Convolutional Neural Networks

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- Ex-team lead of perception team at self-driving trucks
- Open source fan

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МФТИ

Дзен

Revise

Optimization and Regularization in Deep Learning

1. Optimizers
2. Data normalization
3. Regularization

Outline

1. Convolutional layer structure
2. Pooling layers
3. Top architectures overview

Convolutional layer

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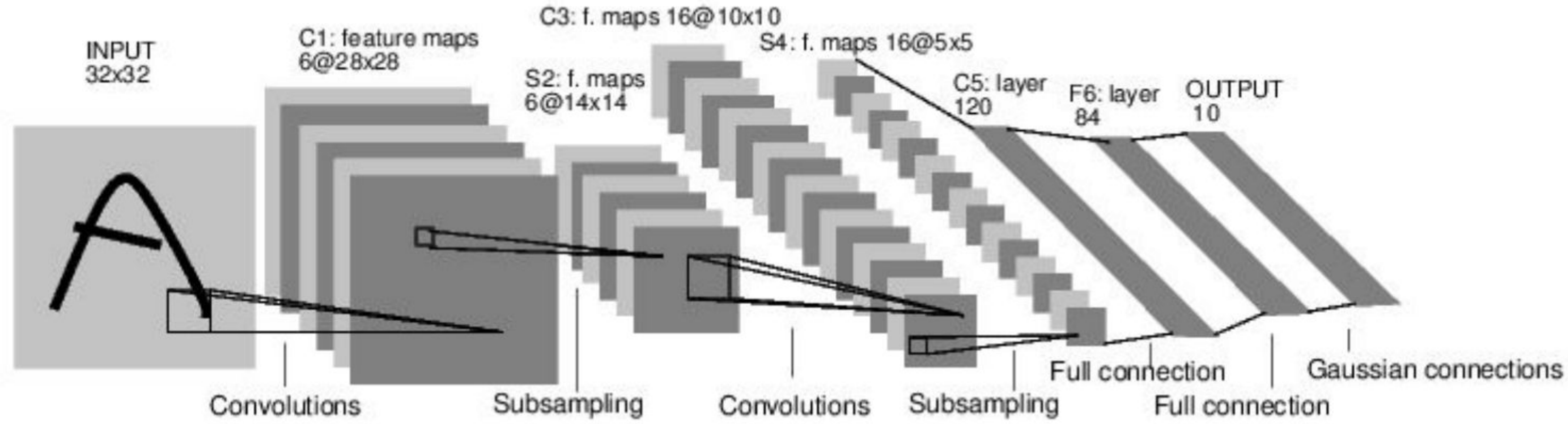
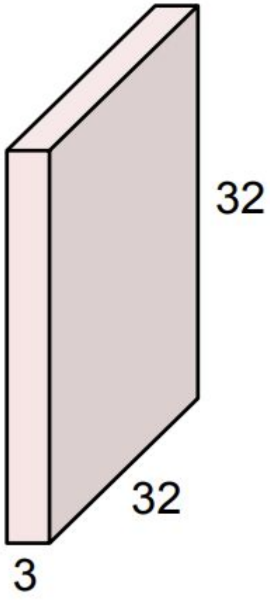
Convolutions in Neural Networks



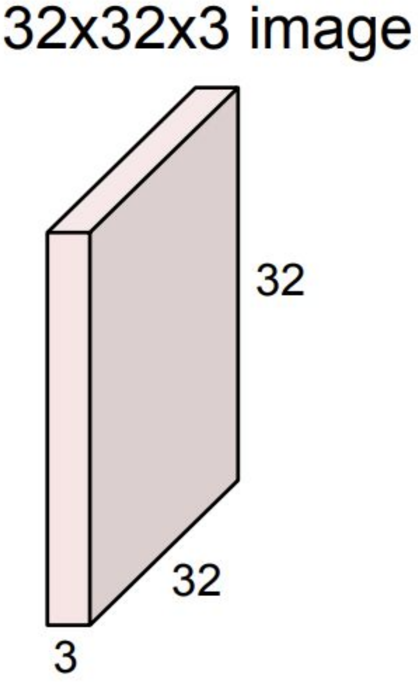
[LeNet-5, LeCun 1998]

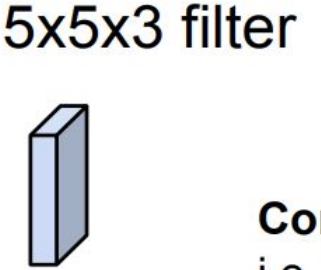
Convolutional layer

32x32x3 image



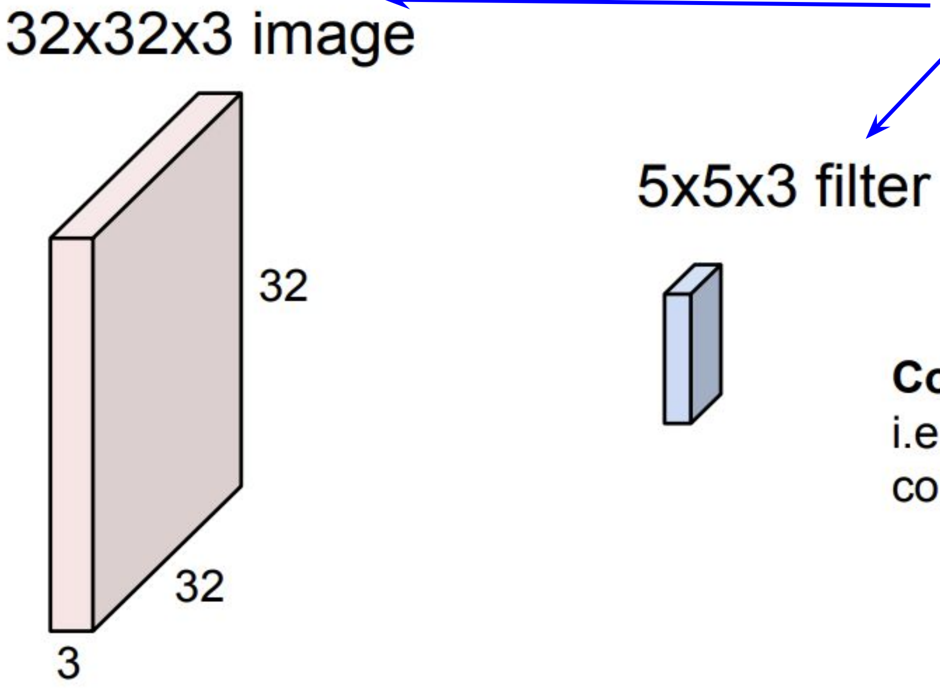
Convolutional layer





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

Convolutional layer



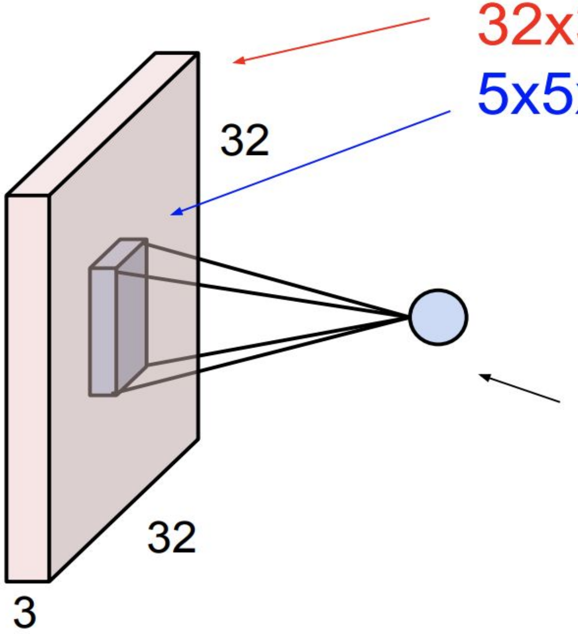
Filters extend the depth of the original image

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

Convolutional layer

32x32x3 image

5x5x3 filter w

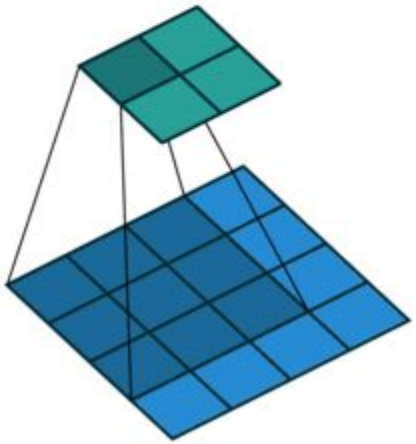


1 number:
the result of taking a dot product between the filter and a small 5x5x3 chunk of the image
(i.e. 5*5*3 = 75-dimensional dot product + bias)

$$w^T x + b$$

Convolutional layer

Convolutional layer

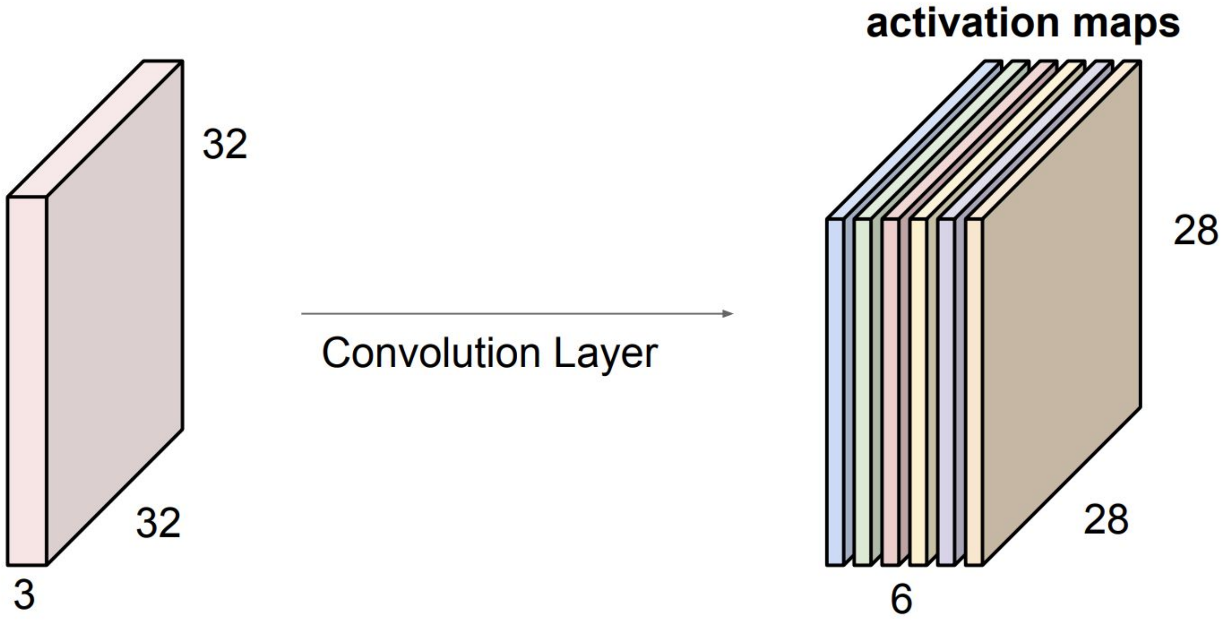


Convolutional layer

convolve (slide) over all spatial locations

Convolutional layer

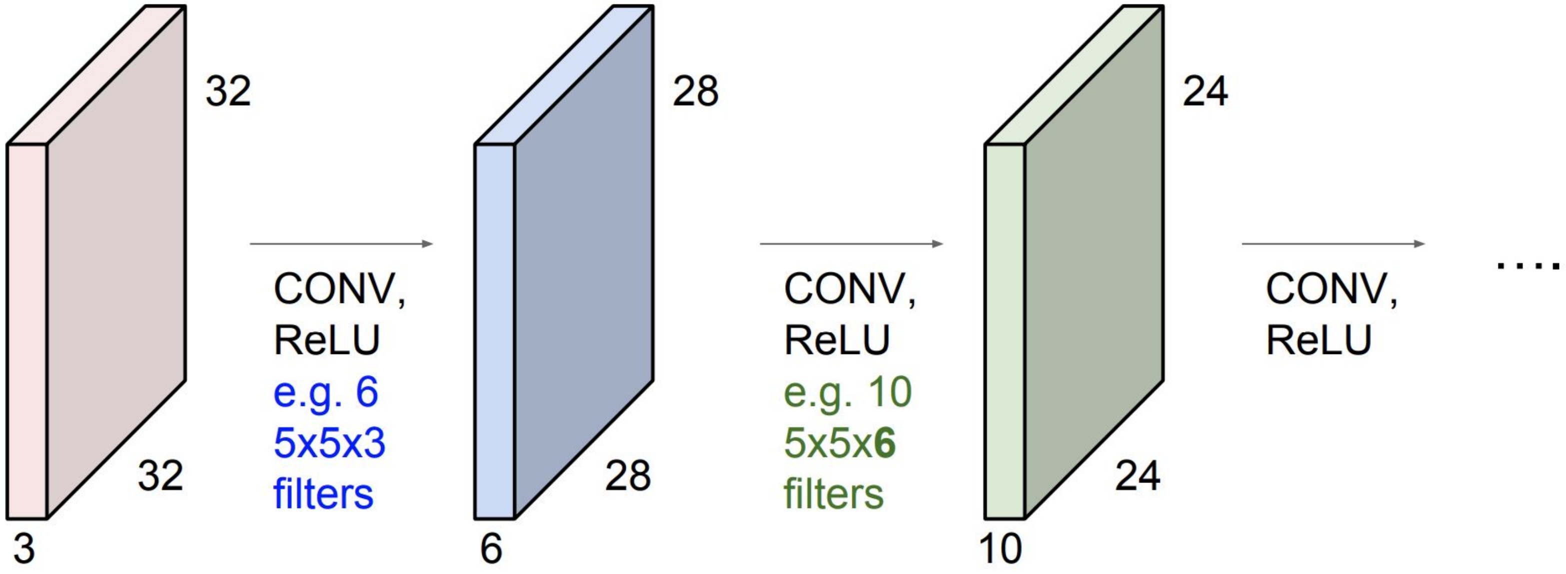
For example, if we had 6 5x5 filters, we'll get 6 separate activation maps:



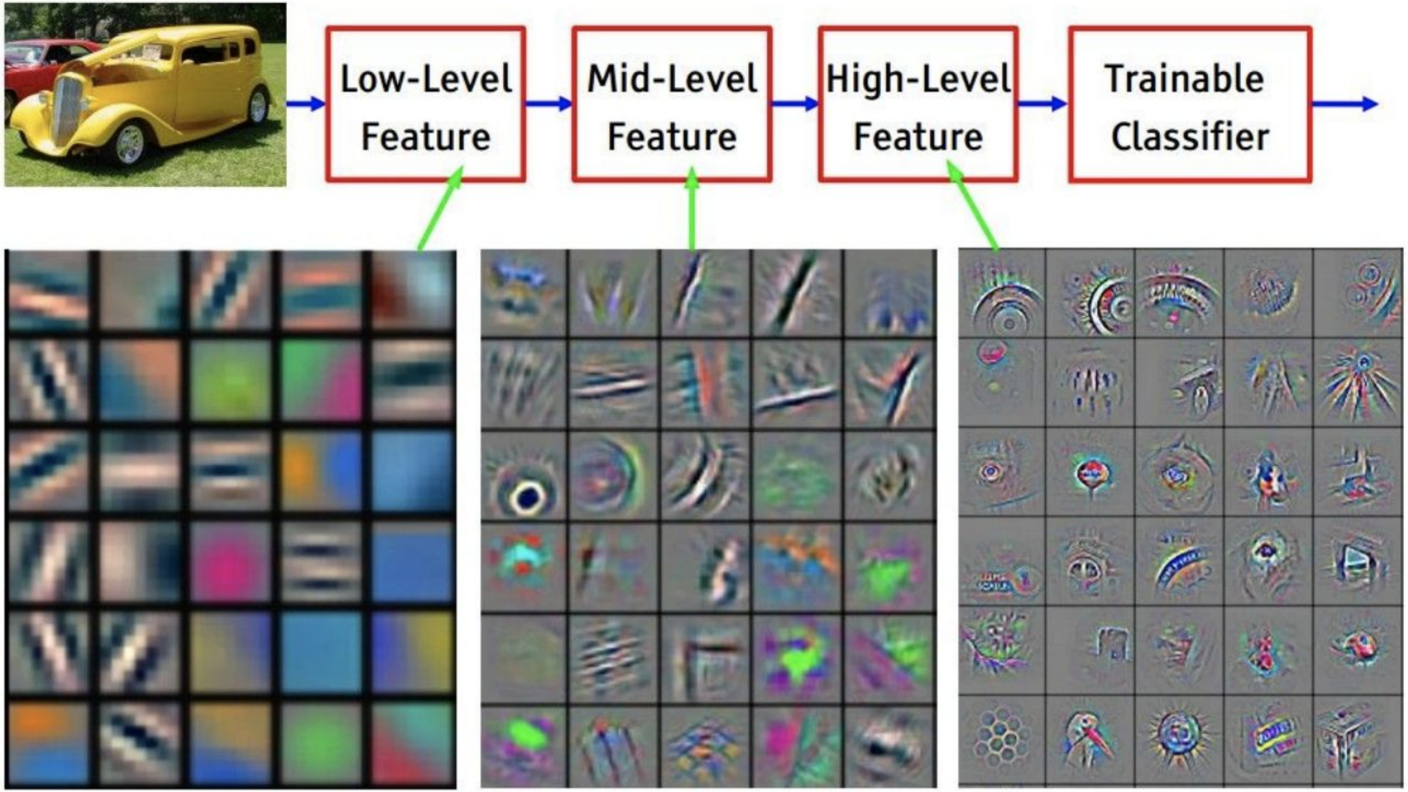
We stack these up to get a "new image" of size 28x28x6!

Convolutional layer

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

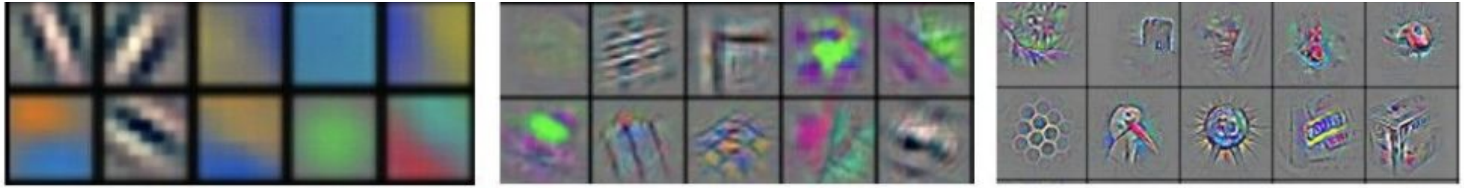


Convolutional layer

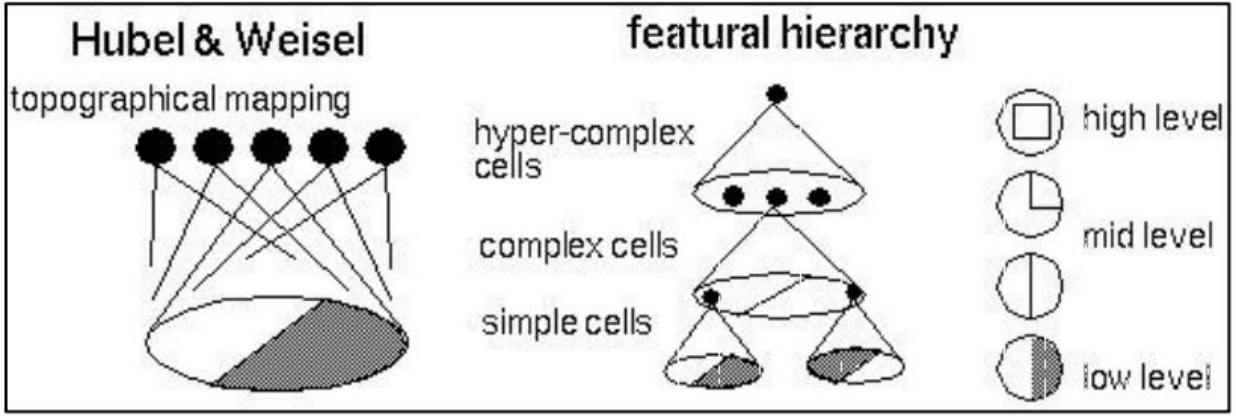


[Visualizing and Understanding Convolutional Networks, Zeiler, Fergus, 2013](#)

