CS60010: Deep Learning

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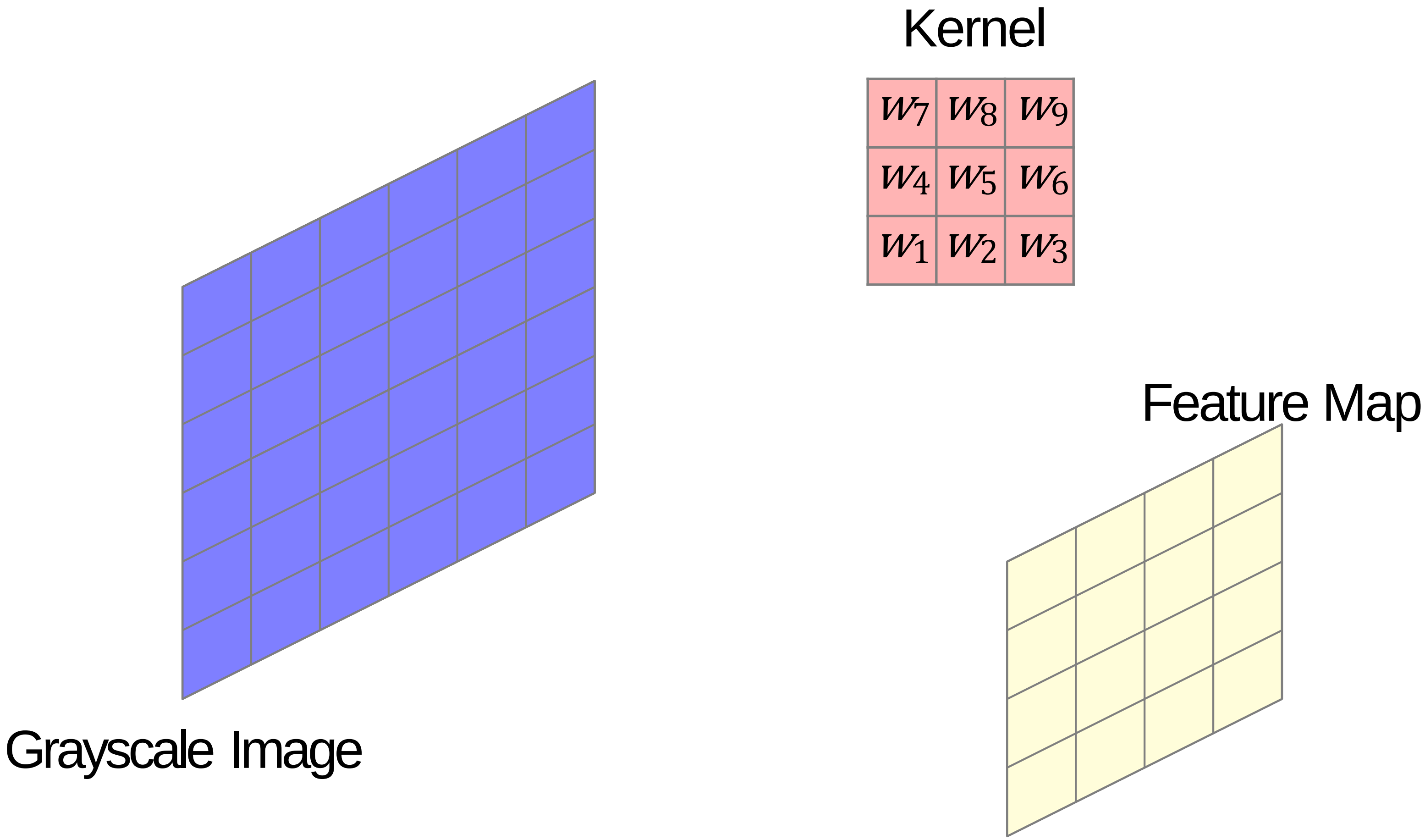
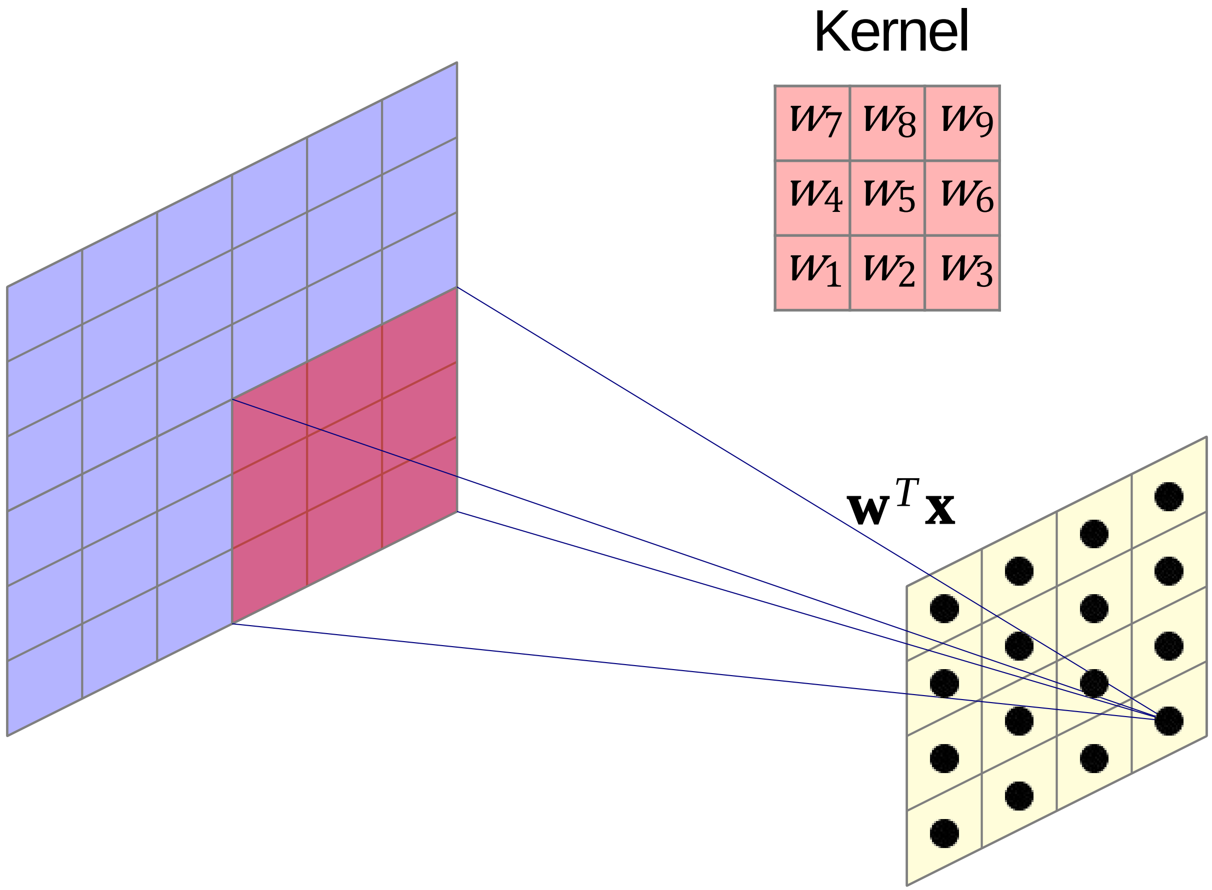
Convolution

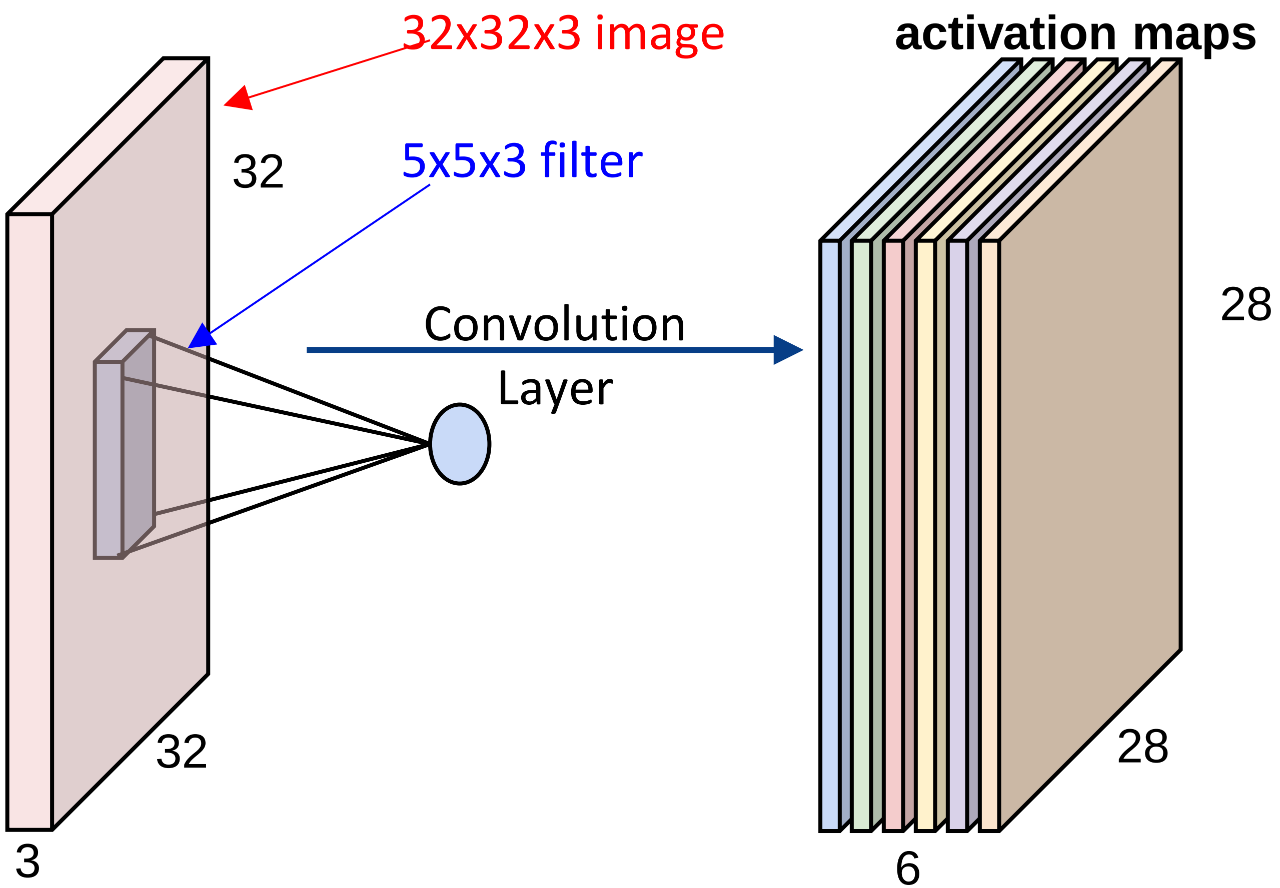


Convolve image with kernel having weights $\mathbf{w}$ (learned by backpropagation)

Convolution



What is the number of parameters?



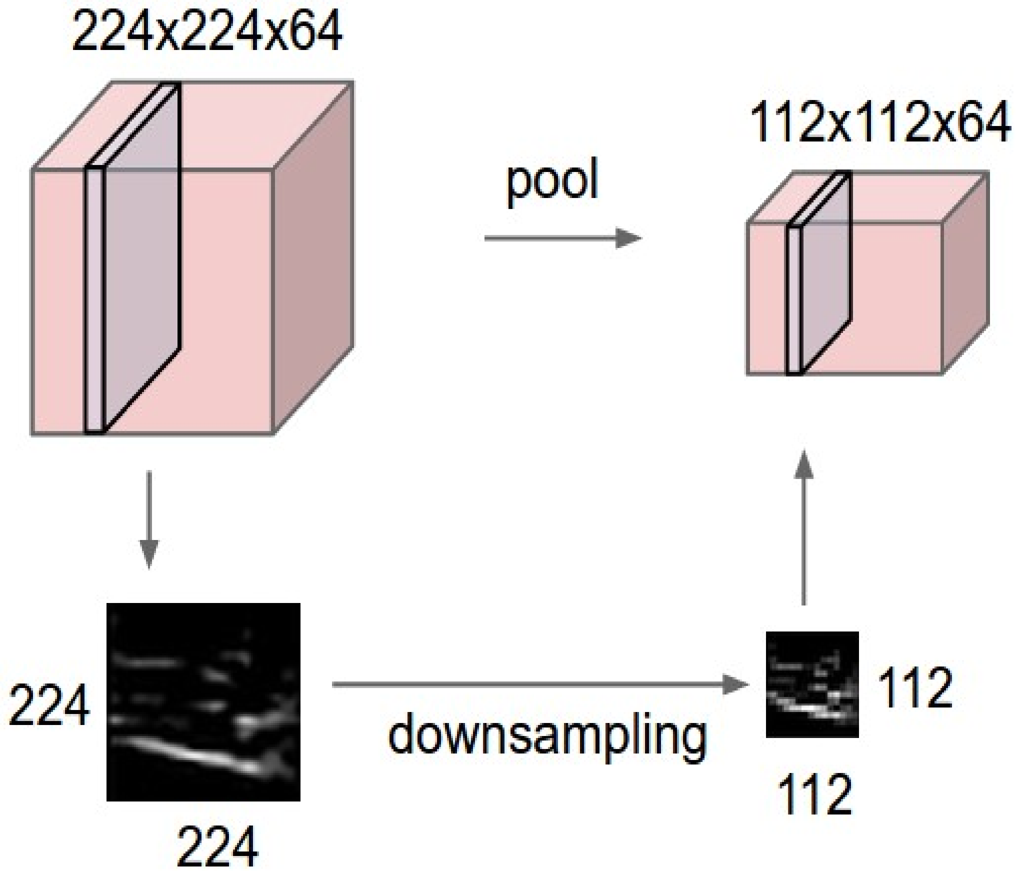
If we had 6 5x5 filters, we'll get 6 activation maps.
We stack these up to get a "new image" of size 28x28x6!

