Machine Learning Course

Lecture 11: Convolutional neural networks

Outline

1. Previous lecture recap: optimizers, regularization.
2. Convolutional layer structure.
3. Pooling layers.
4. Top architectures overview.
5. Q & A.

This lecture is deeply based on Stanford CS231n Lecture 7 materials by Fei-Fei Li & Andrej Karpathy & Justin Johnson

Different layers

- Layers
  a. Dense layer *(done)*
  b. Convolutional layer *(this lecture)*
  c. Pooling layer *(this lecture)*
  d. Dropout layer *(done)*
  e. Batchnorm layer (batch normalization) *(done)*
  f. Embeddings (aka word2vec, GloVe) *(next lecture)*
  g. Recurrent layers *(next lecture)*

Different layers

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Optimizers

There are much more optimizers:

- Momentum
- Adagrad
- Adadelta
- RMSprop
- Adam
- …
- even other NNs

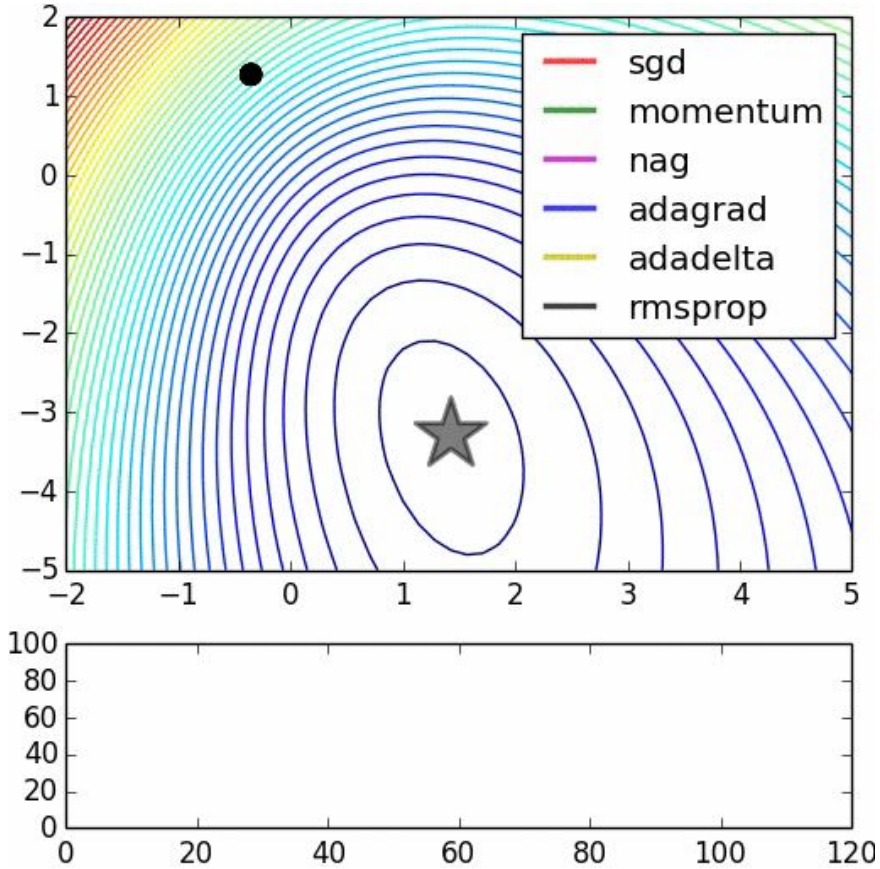
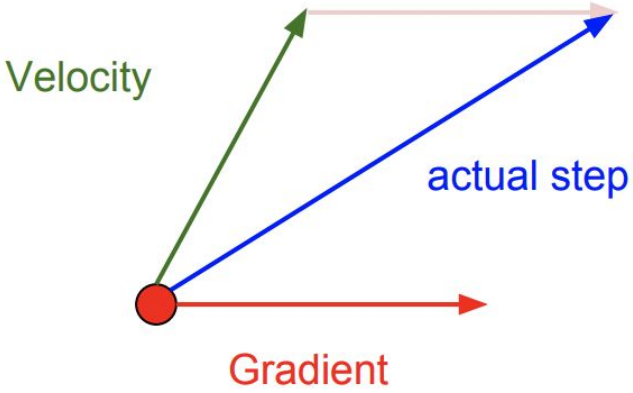


Image credits: Alec Radford

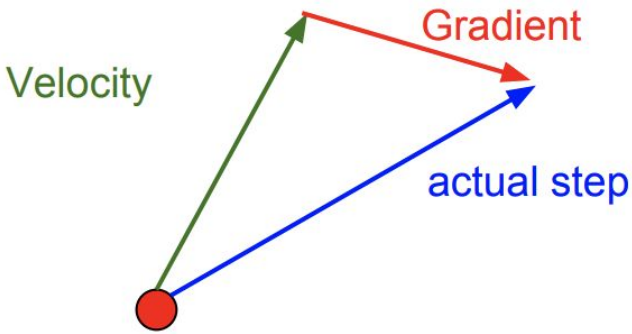
Nesterov momentum

Momentum update:



$$v_{t+1} = \rho v_t + \nabla f(x_t)$$
$$x_{t+1} = x_t - \alpha v_{t+1}$$

Nesterov Momentum



$$v_{t+1} = \rho v_t - \alpha \nabla f(x_t + \rho v_t)$$
$$x_{t+1} = x_t + v_{t+1}$$

source: http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture7.pdf

Adam

Let's combine the momentum idea and RMSProp normalization:

$$v_{t+1} = \gamma v_t + (1-\gamma)\nabla f(x_t)$$

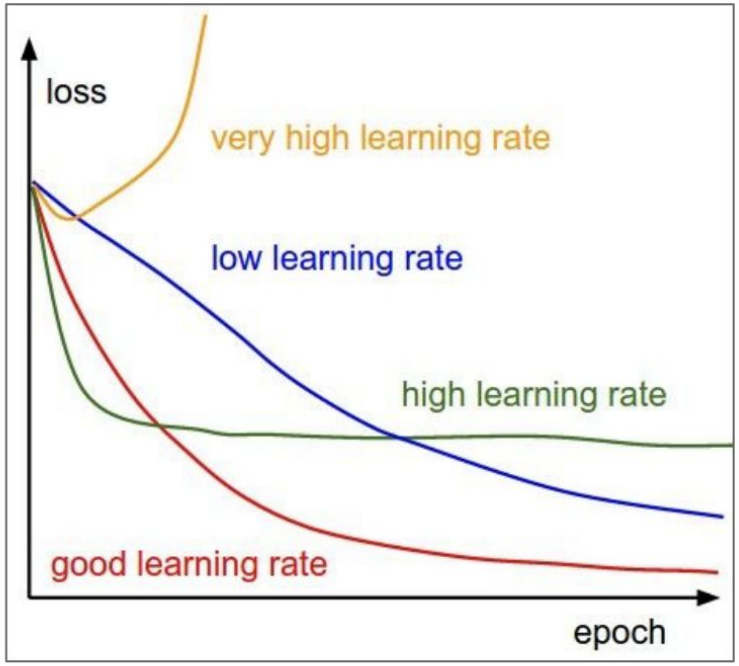
$$\text{cache}_{t+1} = \beta \text{cache}_t + (1-\beta)(\nabla f(x_t))^2$$

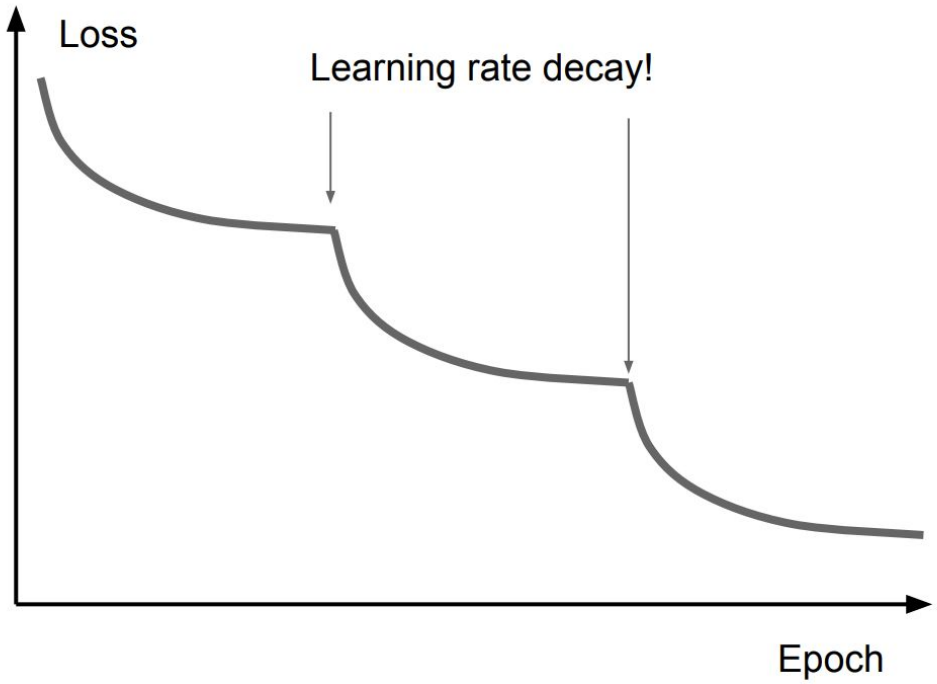
$$x_{t+1} = x_t - \alpha \frac{v_{t+1}}{\text{cache}_{t+1} + \varepsilon}$$

Actually, that's not quite Adam.

Adam full form involves bias correction term. See http://cs231n.github.io/neural-networks-3/ for more info.

Once more: learning rate





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Batch normalization

It's usually a good idea to normalize linear model inputs.

(c) Every machine learning lecturer, ever

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1...m}\}$;
Parameters to be learned: γ, β

Output: $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \qquad \text{// mini-batch mean}$$

$$\sigma^2_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu_{\mathcal{B}})^2 \qquad \text{// mini-batch variance}$$

$$\widehat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma^2_{\mathcal{B}} + \epsilon}} \qquad \text{// normalize}$$

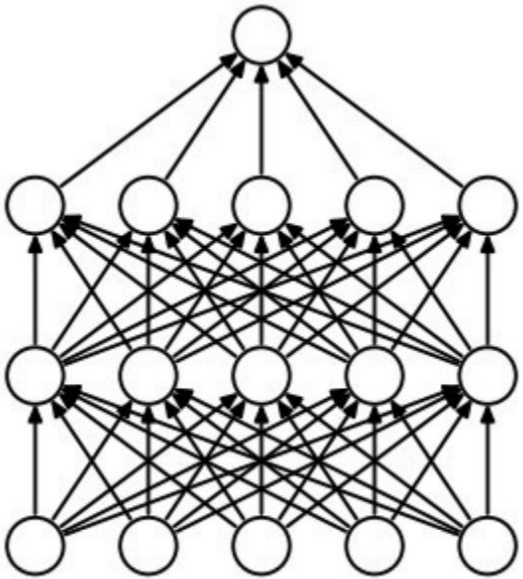
$$y_i \leftarrow \gamma\widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

Original algorithm (2015)

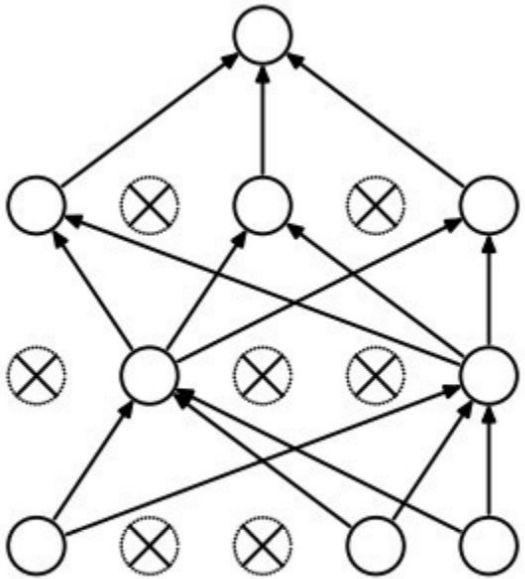
Regularization: Dropout

Some neurons are “dropped” during training.

Prevents overfitting.