Convolutional layer and visual cortex



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



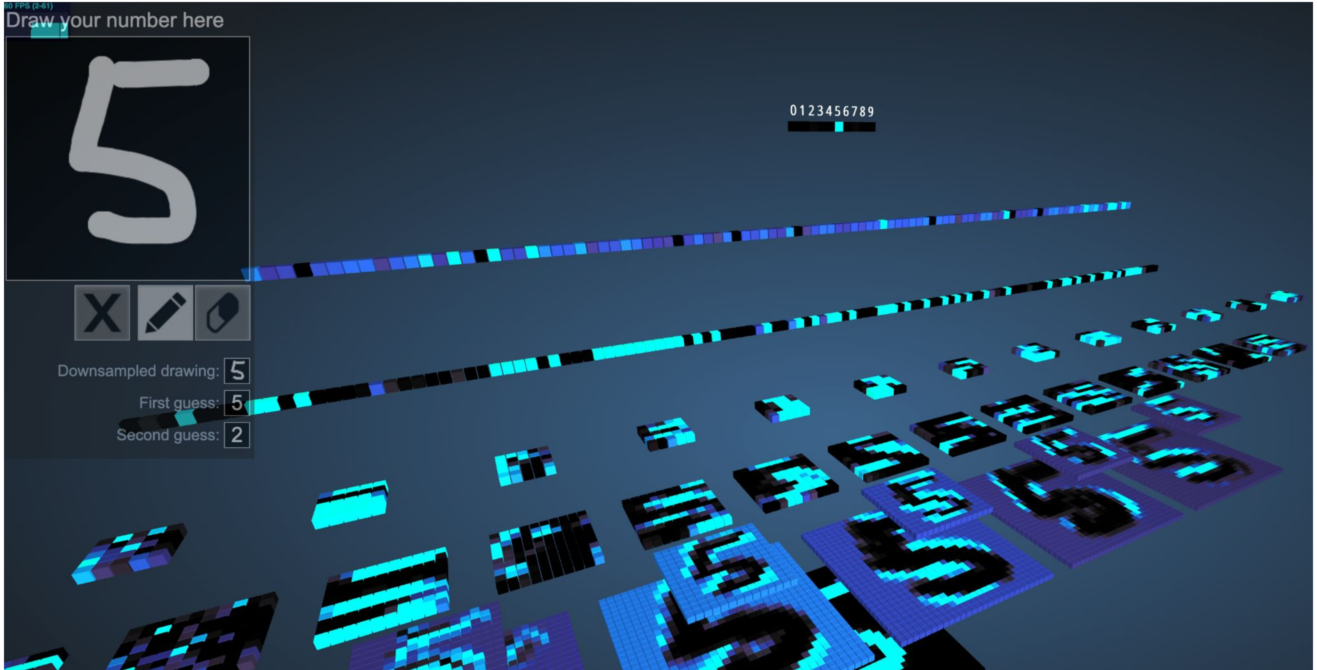
Convolutional layer and visual cortex

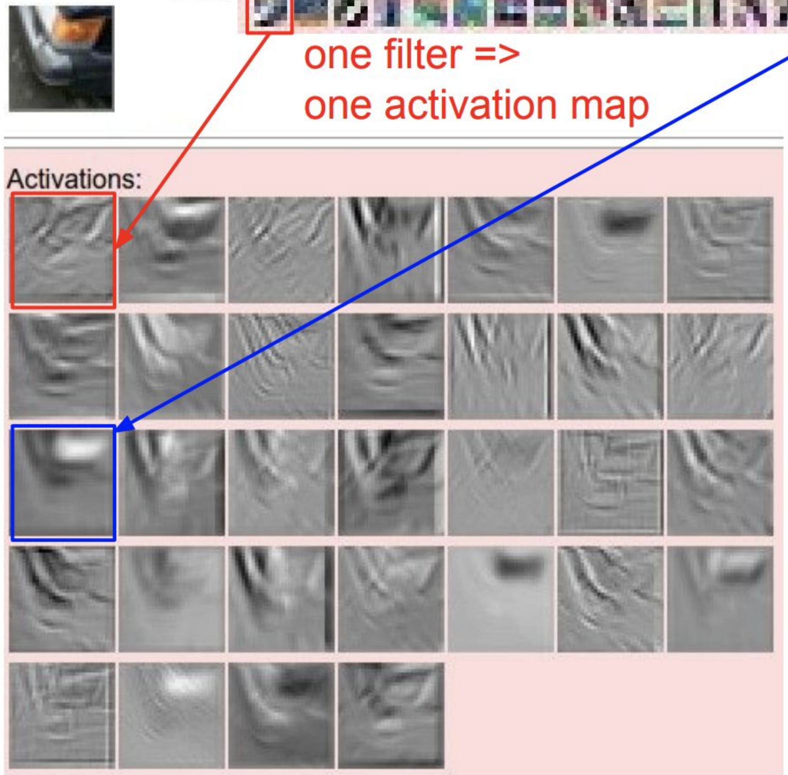
source

MNIST demo

3D demo: https://adamharley.com/nn_vis/cnn/3d.html

2D demo (lightweight): https://adamharley.com/nn_vis/cnn/2d.html



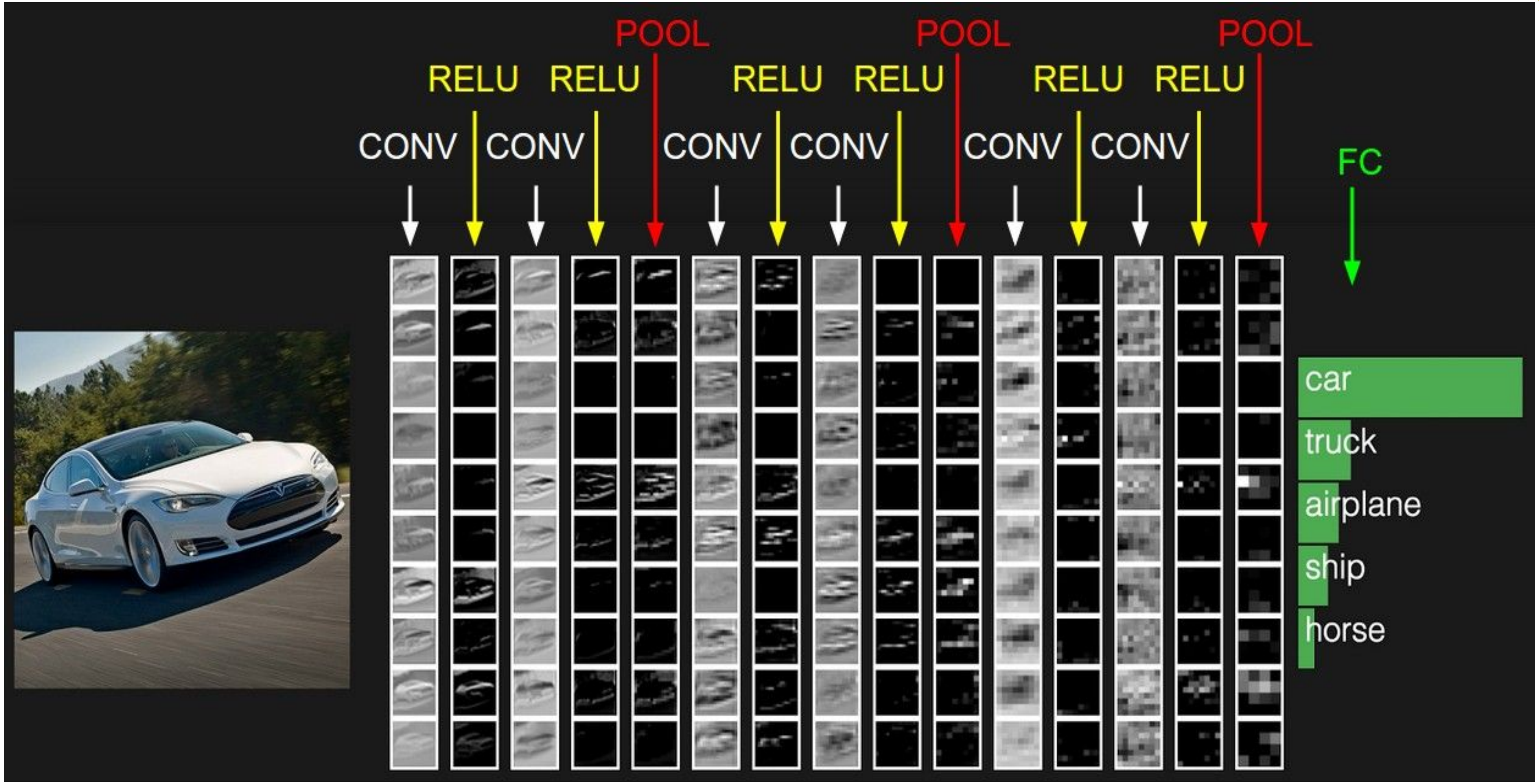


example 5x5 filters
(32 total)

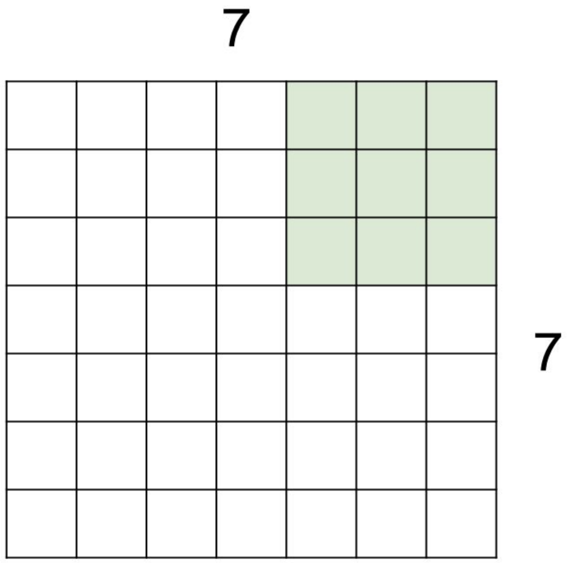
We call the layer convolutional because it is related to convolution of two signals:

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

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


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

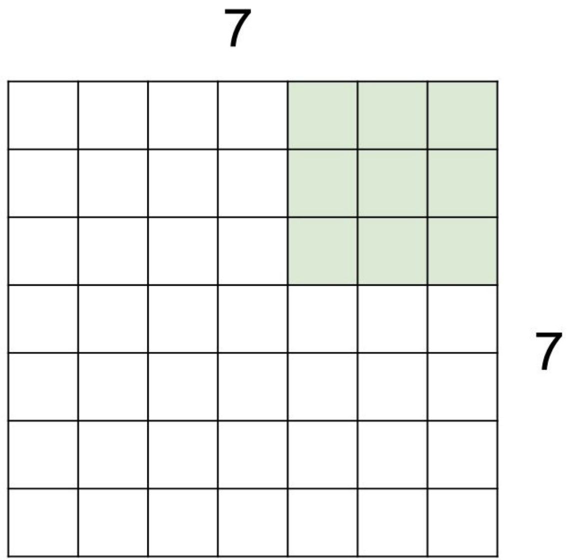
A closer look at spatial dimensions:



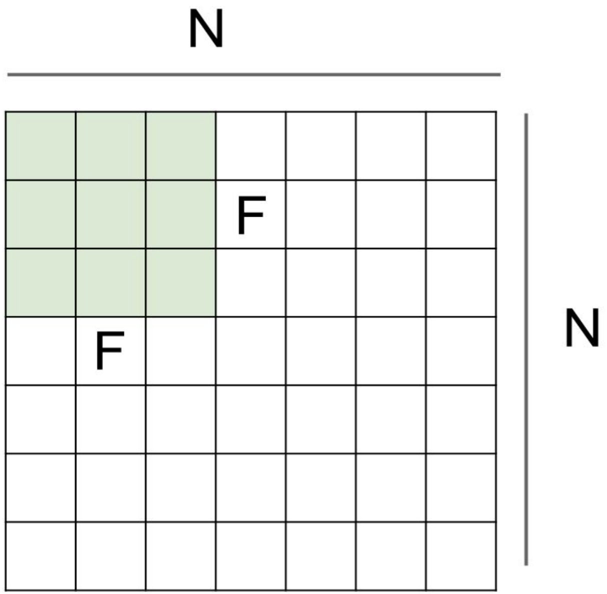
7x7 input (spatially)
assume 3x3 filter

=> 5x5 output

A closer look at spatial dimensions:



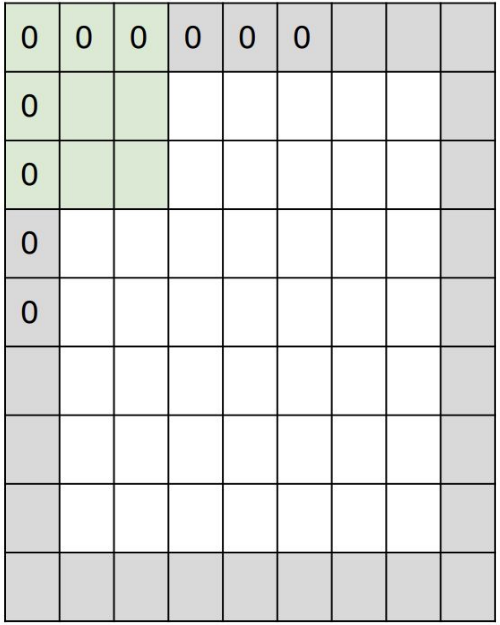
7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**
=> 3x3 output!



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 :\

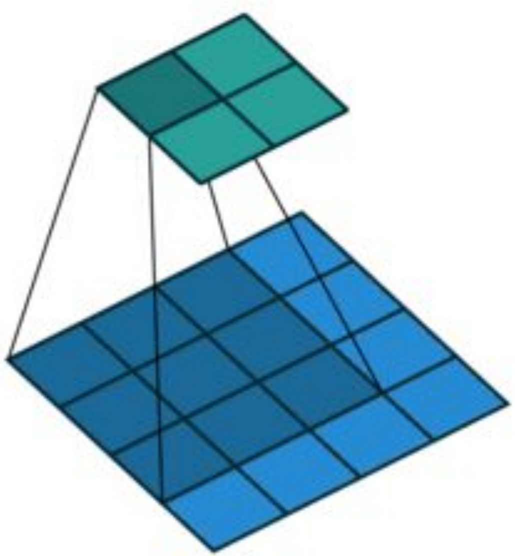
In practice: Common to zero pad the border



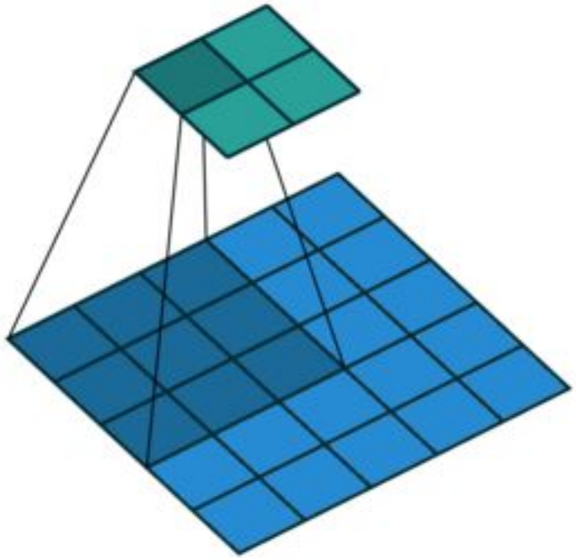
e.g. input 7x7
3x3 filter, applied with **stride 1**
pad with 1 pixel border => what is the output?

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

Strides, padding

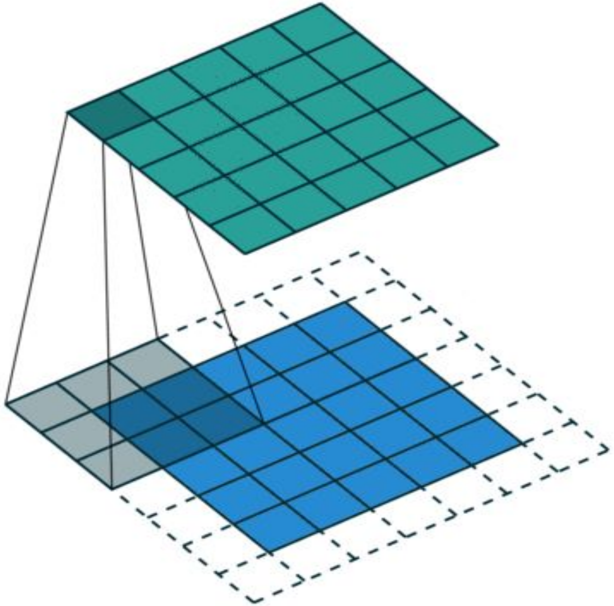


No padding, no strides

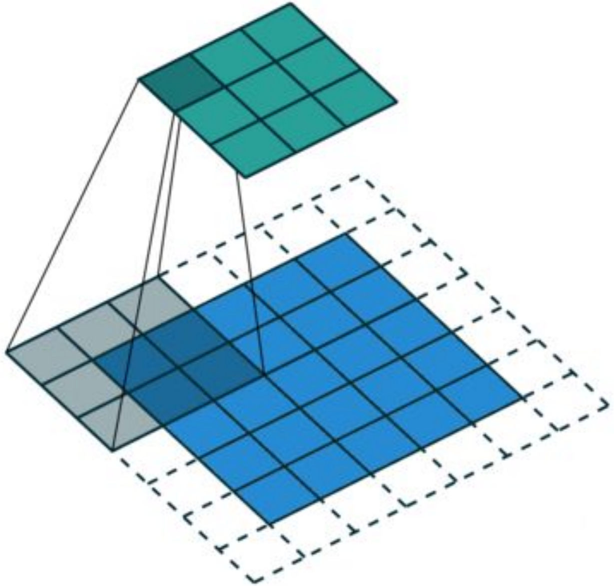


No padding, with strides

Strides, padding



With padding, no strides

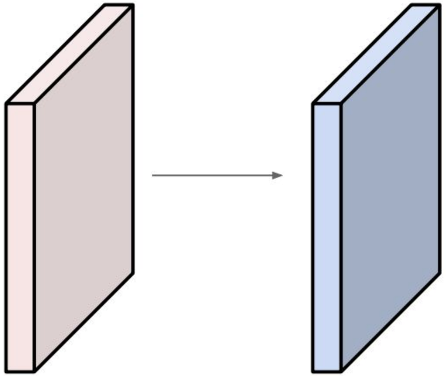


With padding, with strides

Examples time:

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

Output volume size: ?



Examples time:

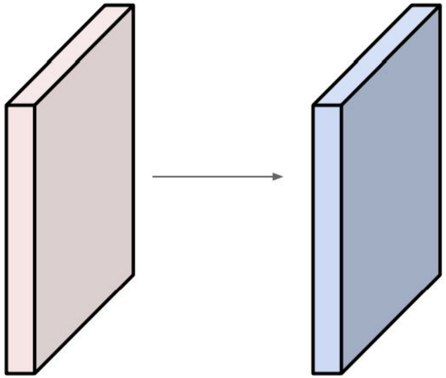
Input volume: **32x32x3**

10 5x5 filters with stride 1, pad 2

Output volume size:

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

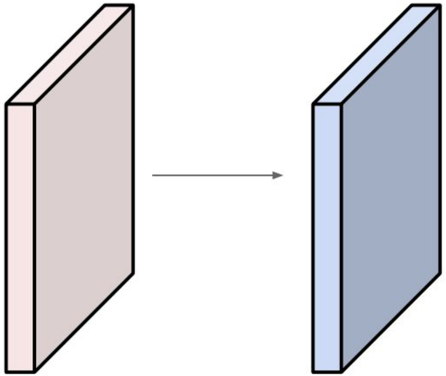
32x32x10



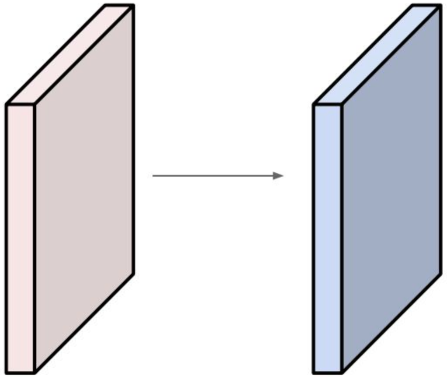
Examples time:

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

Number of parameters in this layer?