Summary. To summarize, the Conv Layer:

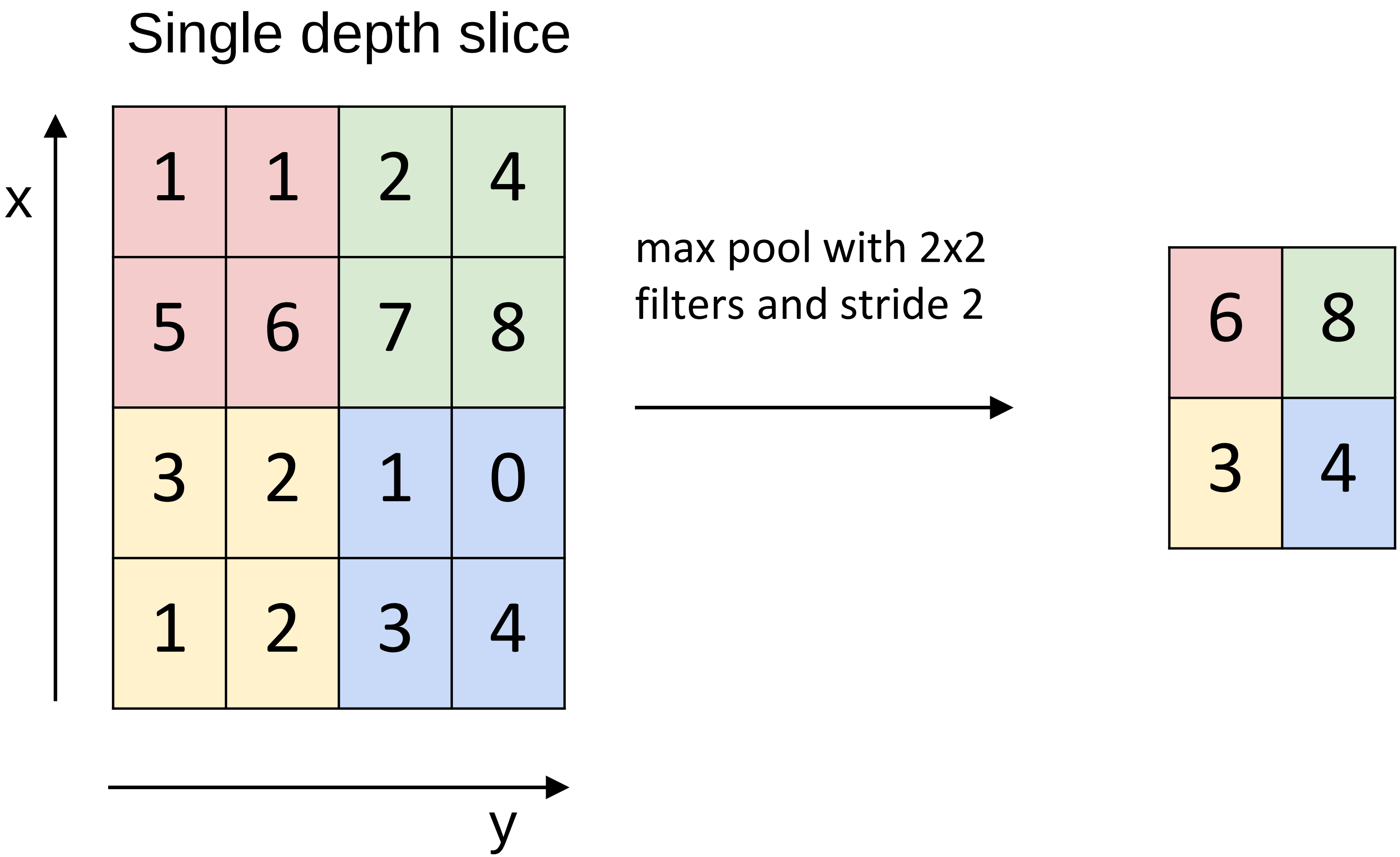
- Accepts a volume of size $W_1 \times H_1 \times D_1$
- Requires four hyperparameters:
  - Number of filters K,
  - their spatial extent F,
  - the stride S,
  - the amount of zero padding P.
- Produces a volume of size $W_2 \times H_2 \times D_2$ where:
  - $W_2 = (W_1 - F + 2P)/S + 1$
  - $H_2 = (H_1 - F + 2P)/S + 1$ (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.

Pooling layer

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

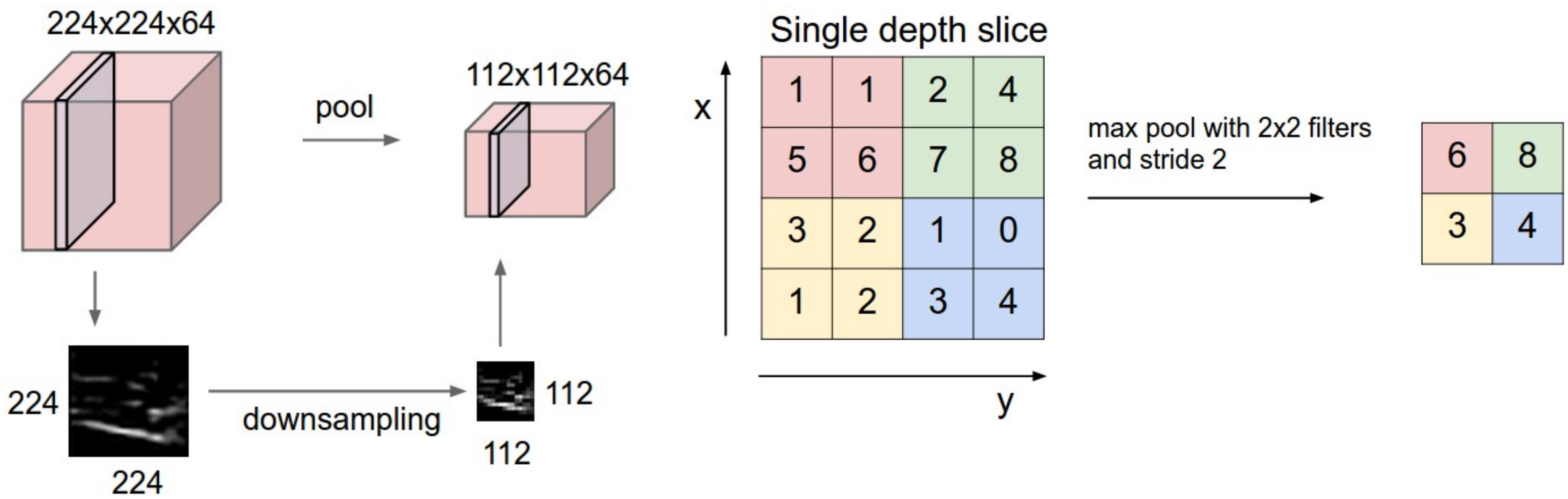


MAX POOLING


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

General pooling

- Other pooling functions: Average pooling, L2-norm pooling



- Backpropagation. the backward pass for a max(x, y) operation routes the gradient to the input that had the highest value in the forward pass.
- Hence, during the forward pass of a pooling layer you may keep track of the index of the max activation (sometimes also called the switches) so that gradient routing is efficient during backpropagation.

Getting rid of pooling

Striving for Simplicity: The All Convolutional Net

- proposes to discard the pooling layer and have an architecture that only consists of repeated CONV layers.
- To reduce the size of the representation they suggest using larger stride in CONV layer once in a while.

- Argument:
  - The purpose of pooling layers is to perform dimensionality reduction to widen subsequent convolutional layers' receptive fields.
  - The same effect can be achieved by using a convolutional layer: using a stride of 2 also reduces the dimensionality of the output and widens the receptive field of higher layers.
- The resulting operation differs from a max-pooling layer in that
  - it cannot perform a true max operation
  - it allows pooling across input channels.

Getting rid of pooling

Very Deep Convolutional Networks for Large-Scale Image Recognition.

- The core idea here is that hand-tuning layer kernel sizes to achieve optimal receptive fields (say, 5×5 or 7×7) can be replaced by simply stacking homogenous 3×3 layers.
  - three stacked 3×3 have a 7×7 receptive field.
  - At the same time, the number of parameters is reduced:
  - a 7×7 layer has 81% more parameters than three stacked 3×3 layers.

[ConvNetJS demo: training on CIFAR-10]

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

Case Studies

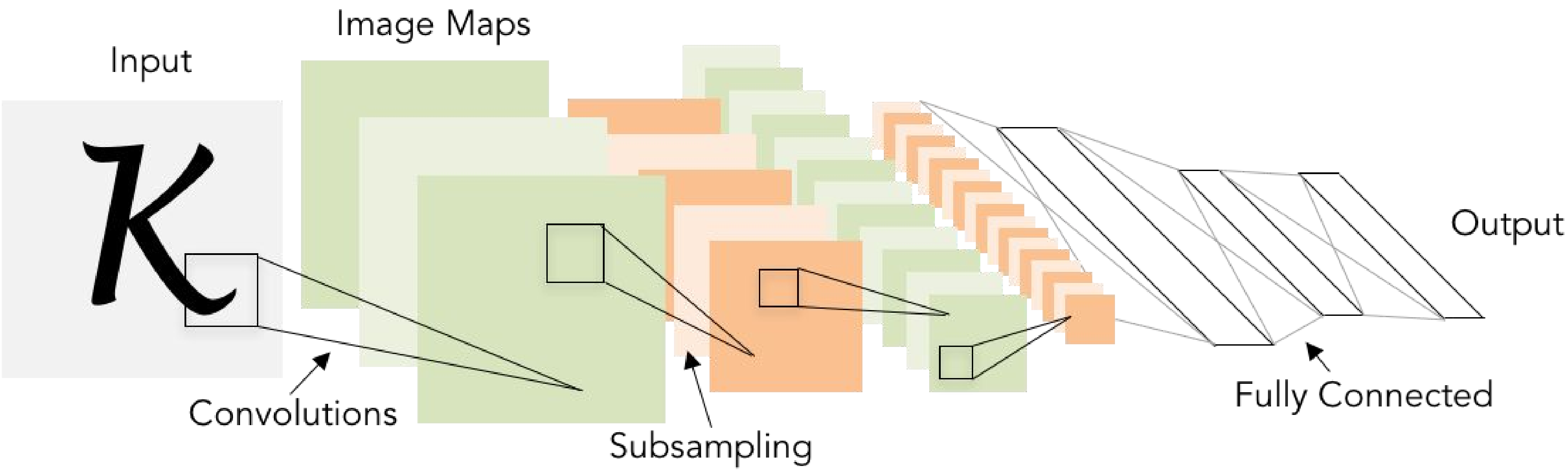
- **LeNet**. The first successful applications of Convolutional Networks were developed by Yann LeCun in 1990's. was used to read zip codes, digits, etc.
- **AlexNet**. popularized Convolutional Networks in Computer Vision, developed by Alex Krizhevsky, Ilya Sutskever and Geoff Hinton.
- The AlexNet was submitted to the ImageNet ILSVRC challenge in 2012 and significantly outperformed the second runner-up (top 5 error of 16% compared to runner-up with 26% error). The Network had a very similar architecture to LeNet, but was deeper, bigger, and featured Convolutional Layers stacked on top of each other
- **ZF Net**. The ILSVRC 2013 winner was a Convolutional Network from Matthew Zeiler and Rob Fergus. It was an improvement on AlexNet by tweaking the architecture hyperparameters, in particular by expanding the size of the middle convolutional layers and making the stride and filter size on the first layer smaller.

