Convolutional Networks

Machine Learning for Image Analysis

-Vedika Agarwal

Overview

1. CNN and some useful applications
    a. Motivation
    b. Other applications
2. Biological Connection
    a. Idea behind it
3. Structure of a CNN
    a. Convolution- the C in CNN
    b. Non-Linearity
    c. Pooling
    d. Fully-Connected Layer
4. Example architectures
5. Beyond Images
6. References

Why Convolutional Networks?

- Wins every computer vision challenge (classification, segmentation, etc.)
- Can be applied in various domains (speech recognition, game prediction, Natural Language Processing etc.)
- Really good performance- Beats human accuracy in some cases

A visual representation

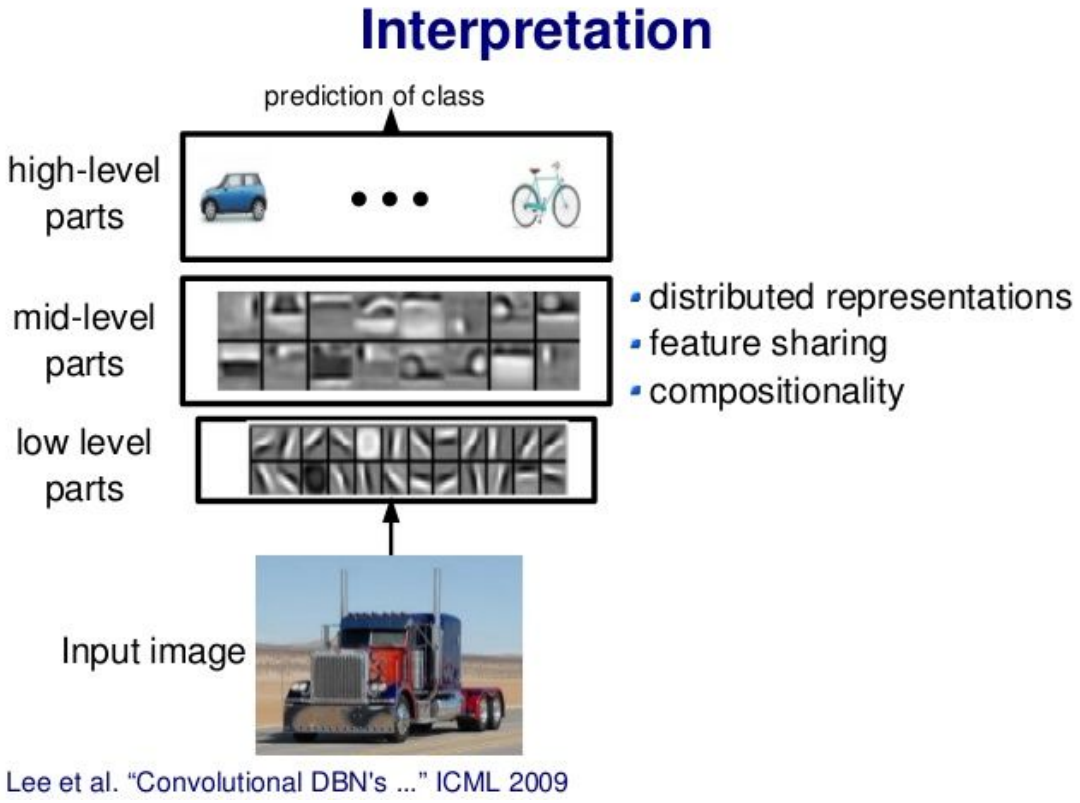
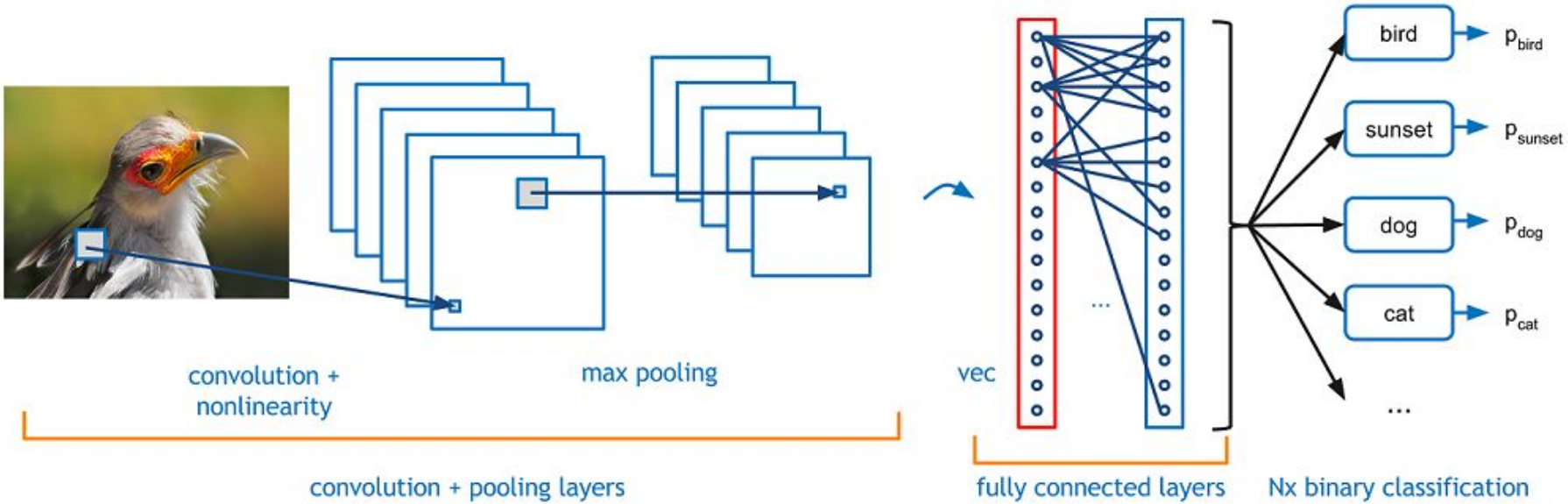
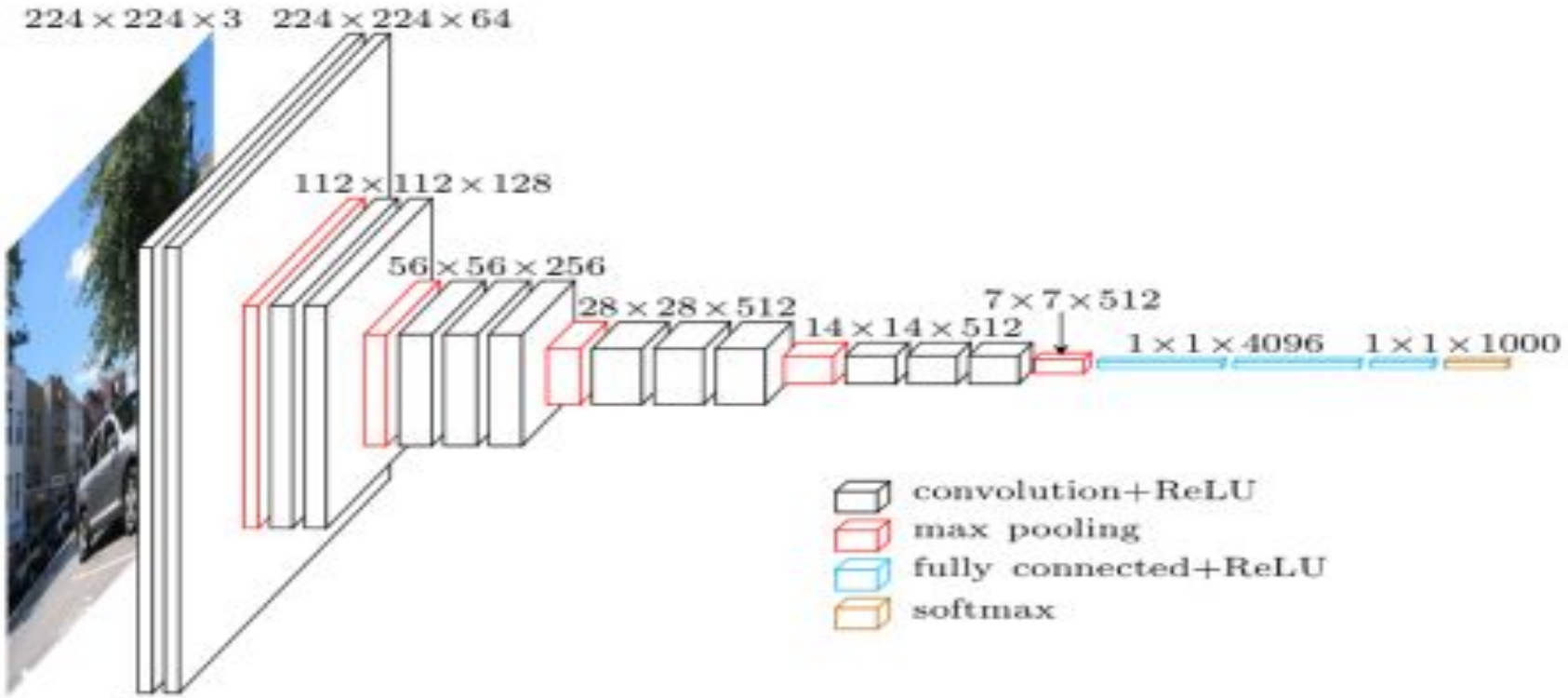


Image Classification



Example- architecture VGGnet



Applications- Visual Recognition

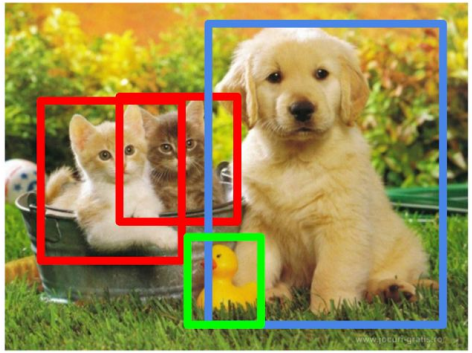
Classification

CAT

Classification + Localization

CAT

Object Detection



CAT, DOG, DUCK

Instance Segmentation

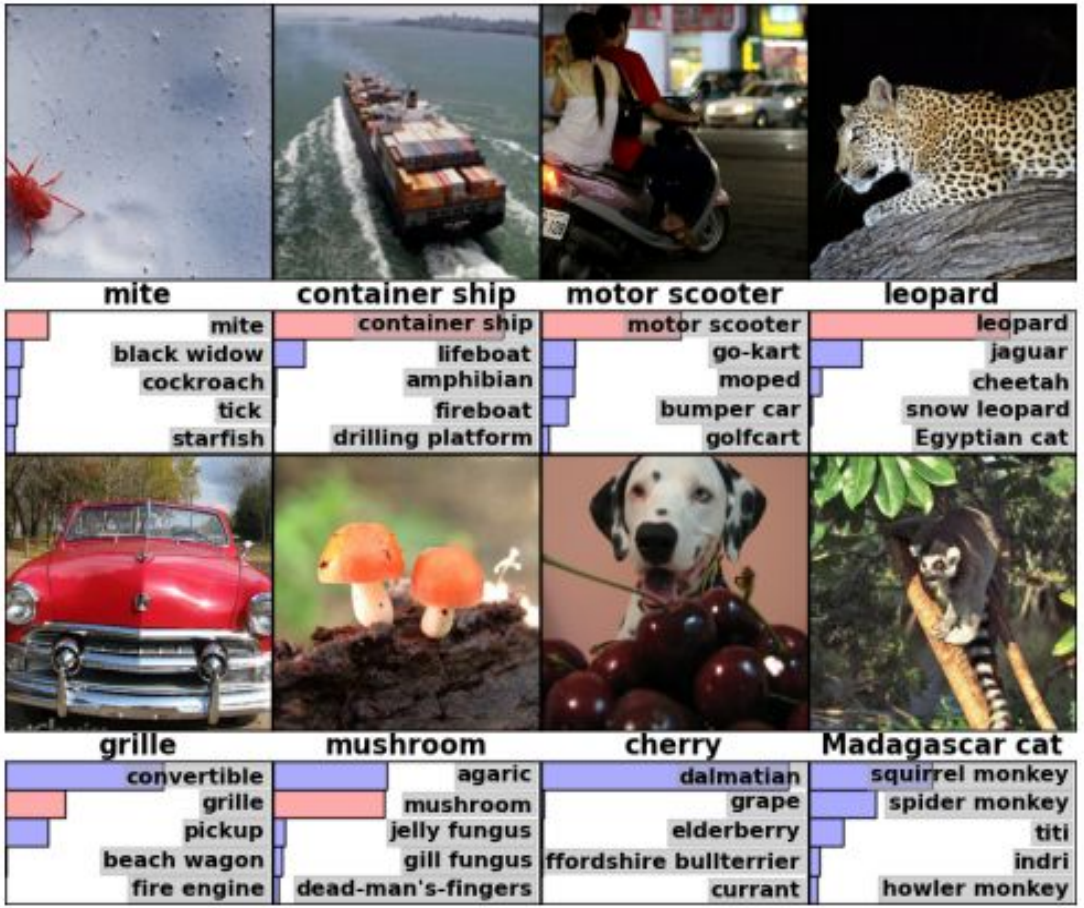
CAT, DOG, DUCK

Single object

Multiple objects

Classification- What?

- Single object, single class
- 2012, **Deep convolutional neural network**, Alex Krizhevsky et al.
- ImageNet- 1 place, top-5 test error rate of 15.3%, compared to 26.2% achieved by the second-best entry.



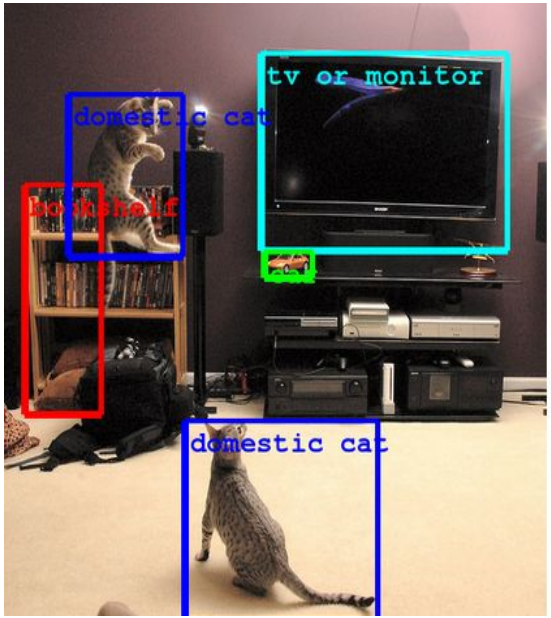
Source: Krizhevsky, A., Sutskever I., and Hinton, G., "Imagenet classification with deep convolutional neural networks", *Advances in neural information processing systems, 2012.*

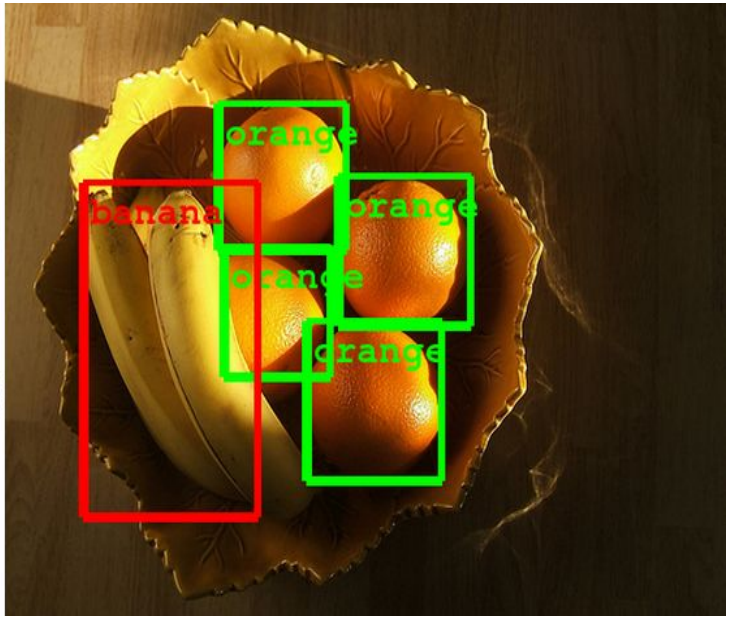
Classification and Localization- What and Where?