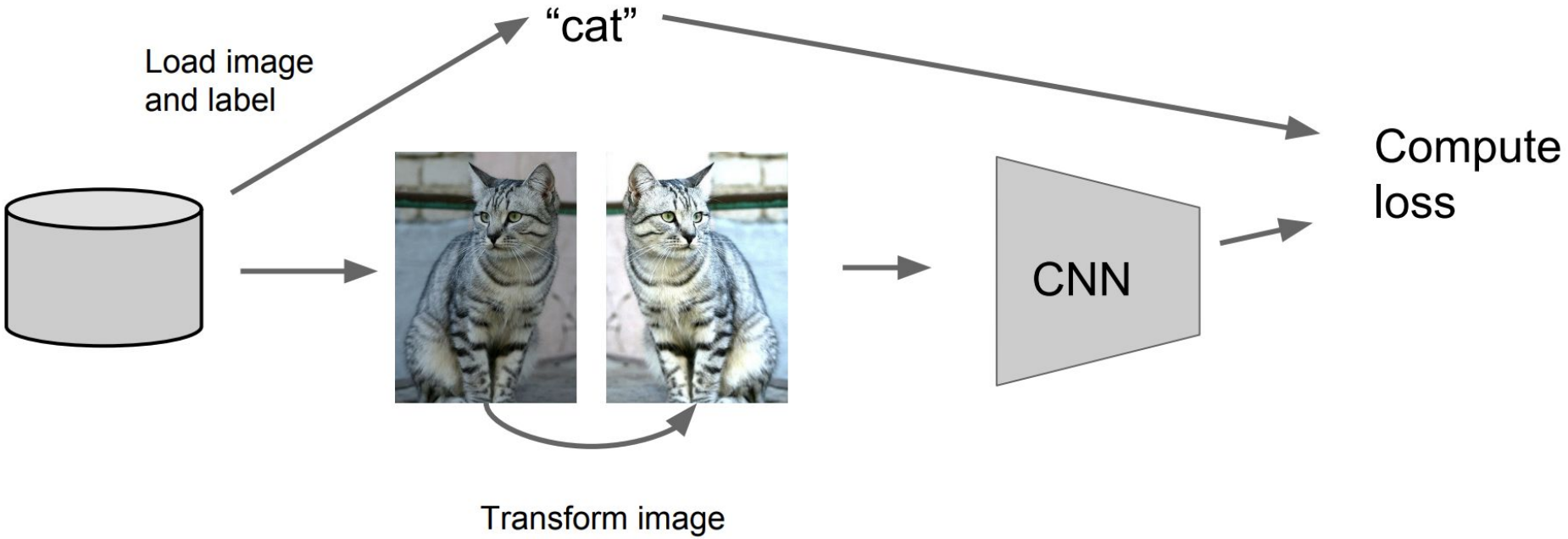
(a) Standard Neural Net



(b) After applying dropout.

Actually, on test case output should be normalized. See sources for more info.

Regularization: data augmentation



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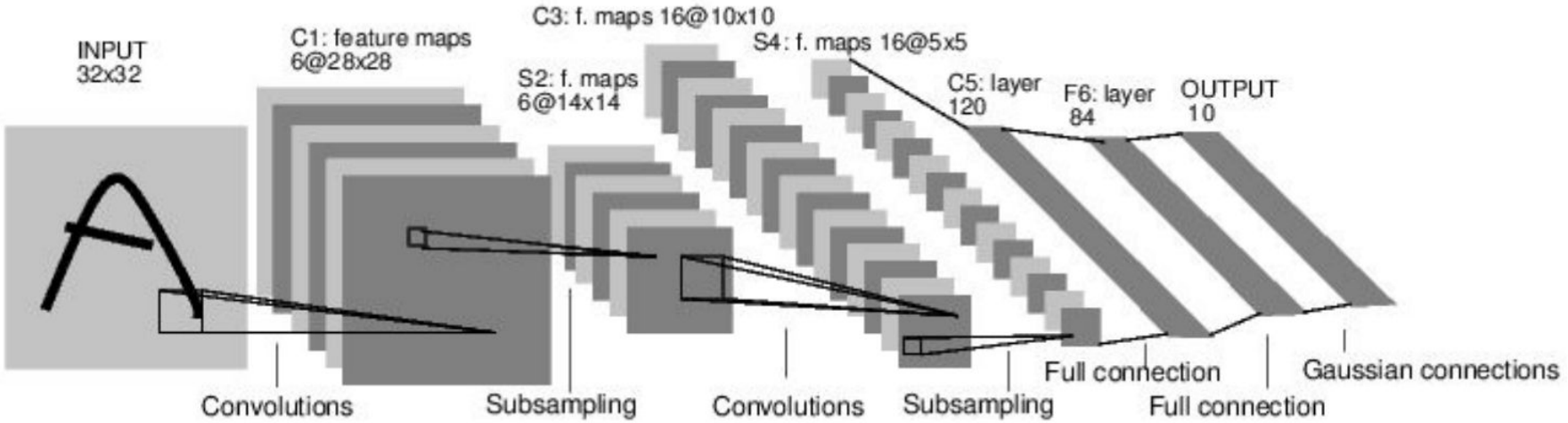
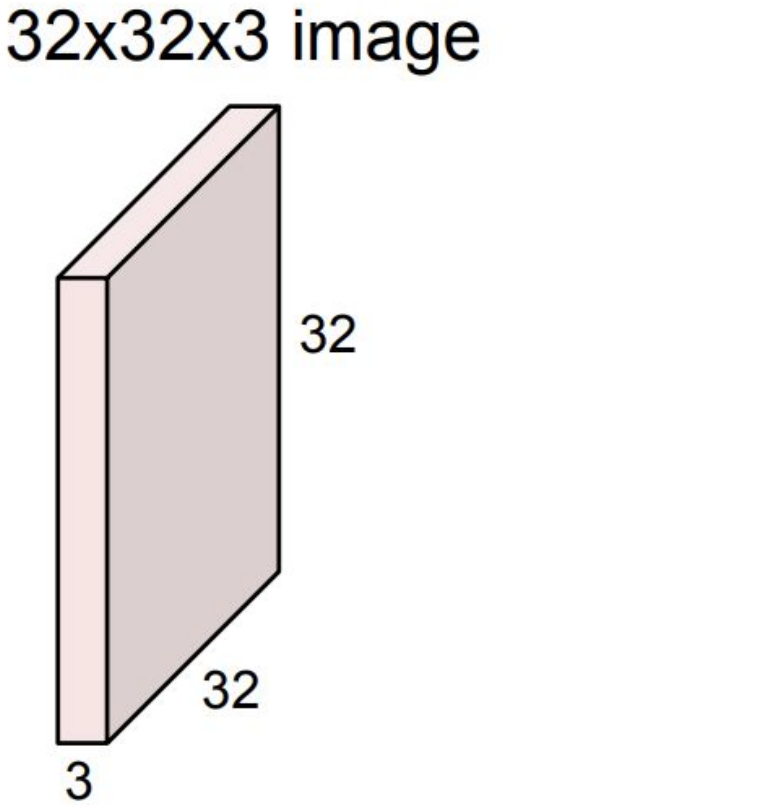
CNN



[LeNet-5, LeCun 1980]

Convolutional layer



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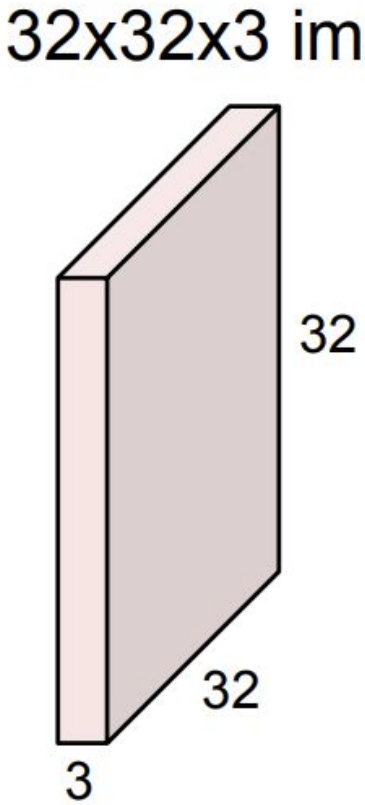
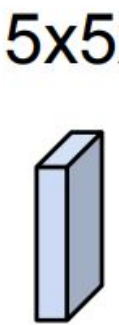
Convolutional layer

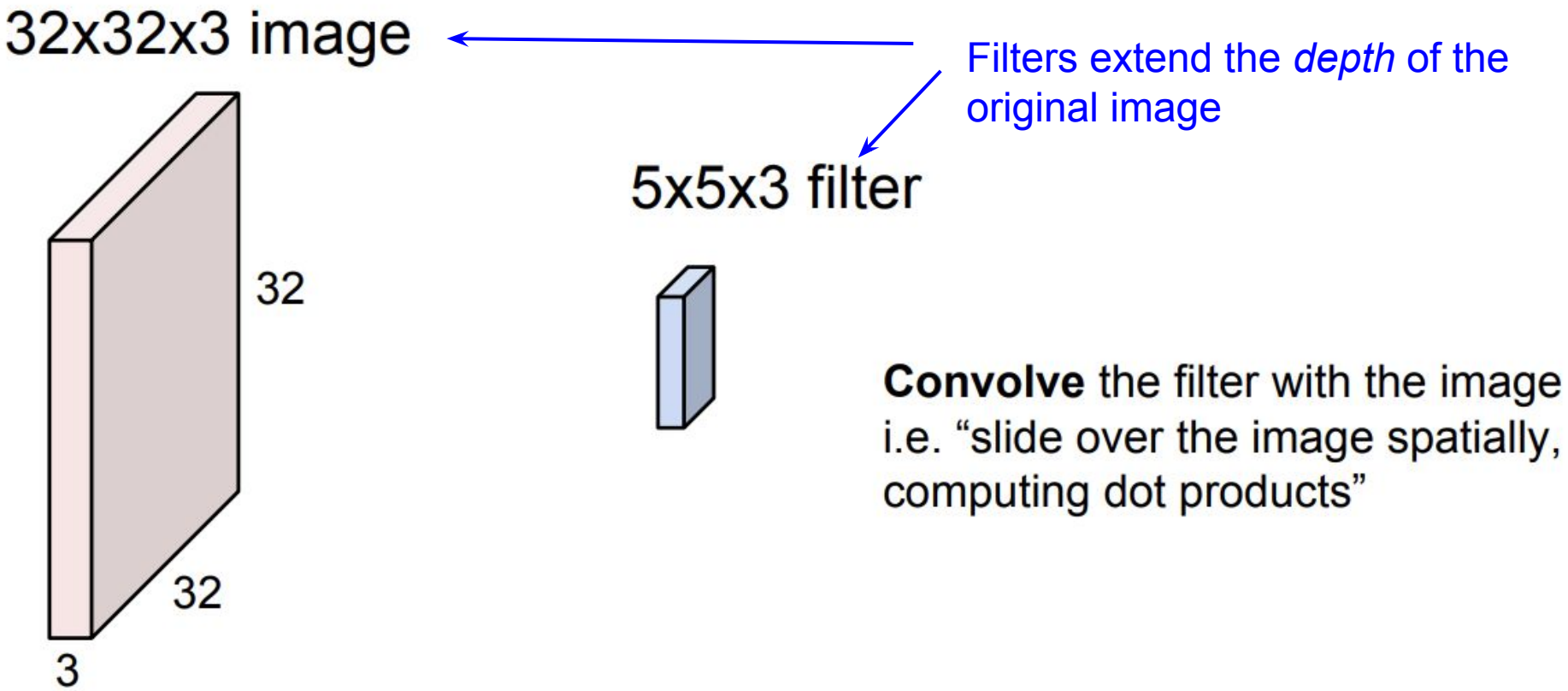




Convolve the filter with the image
i.e. “slide over the image spatially,
computing dot products”

source: http://cs231n.stanford.edu/slides/2016/winter1516_lecture7.pdf

Convolutional layer



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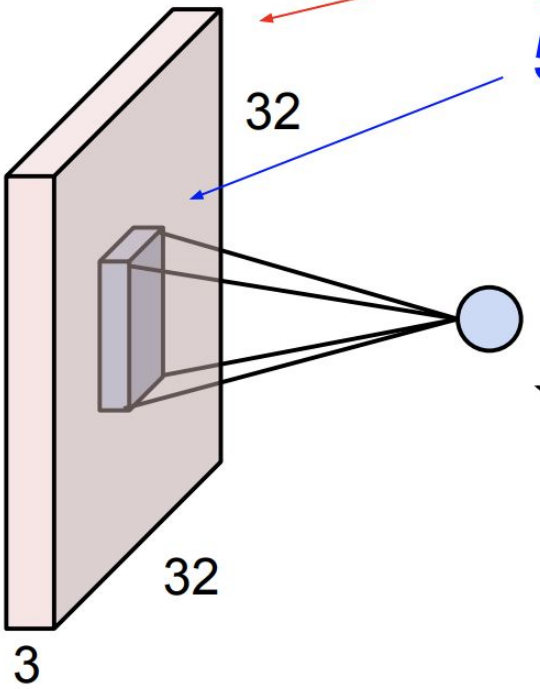
Convolutional layer



