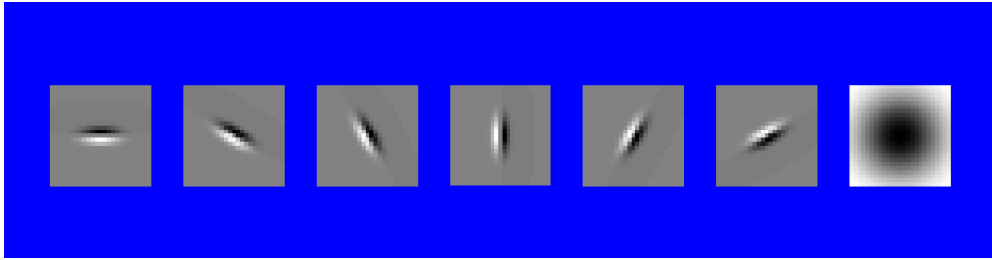
To represent *image*, compute statistics over all pixel feature vectors, e.g. their mean.

$$\begin{array}{l} [r_{(1,1)}^1, r_{(1,1)}^2, \dots, r_{(1,1)}^{38}] \\ \uparrow \quad \swarrow \\ [r_{(1,2)}^1, r_{(1,2)}^2, \dots, r_{(1,2)}^{38}] \\ \text{Pixel location} \quad \text{Filter ID} \\ \text{(row, column)} \quad \dots \\ [r_{(W,H)}^1, r_{(W,H)}^2, \dots, r_{(W,H)}^{38}] \end{array}$$

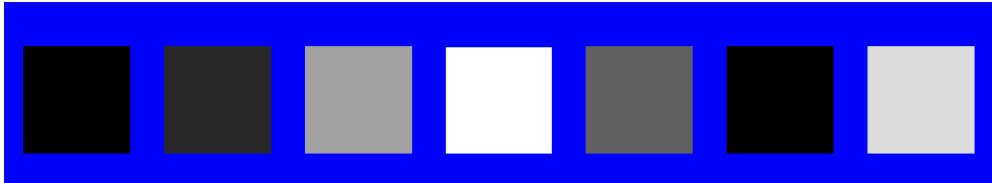
$$[\text{mean}(r_{(:,1)}^1), \text{mean}(r_{(:,2)}^2), \dots, \text{mean}(r_{(:,38)}^{38})]$$

You try: Can you match the texture to the response?

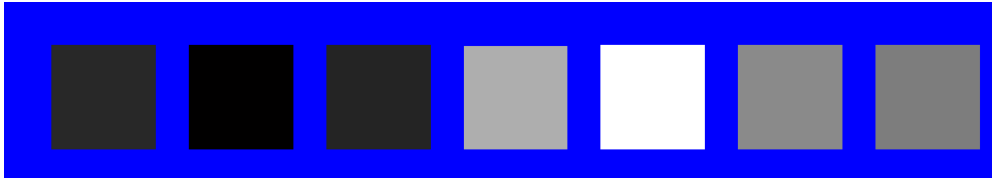
Filters



1



2

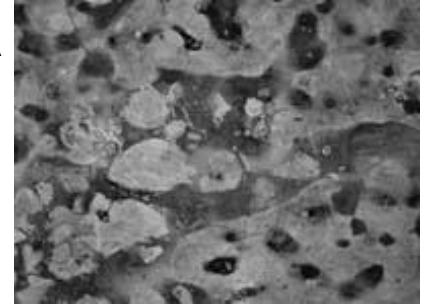


3



Mean abs responses

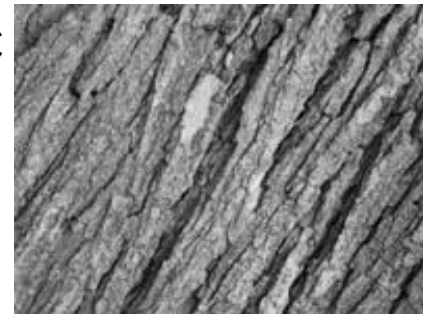
A



B

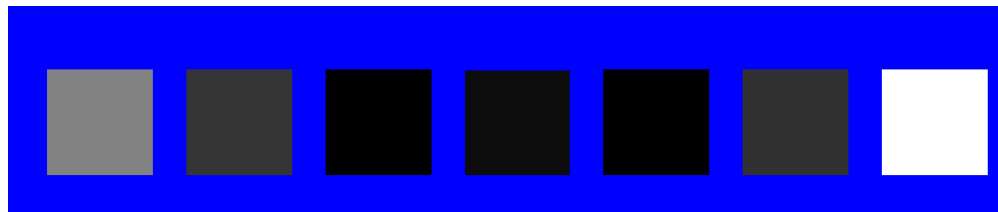
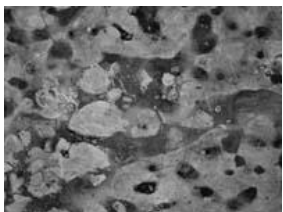
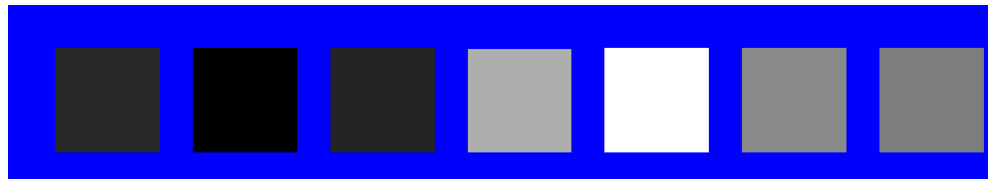
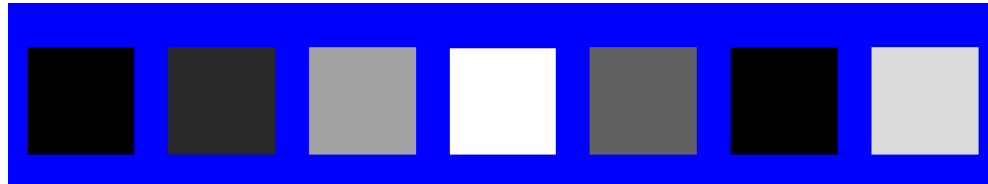
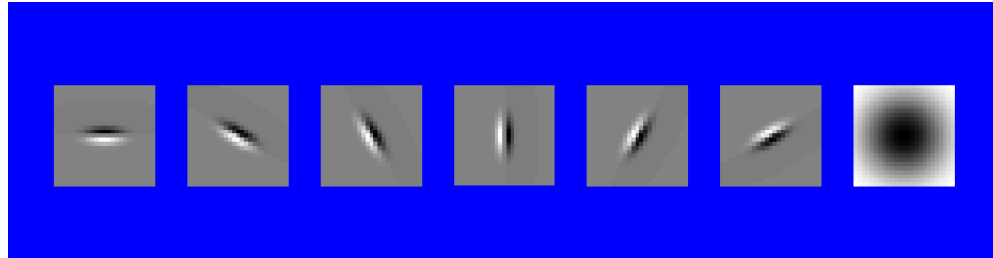


C



Representing texture by mean abs response

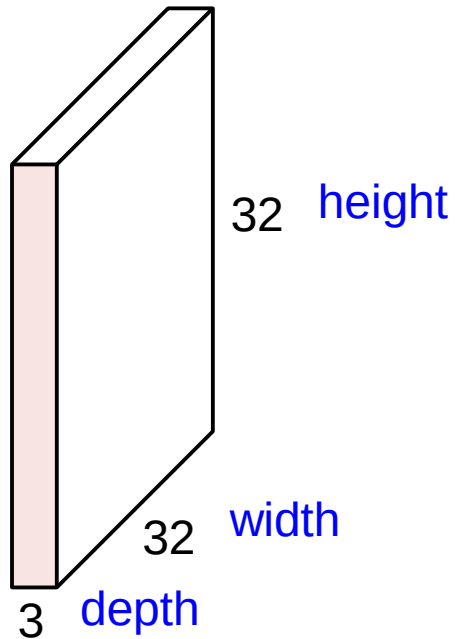
Filters



Mean abs responses

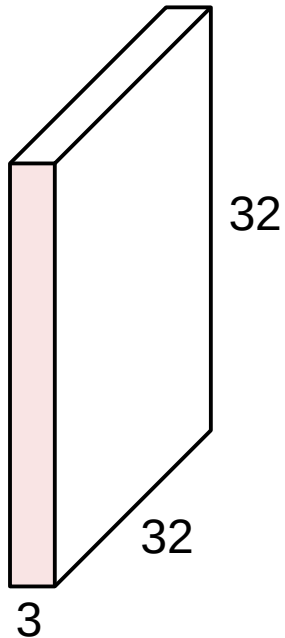
Convolutions: More detail

32x32x3 image



Convolutions: More detail

32x32x3 image



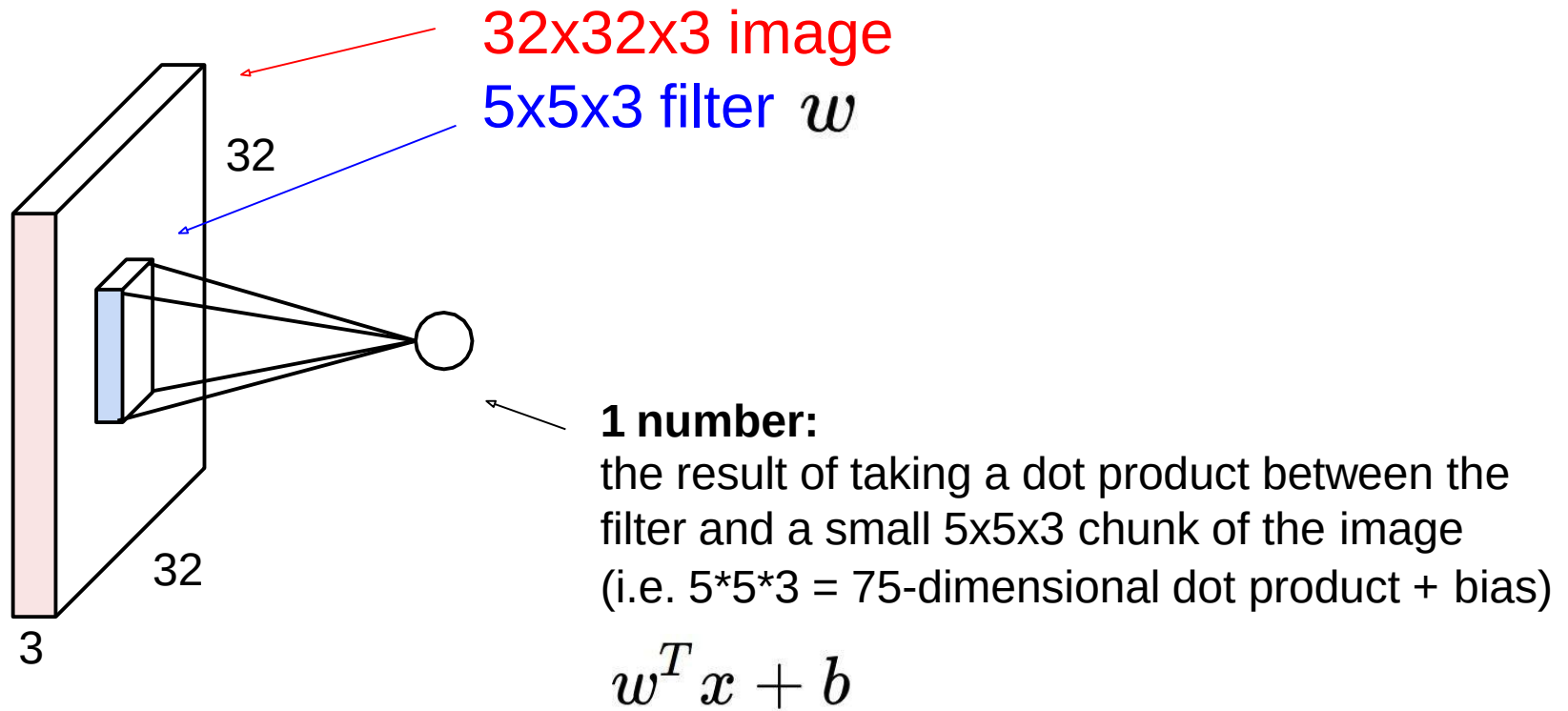
5x5x3 filter



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

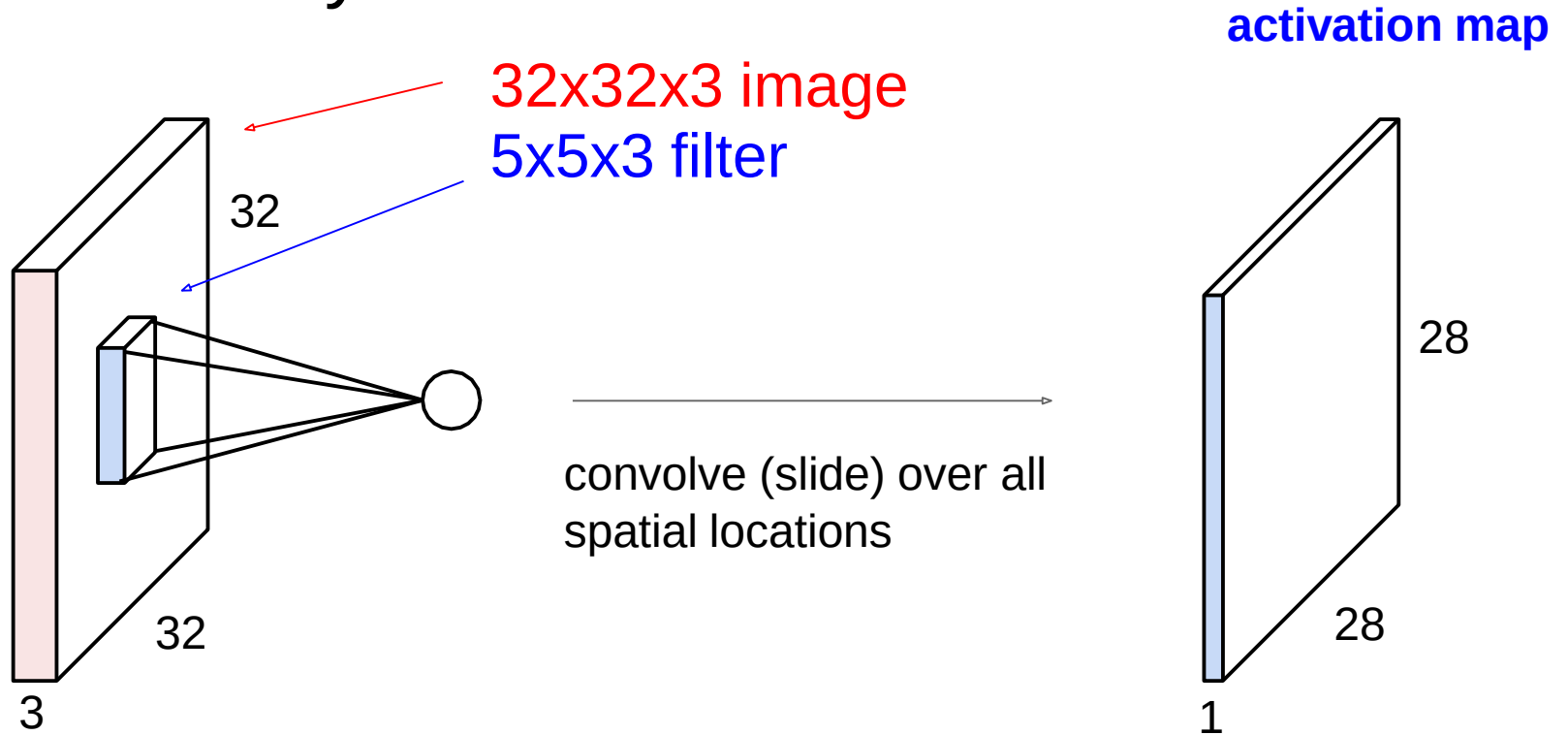
Convolutions: More detail

Convolution Layer



Convolutions: More detail

Convolution Layer



Convolutions: More detail

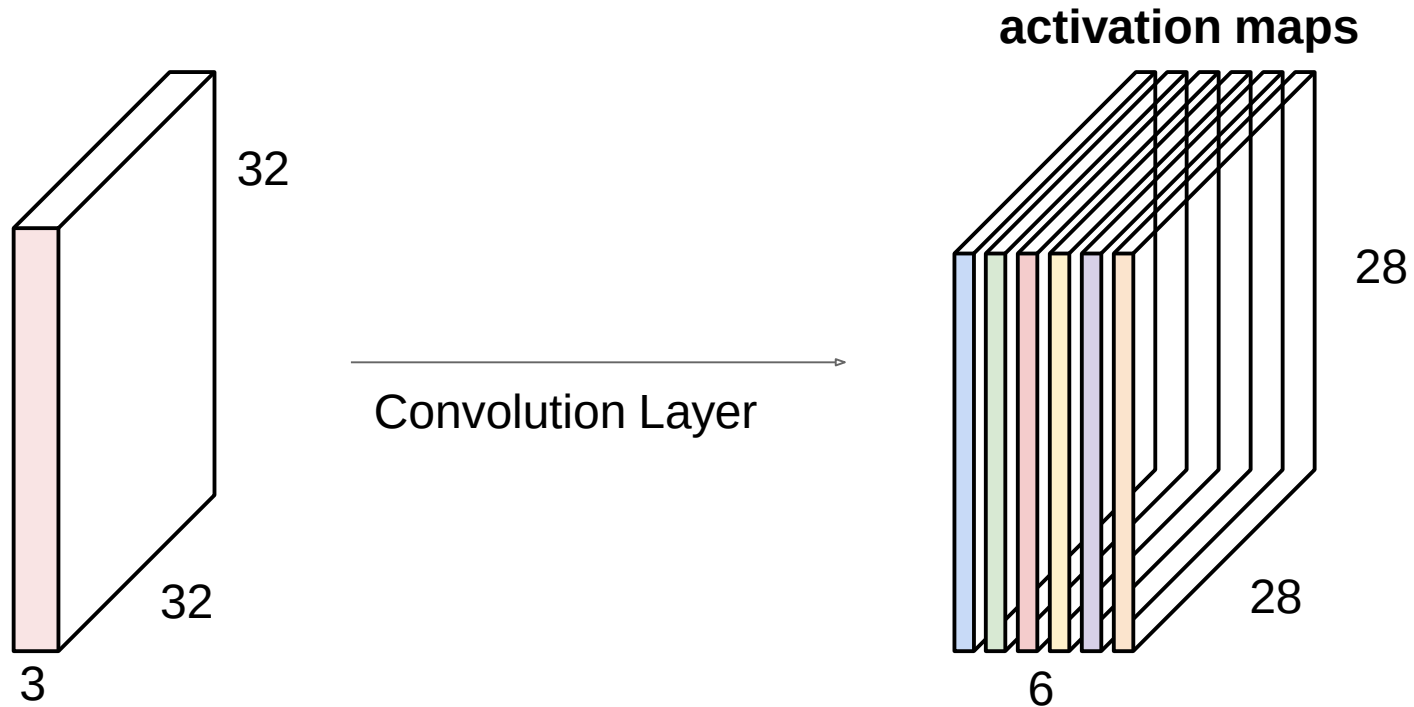
Convolution Layer

consider a second, **green** filter



Convolutions: More detail

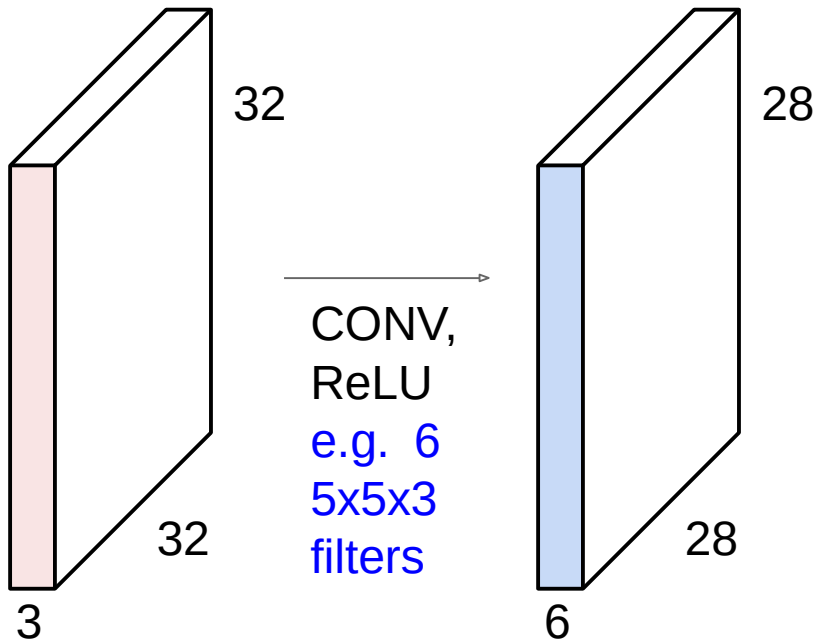
For example, if we had 6 5x5 filters, we'll get 6 separate activation maps:



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

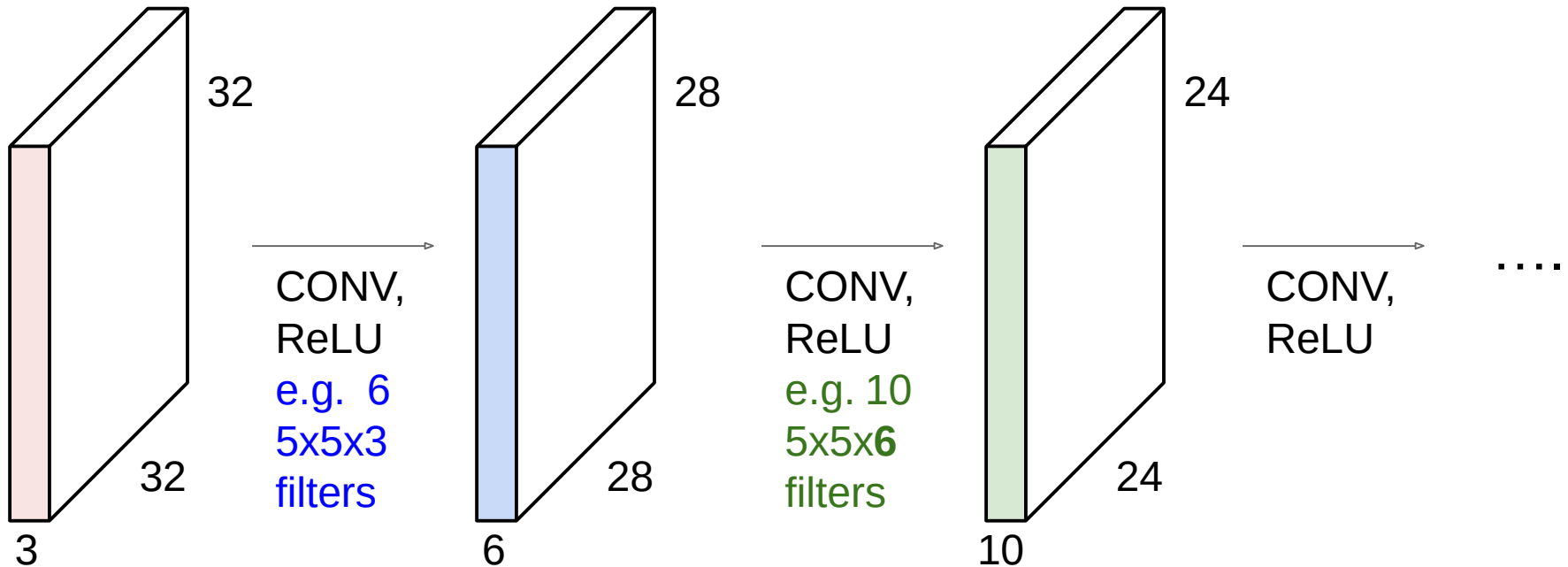
Convolutions: More detail

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



Convolutions: More detail

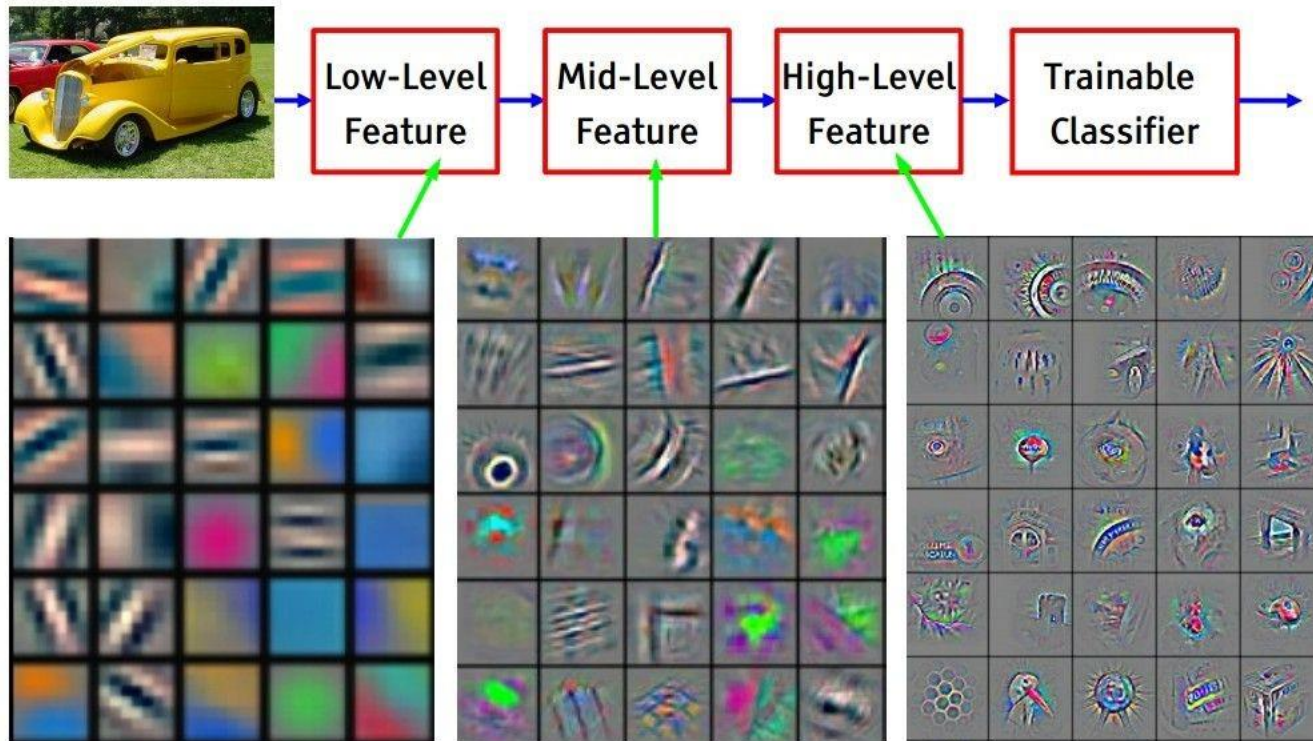
Preview: ConvNet is a sequence of Convolutional Layers, interspersed with activation functions