LeNet

- Yann LeCun and his collaborators developed a really good recognizer for handwritten digits by using backpropagation in a feedforward net with:
  - Many hidden layers
  - Many maps of replicated units in each layer.
  - Pooling of the outputs of nearby replicated units.
  - A wide net that can cope with several characters at once even if they overlap.
  - A clever way of training a complete system, not just a recognizer.
- This net was used for reading ~10% of the checks in North America.
- demos of LENET at http://yann.lecun.com

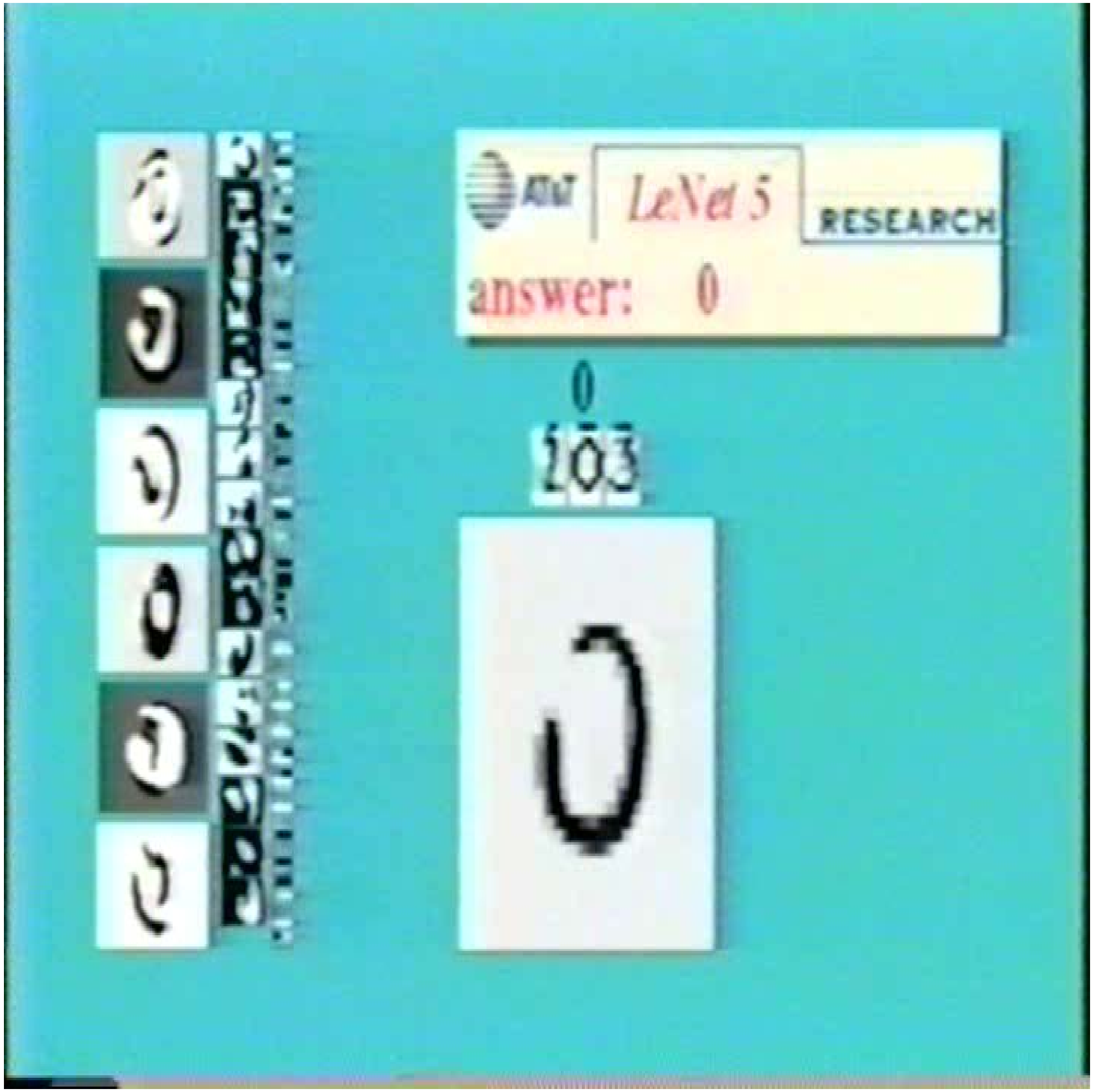
LeNet-5

[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]

Handwritten digit classification

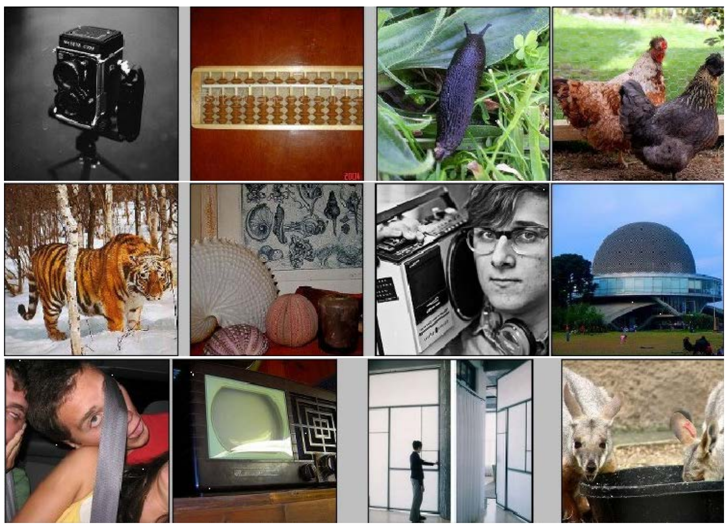


[Courtesy of Yann LeCun]

The 82 errors made by LeNet5

- Notice that most of the errors are cases that people find quite easy.
- The human error rate is probably 20 to 30 errors but nobody has had the patience to measure it.

The arrival of big visual data…



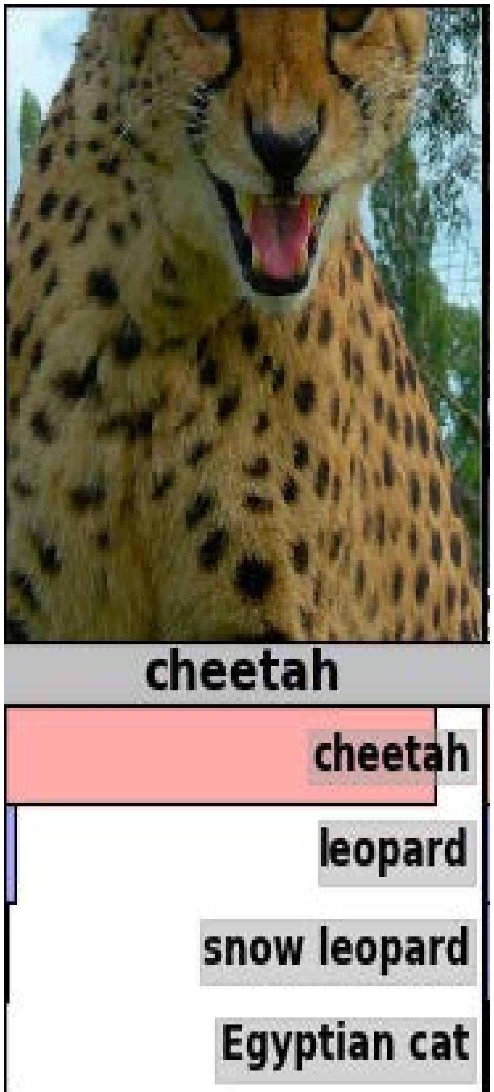
- ~14 million labeled images, 20k classes
- Images gathered from Internet
- Human labels via Amazon MTurk
- ImageNet Large-Scale Visual Recognition Challenge (ILSVRC): 1.2 million training images, 1000 classes

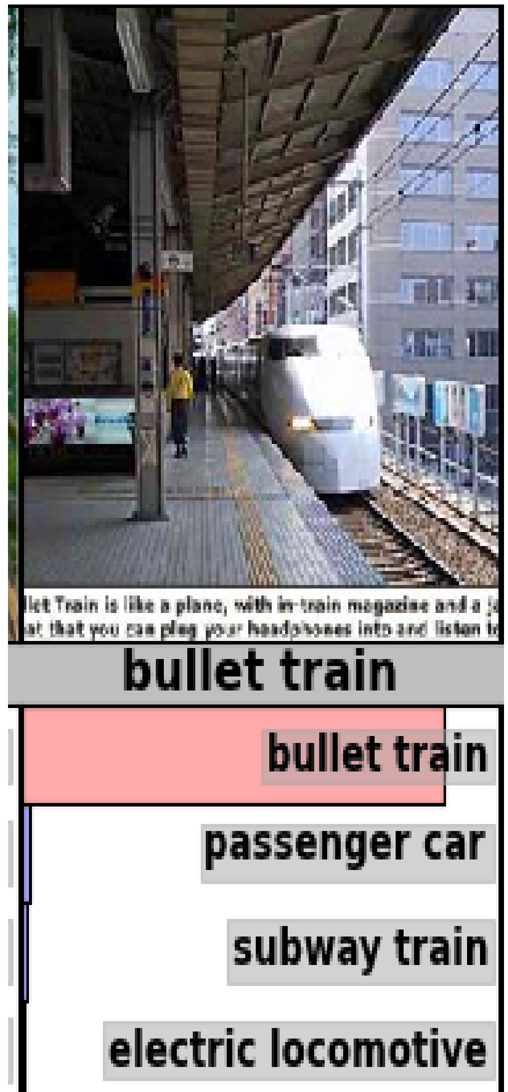
www.image-net.org/challenges/LSVRC/

The ILSVRC-2012 competition on ImageNet

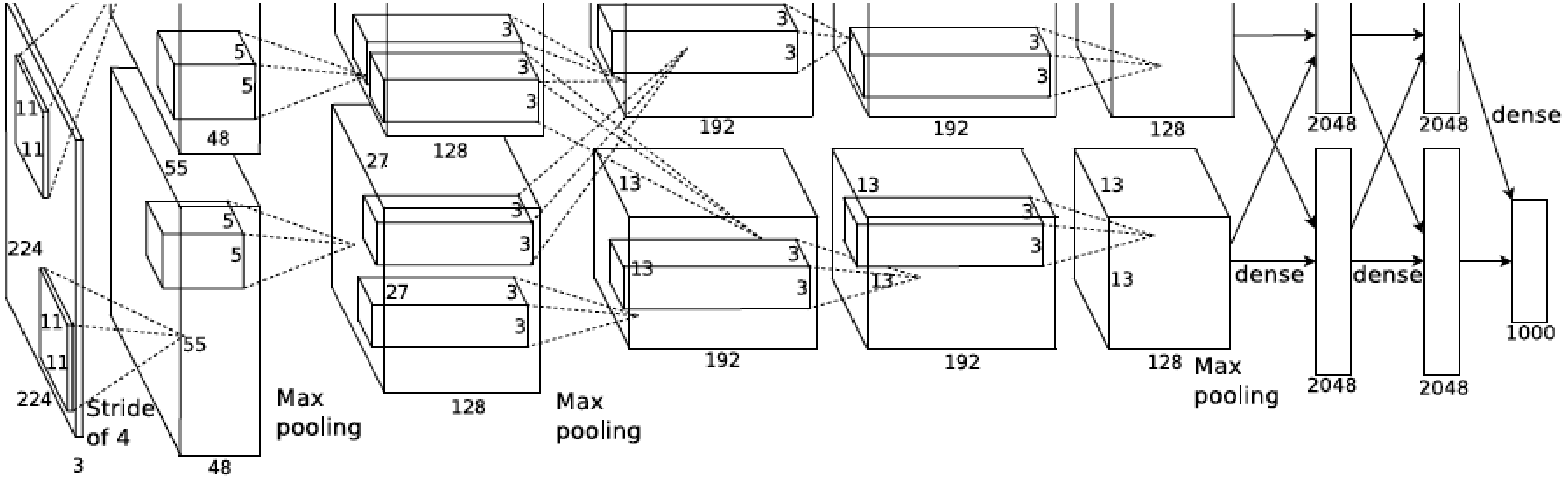
- The dataset has 1.2 million high-resolution training images.
- The classification task:
  - Get the “correct” class in your top 5 bets. There are 1000 classes.
- The localization task:
  - For each bet, put a box around the object. Your box must have at least 50% overlap with the correct box.
- Some of the best existing computer vision methods were tried on this dataset by leading computer vision groups from Oxford, INRIA, XRCE, …
  - Computer vision systems use complicated multi-stage systems.
  - The early stages are typically hand-tuned by optimizing a few parameters.