Examples time:



Input volume: **32x32x3**

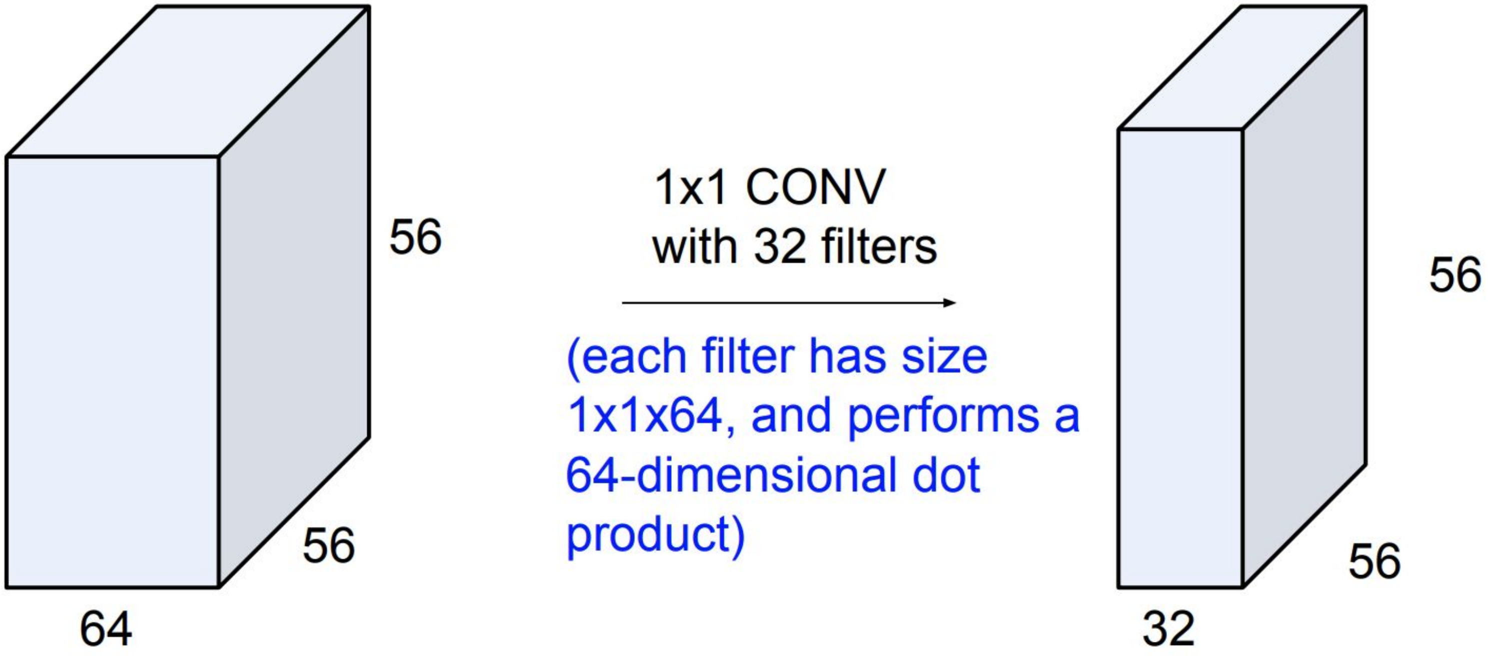
10 5x5 filters with stride 1, pad 2

Number of parameters in this layer?

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

=> 76*10 = **760**

1x1 convolutions



Pooling layer

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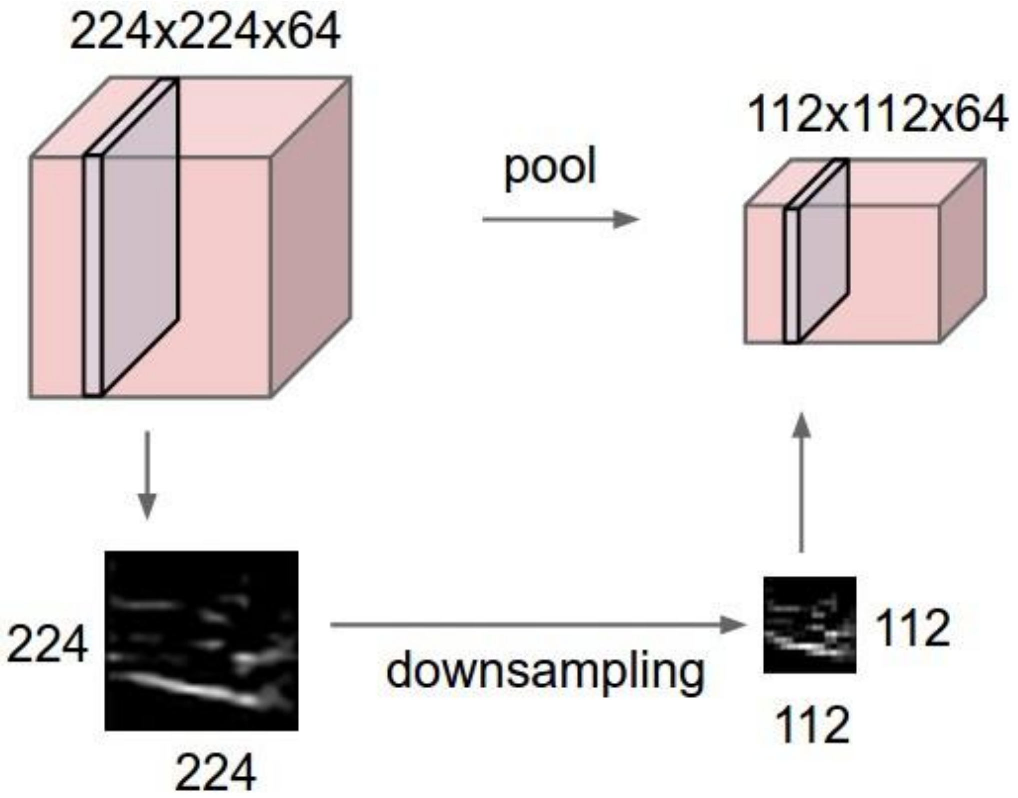
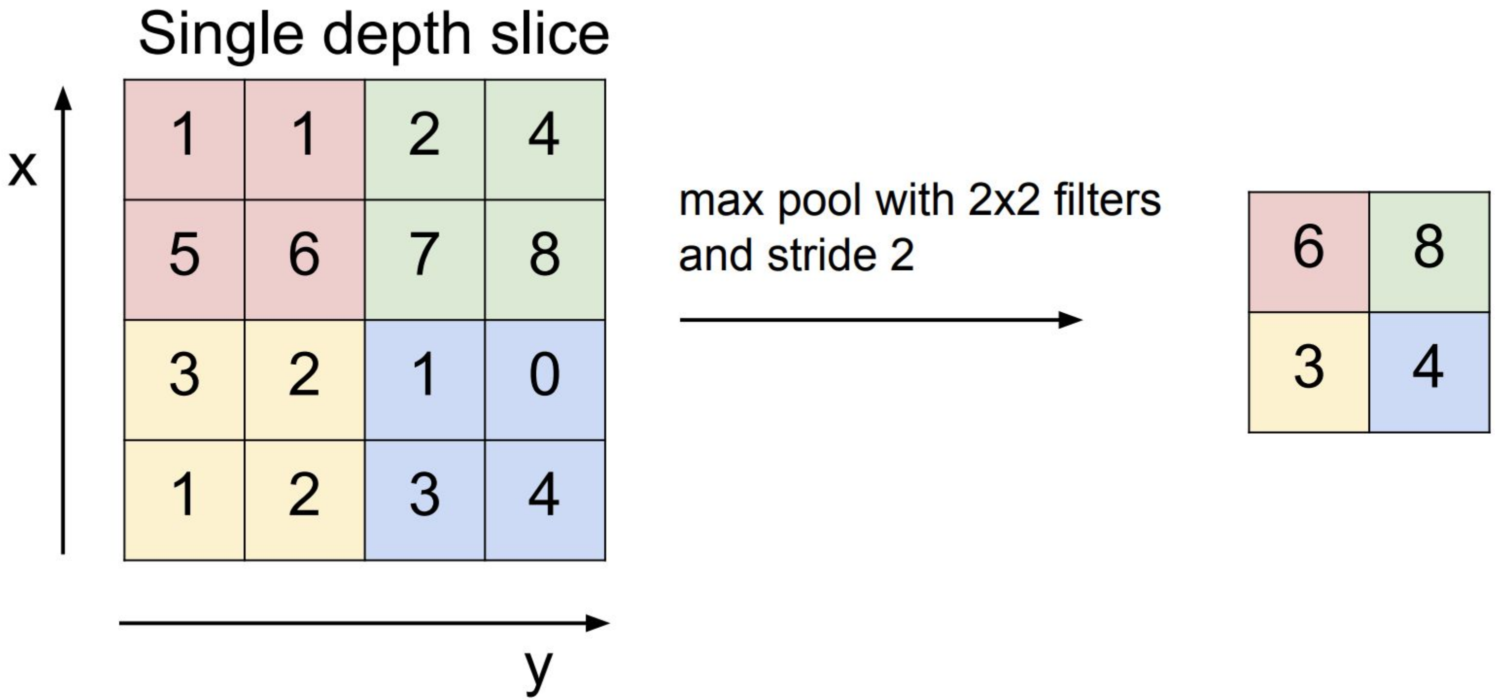
Pooling layer

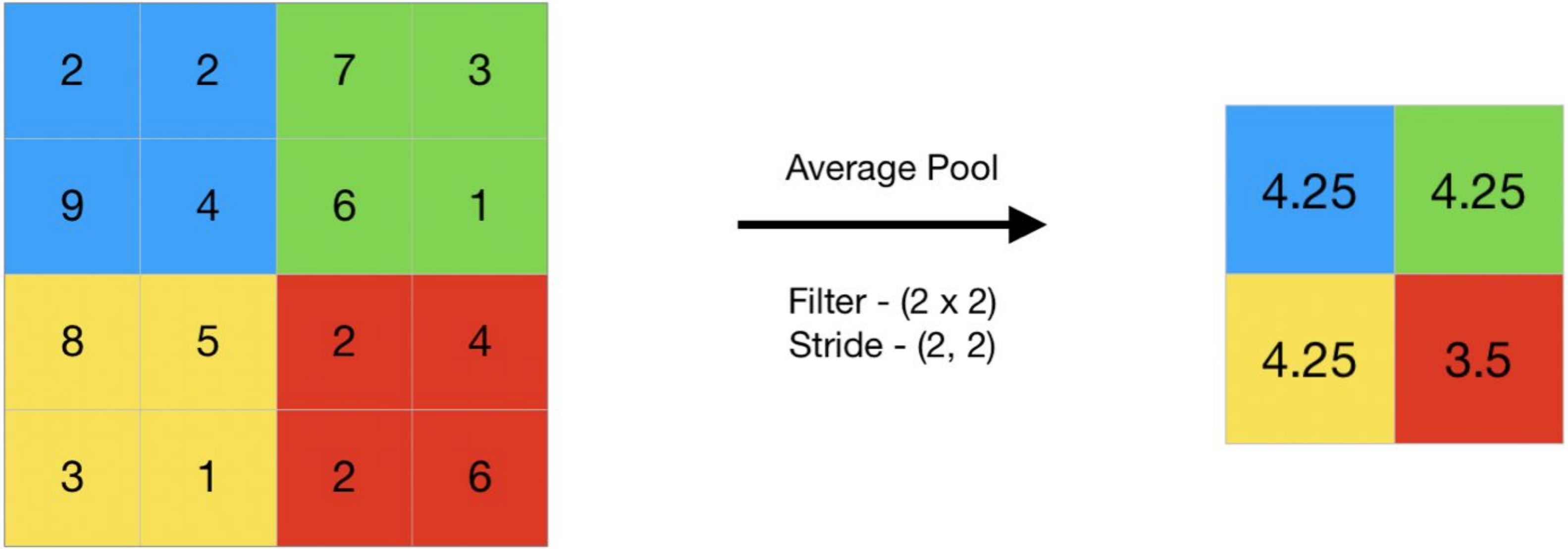


- Makes the representations smaller and more manageable
- Operates over each channel independently
- No trainable params, so doesn't overfit