Convolutions: More detail

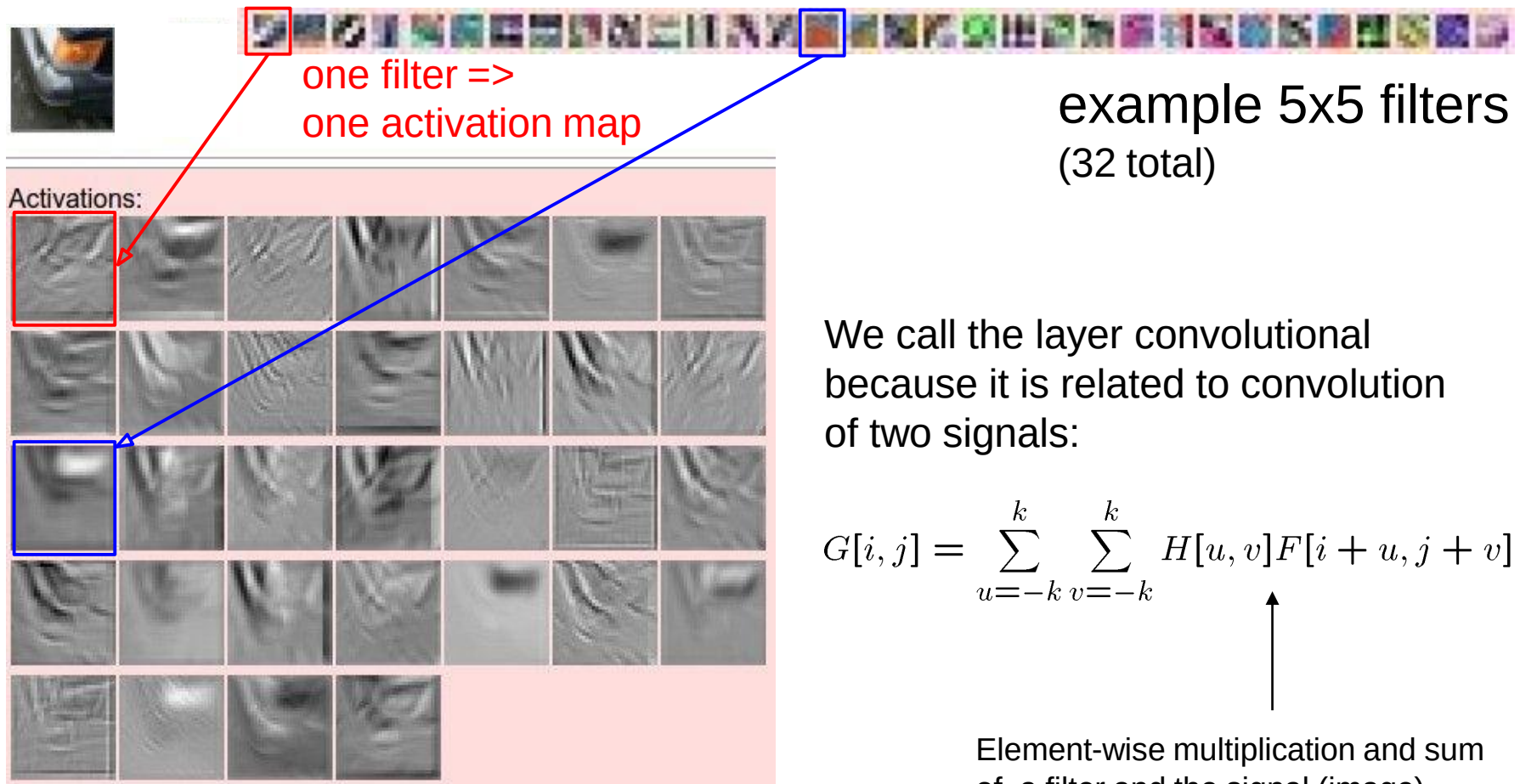
Preview

[From recent Yann LeCun slides]



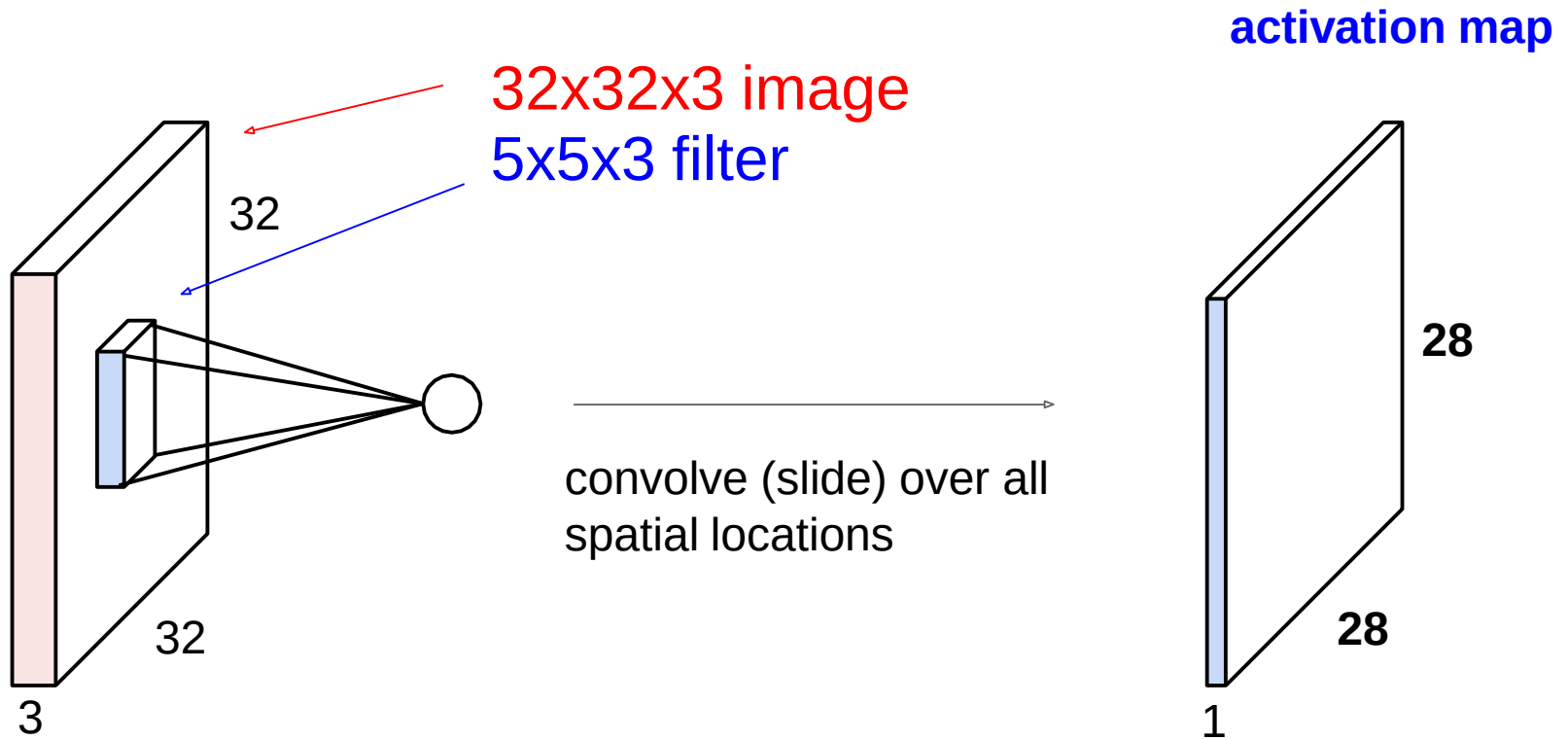
Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

Convolutions: More detail



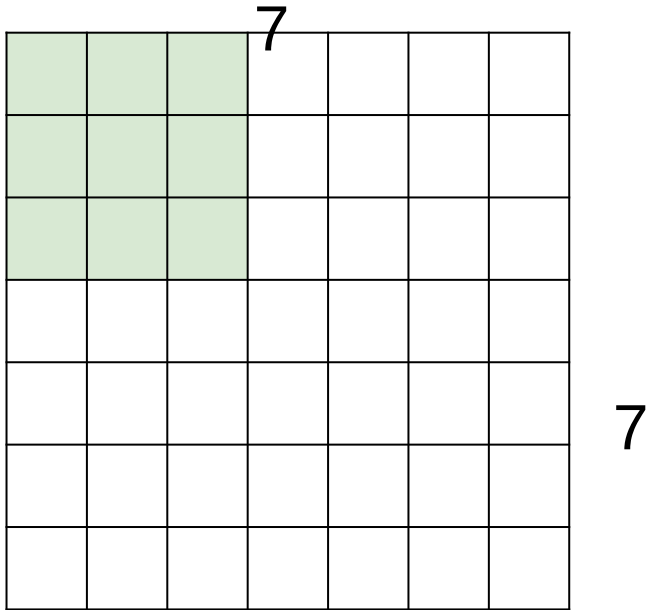
Convolutions: More detail

A closer look at spatial dimensions:



Convolutions: More detail

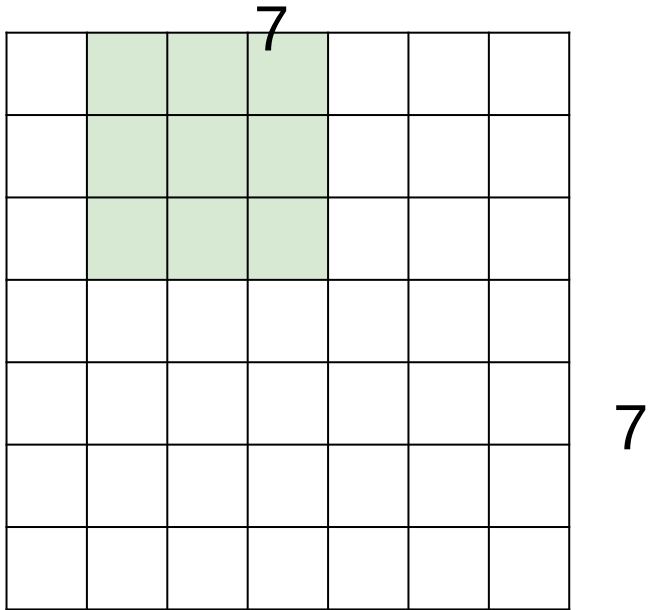
A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter

Convolutions: More detail

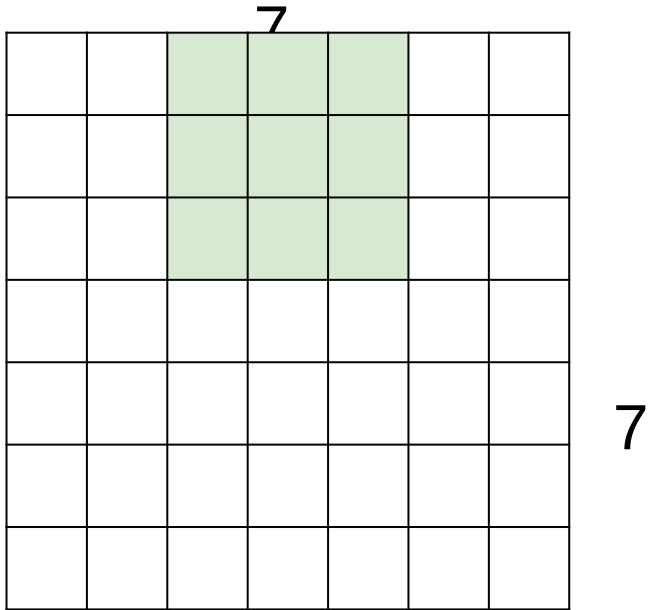
A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter

Convolutions: More detail

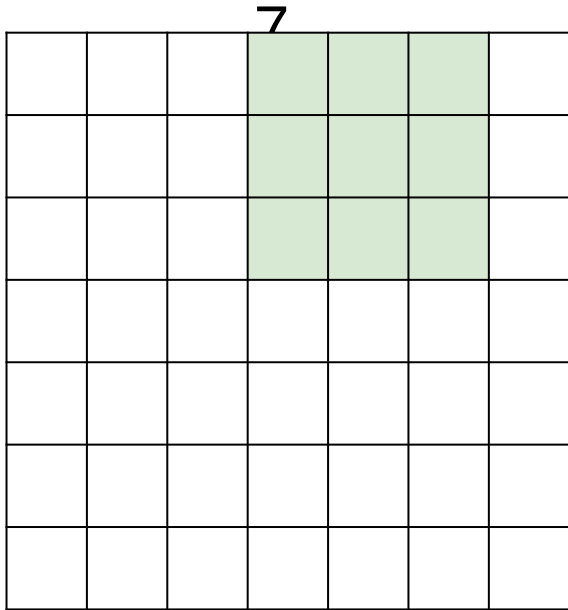
A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter

Convolutions: More detail

A closer look at spatial dimensions:

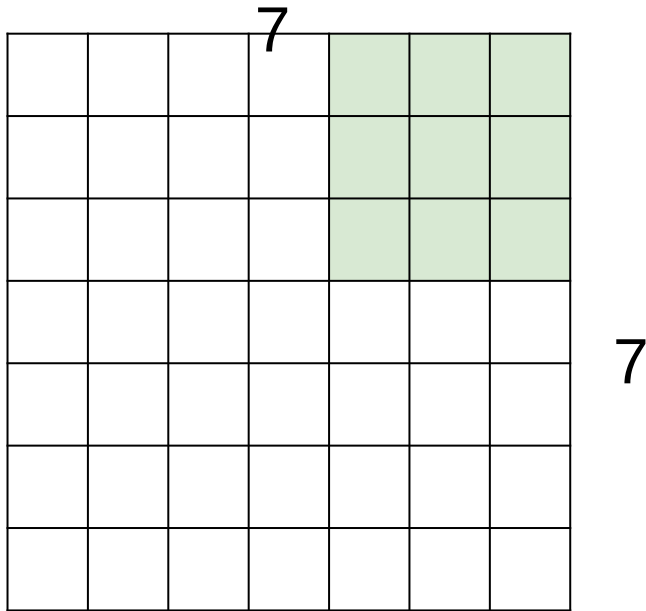


7x7 input (spatially)
assume 3x3 filter

7

Convolutions: More detail

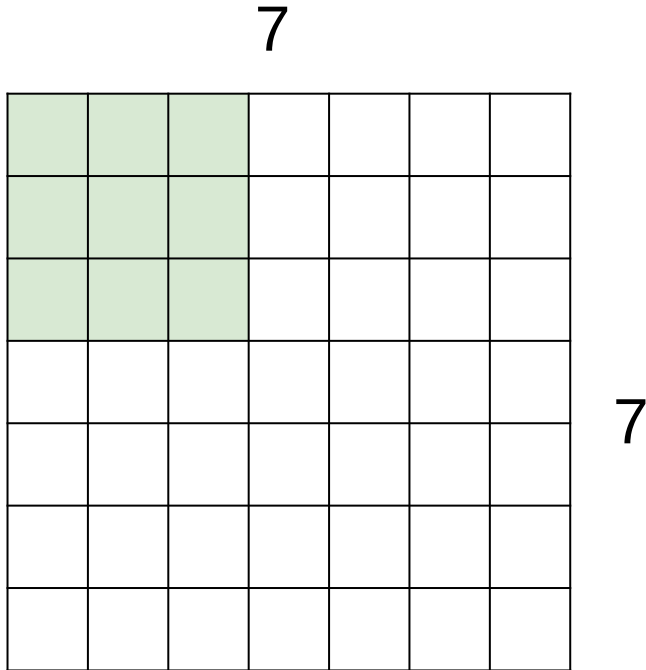
A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter
=> 5x5 output

Convolutions: More detail

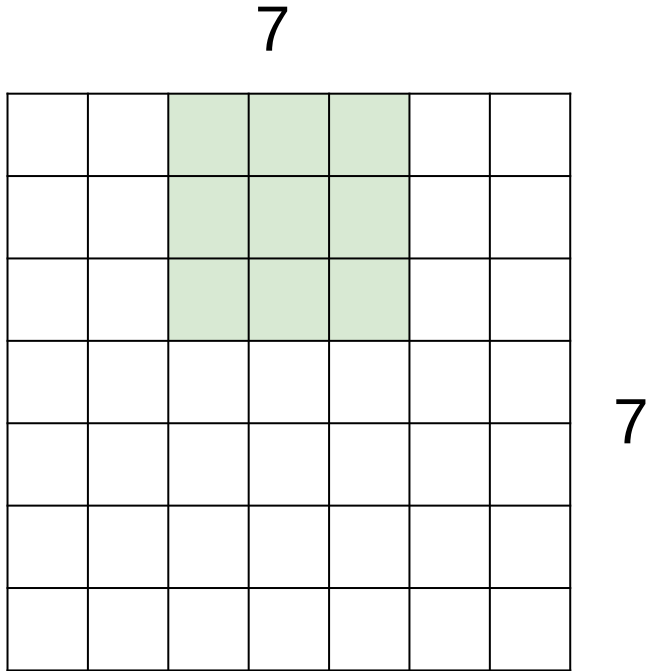
A closer look at spatial dimensions:



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

Convolutions: More detail

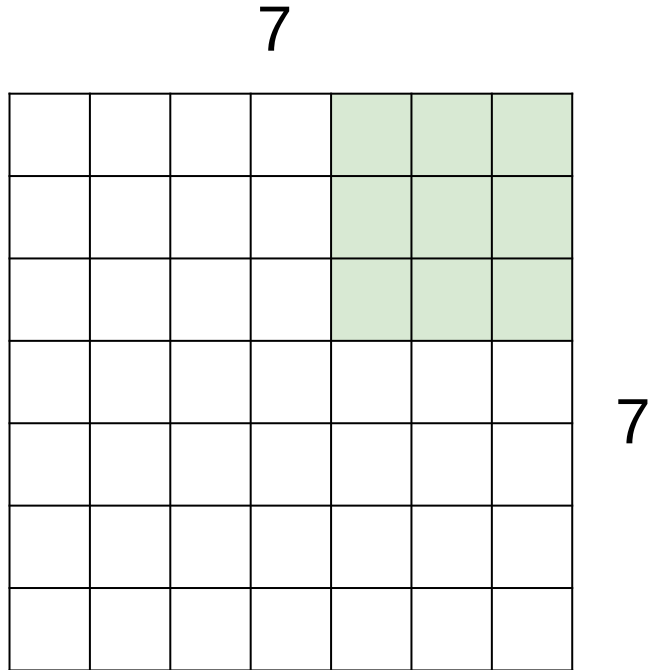
A closer look at spatial dimensions:



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

Convolutions: More detail

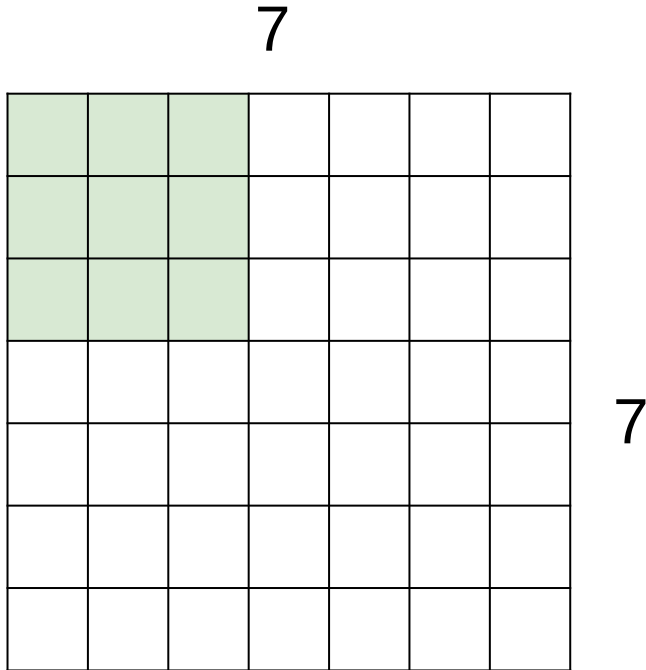
A closer look at spatial dimensions:



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

Convolutions: More detail

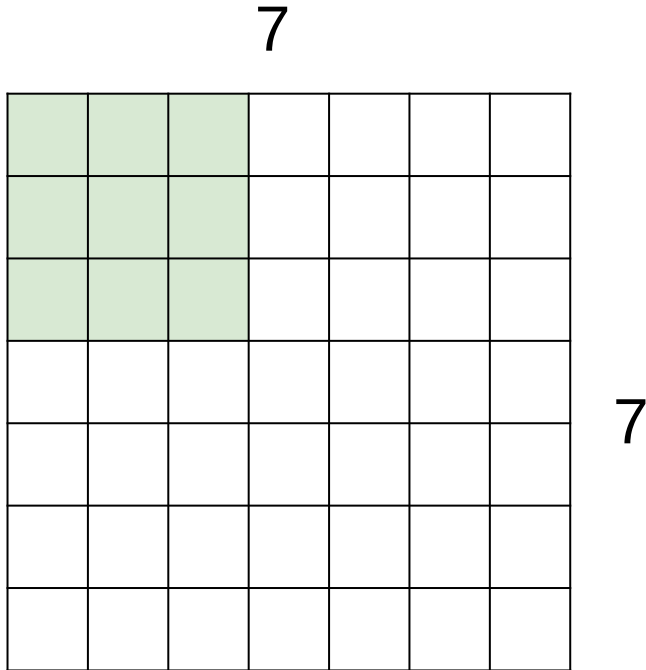
A closer look at spatial dimensions:



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

Convolutions: More detail

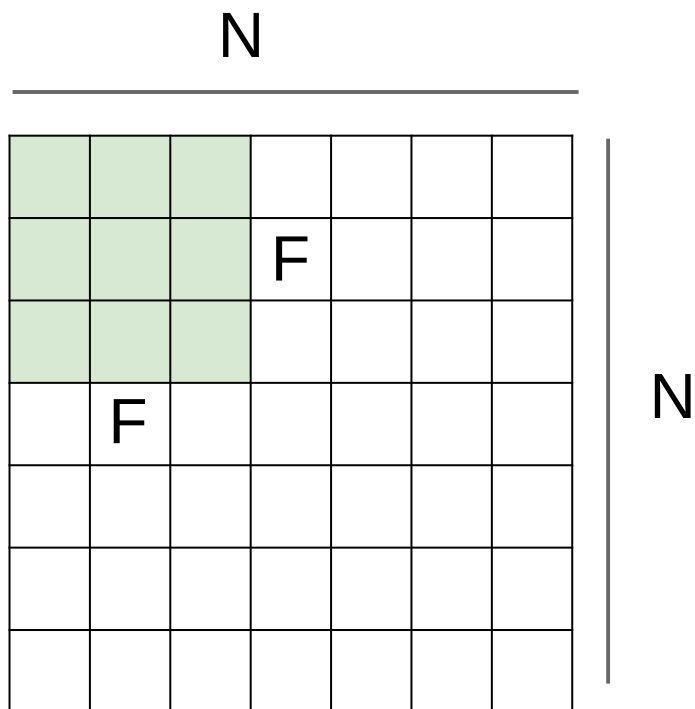
A closer look at spatial dimensions:



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

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

Convolutions: More detail



Output size:

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

e.g. $N = 7$, $F = 3$:

$$\text{stride } 1 \Rightarrow (7 - 3) / 1 + 1 = 5$$

$$\text{stride } 2 \Rightarrow (7 - 3) / 2 + 1 = 3$$

$$\text{stride } 3 \Rightarrow (7 - 3) / 3 + 1 = 2.33 \text{ :}\backslash$$

Convolutions: More detail

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:)

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

Convolutions: More detail

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!

Convolutions: More detail

In practice: Common to zero pad the border

0	0	0	0	0	0			
0								
0								
0								
0								

e.g. input 7x7

3x3 filter, applied with **stride 1**

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

7x7 output!

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

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

$F = 5 \Rightarrow$ zero pad with 2

$F = 7 \Rightarrow$ zero pad with 3

$$(N + 2 * \text{padding} - F) / \text{stride} + 1$$

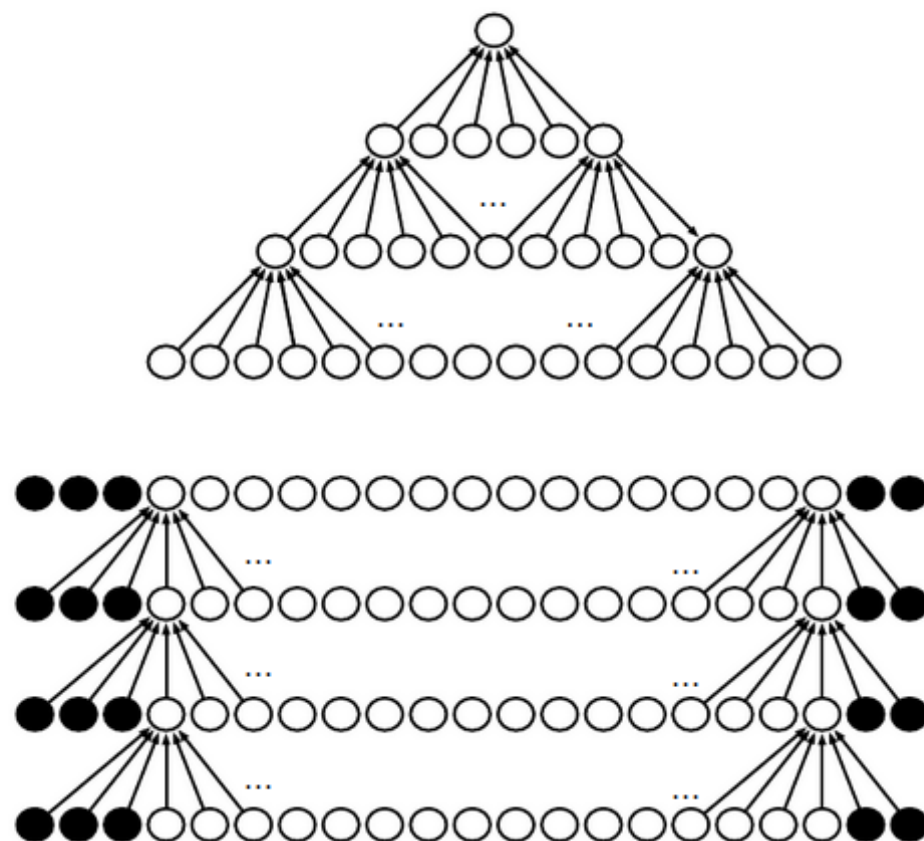


Figure 9.13: The effect of zero padding on network size. Consider a convolutional network with a kernel of width six at every layer. In this example, we do not use any pooling, so only the convolution operation itself shrinks the network size. *(Top)* In this convolutional network, we do not use any implicit zero padding. This causes the representation to shrink by five pixels at each layer. Starting from an input of sixteen pixels, we are only able to have three convolutional layers, and the last layer does not even move the kernel, so arguably only two of the layers are truly convolutional. The rate of shrinking can be mitigated by using smaller kernels, but smaller kernels are less expressive, and some shrinking is inevitable in this kind of architecture. *(Bottom)* By adding five implicit zeros to each layer, we prevent the representation from shrinking with depth. This allows us to make an arbitrarily deep convolutional network.

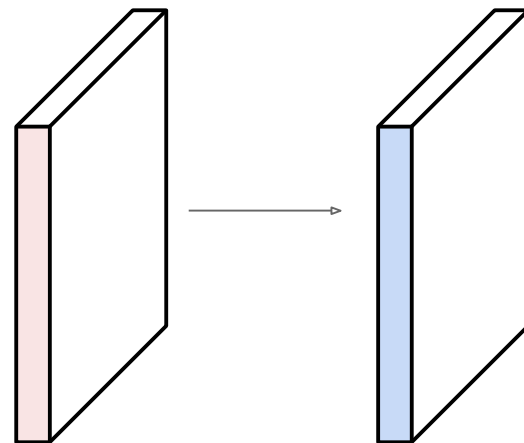
Convolutions: More detail

Examples time:

Input volume: **32x32x3**

10 5x5 filters with stride 1, pad 2

Output volume size: ?



Convolutions: More detail

Examples time:

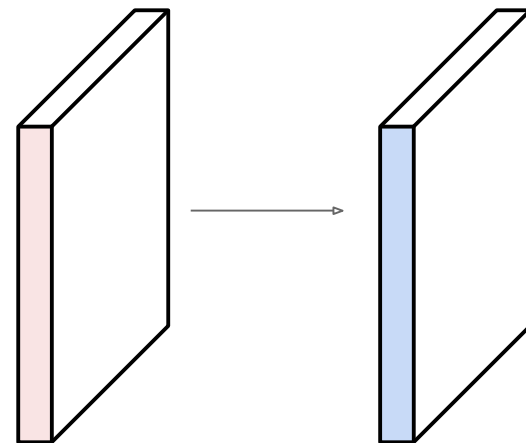
Input volume: **32x32x3**

10 **5x5**x3 filters with stride **1**, pad **2**

Output volume size:

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

32x32x10

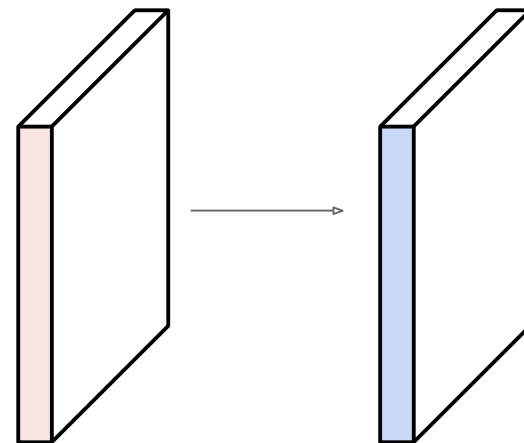


Convolutions: More detail

Examples time:

Input volume: **32x32x3**

10 5x5x3 filters with stride 1, pad 2



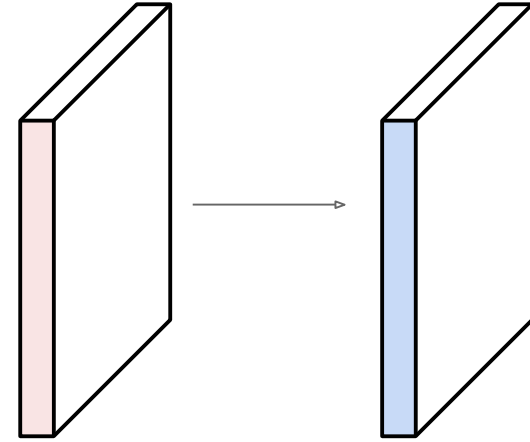
Number of parameters in this layer?