- Multiple objects, multiple class
- 2014, **VGG net** by Oxford group

ImageNet challenge:

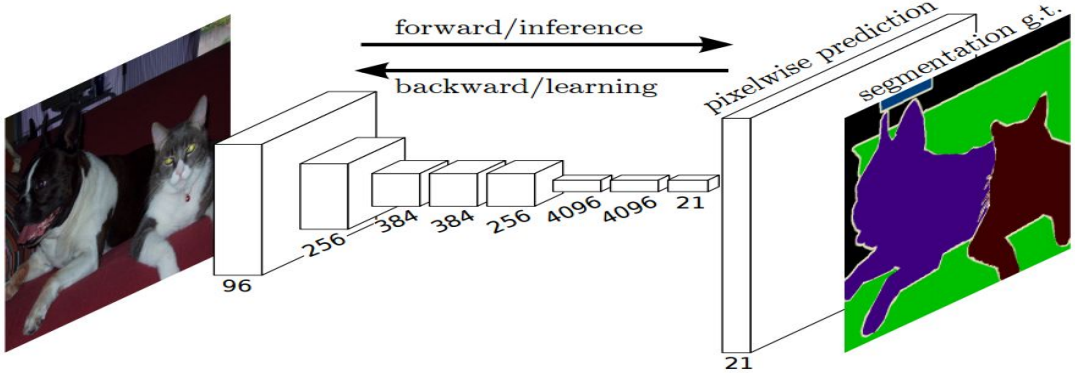
- First in localization
- Second in classification





Source: *K Simonyan and A. Zisserman*, “Very deep convolutional networks for large-scale image recognition,” in ICLR, 2014

Semantic Segmentation- What, Where and Extent?



Given an image- you want to predict the class label for each pixel in the image i.e **pixel-wise semantic labelling**

Source: Fully Convolutional Network, Berkeley group, CVPR 2015

Semantic Segmentation- What, Where and Extent?

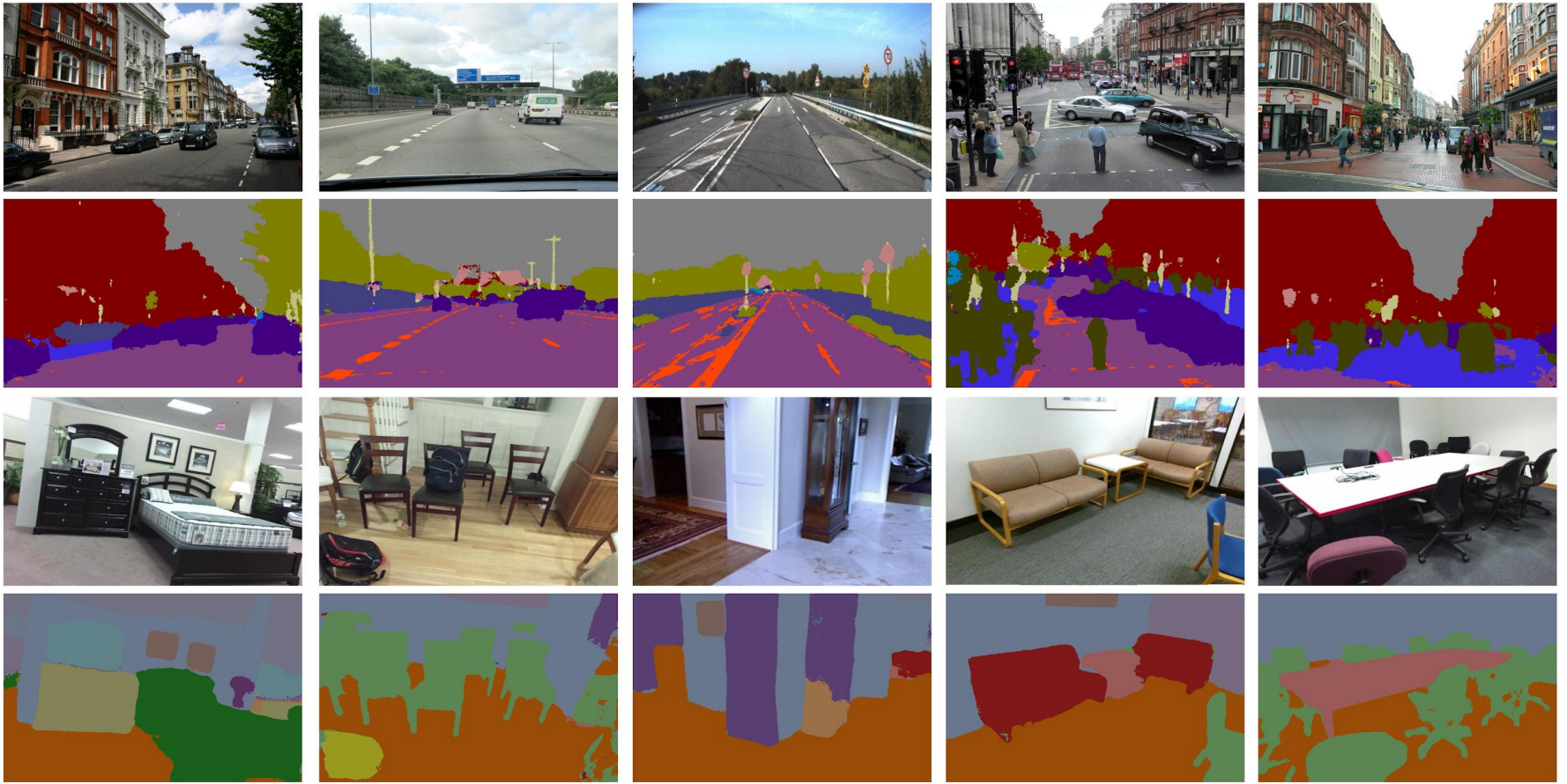
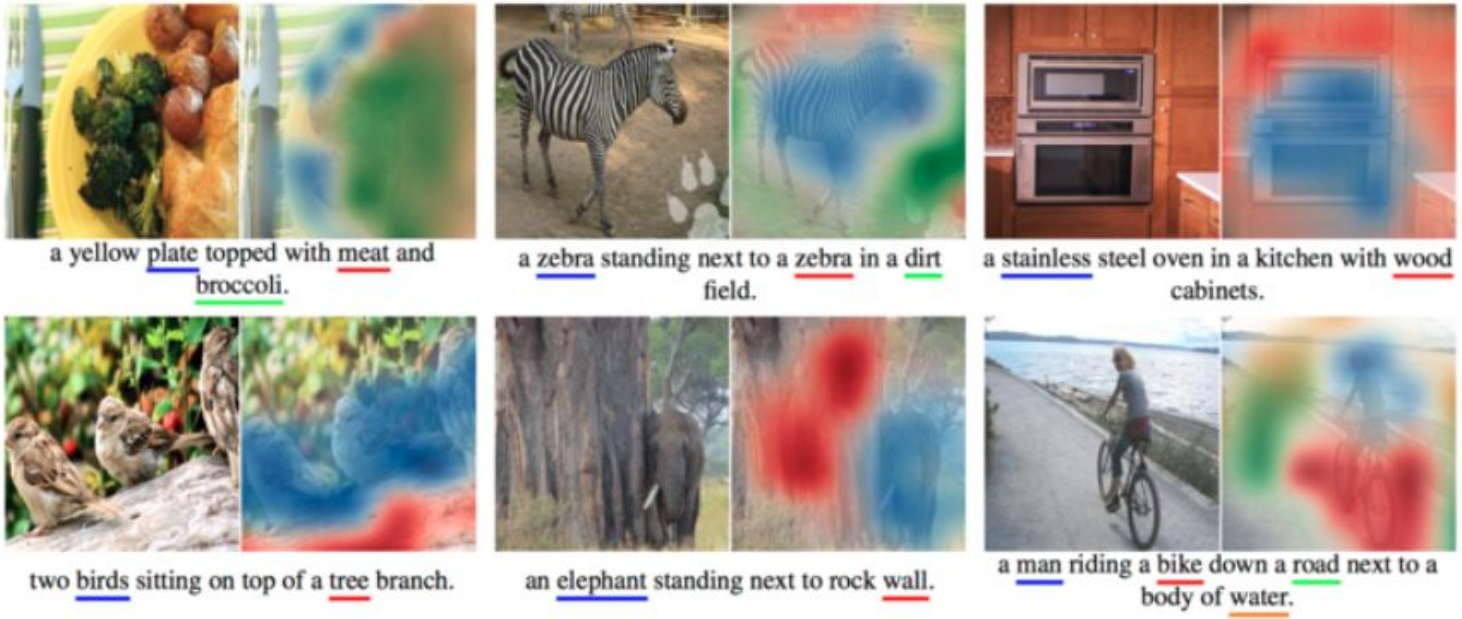


Image Captioning & Visual Attention



Source: *Jiasen Lu^, Caiming Xiong^, Devi Parikh, and Richard Socher. 2016.*
Knowing When to Look: Adaptive Attention via A Visual Sentinel for Image Captioning.

Style Transfer

Mona Lisa restyled by Picasso, van Gogh, and Monet

Source: http://genekogan.com/works/style-transfer/

Applications



- Autonomous vehicles
- Indoor segmentation for Augmented reality systems
- Learn geometry in the image
- Road scene analysis
- Medical Imaging

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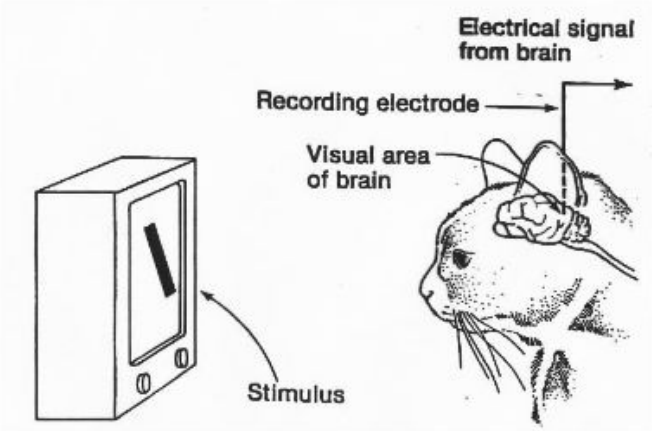
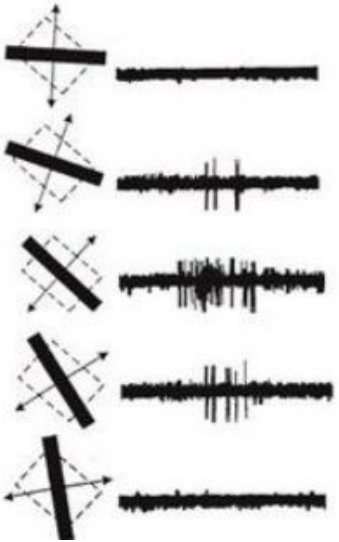
Biological Connection

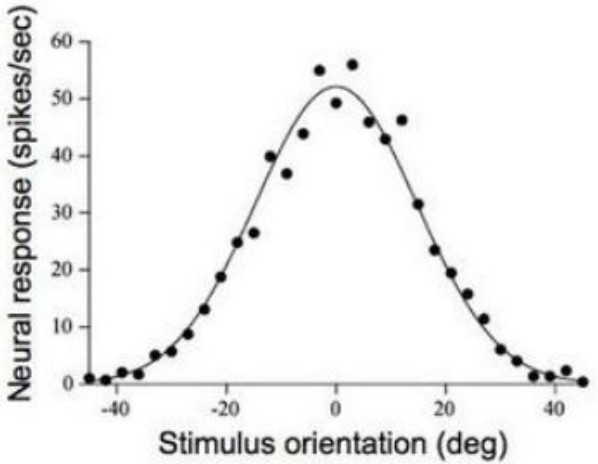
- **Hubel and Wiesel , 1959**



- Some neurons responded only in presence of some edges in certain orientation



- Idea of specialized components having specific tasks is the basis behind CNNs



What is Convolutional Network?

Convolutional network is simply a neural network thats use convolution in place of general matrix multiplication in at least one of their layers

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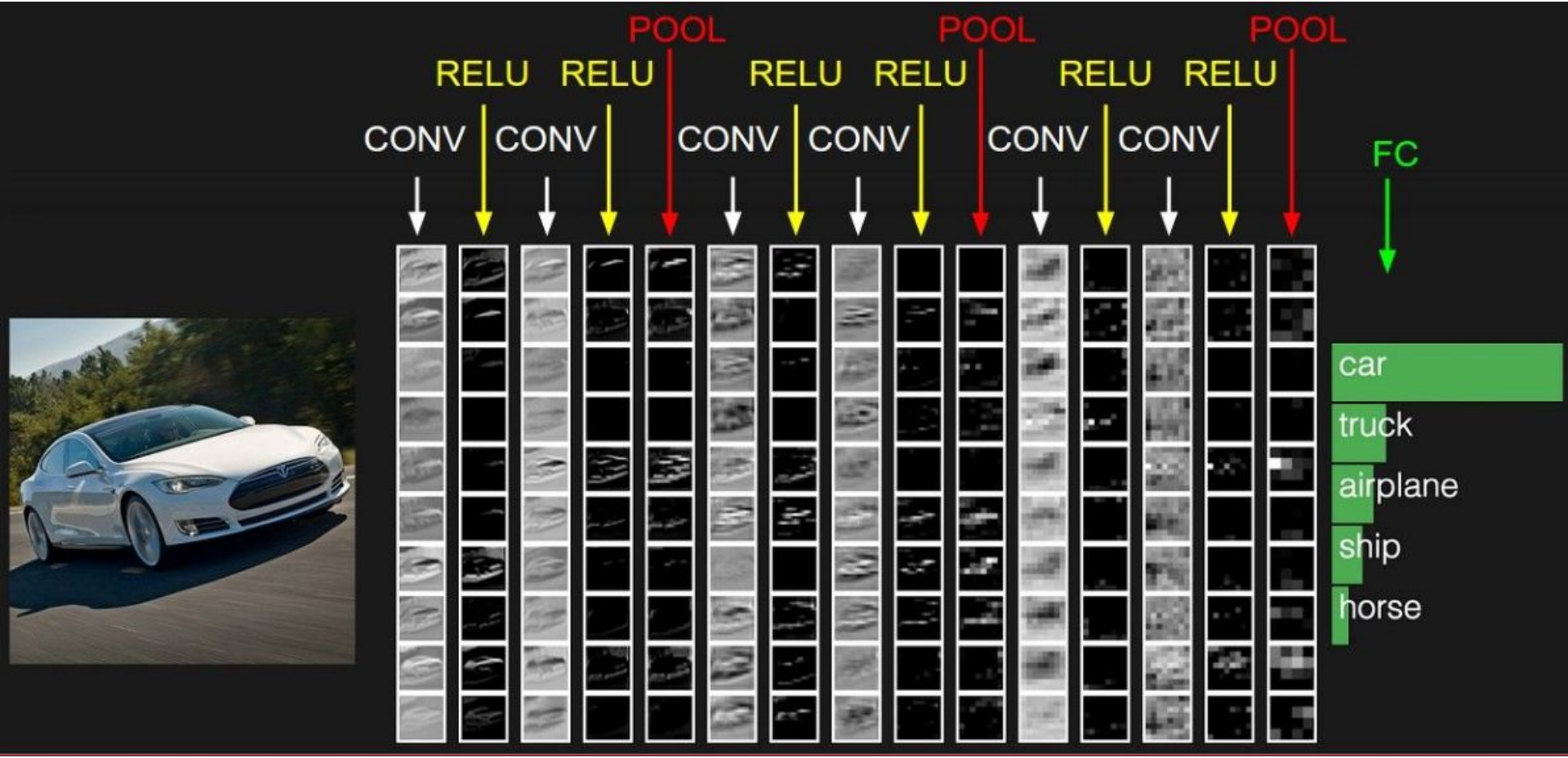
Structure

- Convolutional Layer
- Non-linearity (ReLU)
- Pooling
- Fully Connected Layer

preview


POOL
POOL
POOL
RELU
RELU
RELU
RELU
RELU
RELU
CONV
CONV
CONV
CONV
CONV
CONV
FC
car
truck
airplane
ship
horse