Max pooling

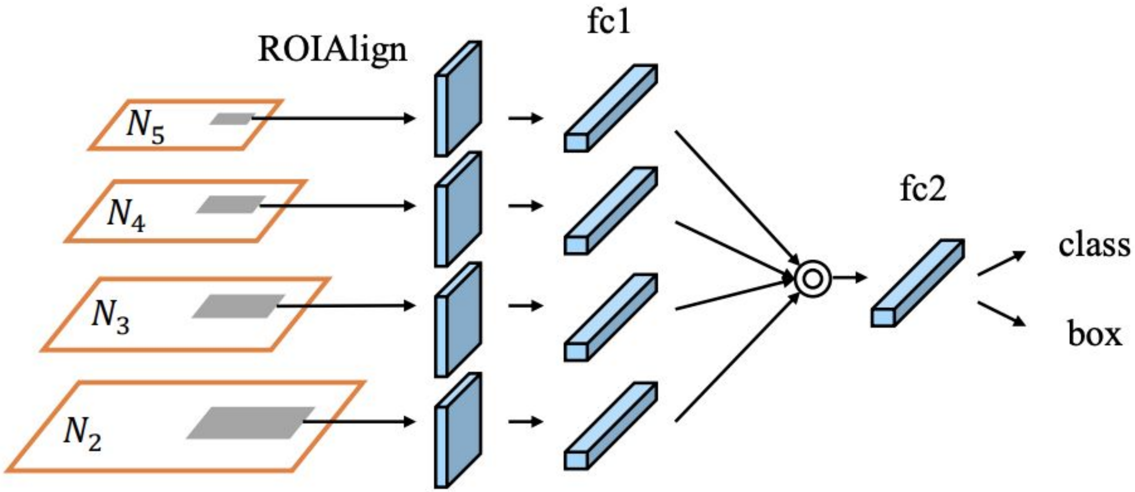

Single depth slice
x
y
1 1 2 4
5 6 7 8
3 2 1 0
1 2 3 4
max pool with 2x2 filters
and stride 2
6 8
3 4

Average pooling



Adaptive pooling

- Pools adaptive region size into fixed output size
- Fixed size is required for following linear layers
- Allows to put arbitrary image size into convolution network
- Both Max- and Average-



torch.nn.AdaptiveAvgPool2d

CNN architectures overview

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03

Image classification then

2007: Asirra

CAPTCHA that asks users to identify cats out of a set of 12 photographs of both cats and dogs.
Solved by **humans in 99.6%** of cases.
Barring a major advance in machine vision, we expect **computers** will have no better than a **1/54,000 chance** of solving it

Elson et al

Image classification now

2014: Asirra on kaggle

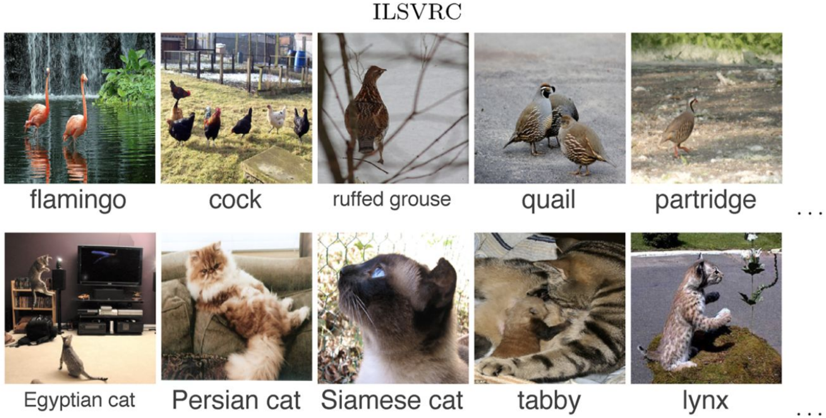
Competition page

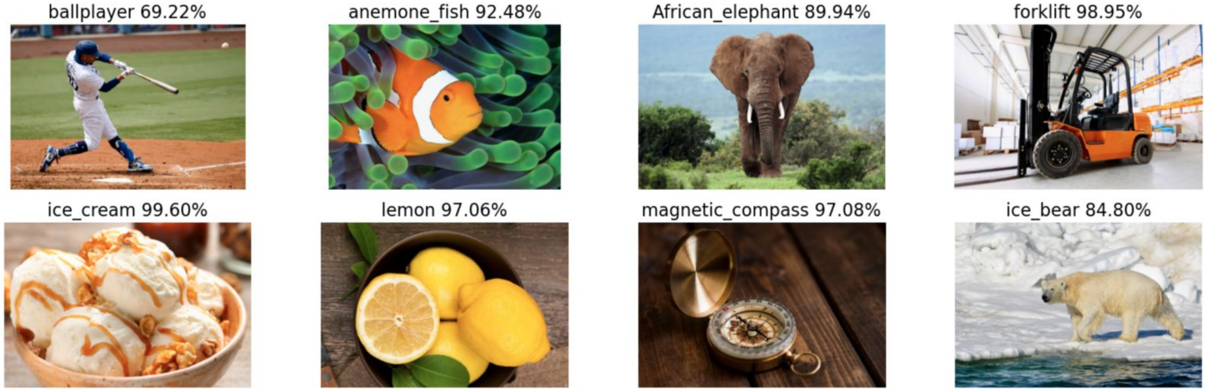
#	△	Team	Members	Score	Entries	Last	Solution
1	—	Pierre Sermanet		0.98914	5	10y	
2	▲ 4	orchid		0.98308	17	10y	
3	—	Owen		0.98171	15	10y	
4	—	Paul Covington		0.98171	3	10y	
5	▼ 3	Maxim Milakov		0.98137	24	10y	
6	▼ 1	we've been in KAIST		0.98102	8	10y	
7	▲ 1	Doug Koch		0.98057	6	10y	
8	▲ 2	fastml.com/cats-and-dogs		0.98000	6	10y	

Last Submission: 02/02/2014, 1:43:19 GMT+4

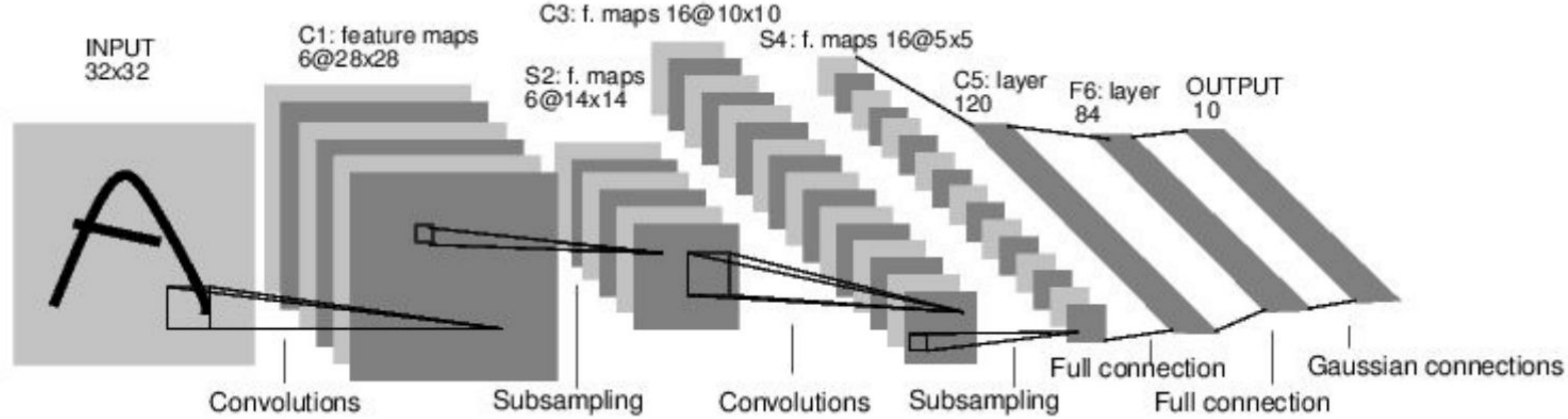
IMAGENET competition

- ImageNet Large Scale Visual Recognition Challenge (ILSVRC)
- 14.2m images
- 1000 classes
- http://image-net.org/explore



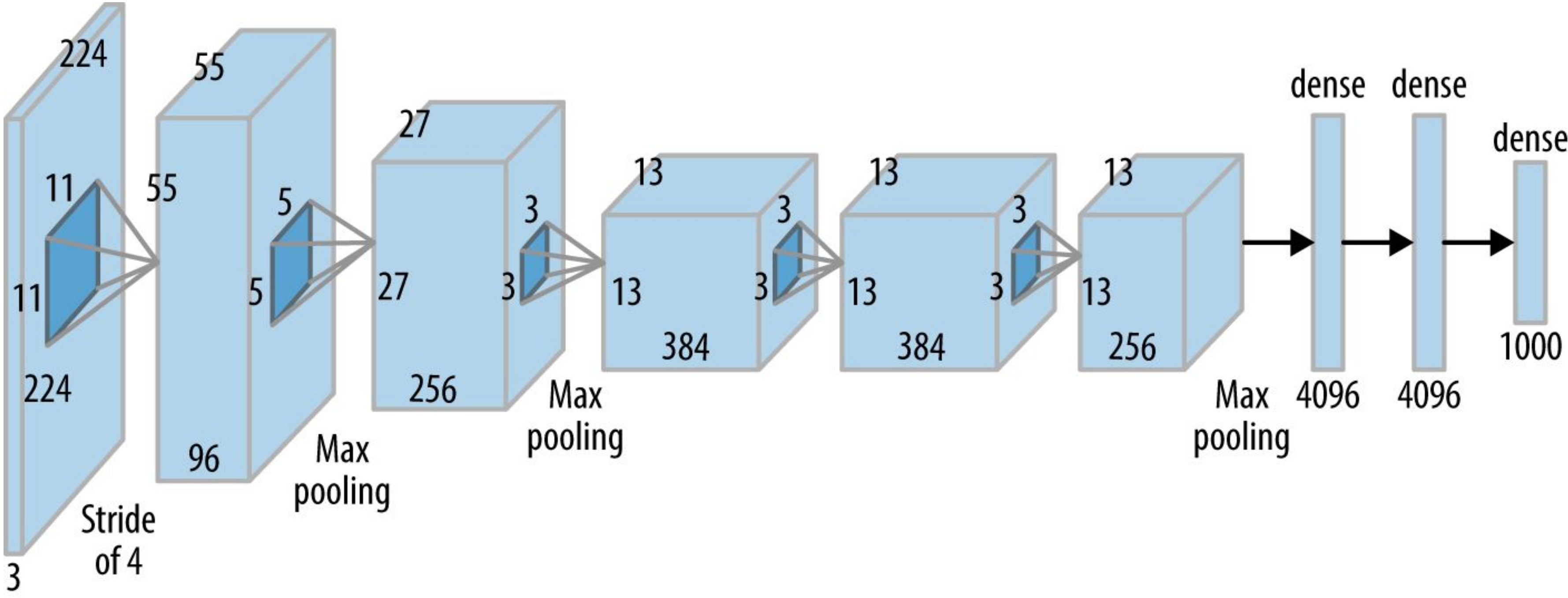


LeNet-5



[LeNet-5, LeCun 1998]

AlexNet



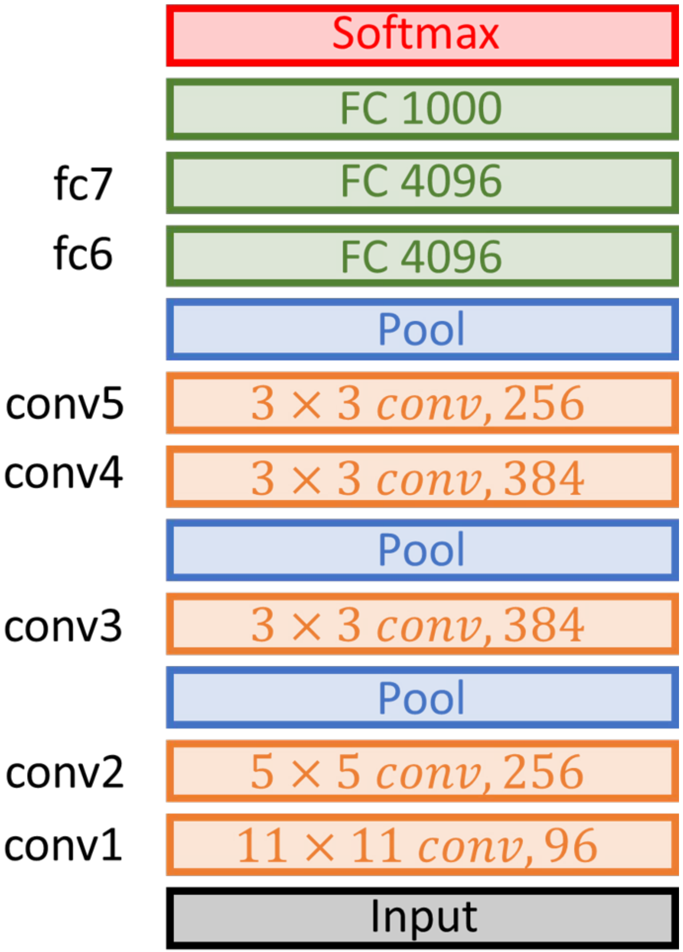
224
224
11
11
3
Stride of 4
55
55
96
5
5
Max pooling
27
27
256
3
3
Max pooling
13
13
384
3
3
13
13
384
3
3
13
13
256
Max pooling
dense
4096
dense
4096
dense
1000