Examples from the test set
(with the network's guesses)





AlexNet: ILSVRC 2012 winner



- Similar framework to LeNet but:
  - Max pooling, ReLU nonlinearity
  - More data and bigger model (7 hidden layers, 650K units, 60M params)
  - GPU implementation (50x speedup over CPU)
    - Trained on two GPUs for a week
  - Dropout regularization

A. Krizhevsky, I. Sutskever, and G. Hinton, [ImageNet Classification with Deep Convolutional Neural Networks](), NIPS 2012

Error rates on the ILSVRC-2012 competition

	classification	classification &localization
University of Toronto (Alex Krizhevsky)	16.4%	34.1%
University of Tokyo	26.1%	53.6%
Oxford University Computer Vision Group	26.9%	50.0%
INRIA (French national research institute in CS) + XRCE (Xerox Research Center Europe)	27.0%	
University of Amsterdam	29.5%	

Tricks that significantly improve generalization

- Train on random 224x224 patches from the 256x256 images to get more data. Also use left-right reflections of the images.
    - At test time, combine the opinions from ten different patches: The four 224x224 corner patches plus the central 224x224 patch plus the reflections of those five patches.

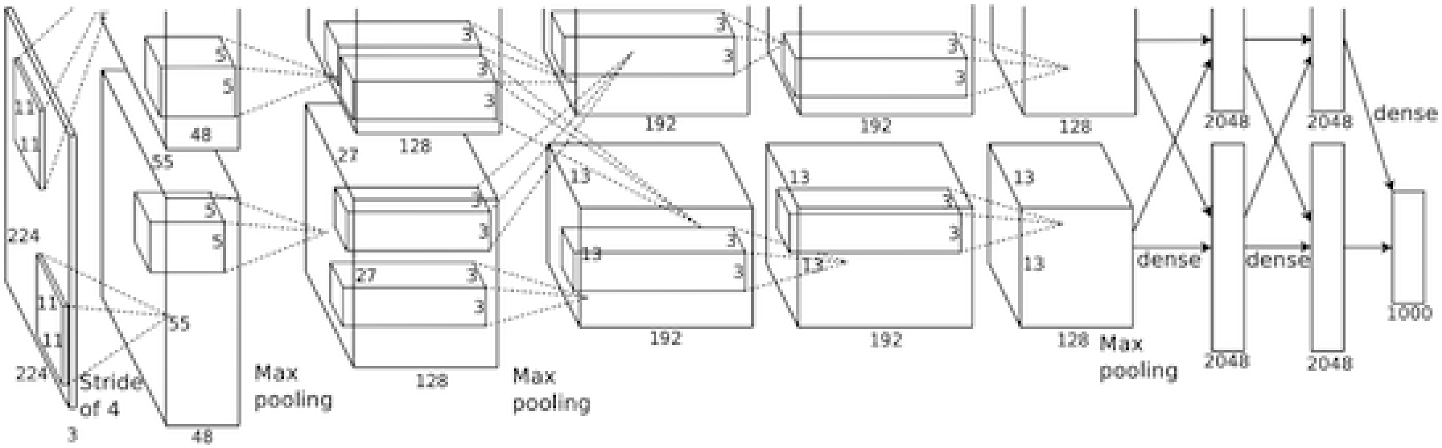
The hardware required for Alex's net

- An efficient implementation of convolutional nets on two Nvidia GTX 580 Graphics Processor Units (over 1000 fast little cores)
  - GPUs are very good for matrix-matrix multiplies.
  - GPUs have very high bandwidth to memory.
- We can spread a network over many cores if we can communicate the states fast enough.
- As cores get cheaper and datasets get bigger, big neural nets will improve faster than old-fashioned (*i.e.* pre Oct 2012) computer vision systems.

Alexnet

[Krizhevsky et al. 2012]

Architecture:
CONV1
MAX POOL1
NORM1
CONV2
MAX POOL2
NORM2
CONV3
CONV4
CONV5
Max POOL3
FC6
FC7
FC8



Input: 227x227x3 images

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

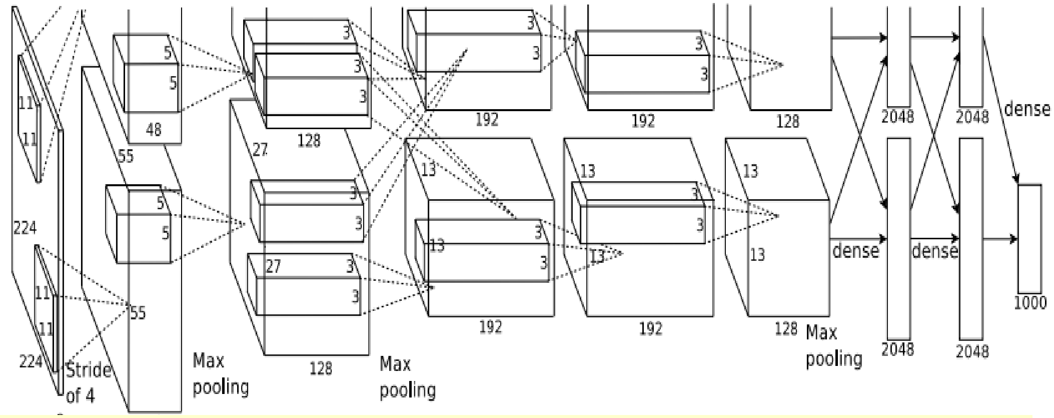
Output volume **[55x55x96]**
Parameters: (11*11*3)*96 = **35K**

(227-11)/4+1 = 55

Case Study: AlexNet

[Krizhevsky et al. 2012]

Architecture:
CONV1
MAX POOL1
NORM1
CONV2
MAX POOL2
NORM2
CONV3
CONV4
CONV5
Max POOL3
FC6
FC7
FC8



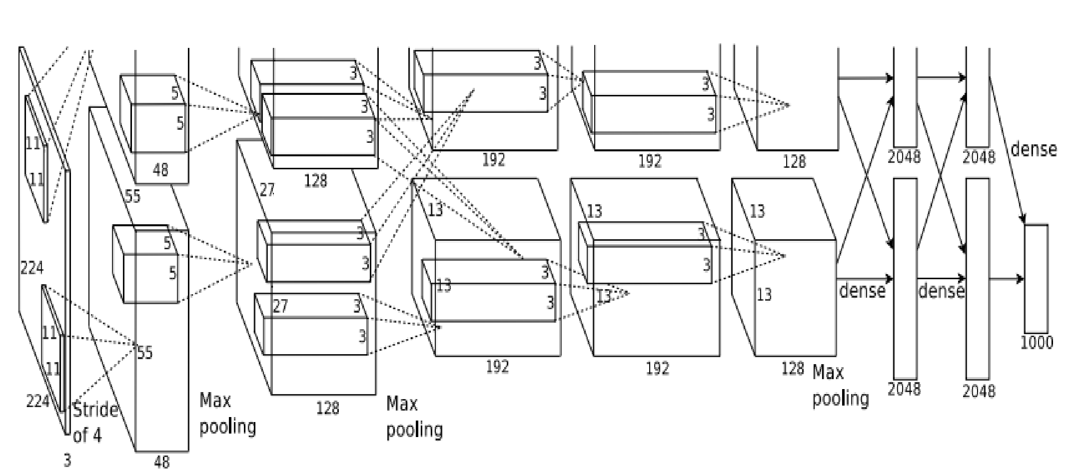
Input: 227x227x3 images
After CONV1: 55x55x96

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

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

Case Study: AlexNet

[Krizhevsky et al. 2012]



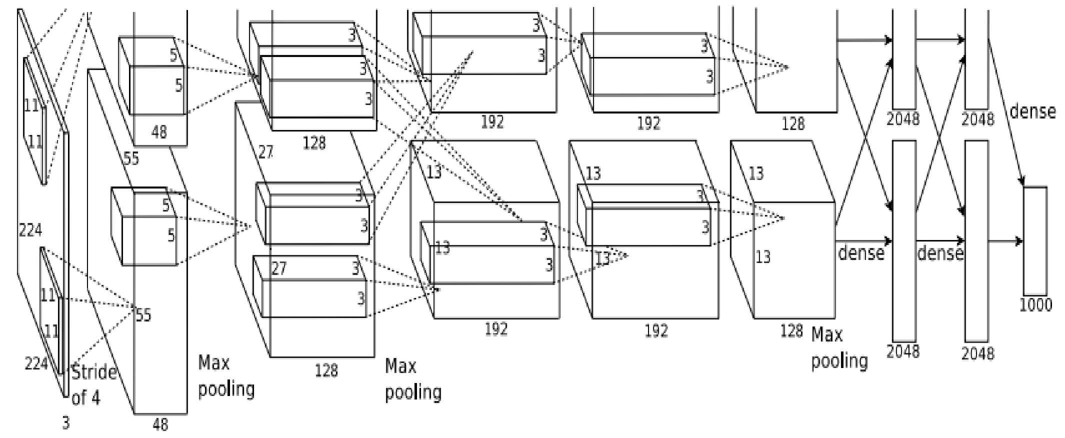
Input: 227x227x3 images
After CONV1: 55x55x96

Second layer (POOL1): 3x3 filters applied at stride 2
Output volume: 27x27x96

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

Case Study: AlexNet

[Krizhevsky et al. 2012]

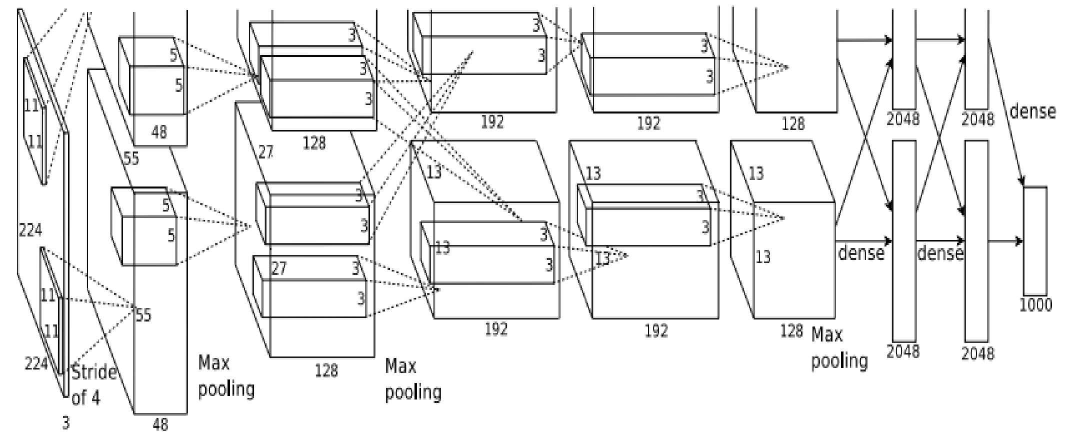


Input: 227x227x3 images
After CONV1: 55x55x96

Second layer (POOL1): 3x3 filters applied at stride 2
Output volume: 27x27x96
Parameters: 0!

Case Study: AlexNet

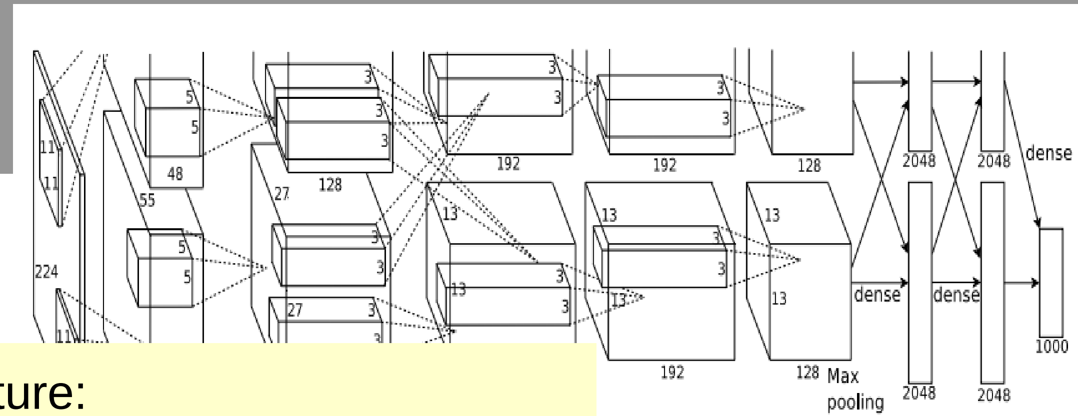
[Krizhevsky et al. 2012]



Input: 227x227x3 images
After CONV1: 55x55x96
After POOL1: 27x27x96
...