32x32x3 image

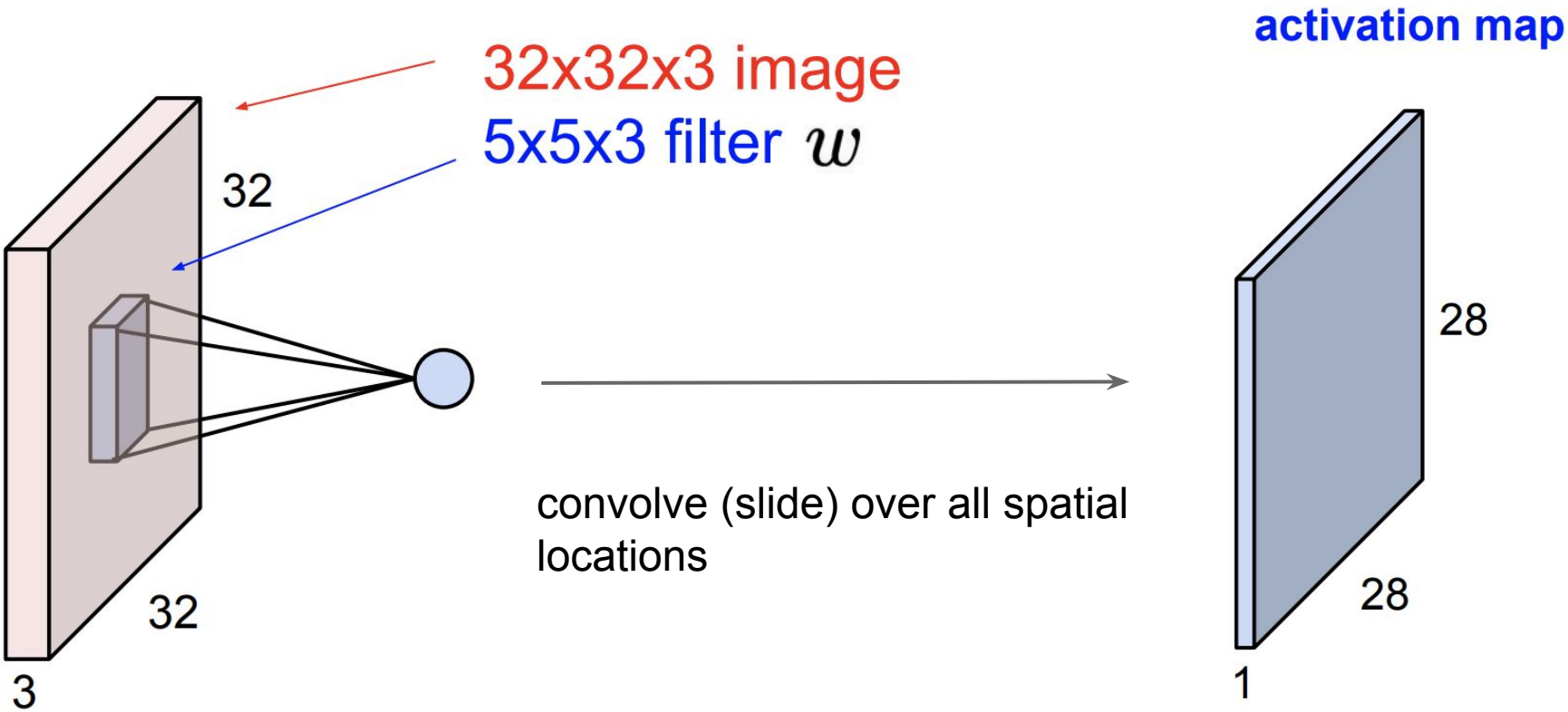
5x5x3 filter w

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)

$$w^T x + b$$

source: http://cs231n.stanford.edu/slides/2016/winter1516_lecture7.pdf

Convolutional layer



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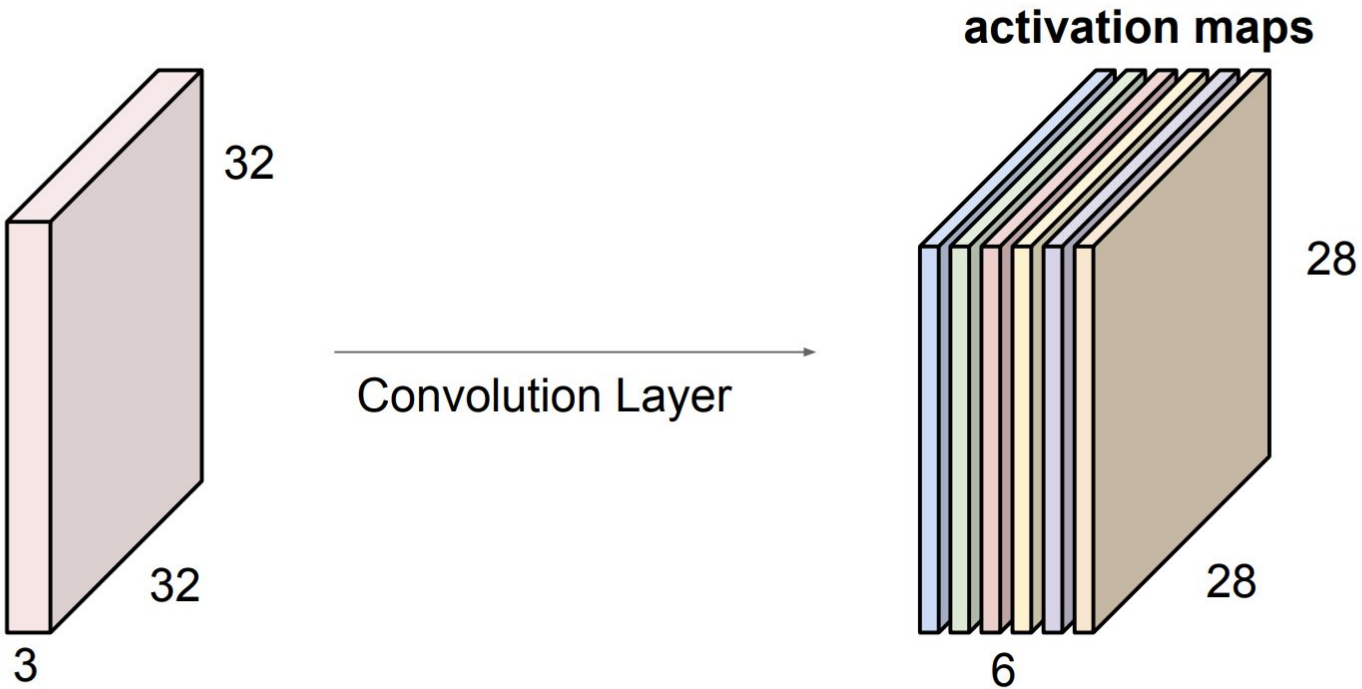
Convolutional layer

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

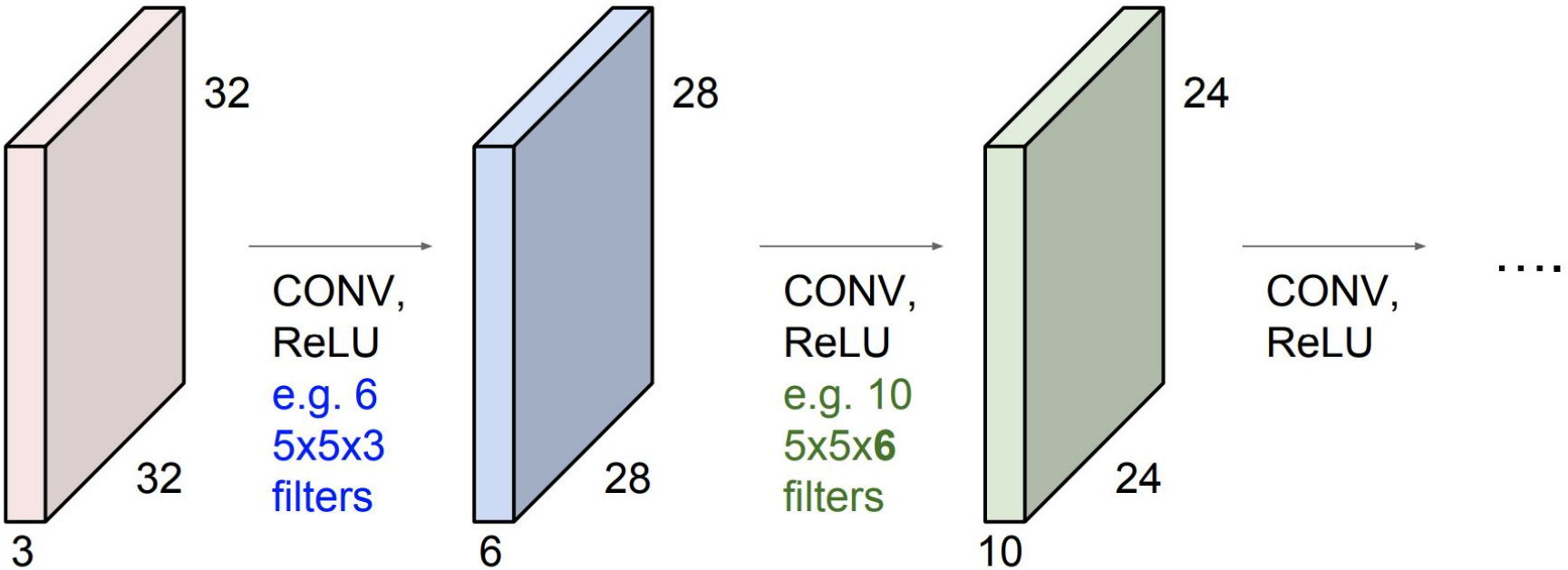


We stack these up to get a "new image" of size 28x28x6!

source: http://cs231n.stanford.edu/slides/2016/winter1516_lecture7.pdf

Convolutional layer

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



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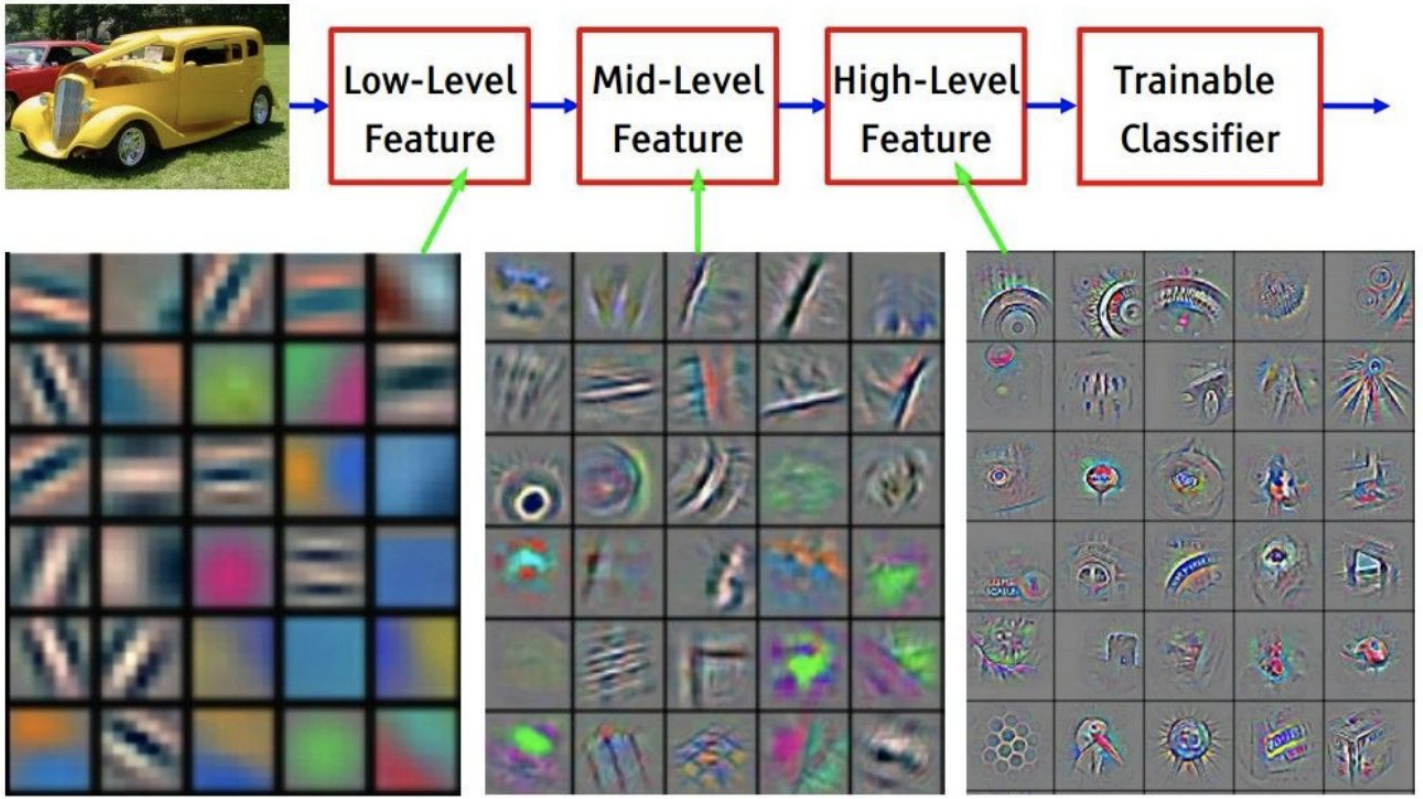
Convolutional layer

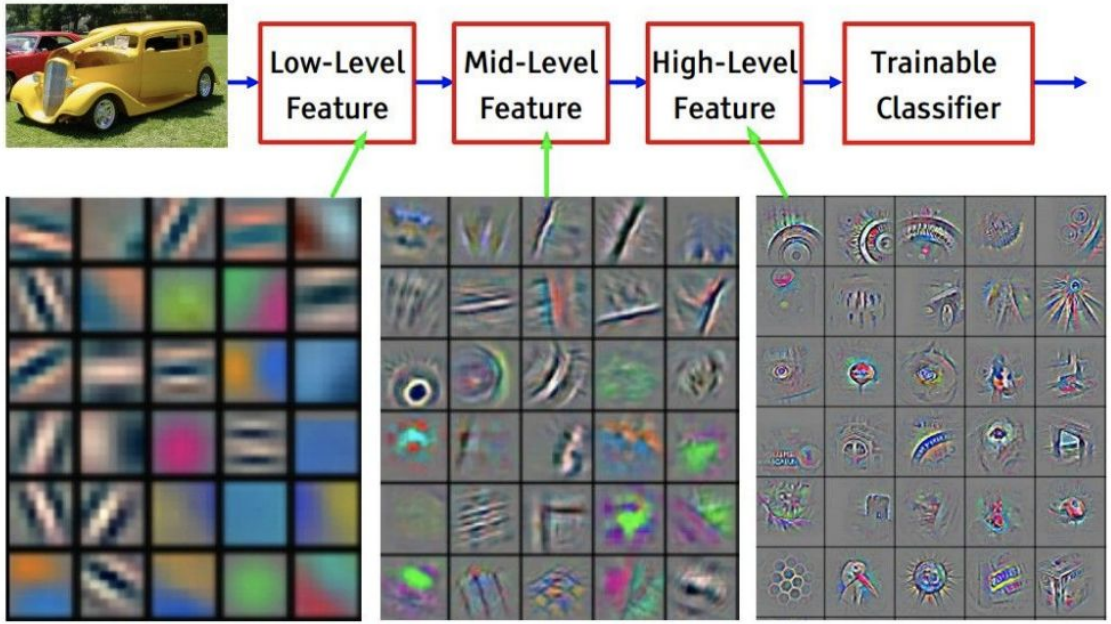


Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

[From Yann LeCun slides]

source: http://cs231n.stanford.edu/slides/2016/winter1516_lecture7.pdf

Convolutional layer and visual cortex



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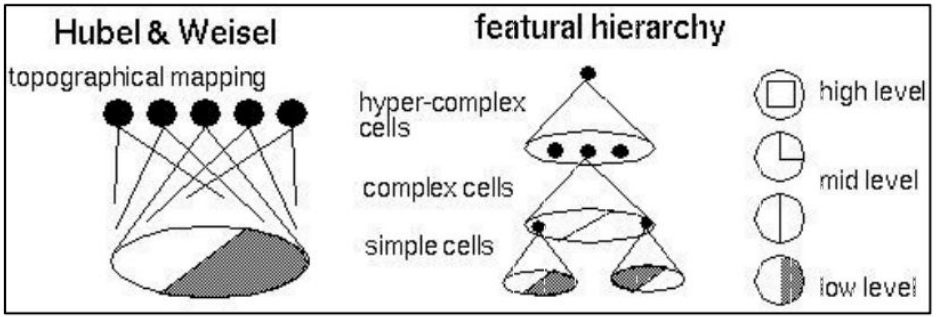