AlexNet

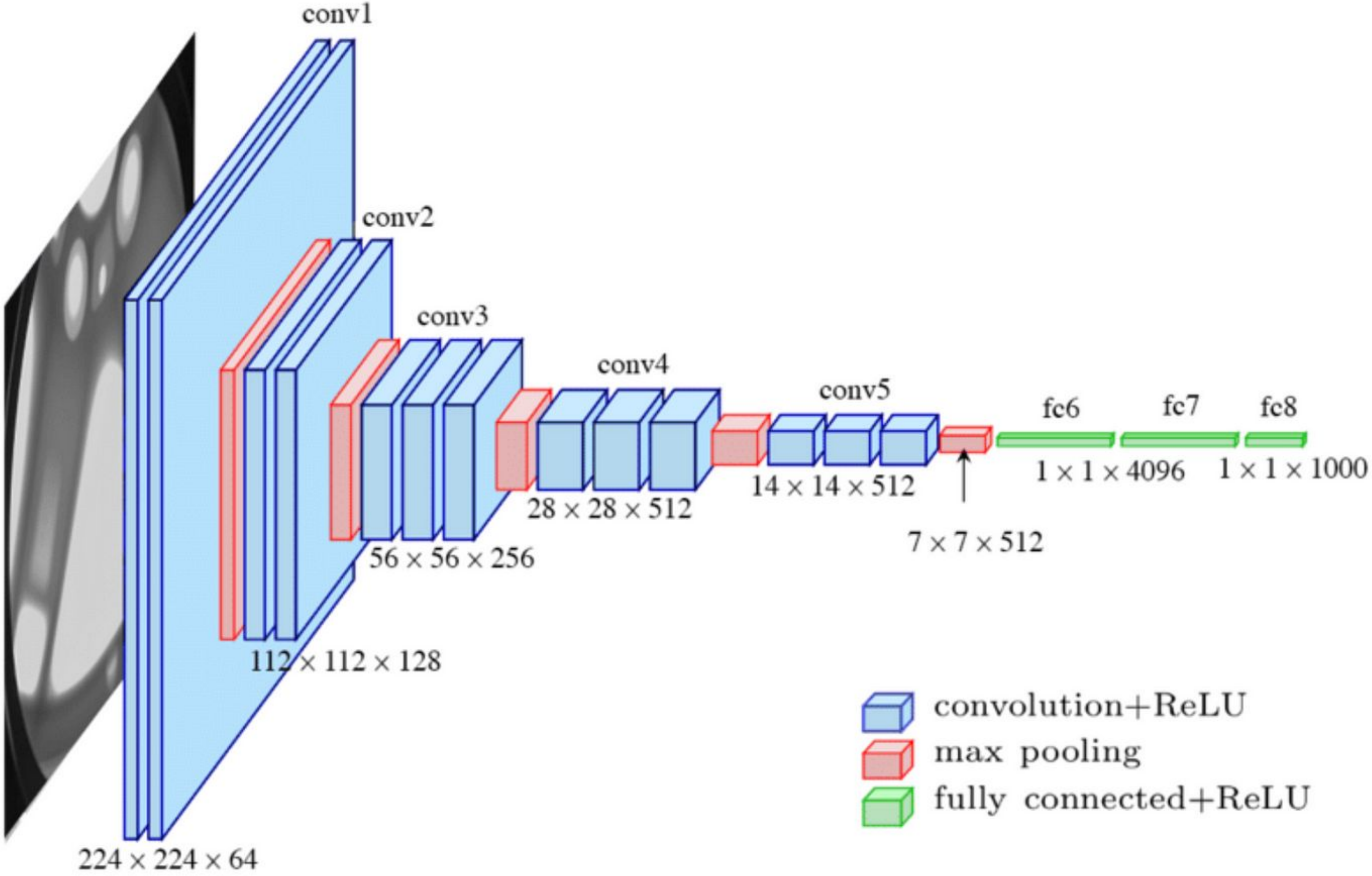
- Krizhevsky et al. 2012
- Used 2 GPUs for training
- First win of ImageNet competition with Deep Neural Networks
- Used big convolutions
- Fully connected at the end
- 7 layers

Takeouts:

- First use of ReLU
- Increasing number of channels
- 16.4%

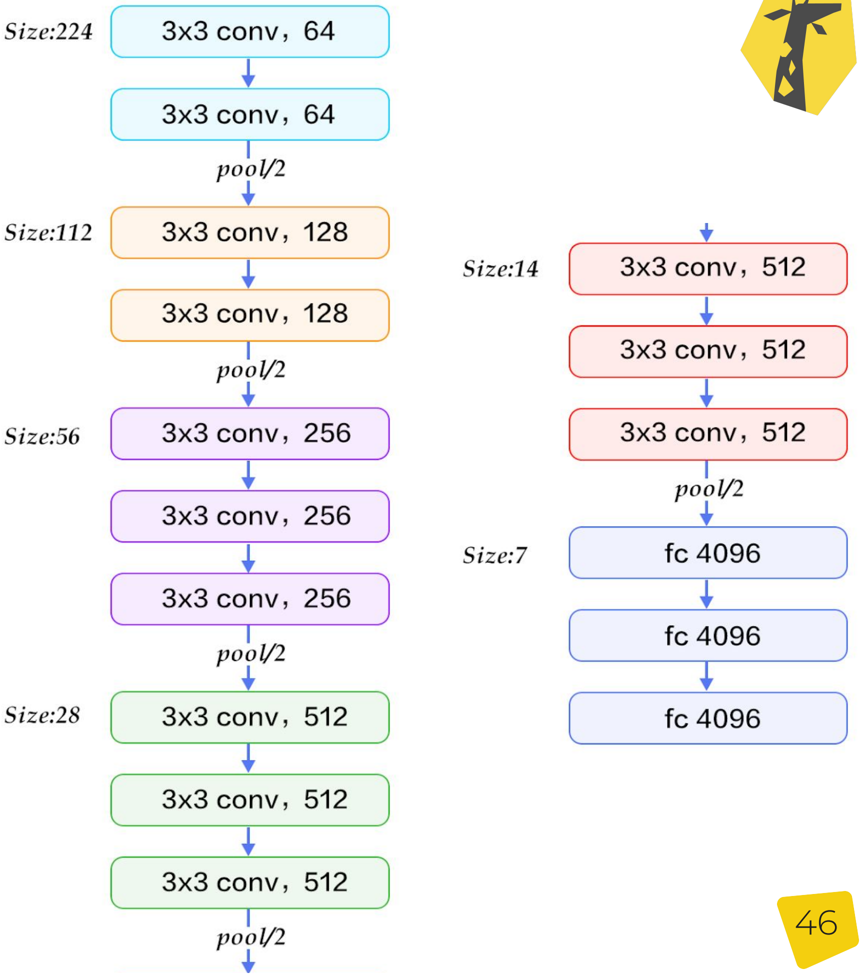


VGGNet

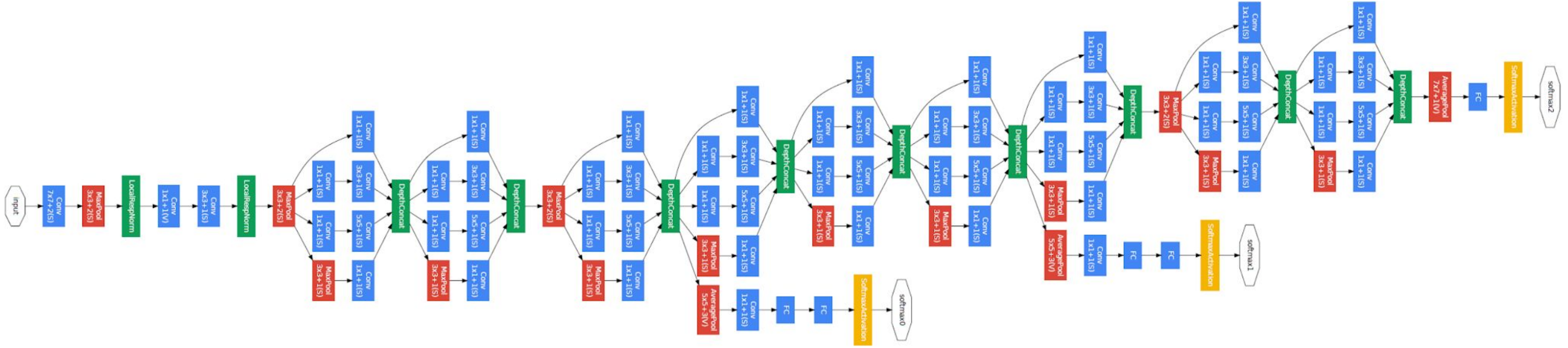

conv1
conv2
conv3
conv4
conv5
fc6
fc7
fc8
224 × 224 × 64
112 × 112 × 128
56 × 56 × 256
28 × 28 × 512
14 × 14 × 512
7 × 7 × 512
1 × 1 × 4096
1 × 1 × 1000
convolution+ReLU
max pooling
fully connected+ReLU

VGGNet

- Simonyan, Zisserman 2014
- All convolutions are 3x3
- Exponentially increasing channels
- 19 layers
- Requires a lot of memory
- Gradient vanishes =(



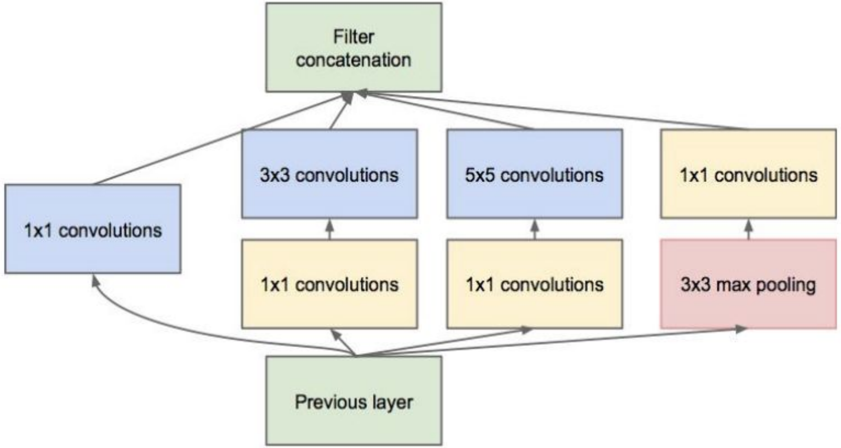
GoogLeNet



Inception module

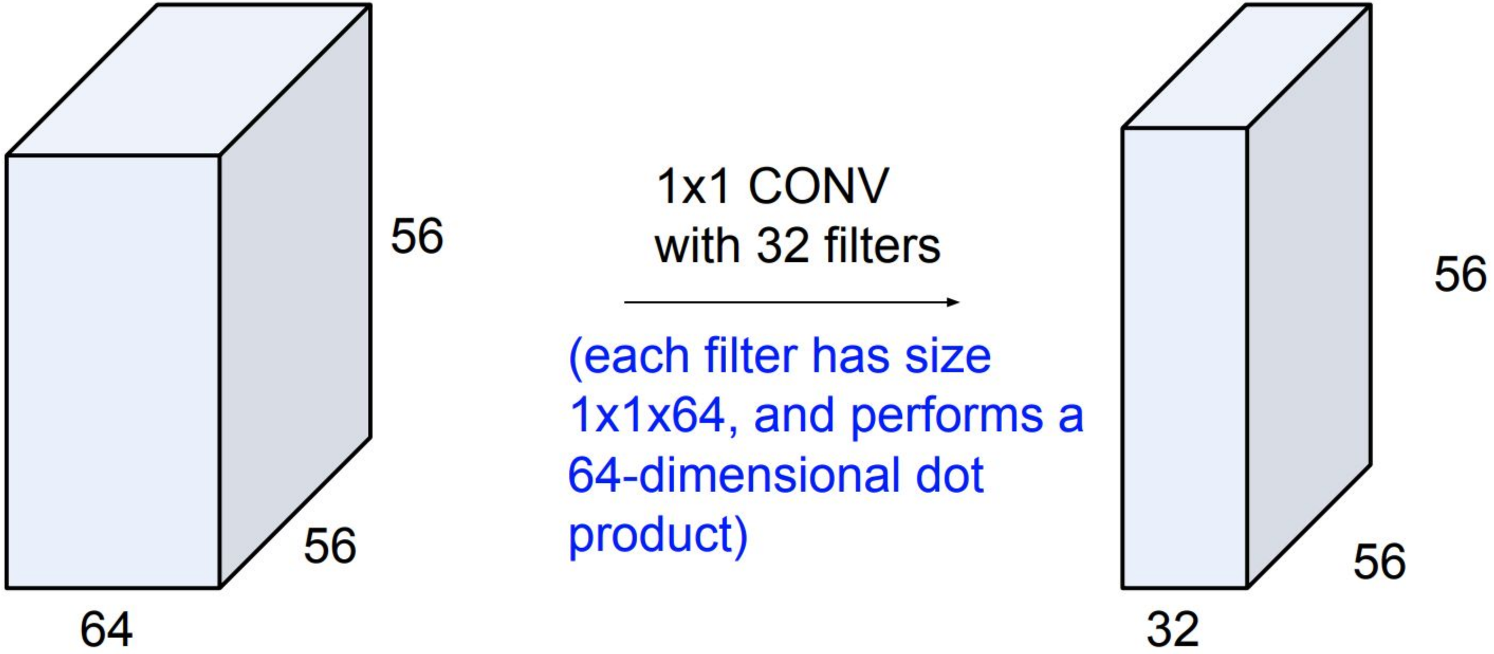
[Szegedy et al., 2014]