Convolutions: More detail

Examples time:

Input volume: **32x32x3**

10 **5x5x3** filters with stride 1, pad 2

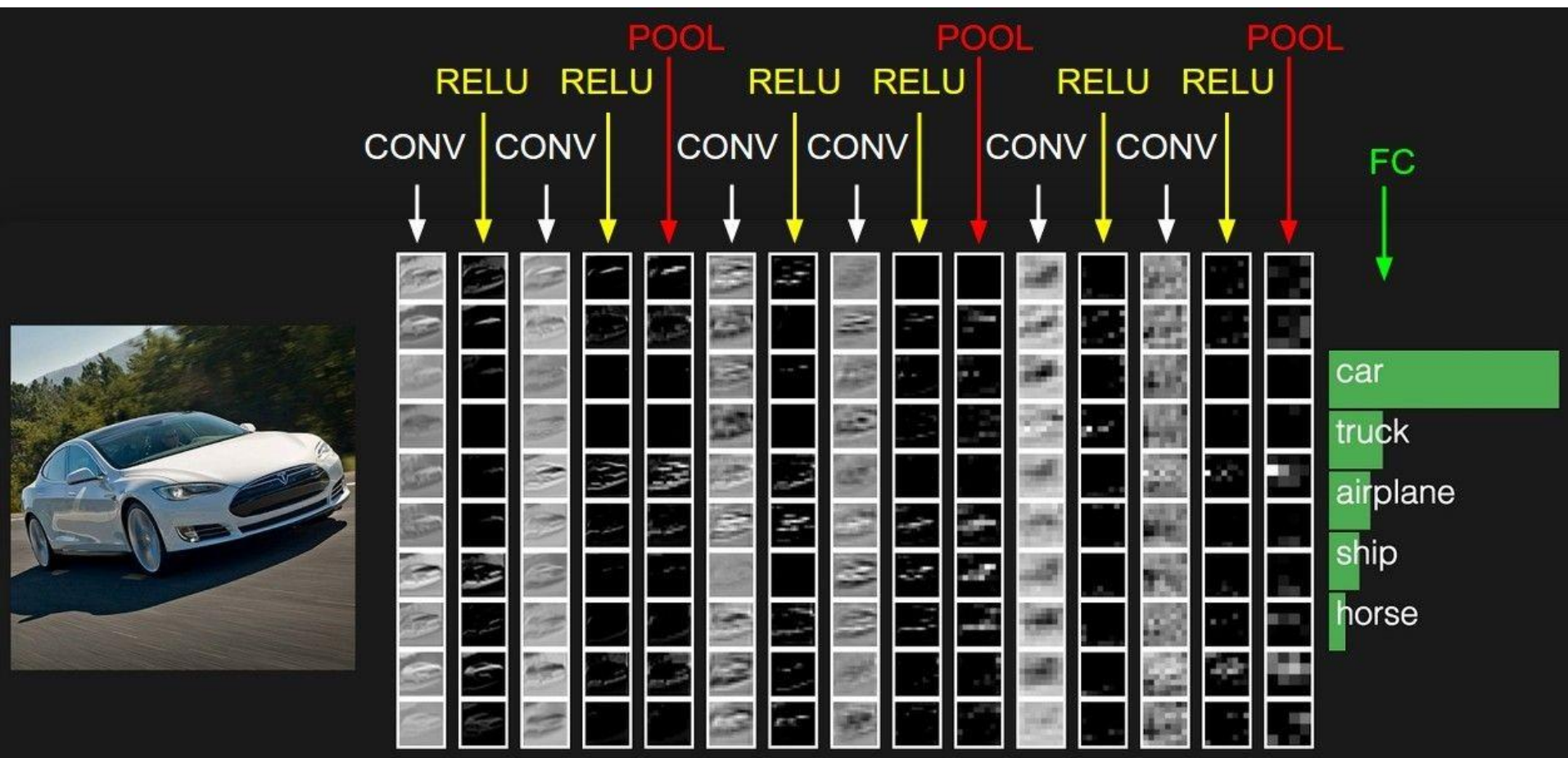


Number of parameters in this layer?

each filter has $5*5*3 + 1 = 76$ params (+1 for bias)

$\Rightarrow 76*10 = 760$

Putting it all together



Some Common Architectures

Case Study: AlexNet

[Krizhevsky et al. 2012]

Architecture:

CONV1

MAX POOL1

NORM1

CONV2

MAX POOL2

NORM2

CONV3

CONV4

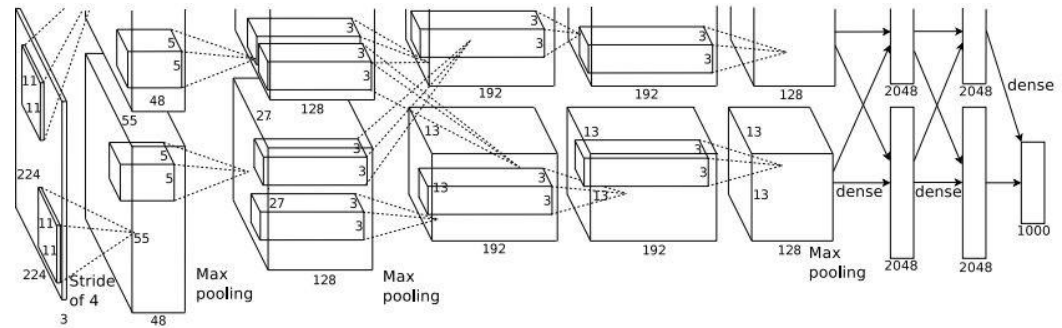
CONV5

Max POOL3

FC6

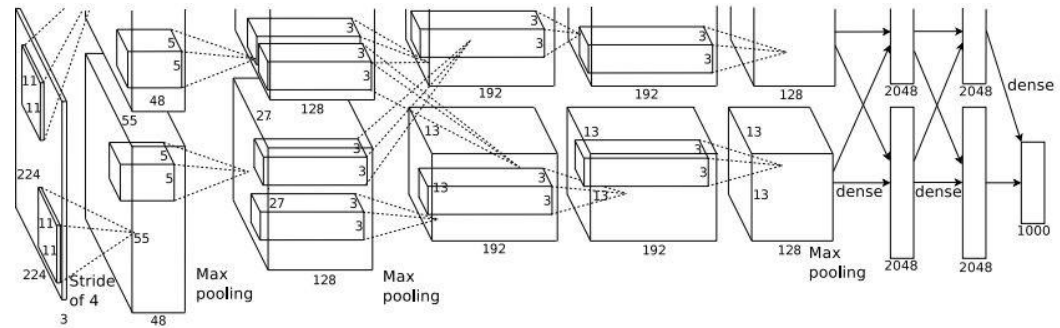
FC7

FC8



Case Study: AlexNet

[Krizhevsky et al. 2012]



Input: 227x227x3 images

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

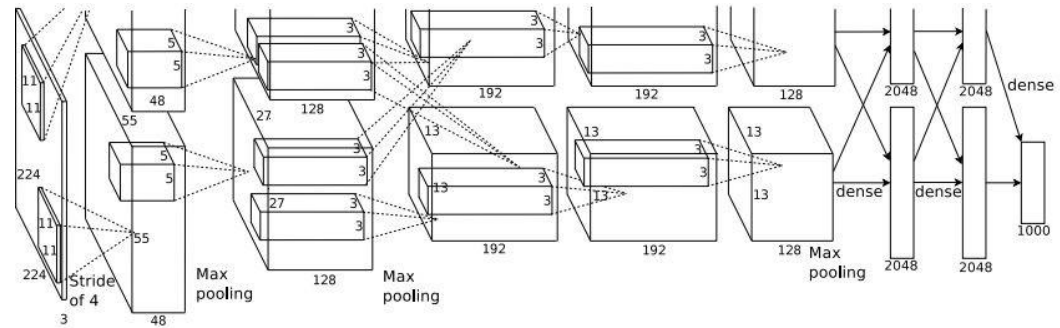
=>

Output volume **[55x55x96]**

Parameters: $(11*11*3)*96 = \mathbf{35K}$

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]

Full (simplified) AlexNet architecture:

[224x224x3] 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

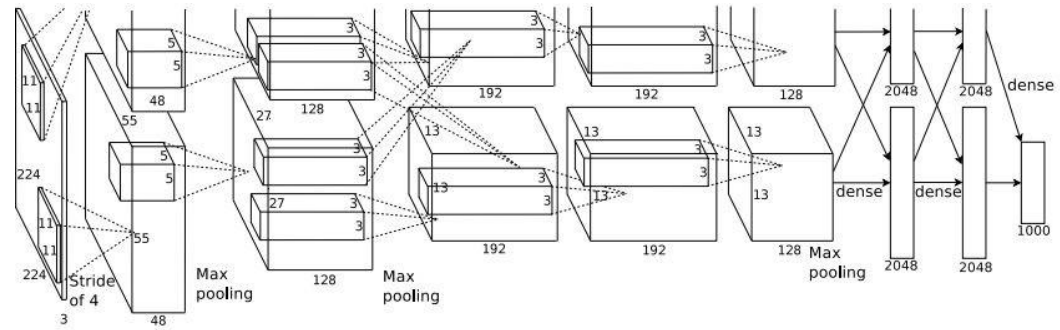
[13x13x256] **CONV5**: 256 3x3 filters at stride 1, pad 1

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

[4096] **FC6**: 4096 neurons

[4096] **FC7**: 4096 neurons

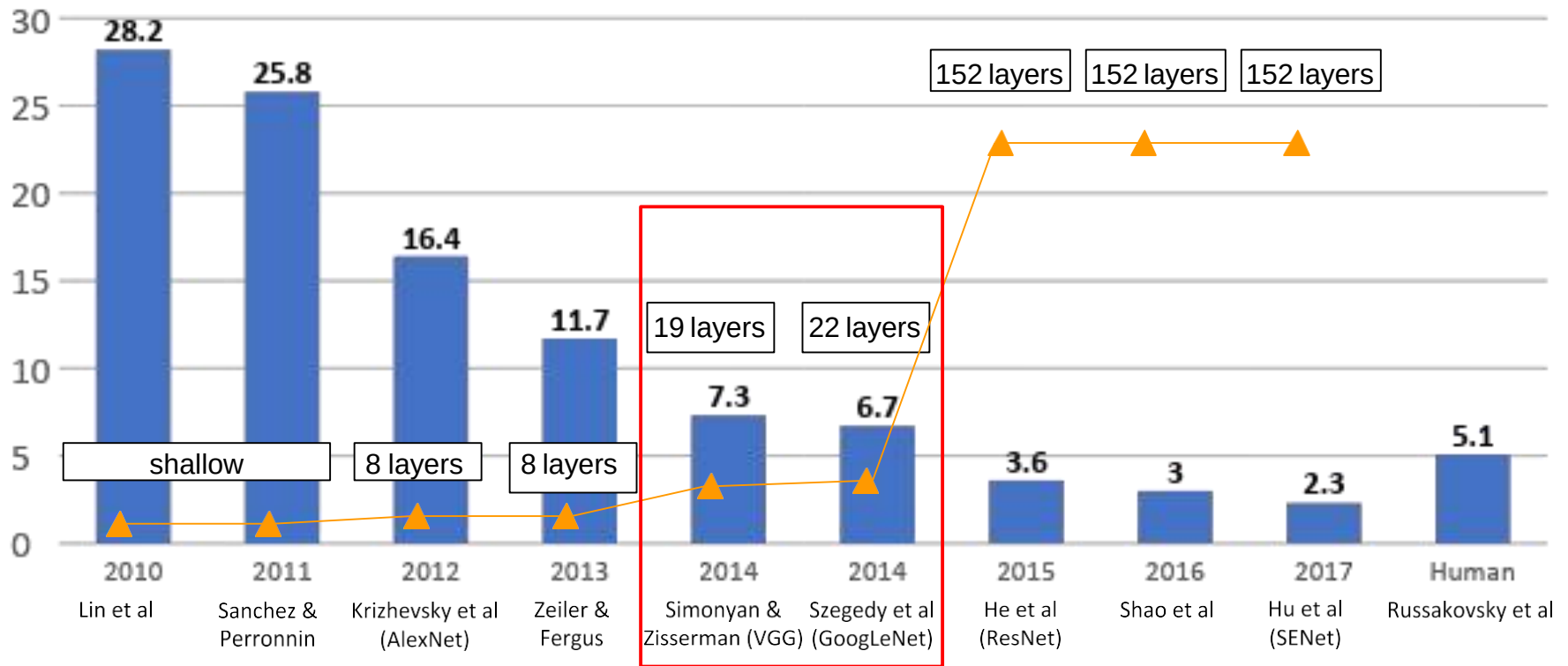
[1000] **FC8**: 1000 neurons (class scores)



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

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



Case Study: VGGNet

[Simonyan and Zisserman, 2014]

Small filters, Deeper networks

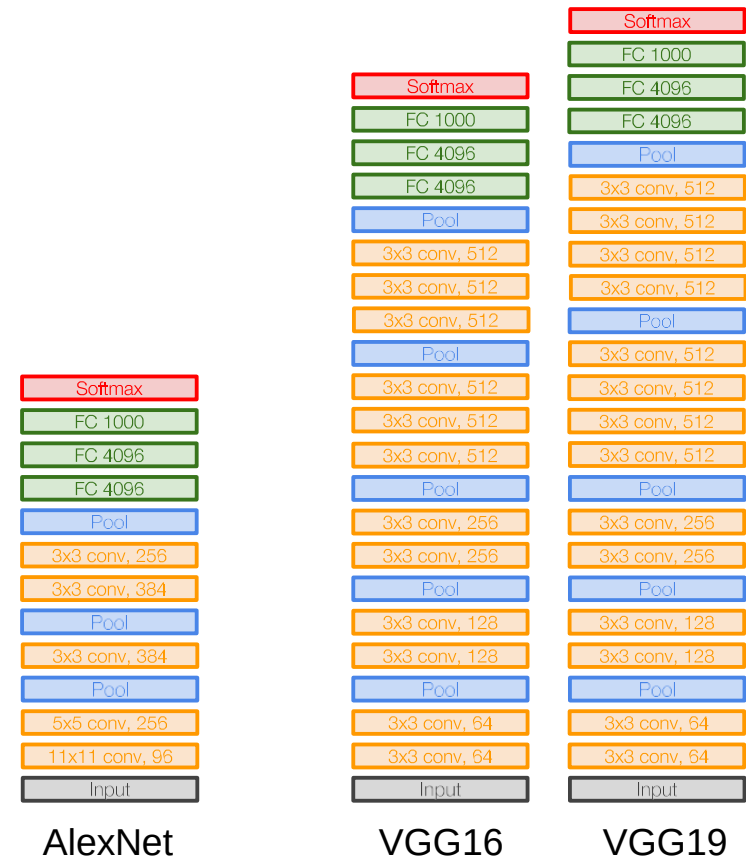
8 layers (AlexNet)

-> 16 - 19 layers (VGG16Net)

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

11.7% top 5 error in ILSVRC'13
(ZFNet)

-> 7.3% top 5 error in ILSVRC'14



Case Study: VGGNet

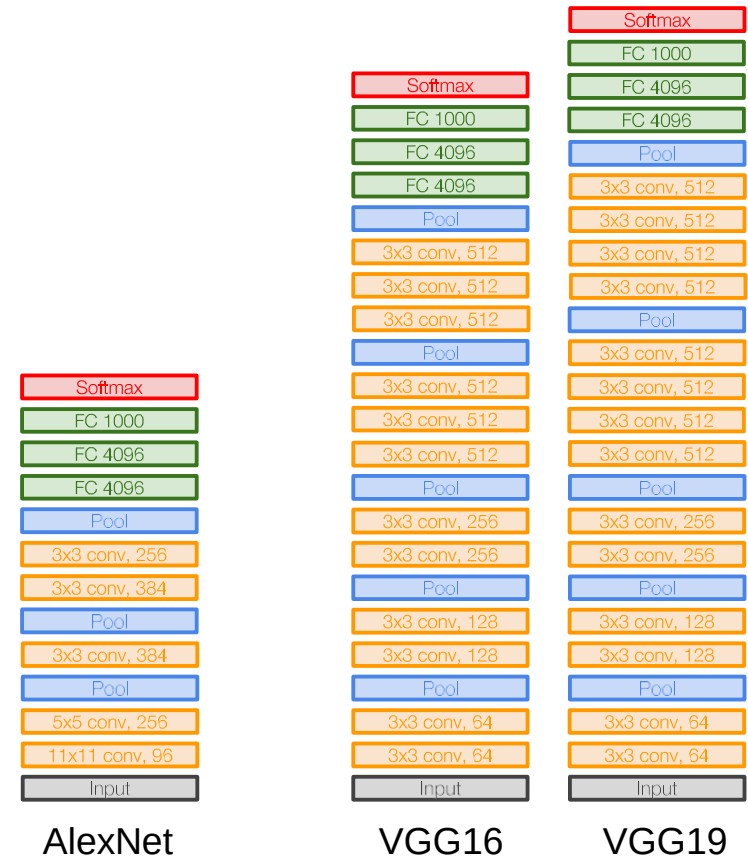
[Simonyan and Zisserman, 2014]

Q: Why use smaller filters? (3x3 conv)

Stack of three 3x3 conv (stride 1) layers has same **effective receptive field** as one 7x7 conv layer

But deeper, more non-linearities

And fewer parameters: $3 * (3^2 C^2)$ vs. $7^2 C^2$ for C channels per layer



AlexNet

VGG16

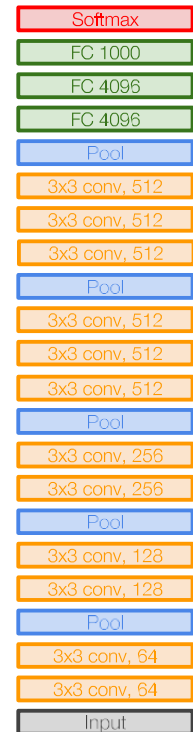
VGG19

Case Study: VGGNet

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

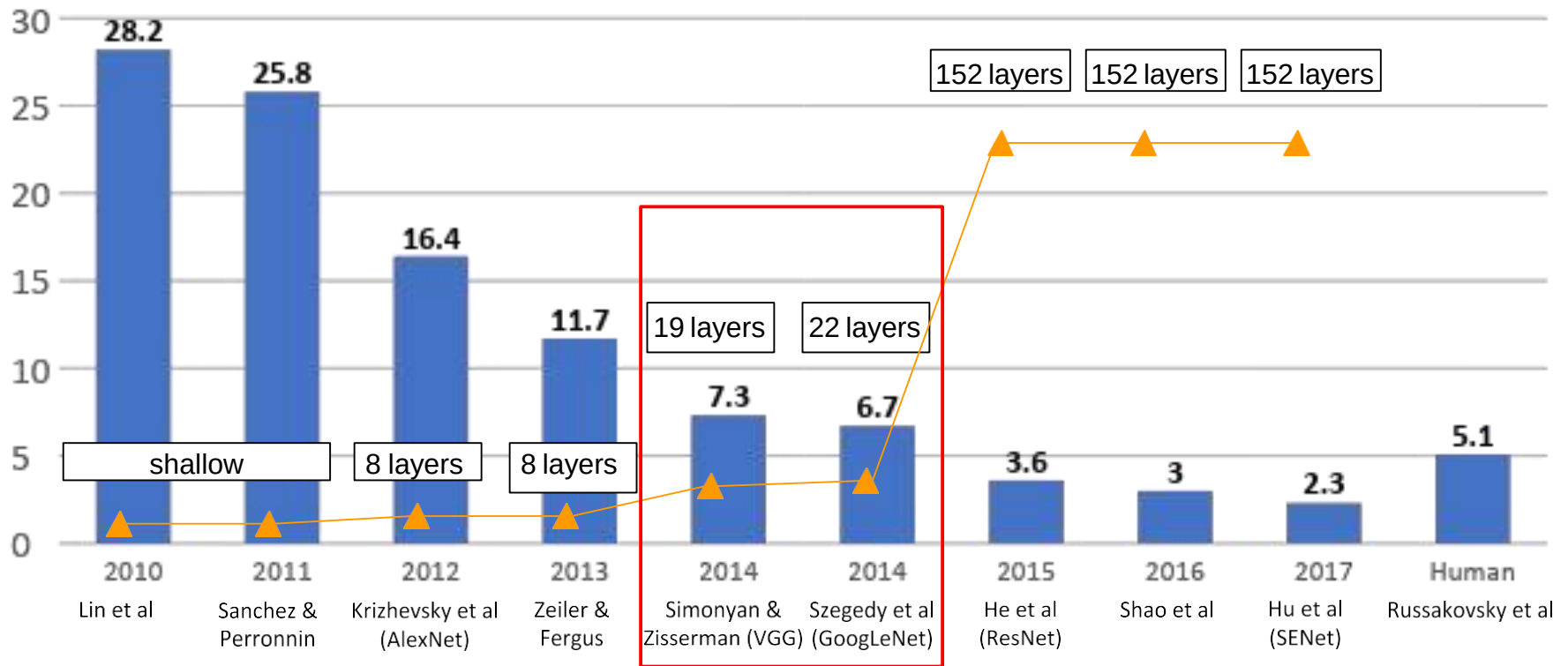
TOTAL memory: $24M * 4 \text{ bytes} \approx 96MB / \text{image}$ (for a forward pass)

TOTAL params: 138M parameters



VGG16

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners

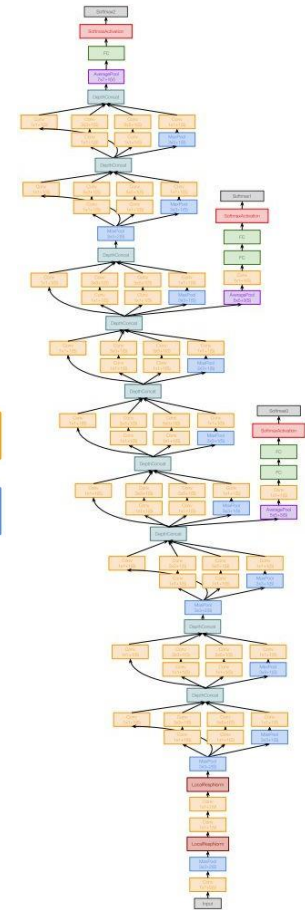
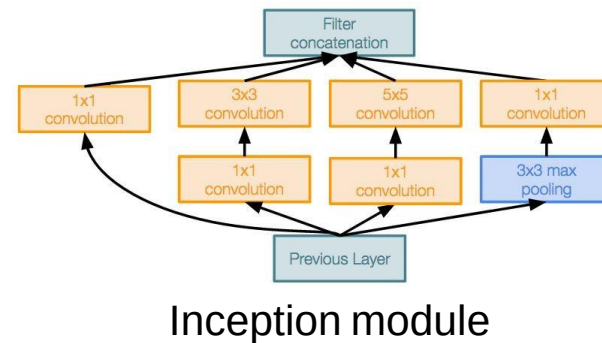


Case Study: GoogLeNet

[Szegedy et al., 2014]

Deeper networks, with computational efficiency

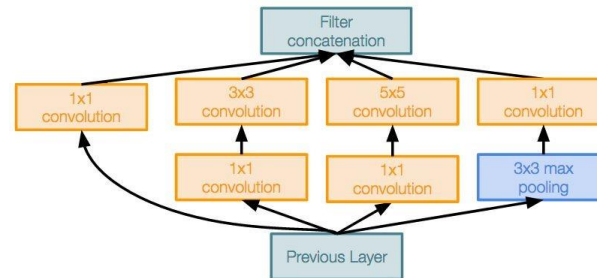
- 22 layers
- Efficient “Inception” module
- No FC layers
- Only 5 million parameters!
12x less than AlexNet
- ILSVRC’14 classification winner
(6.7% top 5 error)



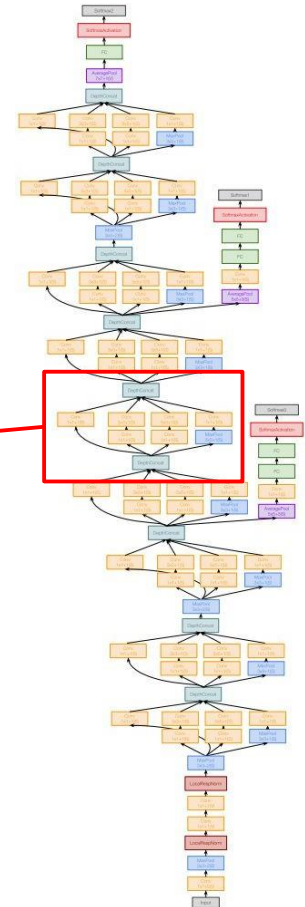
Case Study: GoogLeNet

[Szegedy et al., 2014]

“Inception module”: design a good local network topology (network within a network) and then stack these modules on top of each other

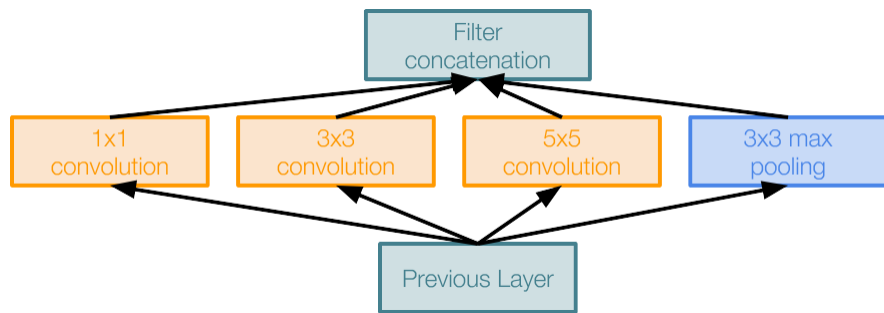


Inception module



Case Study: GoogLeNet

[Szegedy et al., 2014]



Naive Inception module

Apply parallel filter operations on the input from previous layer:

- Multiple receptive field sizes for convolution (1x1, 3x3, 5x5)
- Pooling operation (3x3)

Concatenate all filter outputs together depth-wise

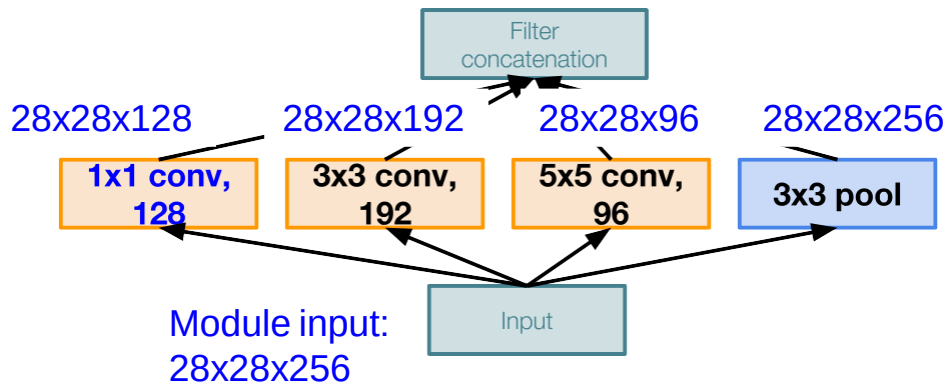
Case Study: GoogLeNet

[Szegedy et al., 2014]

Example:

Q3: What is output size after filter concatenation?

$$28 \times 28 \times (128 + 192 + 96 + 256) = 28 \times 28 \times 672$$



Naive Inception module

Q: What is the problem with this?
[Hint: Computational complexity]

Conv Ops:

[1×1 conv, 128] $28 \times 28 \times 128 \times 1 \times 1 \times 256$

[3×3 conv, 192] $28 \times 28 \times 192 \times 3 \times 3 \times 256$

[5×5 conv, 96] $28 \times 28 \times 96 \times 5 \times 5 \times 256$

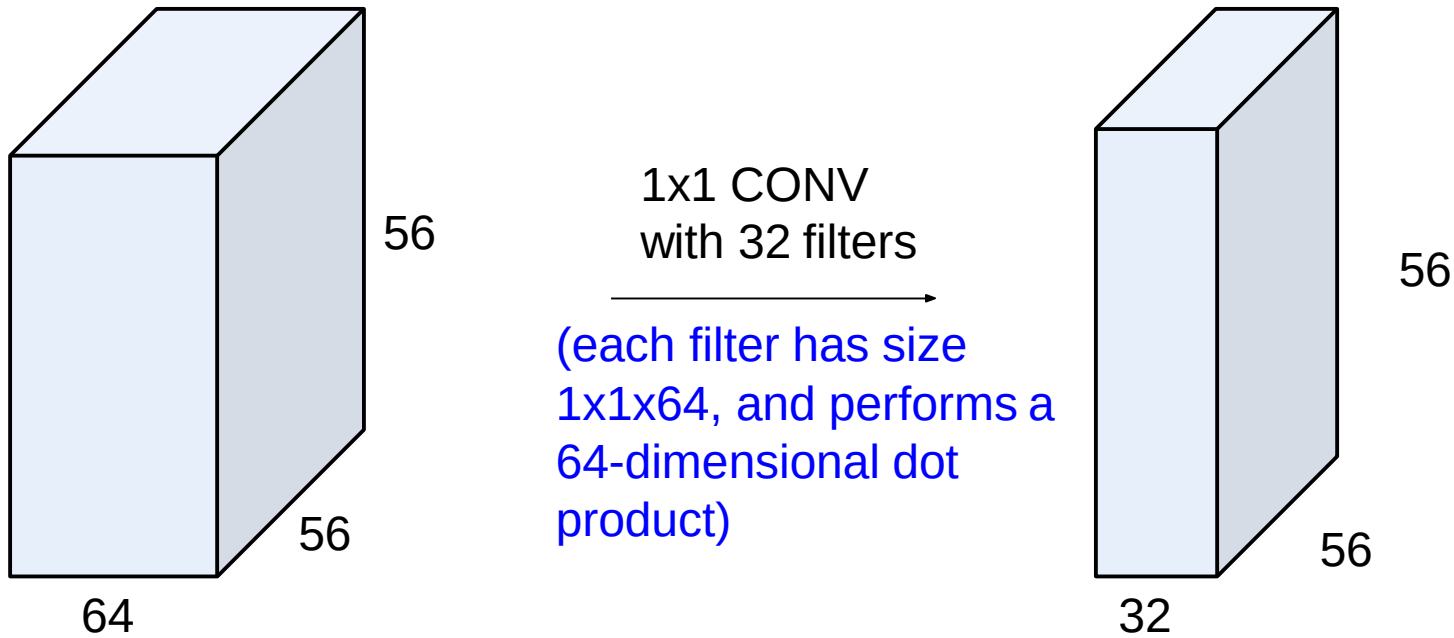
Total: 854M ops

Very expensive compute

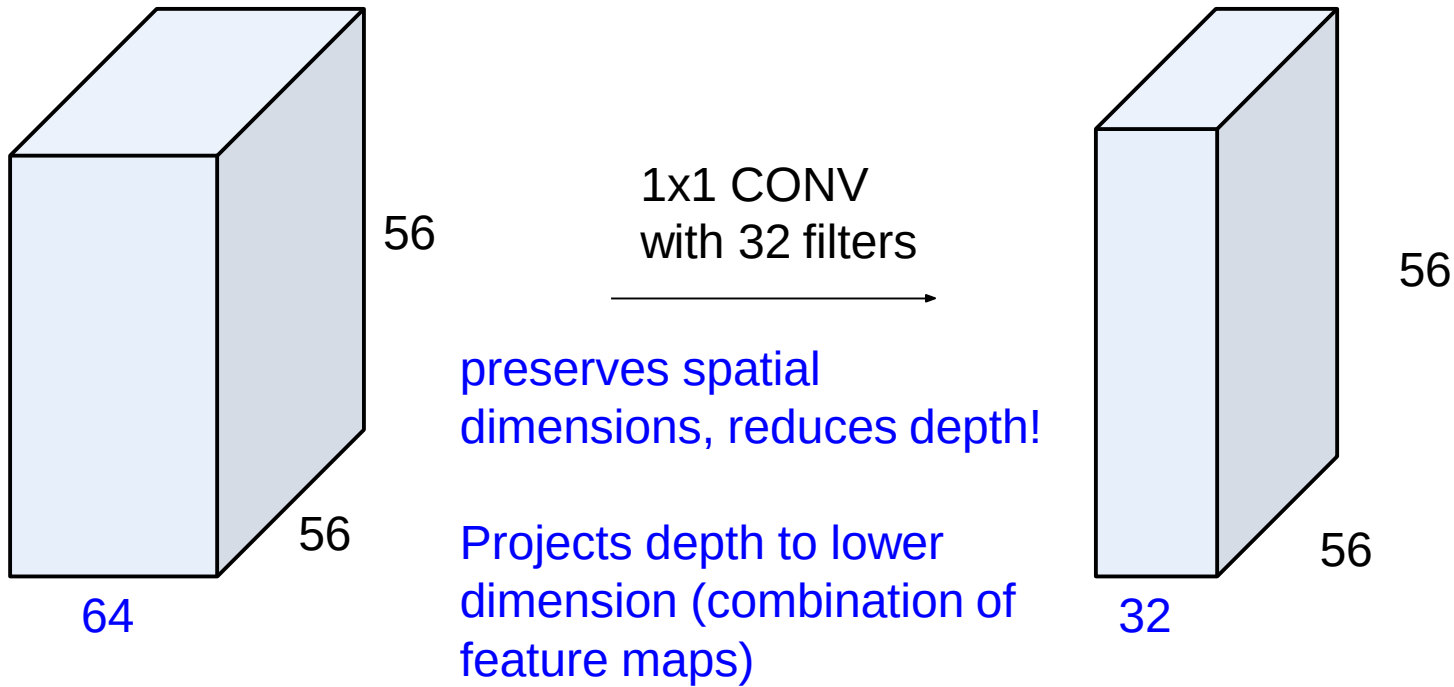
Pooling layer also preserves feature depth, which means total depth after concatenation can only grow at every layer!

Solution: “bottleneck” layers that use 1×1 convolutions to reduce feature depth

1x1 convolutions

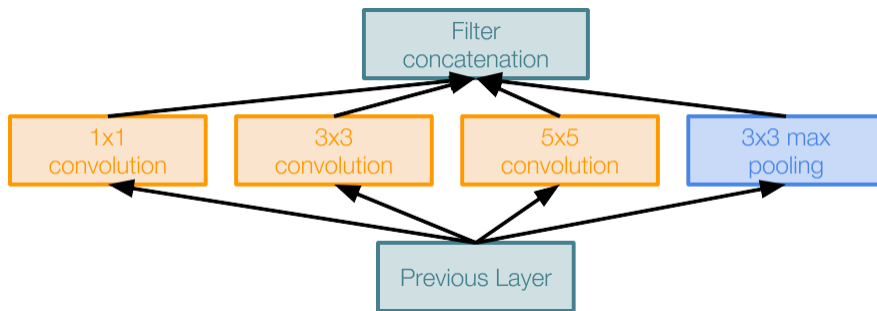


1x1 convolutions



Case Study: GoogLeNet

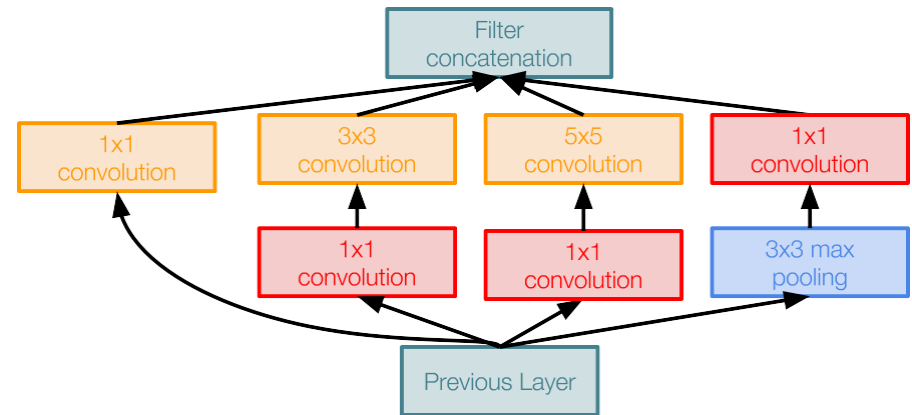
[Szegedy et al., 2014]



Naive Inception module

Total: 854M ops

1x1 conv “bottleneck” layers



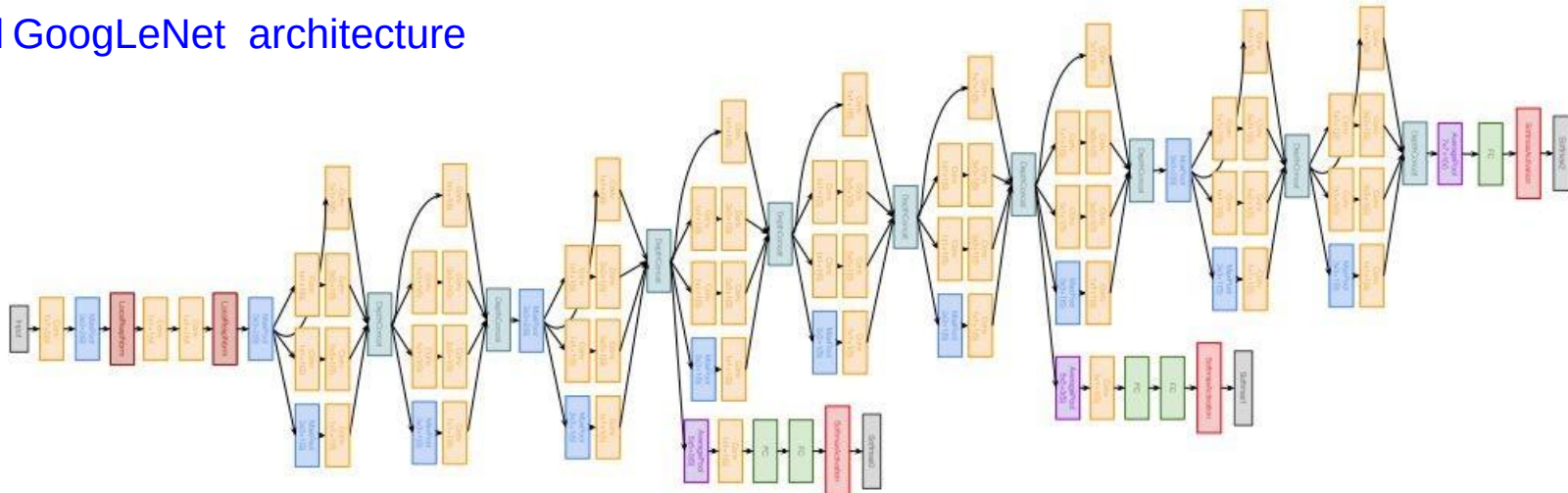
Inception module with dimension reduction

Total: 358M ops

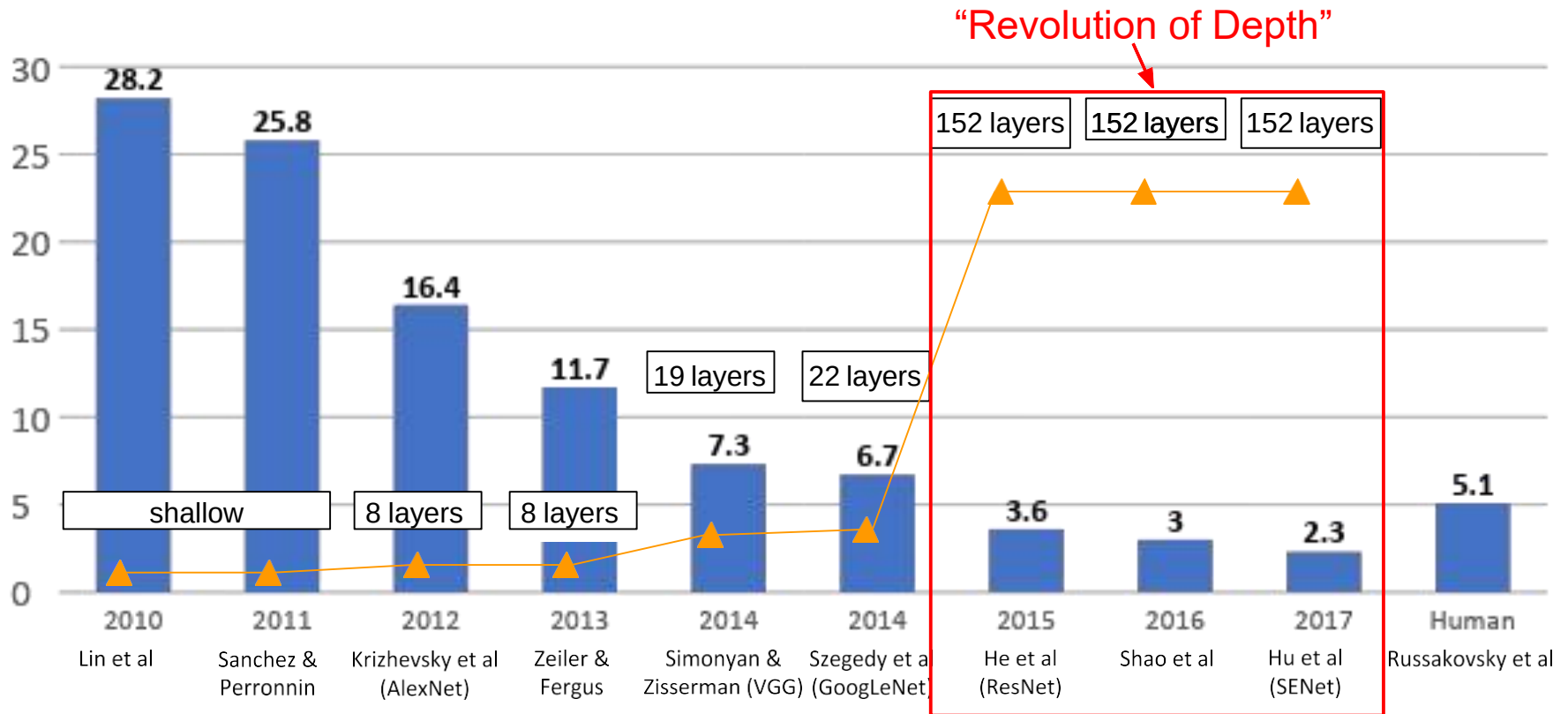
Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet architecture



ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners

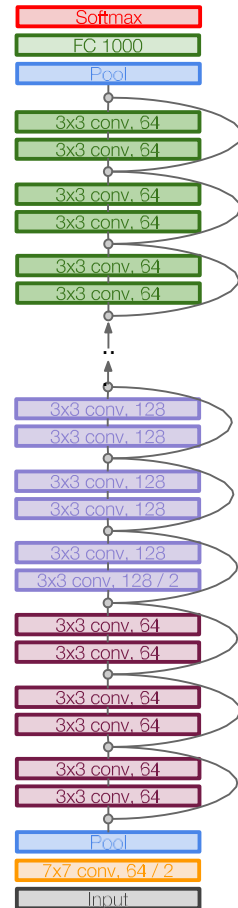
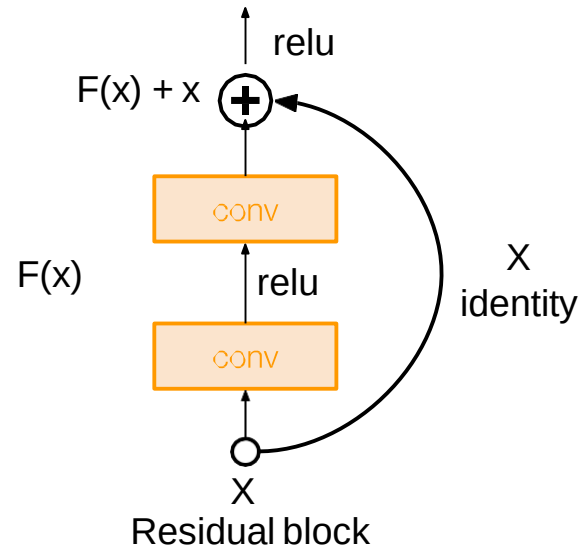


Case Study: ResNet

[He et al., 2016]

Very deep networks using residual connections

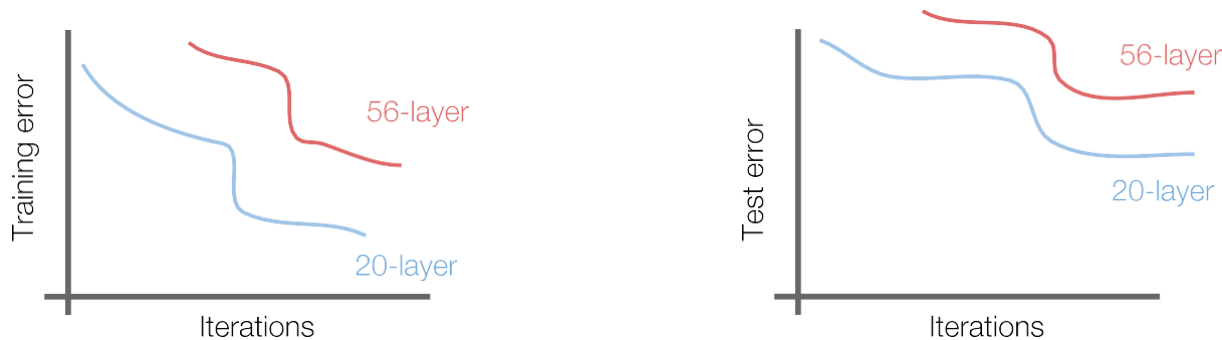
- 152-layer model for ImageNet
- ILSVRC'15 classification winner (3.57% top 5 error)
- Swept all classification and detection competitions in ILSVRC'15 and COCO'15!



Case Study: ResNet

[He et al., 2016]

What happens when we continue stacking deeper layers on a “plain” convolutional neural network?



Q: What's strange about these training and test curves?

[Hint: look at the order of the curves]

56-layer model performs worse on both training and test error

-> The deeper model performs worse, but it's not caused by overfitting!

Case Study: ResNet

[He et al., 2016]

Hypothesis: the problem is an *optimization* problem, deeper models are harder to optimize

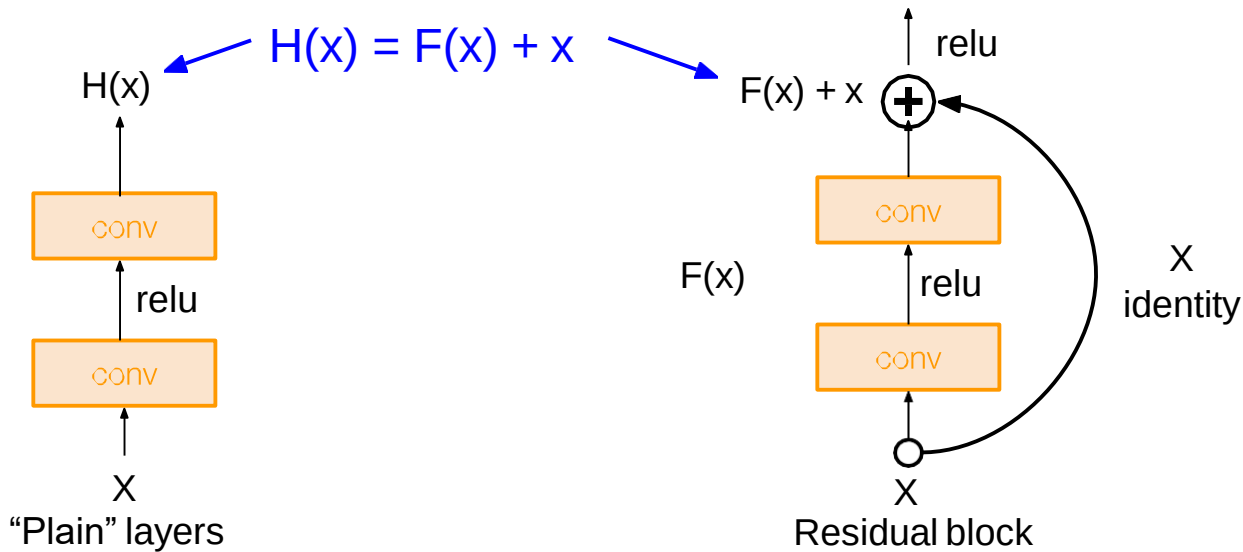
The deeper model should be able to perform at least as well as the shallower model.

A solution by construction is copying the learned layers from the shallower model and setting additional layers to identity mapping.

Case Study: ResNet

[He et al., 2016]

Solution: Use network layers to fit a residual mapping instead of directly trying to fit a desired underlying mapping



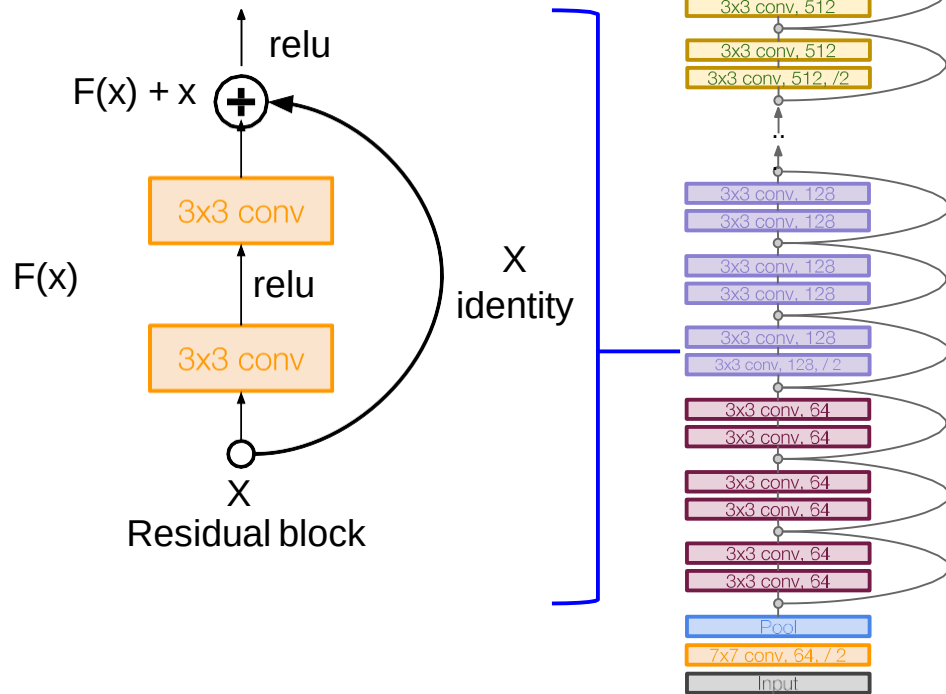
Use layers to
fit residual
 $F(x) = H(x) - x$
instead of
 $H(x)$ directly

Case Study: ResNet

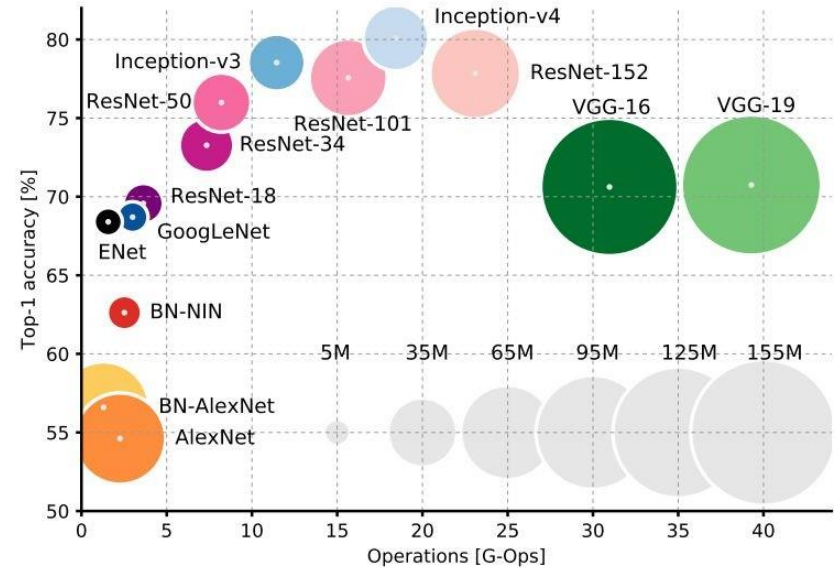
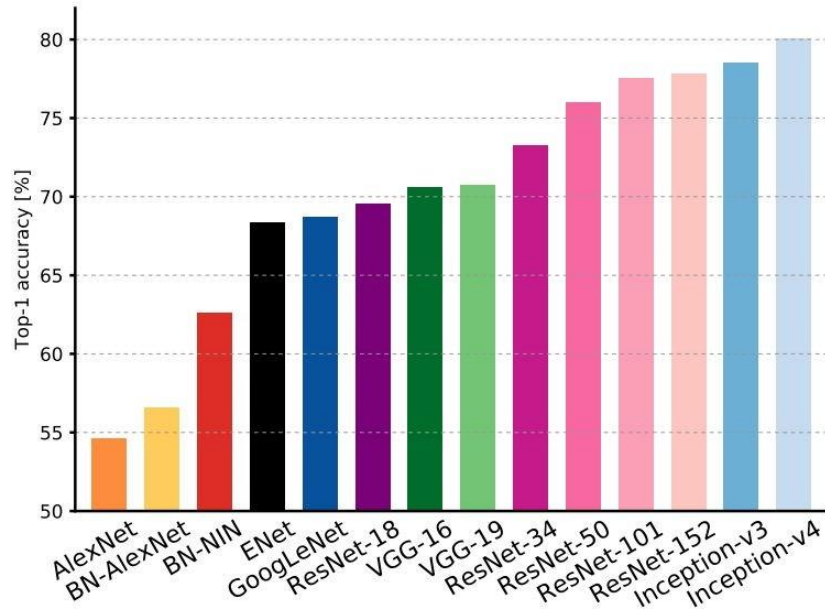
[He et al., 2016]

Full ResNet architecture:

- Stack residual blocks
- Every residual block has two 3x3 conv layers



Comparing complexity...



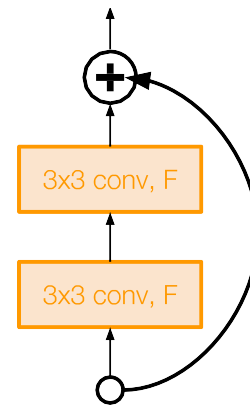
An Analysis of Deep Neural Network Models for Practical Applications, 2017.

Improving ResNets...

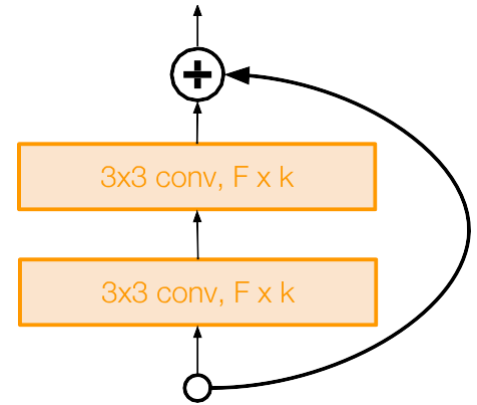
Wide Residual Networks

[Zagoruyko et al. 2016]

- Argues that residuals are the important factor, not depth
- User wider residual blocks ($F \times k$ filters instead of F filters in each layer)
- 50-layer wide ResNet outperforms 152-layer original ResNet
- Increasing width instead of depth more computationally efficient (parallelizable)



Basic residual block



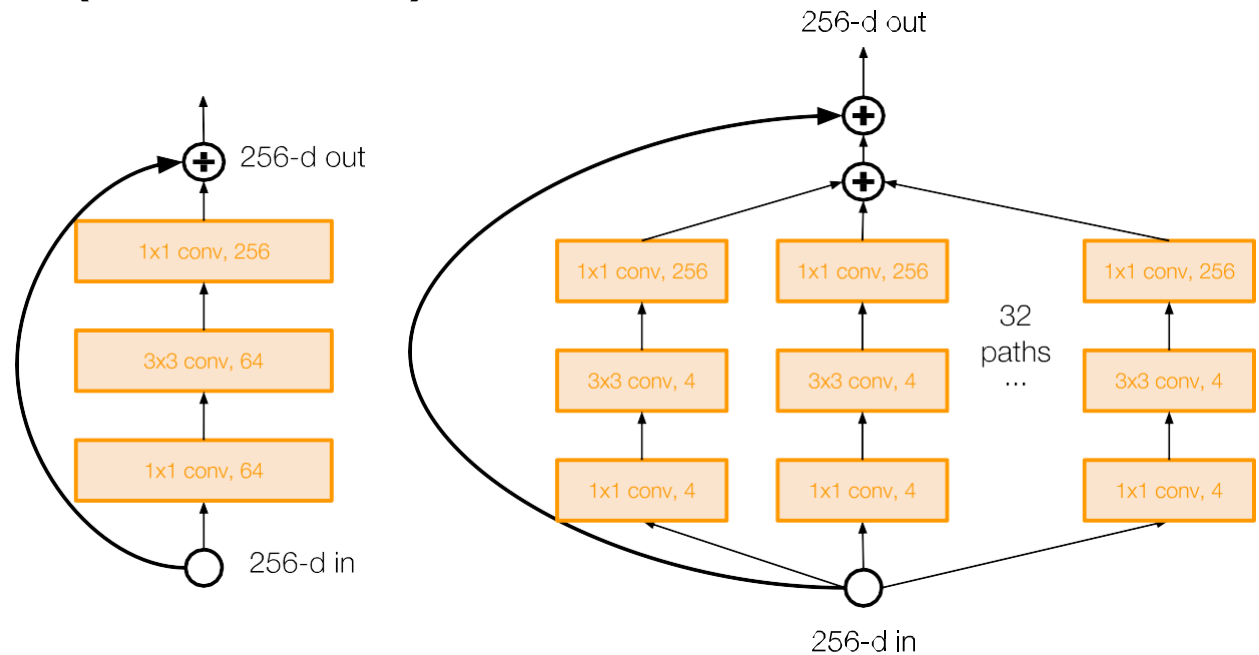
Wide residual block

Improving ResNets...