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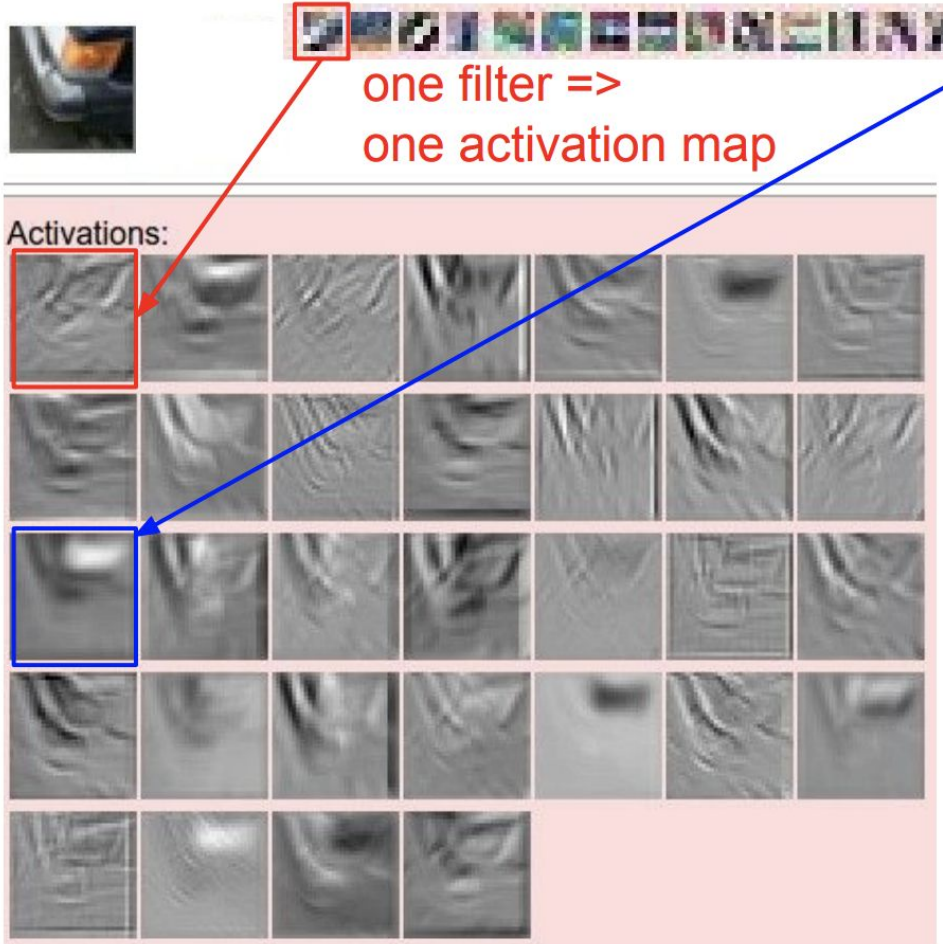


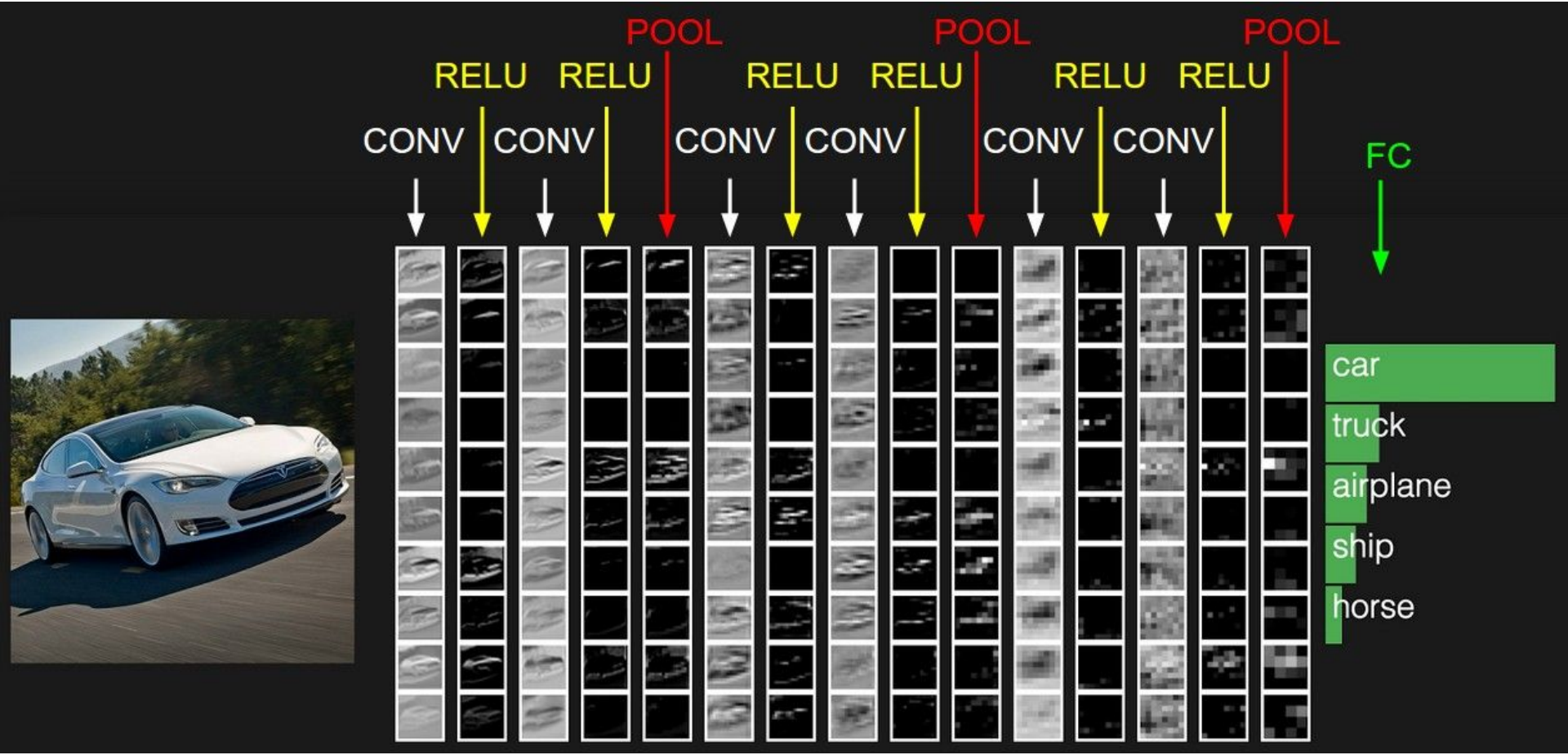
example 5x5 filters
(32 total)

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)

source: http://cs231n.stanford.edu/slides/2016/winter1516_lecture7.pdf



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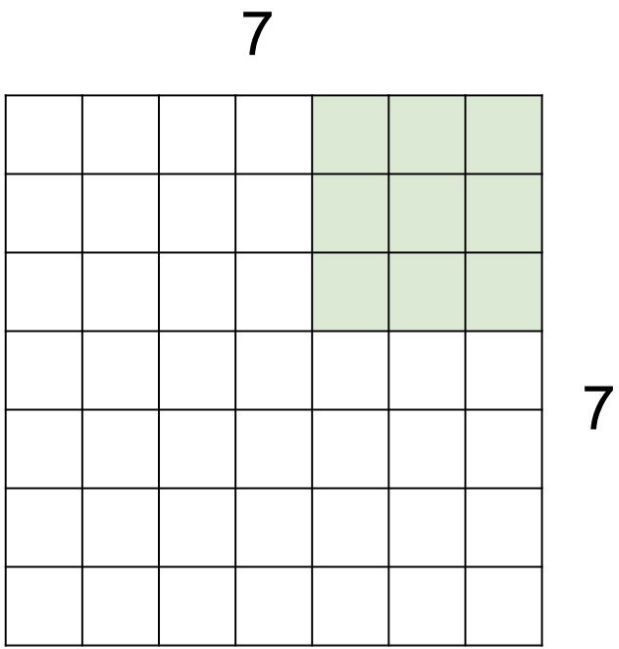
A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter

=> 5x5 output

source: http://cs231n.stanford.edu/slides/2016/winter1516_lecture7.pdf

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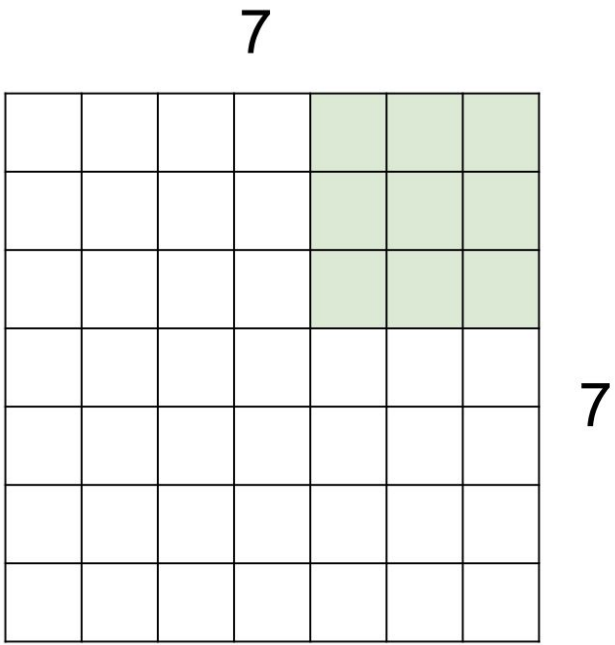
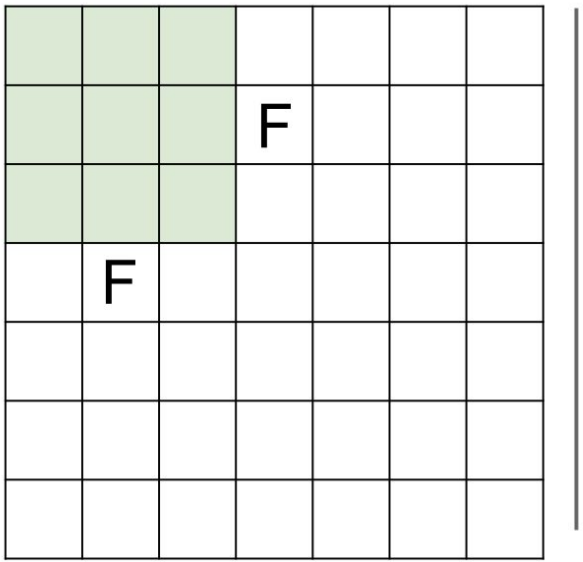


7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**
=> 3x3 output!

