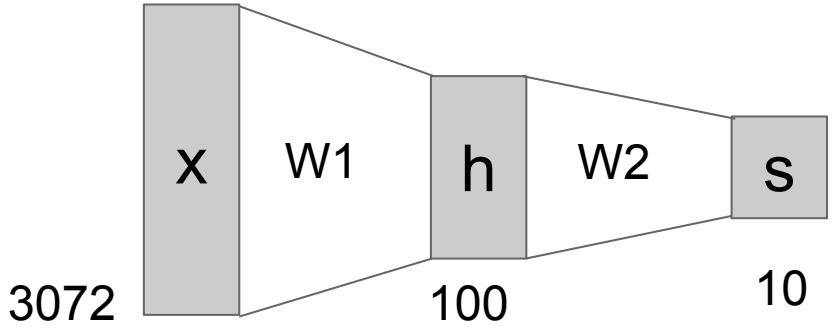
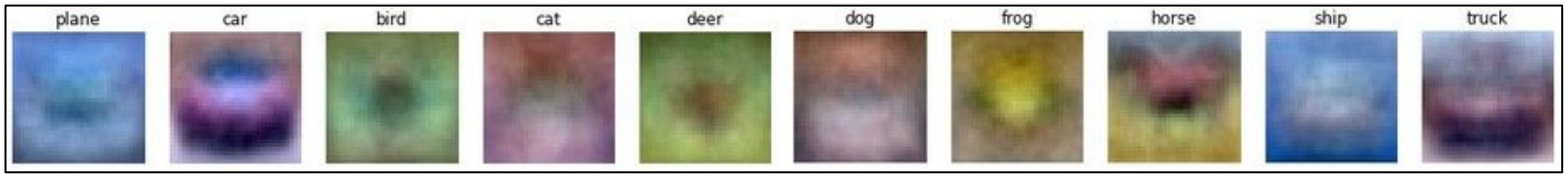
Lecture7
Convolutional Neural Networks

Last time: Neural Networks

Linear score function: $f = Wx$

2-layer Neural Network $f = W_2 \max(0, W_1 x)$





Next: Convolutional Neural Networks

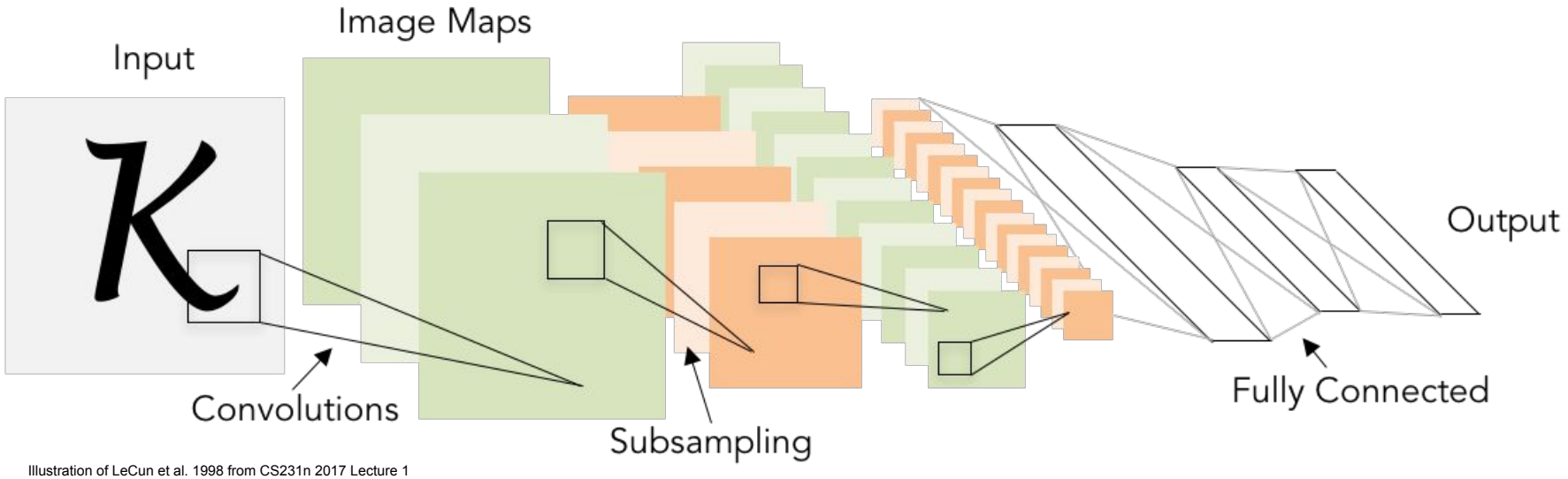
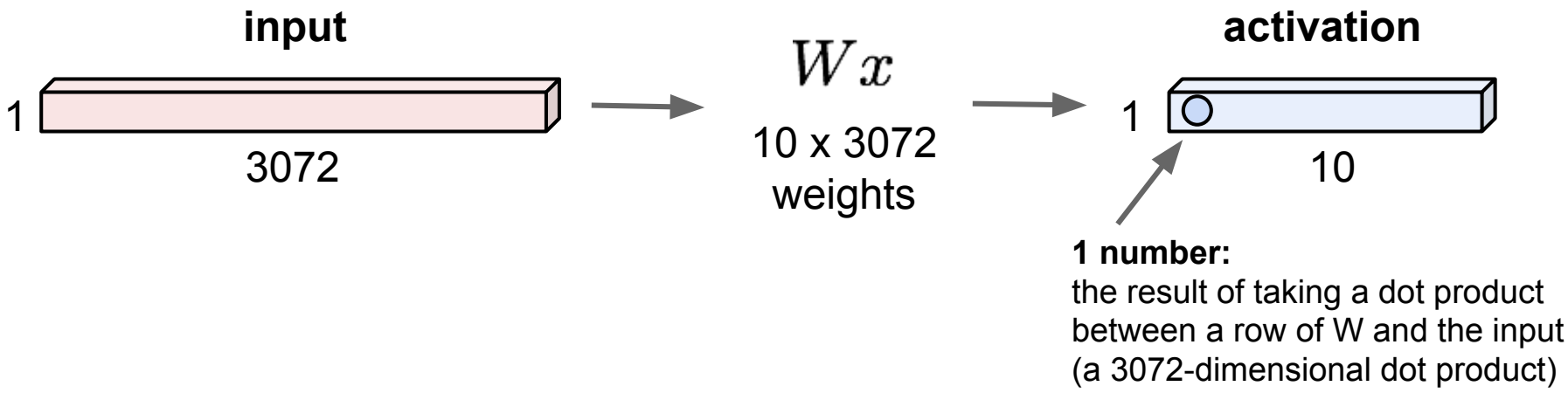


Illustration of LeCun et al. 1998 from CS231n 2017 Lecture 1

Fully connected layer

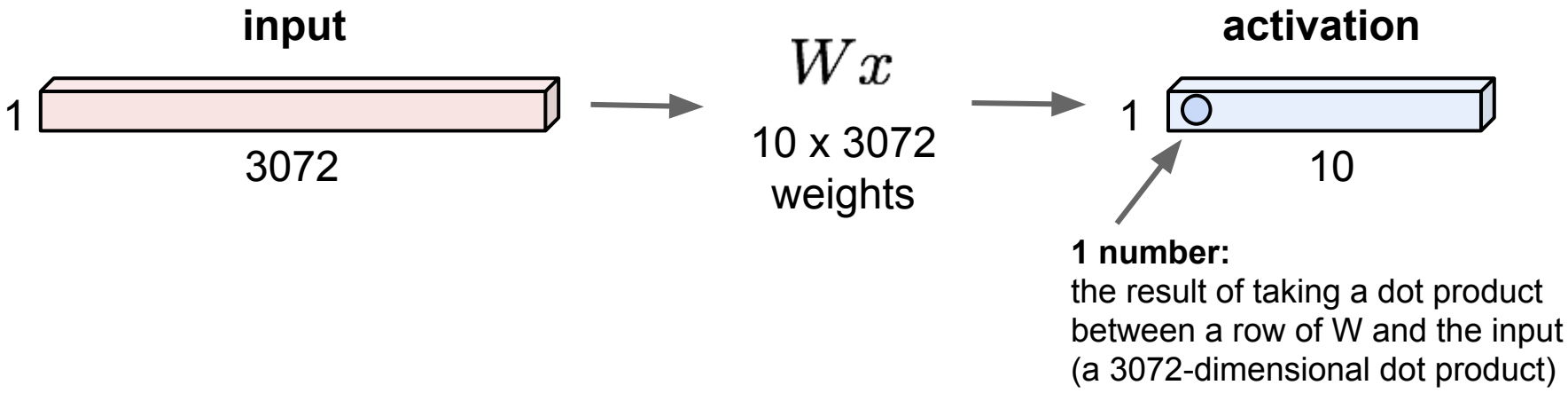
32x32x3 image -> stretch to 3072 x 1



Convolutional Layer

Recall fully connected layer

32x32x3 image -> stretch to 3072 x 1

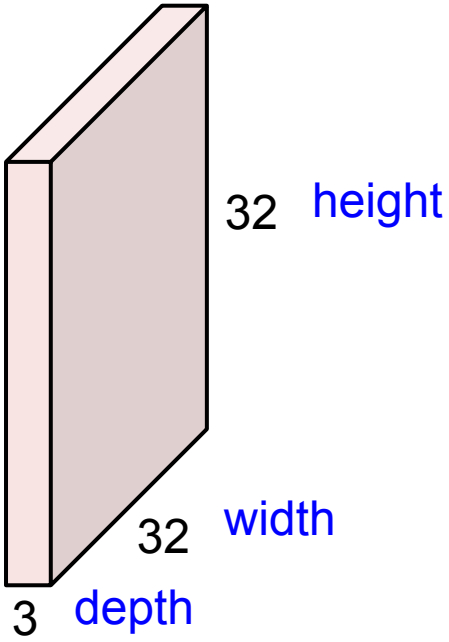


Problem:

The spatial structure of images is broken. Spatially adjacent pixels are no longer close to each other after stretching

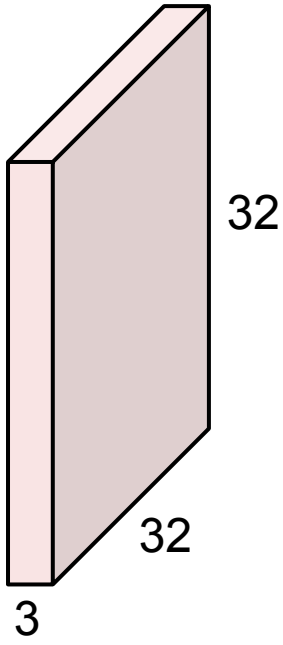
Convolutional layer

32x32x3 image -> preserve spatial structure

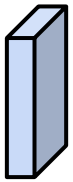


Convolutional Layer

32x32x3 image



5x5x3 filter

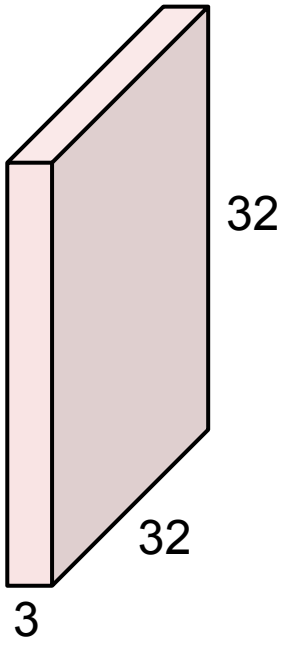


Convolve the filter with the image i.e. “slide over the image spatially, computing dot products”

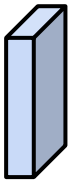
Convolutional Layer

Filters always extend the full depth of the input volume

32x32x3 image



5x5x3 filter

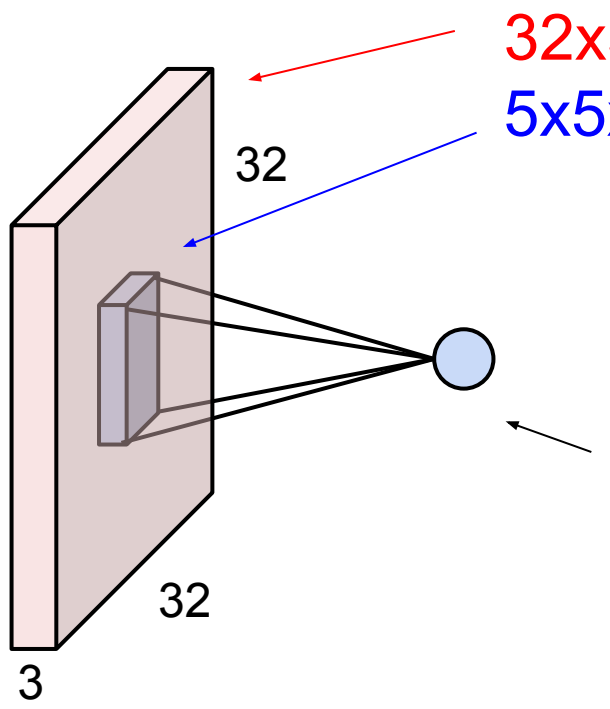


Convolve the filter with the image i.e. “slide over the image spatially, computing dot products”

Filters move spatial-wise, not depth-wise

Q: Will the results be different if we move filters along different directions?

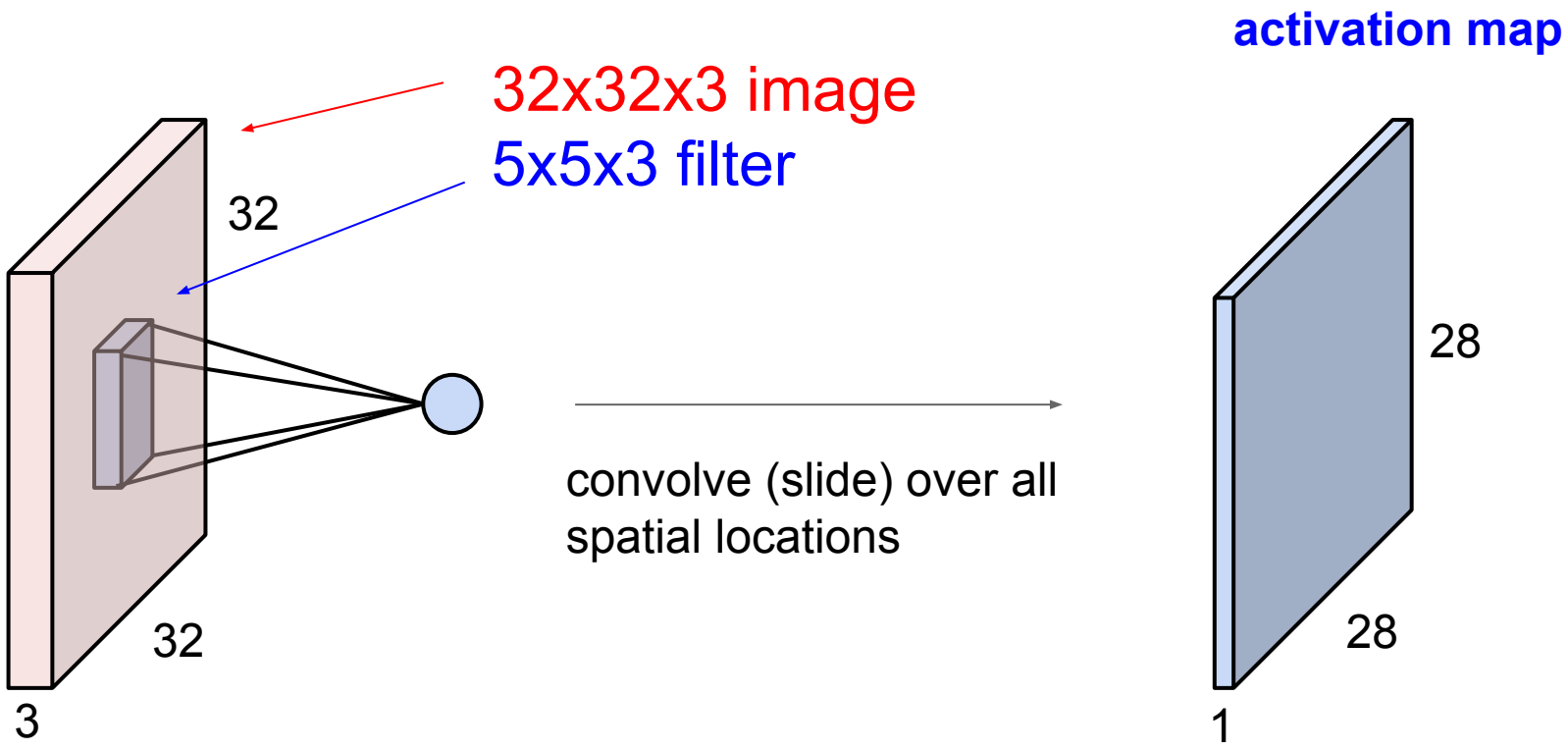
Convolutional Layer



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

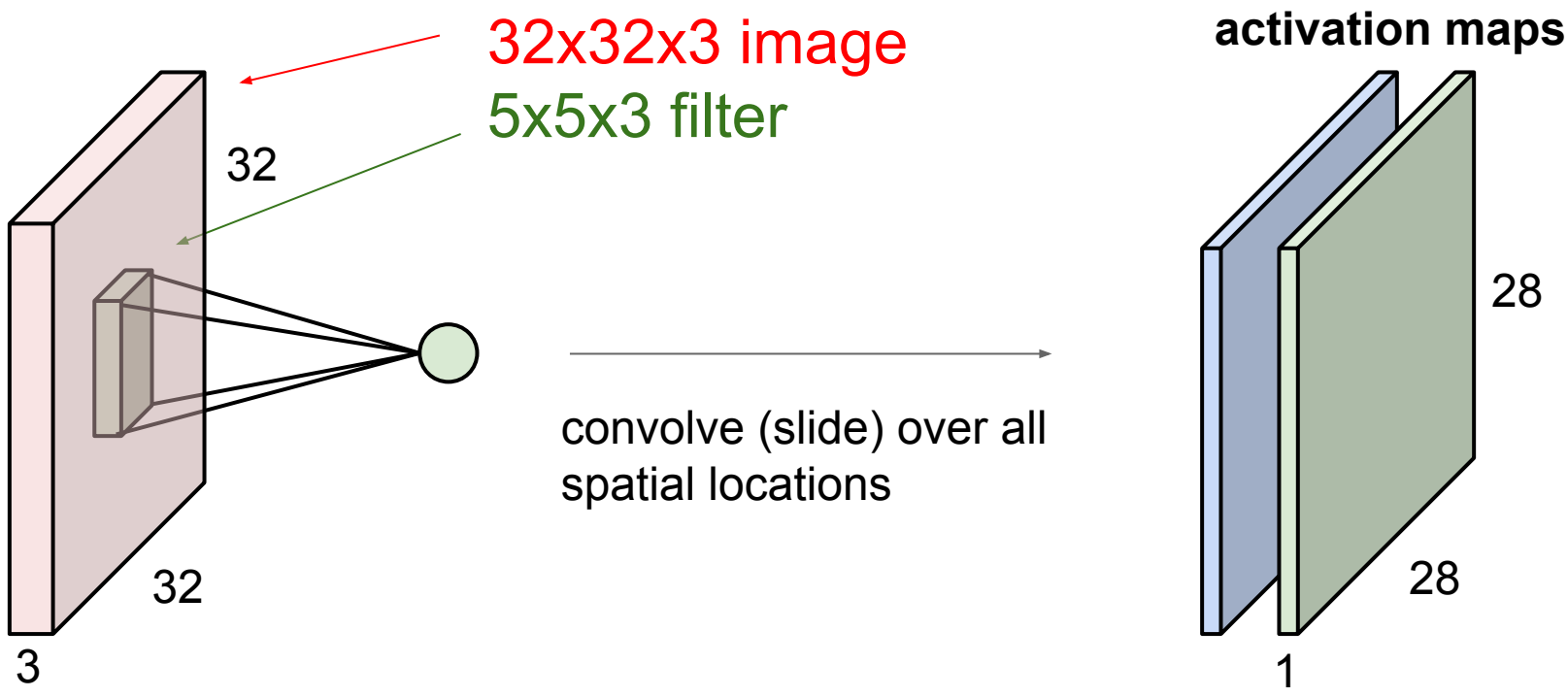


An activation map is a sheet of neuron outputs

1) Each is connected to a small region (receptive field, 感受野) in the input

2) All of them share parameters → translation invariant

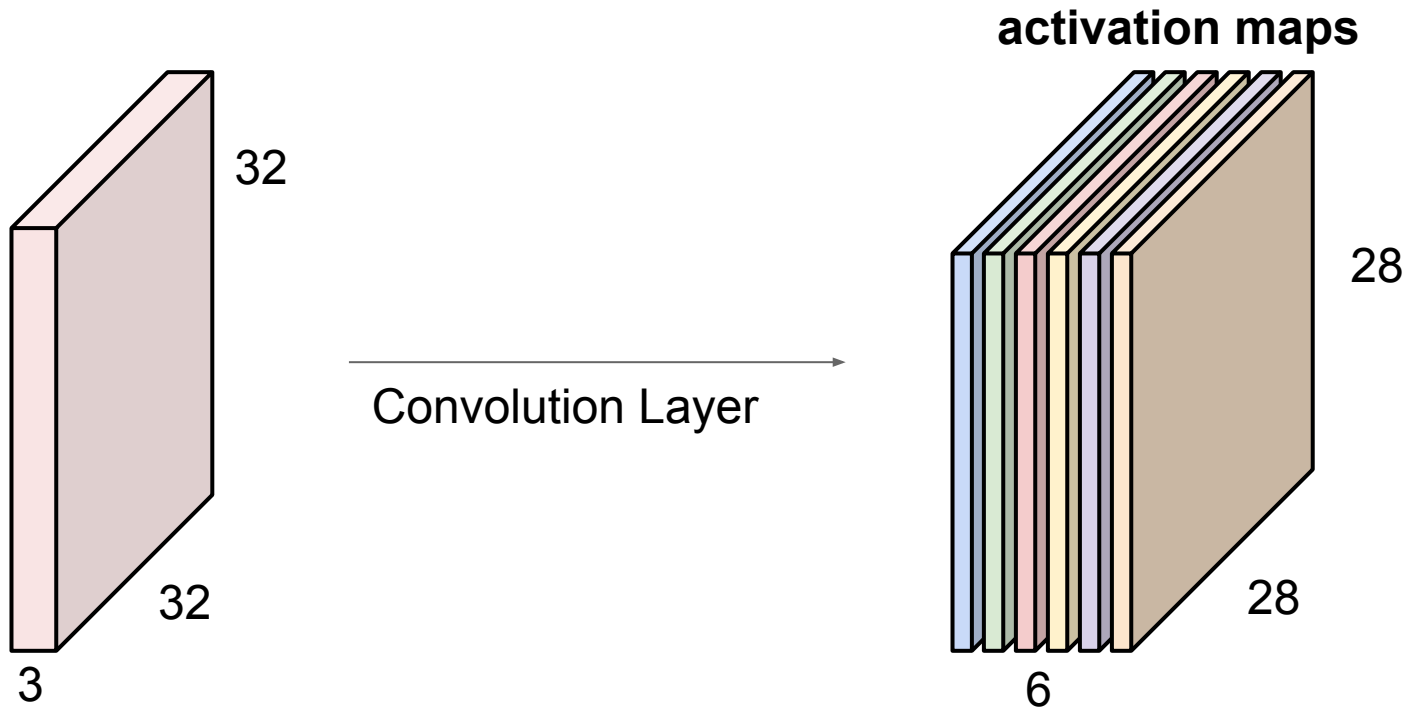
Convolutional Layer



Consider another green filter

Convolutional Layer

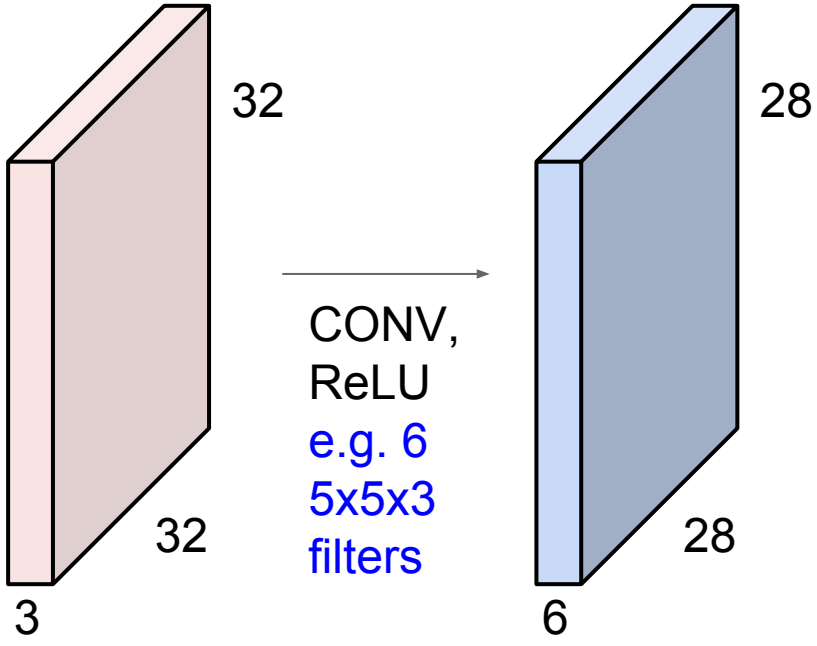
For example, if we had 6 5x5 filters, we'll get 6 separate activation maps:



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

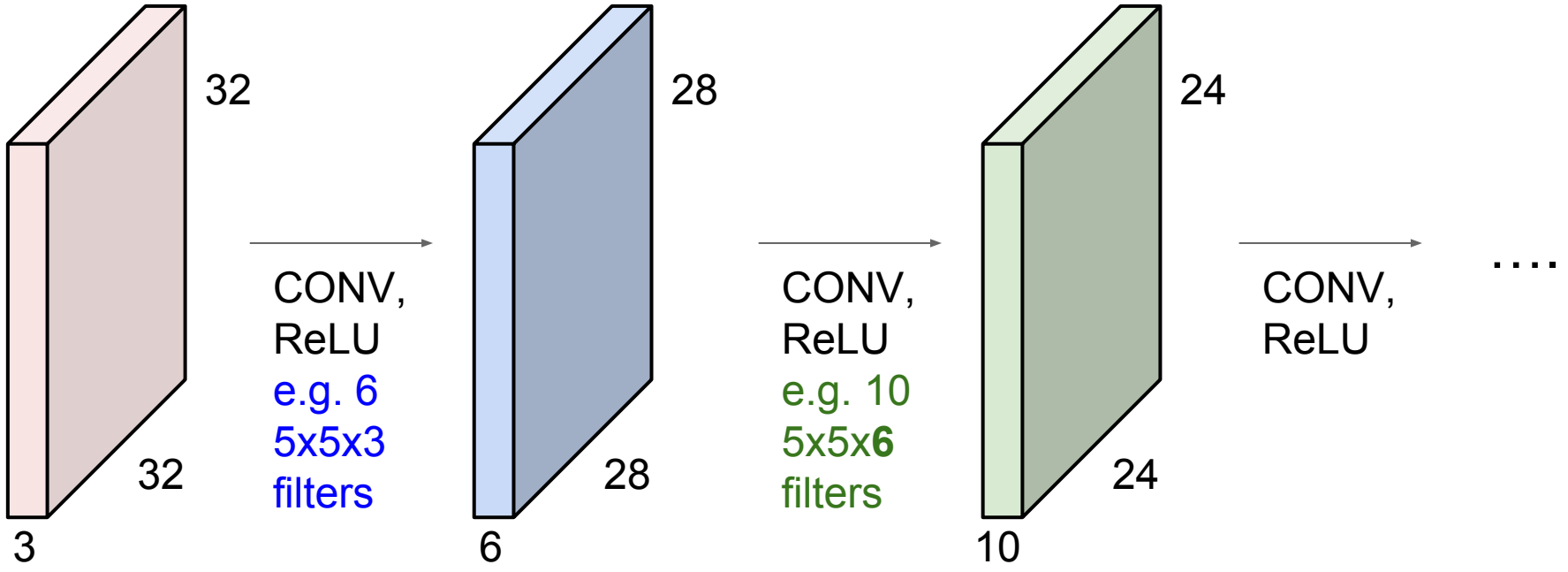
ConvNet

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



ConvNet

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



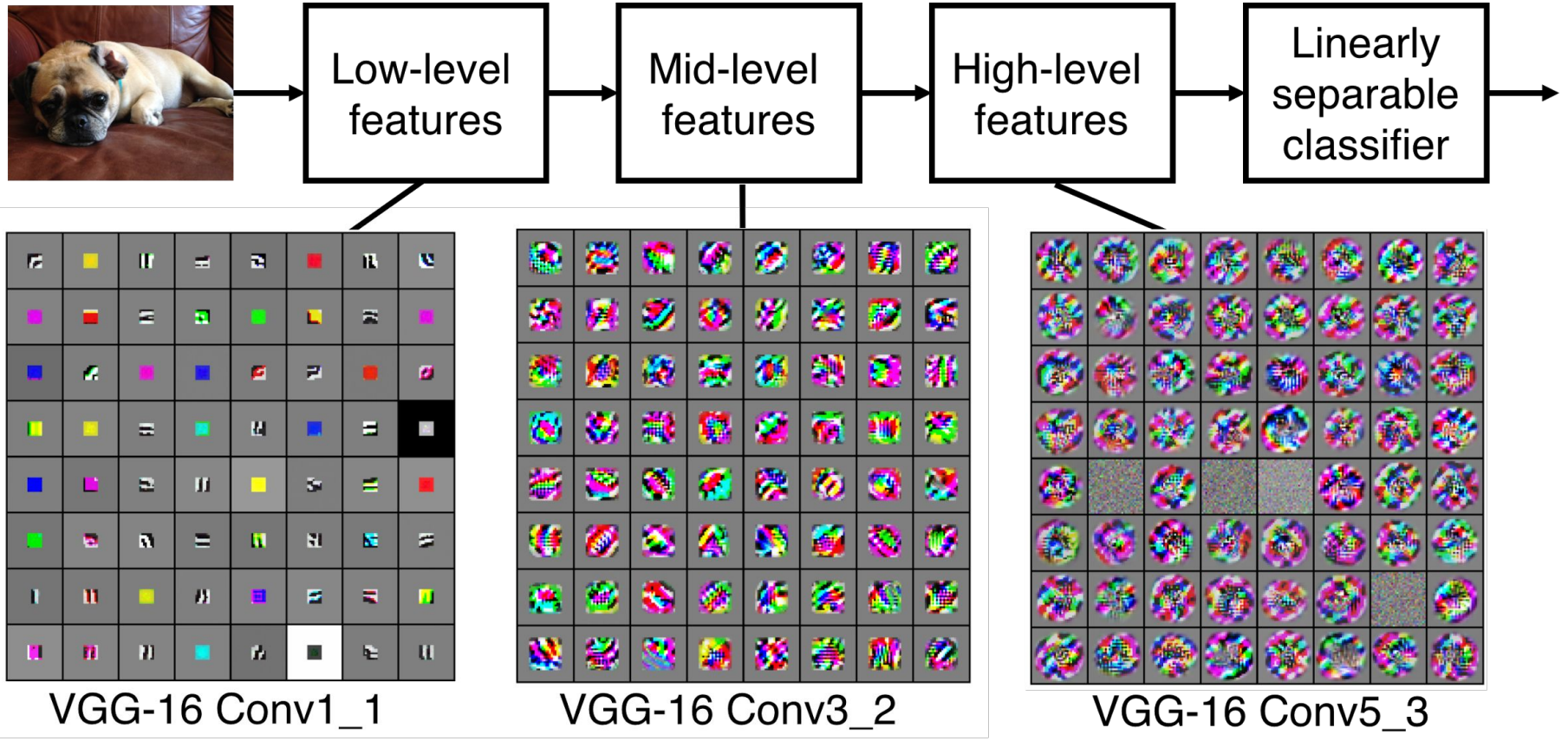
Visualization

Let's see what the Inputs maximizing the activations of conv neurons look like

Preview

[Zeiler and Fergus 2013]

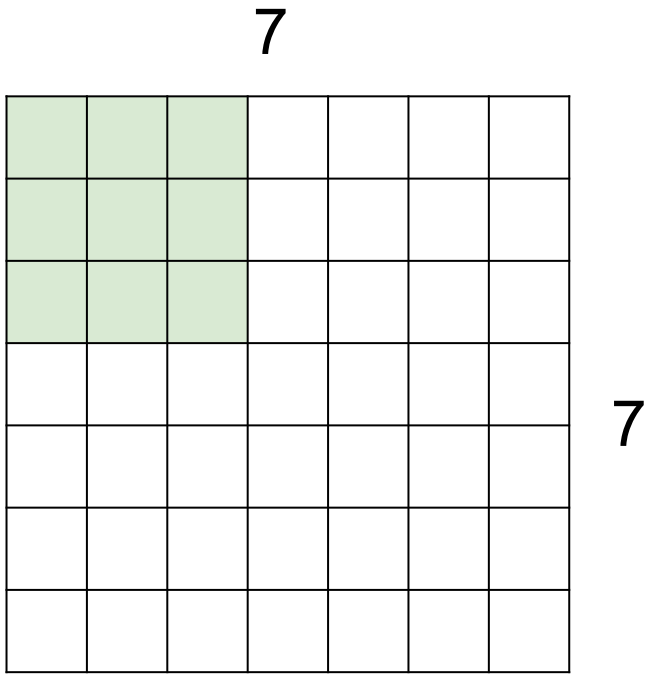
Visualization of VGG-16 by Lane McIntosh. VGG-16 architecture from [Simonyan and Zisserman 2014].



points, edges, …

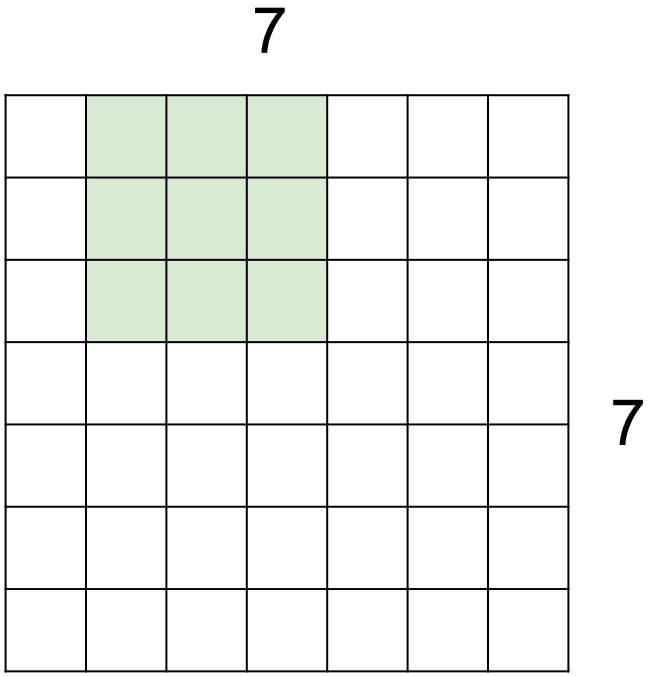
corners, blobs, …

A closer look at spatial dimensions



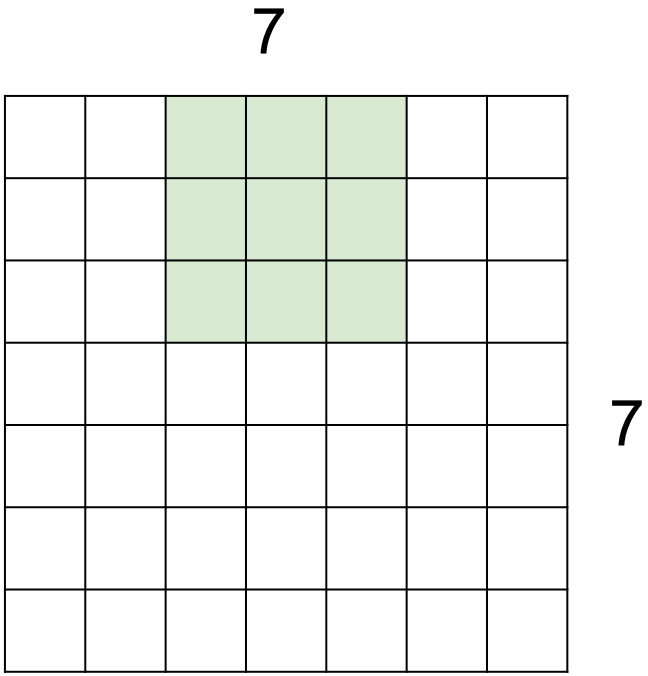
7x7 input (spatially)
assume 3x3 filter

A closer look at spatial dimensions



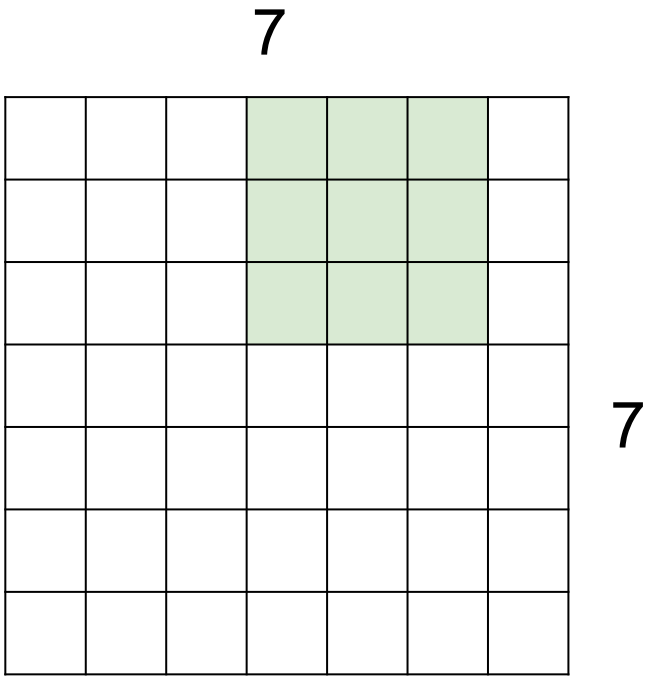
7x7 input (spatially)
assume 3x3 filter

A closer look at spatial dimensions



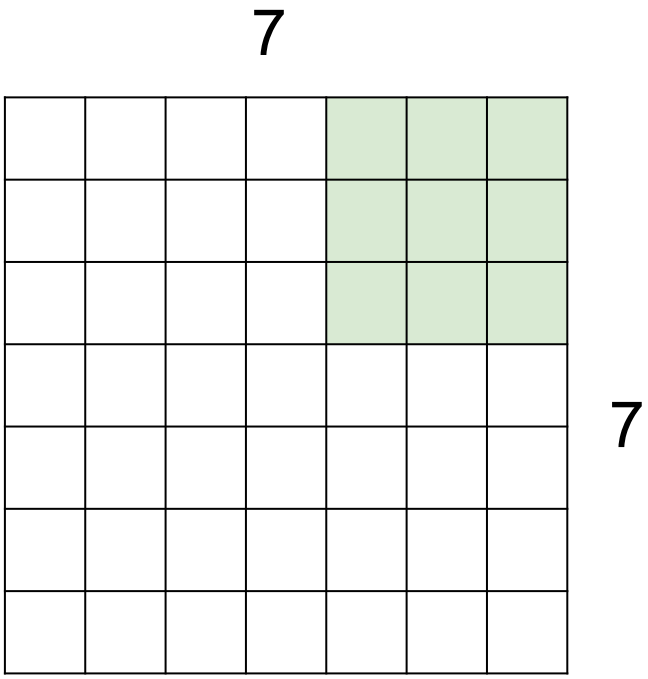
7x7 input (spatially)
assume 3x3 filter

A closer look at spatial dimensions



7x7 input (spatially)
assume 3x3 filter

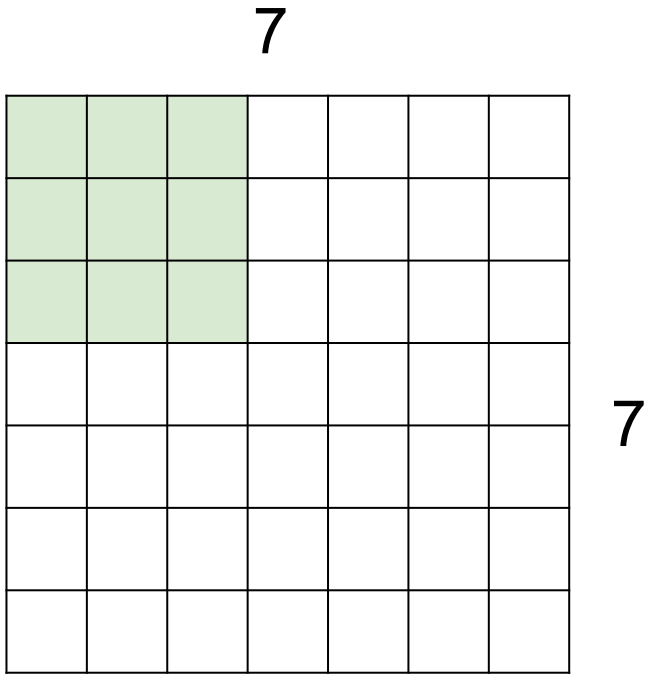
A closer look at spatial dimensions



7x7 input (spatially)
assume 3x3 filter

=> 5x5 output

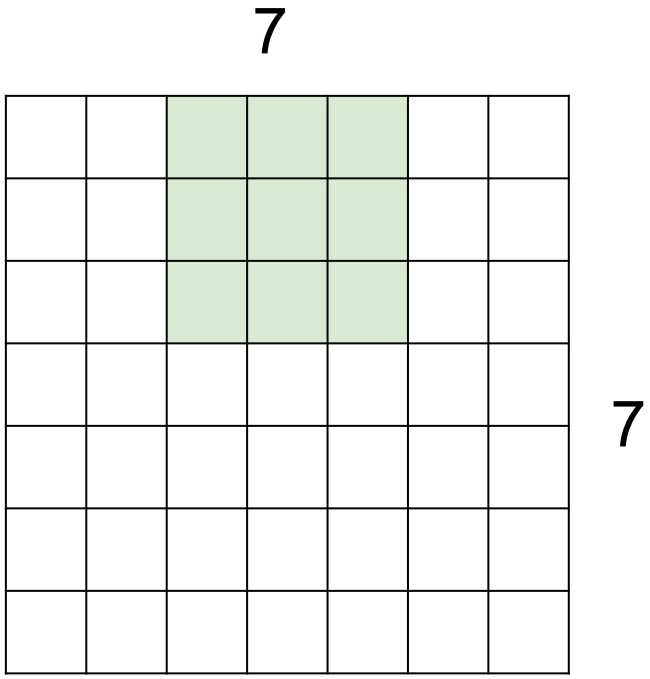
A closer look at spatial dimensions



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

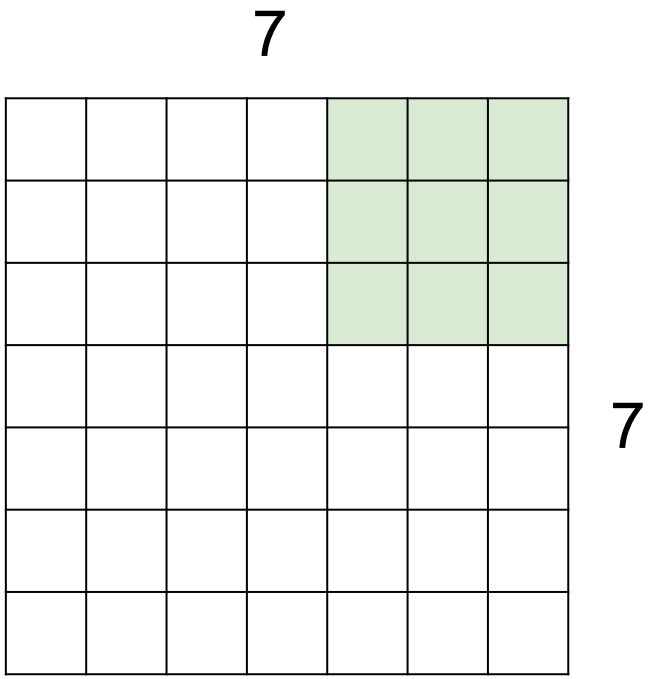
Stride : the step length (in number of pixels) when you move a filter.

A closer look at spatial dimensions



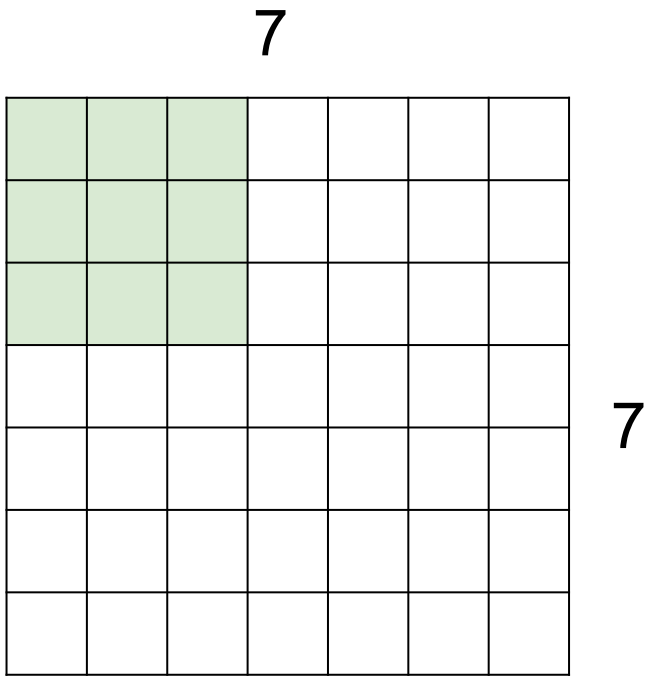
7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**

A closer look at spatial dimensions



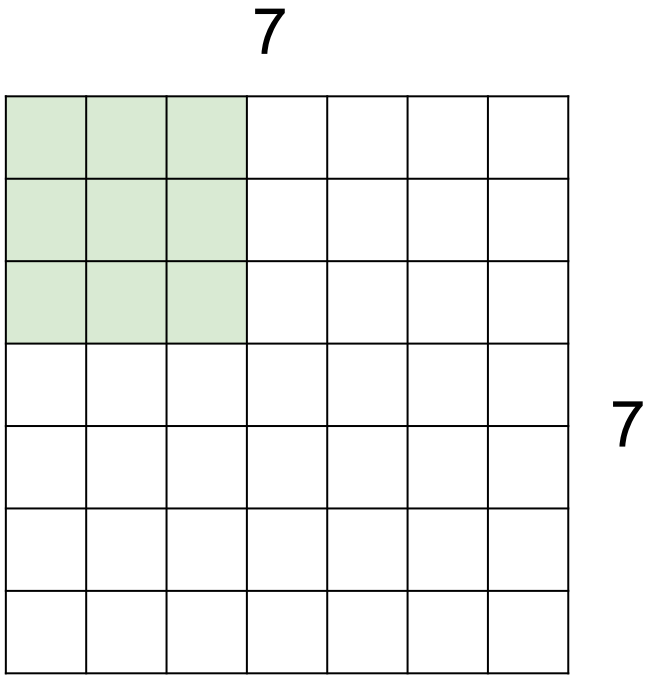
7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**
=> 3x3 output!

A closer look at spatial dimensions



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

A closer look at spatial dimensions

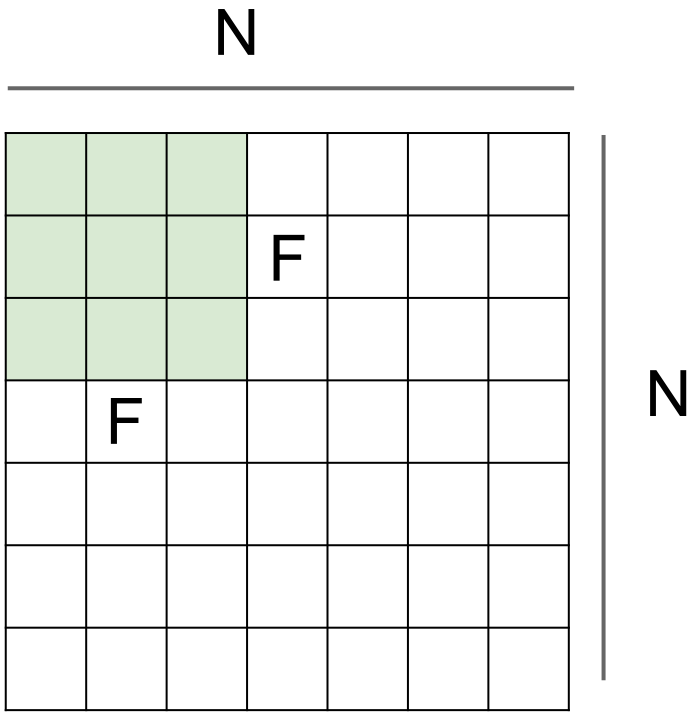


7x7 input (spatially)
assume 3x3 filter
applied **with stride 3?**

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

Leads to asymmetric outputs and avoid doing that!