Aggregated Residual Transformations for Deep Neural Networks (ResNeXt)

[Xie et al. 2016]

- Also from creators of ResNet
- Increases width of residual block through multiple parallel pathways (“cardinality”)
- Parallel pathways similar in spirit to Inception module

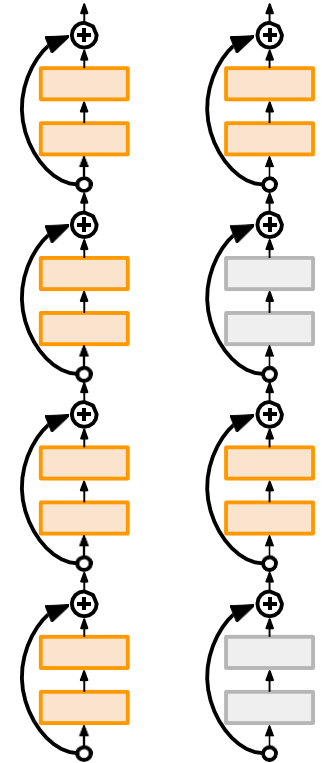


Improving ResNets...

Deep Networks with Stochastic Depth

[Huang et al. 2016]

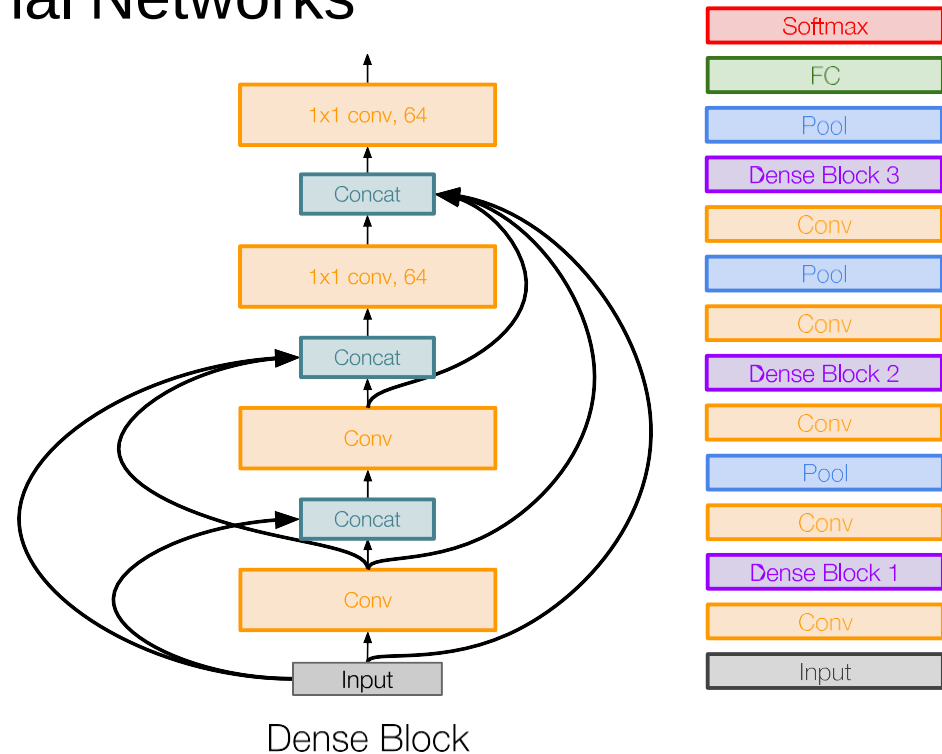
- Motivation: reduce vanishing gradients and training time through short networks during training
- Randomly drop a subset of layers during each training pass
- Bypass with identity function
- Use full deep network at test time



Densely Connected Convolutional Networks

[Huang et al. 2017]

- Dense blocks where each layer is connected to every other layer in feedforward fashion
- Alleviates vanishing gradient, strengthens feature propagation, encourages feature reuse



Summary: CNN Architectures

Case Studies

- AlexNet
- VGG
- GoogLeNet
- ResNet

Also....

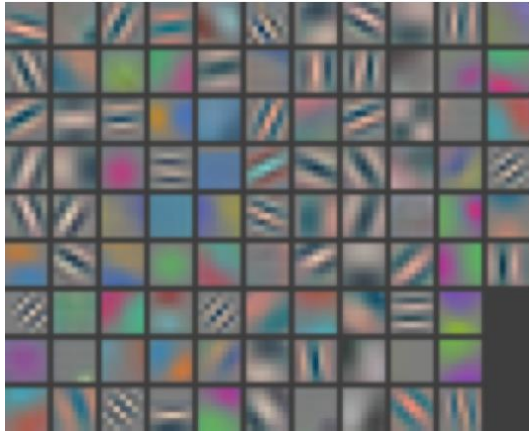
- Wide ResNet
- ResNeXT
- DenseNet

Summary: CNN Architectures

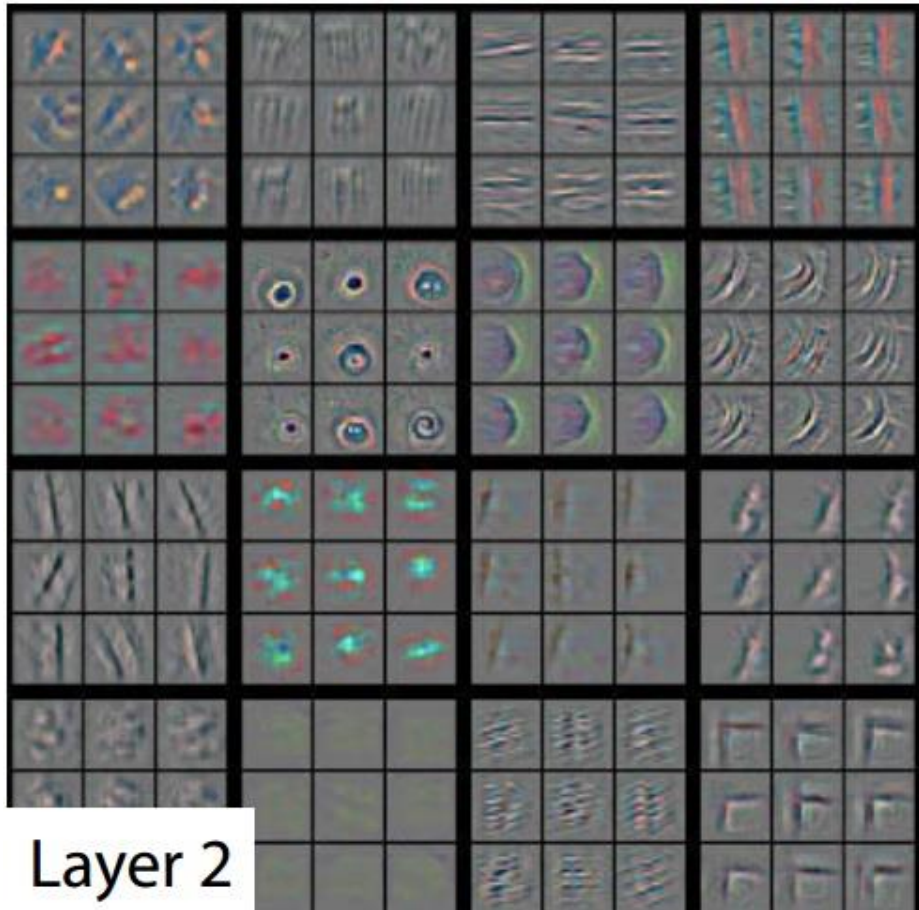
- VGG, GoogLeNet, ResNet all in wide use, available in model zoos
- Trend towards extremely deep networks
- Significant research centers around design of layer / skip connections and improving gradient flow
- Efforts to investigate necessity of depth vs. width and residual connections
- Even more recent trend towards *meta-learning* (e.g. learning what architecture should be)

Understanding CNNs

Layer 1



Layer 2

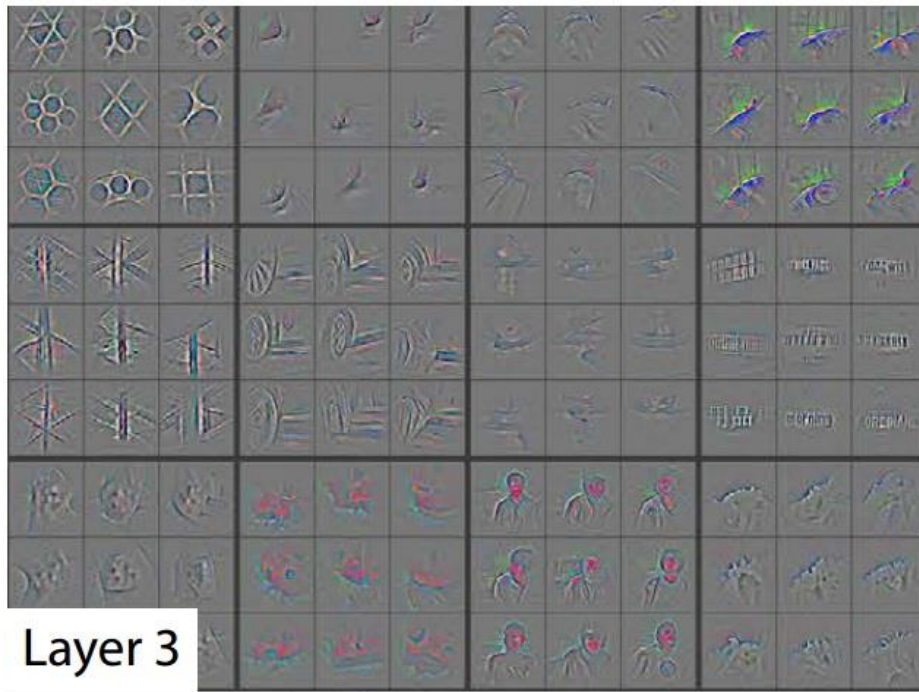


- Activations projected down to pixel level via deconvolution

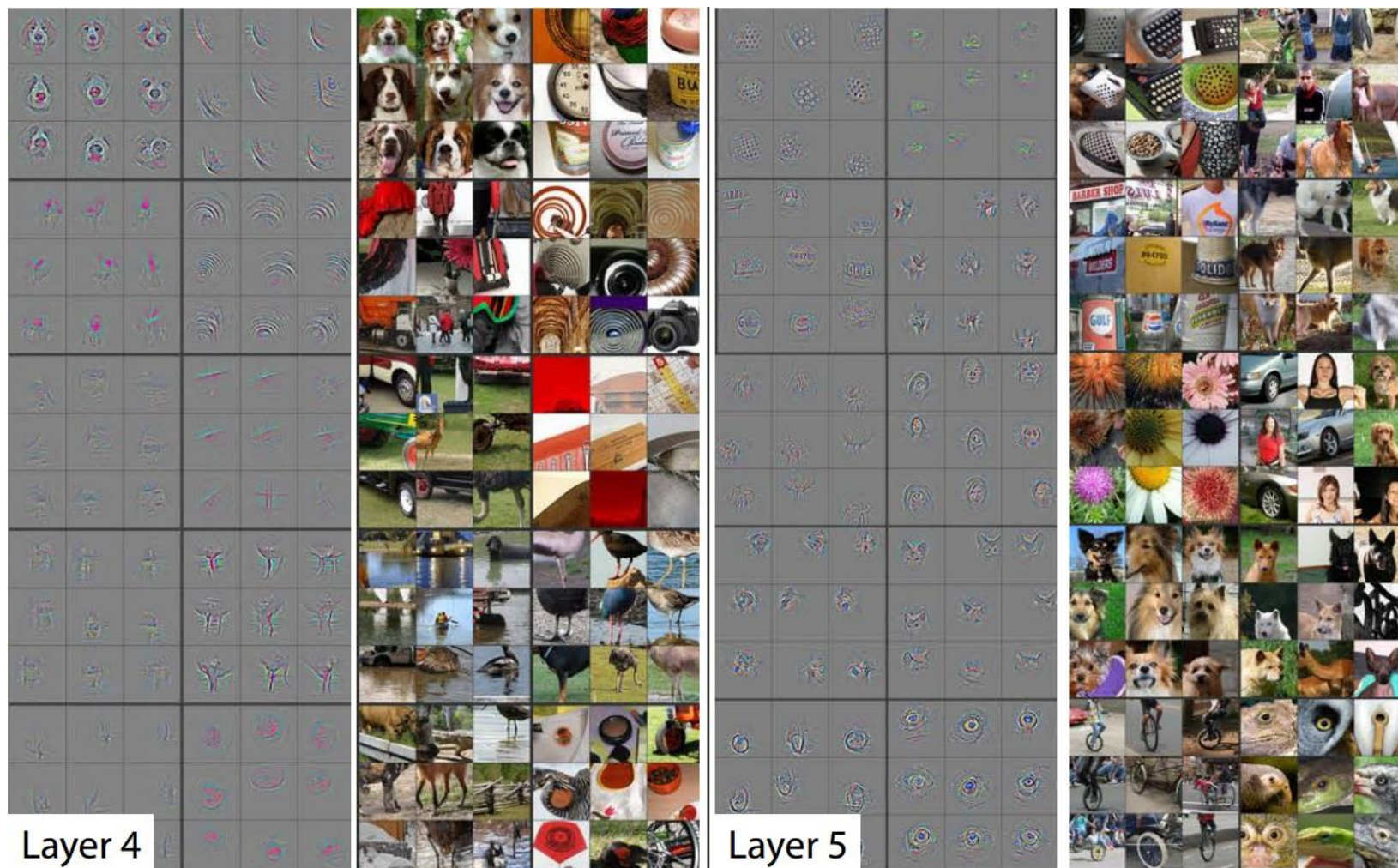


- Patches from validation images that give maximal activation of a given feature map

Layer 3



Layer 4 and 5



Occlusion experiments

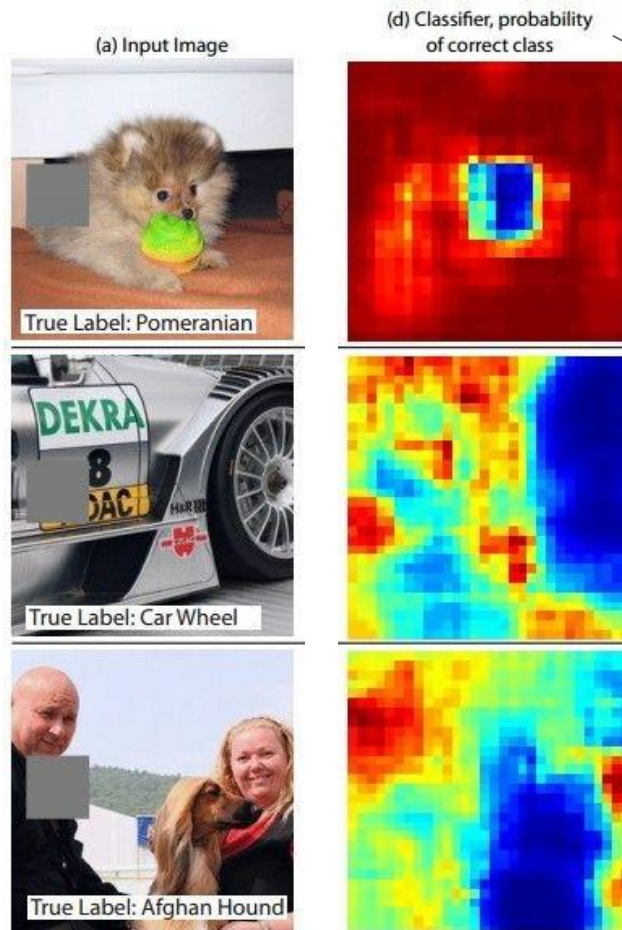


(d) Classifier, probability
of correct class

(as a function of the
position of the
square of zeros in
the original image)

[Zeiler & Fergus 2014]

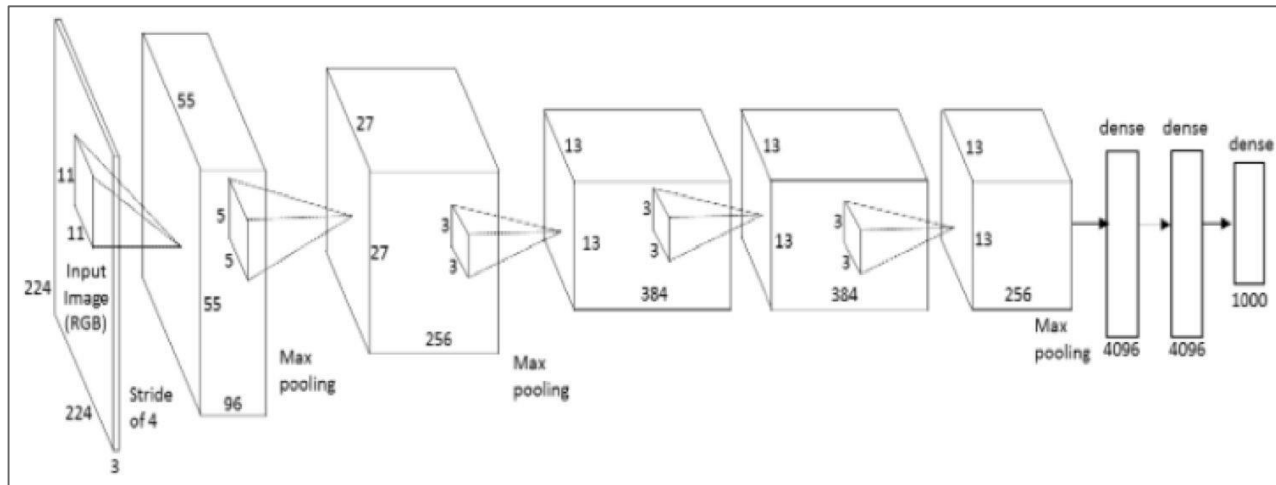
Occlusion experiments



(as a function of the position of the square of zeros in the original image)

[Zeiler & Fergus 2014]

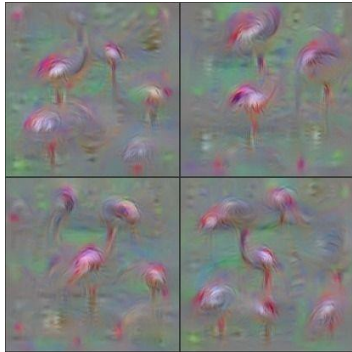
What image maximizes a class score?



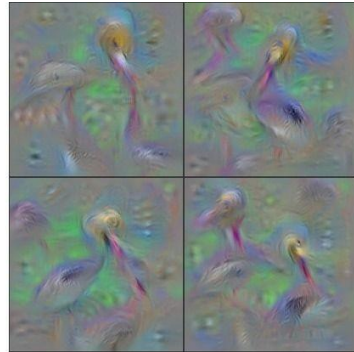
Repeat:

1. Forward an image
2. Set activations in layer of interest to all zero, except for a 1.0 for a neuron of interest
3. Backprop to image
4. Do an “image update”

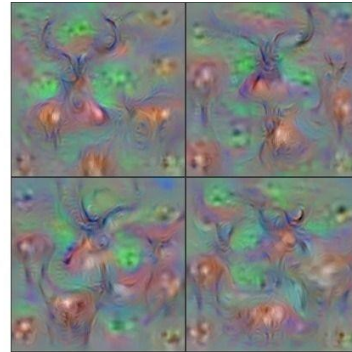
What image maximizes a class score?



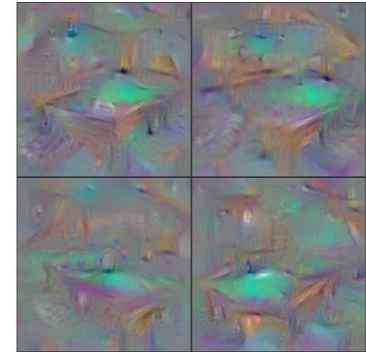
Flamingo



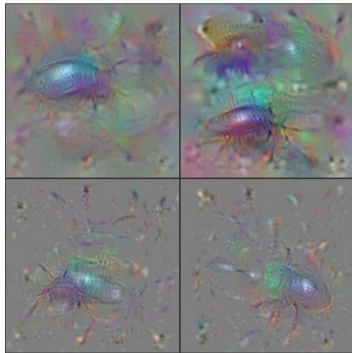
Pelican



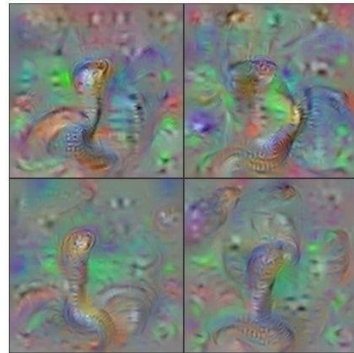
Hartebeest



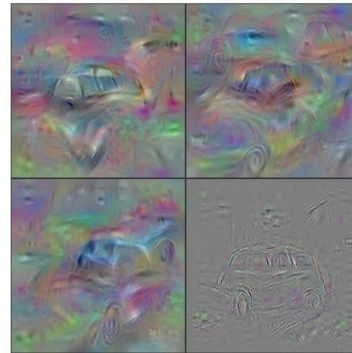
Billiard Table



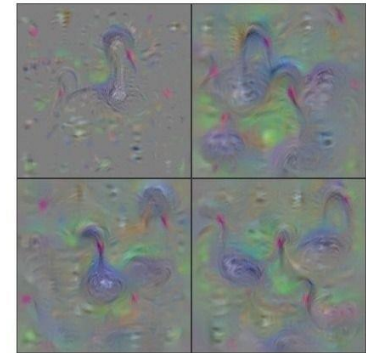
Ground Beetle



Indian Cobra



Station Wagon



Black Swan

[Understanding Neural Networks Through Deep Visualization, Yosinski et al. , 2015]

<http://yosinski.com/deepvis>

What image maximizes a class score?

Layer 8



Pirate Ship

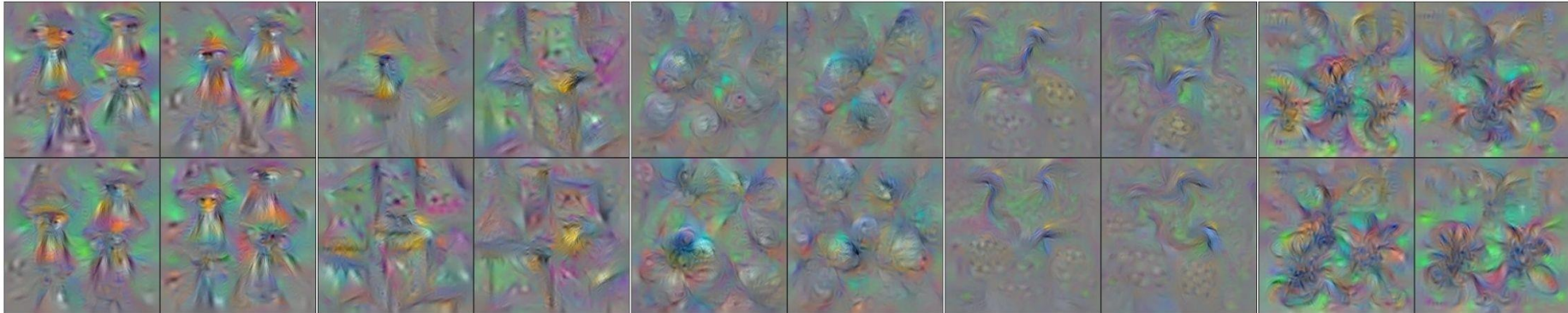
Rocking Chair

Teddy Bear

Windsor Tie

Pitcher

Layer 7



GradCAM

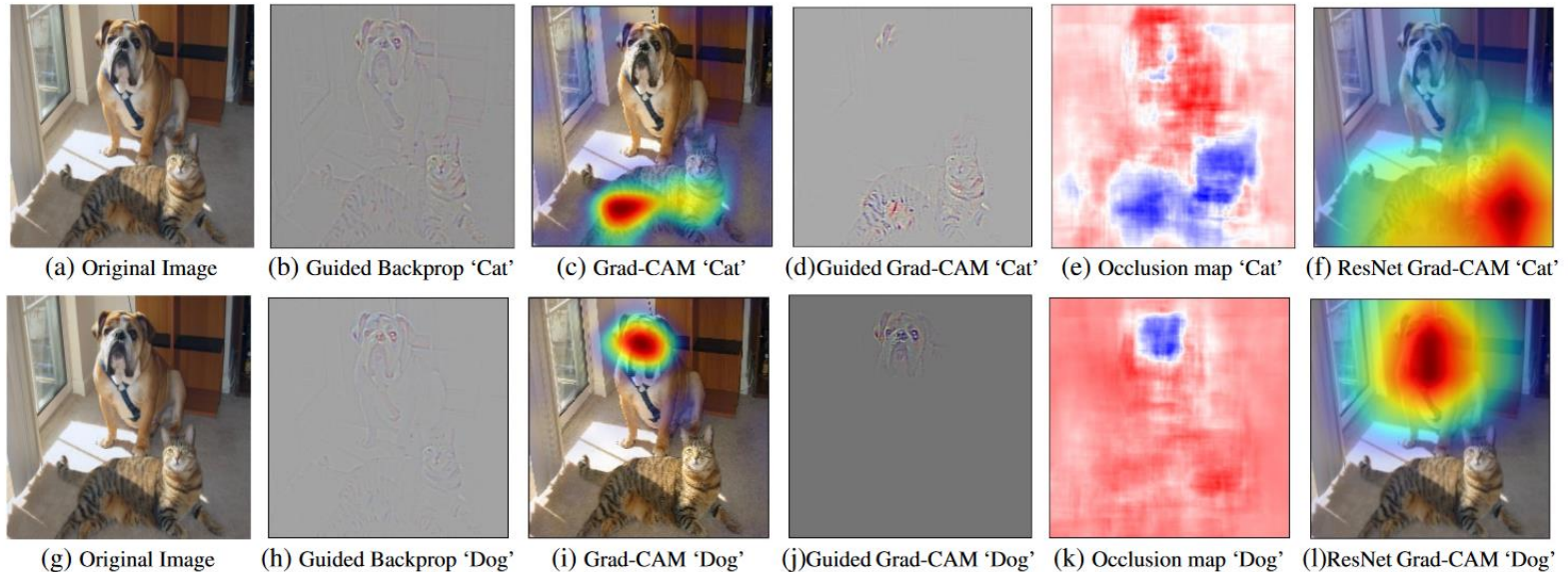
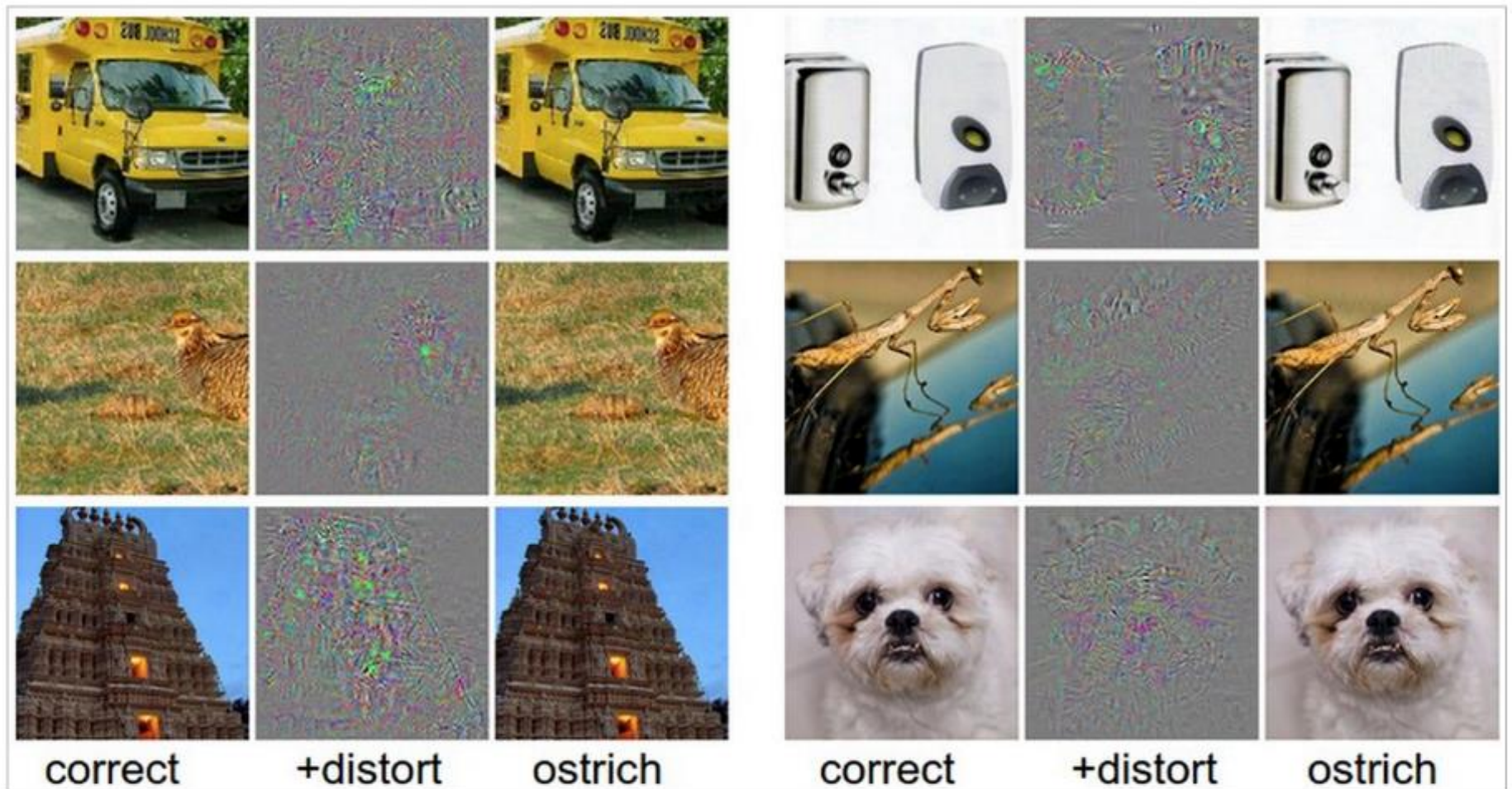


Fig. 1: (a) Original image with a cat and a dog. (b-f) Support for the cat category according to various visualizations for VGG-16 and ResNet. (b) Guided Backpropagation [53]: highlights all contributing features. (c, f) Grad-CAM (Ours): localizes class-discriminative regions, (d) Combining (b) and (c) gives Guided Grad-CAM, which gives high-resolution class-discriminative visualizations. Interestingly, the localizations achieved by our Grad-CAM technique, (c) are very similar to results from occlusion sensitivity (e), while being orders of magnitude cheaper to compute. (f, l) are Grad-CAM visualizations for ResNet-18 layer. Note that in (c, f, i, l), red regions corresponds to high score for class, while in (e, k), blue corresponds to evidence for the class. Figure best viewed in color.