GoogLeNet

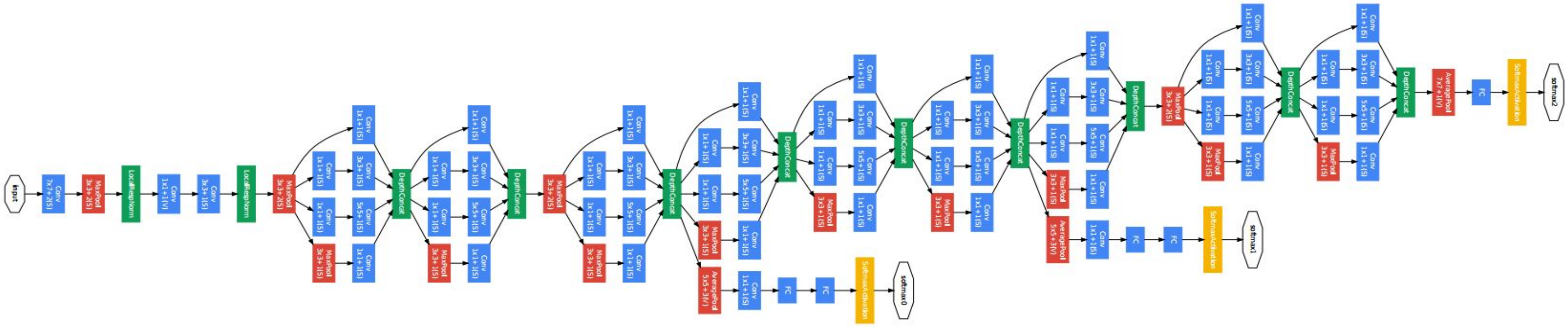


Inception module

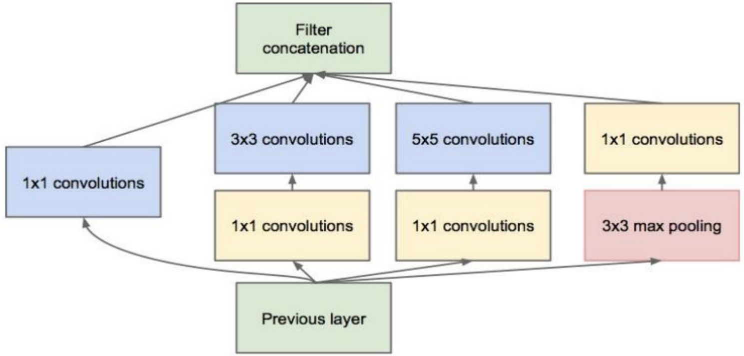
Once again: 1x1 convolutions



GoogLeNet

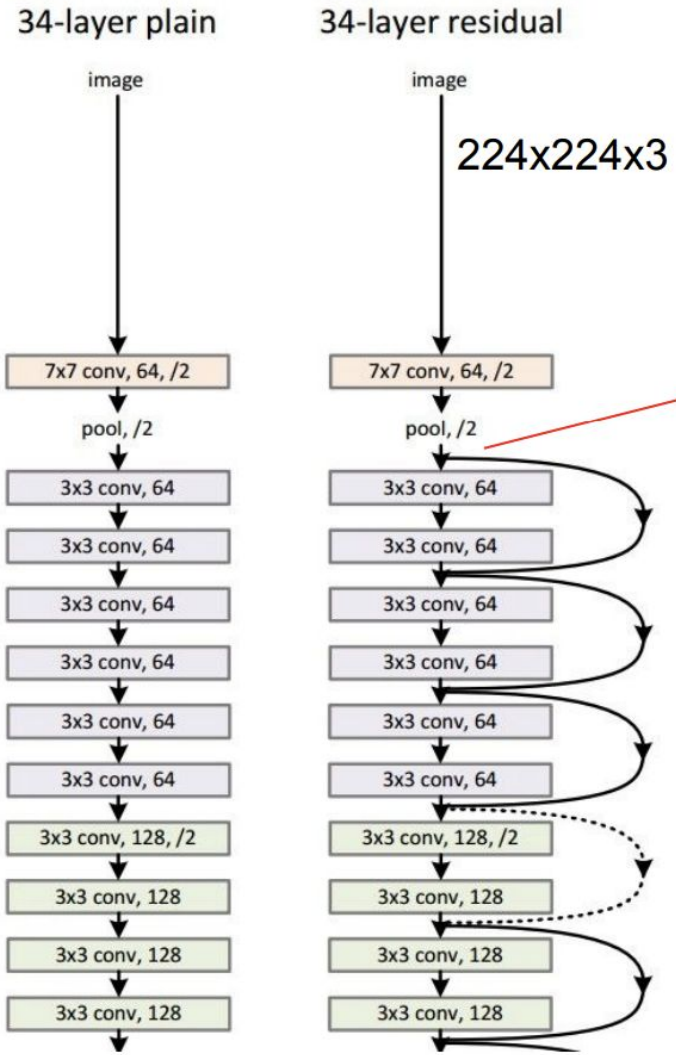


[Szegedy et al., 2014]



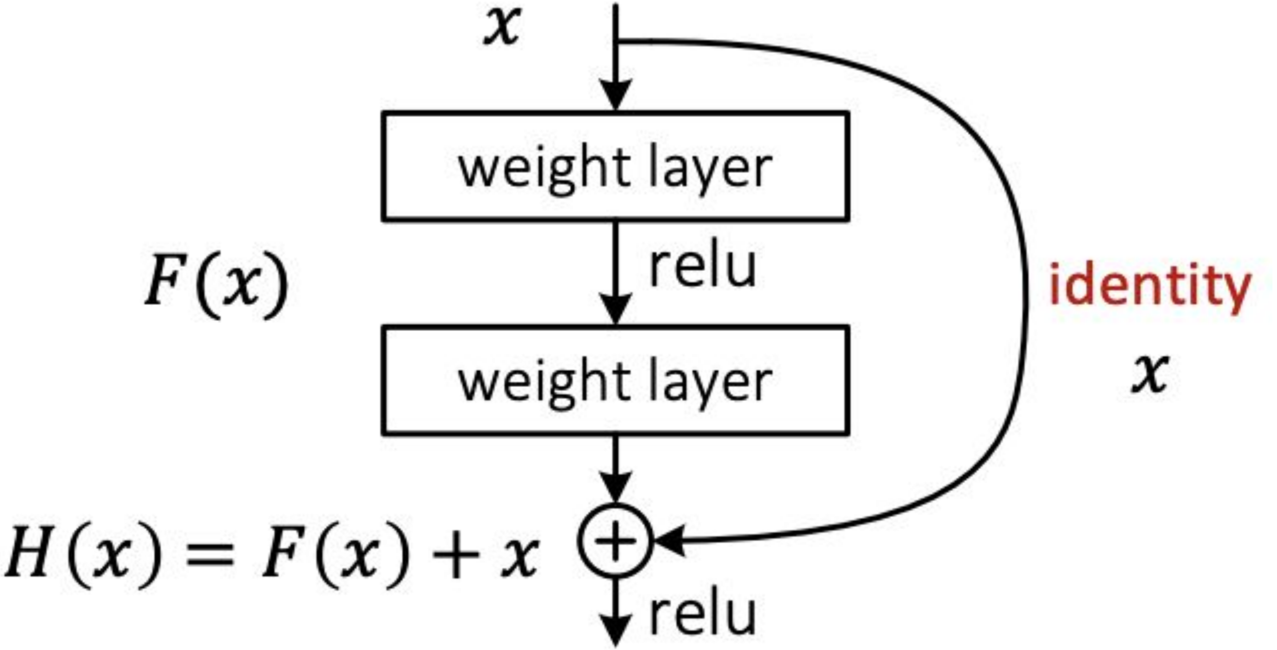
Inception module

ILSVRC 2014 winner (6.7% top 5 error)



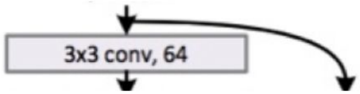
spatial dimension
only 56x56!

Residual Block

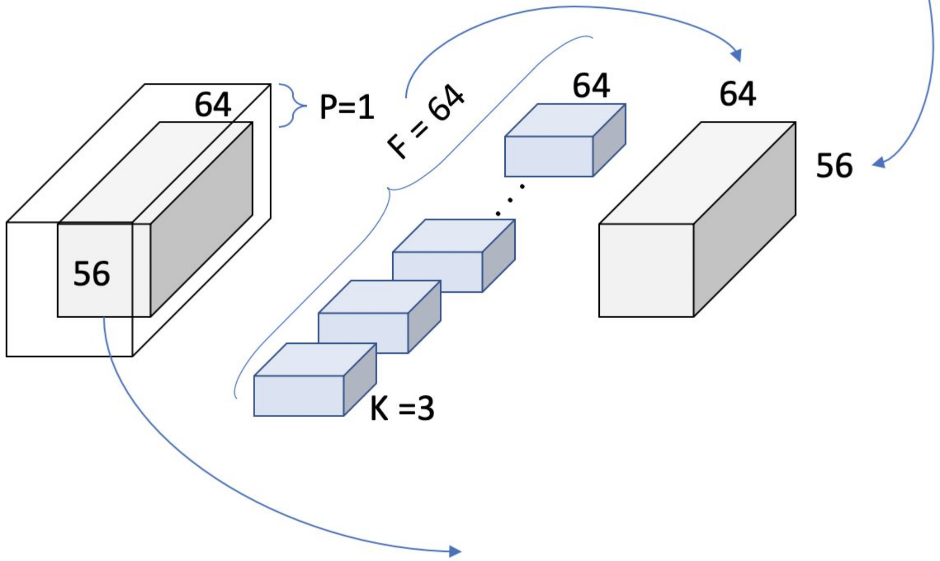


source

Residual Block

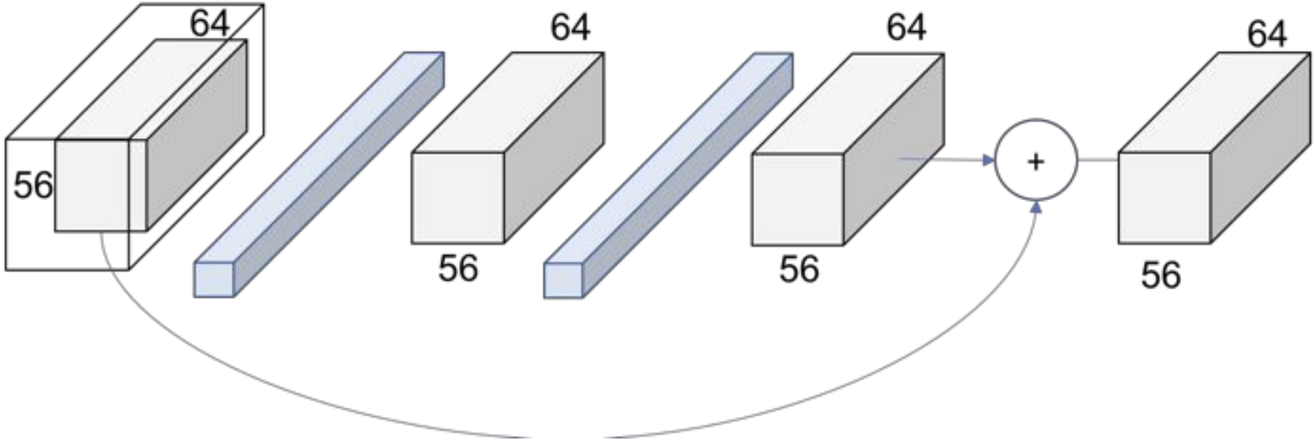


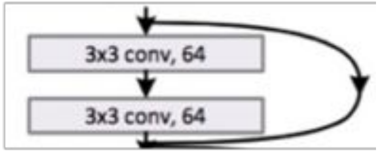
$$O = \frac{I + 2P - K}{S} + 1 = \frac{56 - 3 + 2}{1} + 1 = 56$$