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Convolution

- Primary purpose - to extract features from the input image
- Discrete-convolution in 1D:

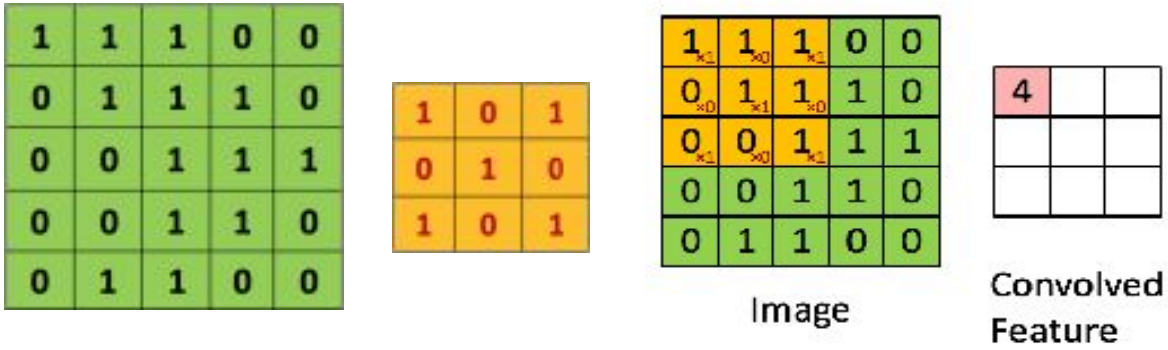
$$(\boldsymbol{f} * \boldsymbol{w})_i \ := \sum_{k=-\infty}^{\infty} f_{i-k}\, w_k$$

- Discrete-convolution in 2D:

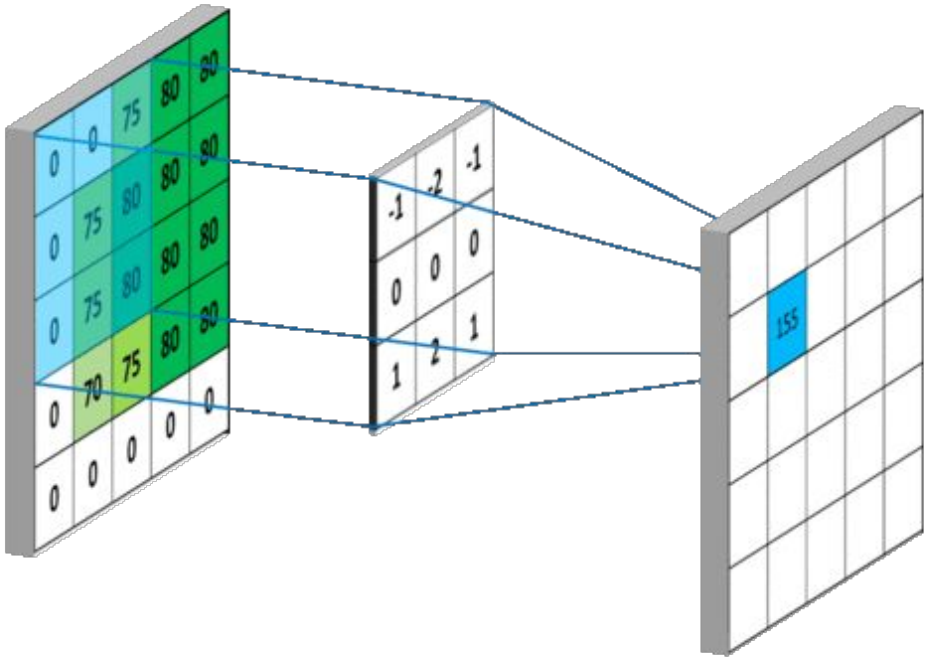
$$(\boldsymbol{f} * \boldsymbol{w})_{i,j} \ := \sum_{k=-\infty}^{\infty} \sum_{\ell=-\infty}^{\infty} f_{i-k,\, j-\ell}\, w_{k,\ell}$$

Convolution

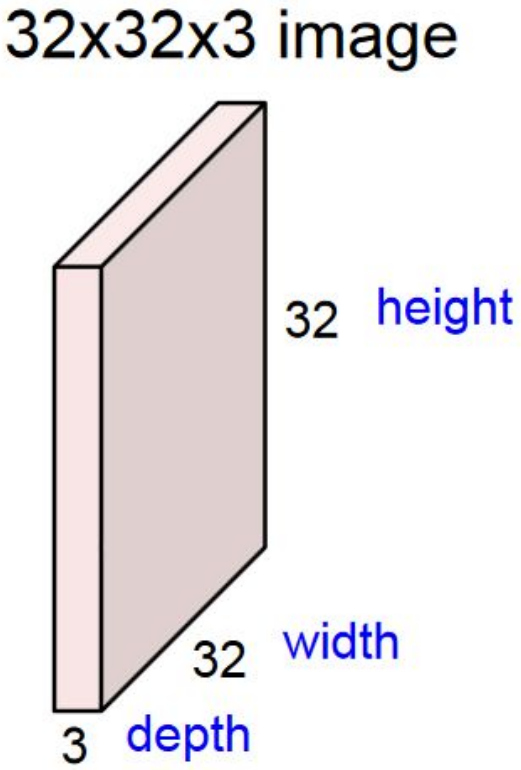
Convolution of the 5 x 5 image and the 3 x 3 matrix can be computed as shown below:



Convolution

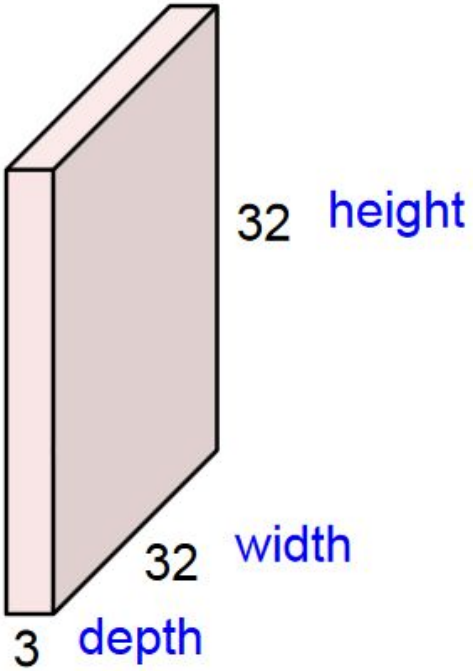


Convolution Layer

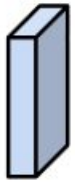


Convolution Layer

32x32x3 image

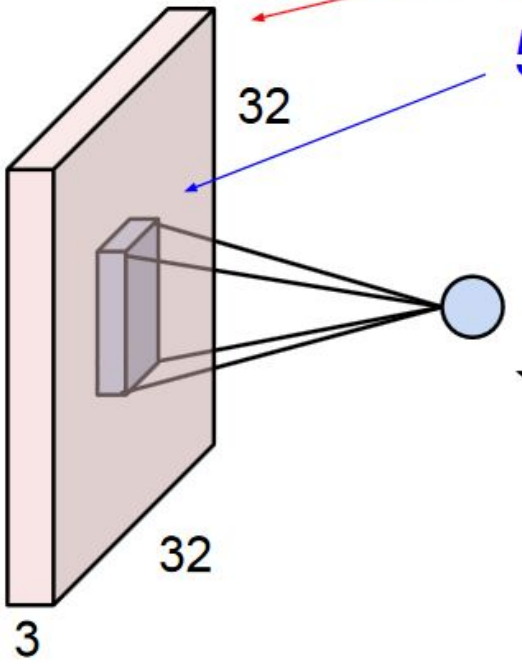


5x5x3 filter



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

Convolution Layer

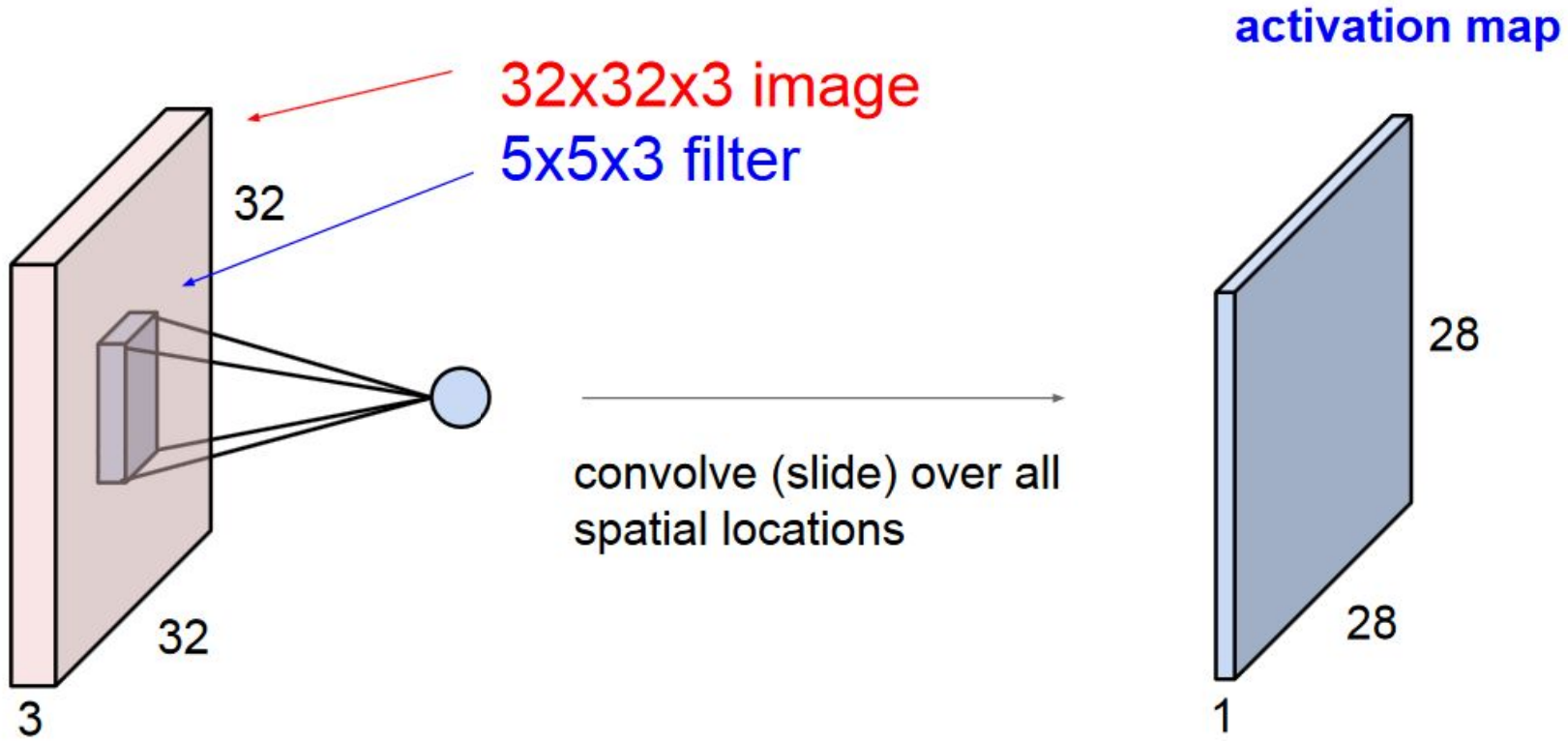


32x32x3 image

5x5x3 filter w

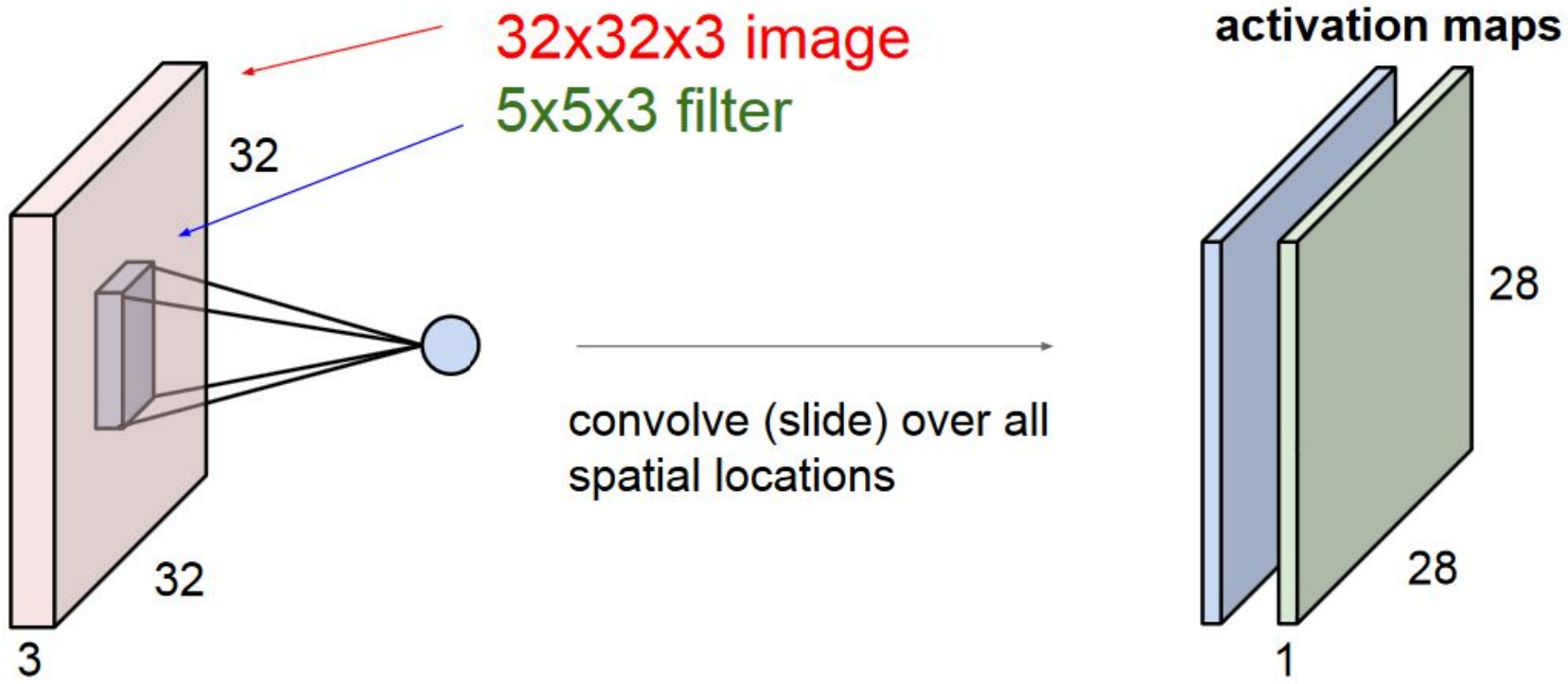
1 number:
the result of taking a dot product between the filter and a small 5x5x3 chunk of the image