source: http://cs231n.stanford.edu/slides/2016/winter1516_lecture7.pdf

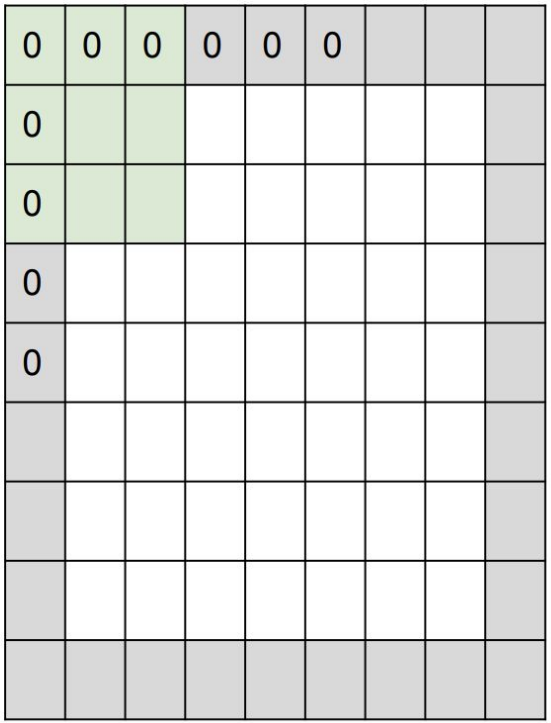


Output size:
(N - F) / stride + 1

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 :\

source: http://cs231n.stanford.edu/slides/2016/winter1516_lecture7.pdf

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)
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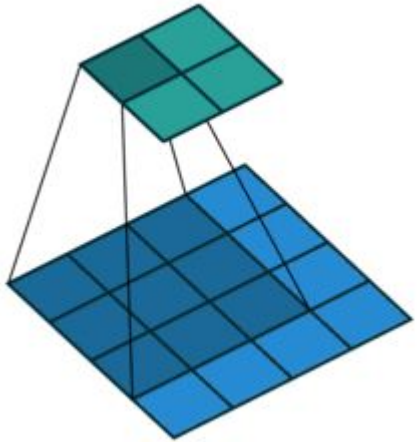
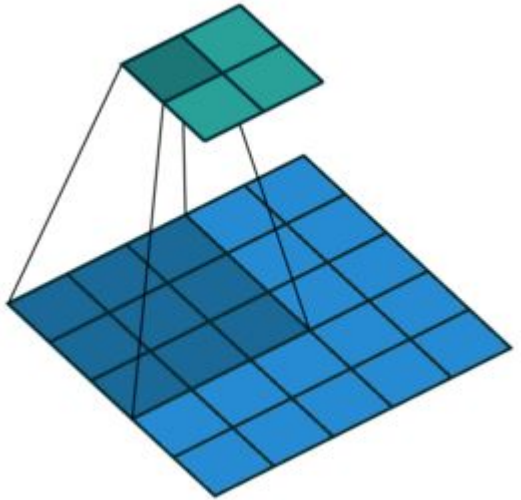
Strides, padding in convolutional layer



No padding,
no strides



No padding,
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Image source: https://github.com/vdumoulin/conv_arithmetic

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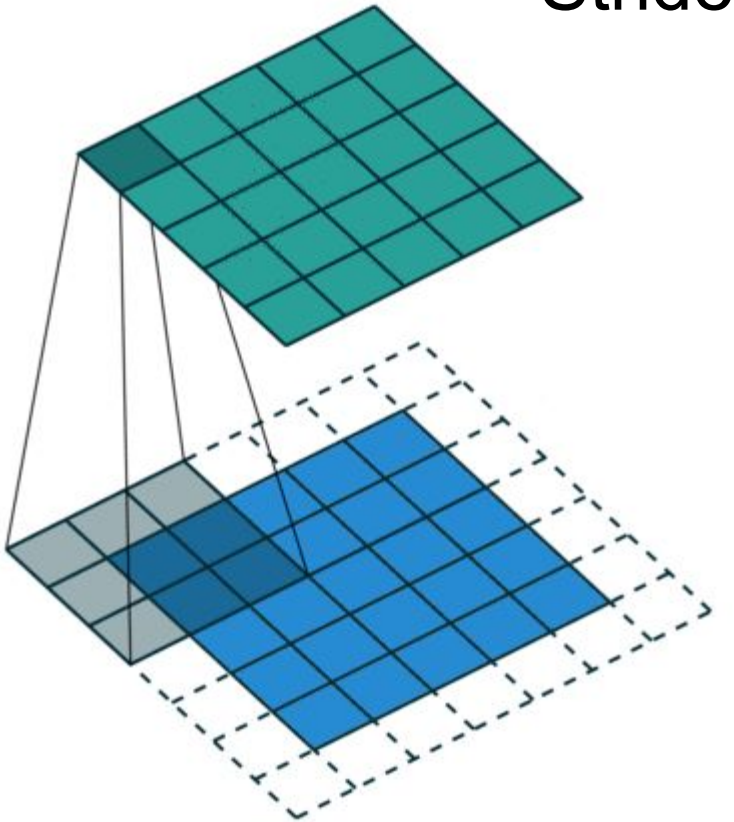
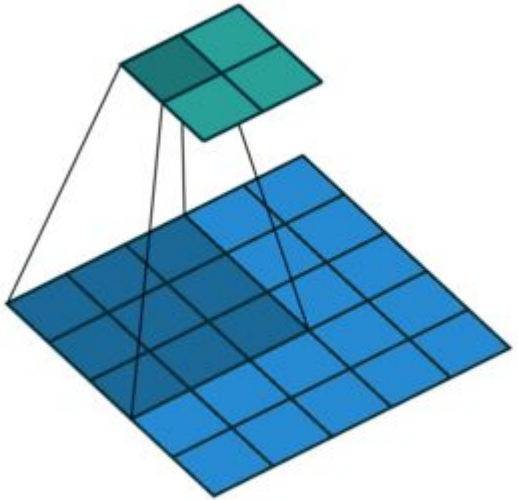


With padding,
no strides



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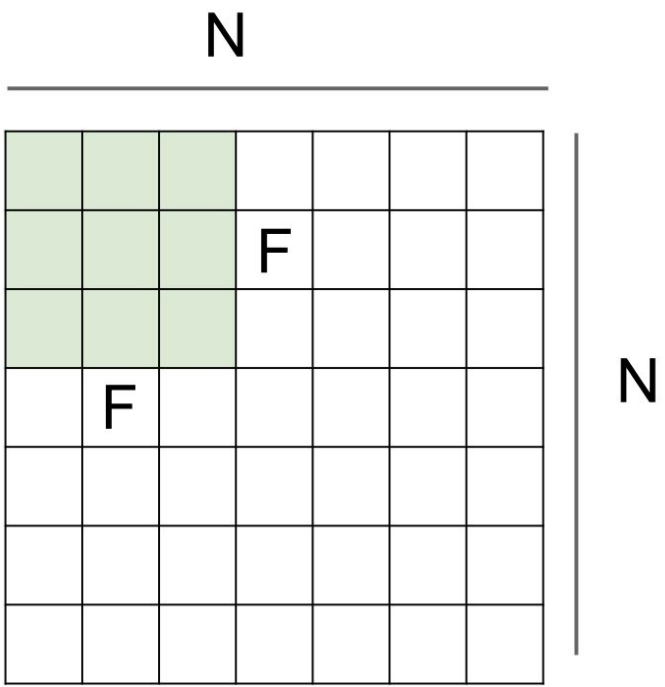

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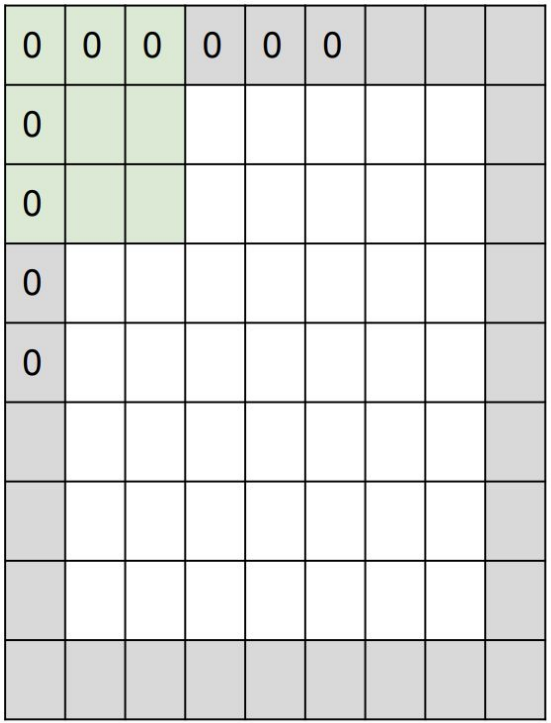

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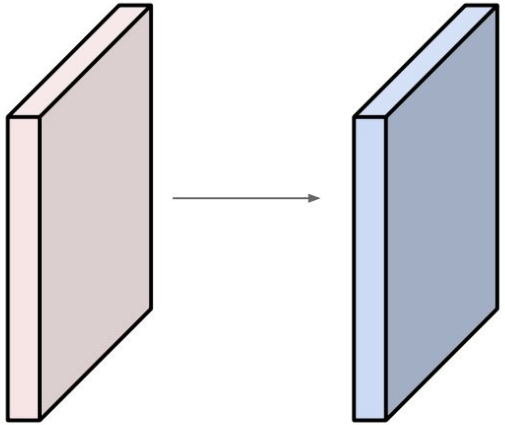
Examples time:



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

Output volume size: ?

source: http://cs231n.stanford.edu/slides/2016/winter1516_lecture7.pdf

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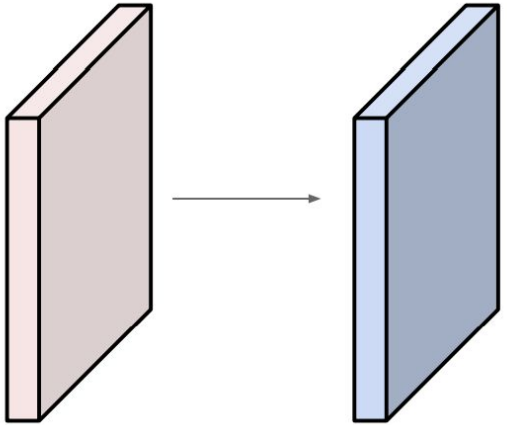
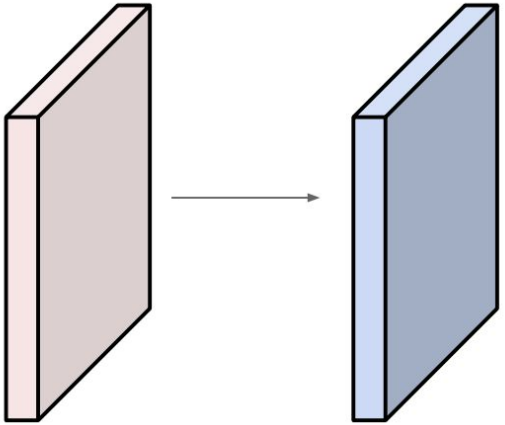


Input volume: **32x32x3**
10 5x5 filters with stride 1, pad 2

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

source: http://cs231n.stanford.edu/slides/2016/winter1516_lecture7.pdf

Examples time:



Input volume: **32x32x3**
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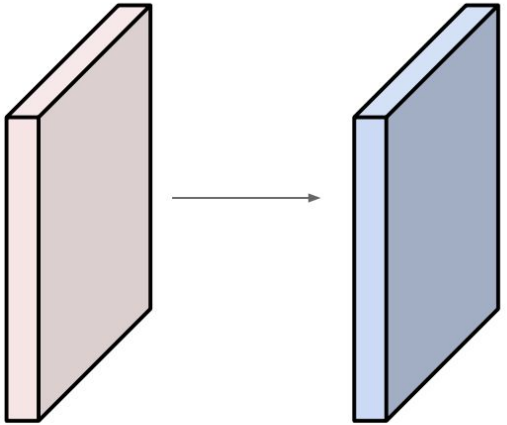
Number of parameters in this layer?

source: http://cs231n.stanford.edu/slides/2016/winter1516_lecture7.pdf

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**

source: http://cs231n.stanford.edu/slides/2016/winter1516_lecture7.pdf

Summary. To summarize, the Conv Layer:

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

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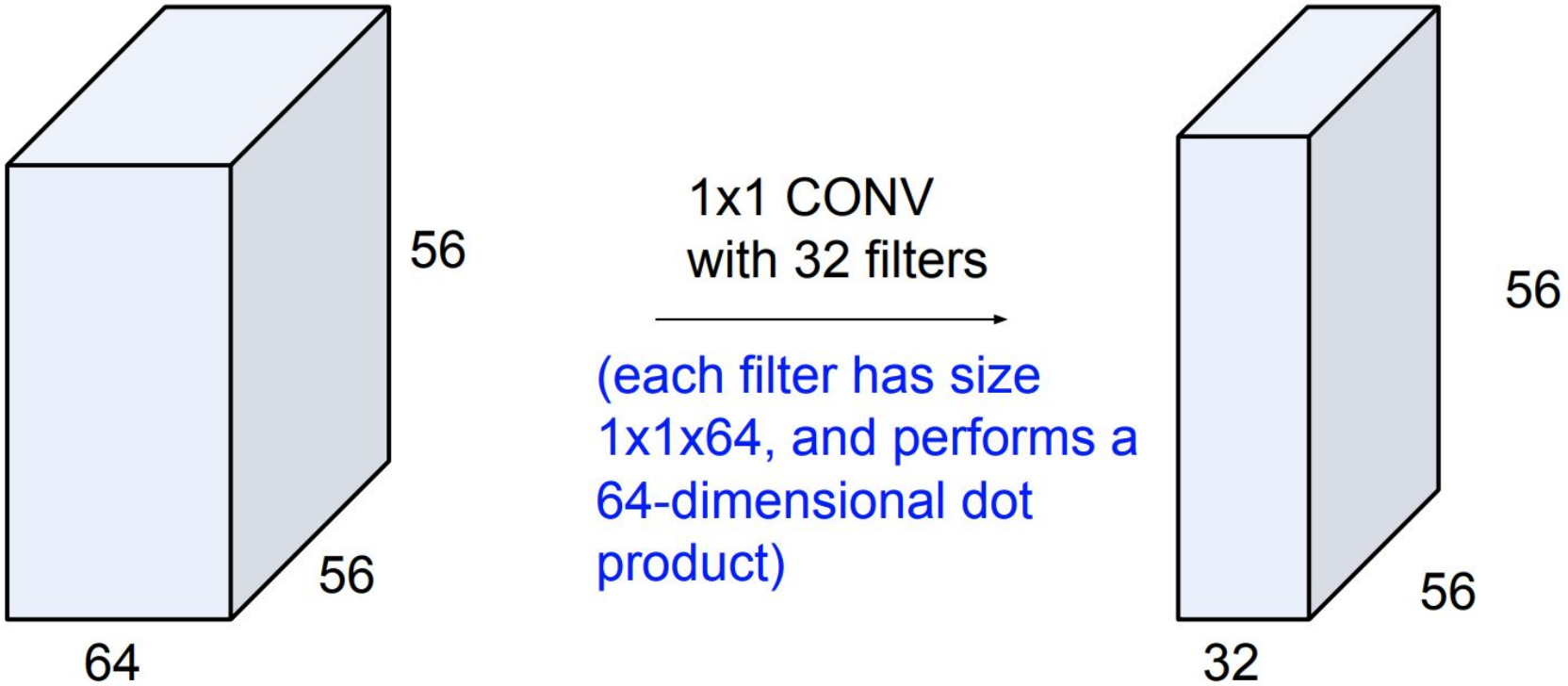
Common settings:

- K = (powers of 2, e.g. 32, 64, 128, 512)
- F = 3, S = 1, P = 1
- F = 5, S = 1, P = 2
- F = 5, S = 2, P = ? (whatever fits)
- F = 1, S = 1, P = 0

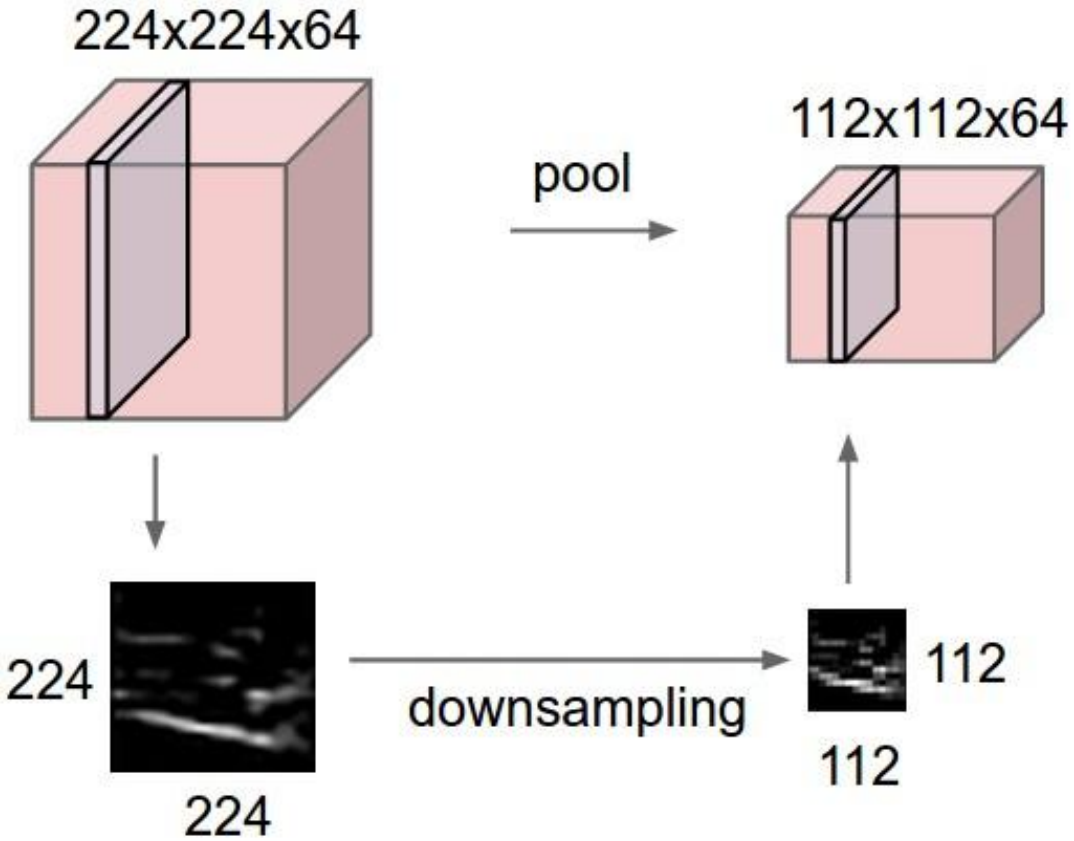
source: http://cs231n.stanford.edu/slides/2016/winter1516_lecture7.pdf

1x1 convolutions



source: http://cs231n.stanford.edu/slides/2016/winter1516_lecture7.pdf

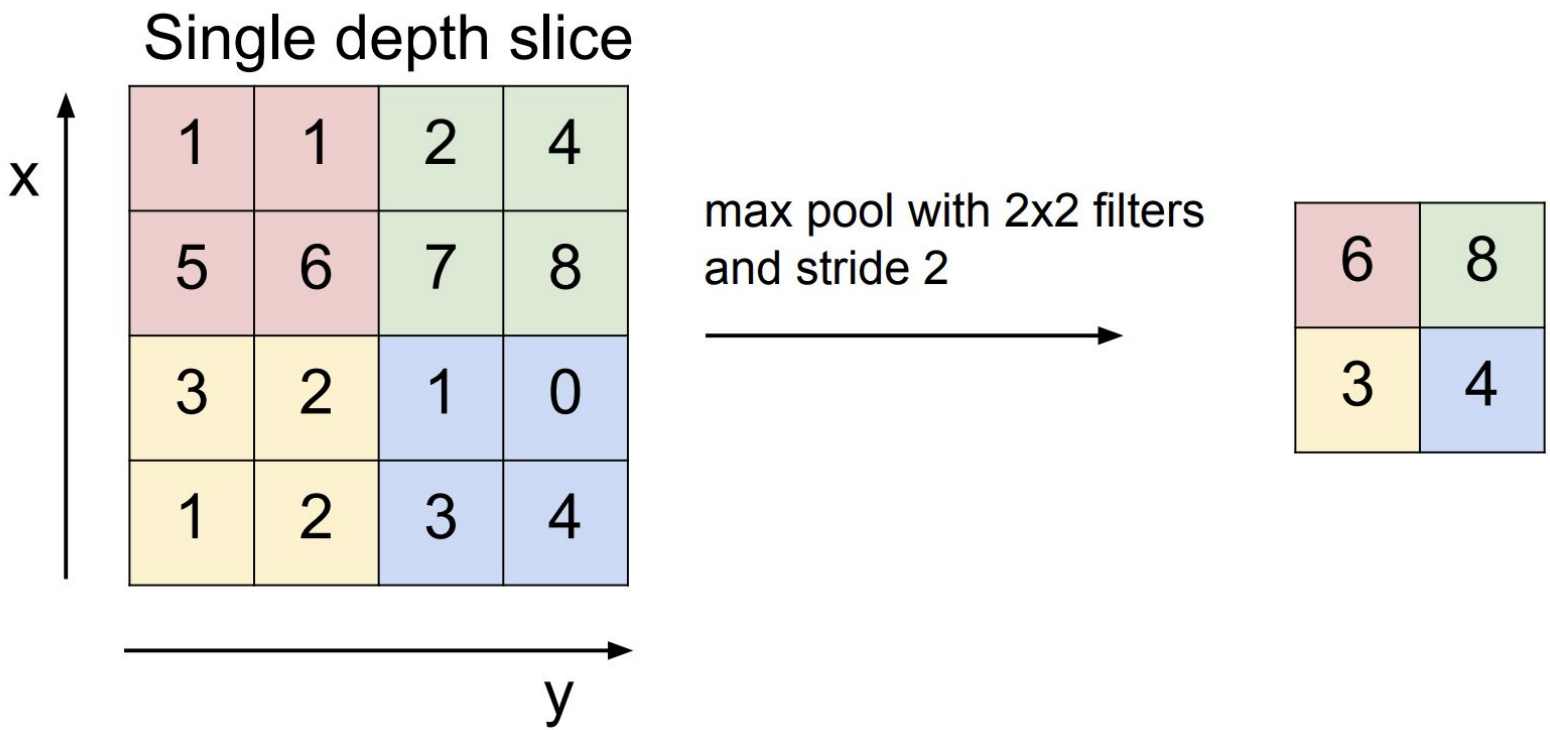
Pooling layer



- Makes the representations smaller and more manageable
- Operates over each activation map independently

source: http://cs231n.stanford.edu/slides/2016/winter1516_lecture7.pdf

Max pooling



source: http://cs231n.stanford.edu/slides/2016/winter1516_lecture7.pdf

Pooling layer: sum up

- Accepts a volume of size $W_1 \times H_1 \times D_1$
- Requires two hyperparameters:
  - their spatial extent F,
  - the stride S,
- Produces a volume of size $W_2 \times H_2 \times D_2$ where:
  - $W_2 = (W_1 - F)/S + 1$
  - $H_2 = (H_1 - F)/S + 1$
  - $D_2 = D_1$
- Introduces zero parameters since it computes a fixed function of the input
- For Pooling layers, it is not common to pad the input using zero-padding.

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Common settings:

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

source: http://cs231n.stanford.edu/slides/2016/winter1516_lecture7.pdf

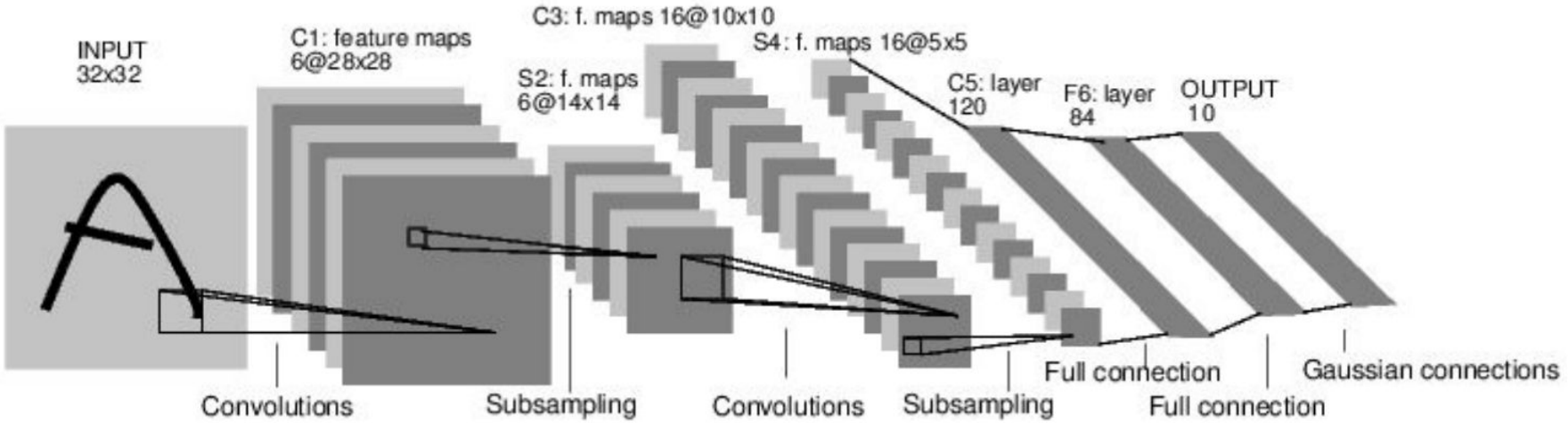
Example time

Great in-browser CNN (using js) demo by Andrej Karpathy:

https://cs.stanford.edu/people/karpathy/convnetjs/demo/cifar10.html

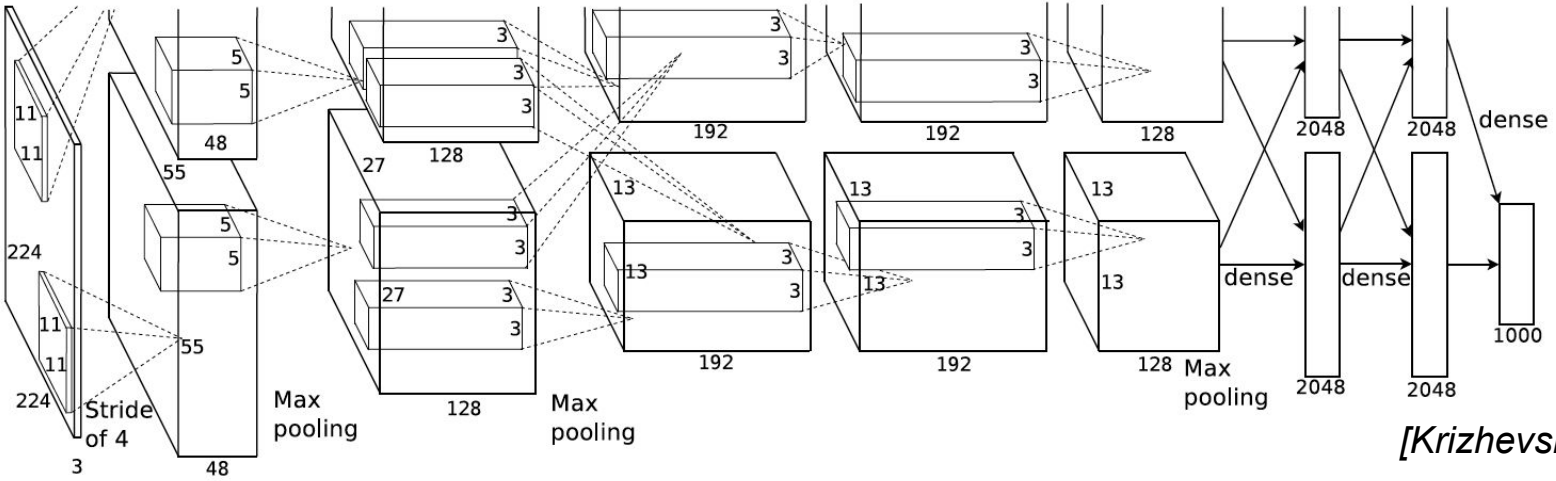
Architectures overview

LeNet-5



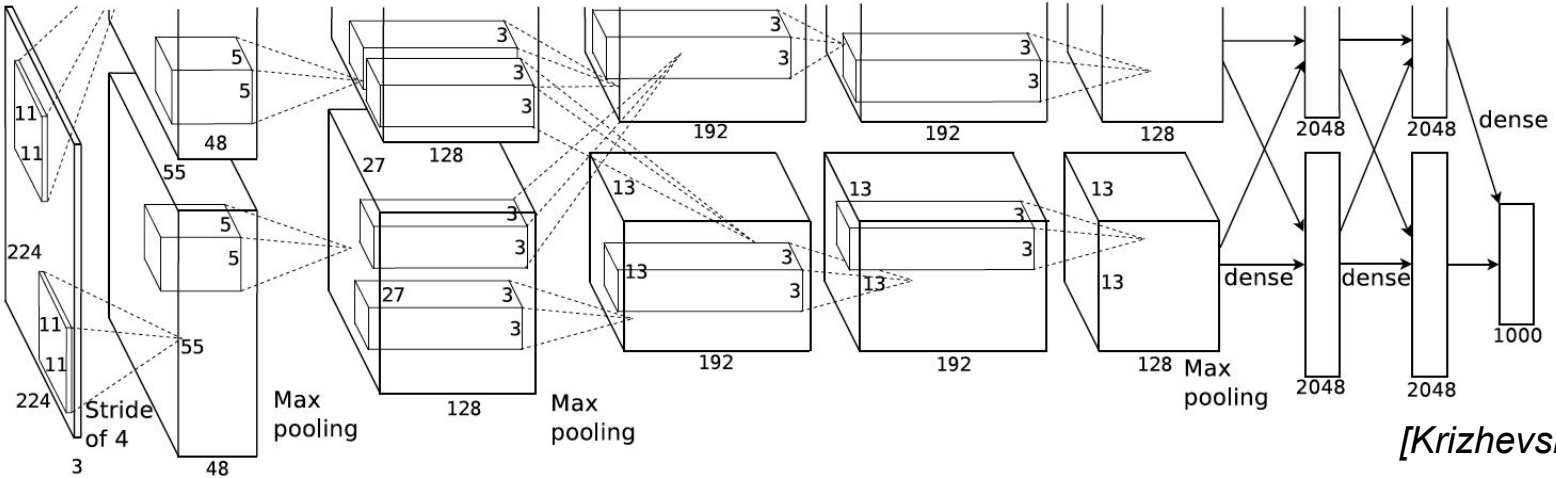
[LeNet-5, LeCun 1980]

AlexNet



[Krizhevsky et al. 2012]

AlexNet

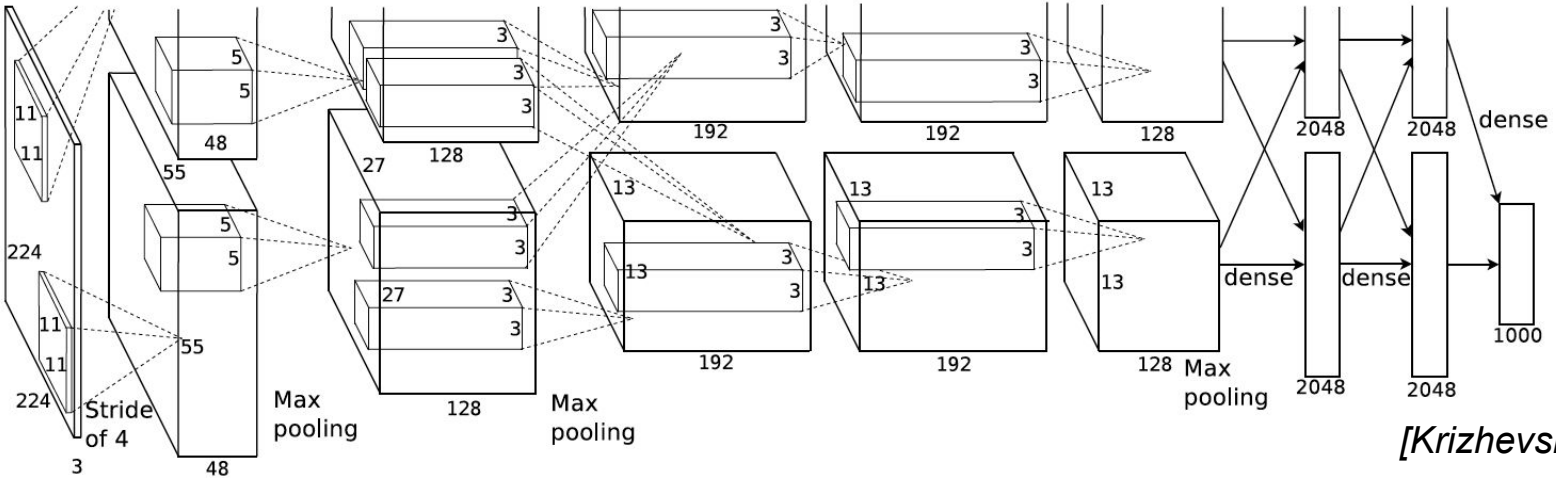


[Krizhevsky et al. 2012]

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)

source: http://cs231n.stanford.edu/slides/2016/winter1516_lecture7.pdf

AlexNet



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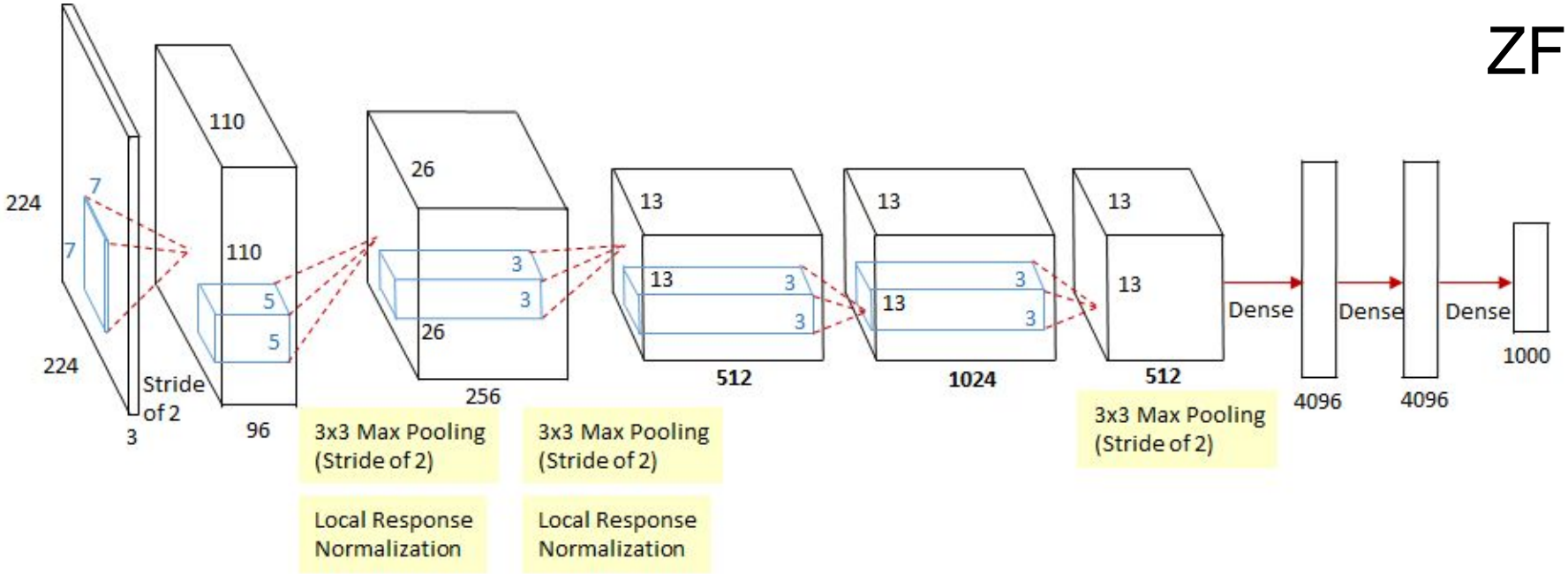
Details/Retrospectives:
- first use of ReLU
- used Norm layers (not common anymore)
- heavy data augmentation
- dropout 0.5
- batch size 128
- SGD Momentum 0.9
- Learning rate 1e-2, reduced by 10 manually when val accuracy plateaus
- L2 weight decay 5e-4
- 7 CNN ensemble: 18.2% -> 15.4%

source: http://cs231n.stanford.edu/slides/2016/winter1516_lecture7.pdf

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%

source: http://cs231n.stanford.edu/slides/2016/winter1516_lecture7.pdf

VGGNet

(not counting biases)

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
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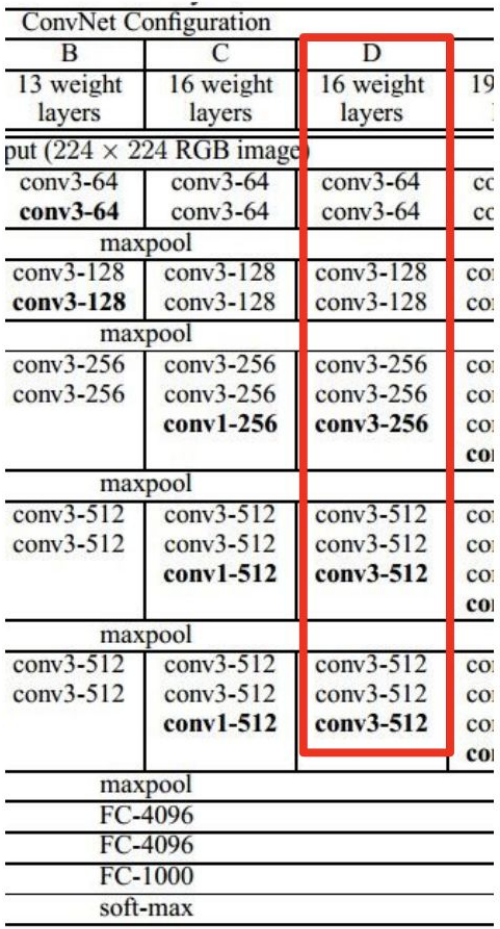
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
POOL2: [7x7x512] memory: 7*7*512=25K params: 0
FC: [1x1x4096] memory: 4096 params: 7*7*512*4096 = 102,760,448
FC: [1x1x4096] memory: 4096 params: 4096*4096 = 16,777,216
FC: [1x1x1000] memory: 1000 params: 4096*1000 = 4,096,000

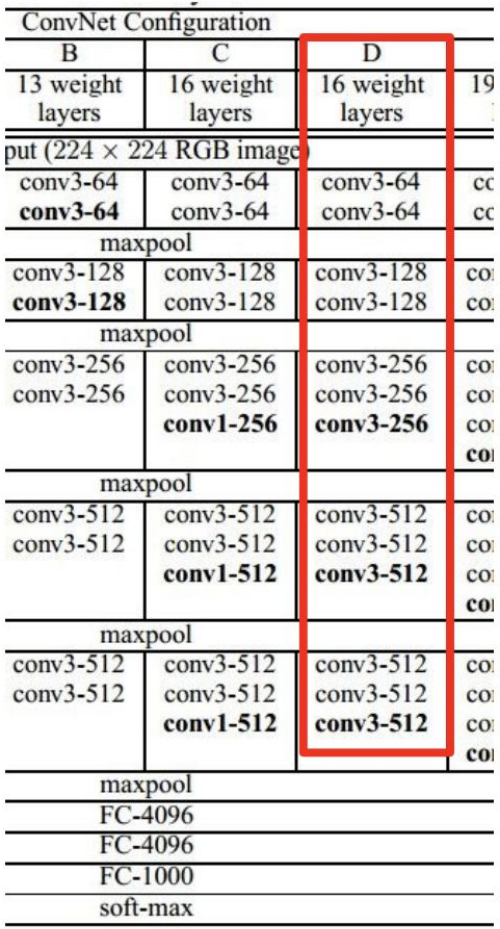
TOTAL memory: 24M * 4 bytes ~= 93MB / image (only forward! ~*2 for bwd)
TOTAL params: 138M parameters



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

VGGNet

7.3% top 5 error



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maxpool			
conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	co co
maxpool			
conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	co co co **co**
maxpool			
conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	co co co **co**
maxpool			
conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	co co co **co**
maxpool			
FC-4096			
FC-4096			
FC-1000			
soft-max			