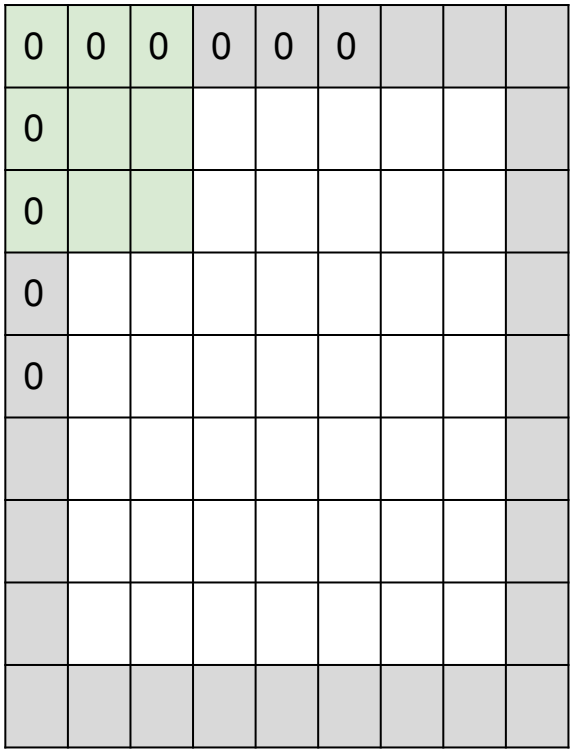
A closer look at spatial dimensions



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 :\

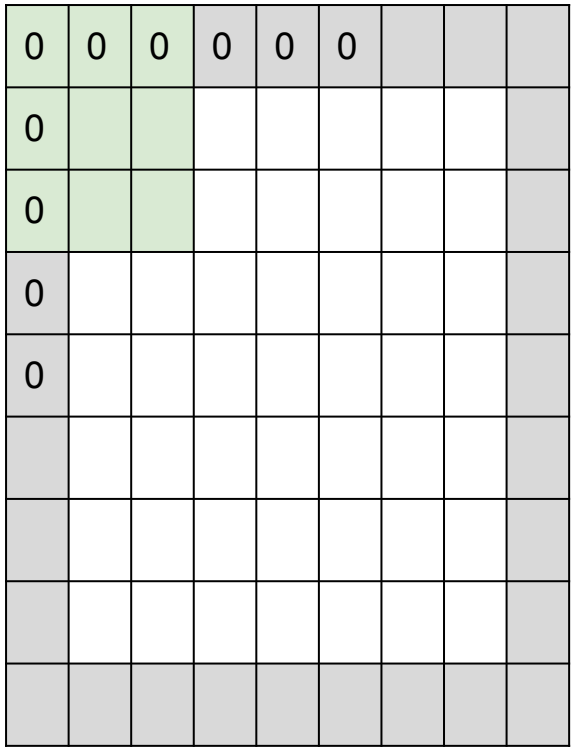
In practice: common to zero pad the border



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

(recall:)
(N - F) / stride + 1

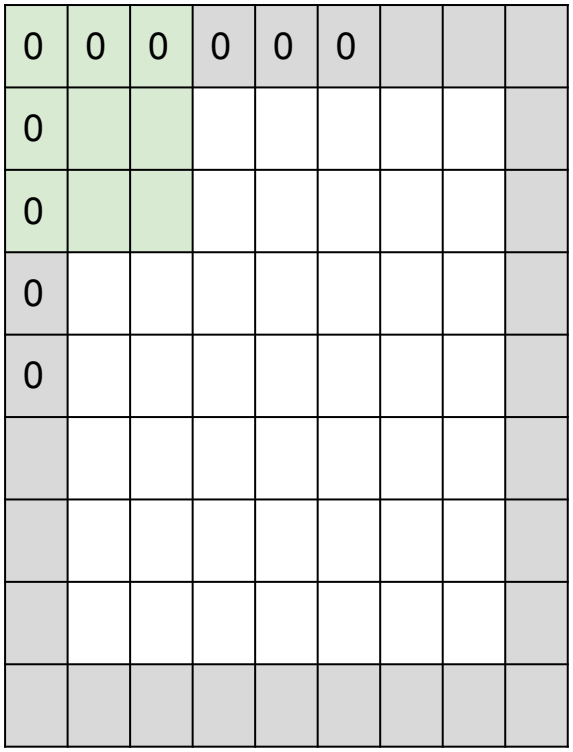
In practice: common to zero pad the border



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

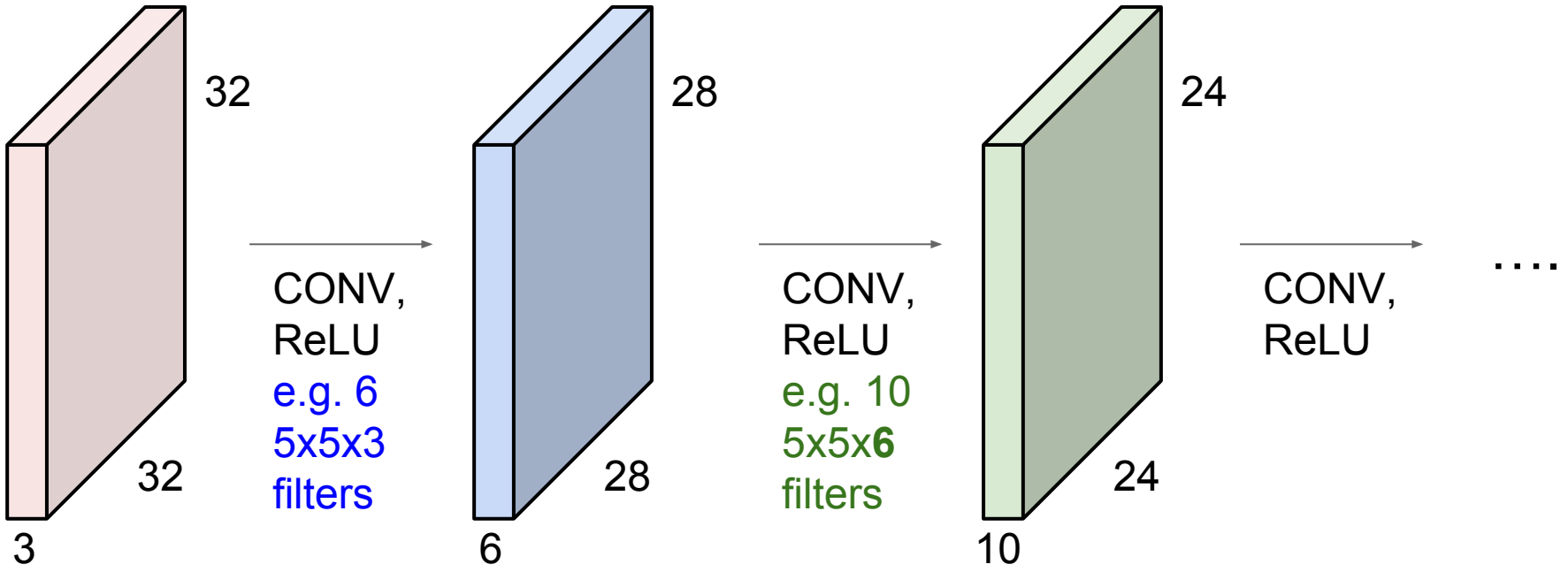


e.g. input 7x7
3x3 filter, applied with **stride 1**
pad with 1 pixel border => what is the output?

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

In practice: common to zero pad the border

Remember back to…
E.g. 32x32 input convolved repeatedly with 5x5 filters shrinks volumes spatially! (32 -> 28 -> 24 ...). Shrinking too fast is not good, doesn't work well.



Now it is possible to build a very deep ConvNet

Example

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

Output volume size: ?

Example

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

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

Example

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

Number of parameters in this layer?

Example

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
=> 76*10 = **760**

Example

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

Number of add&mul operations in this layer?

Example

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

Number of add&mul operations in this layer?
each output neuron has 5x5x3 ops, and there are 32x32x10 output neurons =>
32x32x10x5x5x3

Summary

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.

Summary

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

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,
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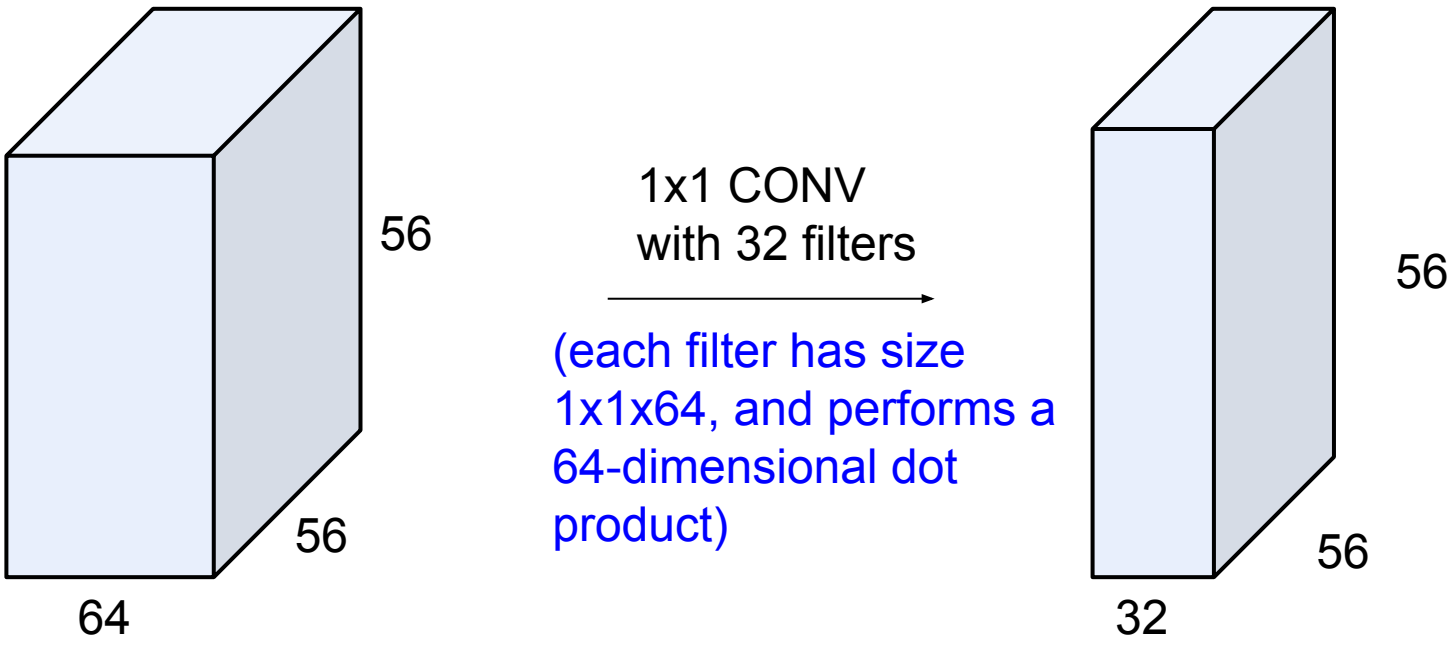
1x1 convolution

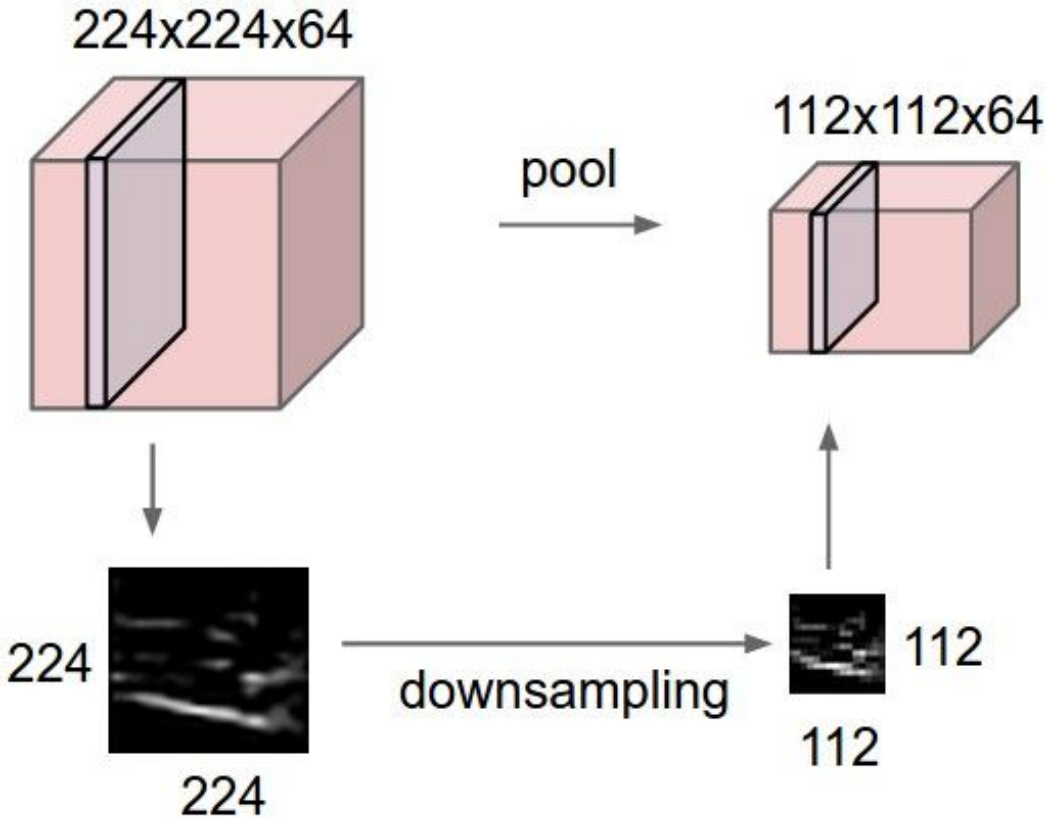


Q: Is a fully-connected layer a convolutional layer?

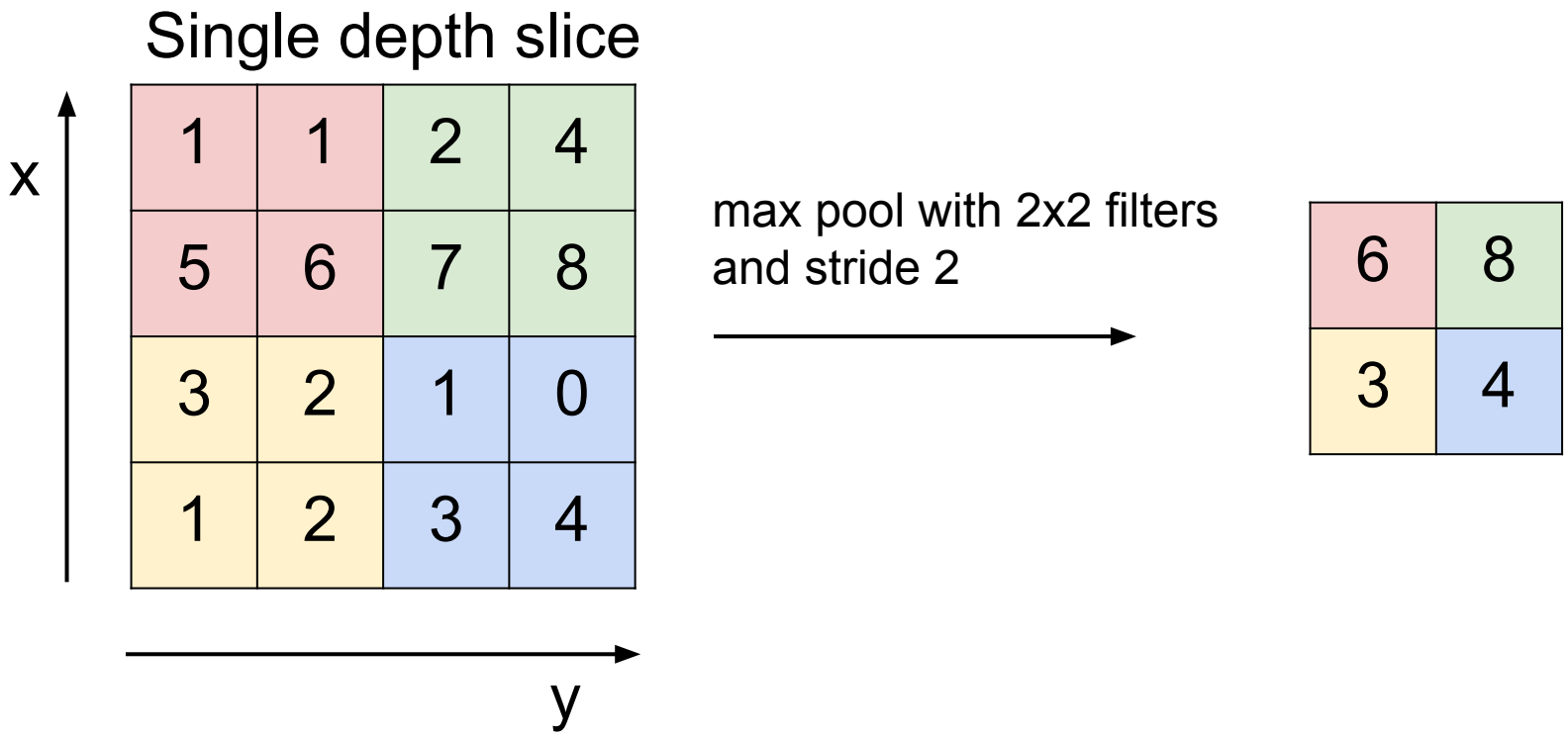
Pooling Layer

Pooling layer

- To make the representations smaller and more manageable
- Operates over each activation map independently: output-depth = input-depth



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

Summary

- Accepts a volume of size $W_1 \times H_1 \times D_1$
- Requires three 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
- Note that it is not common to use zero-padding for Pooling layers

Summary

Common settings:

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

- Accepts a volume of size $W_1 \times H_1 \times D_1$
- Requires three 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
- Note that it is not common to use zero-padding for Pooling layers

Convolution + Pooling ≈ Translation invariance

- Convolution: local feature detector
- Pooling: invariant to small translation



Taking-home messages

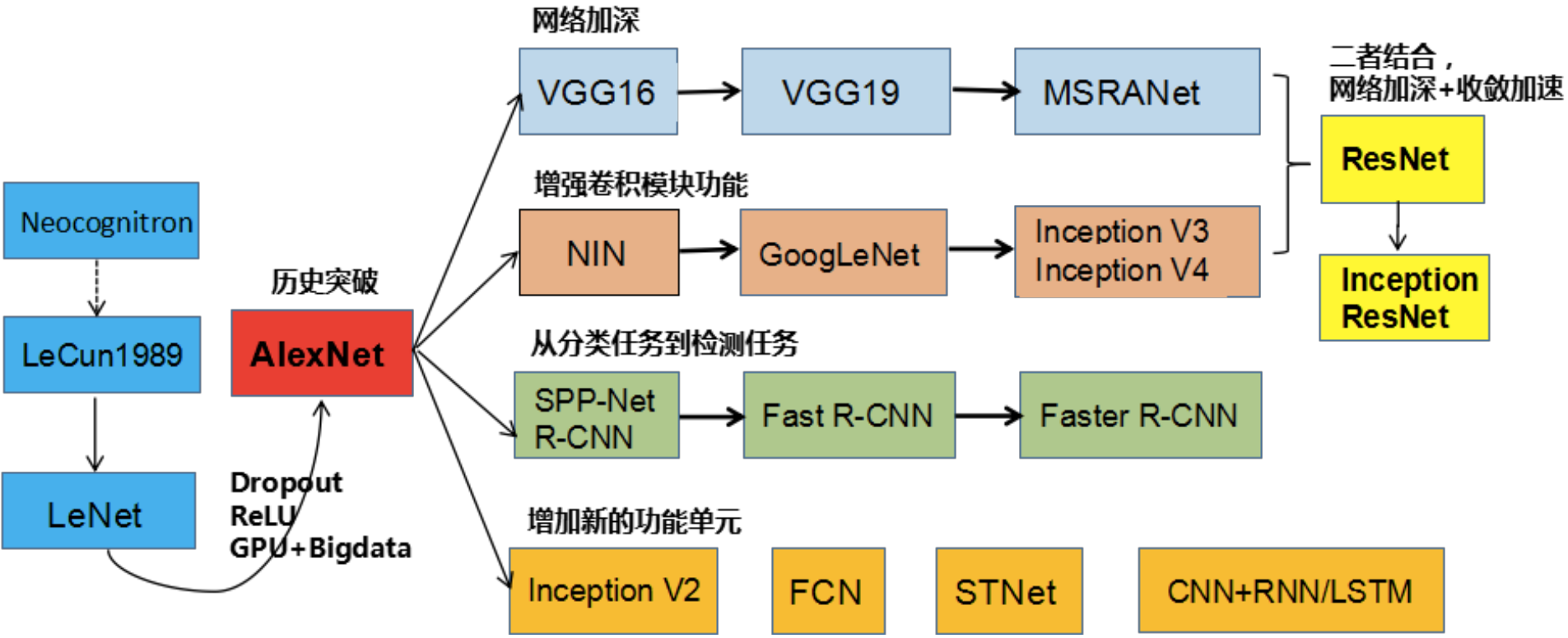
- ConvNets stack CONV, POOL, FC layers
- Trend towards smaller filters and deeper architechtures
- Trend towards getting rid of POOL/FC layers (just CONV)
- Typical architectures look like:

  [(CONV-RELU)*N-POOL?]*M-(FC-RELU)*K-SOFTMAX

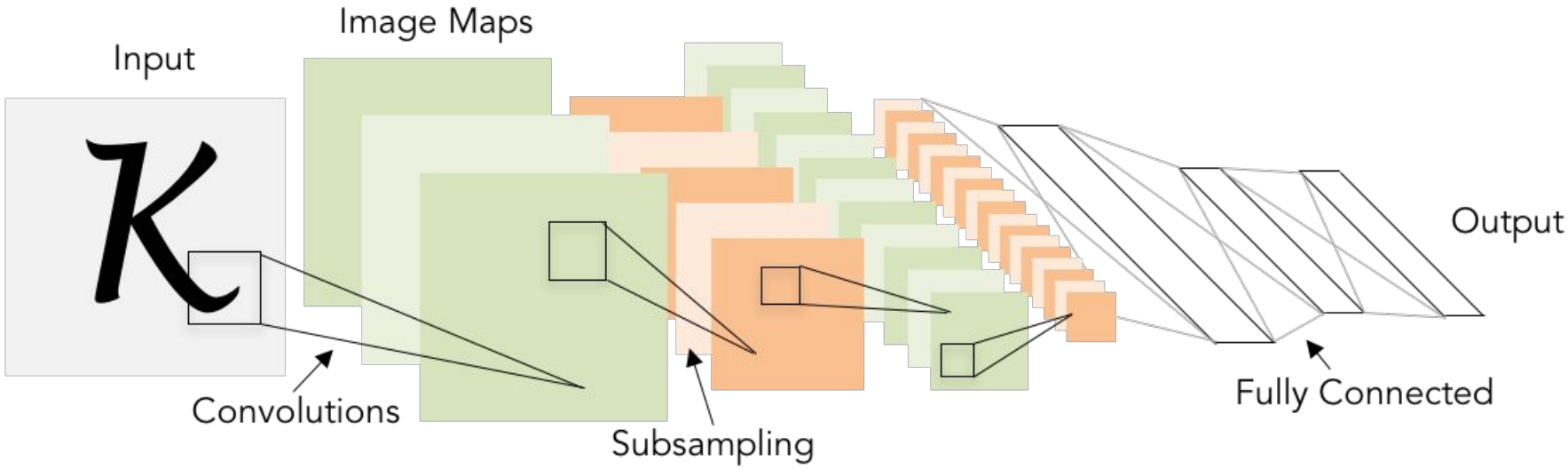
  where N is usually up to ~5, M is large, 0 <= K <= 2. But recent advances such as ResNet challenge this paradigm
- Convolution + Pooling ≈ Translation invariance

CNN Architectures

The evolution of CNN architectures



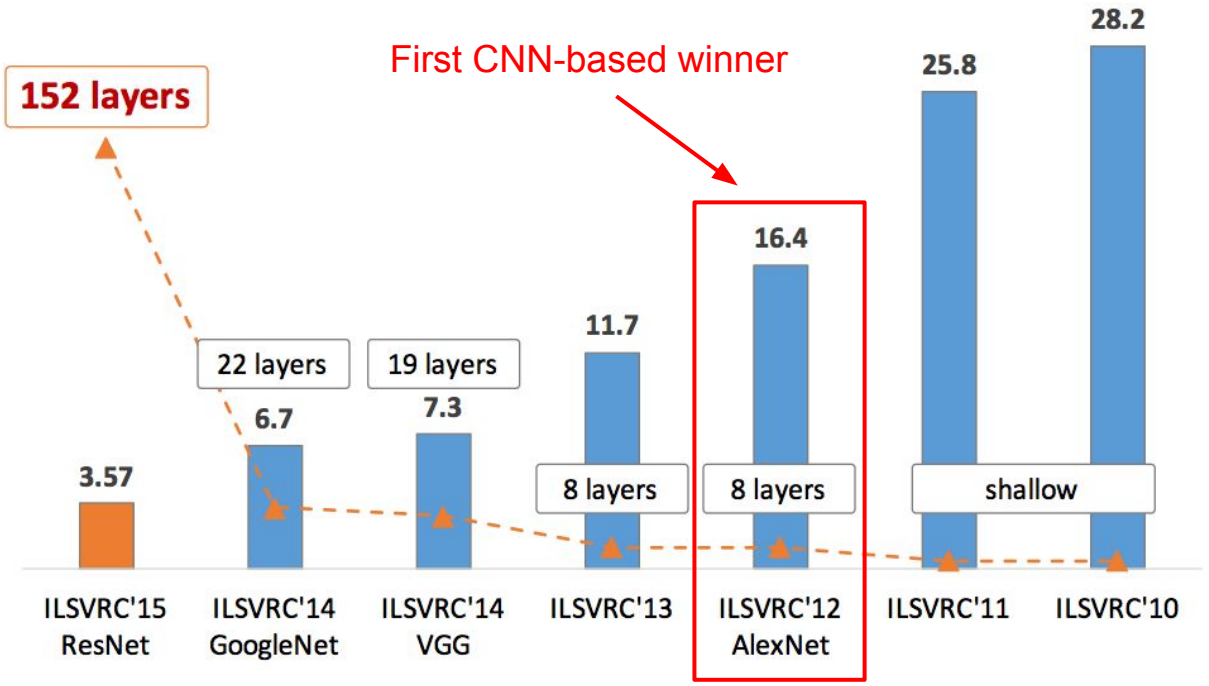
LeNet-5 [LeCun et al., 1998]



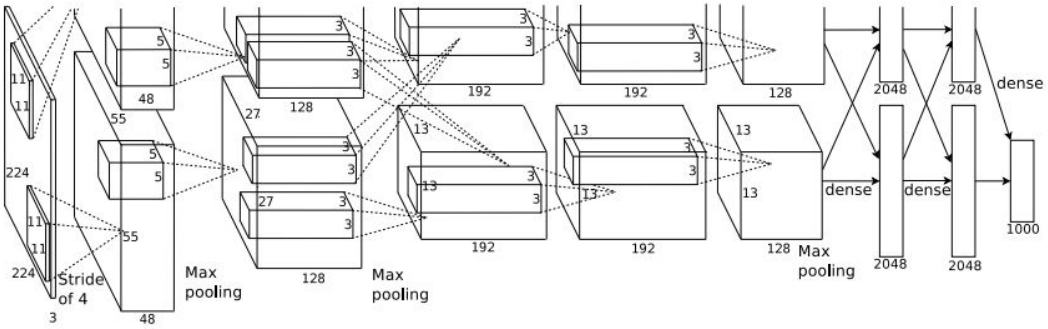
Conv filters were 5x5, applied at stride 1
Subsampling (Pooling) layers were 2x2 applied at stride 2
i.e. architecture is [CONV-POOL-CONV-POOL-FC-FC]