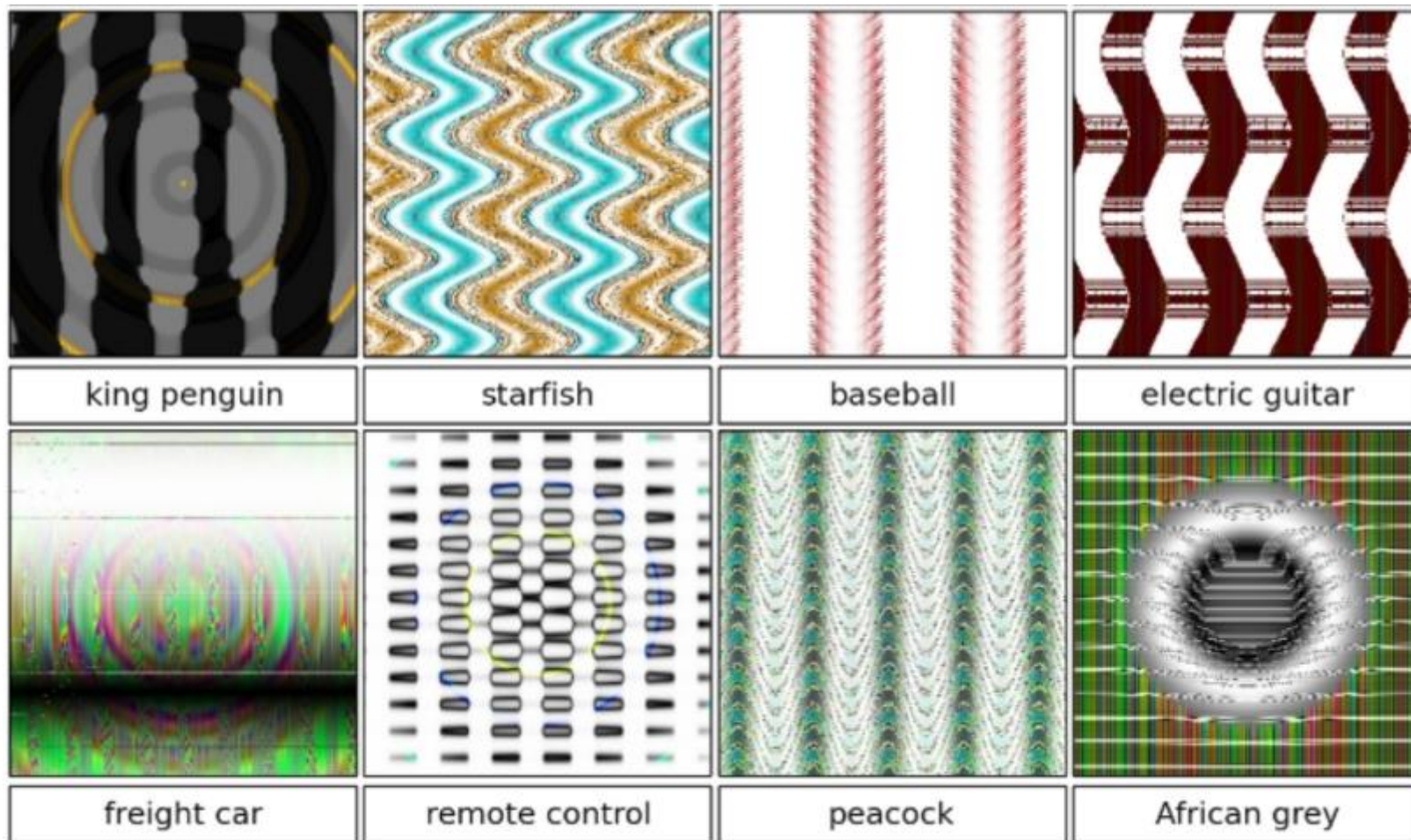
Breaking CNNs



Take a correctly classified image (left image in both columns), and add a tiny distortion (middle) to fool the ConvNet with the resulting image (right).

Intriguing properties of neural networks [[Szegedy ICLR 2014](#)]

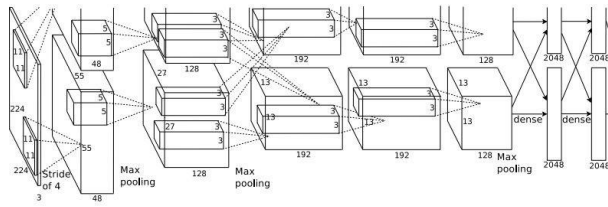
Breaking CNNs



Deep Neural Networks are Easily Fooled: High Confidence Predictions for Unrecognizable Images [[Nguyen et al. CVPR 2015](#)]

Applications in computer vision

Image Classification



Vector:
4096

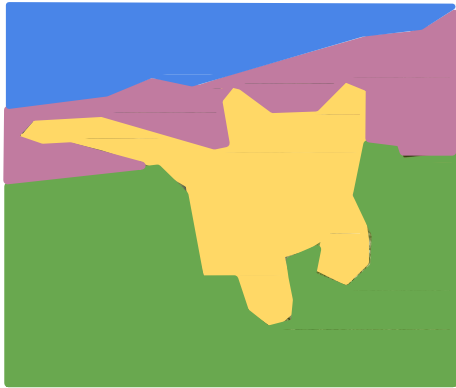
→
Fully-Connected:
4096 to 1000

Class Scores

Cat: 0.9
Dog: 0.05
Car: 0.01
...

Other Computer Vision Tasks

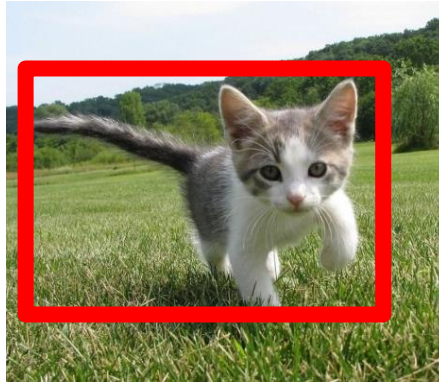
Semantic Segmentation



GRASS, CAT,
TREE, SKY

No objects, just pixels

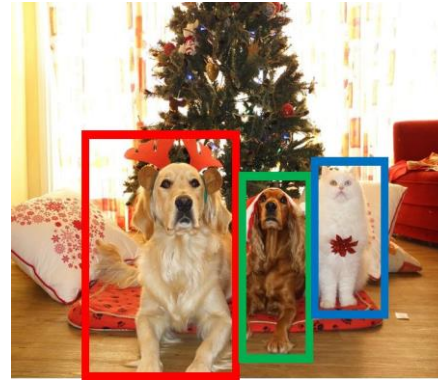
**Classification
+ Localization**



CAT

Single Object

**Object
Detection**



DOG, DOG, CAT

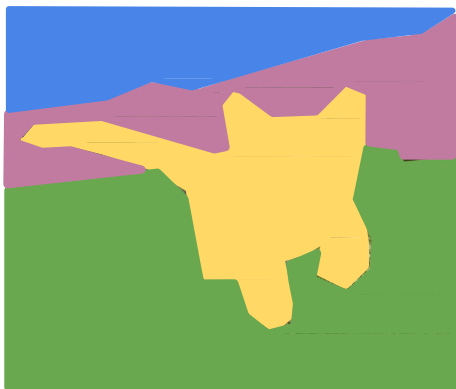
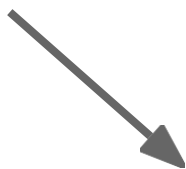
Multiple Object

**Instance
Segmentation**



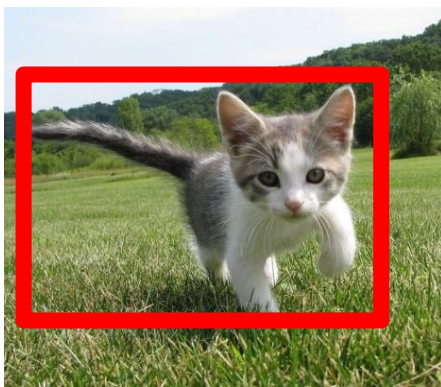
DOG, DOG, CAT

Classification + Localization



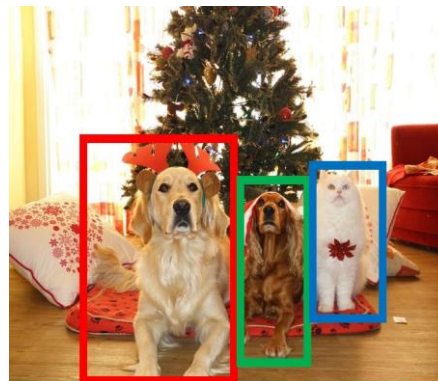
GRASS, CAT,
TREE, SKY

No objects, just pixels



CAT

Single Object



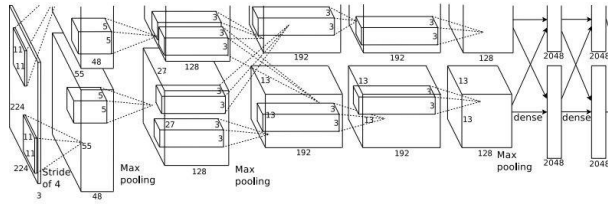
DOG, DOG, CAT

Multiple Object



DOG, DOG, CAT

Classification + Localization



**Fully
Connected:**
4096 to 1000

Class Scores

Cat: 0.9
Dog: 0.05
Car: 0.01
...

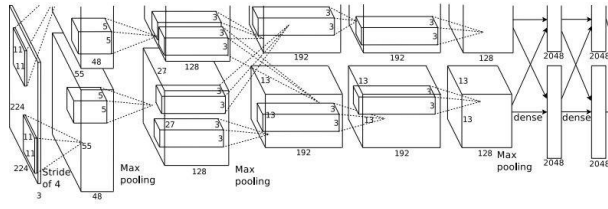
Vector:
4096

**Fully
Connected:**
4096 to 4

**Box
Coordinates**
(x, y, w, h)

Treat localization as a
regression problem!

Classification + Localization



Fully Connected:
4096 to 1000

Class Scores

Cat: 0.9
Dog: 0.05
Car: 0.01
...

Correct label:
Cat

Softmax Loss

Vector:
4096

Fully Connected:
4096 to 4

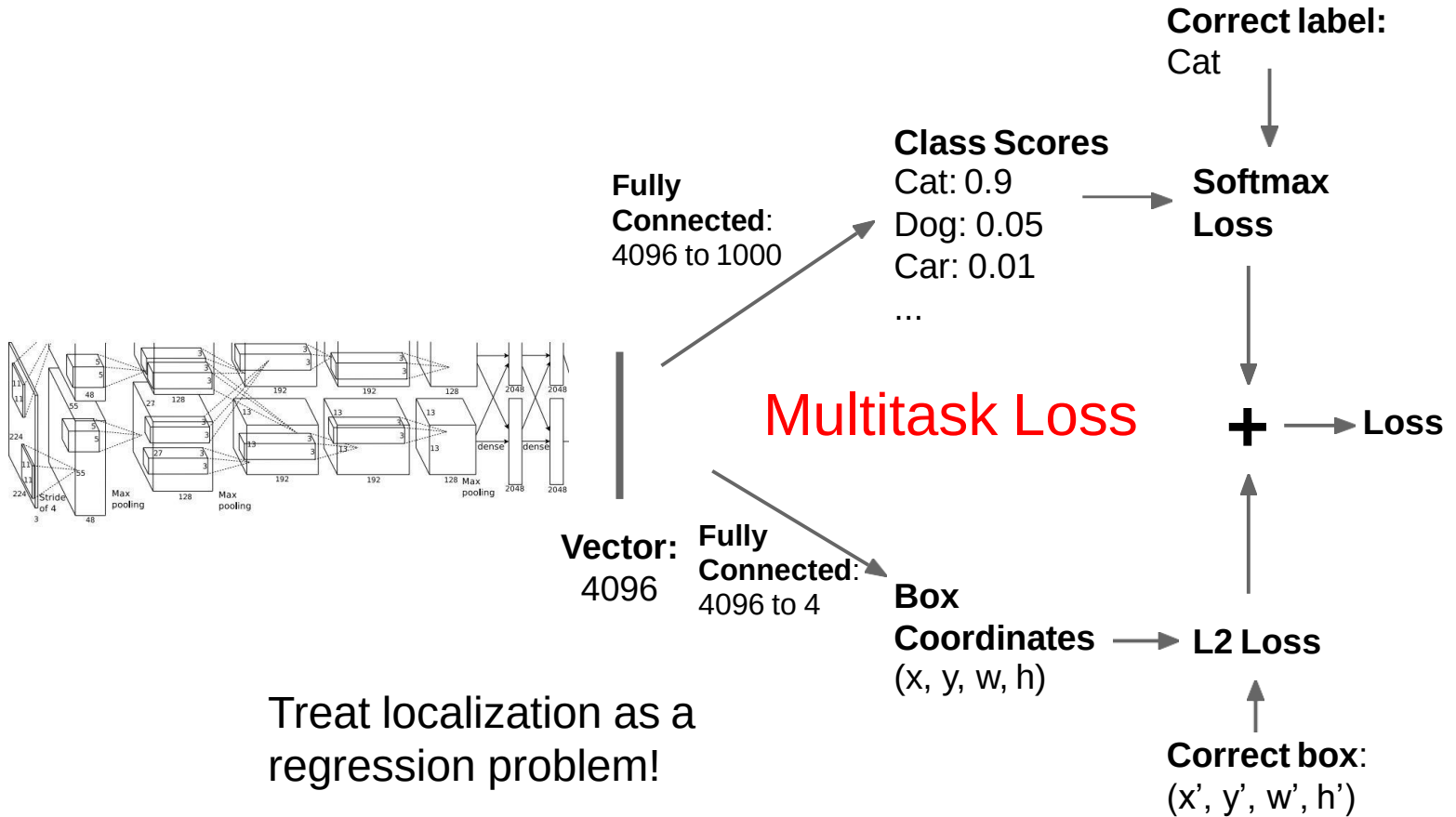
Box Coordinates
(x, y, w, h)

L2 Loss

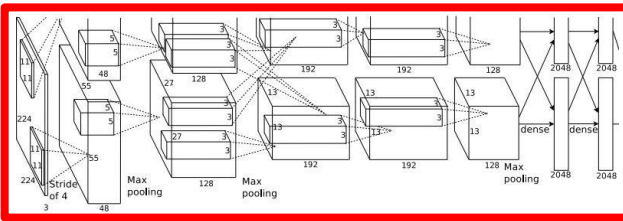
Correct box:
(x', y', w', h')

Treat localization as a regression problem!

Classification + Localization



Classification + Localization



Often pretrained on ImageNet
(Transfer learning)

Vector:
4096

Fully
Connected:
4096 to 1000

Class Scores

Cat: 0.9
Dog: 0.05
Car: 0.01
...

Correct label:
Cat

**Softmax
Loss**

+ → **Loss**

Fully
Connected:
4096 to 4

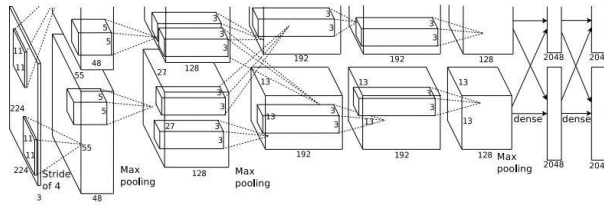
**Box
Coordinates**
(x, y, w, h)

L2 Loss

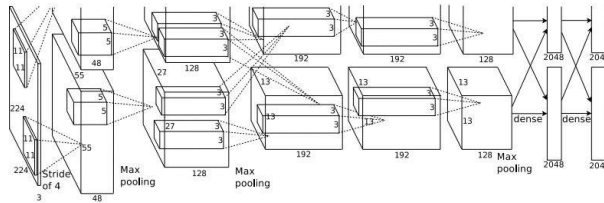
Correct box:
(x', y', w', h')

Treat localization as a
regression problem!

Object Detection as Regression?



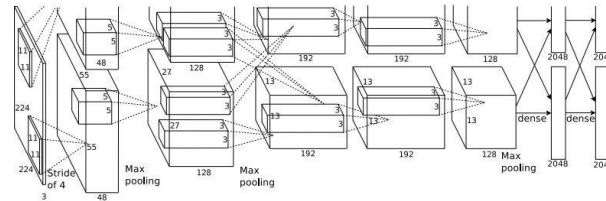
CAT: (x, y, w, h)



DOG: (x, y, w, h)

DOG: (x, y, w, h)

CAT: (x, y, w, h)

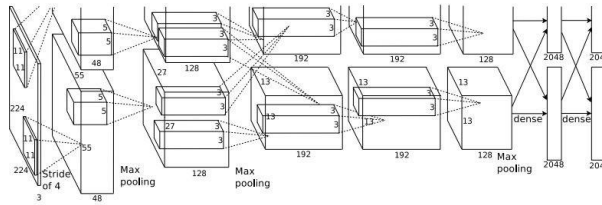


DUCK: (x, y, w, h)

DUCK: (x, y, w, h)

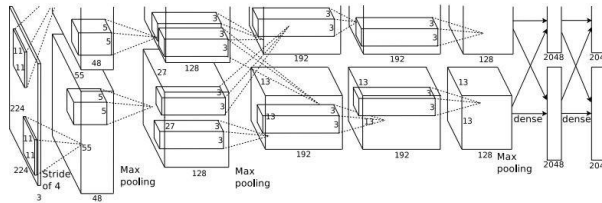
....

Object Detection as Regression?



CAT: (x, y, w, h)

4 numbers

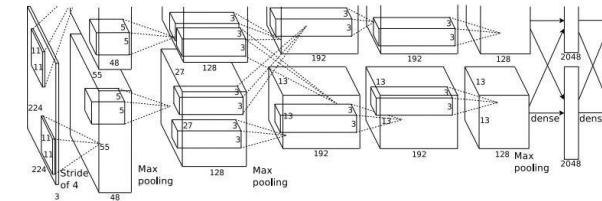


DOG: (x, y, w, h)

DOG: (x, y, w, h)

CAT: (x, y, w, h)

16 numbers



DUCK: (x, y, w, h)

DUCK: (x, y, w, h)

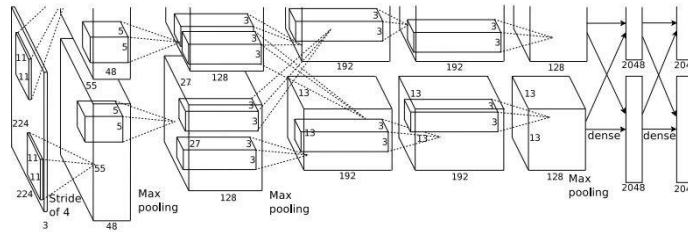
Many
numbers!

....

Each image needs a different
number of outputs!

Object Detection as Classification: Sliding Window

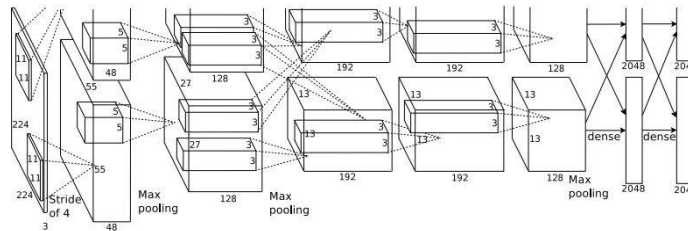
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Dog? NO
Cat? NO
Background? YES

Object Detection as Classification: Sliding Window

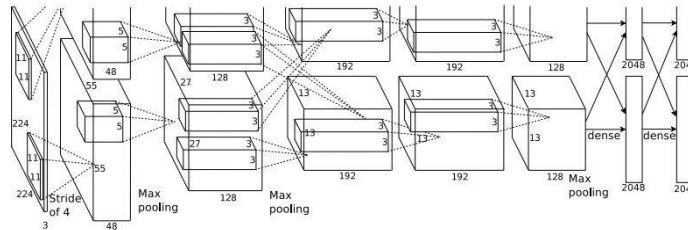
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Dog? YES
Cat? NO
Background? NO

Object Detection as Classification: Sliding Window

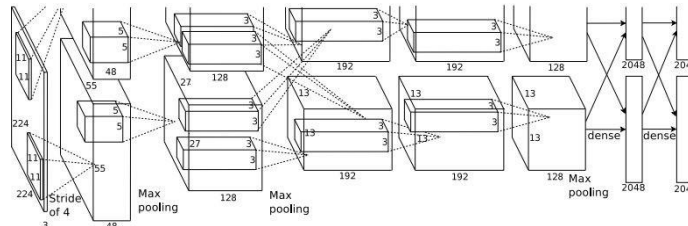
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Dog? YES
Cat? NO
Background? NO

Object Detection as Classification: Sliding Window

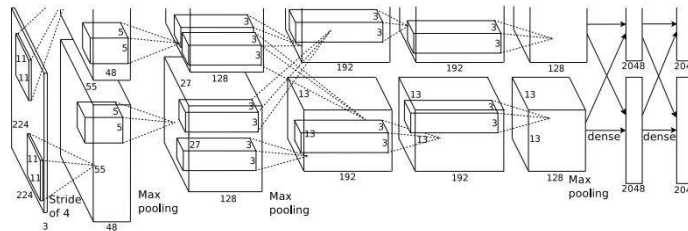
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Dog? NO
Cat? YES
Background? NO

Object Detection as Classification: Sliding Window

Apply a CNN to many different crops of the image, CNN classifies each crop as object or background

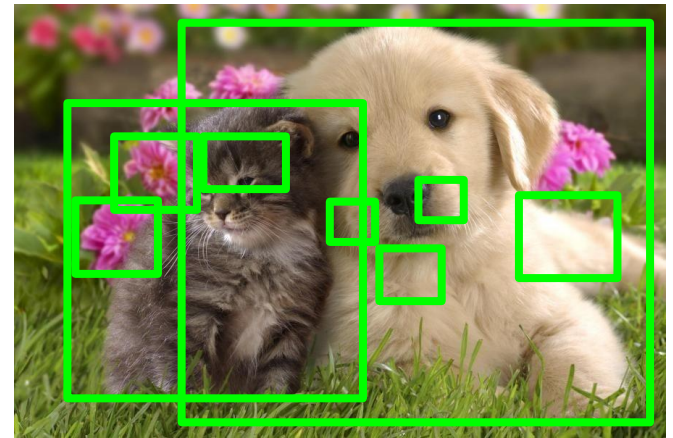


Dog? NO
Cat? YES
Background? NO

Problem: Need to apply CNN to huge number of locations and scales, very computationally expensive!

Region Proposals

- Find “blobby” image regions that are likely to contain objects
- Relatively fast to run; e.g. Selective Search gives 1000 region proposals in a few seconds on CPU



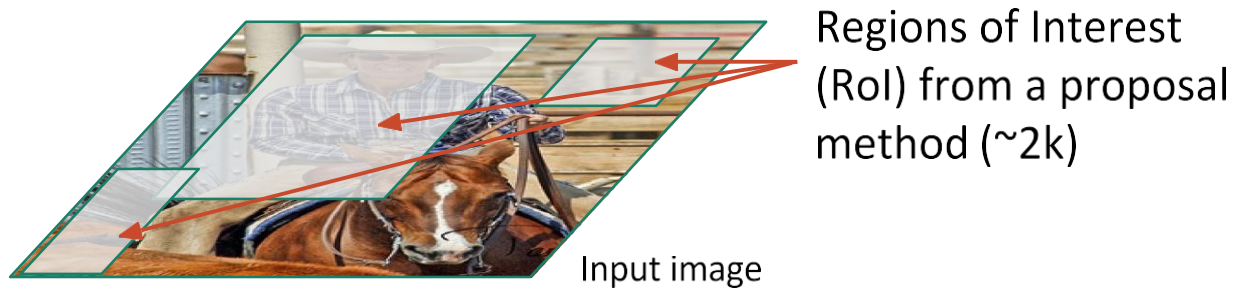
Alexe et al, "Measuring the objectness of image windows", TPAMI 2012
Uijlings et al, "Selective Search for Object Recognition", IJCV 2013
Cheng et al, "BING: Binarized normed gradients for objectness estimation at 300fps", CVPR 2014
Zitnick and Dollar, "Edge boxes: Locating object proposals from edges", ECCV 2014