Case Study: AlexNet

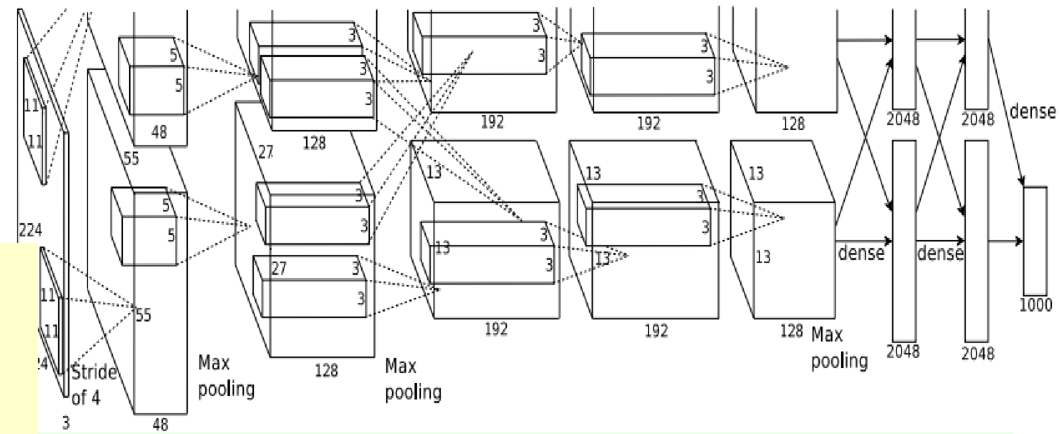
[Krizhevsky et al. 2012]



Full (simplified) AlexNet architecture:
[227x227x3] INPUT
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] NORM2: Normalization layer
[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1
[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1
[6x6x256] MAX POOL3: 3x3 filters at stride 2
[4096] FC6: 4096 neurons
[4096] FC7: 4096 neurons
[1000] FC8: 1000 neurons (class scores)

Case Study: AlexNet

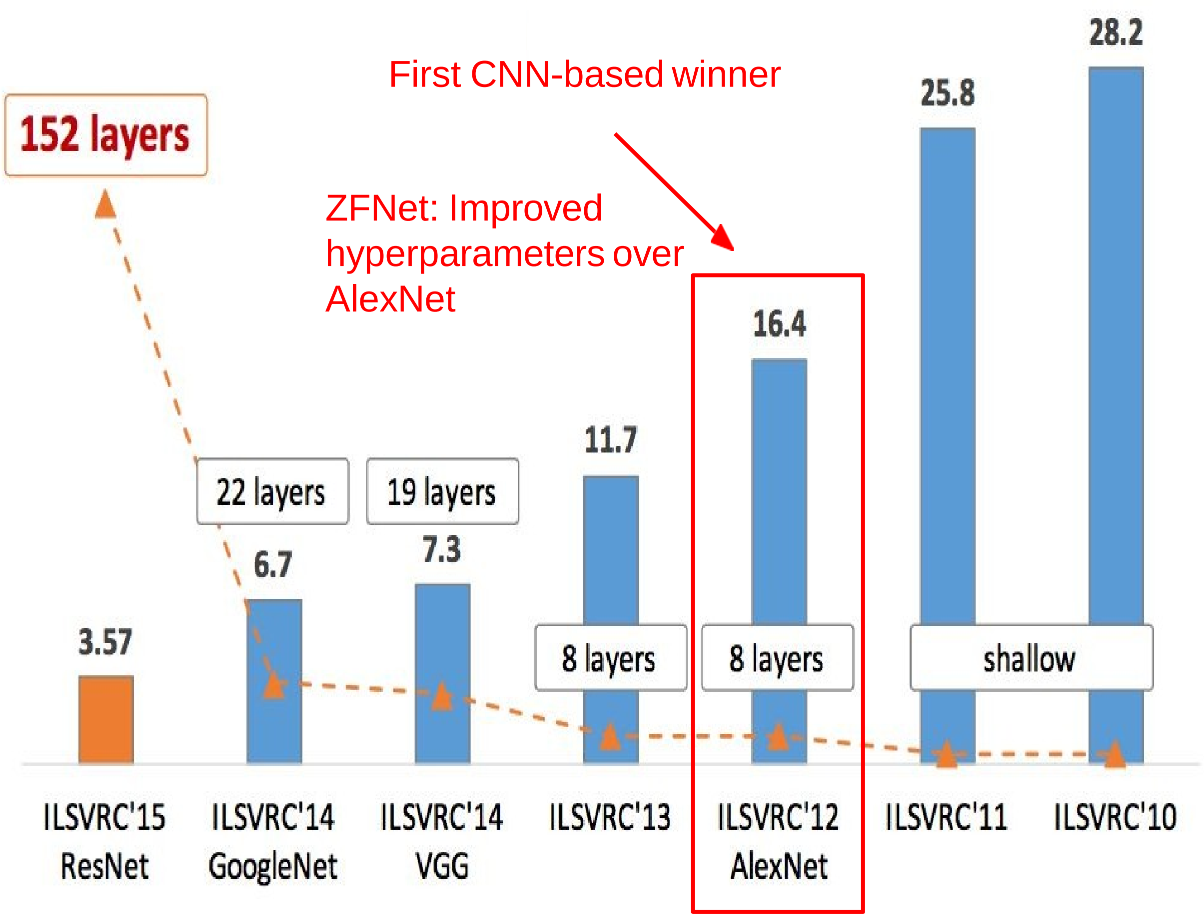
[Krizhevsky et al. 2012]



Full (simplified) AlexNet architecture:
[227x227x3] INPUT
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] NORM2: Normalization layer
[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1
[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1
[6x6x256] MAX POOL3: 3x3 filters at stride 2
[4096] FC6: 4096 neurons
[4096] FC7: 4096 neurons
[1000] FC8: 1000 neurons (class scores)

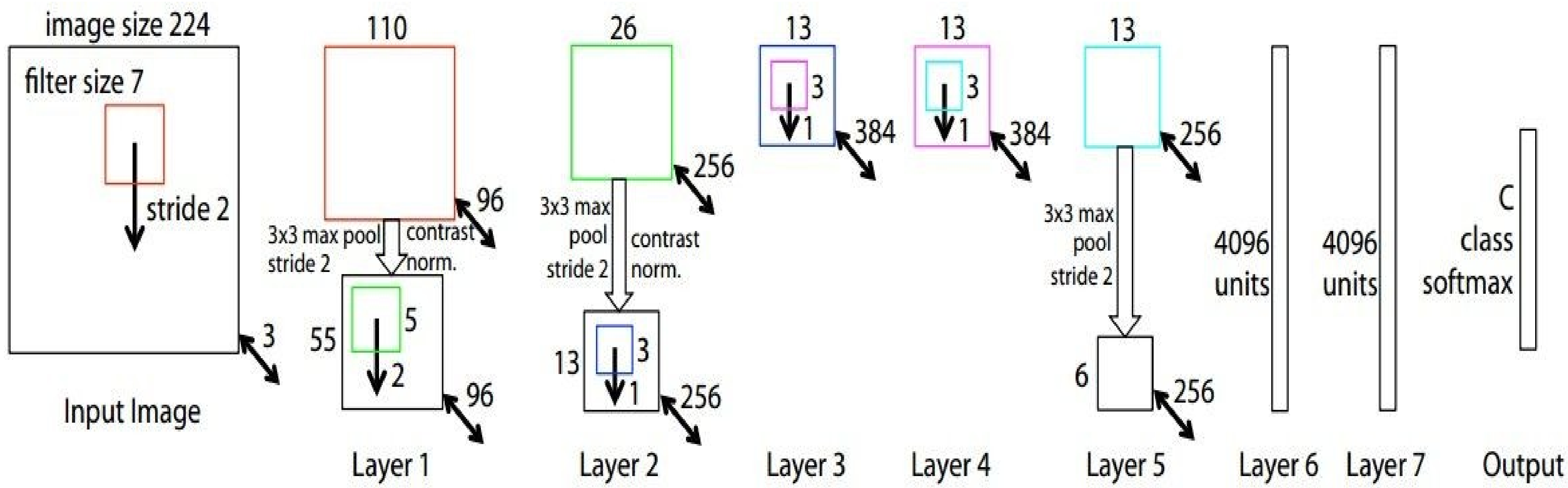
Details/Retrospectives:
- first use of ReLU
- used Norm layers (not common anymore)
- heavy data augmentation
- dropout 0.5
- batch size 128
- SGD Momentum 0.9
- Learning rate 1e-2, reduced by 10 manually when val accuracy plateaus
- L2 weight decay 5e-4
- 7 CNN ensemble: 18.2% -> 15.4%

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



ZFNet

[Zeiler and Fergus, 2013]

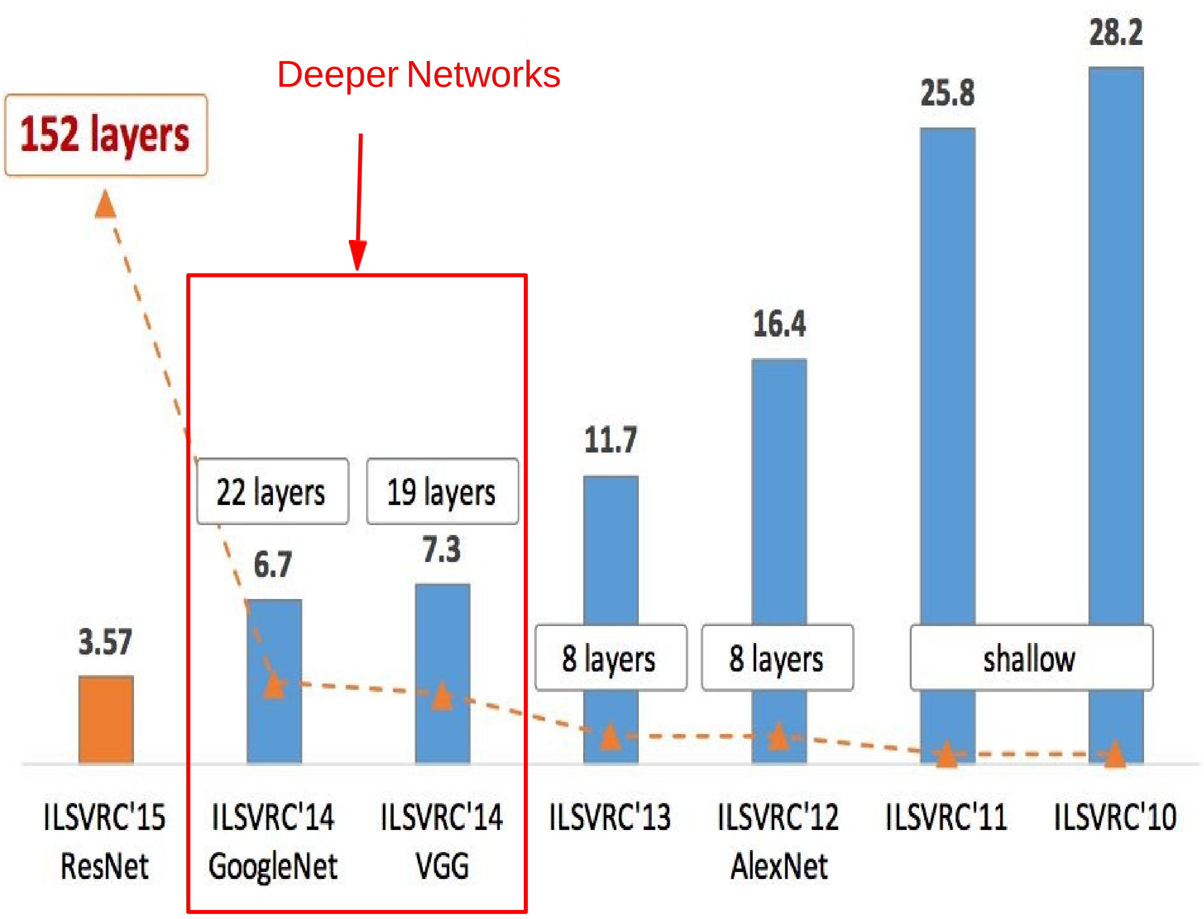


TODO: remake figure

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: 16.4% -> 11.7%

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



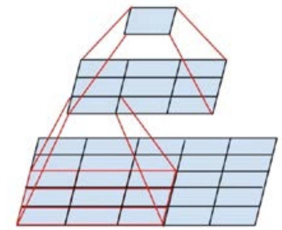
VGGNet: ILSVRC 2014 2nd place

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

- Sequence of deeper networks trained progressively
- Large receptive fields replaced by successive layers of 3x3 convolutions (with ReLU in between)



- One 7x7 conv layer with C feature maps needs $49C^2$ weights, three 3x3 conv layers need only $27C^2$ weights
- Experimented with 1x1 convolutions