AlexNet [Krizhevsky et al. 2012]

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



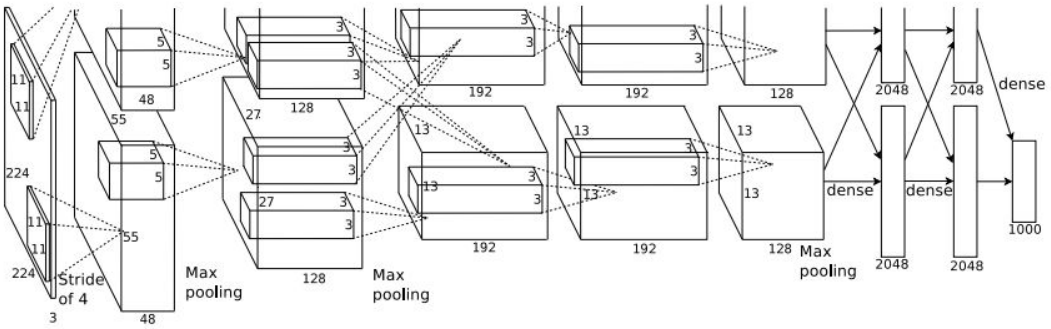
AlexNet [Krizhevsky et al. 2012]



Architecture:

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

AlexNet [Krizhevsky et al. 2012]



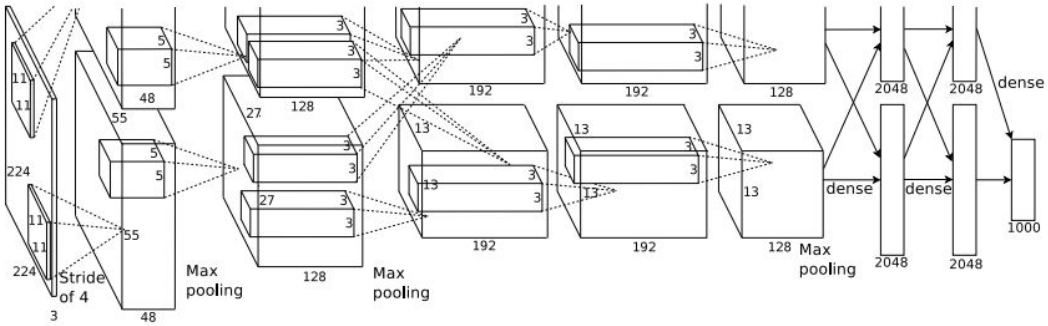
Input: 227x227x3 images

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

=>

Q: what is the output volume size? Hint: (227-11)/4+1 = 55

AlexNet [Krizhevsky et al. 2012]

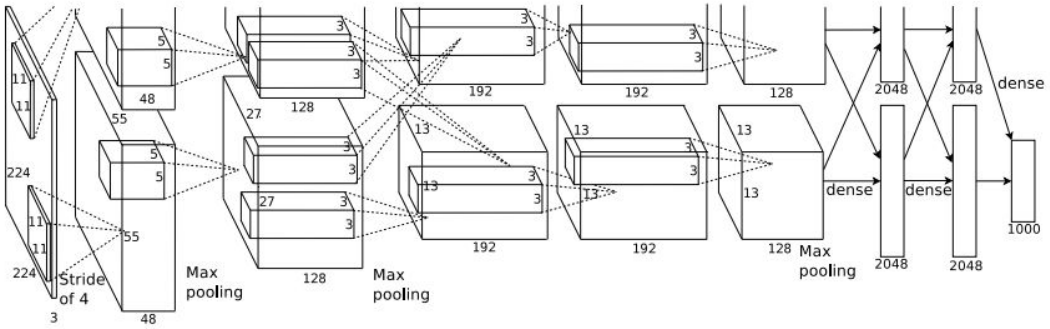


Input: 227x227x3 images

First layer (CONV1): 96 11x11 filters applied at stride 4
=>
Output volume **[55x55x96]**

Q: What is the total number of parameters in this layer?

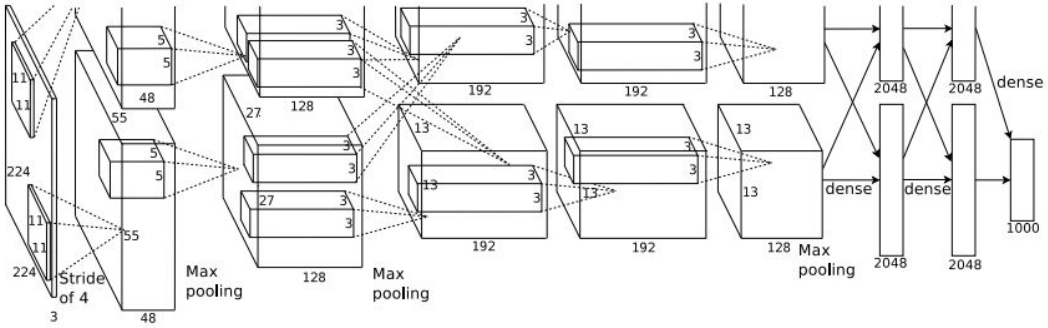
AlexNet [Krizhevsky et al. 2012]



Input: 227x227x3 images

First layer (CONV1): 96 11x11 filters applied at stride 4
=>
Output volume **[55x55x96]**
Parameters: (11*11*3)*96 **= 35K**

AlexNet [Krizhevsky et al. 2012]

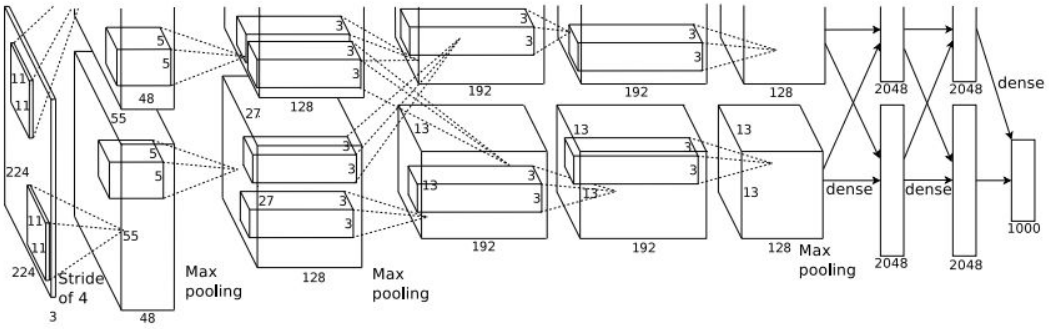


Input: 227x227x3 images
After CONV1: 55x55x96

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

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

AlexNet [Krizhevsky et al. 2012]

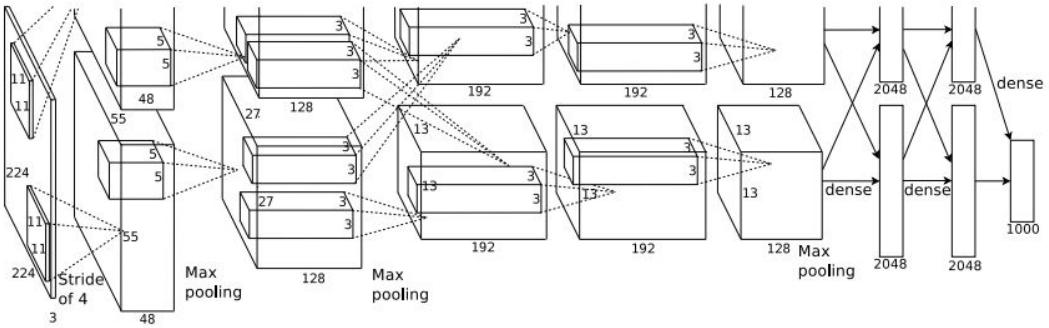


Input: 227x227x3 images
After CONV1: 55x55x96

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

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

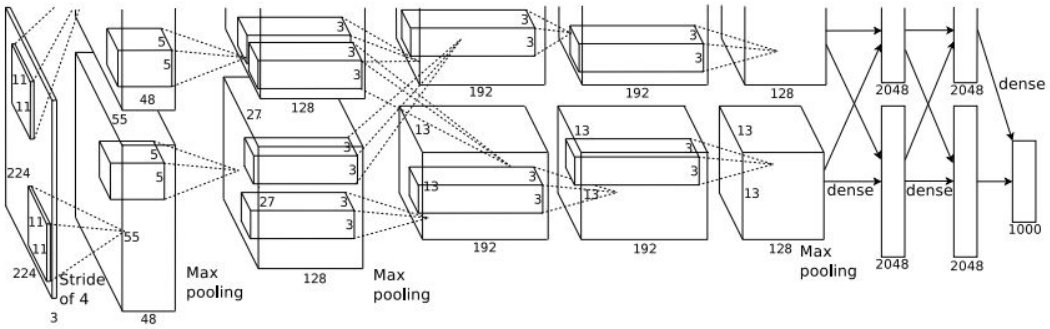
AlexNet [Krizhevsky et al. 2012]



Input: 227x227x3 images
After CONV1: 55x55x96

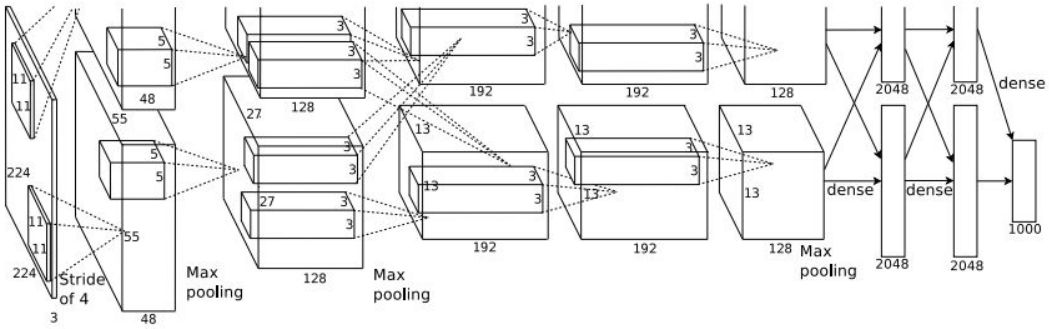
Second layer (POOL1): 3x3 filters applied at stride 2
Output volume: 27x27x96
Parameters: 0!

AlexNet [Krizhevsky et al. 2012]



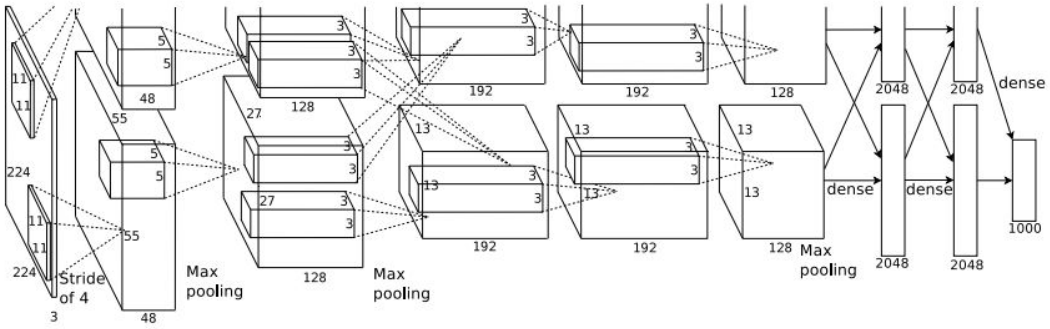
Input: 227x227x3 images
After CONV1: 55x55x96
After POOL1: 27x27x96
...

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)

AlexNet [Krizhevsky et al. 2012]



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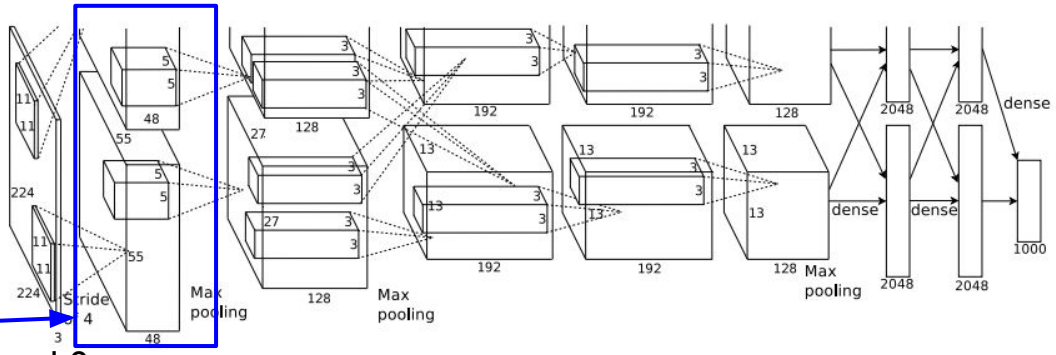
[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1
[6x6x256] MAX POOL3: 3x3 filters at stride 2
[4096] FC6: 4096 neurons
[4096] FC7: 4096 neurons
[1000] FC8: 1000 neurons (class scores)

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%

AlexNet [Krizhevsky et al. 2012]

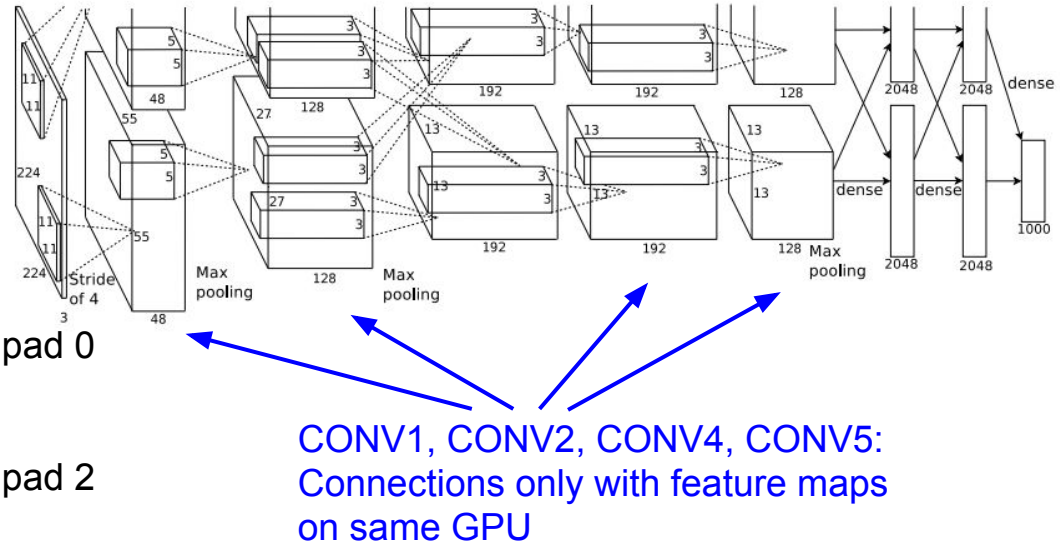


[55x55x48] x 2

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)

Historical note: Trained on GTX 580 GPU with only 3 GB of memory. Network spread across 2 GPUs, half the neurons (feature maps) on each GPU.

AlexNet [Krizhevsky et al. 2012]



CONV1, CONV2, CONV4, CONV5: Connections only with feature maps on same GPU

Full (simplified) AlexNet architecture:
[227x227x3] INPUT
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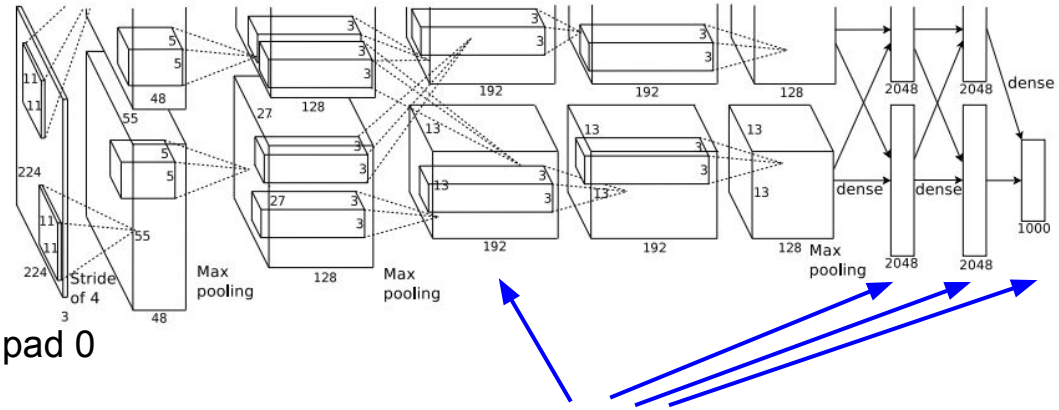
AlexNet [Krizhevsky et al. 2012]



Full (simplified) AlexNet architecture:
[227x227x3] INPUT
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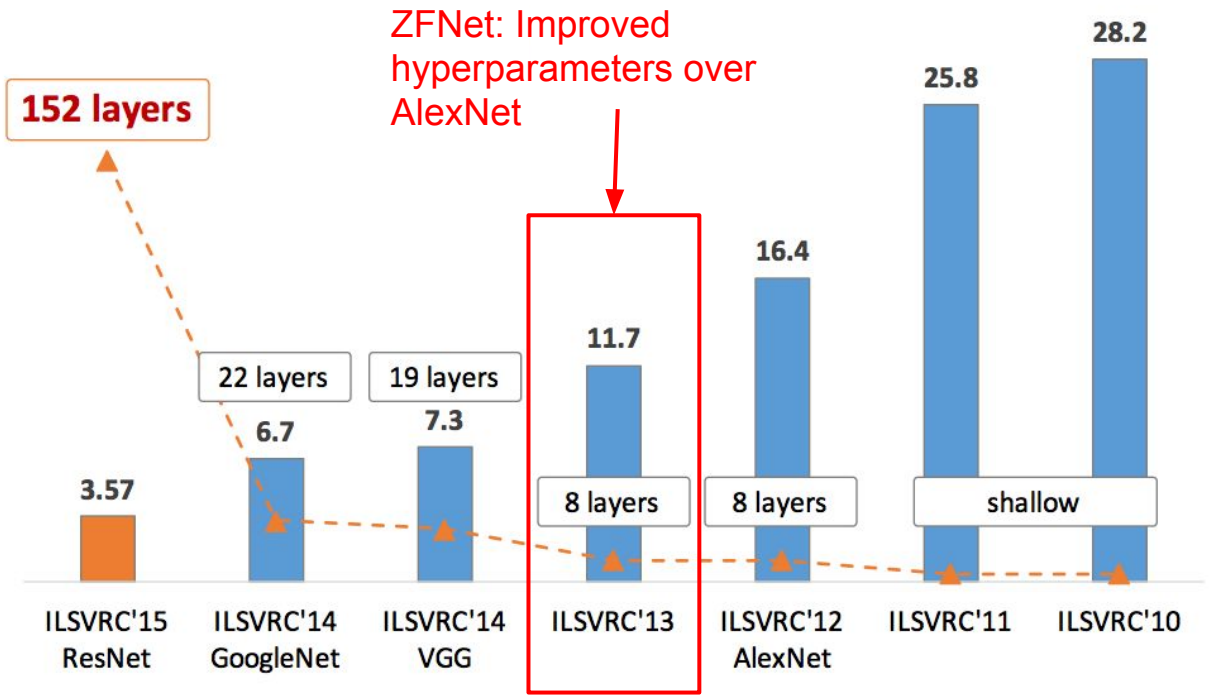
[13x13x256] NORM2: Normalization layer
[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1
[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1
[6x6x256] MAX POOL3: 3x3 filters at stride 2
[4096] FC6: 4096 neurons
[4096] FC7: 4096 neurons
[1000] FC8: 1000 neurons (class scores)

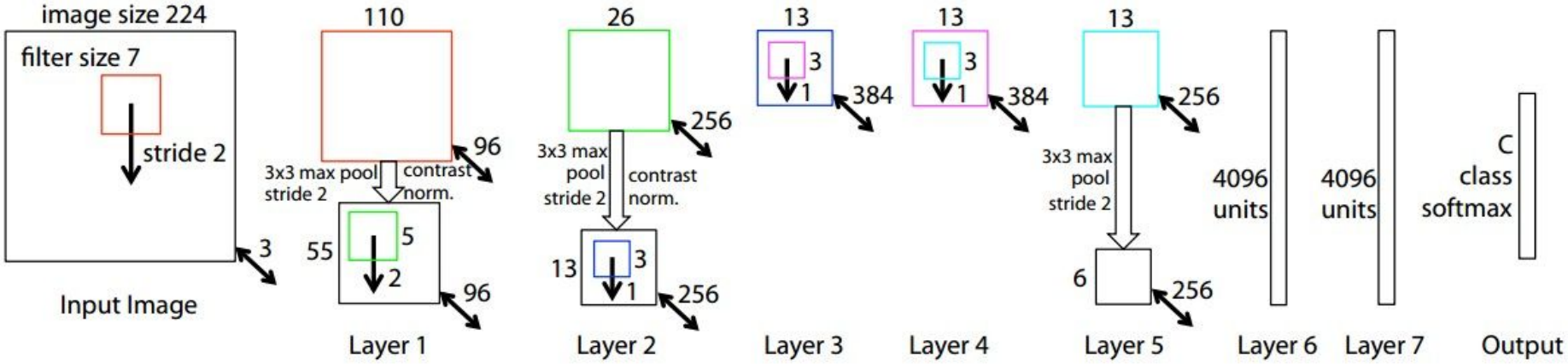
CONV3, FC6, FC7, FC8:
Connections with all feature maps in preceding layer, communication across GPUs

ZFNet [Zeiler and Fergus, 2013]

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



ZFNet [Zeiler and Fergus, 2013]

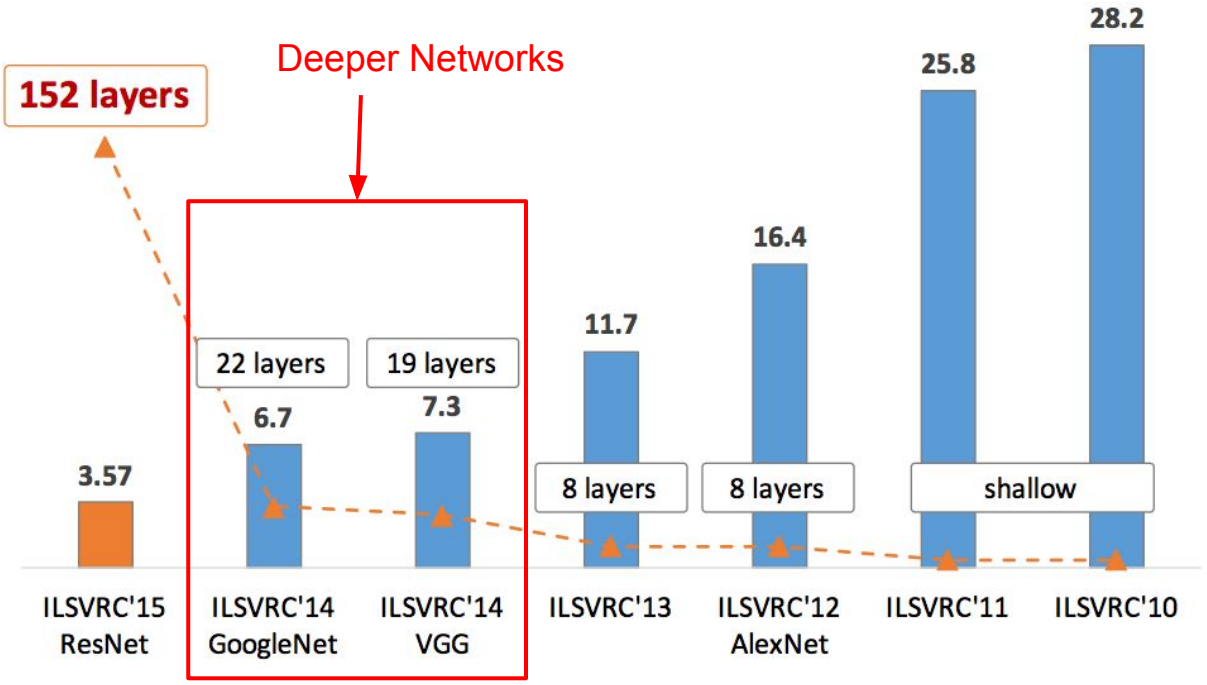


AlexNet but:
CONV1: change from (11x11 stride 4) to (7x7 stride 2)
CONV3,4,5: instead of 384, 384, 256 filters use 512, 1024, 512

ImageNet top 5 error: 16.4% -> 11.7%

VGGNet [Simonyan and Zisserman, 2014]