Convolution Layer

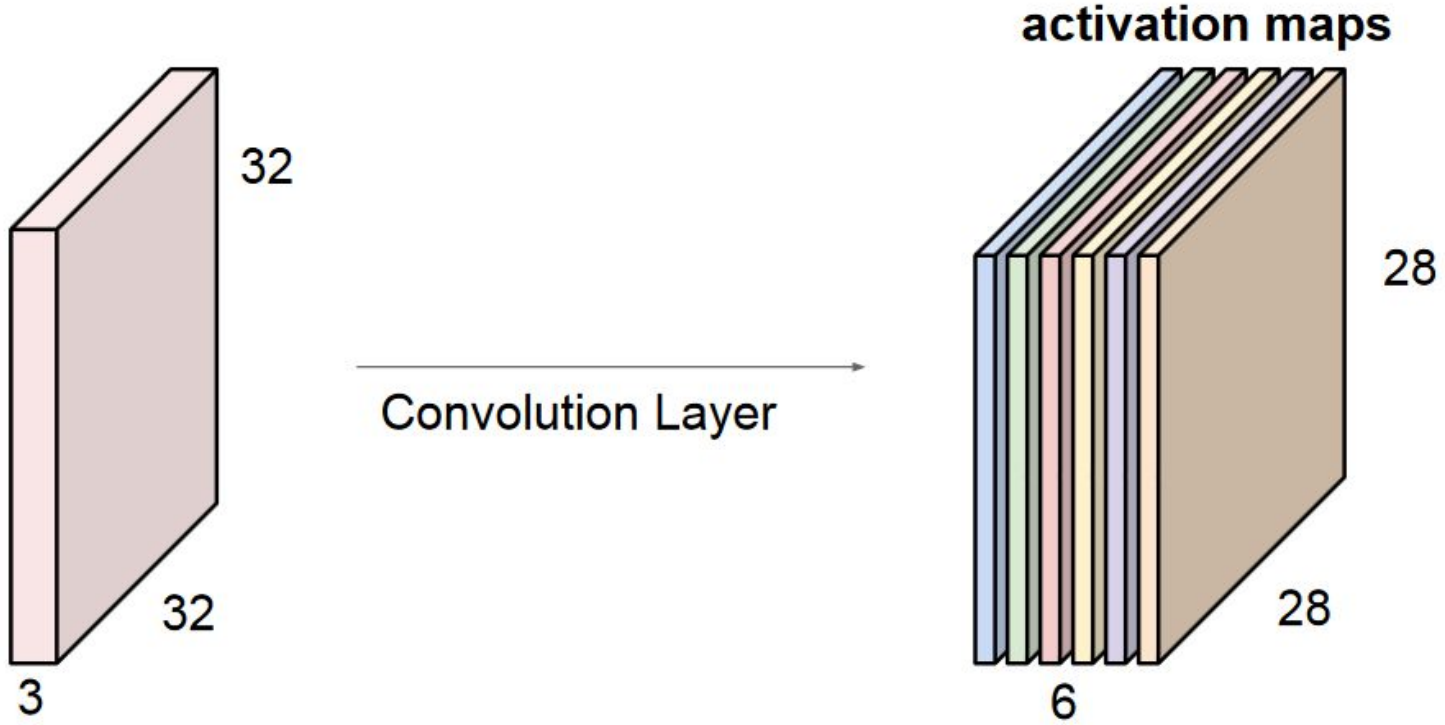


Convolution Layer

consider a second, green filter



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



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

Different filters, Different feature maps

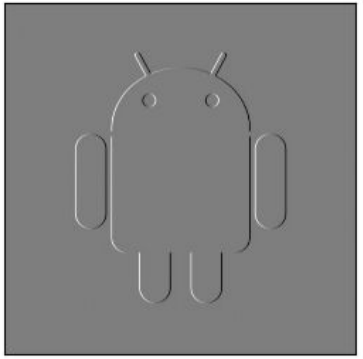
-1	-2	-1
0	0	0
1	2	1

Finds horizontals

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

Finds verticals

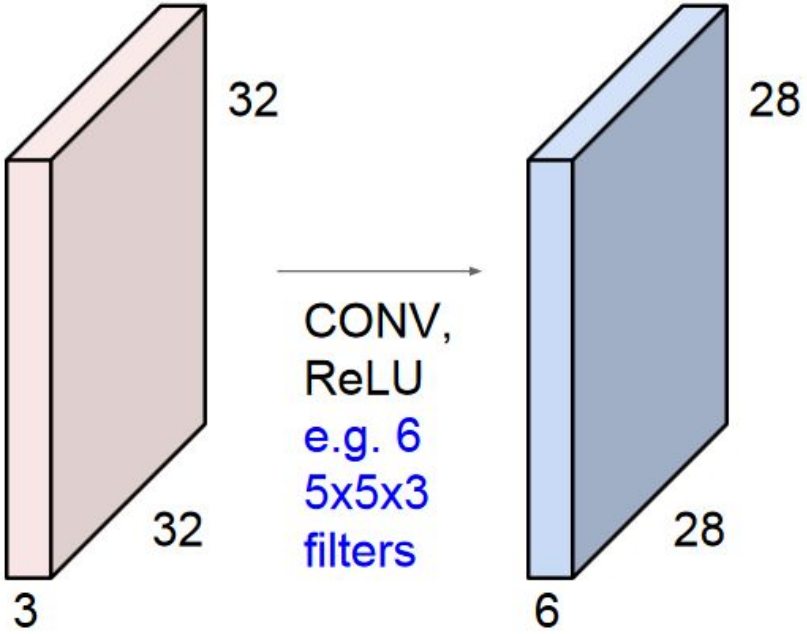
Horizontal Sobel

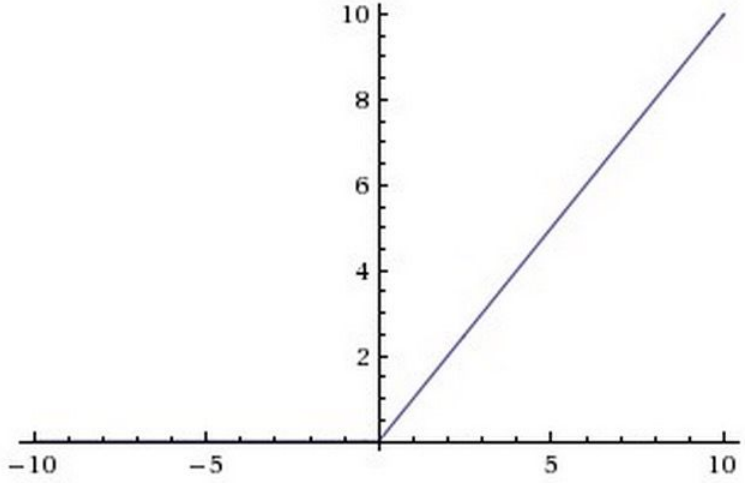


Vertical Sobel

Input

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





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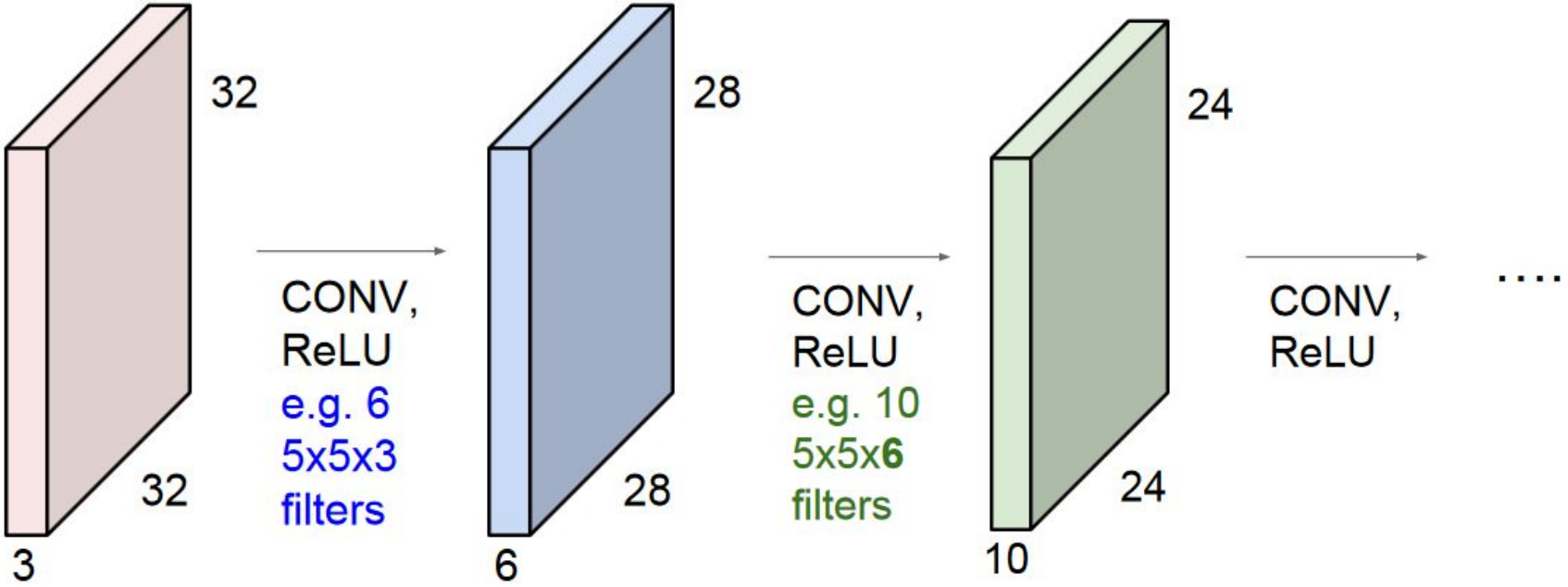
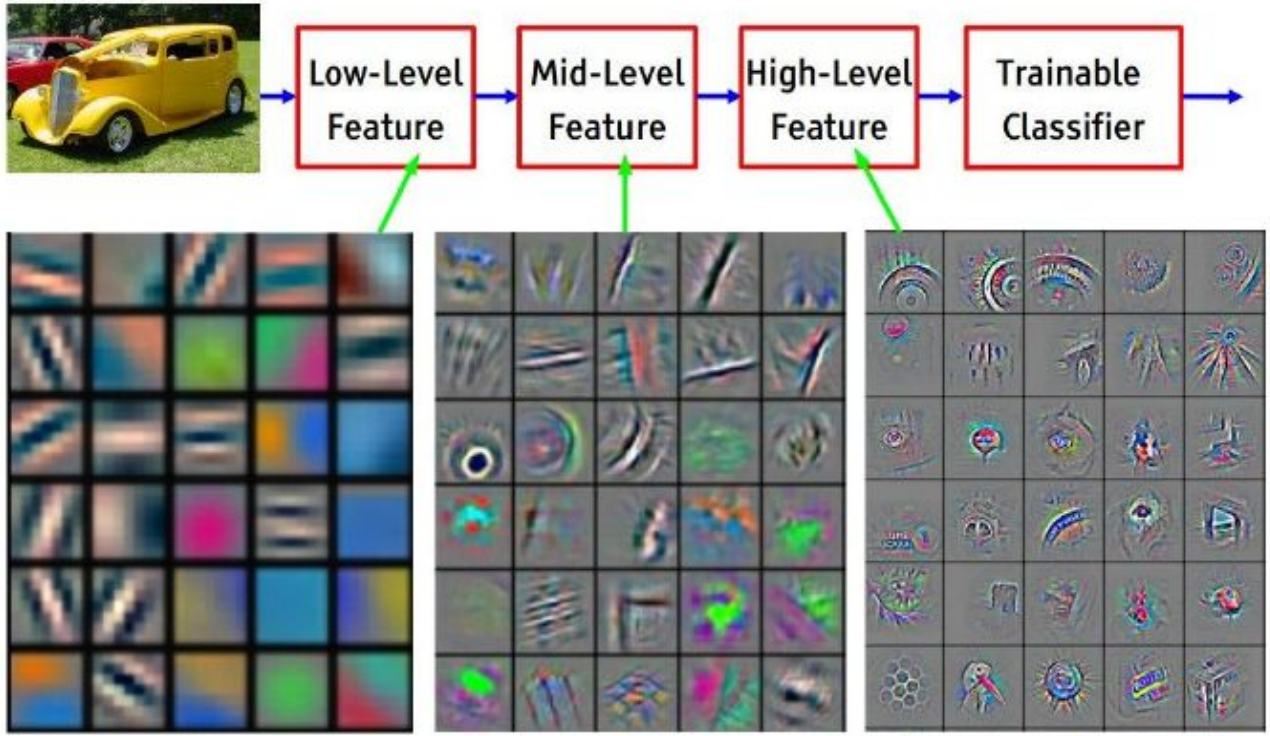
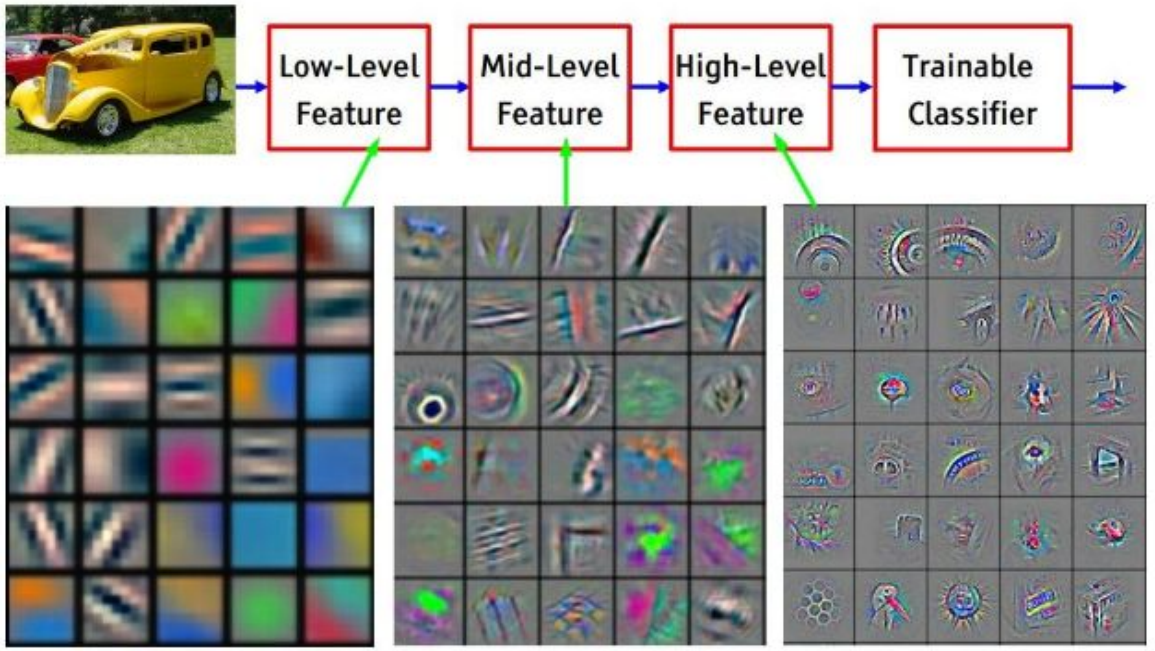


Visualizing Convolutional Networks



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



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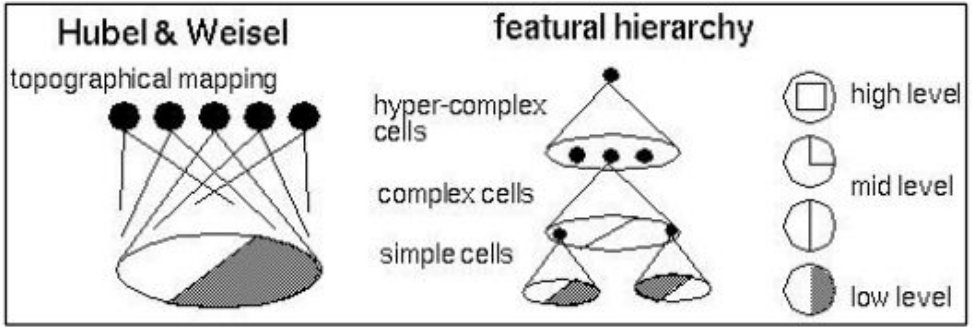
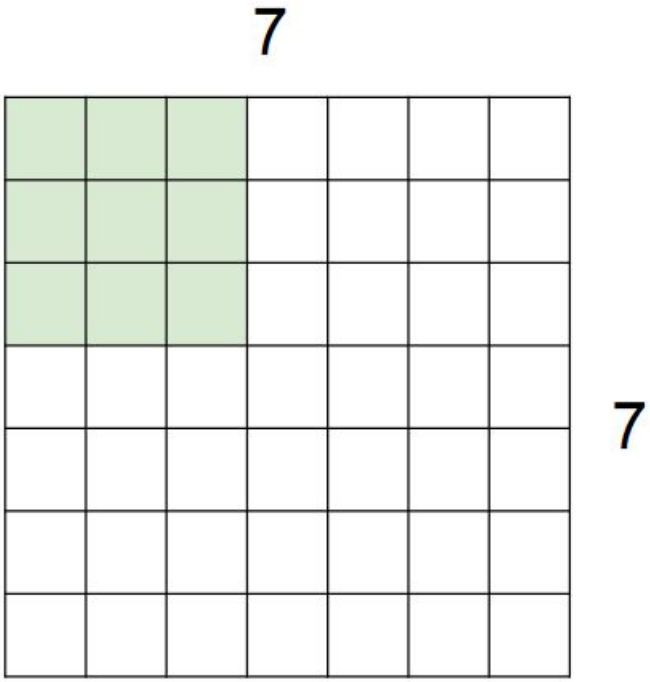
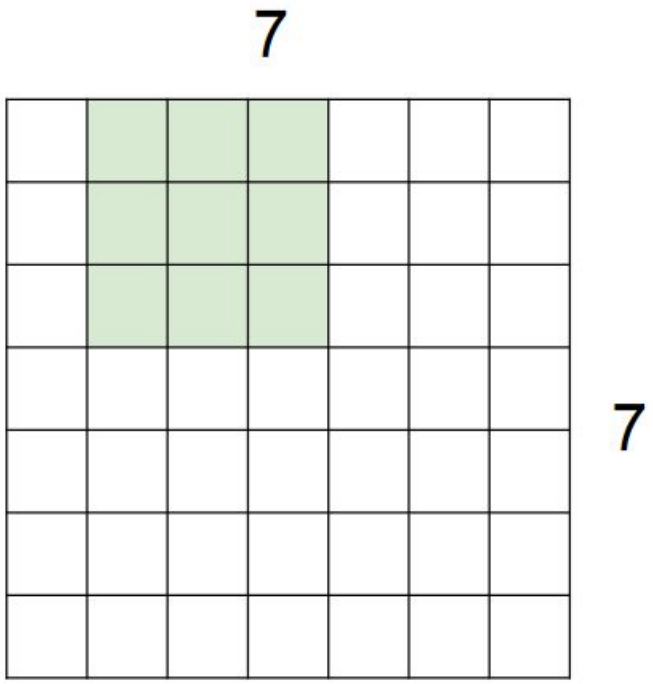