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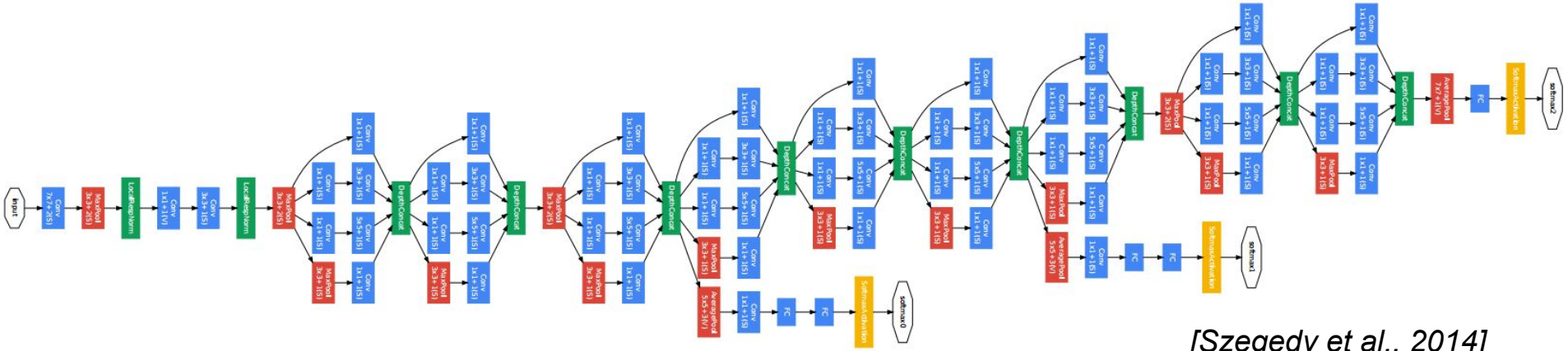
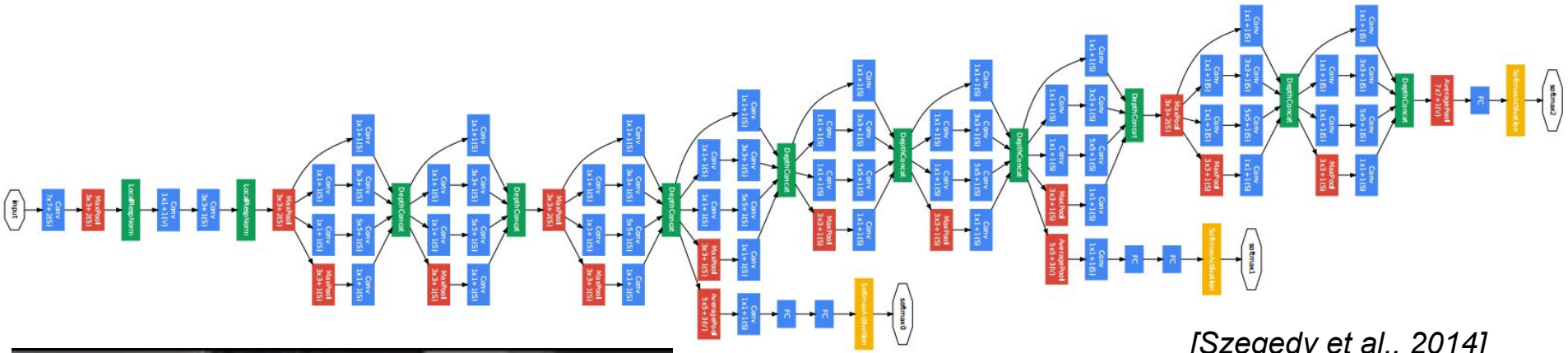
GoogLe net



[Szegedy et al., 2014]

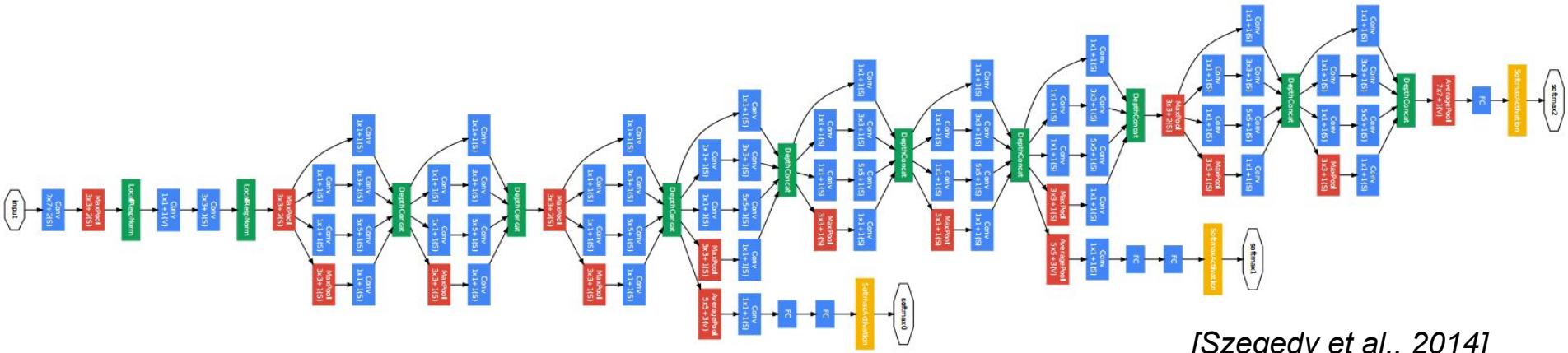
GoogLe net



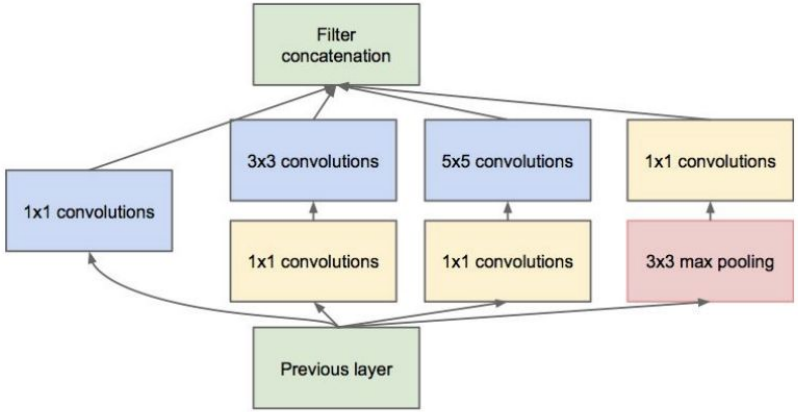
[Szegedy et al., 2014]

Inception module

GoogLe net



[Szegedy et al., 2014]



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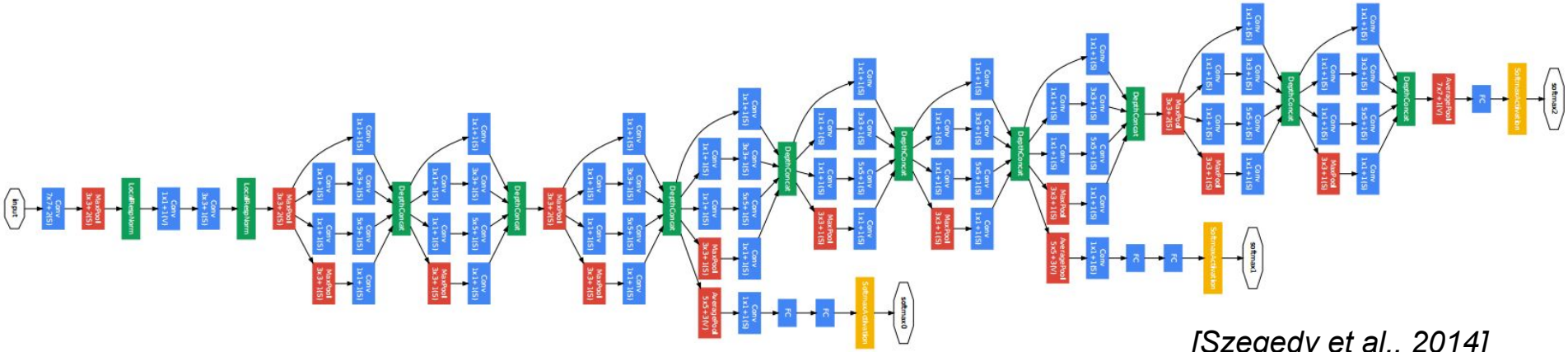
GoogLe net



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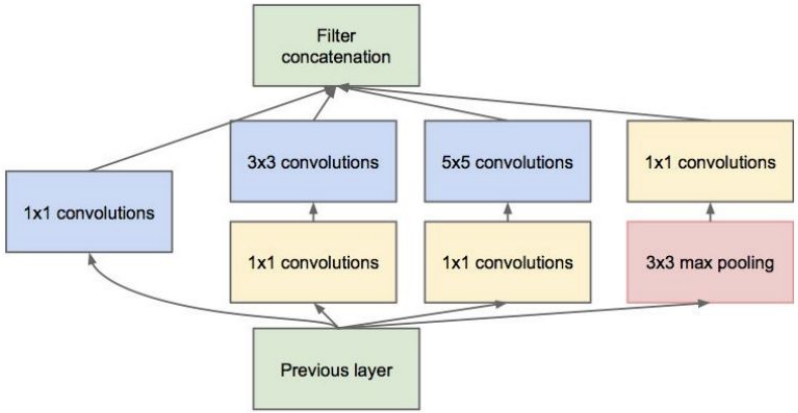
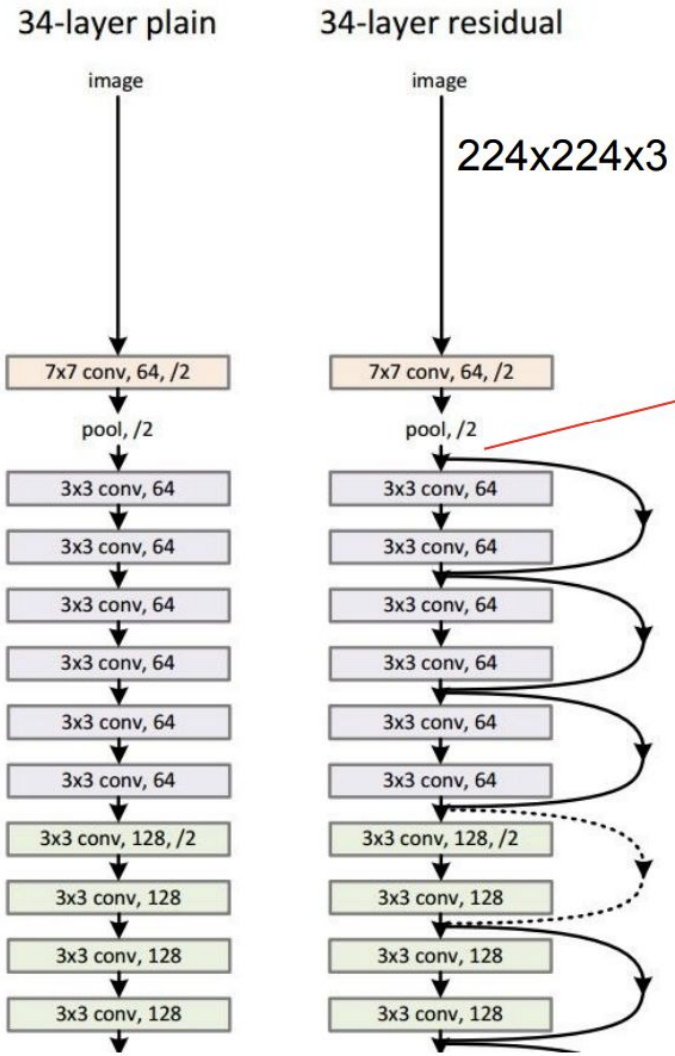


Inception module

ILSVRC 2014 winner (6.7% top 5 error)

ResNet

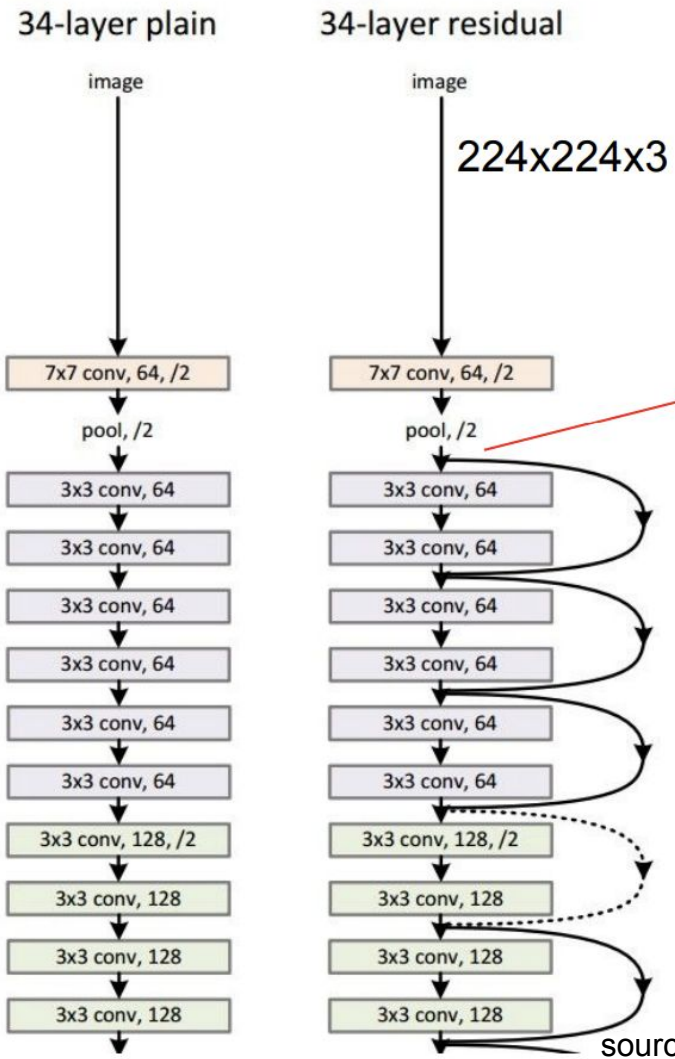


[He et al., 2015]

spatial dimension
only 56x56!

ILSVRC 2015 winner (3.6% top 5 error)

ResNet



[He et al., 2015]

spatial dimension
only 56x56!

- 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)

source: http://cs231n.stanford.edu/slides/2016/winter1516_lecture7.pdf

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.

Q & A

That’s all. Feel free to ask any questions.