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



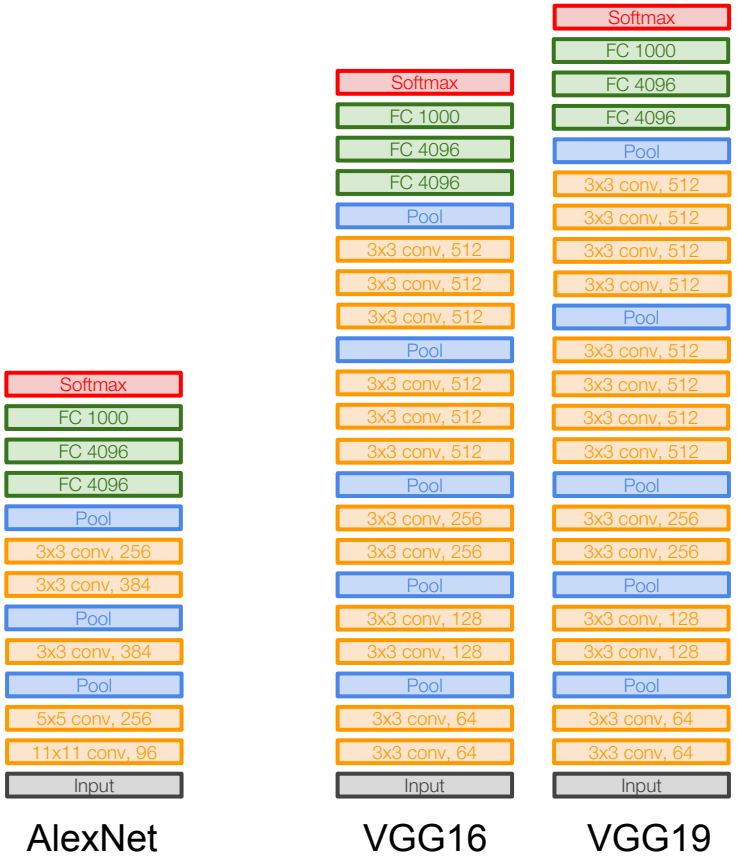
VGGNet [Simonyan and Zisserman, 2014]

Small filters, Deeper networks

8 layers (AlexNet)
-> 16 - 19 layers (VGG16Net)

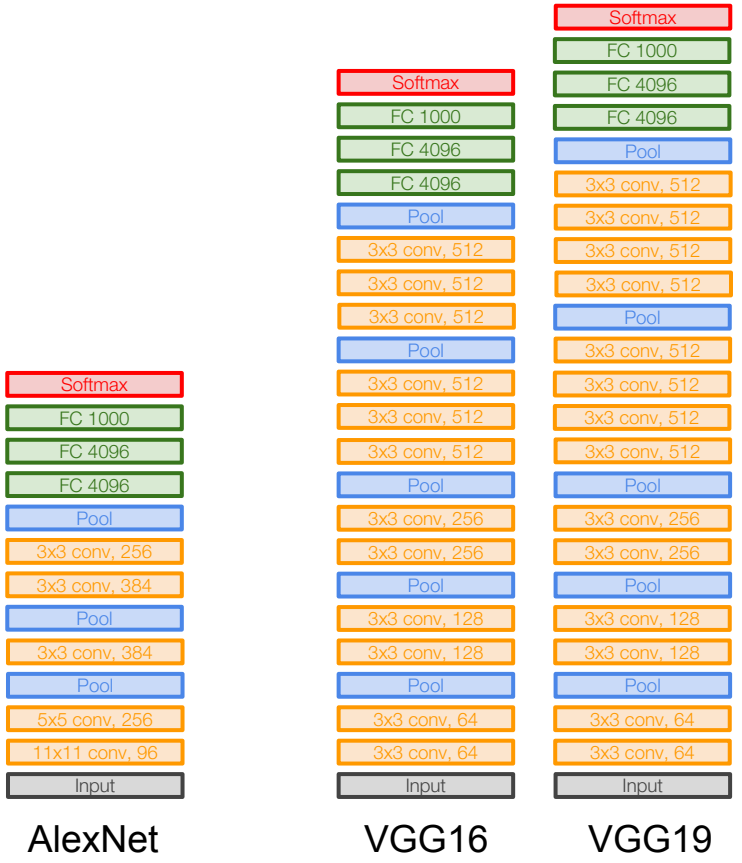
Only 3x3 CONV stride 1, pad 1
and 2x2 MAX POOL stride 2

11.7% top 5 error in ILSVRC'13
(ZFNet)
-> 7.3% top 5 error in ILSVRC'14



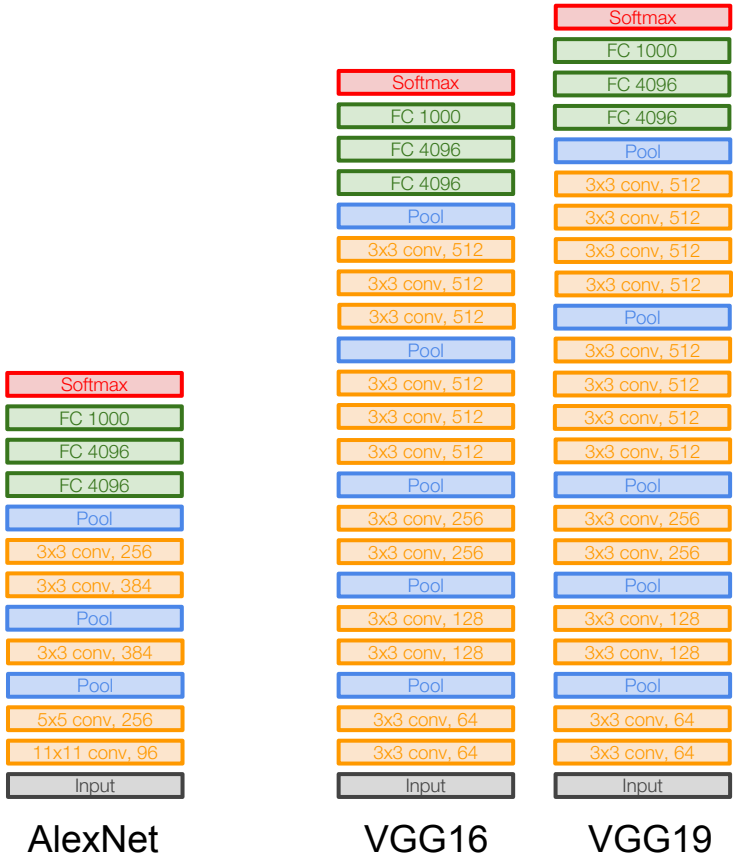
VGGNet [Simonyan and Zisserman, 2014]

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



VGGNet [Simonyan and Zisserman, 2014]

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

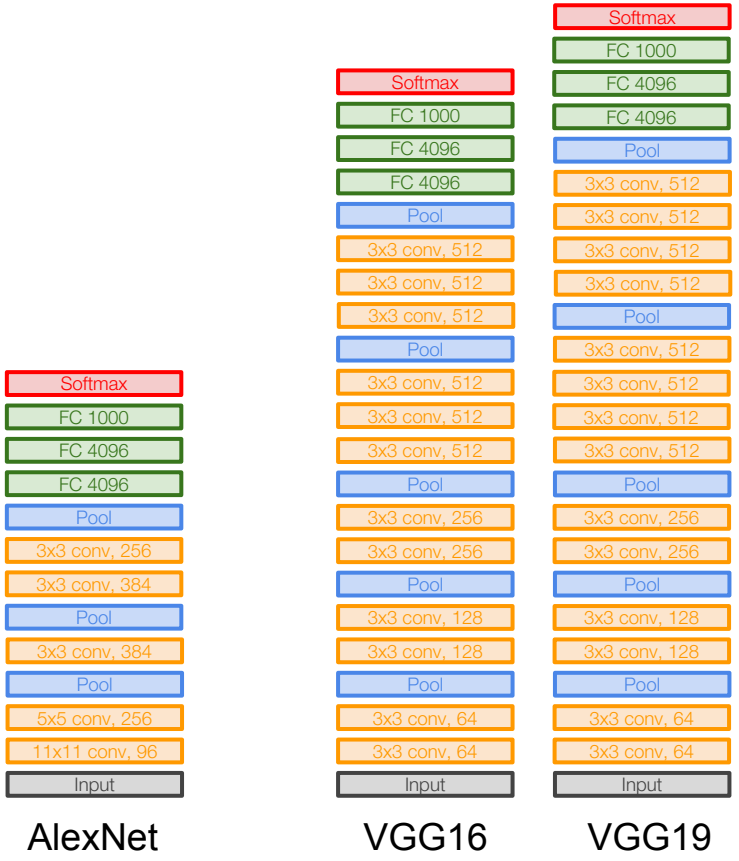


VGGNet [Simonyan and Zisserman, 2014]

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

[7x7]



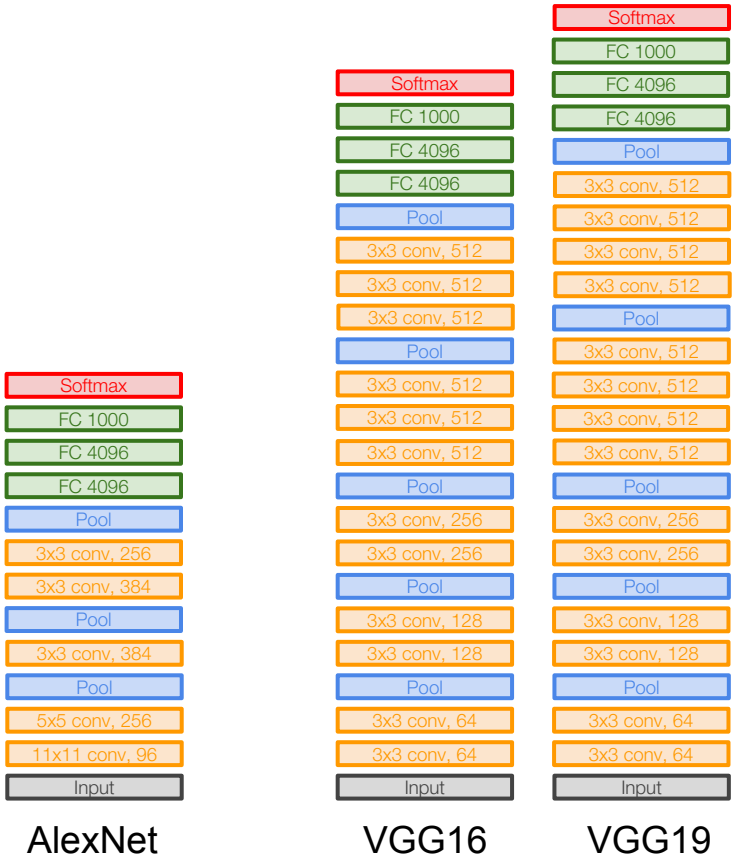
VGGNet [Simonyan and Zisserman, 2014]

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

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

But deeper, more non-linearities

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



VGGNet [Simonyan and Zisserman, 2014]

(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
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

VGG16

VGGNet [Simonyan and Zisserman, 2014]

(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
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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

Note:

Most memory is in early CONV

Most params are in late FC

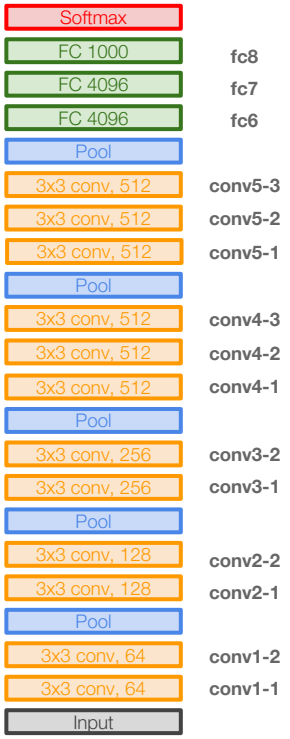
TOTAL memory: 24M * 4 bytes ~= 96MB / image (only forward! ~*2 for bwd)
TOTAL params: 138M parameters

VGGNet [Simonyan and Zisserman, 2014]

(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
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



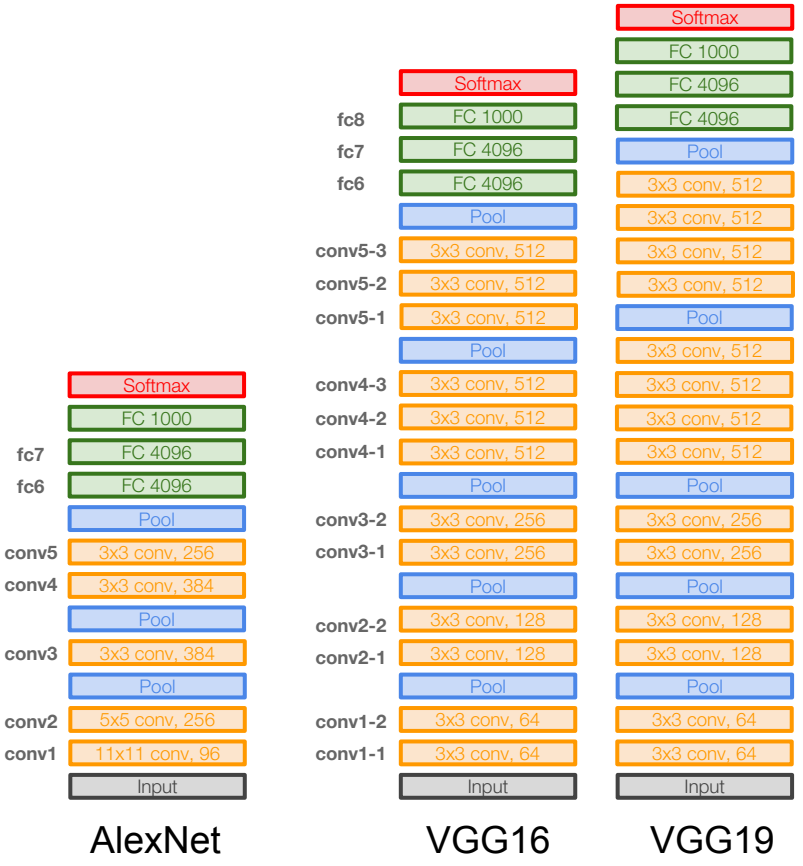
VGG16

Common names

VGGNet [Simonyan and Zisserman, 2014]

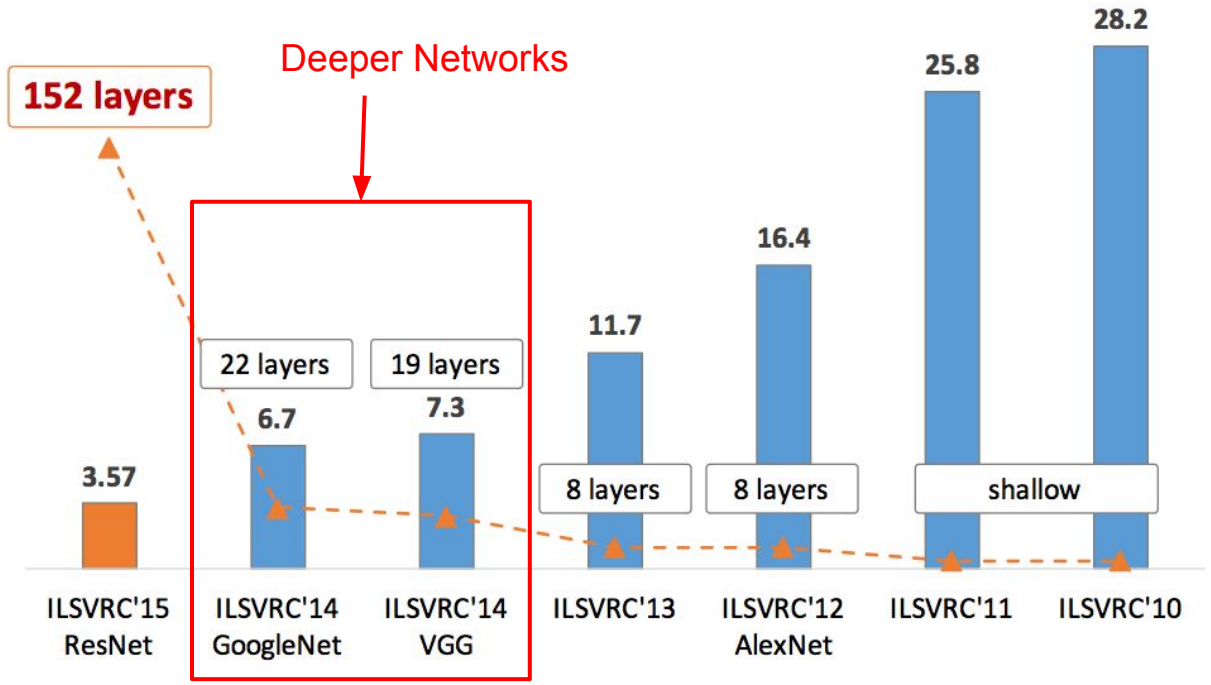
Details:

- ILSVRC'14 2nd in classification, 1st in localization
- Similar training procedure as Krizhevsky 2012
- No Local Response Normalisation (LRN)
- Use VGG16 or VGG19 (VGG19 only slightly better, more memory)
- Use ensembles for best results
- FC7 features generalize well to other tasks



GoogLeNet [Szegedy et al., 2014]

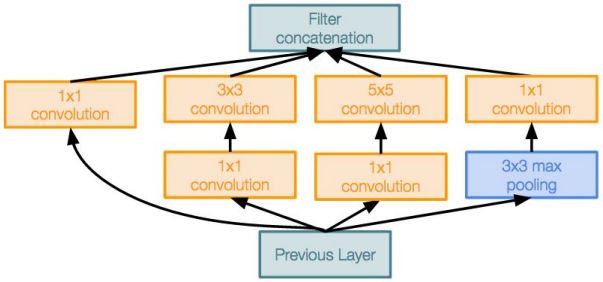
ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



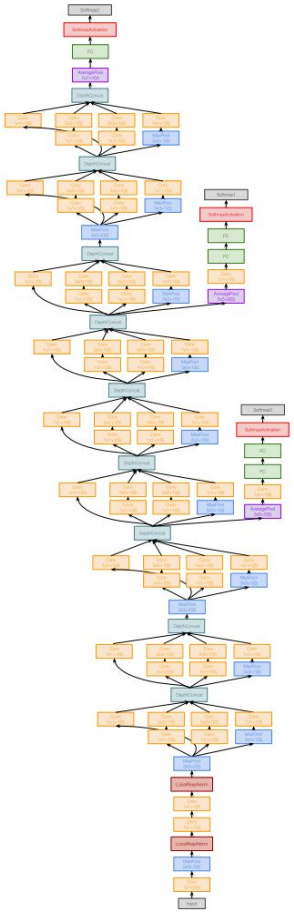
GoogLeNet [Szegedy et al., 2014]

Deeper networks, with computational efficiency

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

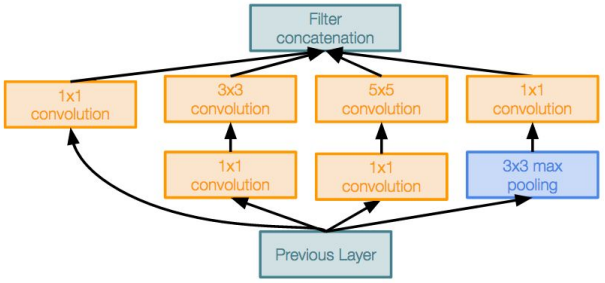


Inception module

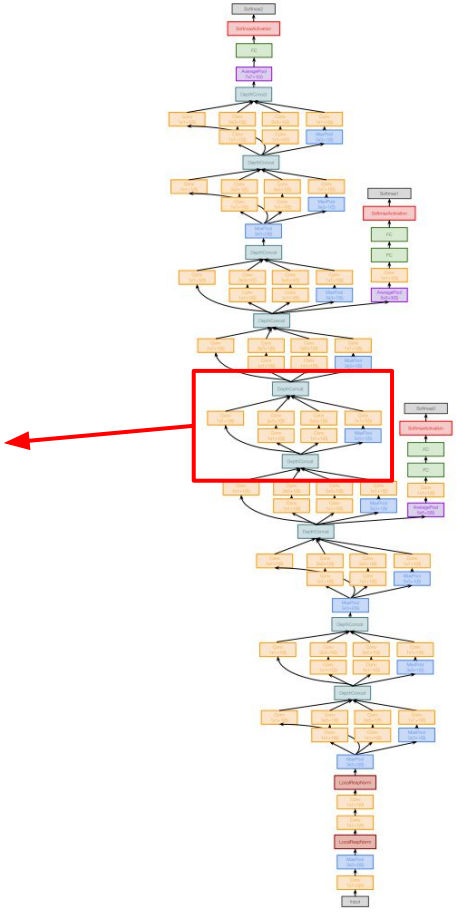


GoogLeNet [Szegedy et al., 2014]

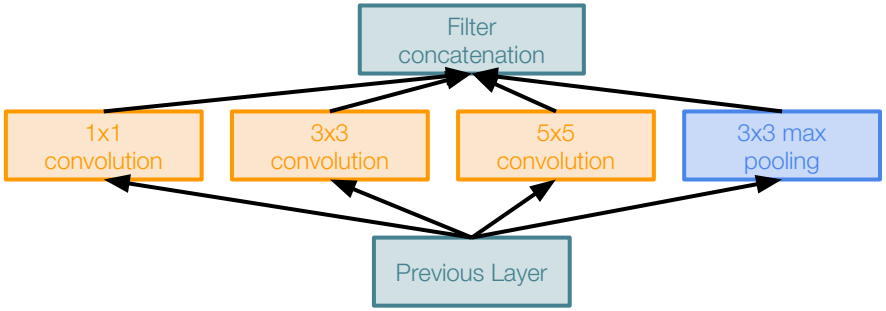
"Inception module": design a good local network topology (network within a network) and then stack these modules on top of each other



Inception module



GoogLeNet [Szegedy et al., 2014]



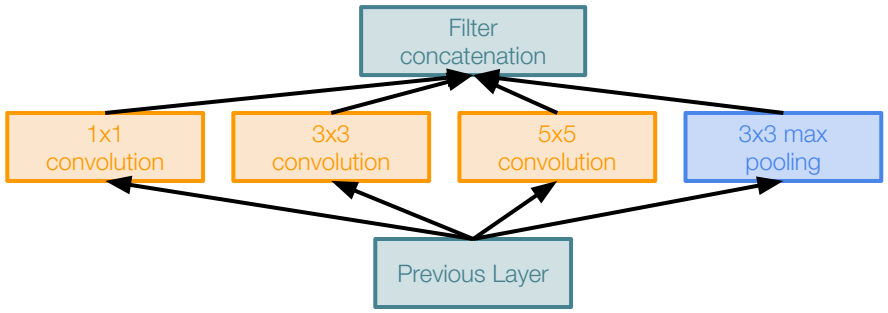
Naive Inception module

Apply parallel filter operations on the input from previous layer:

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

Concatenate all filter outputs together depth-wise

GoogLeNet [Szegedy et al., 2014]



Naive Inception module

Apply parallel filter operations on the input from previous layer:

- Multiple receptive field sizes for convolution (1x1, 3x3, 5x5)
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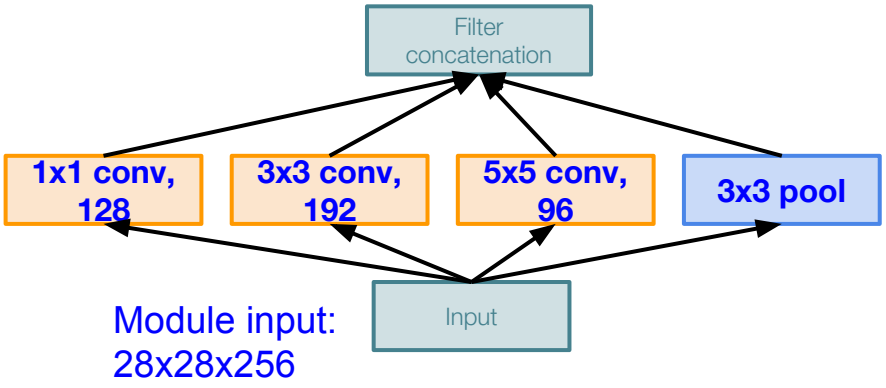
Q: What is the problem with this? [Hint: Computational complexity]

GoogLeNet [Szegedy et al., 2014]

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

Example:



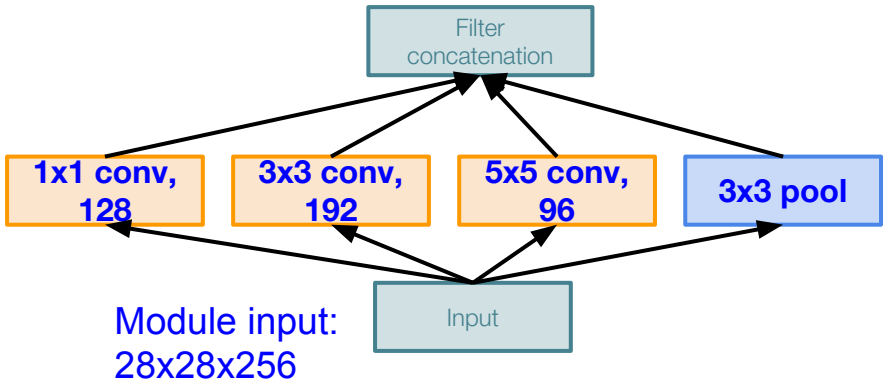
Naive Inception module

GoogLeNet [Szegedy et al., 2014]

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

Example:

Q1: What is the output size of the 1x1 conv, with 128 filters?