source

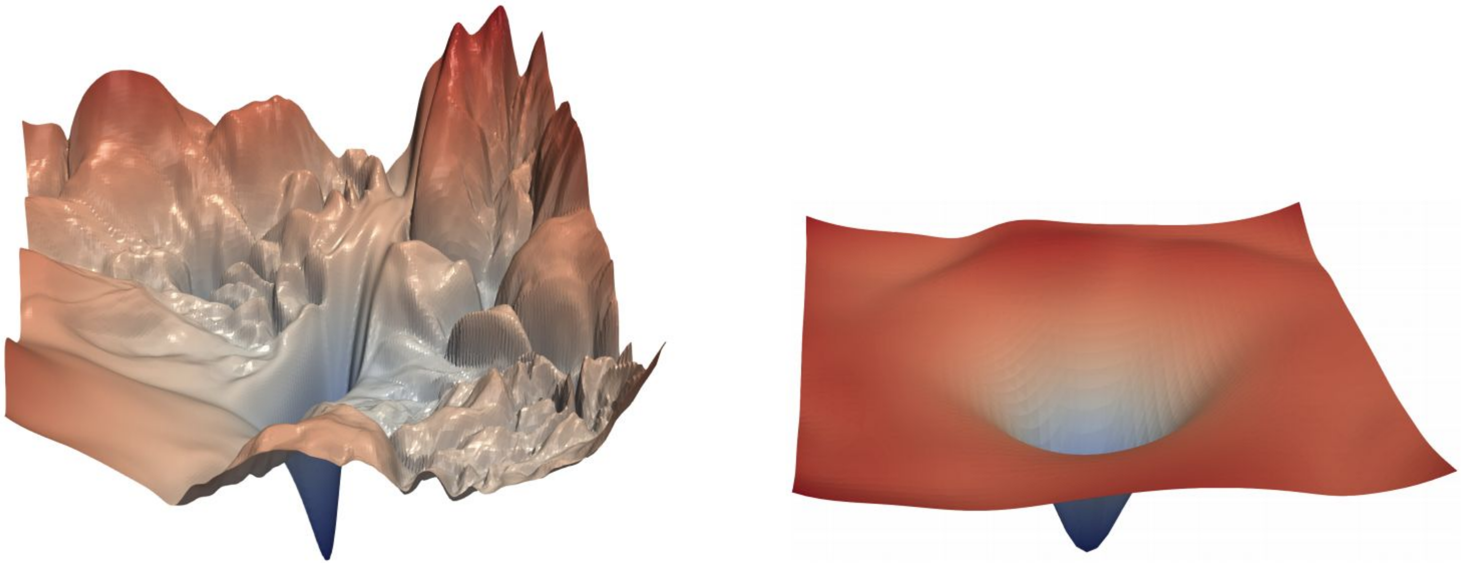
Residual Block





source

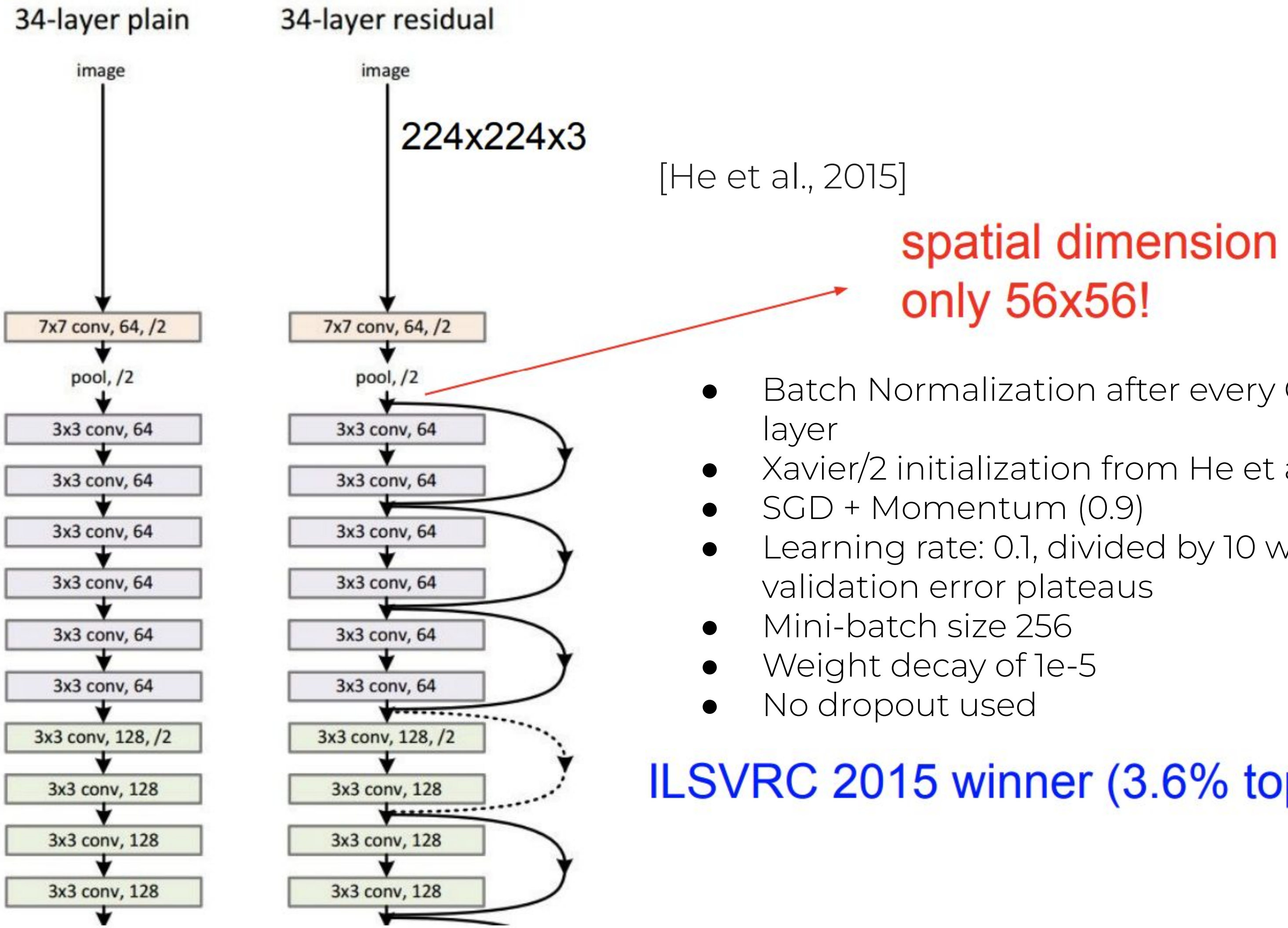
Residual Block



(a) without skip connections (b) with skip connections

Figure 1: The loss surfaces of ResNet-56 with/without skip connections. The proposed filter normalization scheme is used to enable comparisons of sharpness/flatness between the two figures.

source NeurIPS 2018



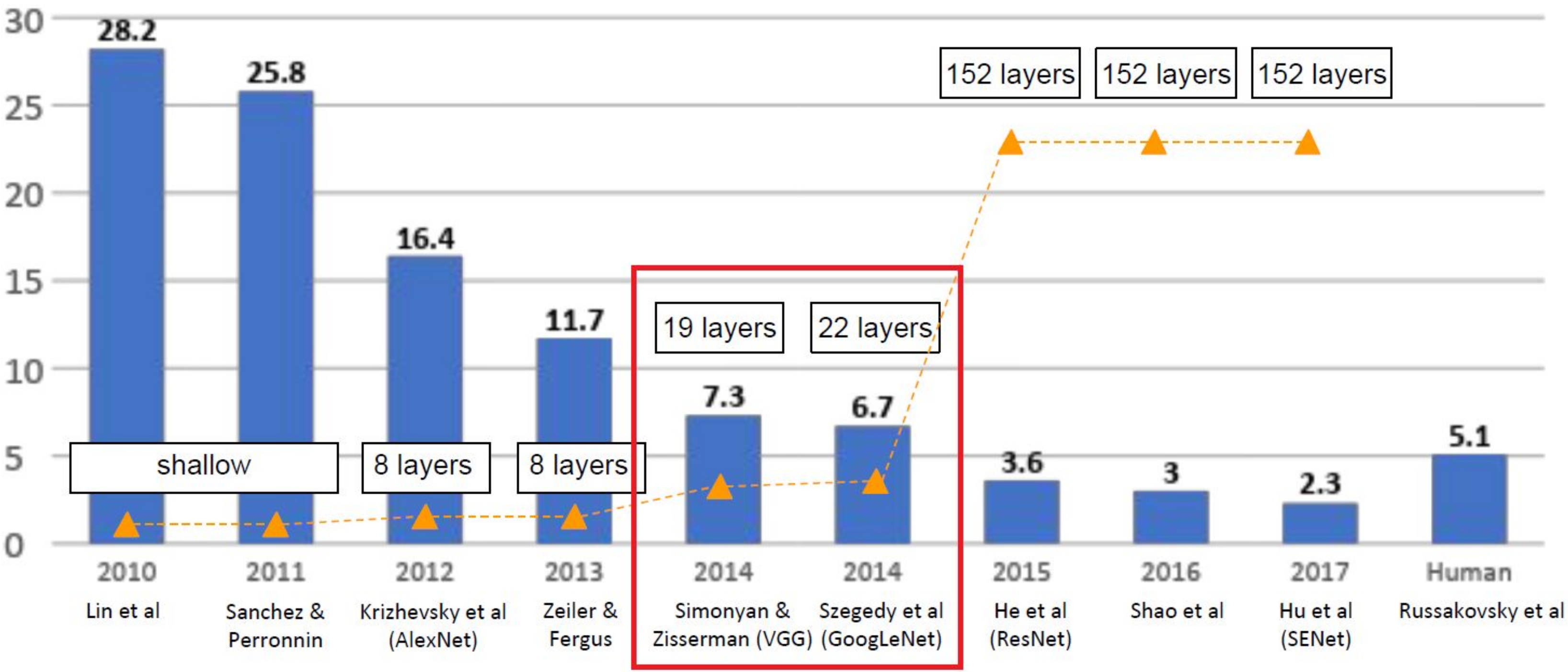
[He et al., 2015]

- Batch Normalization after every CONV layer
- Xavier/2 initialization from He et al.
- SGD + Momentum (0.9)
- Learning rate: 0.1, divided by 10 when validation error plateaus
- Mini-batch size 256
- Weight decay of 1e-5
- No dropout used

ILSVRC 2015 winner (3.6% top 5 error)

ResNet

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



Vanishing gradient in non-RNN

Vanishing gradient is present in **all** deep neural network architectures.

- Due to chain rule / choice of nonlinearity function, gradient can become vanishingly small during backpropagation
- Lower levels are hard to train and are trained slower
- Solutions
    - skip-connections (ResNet)

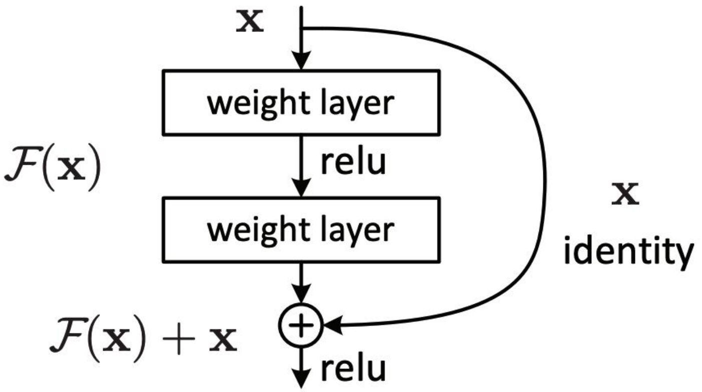


Figure 2. Residual learning: a building block.

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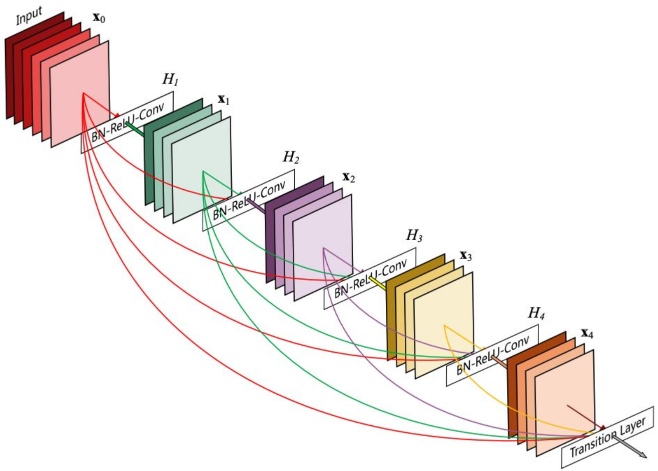
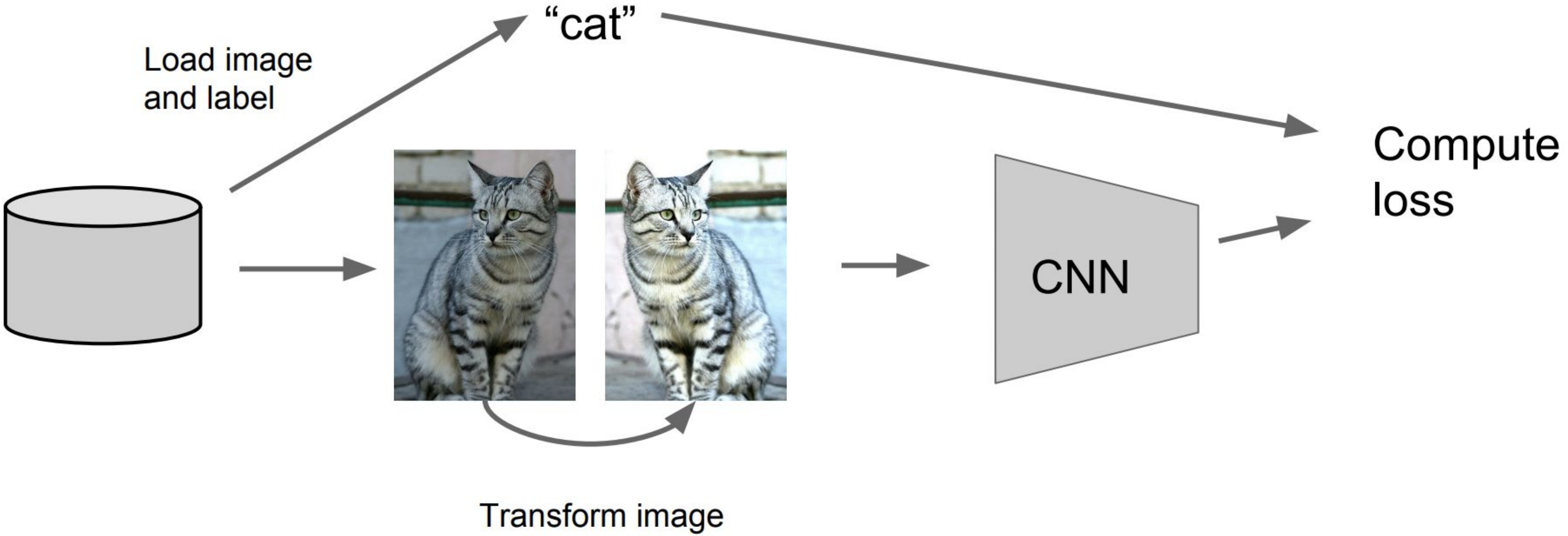
- Solutions
  - skip-connections (ResNet)
  - dense connections (DenseNet)



Recap: data augmentation



Summary

- ConvNets stack convolutional, pooling and dense layers
- Trend towards smaller filters and deeper architectures
- 1x1 convolutions are meaningful
- Humanity is already beaten on ImageNet.

Revise

1. Convolutional layer structure
2. Pooling layers
3. Top architectures overview

Thanks for attention!

Questions?

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