K. Simonyan and A. Zisserman, Very Deep Convolutional Networks for Large-Scale Image Recognition, ICLR 2015

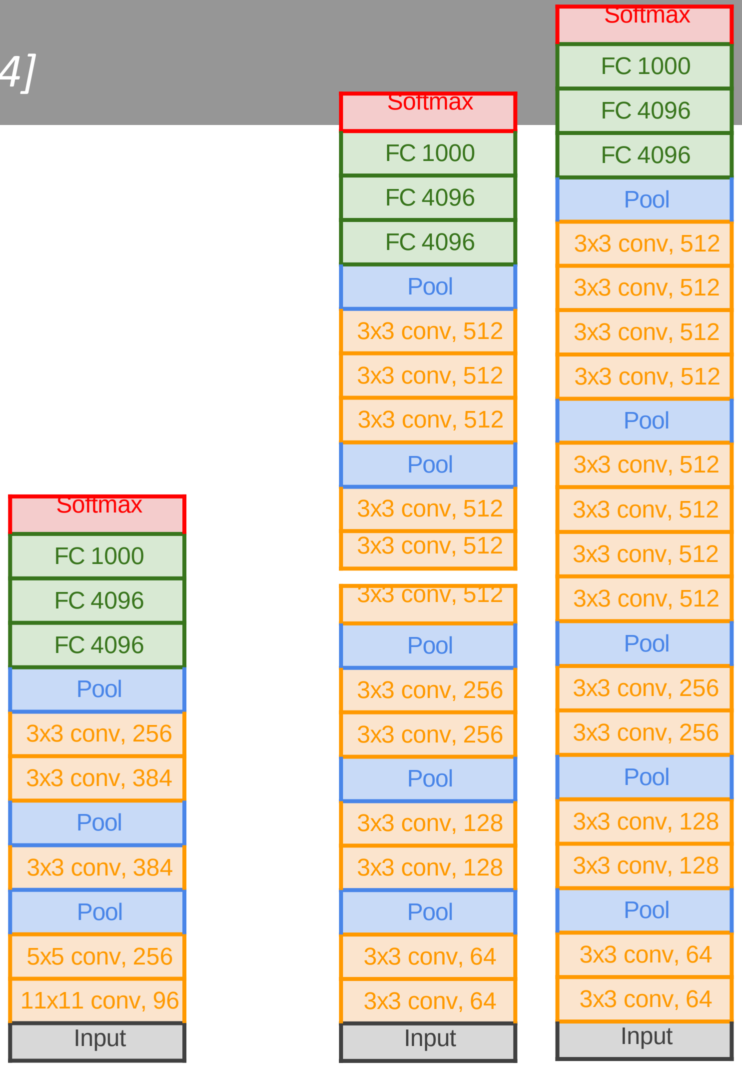
VGGNet *[Simonyan and Zisserman, 2014]*

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



AlexNet VGG16 VGG19

VGGNet

[Simonyan and Zisserman, 2014]

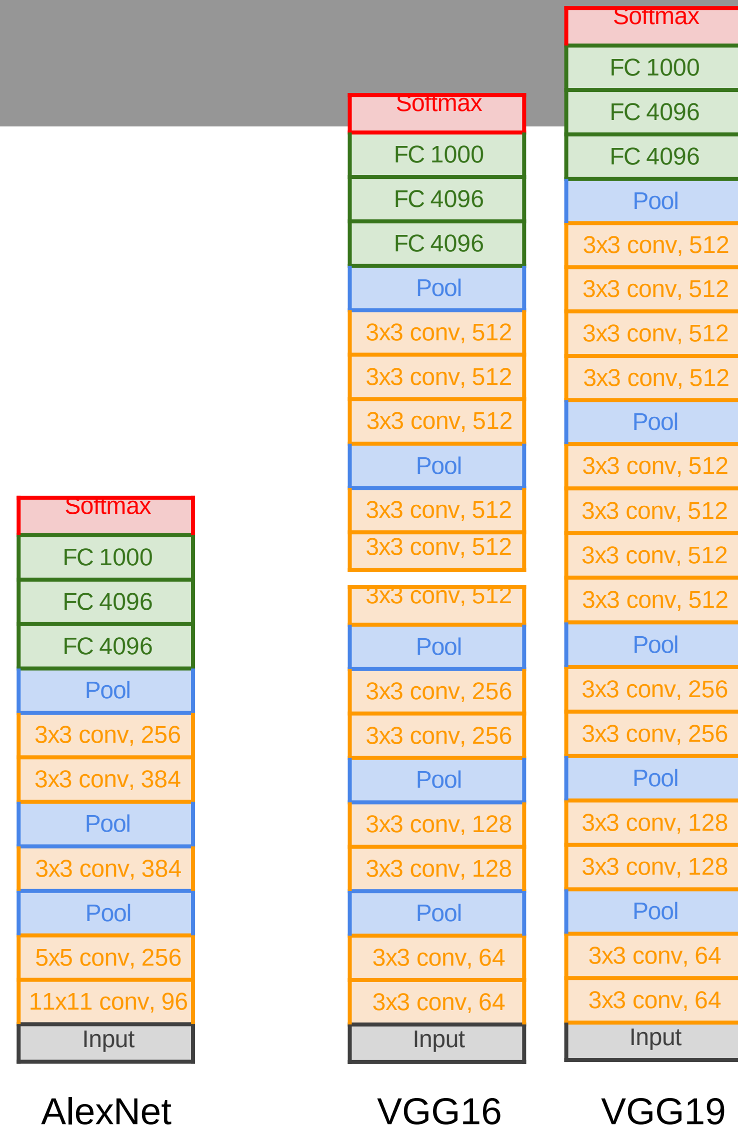
Q: Why use smaller filters? (3x3 conv)

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

Q: What is the effective receptive field of three 3x3 conv (stride 1) layers?
[7x7]

But deeper, more non-linearities

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



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 bytes ~= 96MB / image (only forward! ~*2 for bwd)
TOTAL params: 138M parameters

VGG16

Note:

Most memory is in early CONV

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
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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

Most params are in late FC

TOTAL memory: 24M * 4 bytes ~= 96MB / image (only forward! ~*2 for bwd)

TOTAL params: 138M parameters

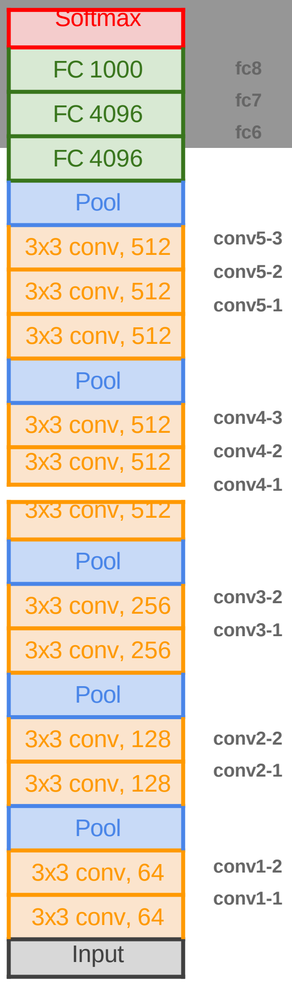
INPUT: [224x224x3] memory: 224*224*3=150K params: 0

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 bytes ~= 96MB / image (only forward! ~*2 for bwd)