Naive Inception module

GoogLeNet [Szegedy et al., 2014]

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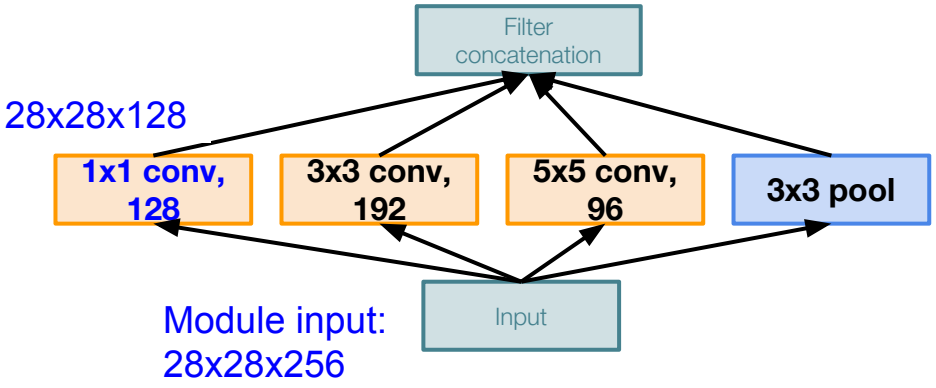

Naive Inception module

GoogLeNet [Szegedy et al., 2014]

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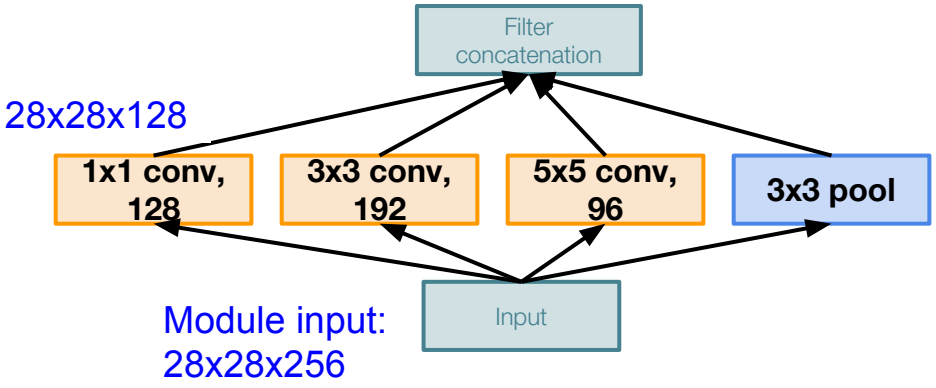
Example:

Q2: What are the output sizes of all different filter operations?



Naive Inception module

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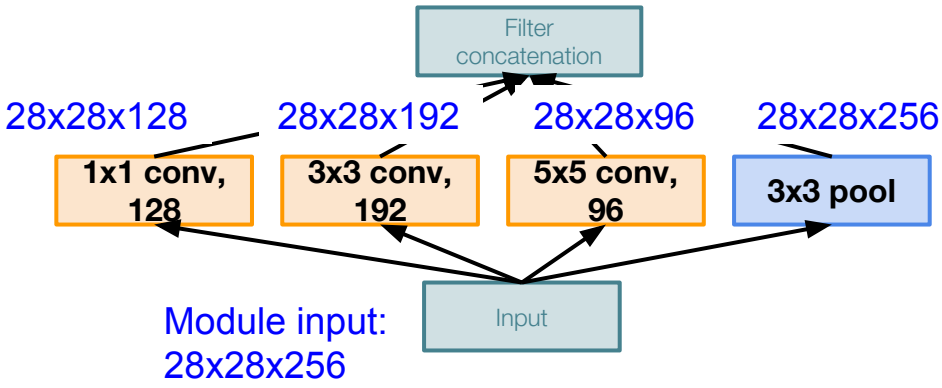

Naive Inception module

GoogLeNet [Szegedy et al., 2014]

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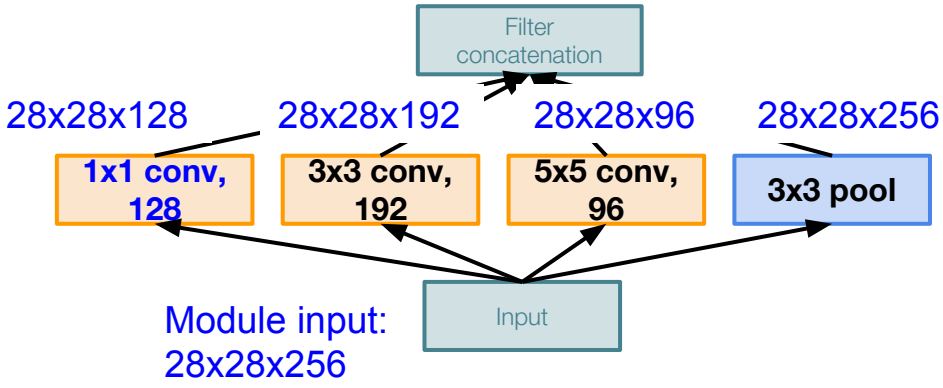
Example:

Q3:What is output size after filter concatenation?



Naive Inception module

GoogLeNet [Szegedy et al., 2014]

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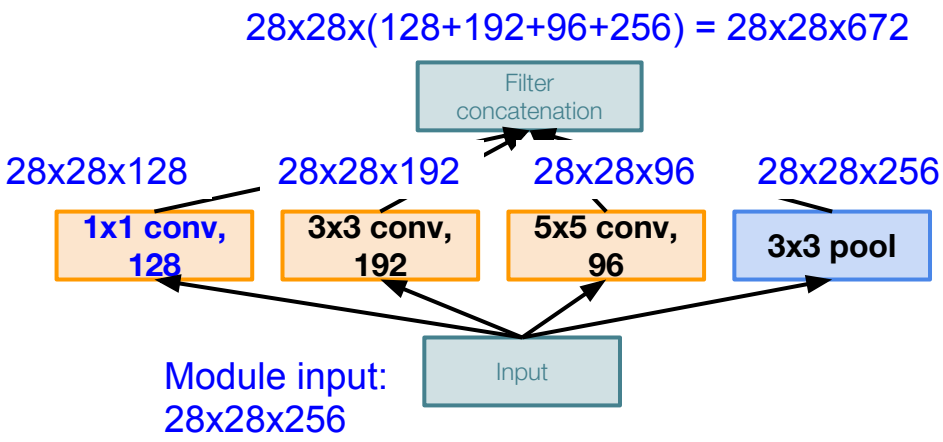

Naive Inception module

Conv Ops:
[1x1 conv, 128] 28x28x128x1x1x256
[3x3 conv, 192] 28x28x192x3x3x256
[5x5 conv, 96] 28x28x96x5x5x256
Total: 854M ops

GoogLeNet [Szegedy et al., 2014]

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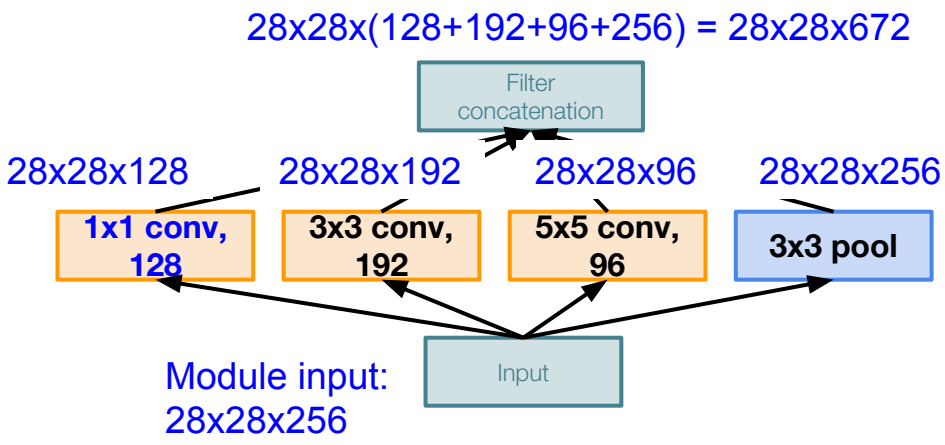

Naive Inception module

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[5x5 conv, 96] 28x28x96x5x5x256
Total: 854M ops

Very expensive compute

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

GoogLeNet [Szegedy et al., 2014]

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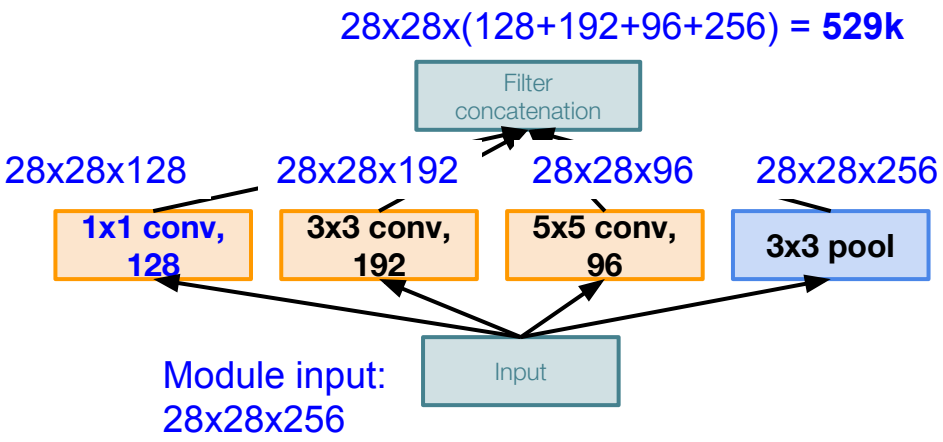
Example:

Q3:What is output size after filter concatenation?

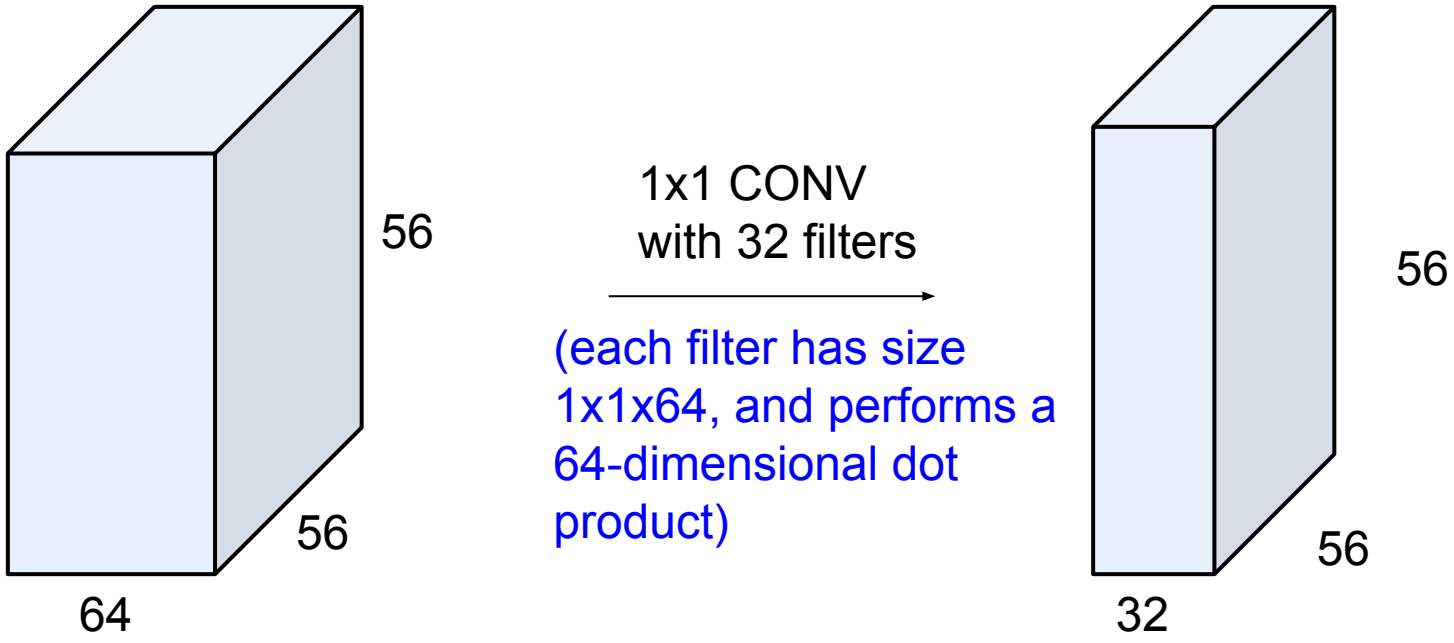


Naive Inception module

Solution: “bottleneck” layers that use 1x1 convolutions to reduce feature depth

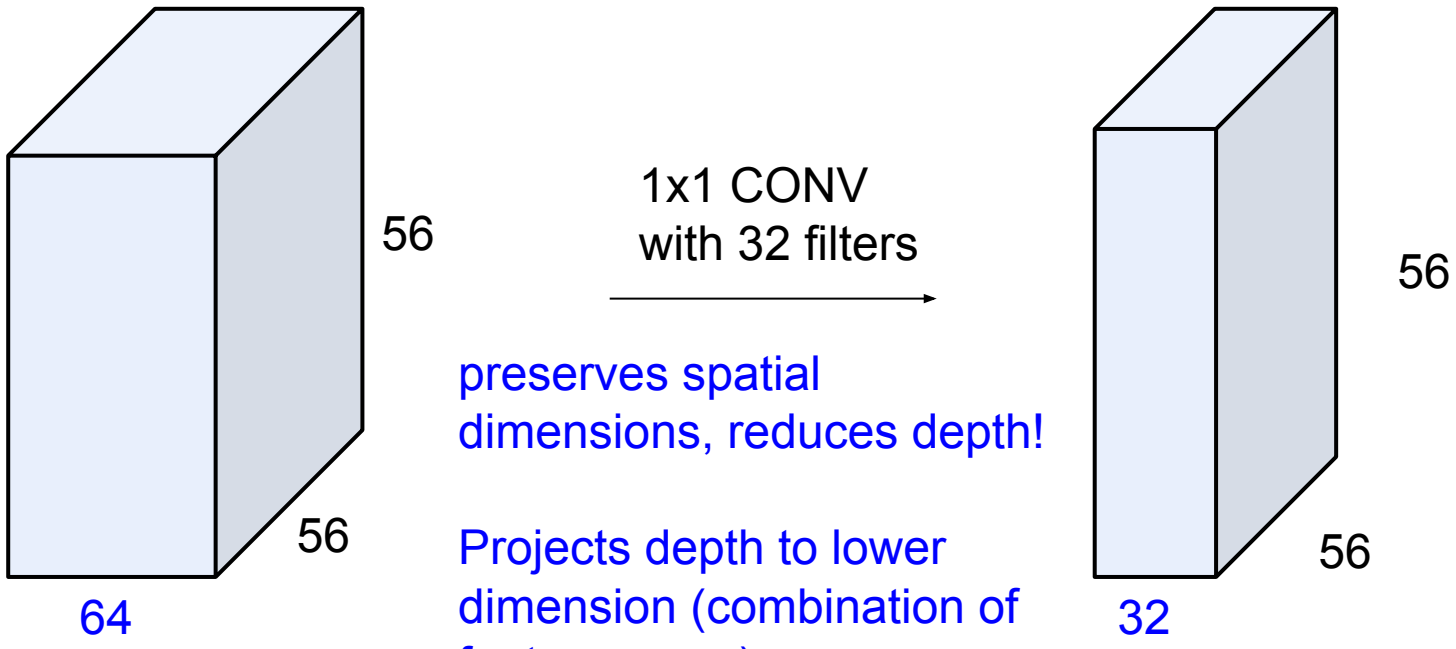
GoogLeNet [Szegedy et al., 2014]

Reminder: 1x1 convolutions



GoogLeNet [Szegedy et al., 2014]

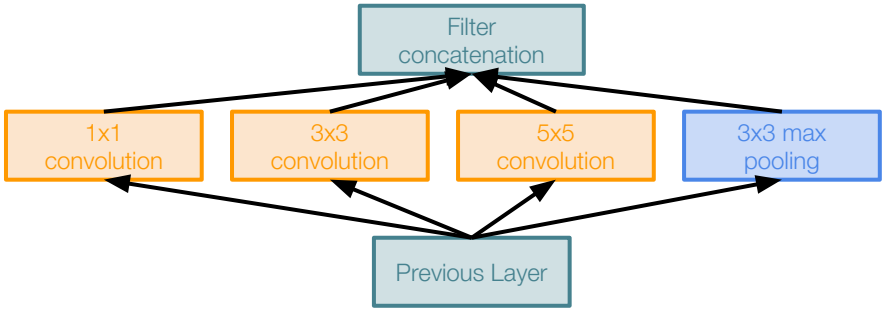
Reminder: 1x1 convolutions



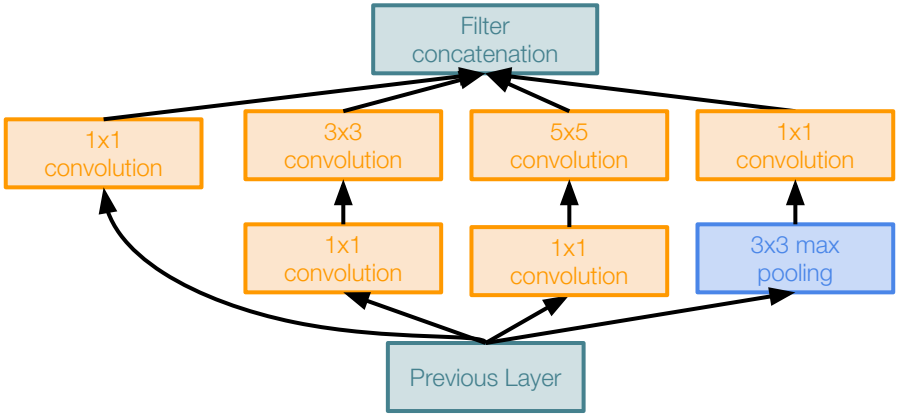
preserves spatial dimensions, reduces depth!

Projects depth to lower dimension (combination of feature maps)

GoogLeNet [Szegedy et al., 2014]

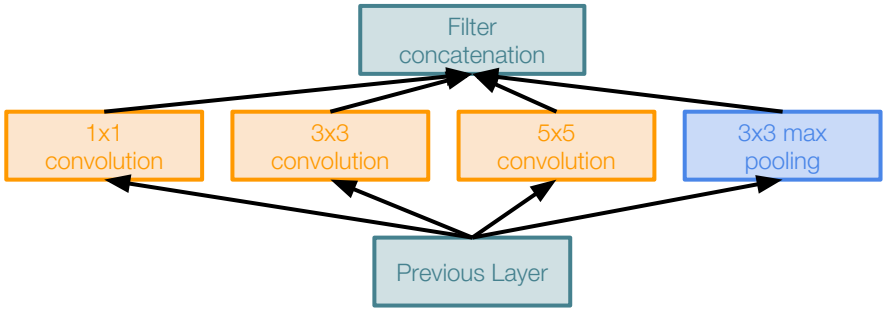


Naive Inception module



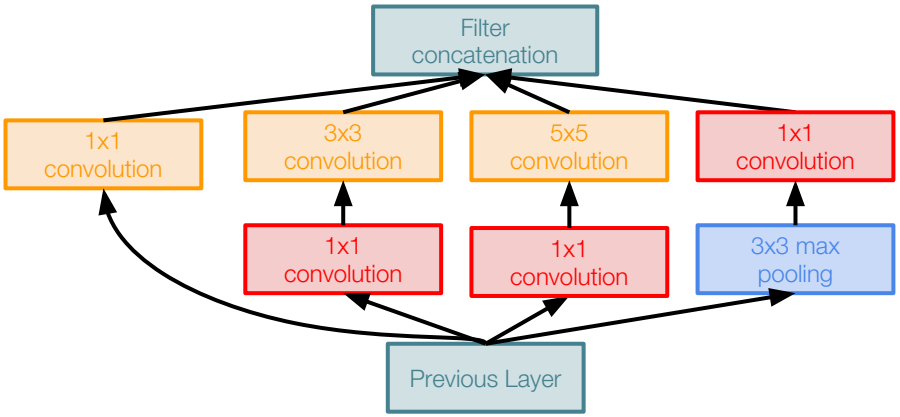
Inception module with dimension reduction

GoogLeNet [Szegedy et al., 2014]



Naive Inception module

1x1 conv "bottleneck" layers



Inception module with dimension reduction

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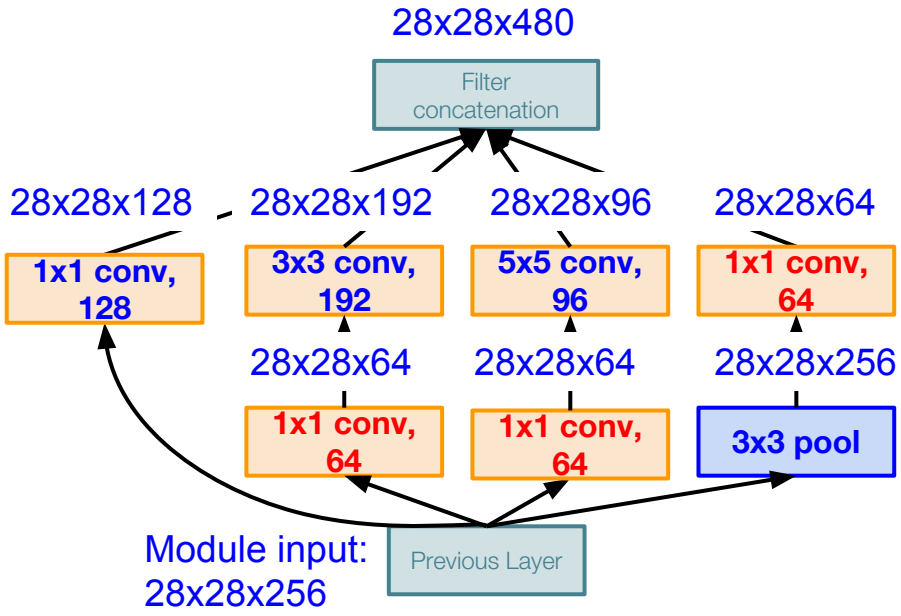


Inception module with dimension reduction

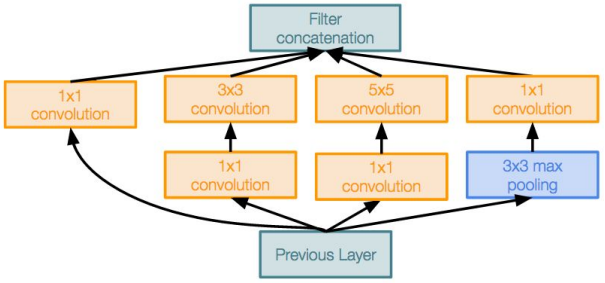
Using same parallel layers as naive example, and adding "1x1 conv, 64 filter" bottlenecks:

Conv Ops:
[1x1 conv, 64] 28x28x64x1x1x256
[1x1 conv, 64] 28x28x64x1x1x256
[1x1 conv, 128] 28x28x128x1x1x256
[3x3 conv, 192] 28x28x192x3x3x64
[5x5 conv, 96] 28x28x96x5x5x64
[1x1 conv, 64] 28x28x64x1x1x256
Total: 358M ops

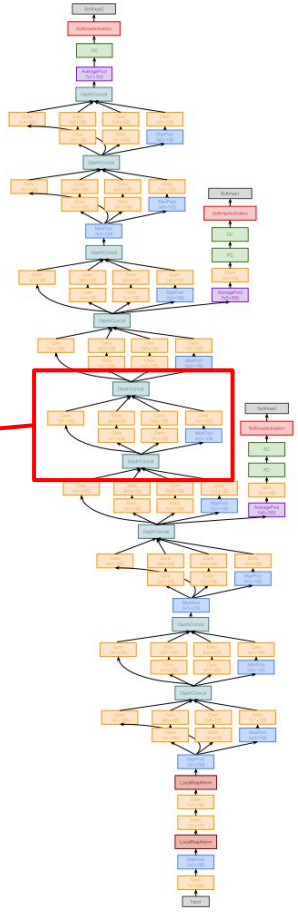
Compared to 854M ops for naive version
Bottleneck can also reduce depth after pooling layer

GoogLeNet [Szegedy et al., 2014]

Stack Inception modules with dimension reduction on top of each other

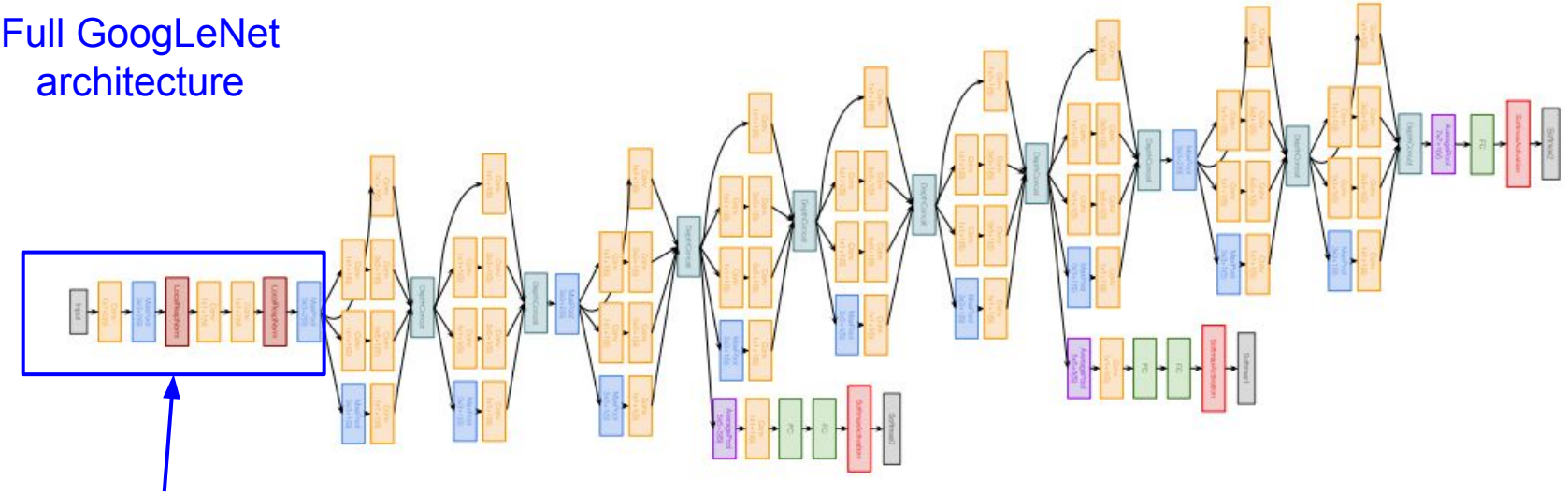


Inception module



GoogLeNet [Szegedy et al., 2014]