A closer look at spatial dimensions: Stride



7x7 input (spatially)
assume 3x3 filter

A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter

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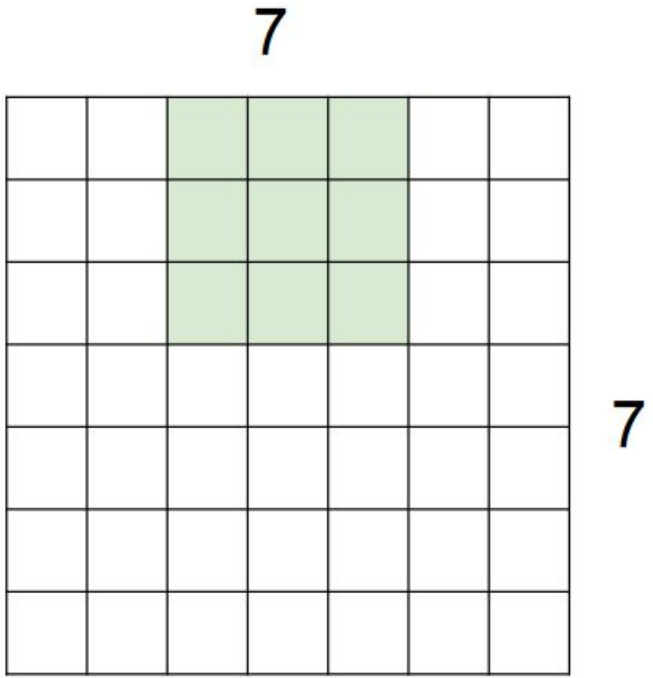
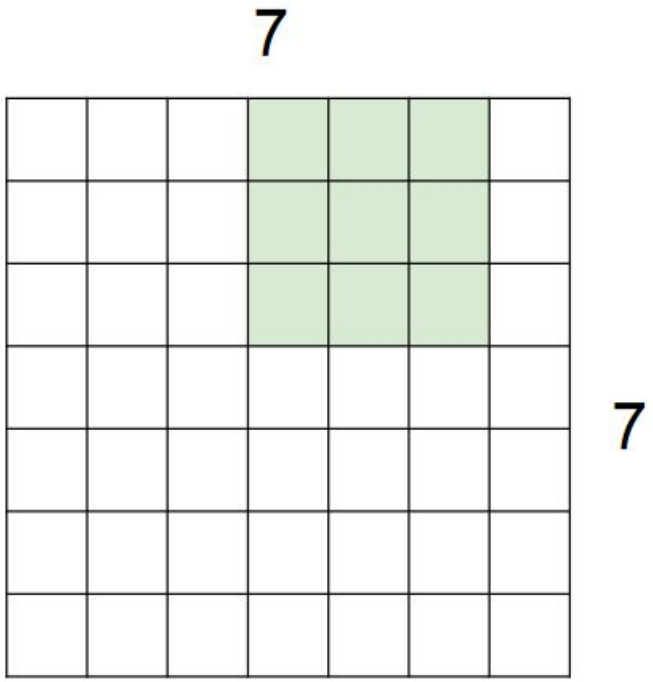


7x7 input (spatially)
assume 3x3 filter

A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter

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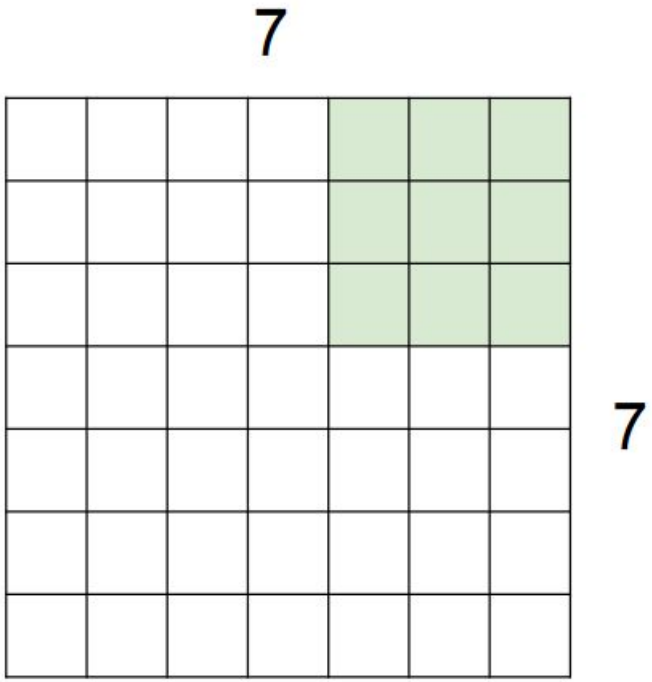
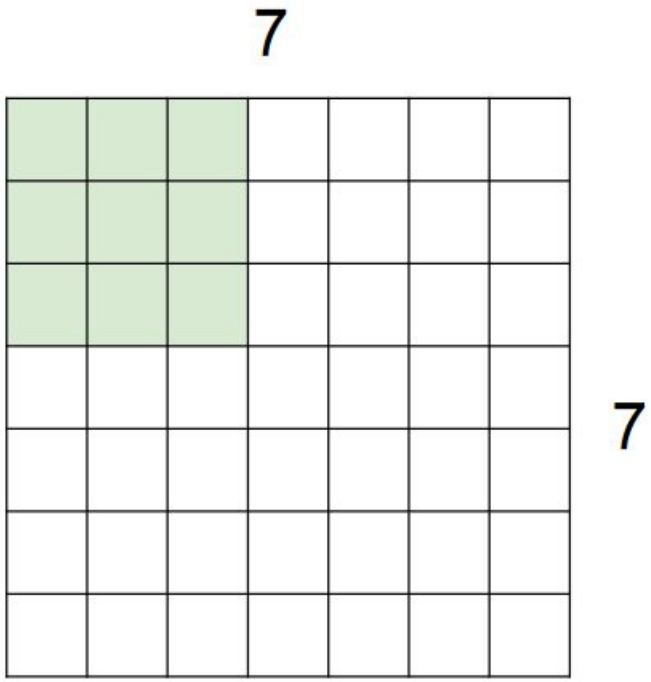


7x7 input (spatially)
assume 3x3 filter

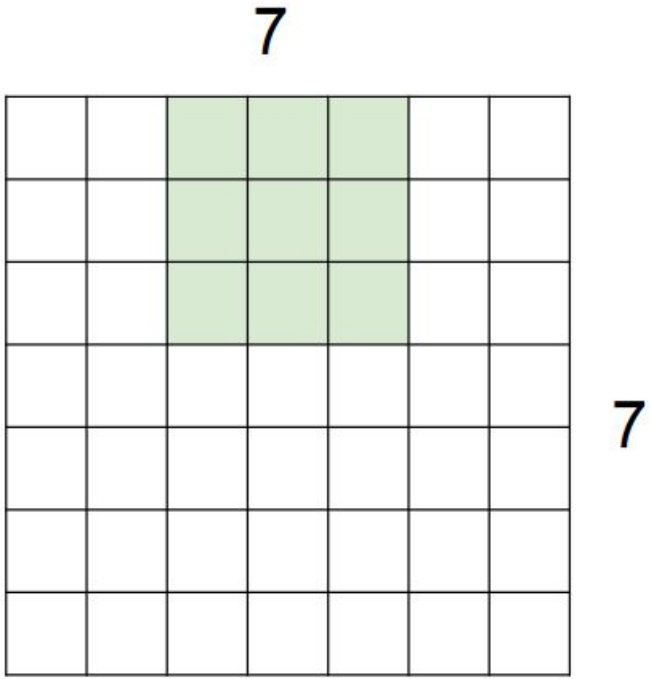
=> 5x5 output

A closer look at spatial dimensions:



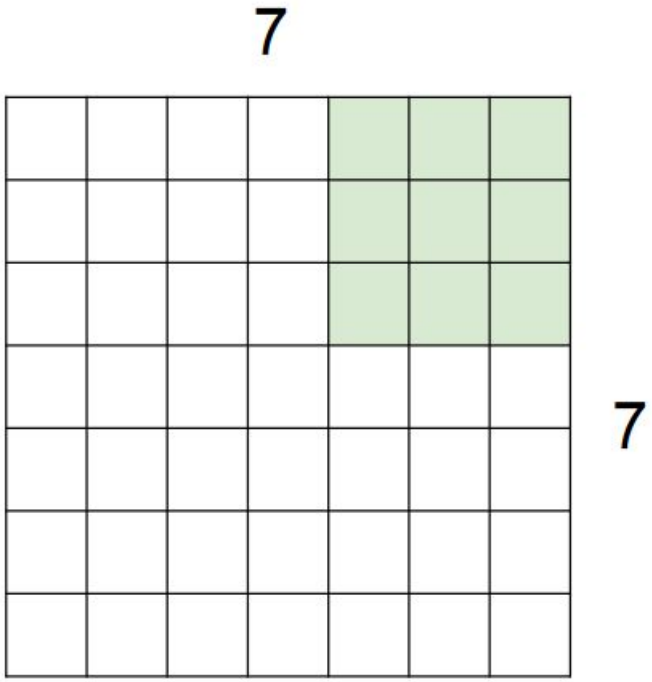
7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**

A closer look at spatial dimensions:



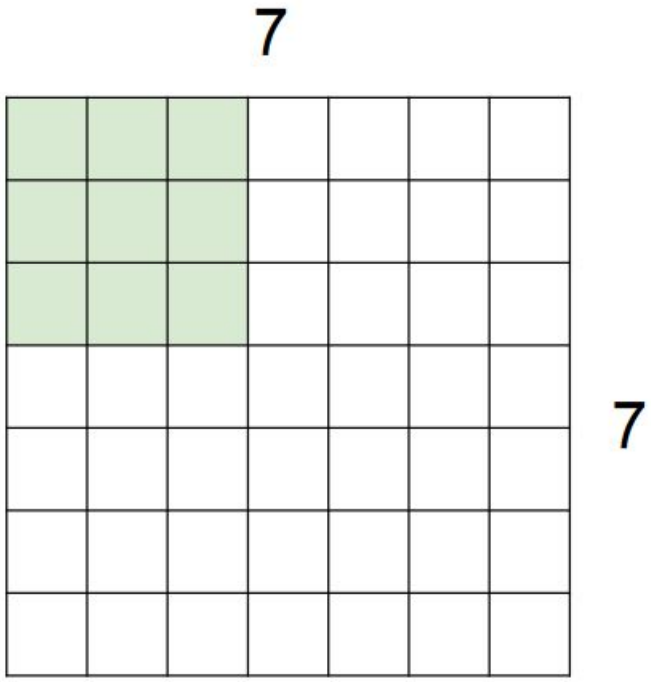
7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**

A closer look at spatial dimensions:



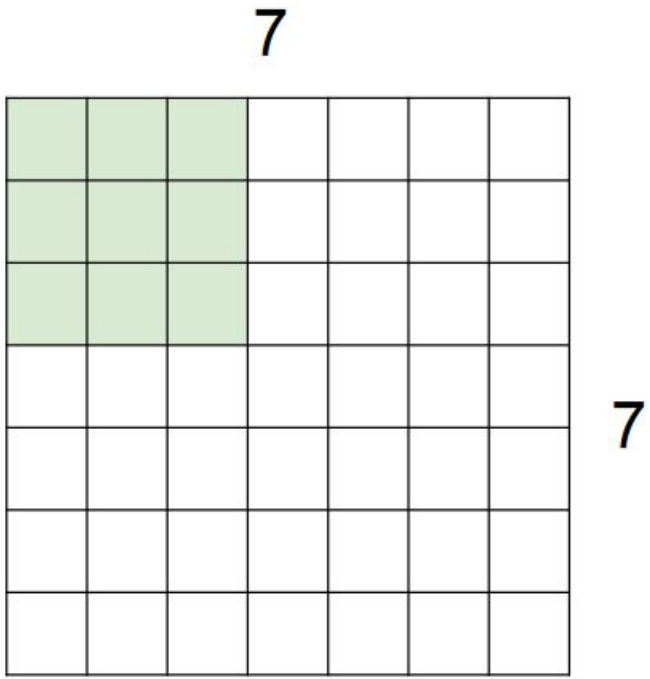
7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**
=> 3x3 output!

A closer look at spatial dimensions:



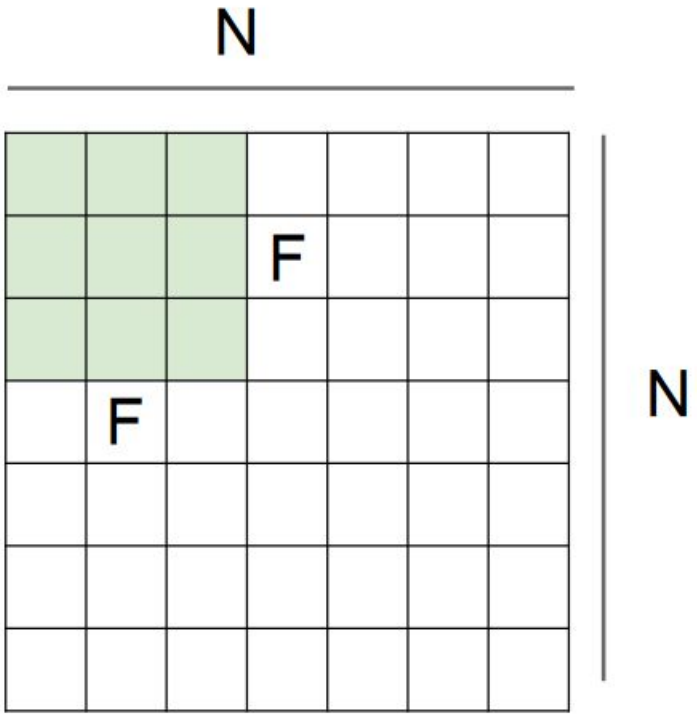
7x7 input (spatially)
assume 3x3 filter
applied **with stride 3?**

A closer look at spatial dimensions:



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

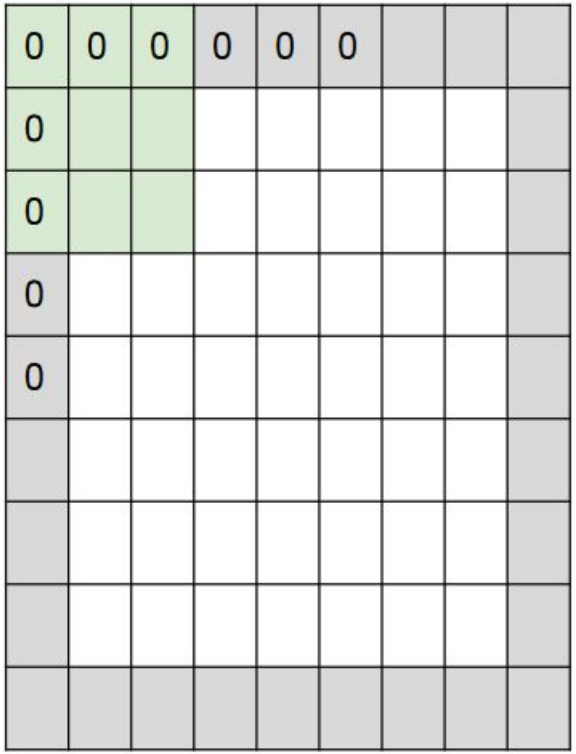
doesn't fit!
cannot apply 3x3 filter on
7x7 input with stride 3.