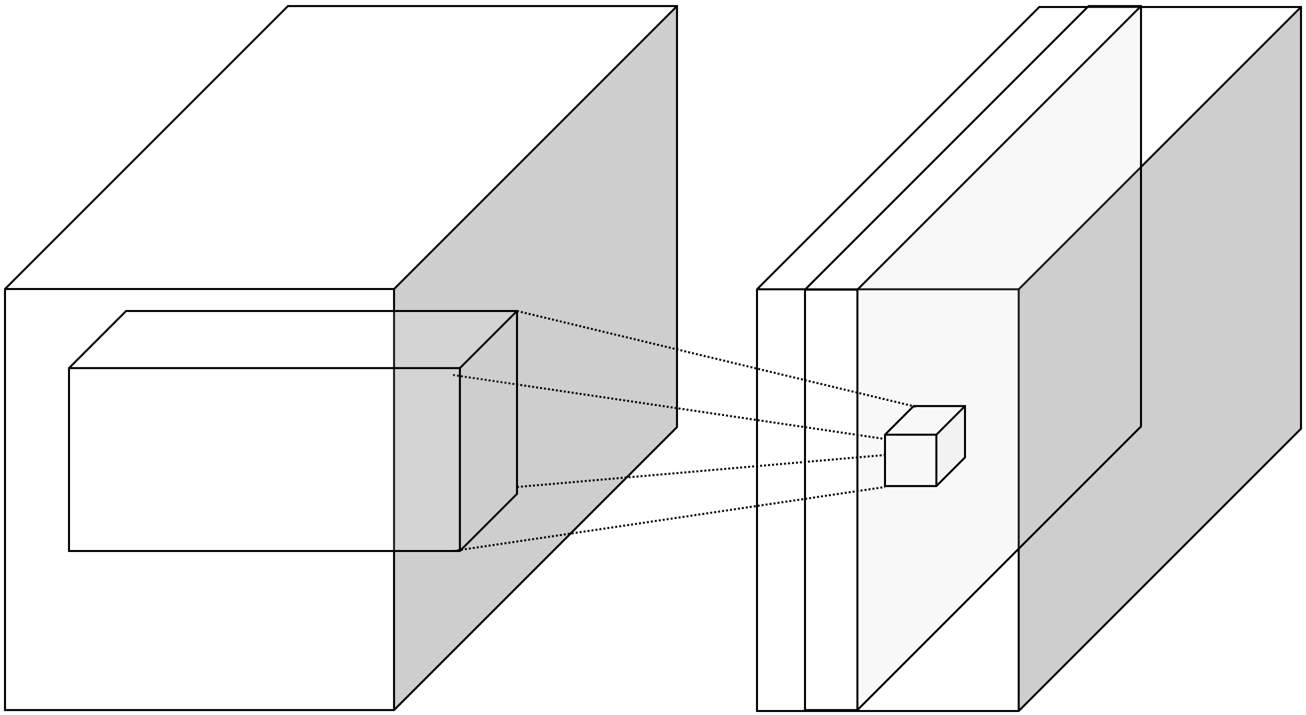
TOTAL params: 138M parameters



VGG16

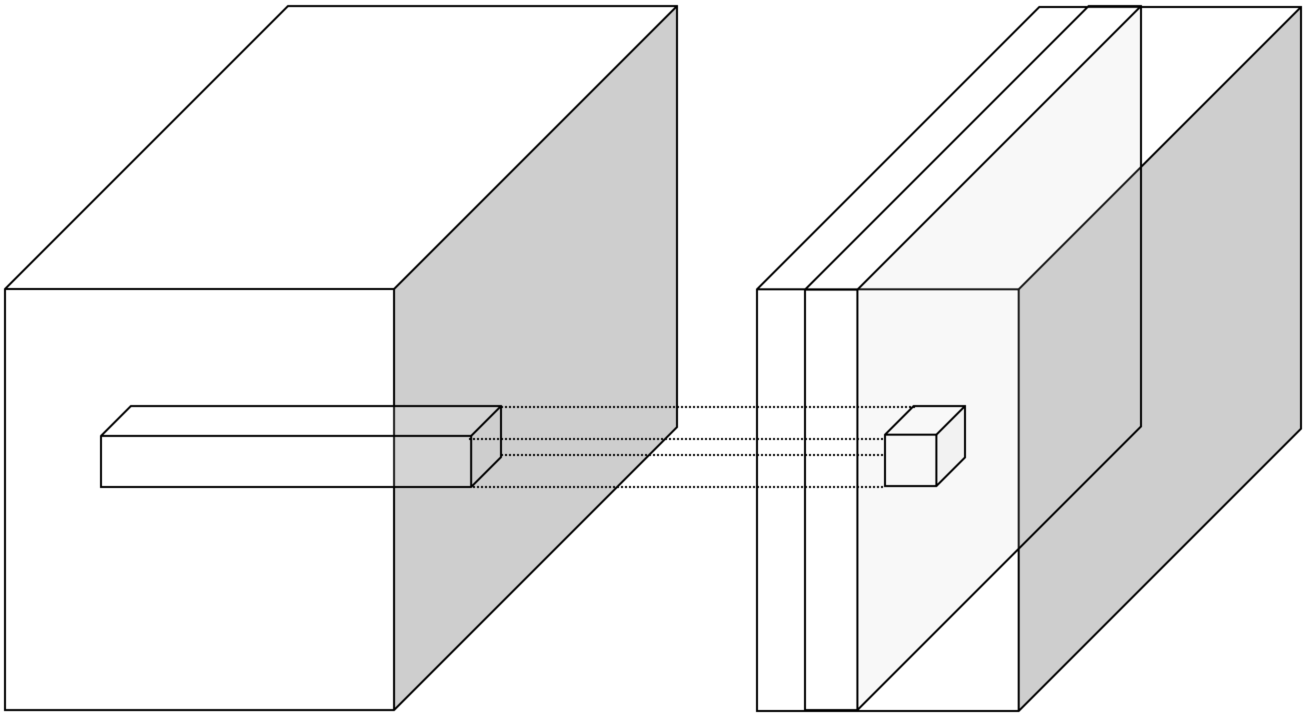
Common names

1x1 convolutions



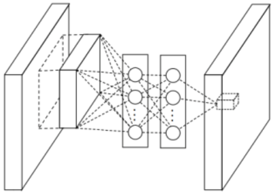
conv layer

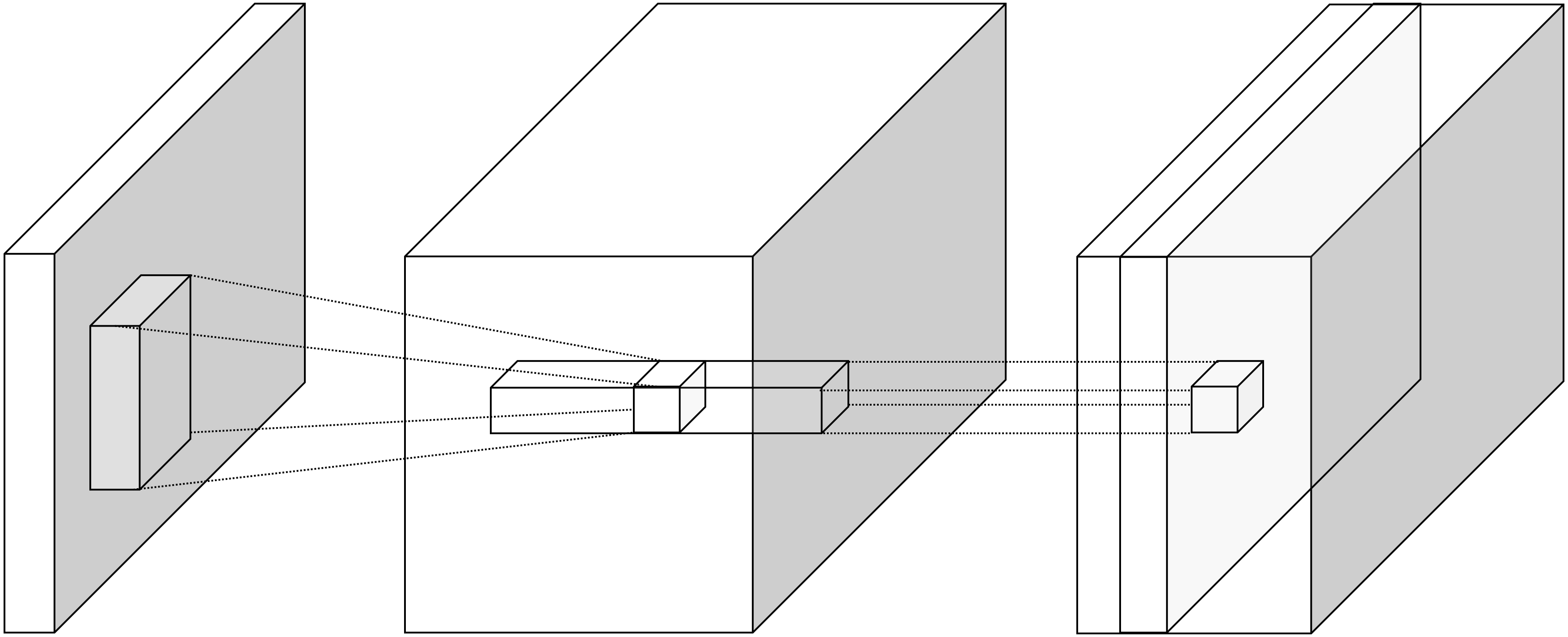
1x1 convolutions



1x1 conv layer

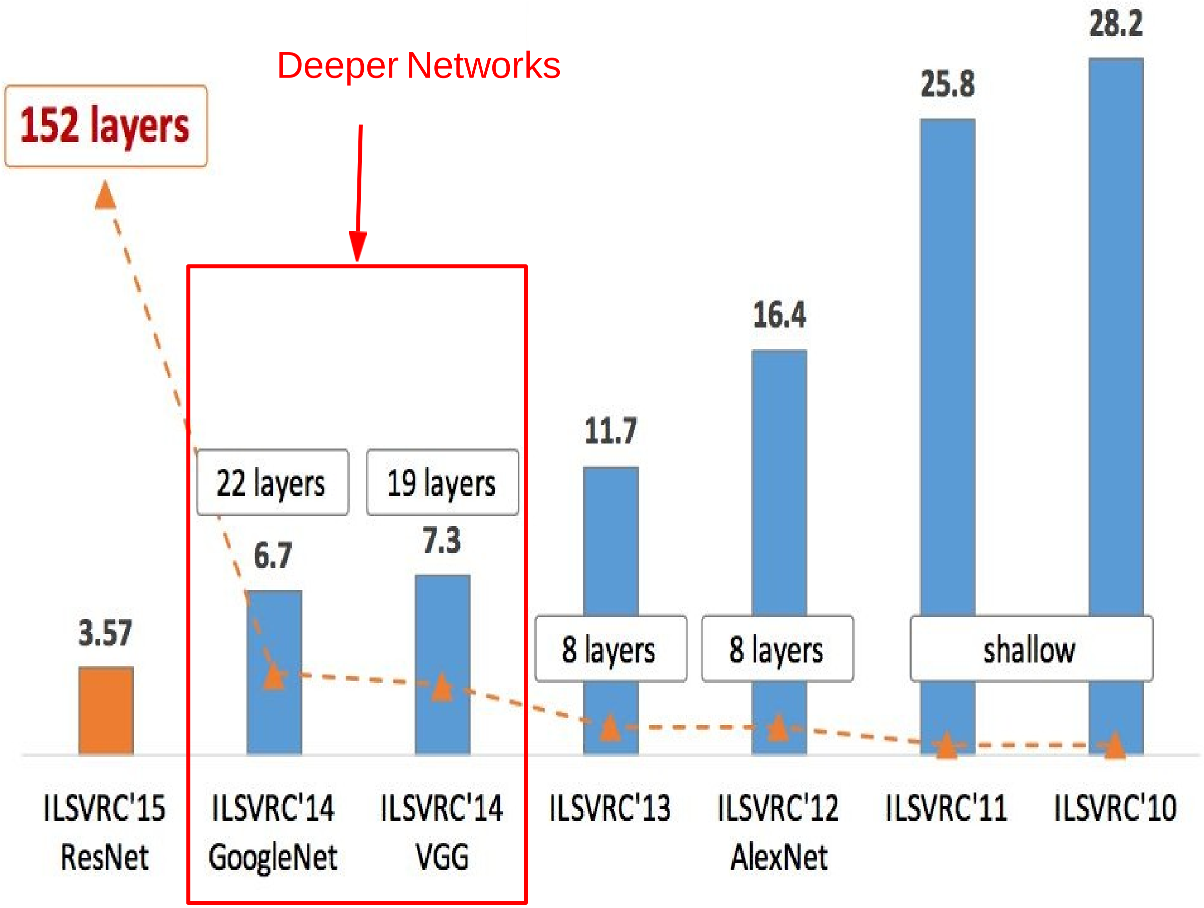
1x1 convolutions





1x1 conv layer

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



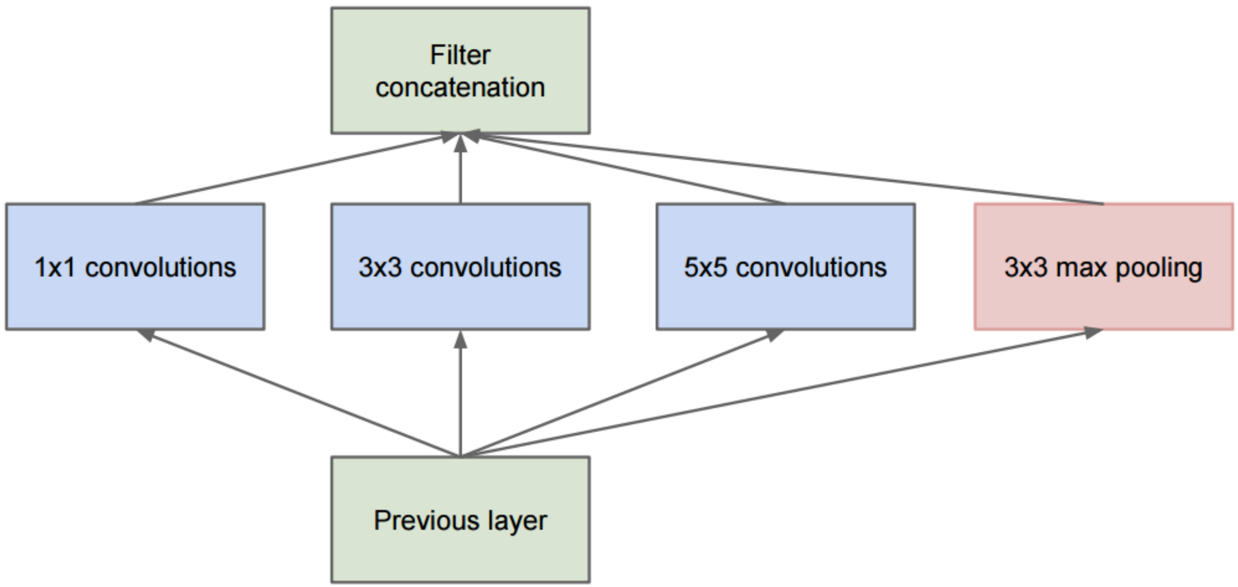
GoogLeNet: ILSVRC 2014 winner

- The Inception Module
  - *Inception Module* dramatically reduced the number of parameters in the network
    (4M, compared to AlexNet with 60M).
  - Uses Average Pooling instead of Fully Connected layers at the top of the ConvNet
  - Several followup versions to the GoogLeNet, most recently Inception-v4.

C. Szegedy et al., Going deeper with convolutions, CVPR 2015

GoogLeNet

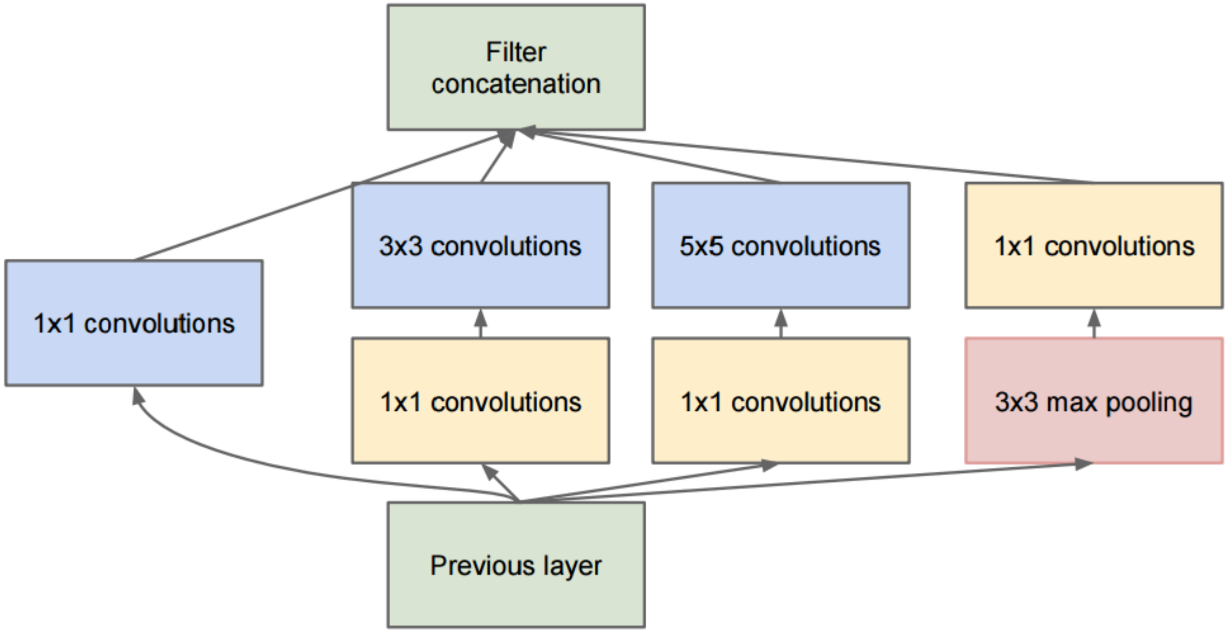
- The Inception Module
  - Parallel paths with different receptive field sizes and operations are meant to capture sparse patterns of correlations in the stack of feature maps