R-CNN

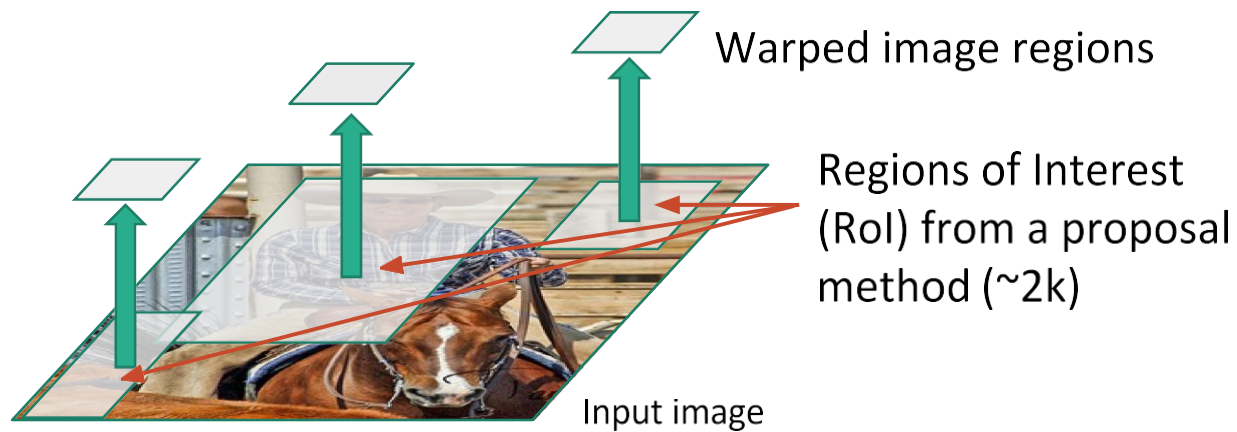


Input image

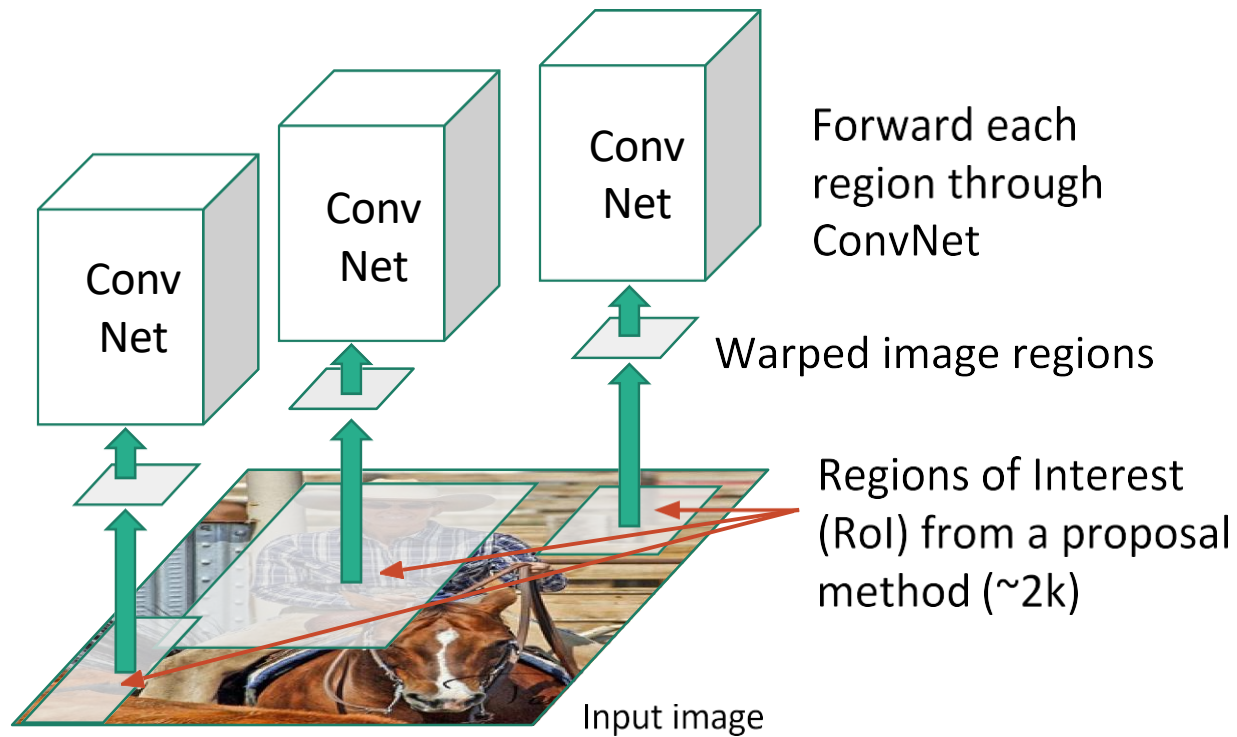
R-CNN



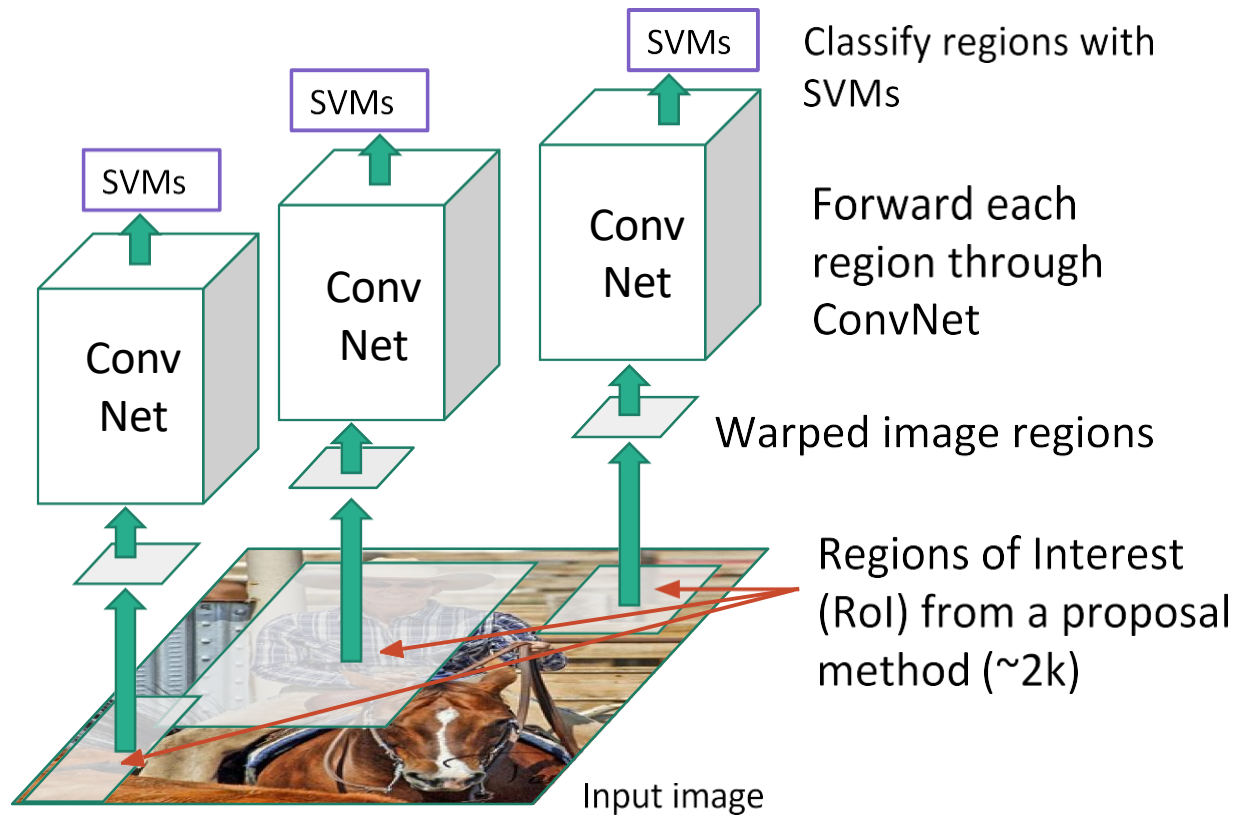
R-CNN



R-CNN

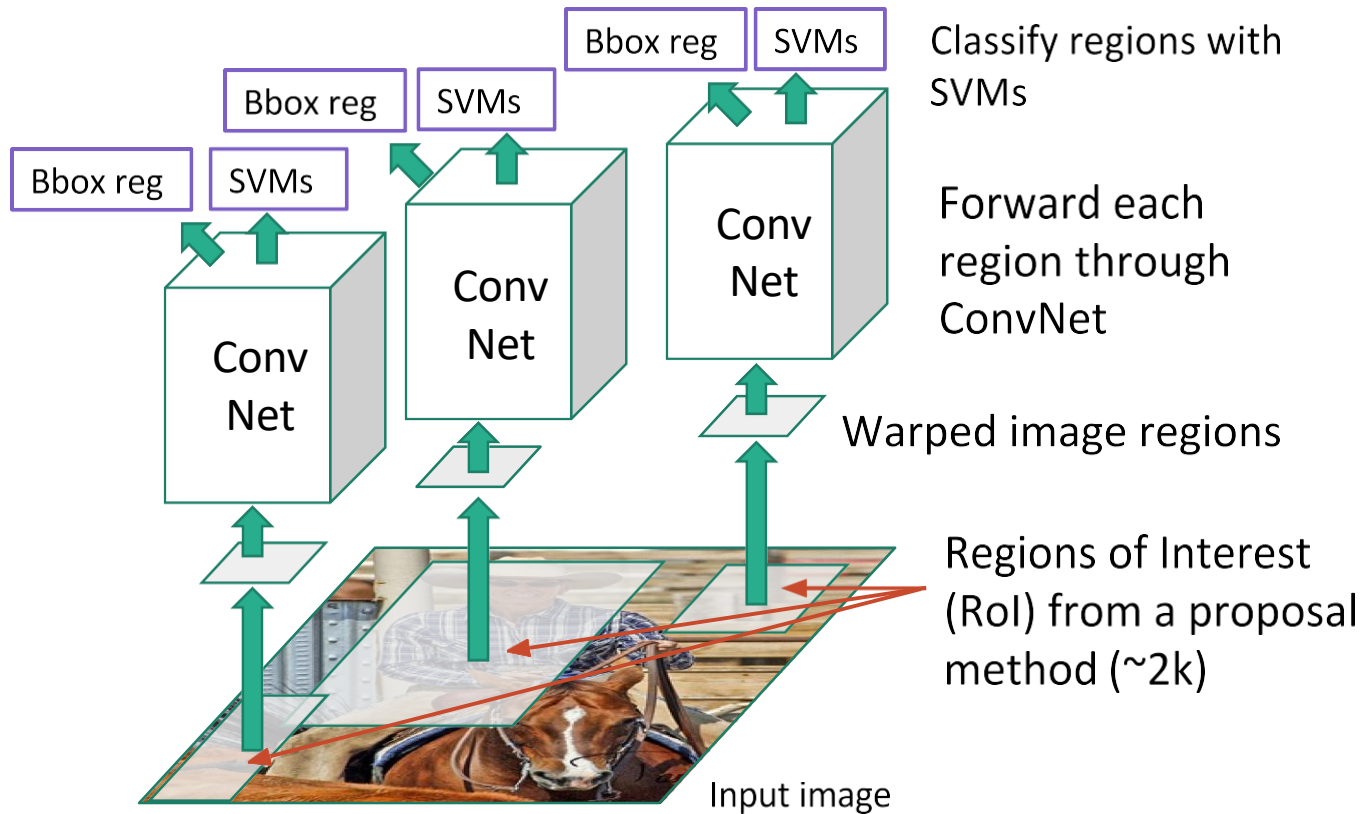


R-CNN



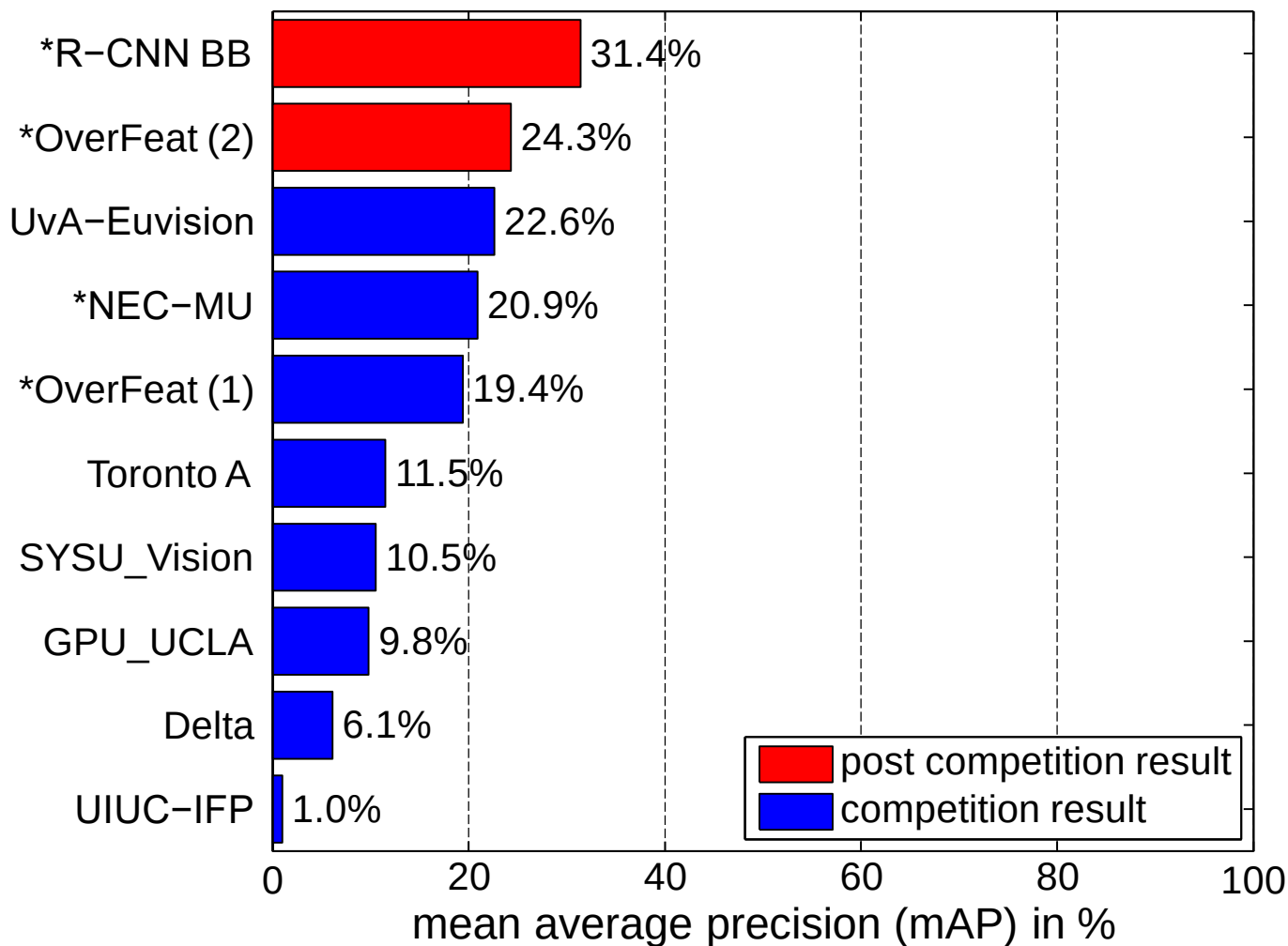
R-CNN

Linear Regression for bounding box offsets



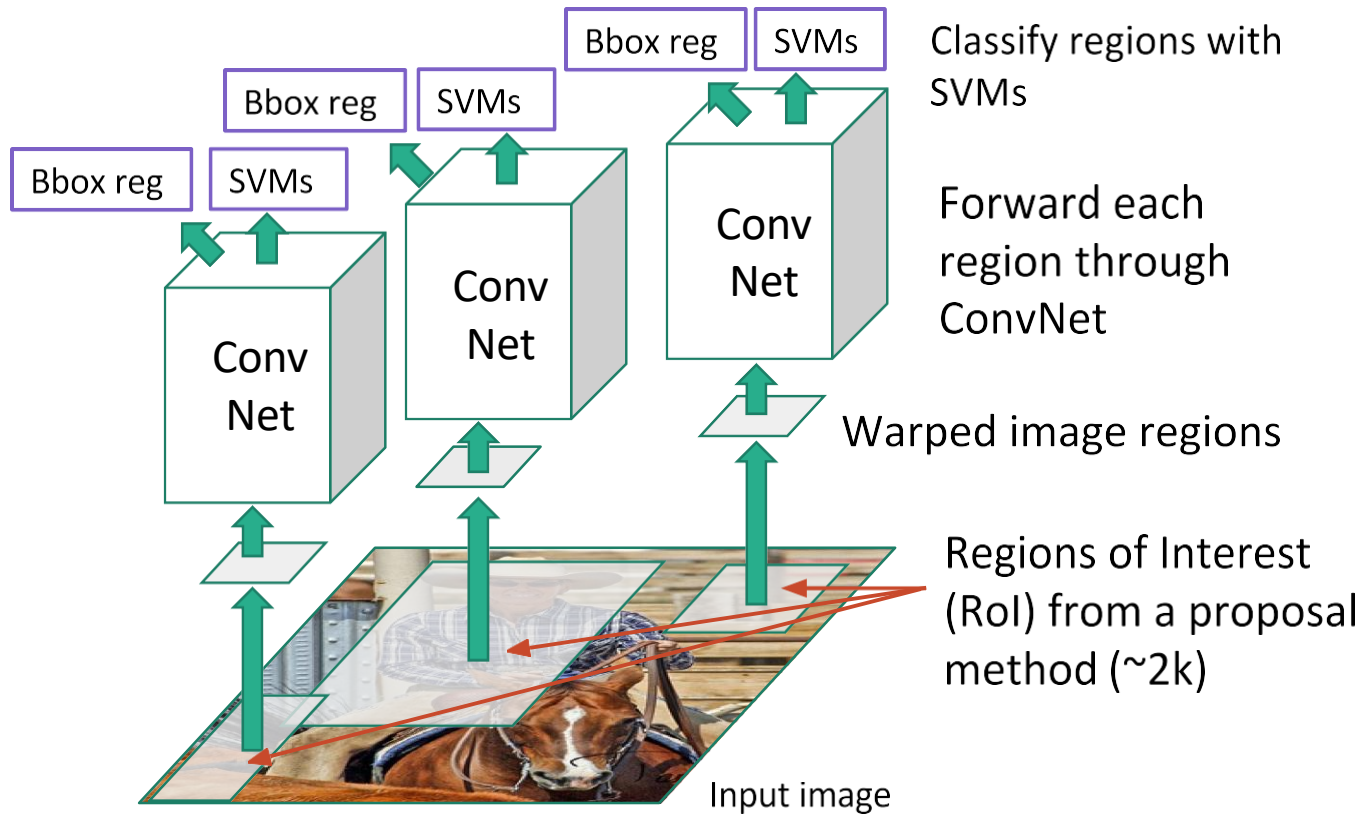
R-CNN on ImageNet detection

ILSVRC2013 detection test set mAP



R-CNN

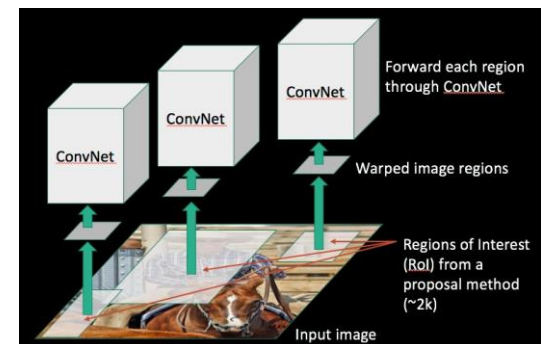
Linear Regression for bounding box offsets



Post hoc component

What's wrong with slow R-CNN?

- Ad hoc training objectives
 - Fine-tune network with softmax classifier (log loss)
 - Train post-hoc linear SVMs (hinge loss)
 - Train post-hoc bounding-box regressions (least squares)
- Training is slow (84h), takes a lot of disk space
- Inference (detection) is slow
 - 47s / image with VGG16 [Simonyan & Zisserman, ICLR15]



Fast R-CNN

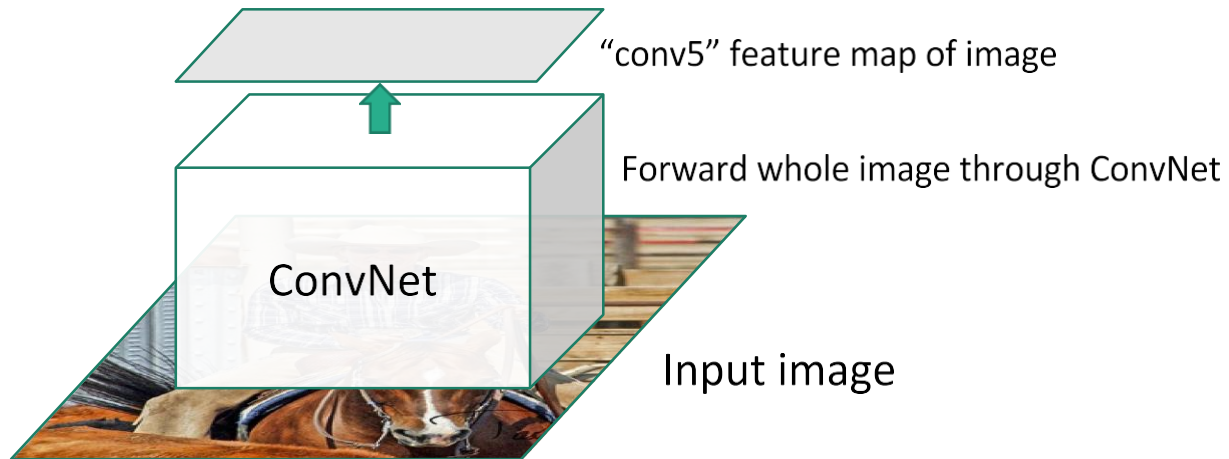
- Fast test time
- One network, trained in one stage
- Higher mean average precision