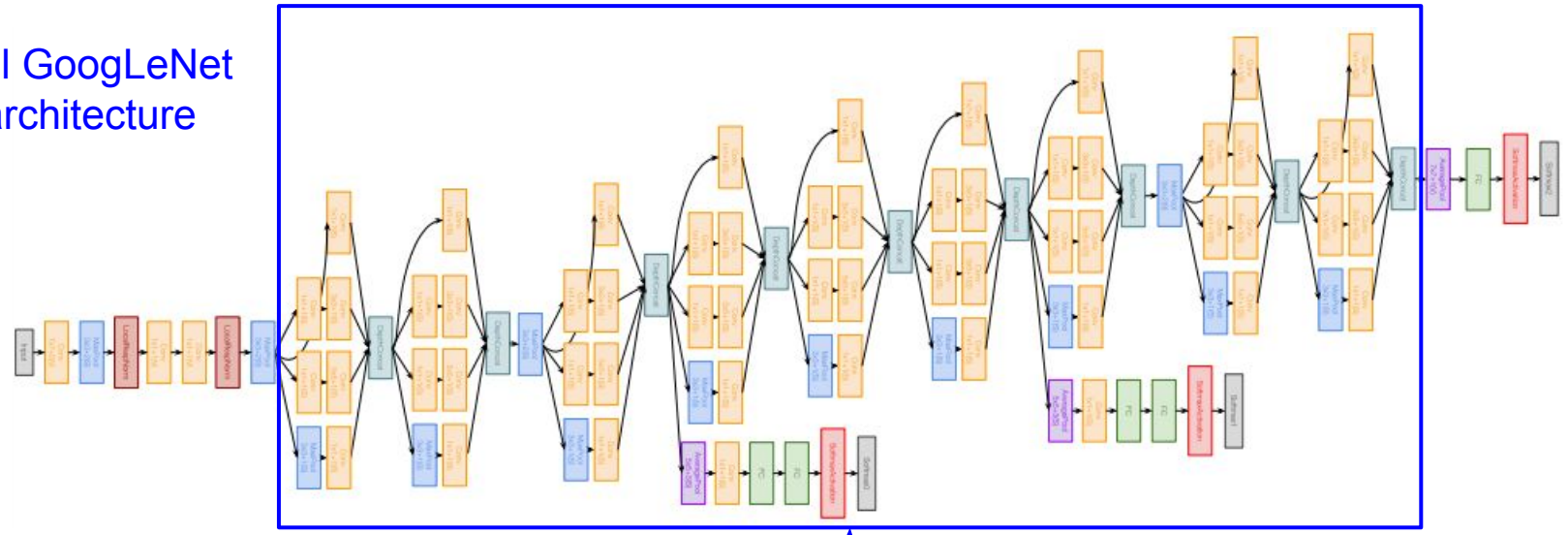
Full GoogLeNet architecture



Stem Network: Conv-Pool- 2x Conv-Pool

GoogLeNet [Szegedy et al., 2014]

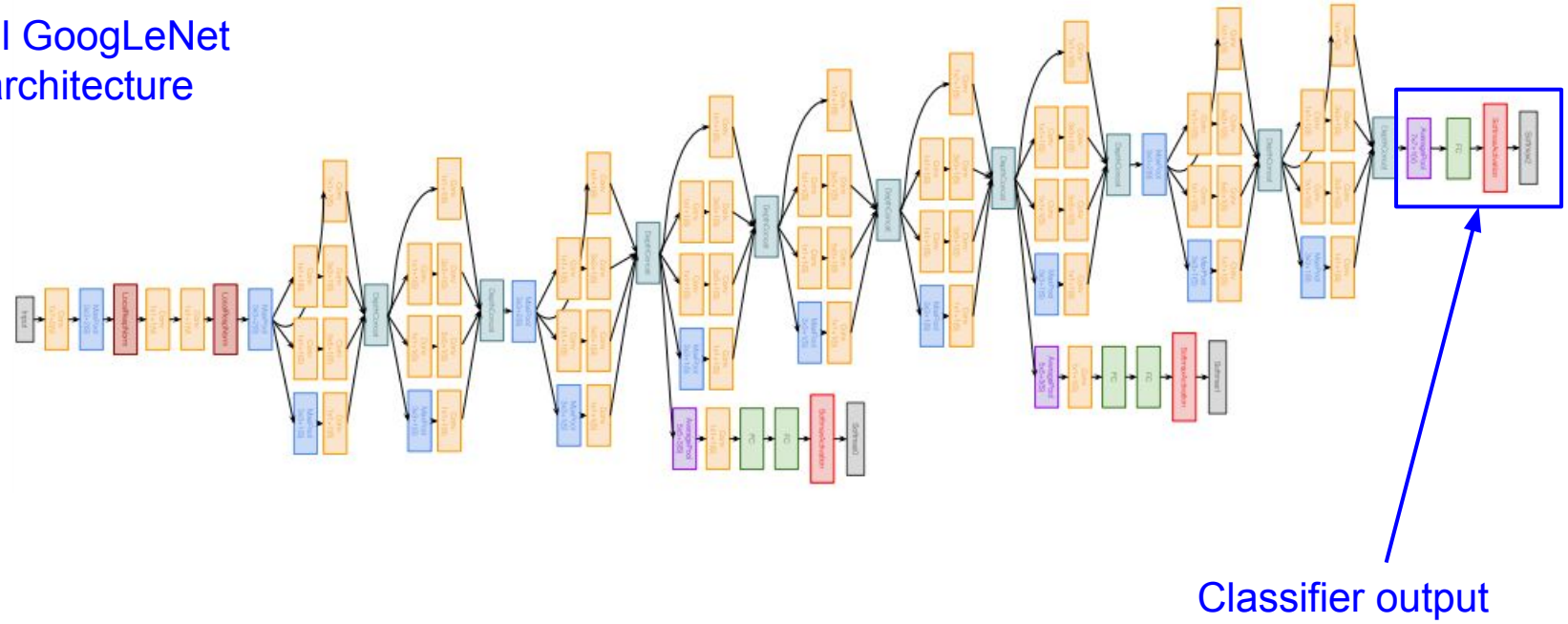
Full GoogLeNet architecture



Stacked Inception Modules

GoogLeNet [Szegedy et al., 2014]

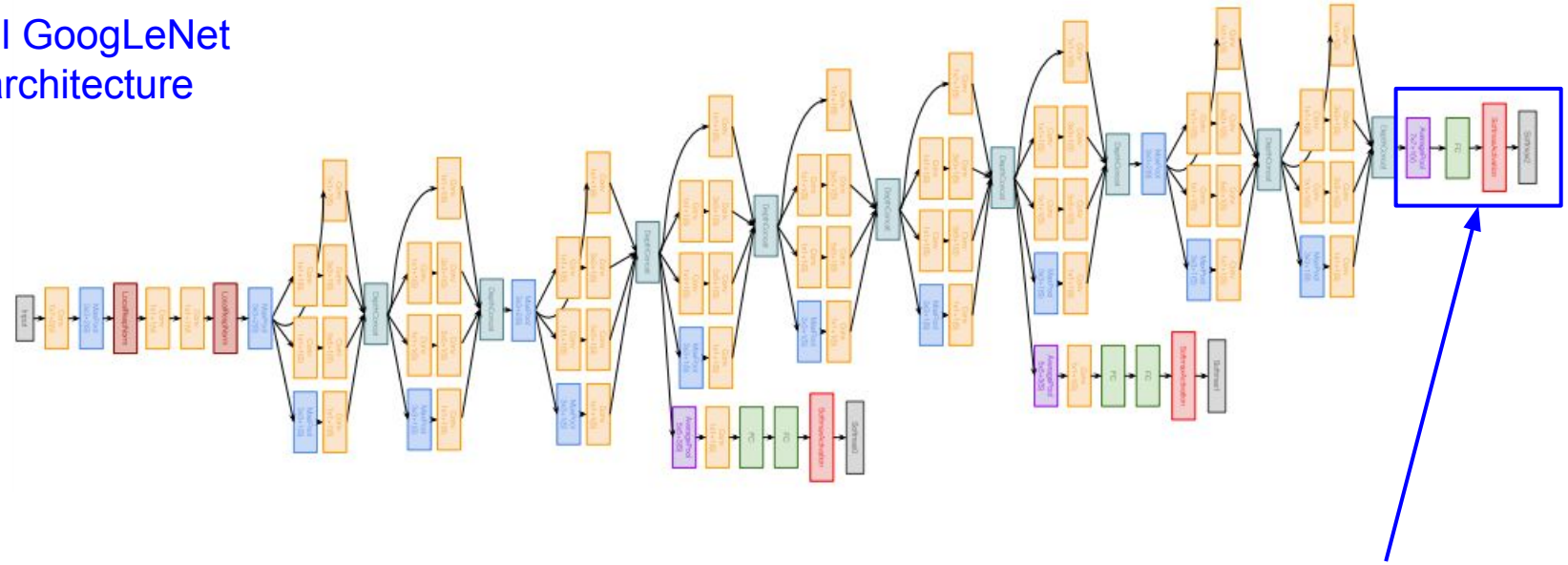
Full GoogLeNet architecture



Classifier output

GoogLeNet [Szegedy et al., 2014]

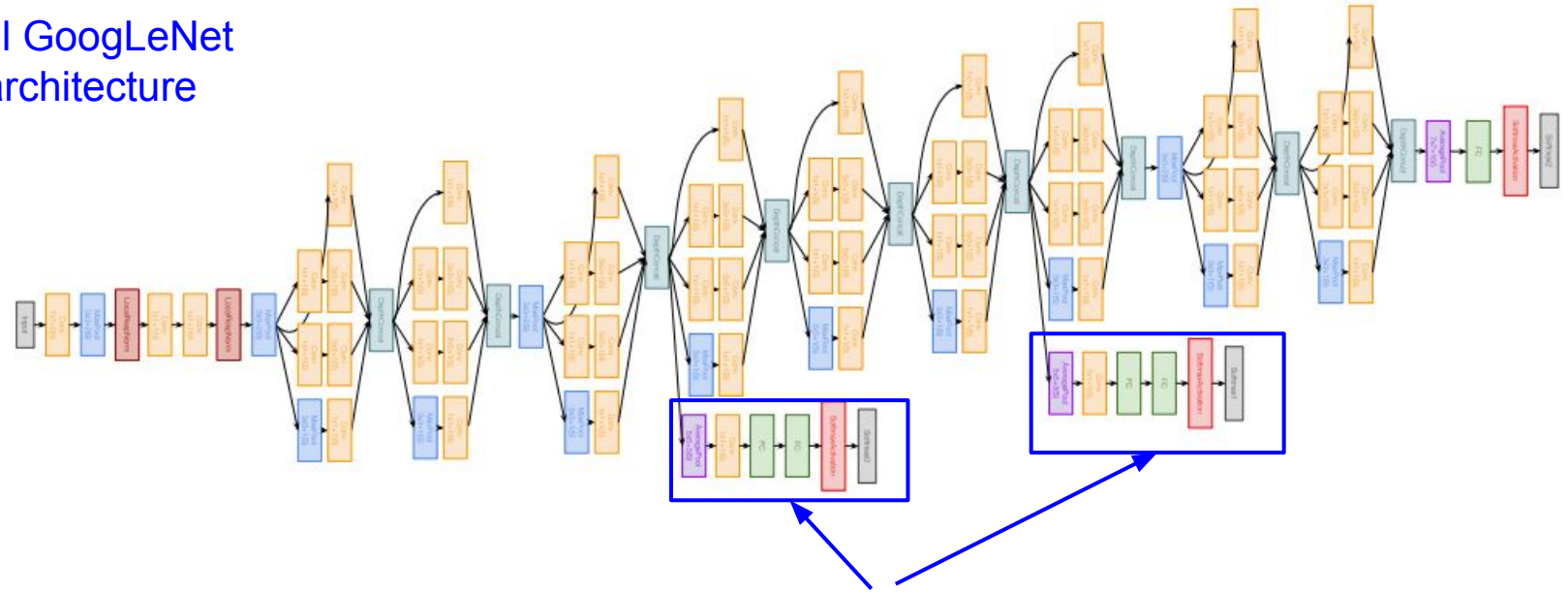
Full GoogLeNet architecture



Classifier output
(removed expensive FC layers!)

GoogLeNet [Szegedy et al., 2014]

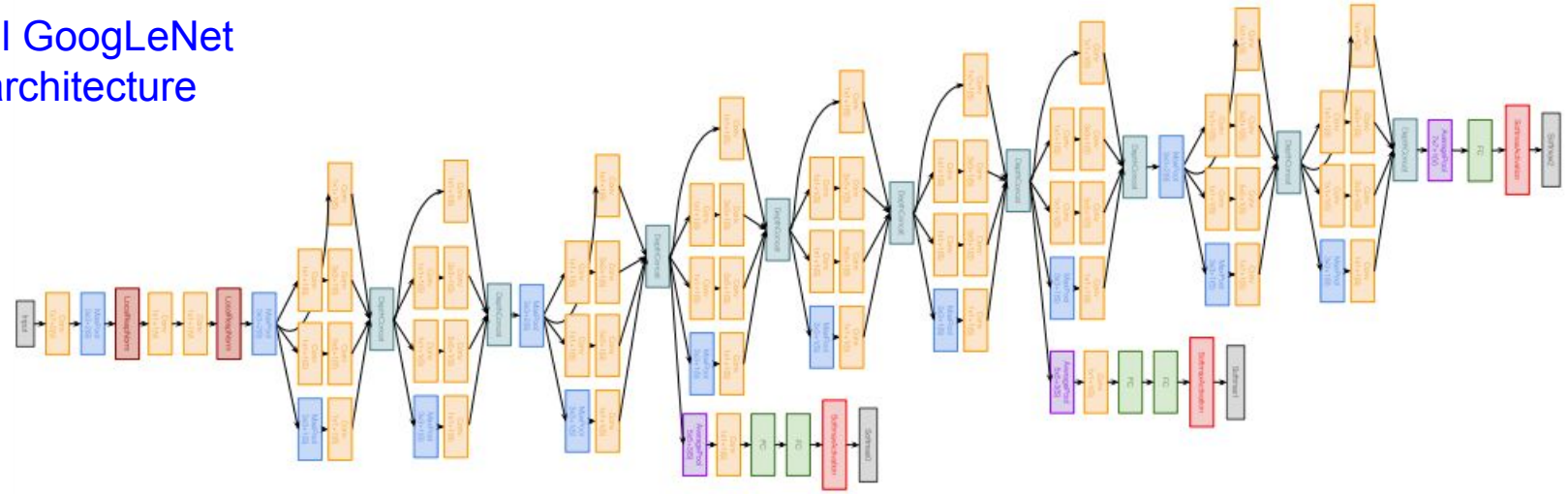
Full GoogLeNet architecture



Auxiliary classification outputs to inject additional gradient at lower layers
(AvgPool-1x1Conv-FC-FC-Softmax)

GoogLeNet [Szegedy et al., 2014]

Full GoogLeNet architecture

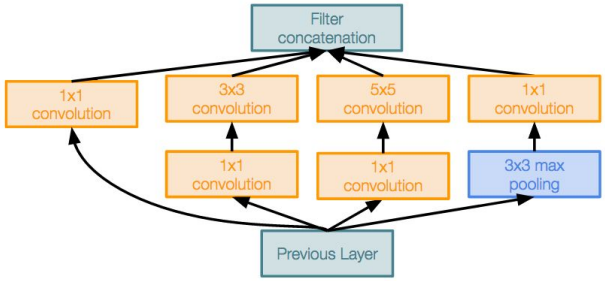


22 total layers with weights (including each parallel layer in an Inception module)

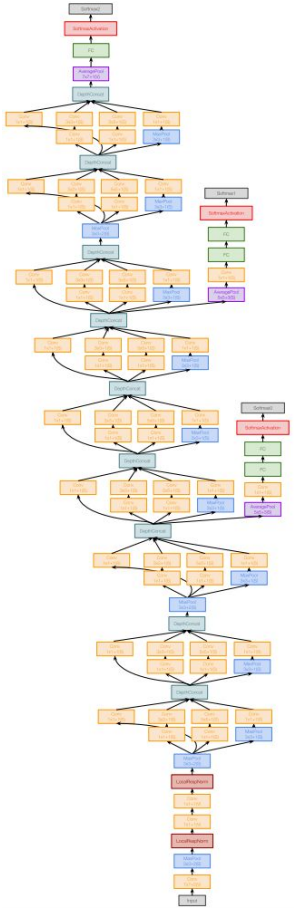
GoogLeNet [Szegedy et al., 2014]

Deeper networks, with computational efficiency

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

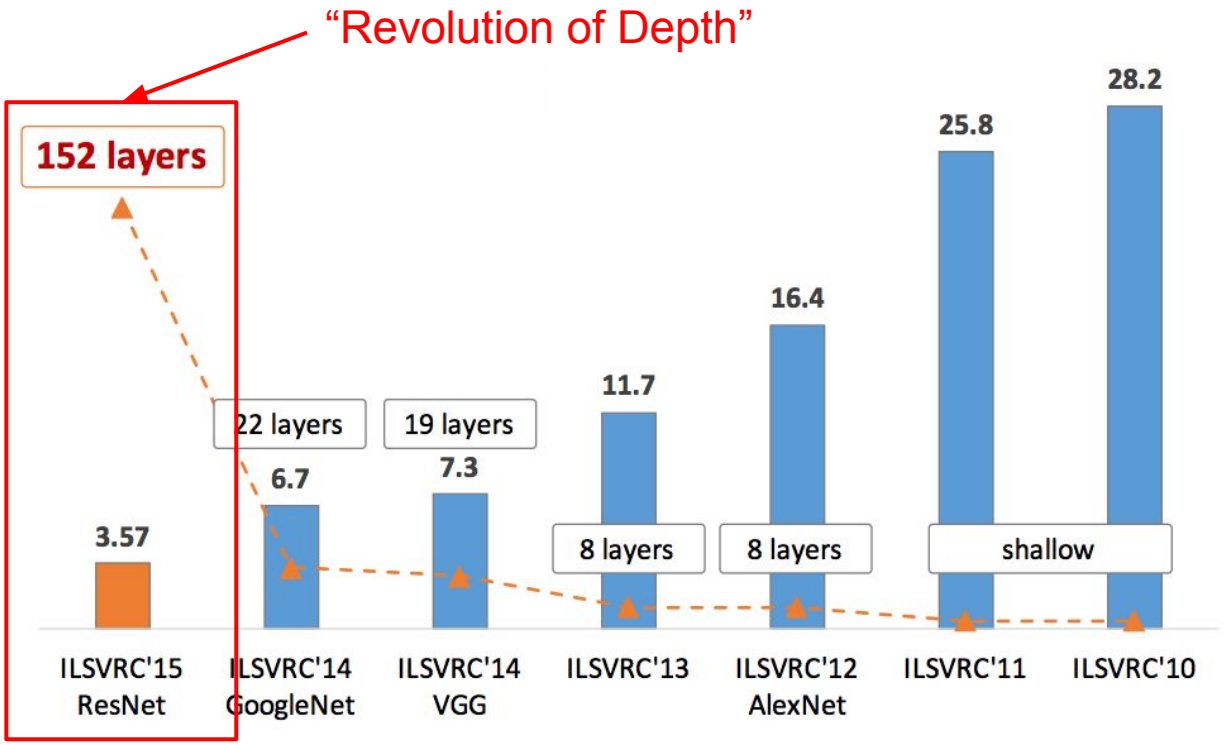


Inception module



ResNet [He et al., 2015]

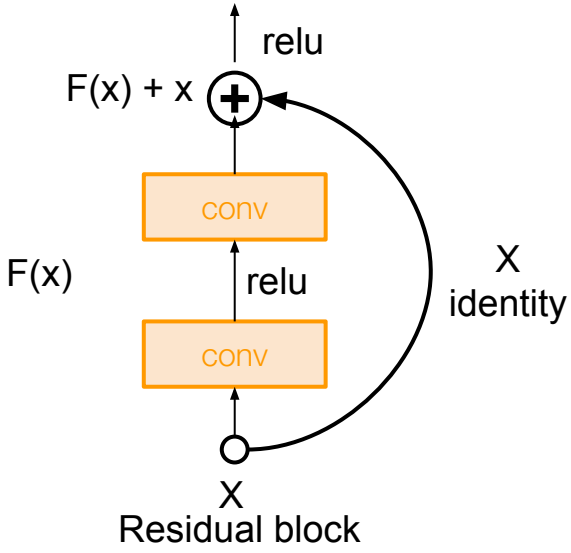
ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners

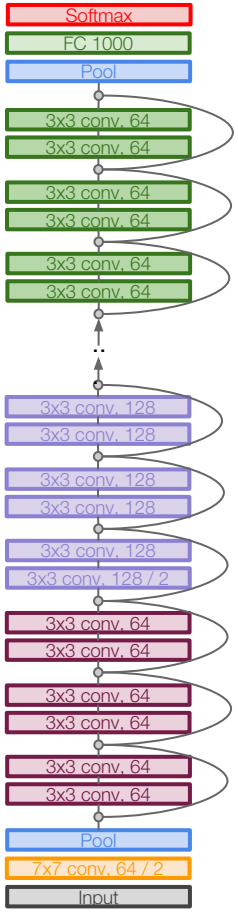


ResNet [He et al., 2015]

Very deep networks using residual connections

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





ResNet [He et al., 2015]

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

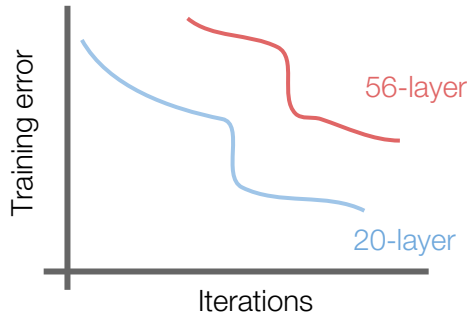
ResNet [He et al., 2015]

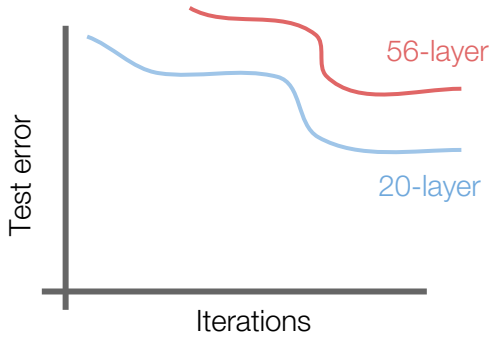
What happens when we continue stacking deeper layers on a “plain” convolutional neural network?

Q: What’s strange about these training and test curves?
[Hint: look at the order of the curves]

ResNet [He et al., 2015]

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





56-layer model performs worse on both training and test error
-> The deeper model performs worse, but it’s not caused by overfitting!

ResNet [He et al., 2015]

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

ResNet [He et al., 2015]

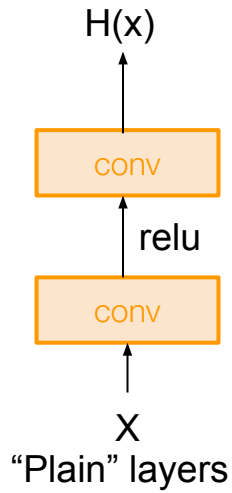
Hypothesis: the problem is an *optimization* problem, deeper models are harder to optimize

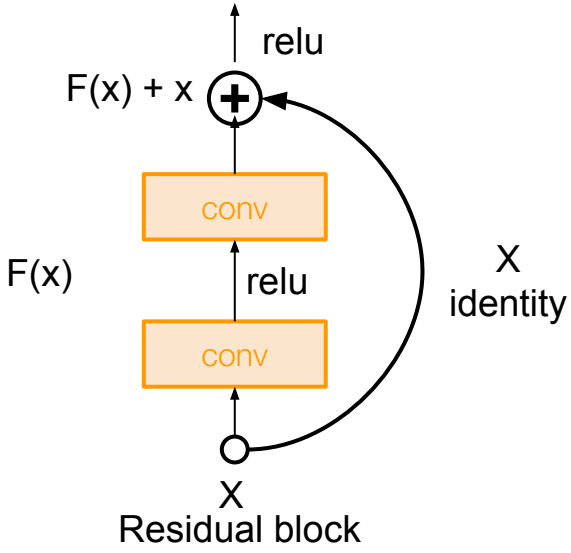
The deeper model should be able to perform at least as well as the shallower model.