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

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

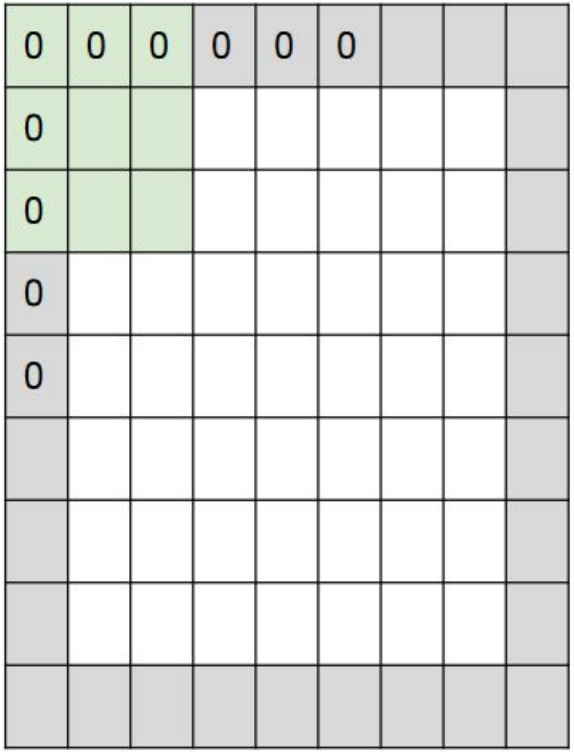
In practice: Common to zero pad the border



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

(N - F) / stride + 1

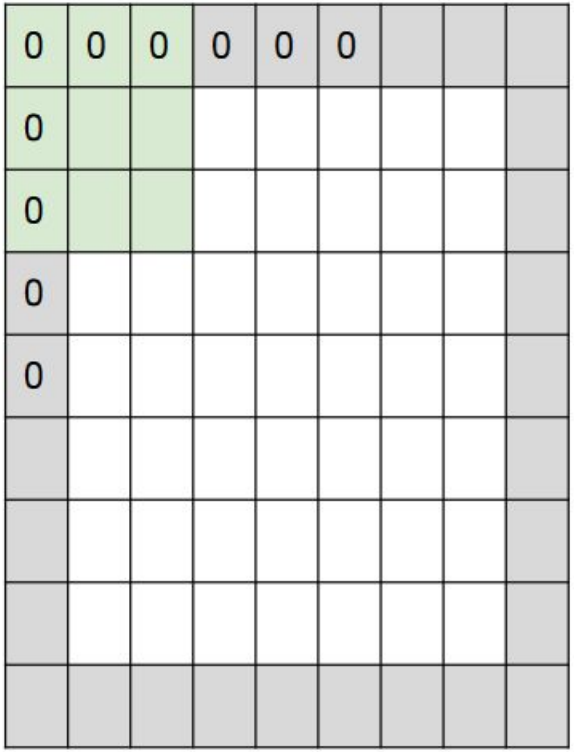
In practice: Common to zero pad the border



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

7x7 output!

In practice: Common to zero pad the border



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

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

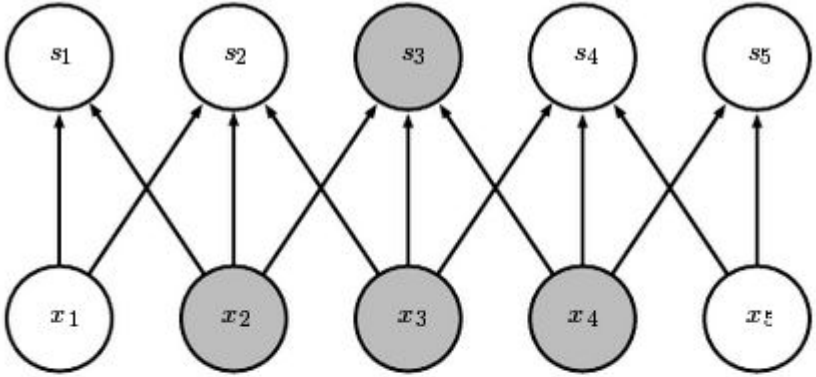
Reasons why convolution is cool

Reason 1: Sparse connectivity

Reason 2: Parameter sharing

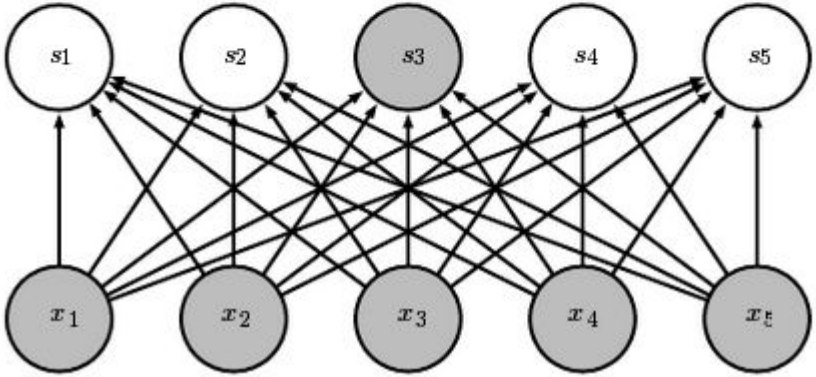
Reason 3: Deeper layers- wider receptive field

Sparse Connectivity



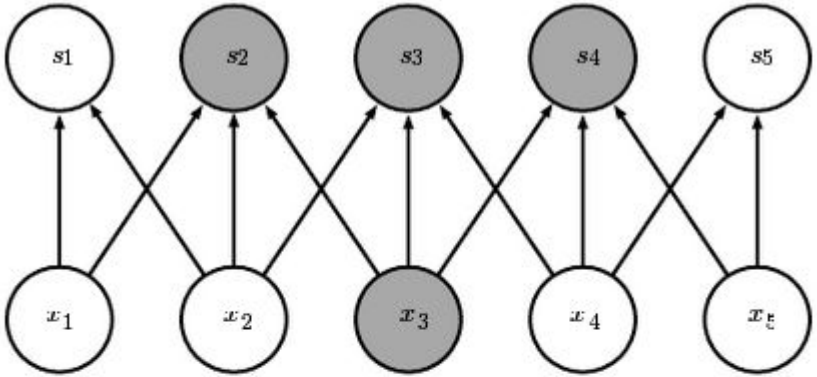
Viewed from above:

Sparse connection => s3 affected by only x1,x21,x3



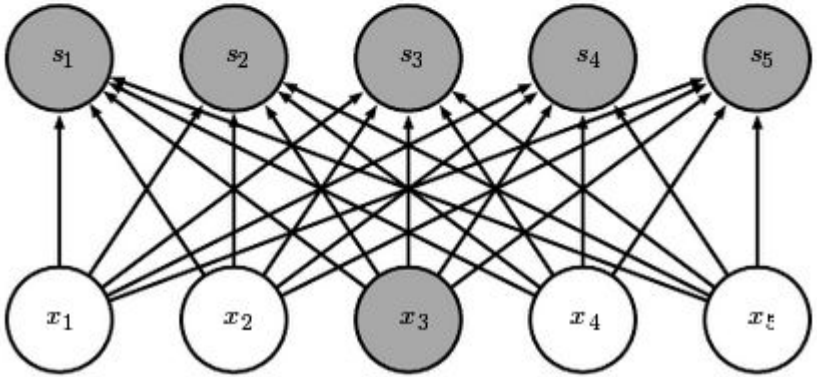
No longer sparse =>s3 affects all the input units

Sparse Connectivity



Viewed from below:

Sparse connection => x3 affects only s2,s3,s4



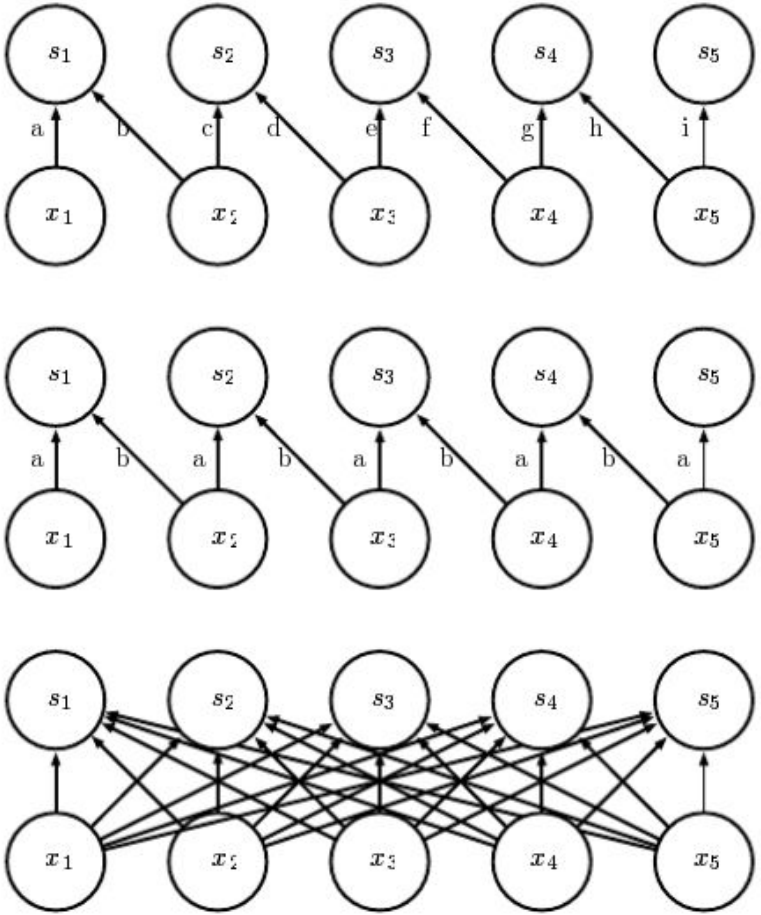
No longer sparse =>x3 affects all the output units

Parameter sharing

- In convolutional net - learn the values of a particular kernel which is used for the entire image

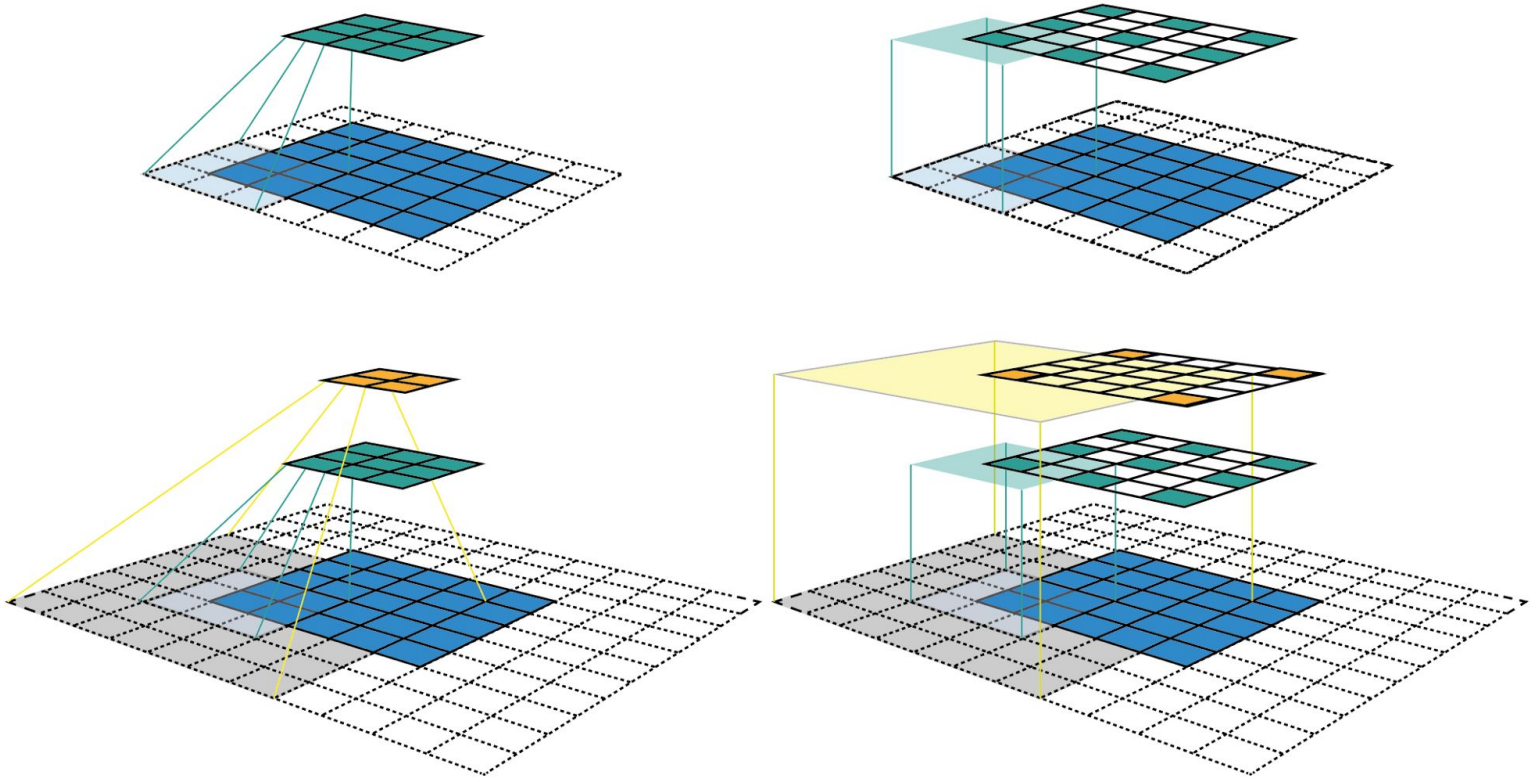
1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