Fast R-CNN

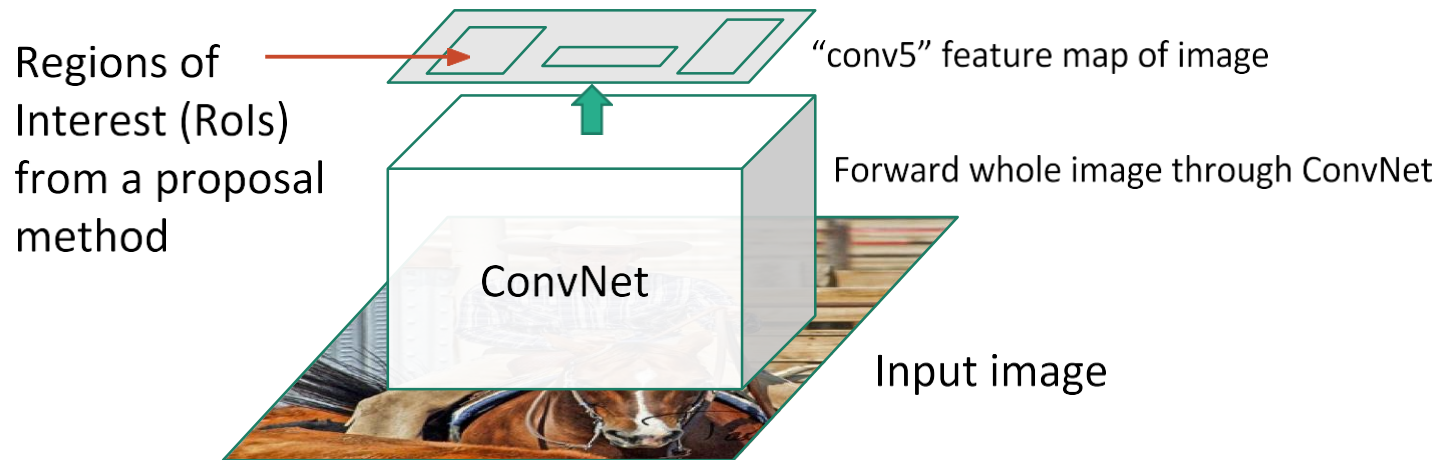


Input image

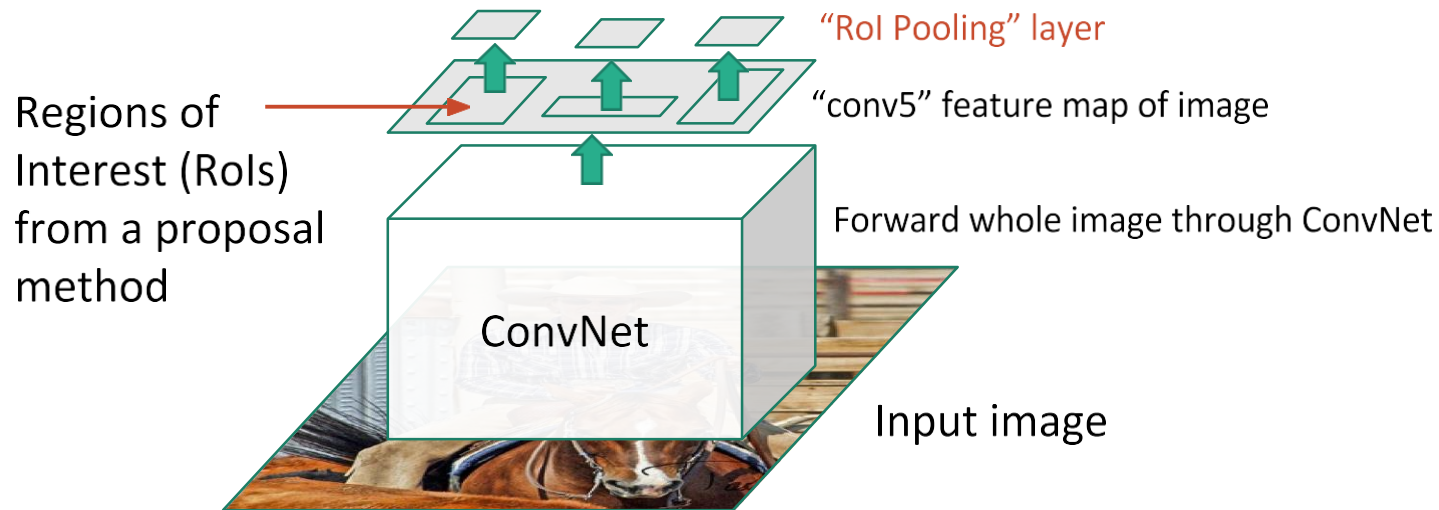
Fast R-CNN



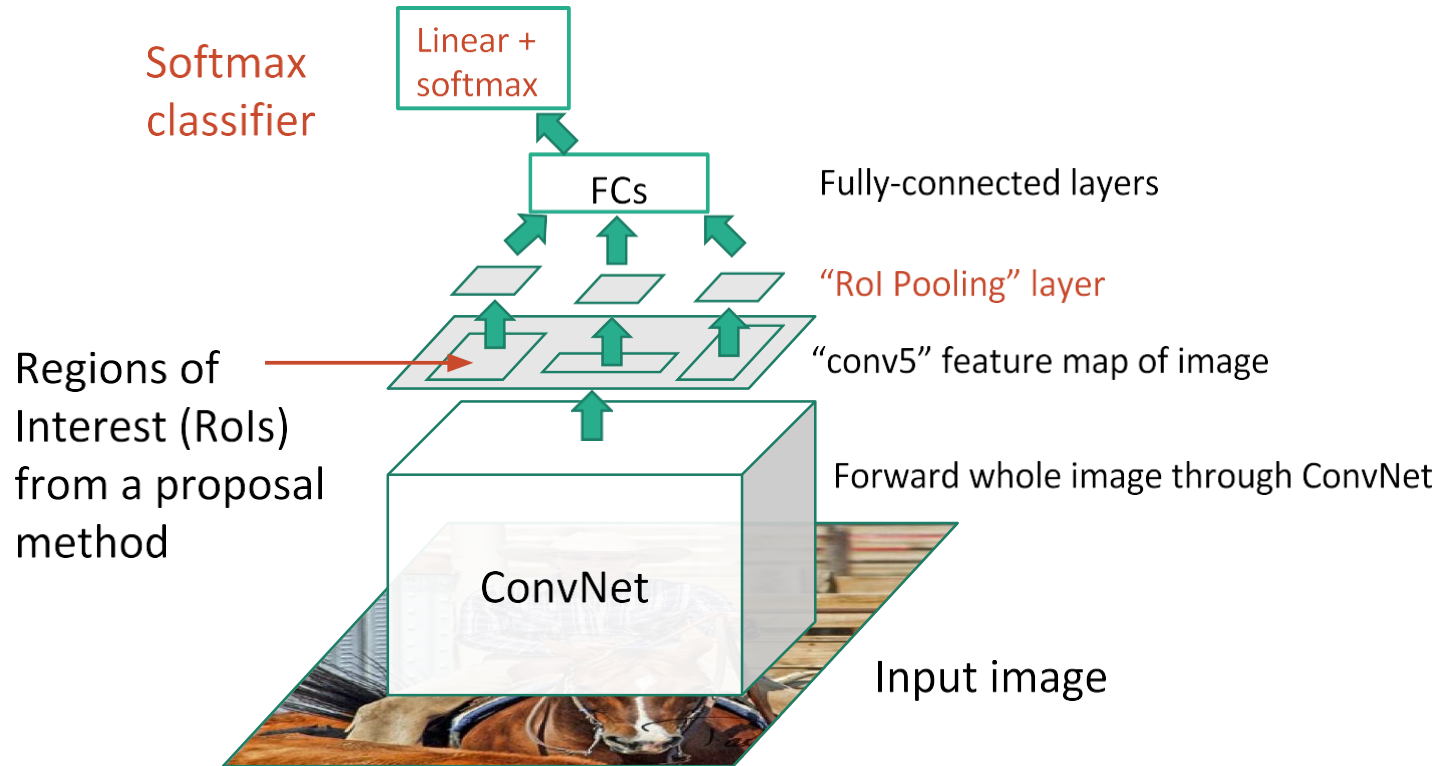
Fast R-CNN



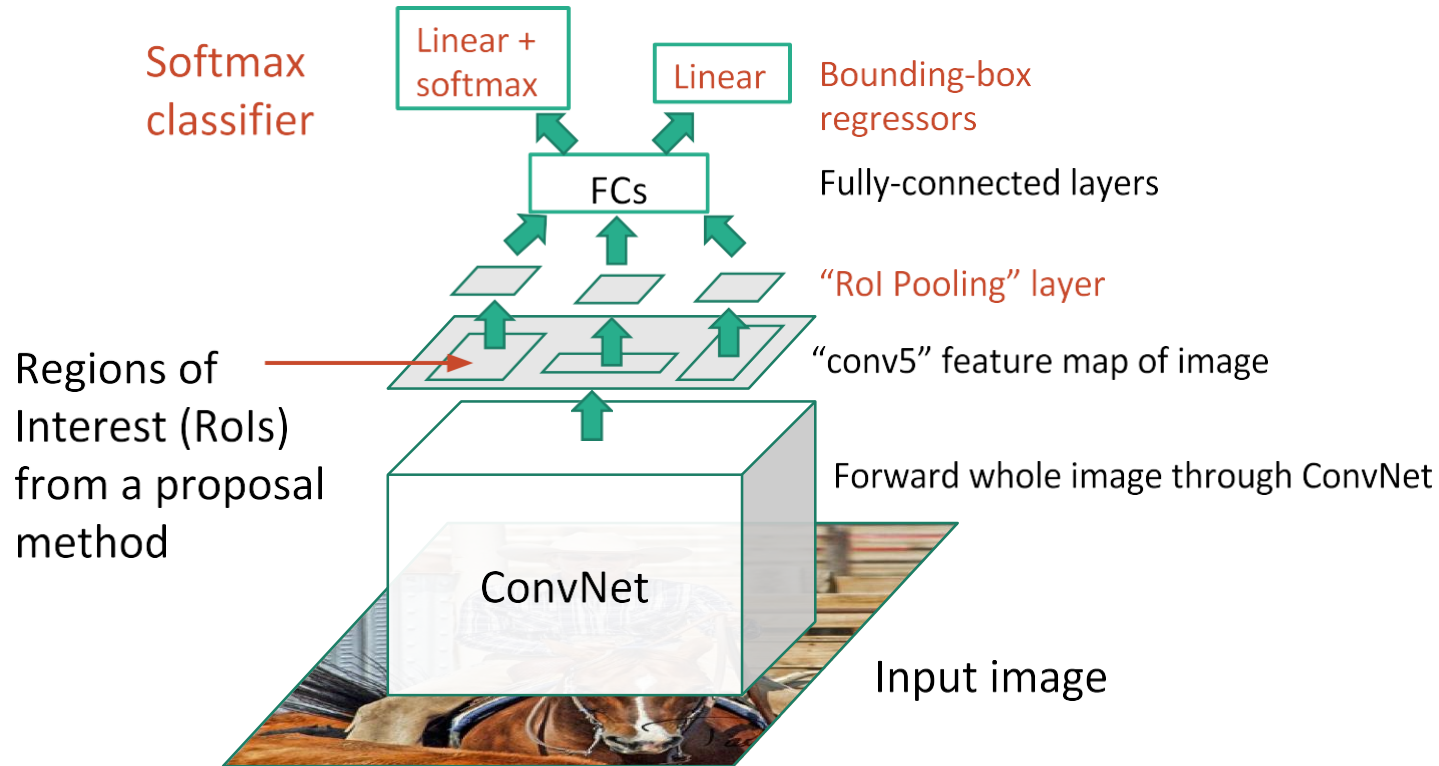
Fast R-CNN



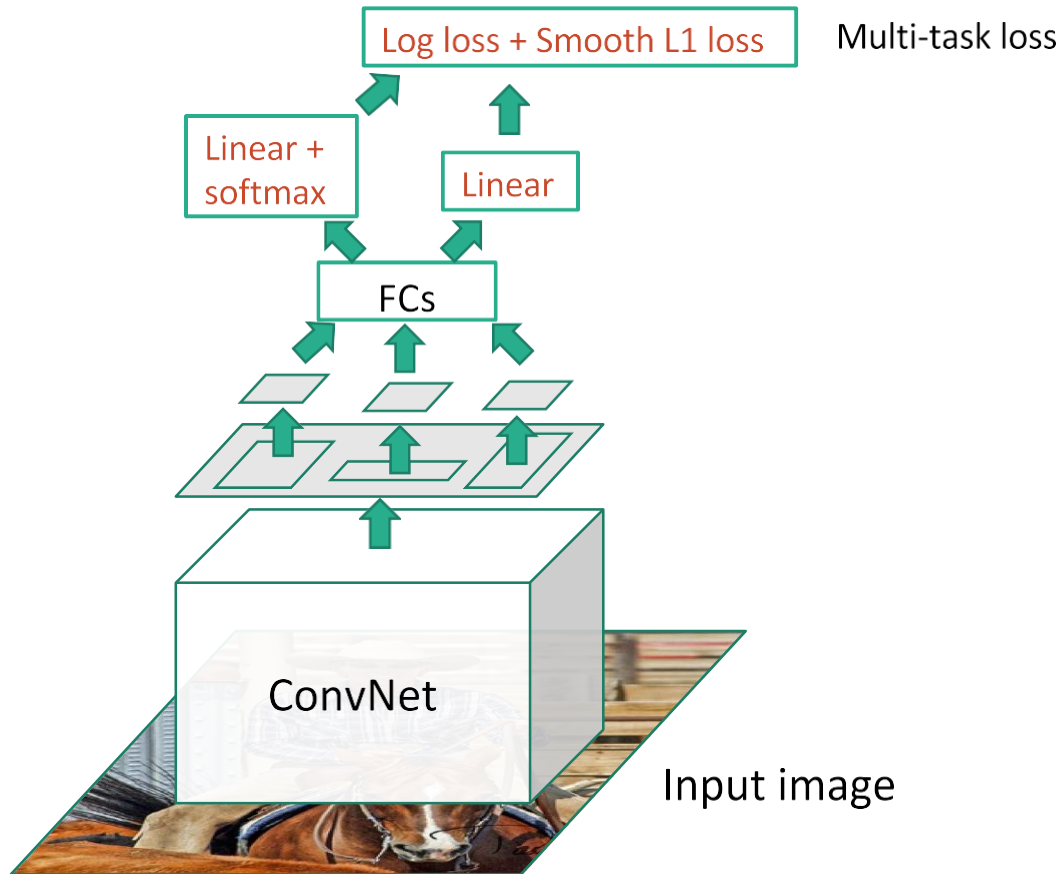
Fast R-CNN



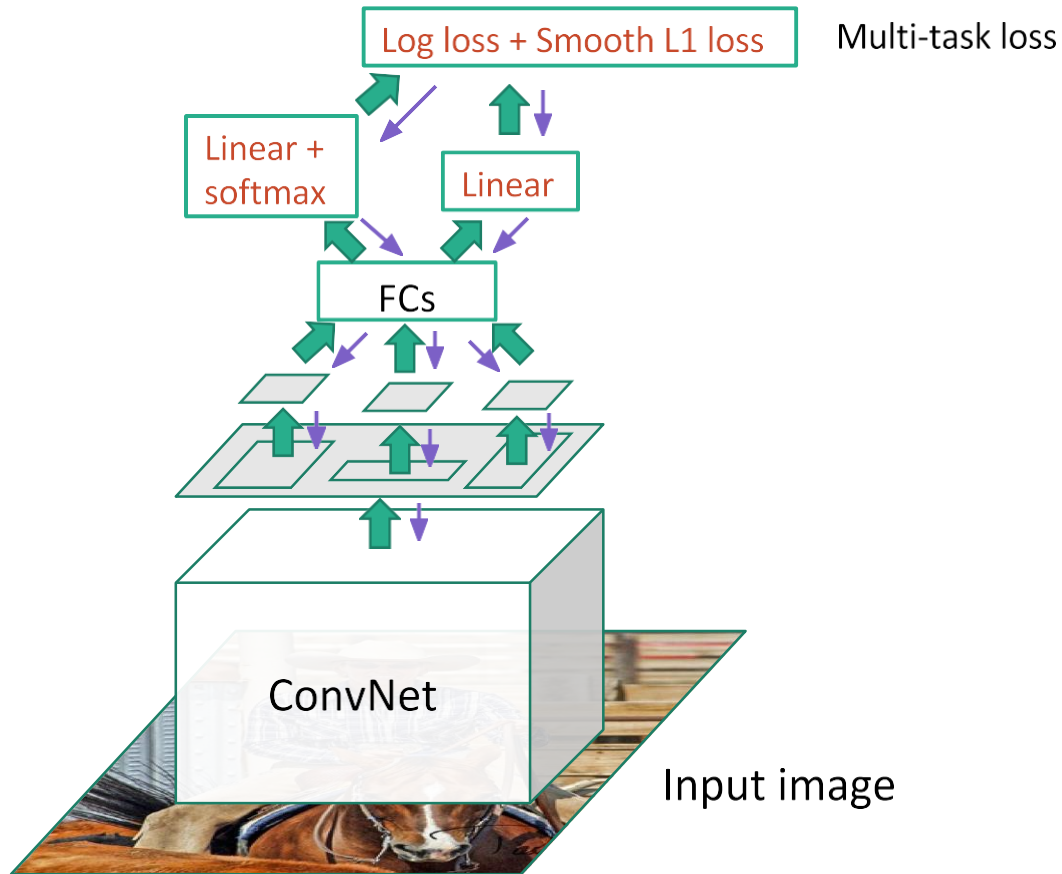
Fast R-CNN



Fast R-CNN (Training)



Fast R-CNN (Training)



Fast R-CNN vs R-CNN

	Fast R-CNN	R-CNN
Train time (h)	9.5	84
Speedup	8.8x	1x
Test time / image	0.32s	47.0s
Test speedup	146x	1x
mAP	66.9%	66.0%

Timings exclude object proposal time, which is equal for all methods.
All methods use VGG16 from Simonyan and Zisserman.

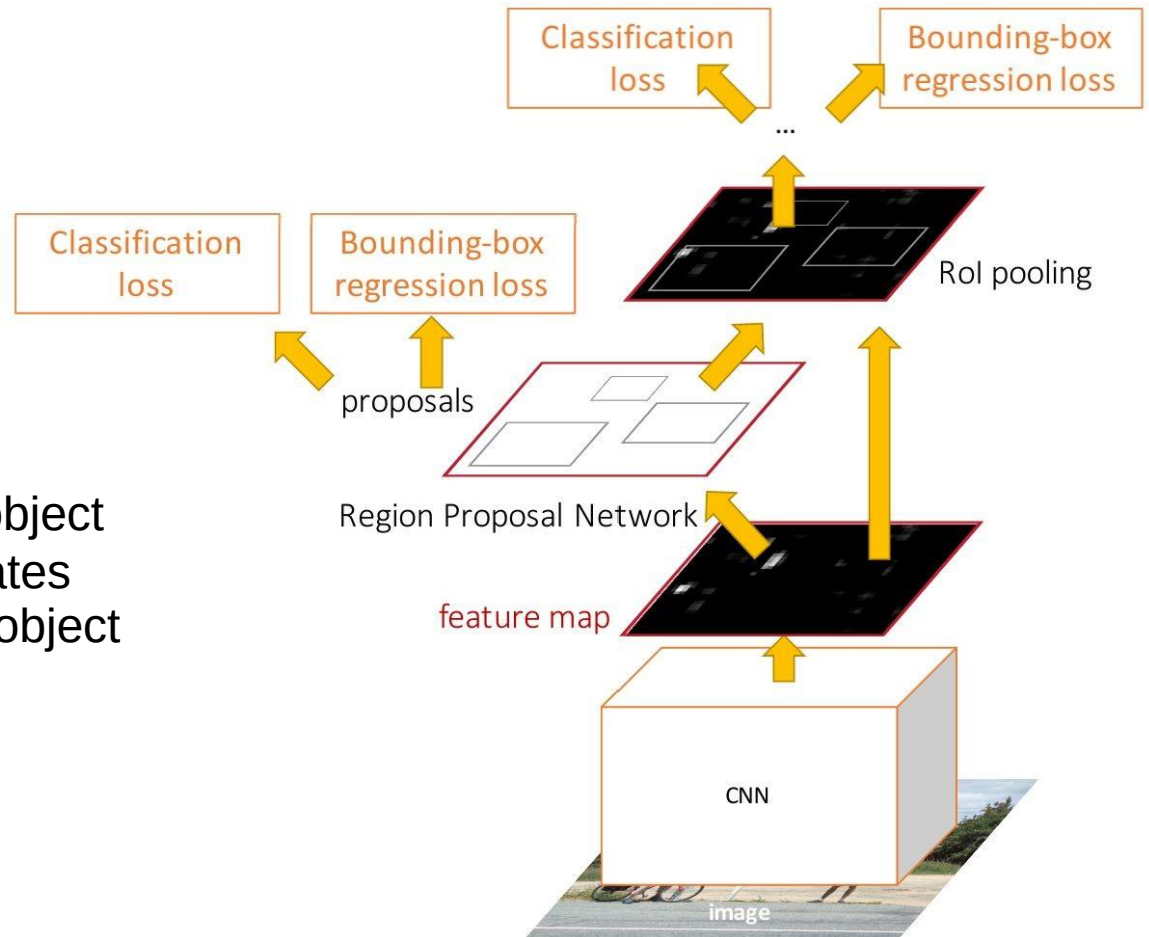
Faster R-CNN

Make CNN do proposals!

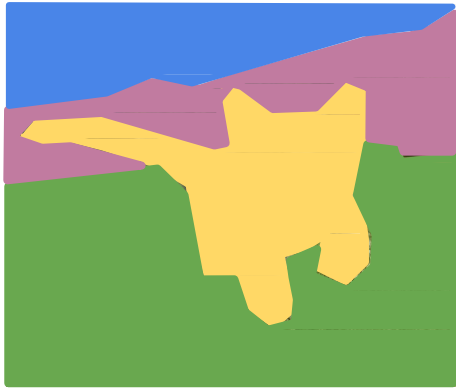
Insert **Region Proposal Network (RPN)** to predict proposals from features

Jointly train with 4 losses:

1. RPN classify object / not object
2. RPN regress box coordinates
3. Final classification score (object classes)
4. Final box coordinates

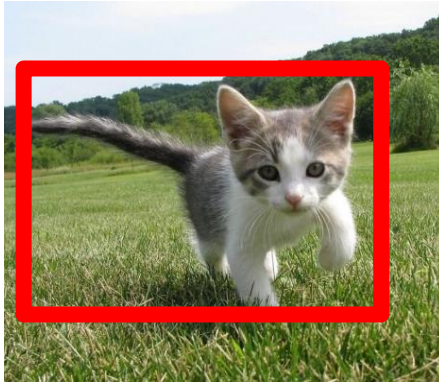


Semantic Segmentation



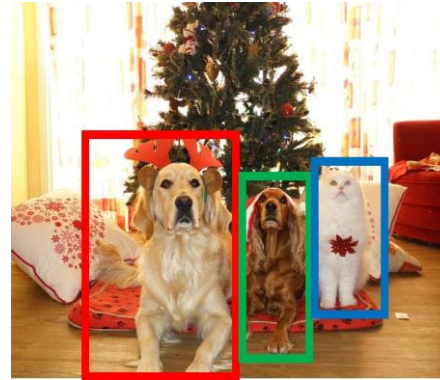
GRASS, CAT,
TREE, SKY

No objects, just pixels



CAT

Single Object



DOG, DOG, CAT



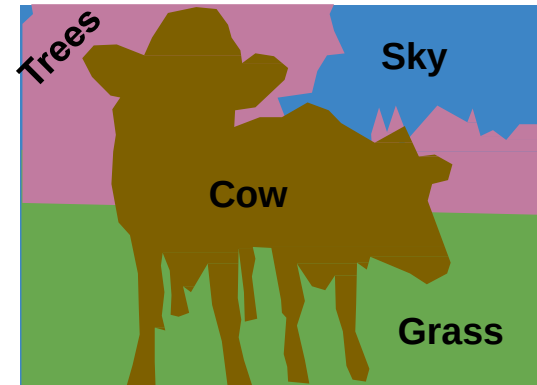
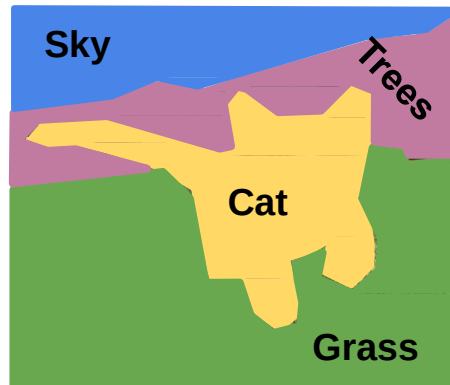
DOG, DOG, CAT

Multiple Object

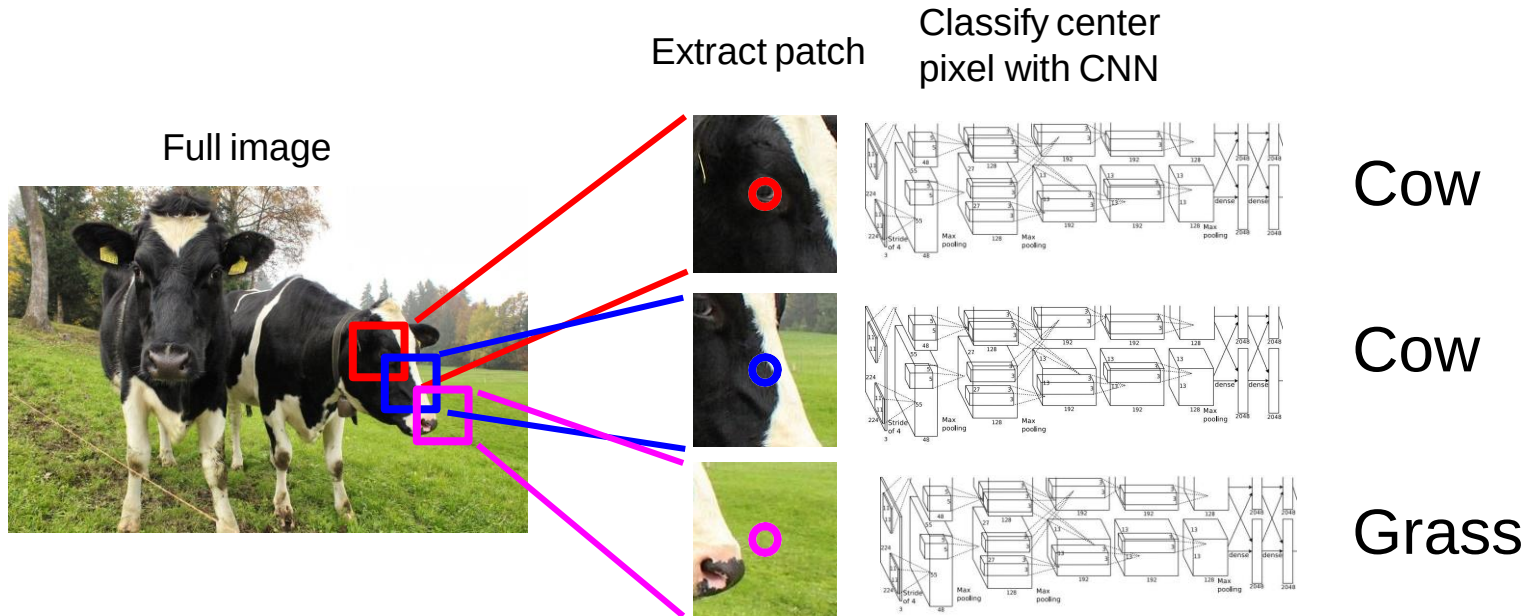
Semantic Segmentation

Label each pixel in the image with a category label

Don't differentiate instances, only care about pixels



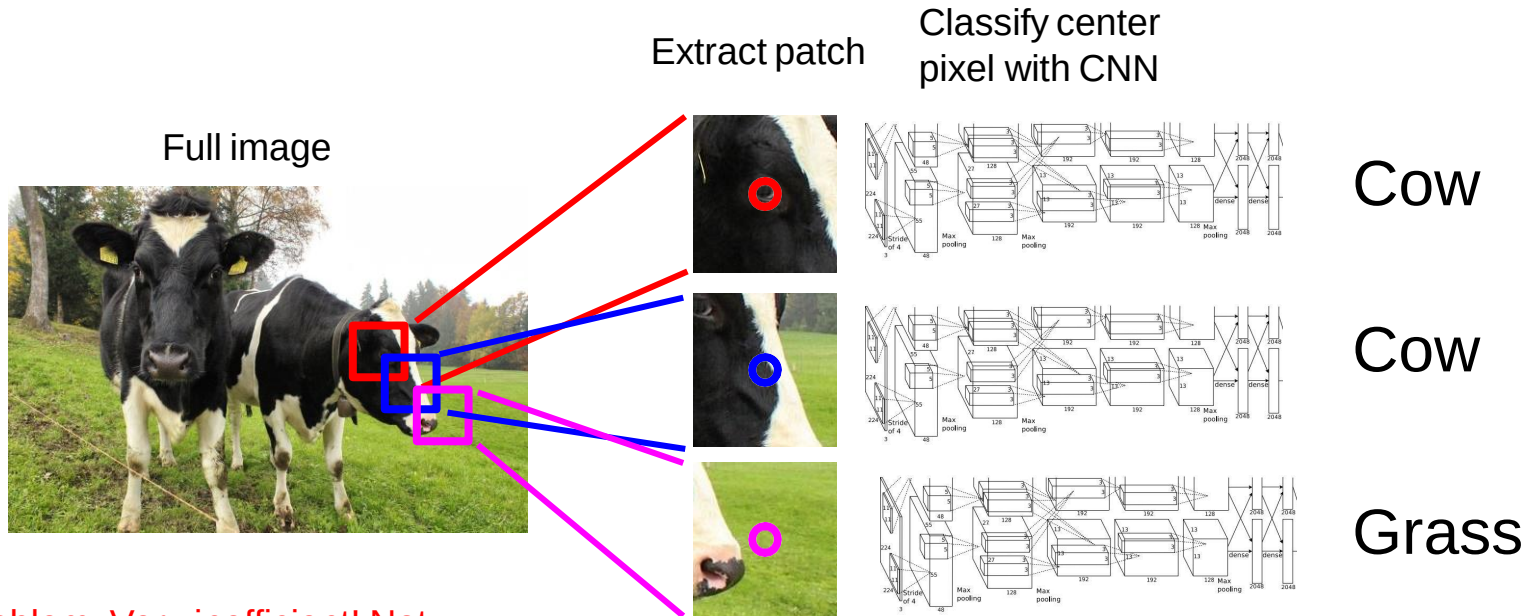
Semantic Segmentation Idea: Sliding Window



Farabet et al, "Learning Hierarchical Features for Scene Labeling," TPAMI 2013

Pinheiro and Collobert, "Recurrent Convolutional Neural Networks for Scene Labeling", ICML 2014

Semantic Segmentation Idea: Sliding Window

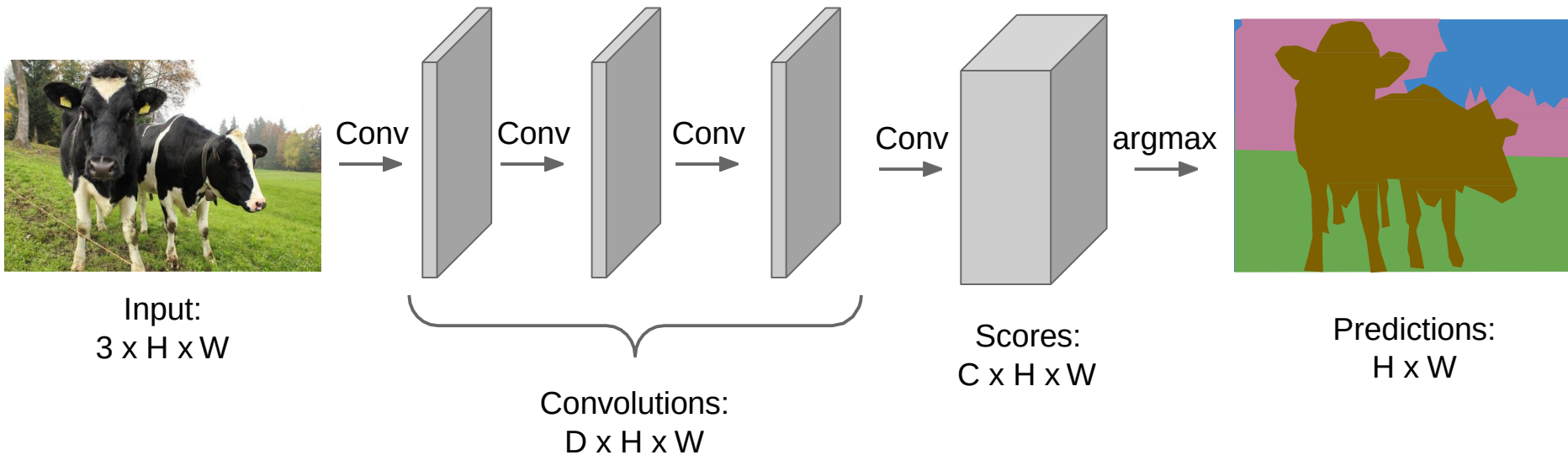


Farabet et al, "Learning Hierarchical Features for Scene Labeling," TPAMI 2013

Pinheiro and Collobert, "Recurrent Convolutional Neural Networks for Scene Labeling", ICML 2014

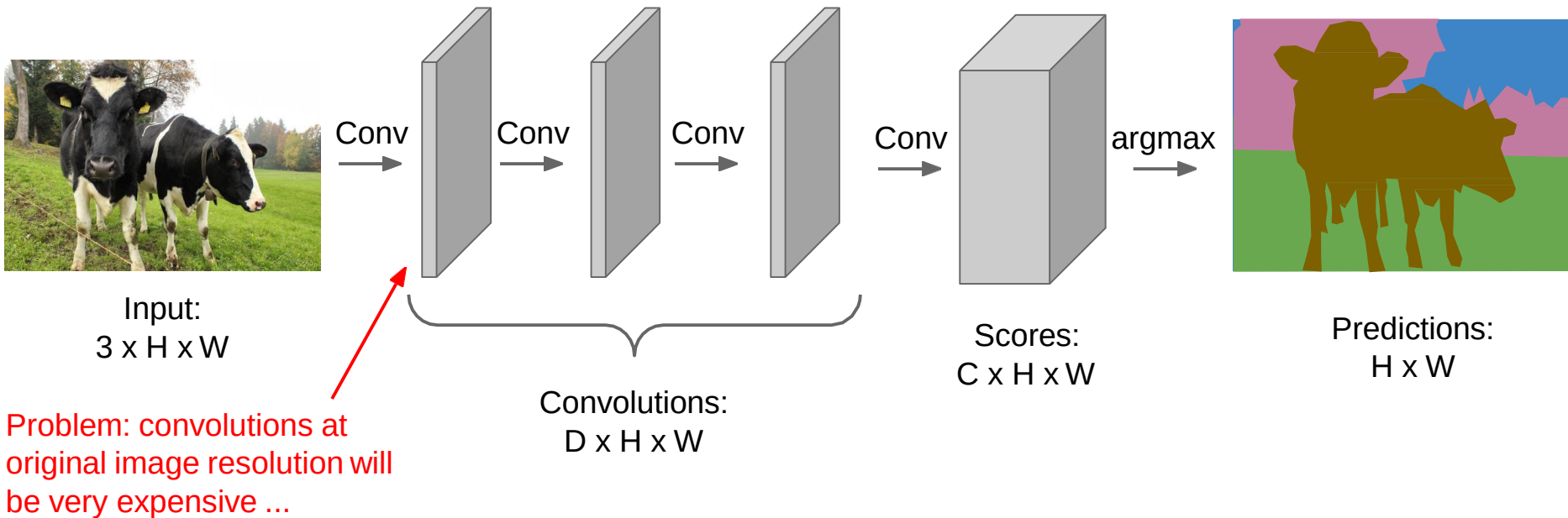
Semantic Segmentation Idea: Fully Convolutional

Design a network as a bunch of convolutional layers
to make predictions for pixels all at once!



Semantic Segmentation Idea: Fully Convolutional

Design a network as a bunch of convolutional layers to make predictions for pixels all at once!

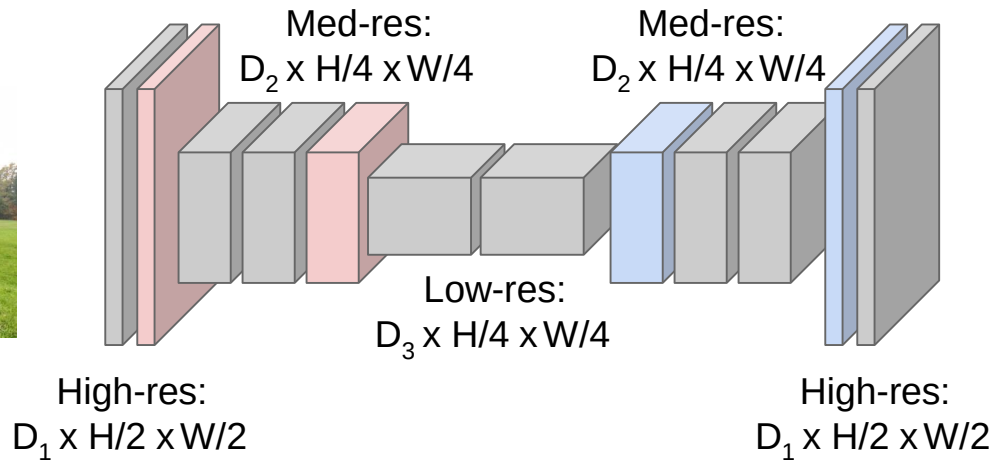


Semantic Segmentation Idea: Fully Convolutional

Design network as a bunch of convolutional layers, with **downsampling** and **upsampling** inside the network!



Input:
 $3 \times H \times W$



Predictions:
 $H \times W$

Long, Shelhamer, and Darrell, "Fully Convolutional Networks for Semantic Segmentation", CVPR 2015
Noh et al, "Learning Deconvolution Network for Semantic Segmentation", ICCV 2015