C. Szegedy et al., [Going deeper with convolutions](), CVPR 2015

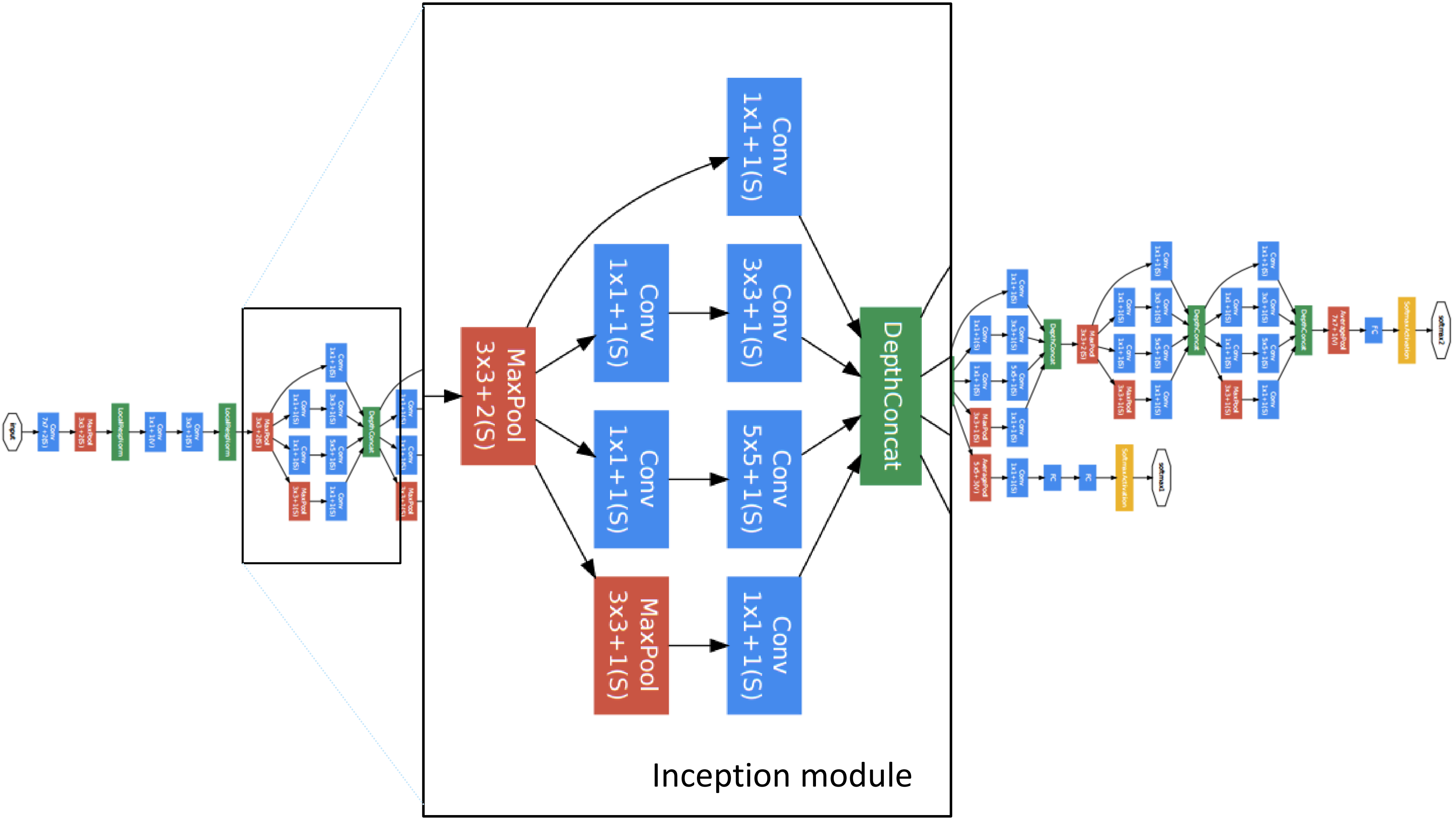
GoogLeNet

- The Inception Module
  - Parallel paths with different receptive field sizes and operations are meant to capture sparse patterns of correlations in the stack of feature maps
  - Use 1x1 convolutions for dimensionality reduction before expensive convolutions



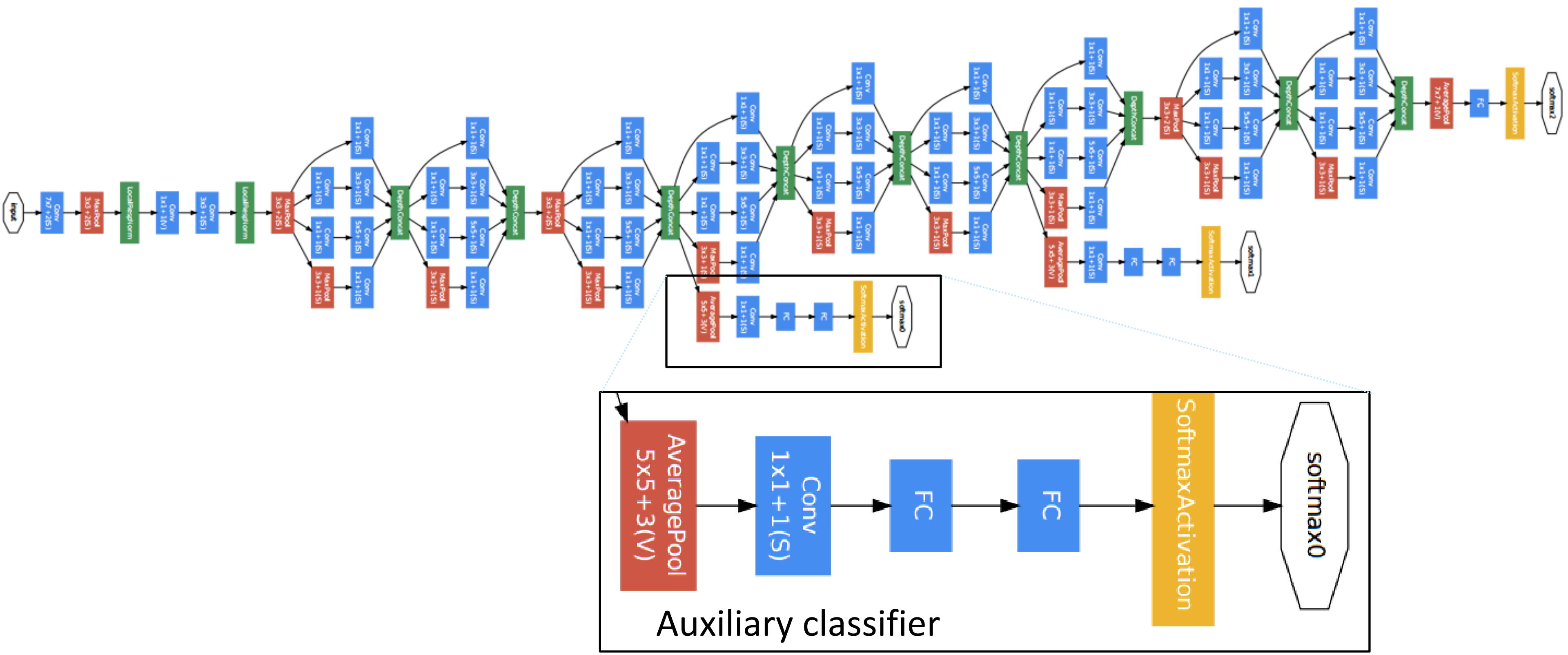
C. Szegedy et al., [Going deeper with convolutions](), CVPR 2015

GoogLeNet



C. Szegedy et al., [Going deeper with convolutions](), CVPR 2015

GoogLeNet



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GoogLeNet

- An alternative view:

type	patch size/ stride	output size	depth	#1×1	#3×3 reduce	#3×3	#5×5 reduce	#5×5	pool proj	params	ops
convolution	7×7/2	112×112×64	1							2.7K	34M
max pool	3×3/2	56×56×64	0								
convolution	3×3/1	56×56×192	2		64	192				112K	360M
max pool	3×3/2	28×28×192	0								
inception (3a)		28×28×256	2	64	96	128	16	32	32	159K	128M
inception (3b)		28×28×480	2	128	128	192	32	96	64	380K	304M
max pool	3×3/2	14×14×480	0								
inception (4a)		14×14×512	2	192	96	208	16	48	64	364K	73M
inception (4b)		14×14×512	2	160	112	224	24	64	64	437K	88M
inception (4c)		14×14×512	2	128	128	256	24	64	64	463K	100M
inception (4d)		14×14×528	2	112	144	288	32	64	64	580K	119M
inception (4e)		14×14×832	2	256	160	320	32	128	128	840K	170M
max pool	3×3/2	7×7×832	0								
inception (5a)		7×7×832	2	256	160	320	32	128	128	1072K	54M
inception (5b)		7×7×1024	2	384	192	384	48	128	128	1388K	71M
avg pool	7×7/1	1×1×1024	0								
dropout (40%)		1×1×1024	0								
linear		1×1×1000	1							1000K	1M
softmax		1×1×1000	0								

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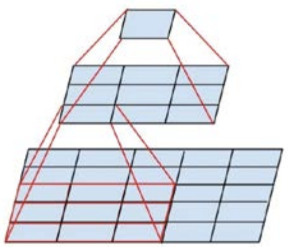
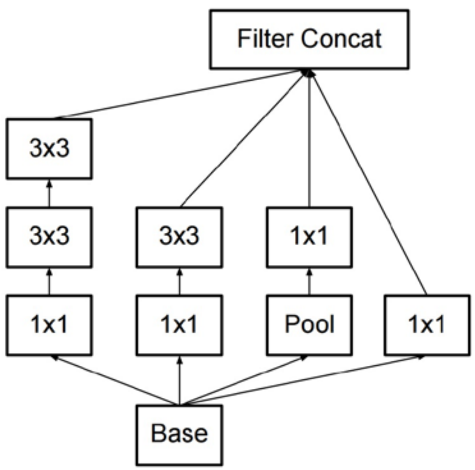
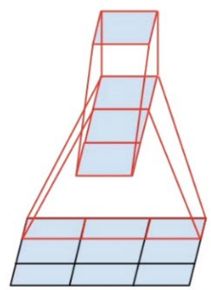
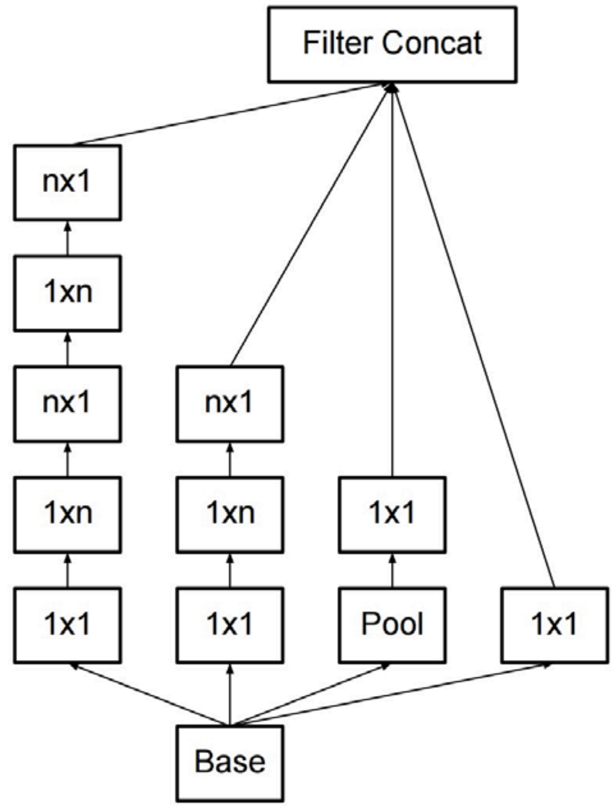
Inception v2, v3

- Regularize training with batch normalization, reducing importance of auxiliary classifiers
- More variants of inception modules with aggressive factorization of filters





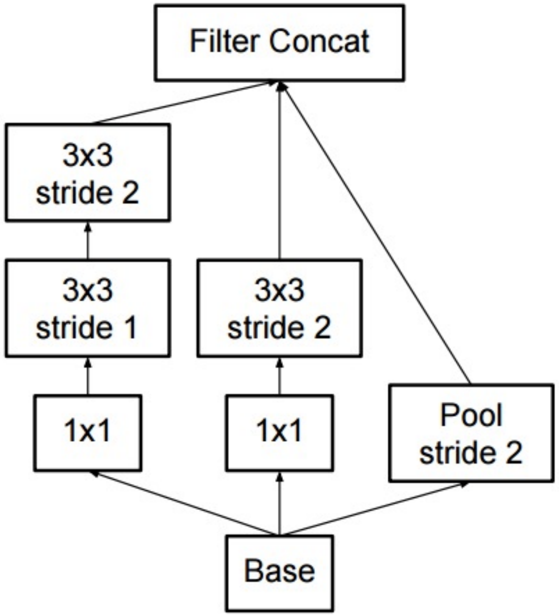




C. Szegedy et al., Rethinking the inception architecture for computer vision, CVPR 2016

Inception v2, v3

- Regularize training with batch normalization, reducing importance of auxiliary classifiers
- More variants of inception modules with aggressive factorization of filters
- Increase the number of feature maps while decreasing spatial resolution (pooling)



C. Szegedy et al., Rethinking the inception architecture for computer vision, CVPR 2016