1	0	1
0	1	0
1	0	1

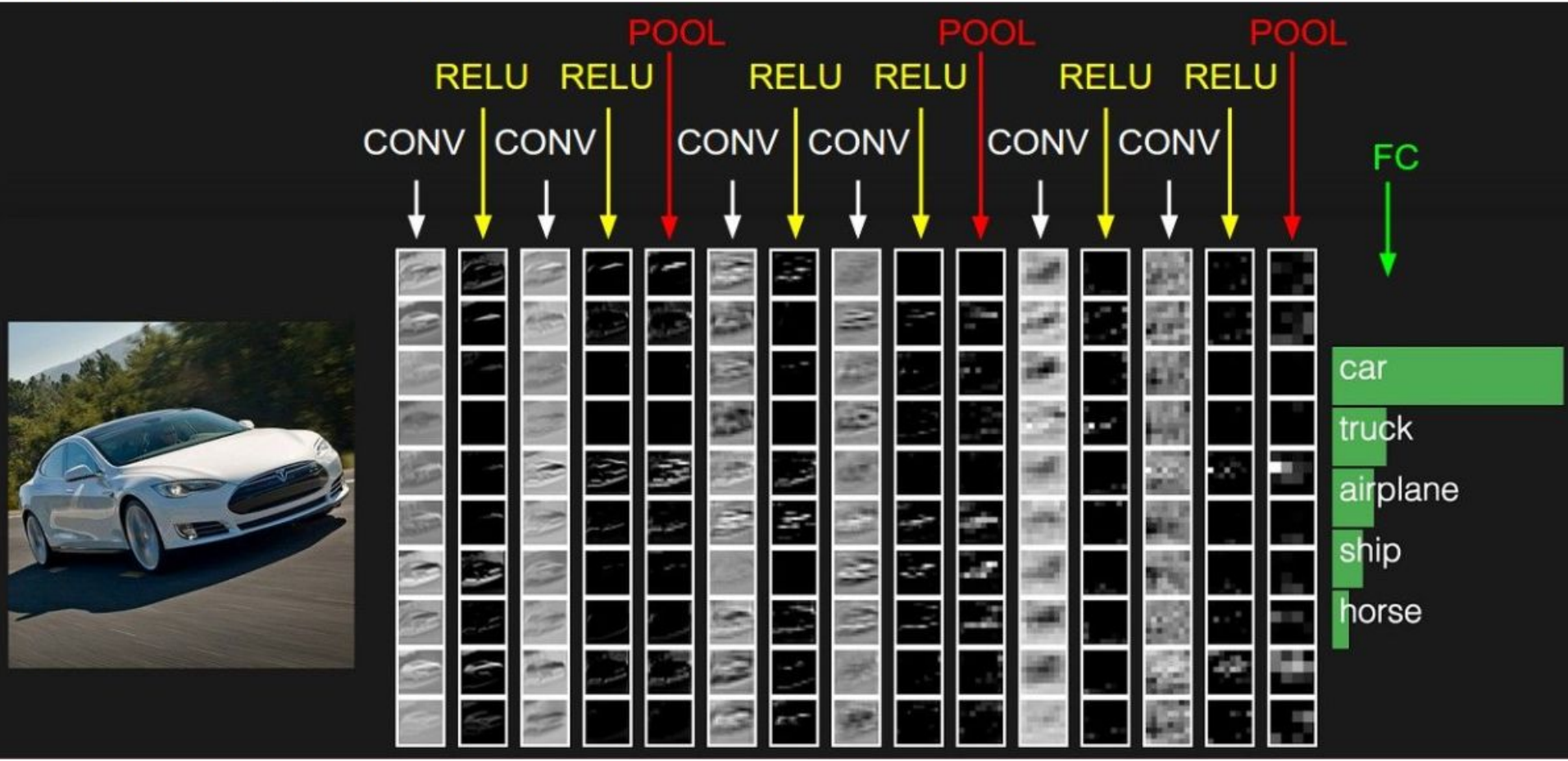


Convolution is thus drastically more efficient than dense matrix multiplication

Deeper layer- wider receptive field



two more layers to go: POOL/FC



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   a. Idea behind it
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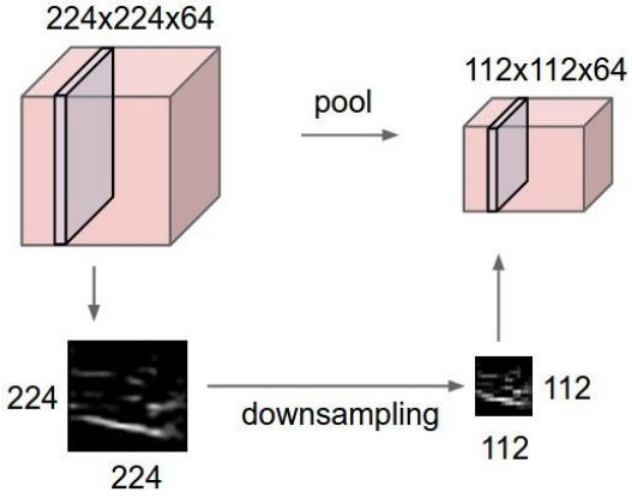
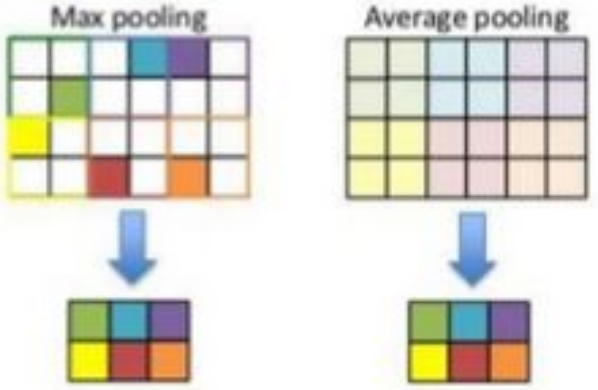
Pooling

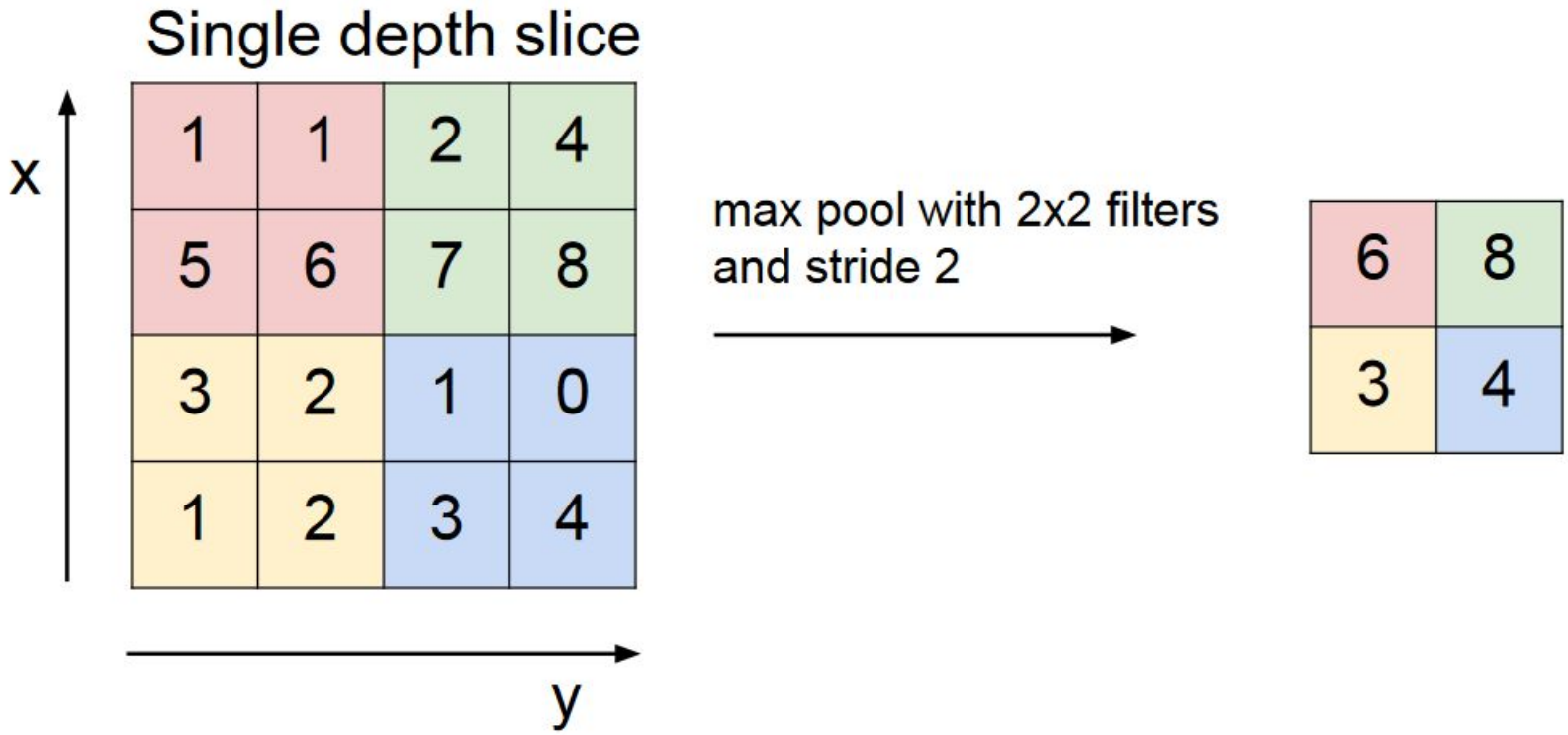
Reduces dimensionality of feature maps- but retains the most important information

Different types: max, average, sum

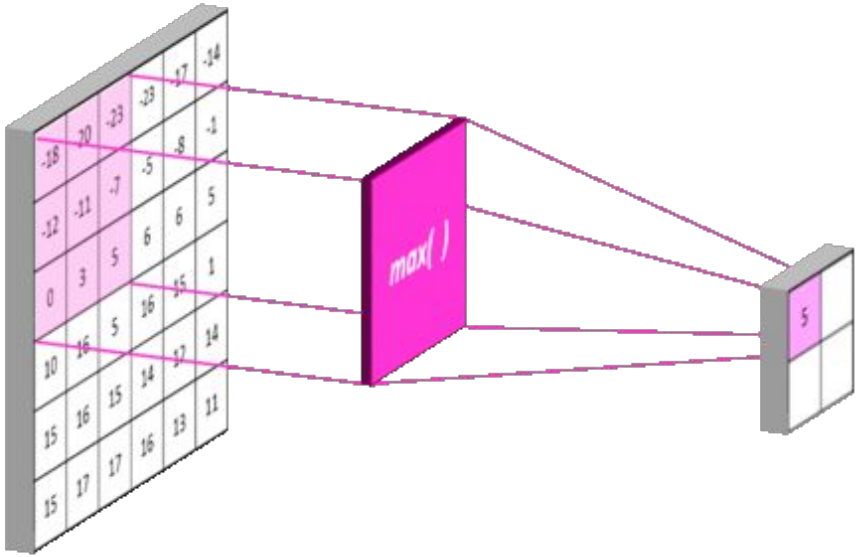




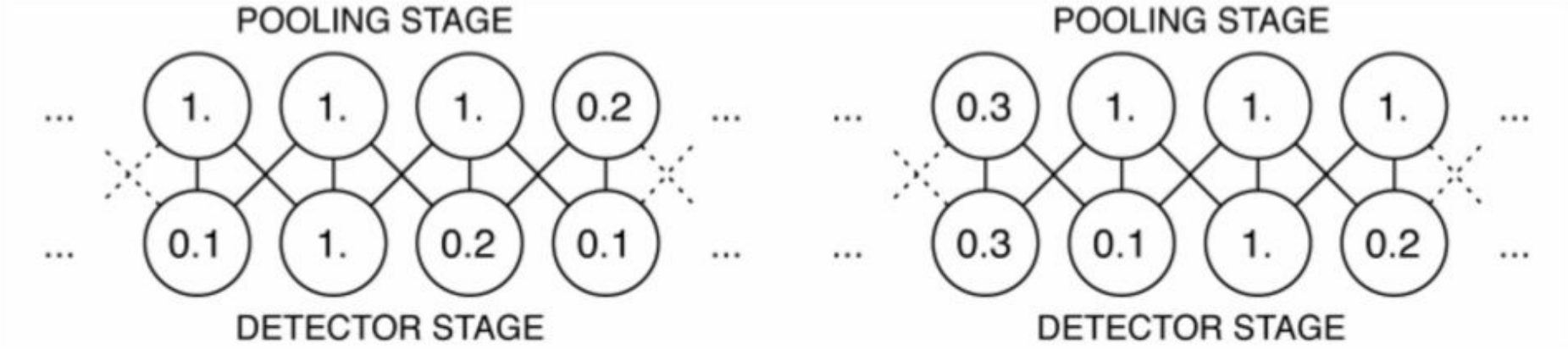
MAX POOLING


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

Max Pooling


-16
20
-23
-23
17
-14
-12
-11
-7
-5
-8
-1
0
3
5
6
6
5
10
16
5
16
15
14
17
1
15
16
15
14
17
14
15
17
17
16
13
11
max( )
5

Invariant to small transformations



Pooling, in particular

- makes the input representations (feature dimension) smaller and more manageable
- reduces the number of parameters and computations in the network
- makes network invariant to small transformations, distortions and translations in the input image

(a) basic (b) *rot* (c) *scale* (d) *trans*

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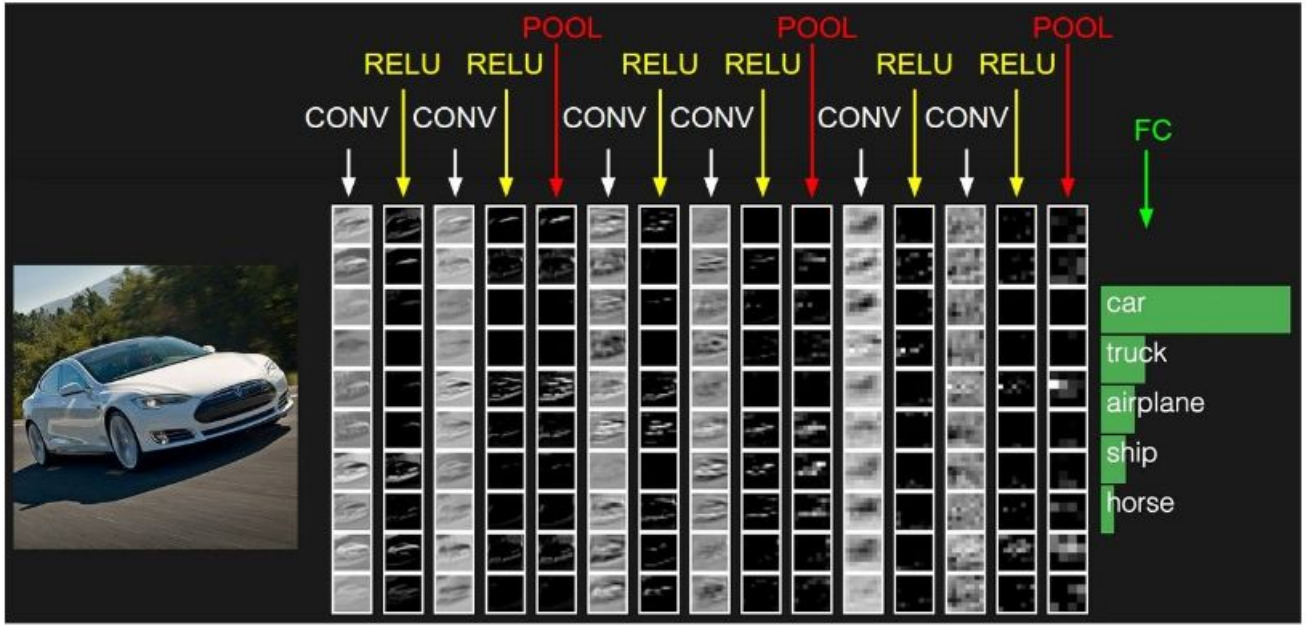
Fully Connected Layer (FC layer)

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



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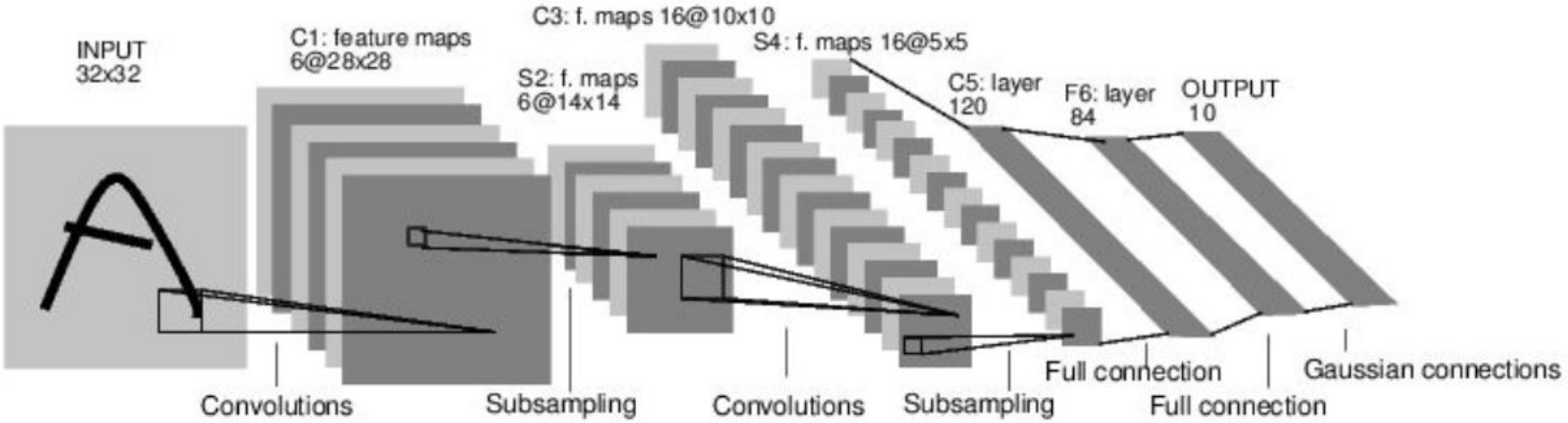
Case Study: LeNet-5

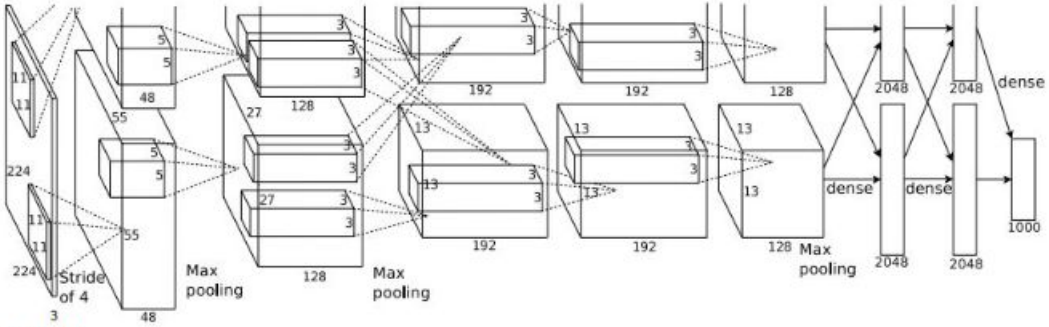
[LeCun et al., 1998]



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]

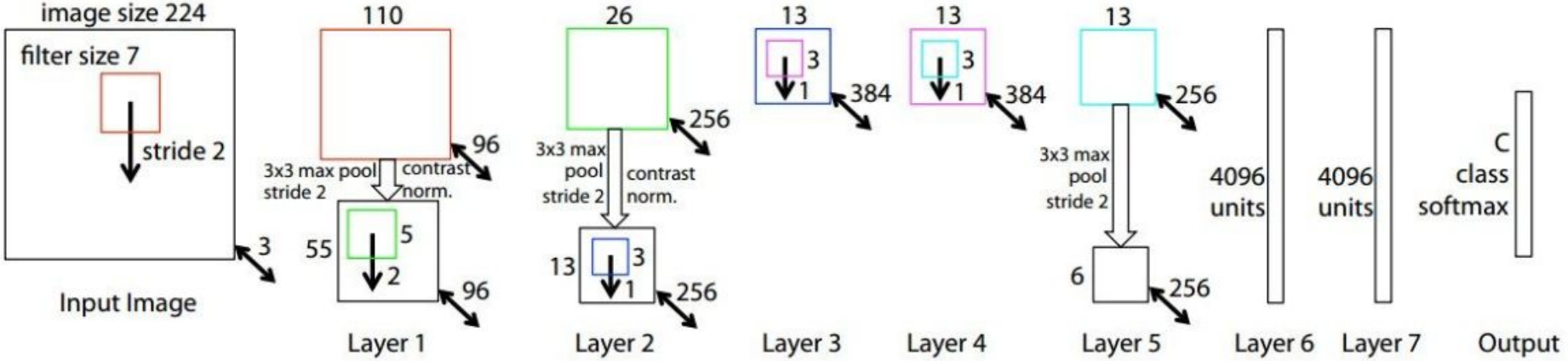


Full (simplified) AlexNet architecture:
[227x227x3] INPUT
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] 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

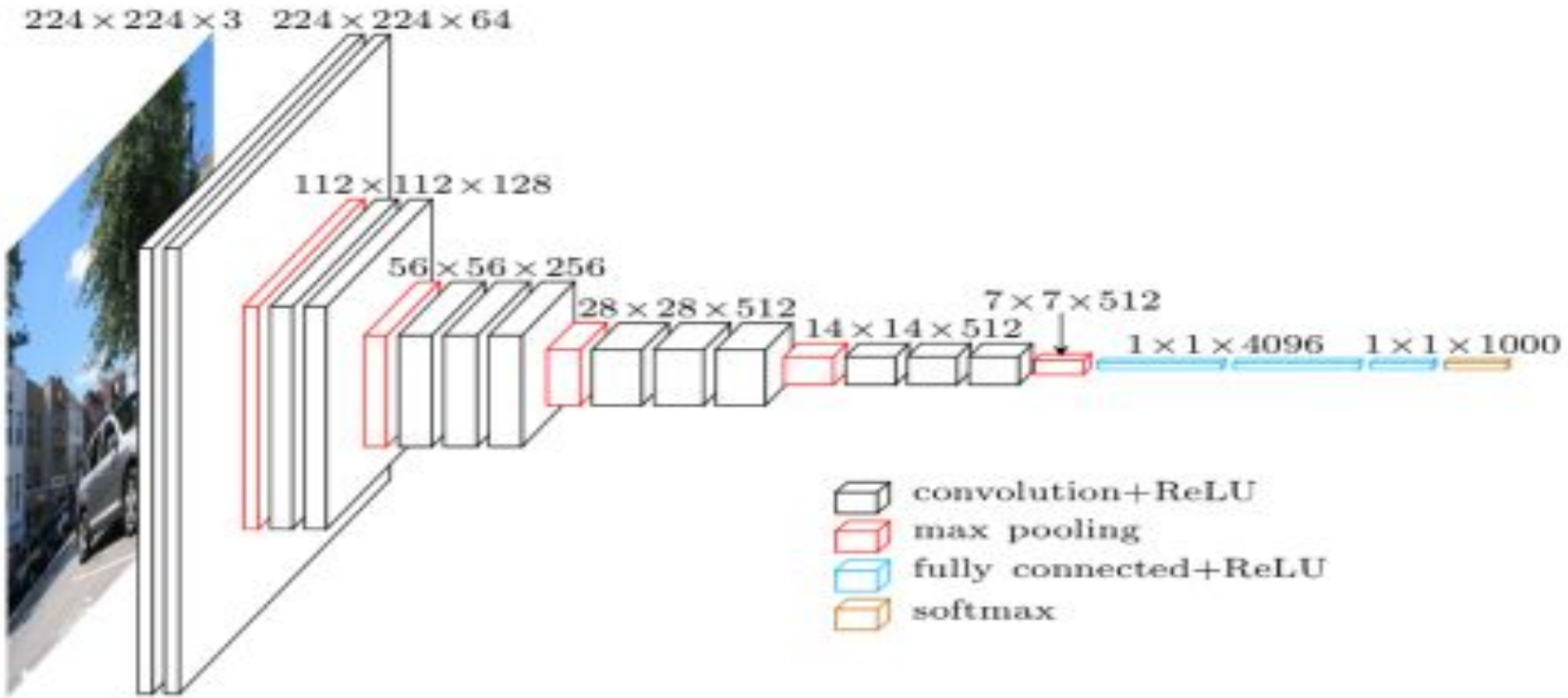
11.2% top 5 error in ILSVRC 2013
->
7.3% top 5 error

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 **conv1-256**	conv3-256 conv3-256 **conv3-256**	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).

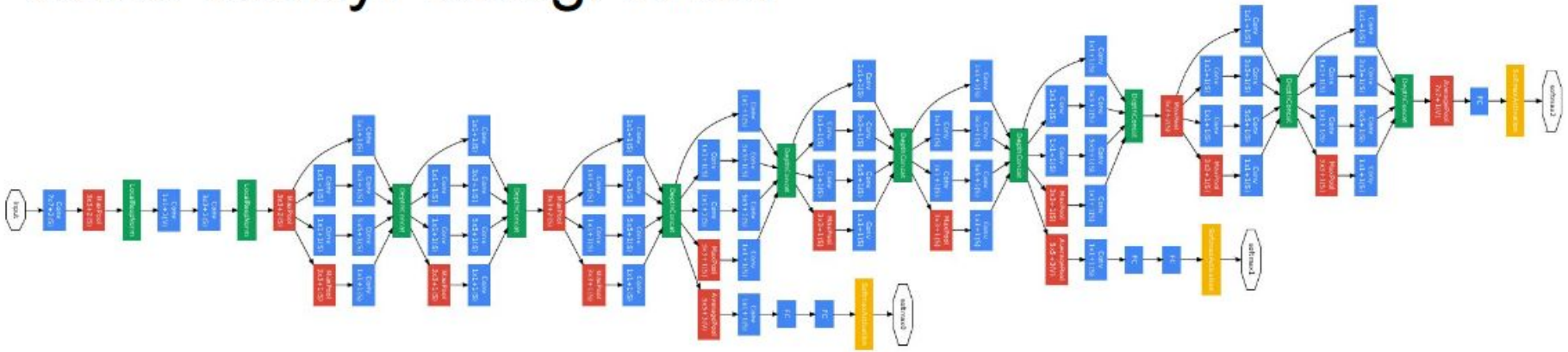
Network	A,A-LRN	B	C	D	E
Number of parameters	133	133	134	138	144

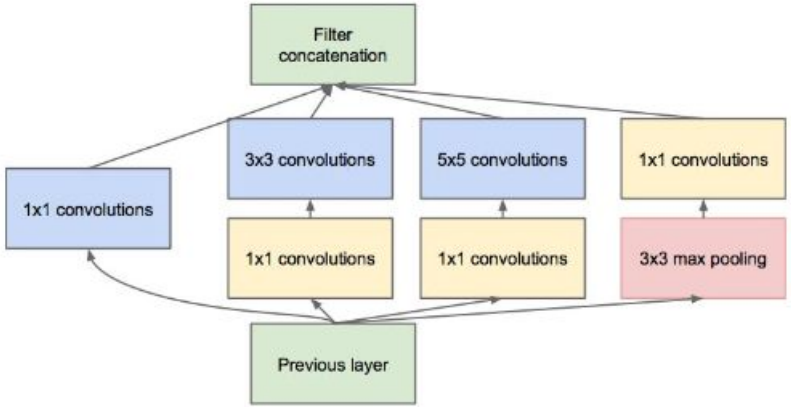
Case Study: VGGNet



Case Study: GoogLeNet

[Szegedy et al., 2014]



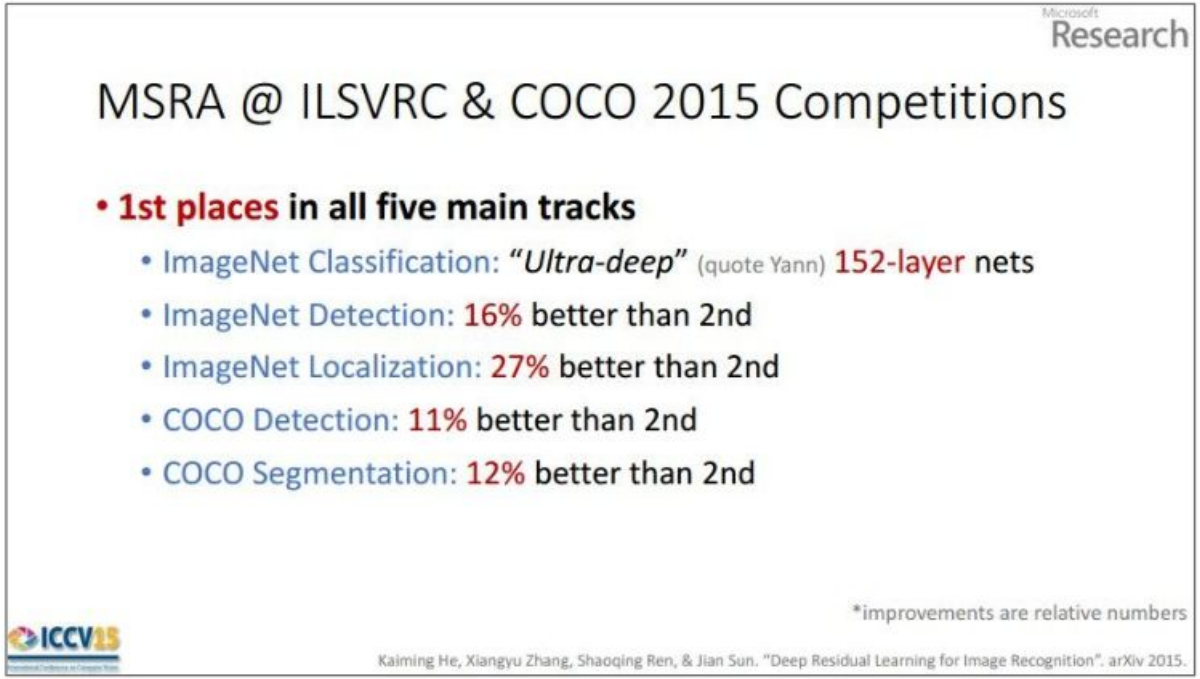


Inception module

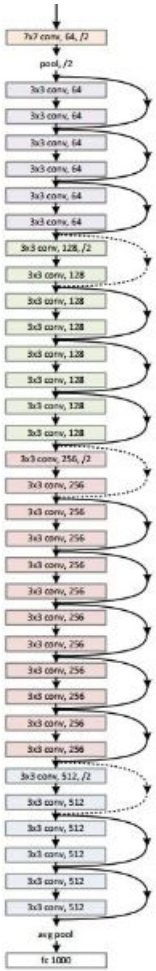
ILSVRC 2014 winner (6.7% top 5 error)

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

ILSVRC 2015 winner (3.6% top 5 error)



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



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

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times23$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

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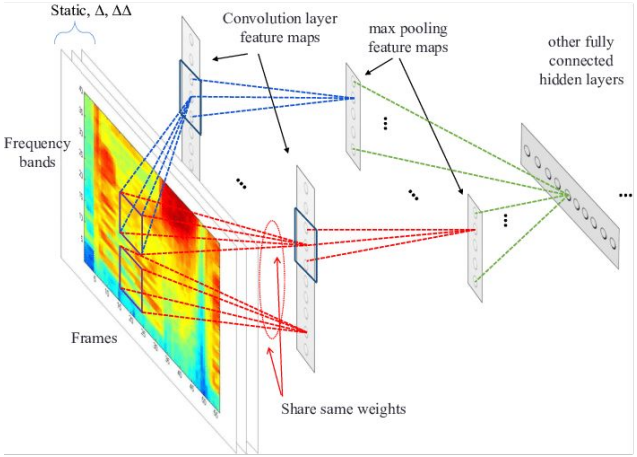
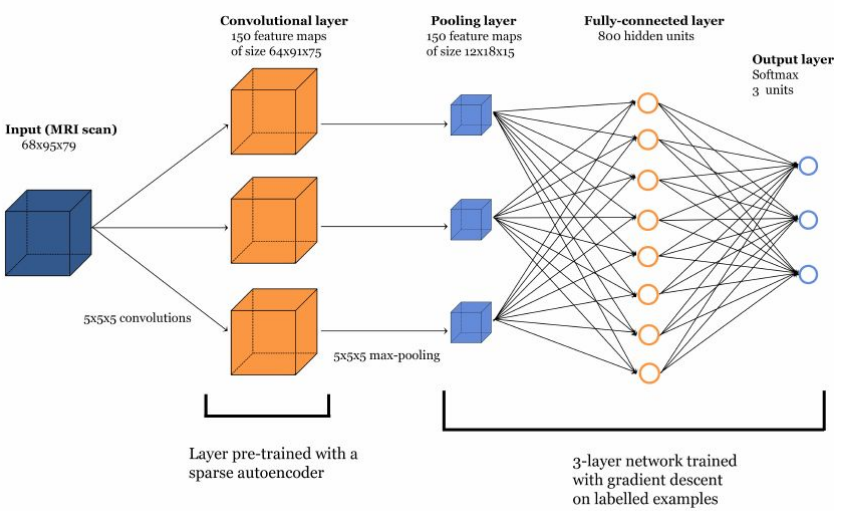
Beyond Images

Convolution can also be used to process:

- 1D: Audio waveform; skeleton animation data
- 2D: Audio data with Fourier transform; Images!
- 3D: Volumetric data, video data





Conclusion

- ConvNets - super important tool, especially for computer vision tasks
- ConvNets stack CONV,POOL,FC layers
- Understanding of CONV and POOL layers
- Visualizing Convolutional network and neuroscientific basis
- Some standard architectures

References

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Thank You!