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

ResNet [He et al., 2015]

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





ResNet [He et al., 2015]

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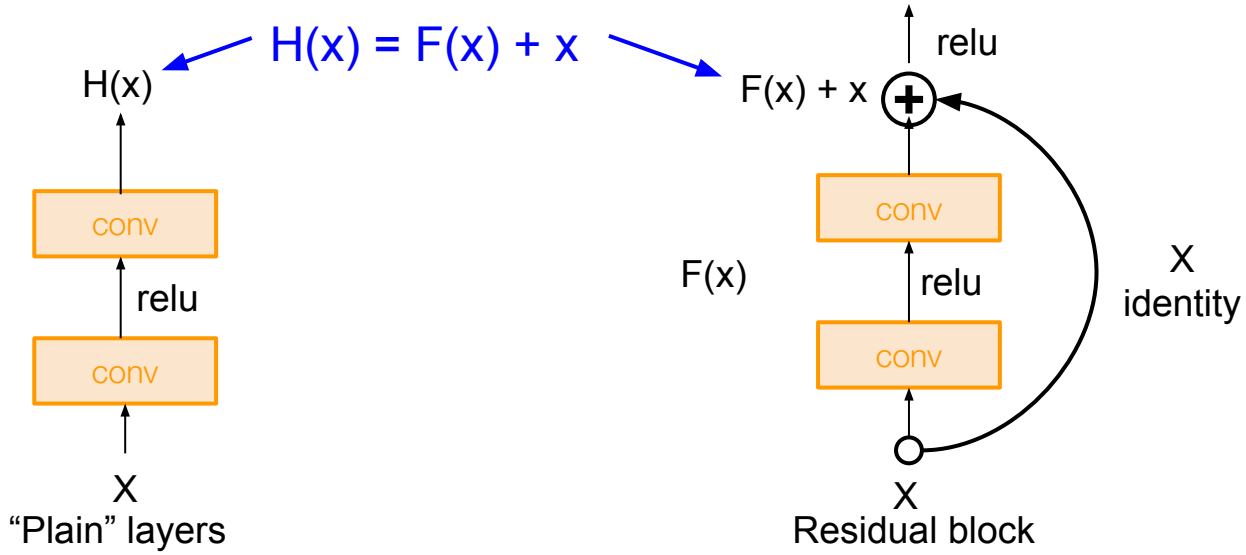


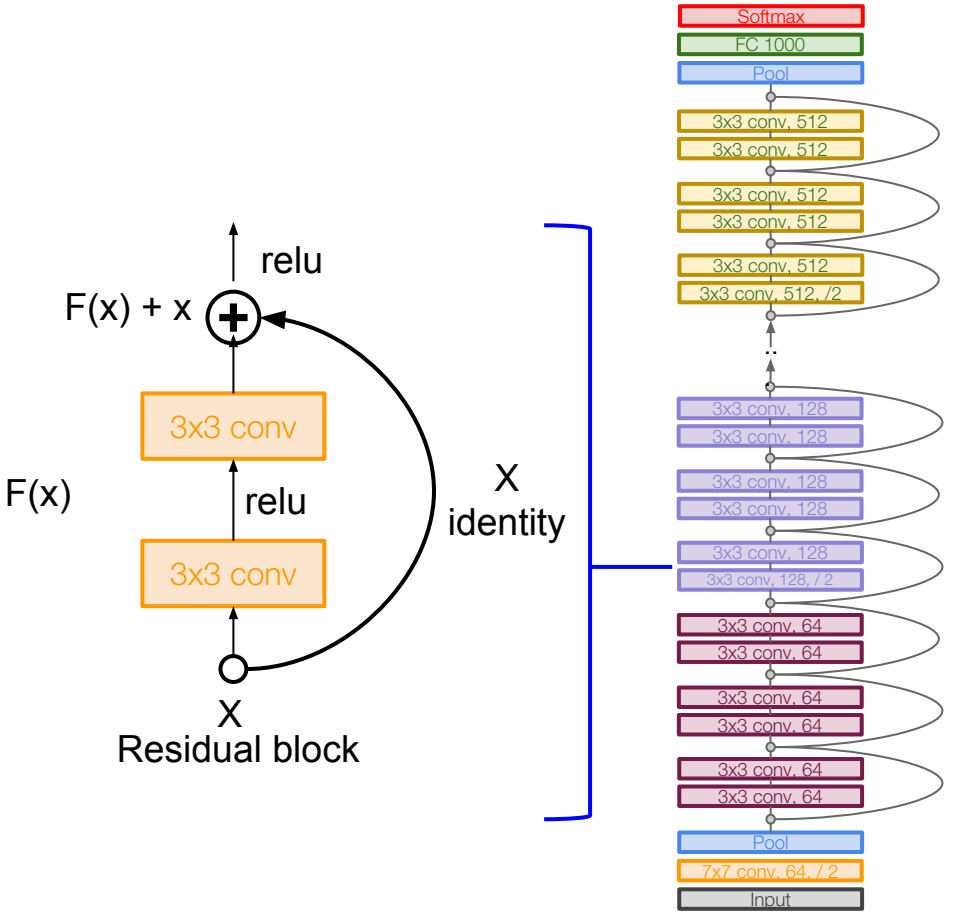
Use layers to fit residual F(x) = H(x) - x instead of H(x) directly

He et al. hypothesize that it is easier to optimize the residual mapping than to optimize the original, unreferenced mapping

ResNet [He et al., 2015]

Full ResNet architecture:

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



ResNet [He et al., 2015]

Full ResNet architecture:

- Stack residual blocks
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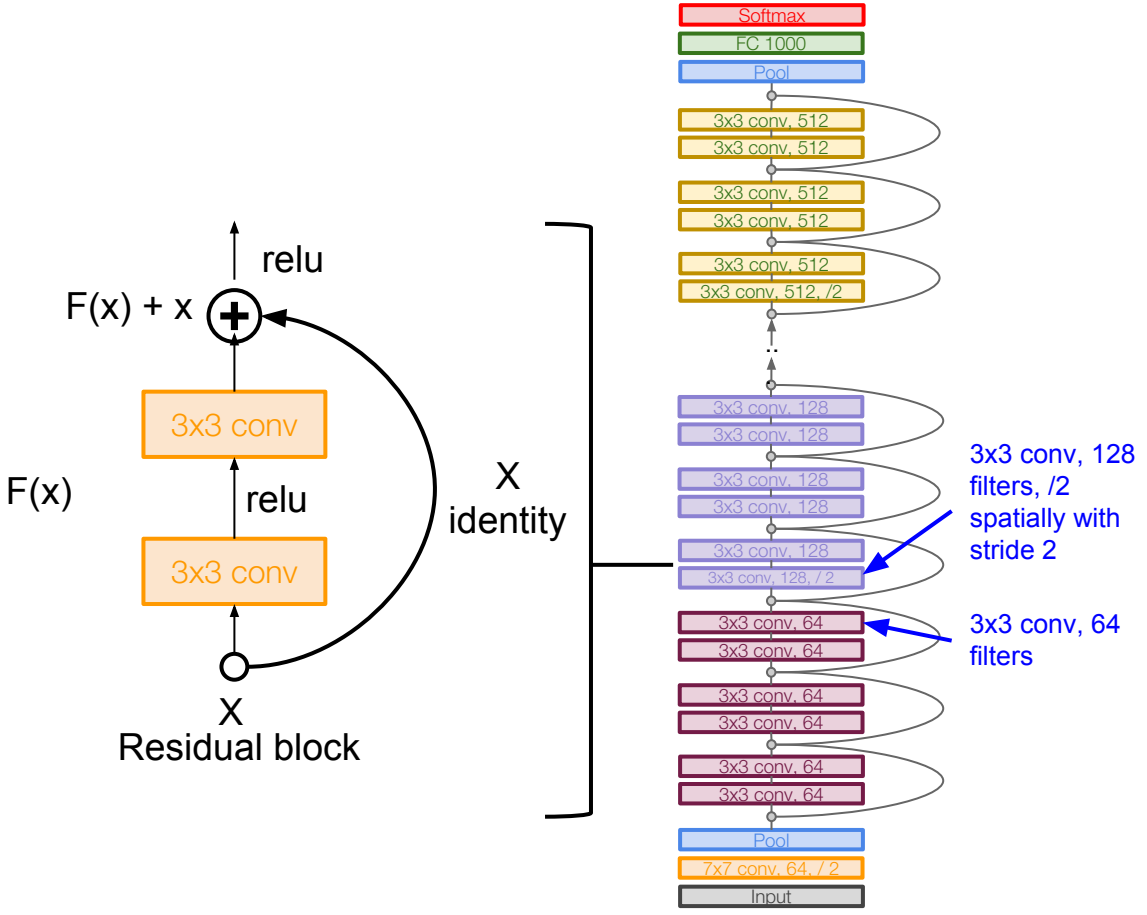
- Periodically, double # of filters and downsample spatially using stride 2 (/2 in each dimension)



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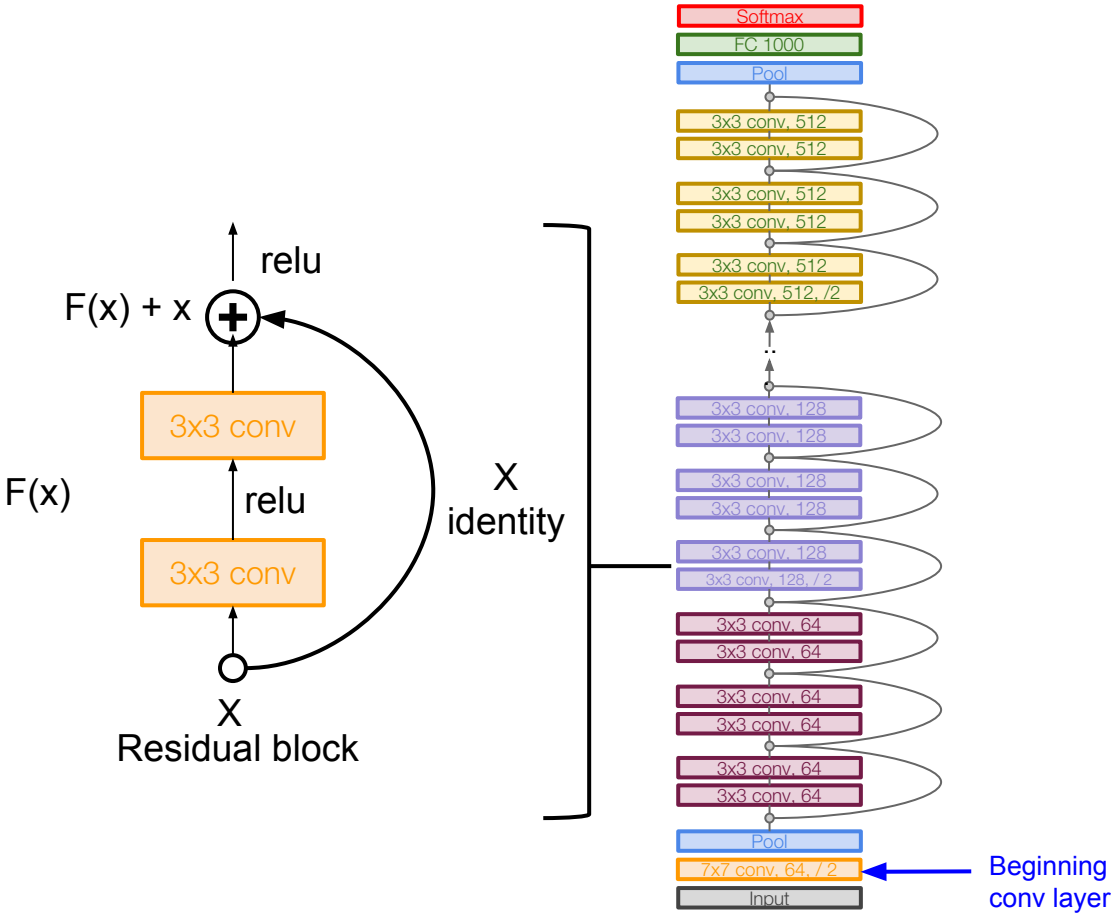

ResNet [He et al., 2015]

Full ResNet architecture:

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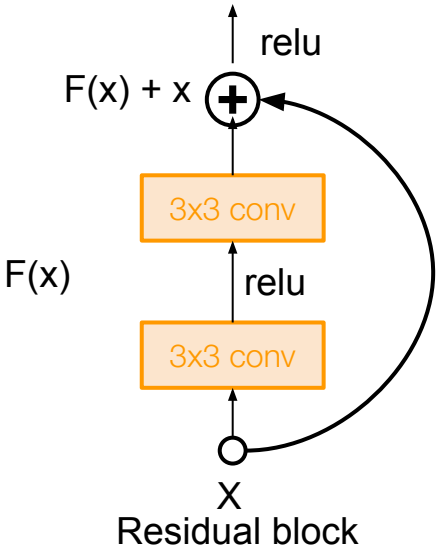
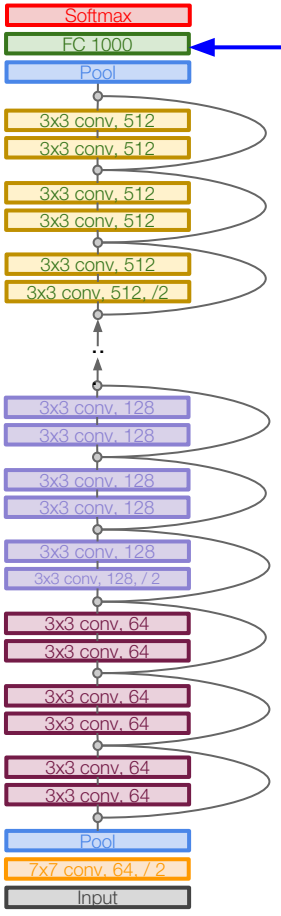
- Additional conv layer at the beginning
- No FC layers at the end (only FC 1000 to output classes)



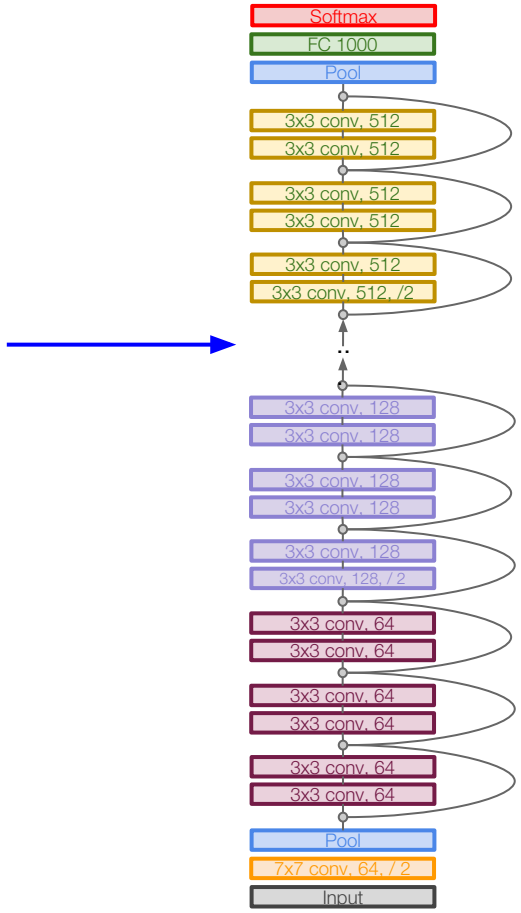


No FC layers besides FC 1000 to output classes

Global average pooling layer after last conv layer

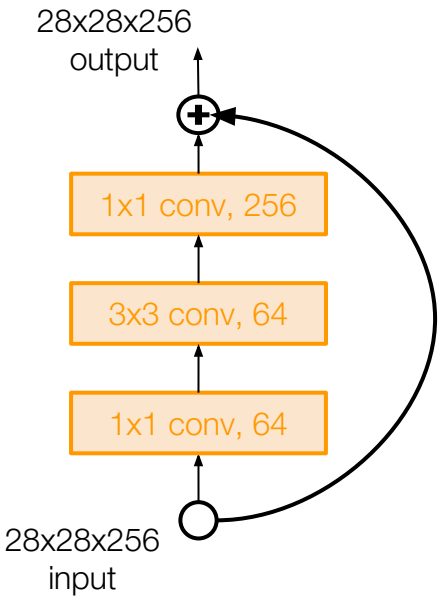
ResNet [He et al., 2015]

Total depths of 34, 50, 101, or
152 layers for ImageNet



ResNet [He et al., 2015]

For deeper networks
(ResNet-50+), use “bottleneck”
layer to improve efficiency
(similar to GoogLeNet)



ResNet [He et al., 2015]

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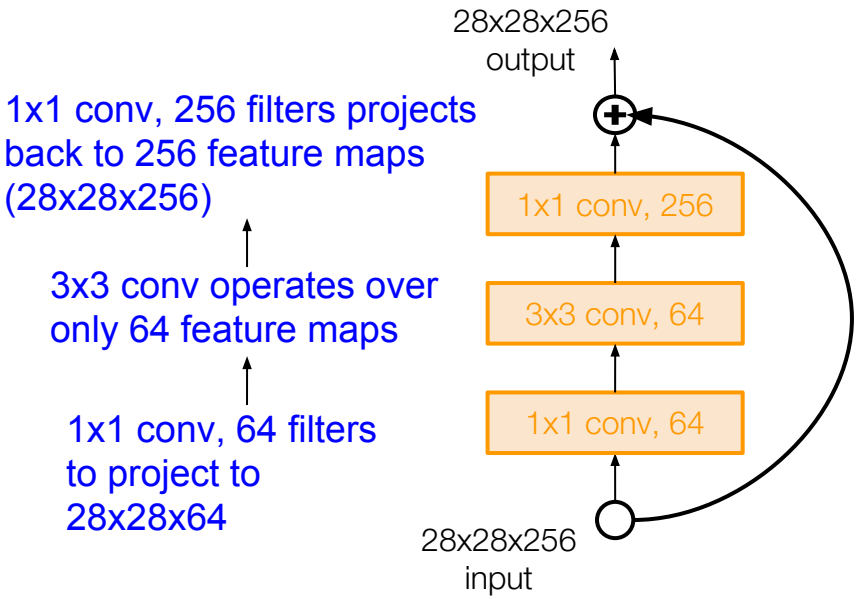


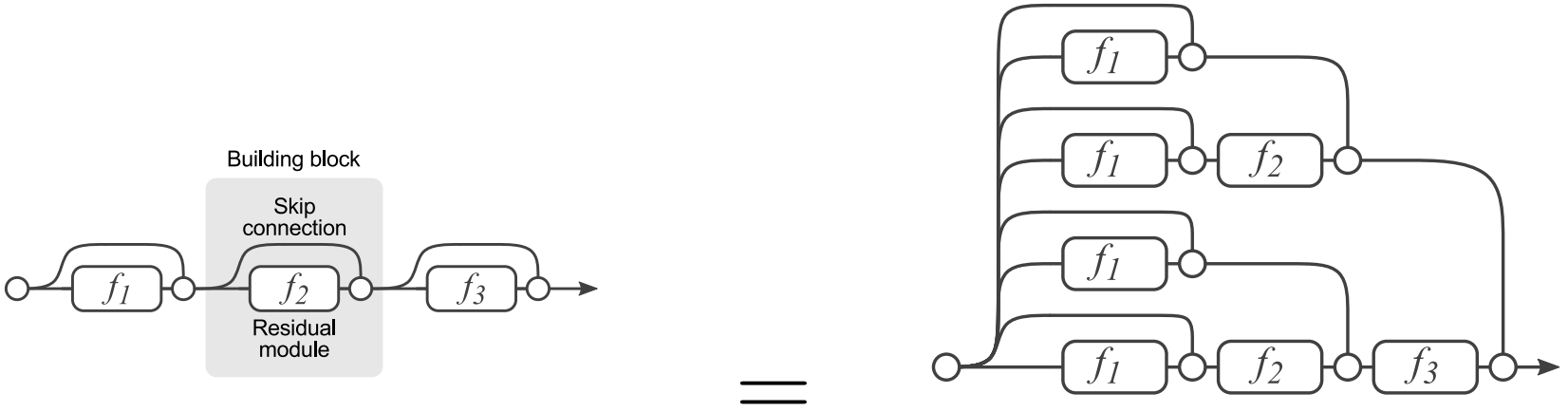
ResNet [He et al., 2015]

Training ResNet in practice:

- 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

ResNet [He et al., 2015]

Residual Networks Behave Like Ensembles of Relatively Shallow Networks
[A. Veit et al., NIPS, 2016]



(a) Conventional 3-block residual network

(b) Unraveled view of (a)

N residual blocks → 2^N paths

ResNet [He et al., 2015]

Residual Networks Behave Like Ensembles of Relatively Shallow Networks
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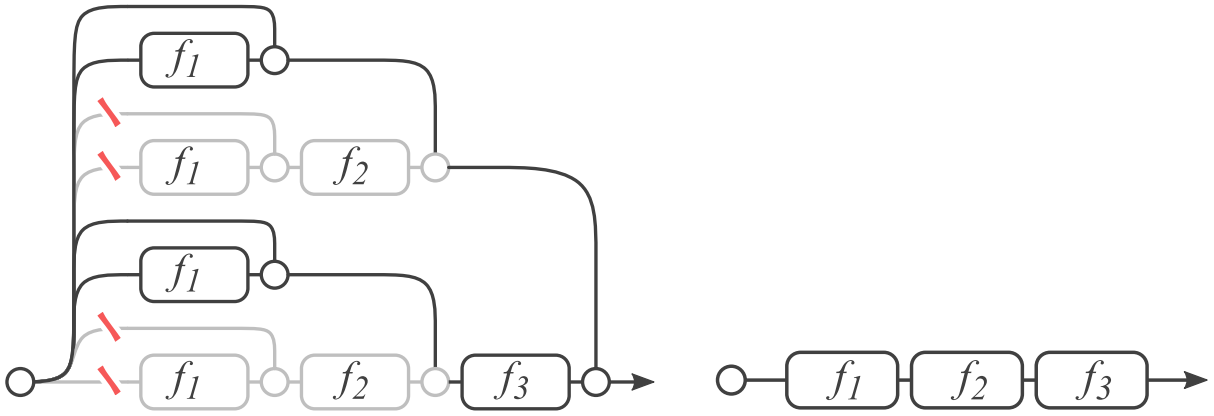

(a) Deleting f_2 from unraveled view (b) Ordinary feedforward network

Figure 2: Deleting a layer in residual networks at test time (a) is equivalent to zeroing half of the paths. In ordinary feed-forward networks (b) such as VGG or AlexNet, deleting individual layers alters the only viable path from input to output.

ResNet [He et al., 2015]

Residual Networks Behave Like Ensembles of Relatively Shallow Networks
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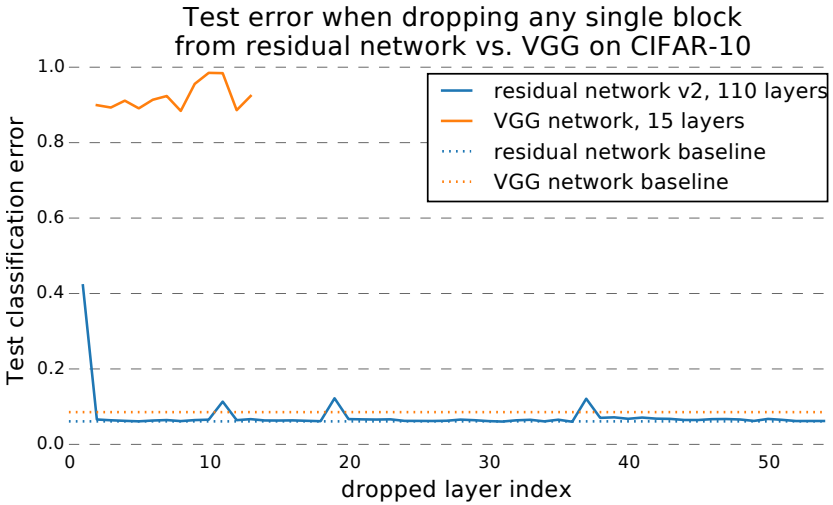

Figure 3: Deleting individual layers from VGG and a residual network on CIFAR-10. VGG performance drops to random chance when any one of its layers is deleted, but deleting individual modules from residual networks has a minimal impact on performance. Removing downsampling modules has a slightly higher impact.

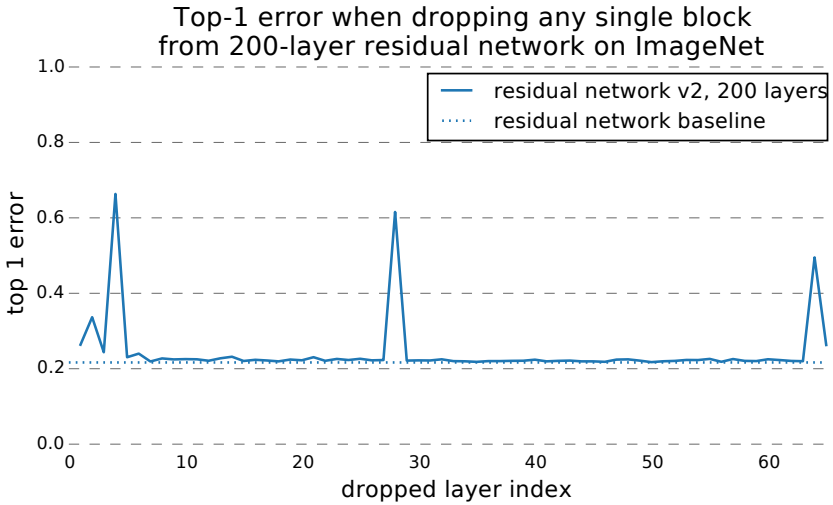

Figure 4: Results when dropping individual blocks from residual networks trained on ImageNet are similar to CIFAR results. However, downsampling layers tend to have more impact on ImageNet.

ResNet [He et al., 2015]

Residual Networks Behave Like Ensembles of Relatively Shallow Networks
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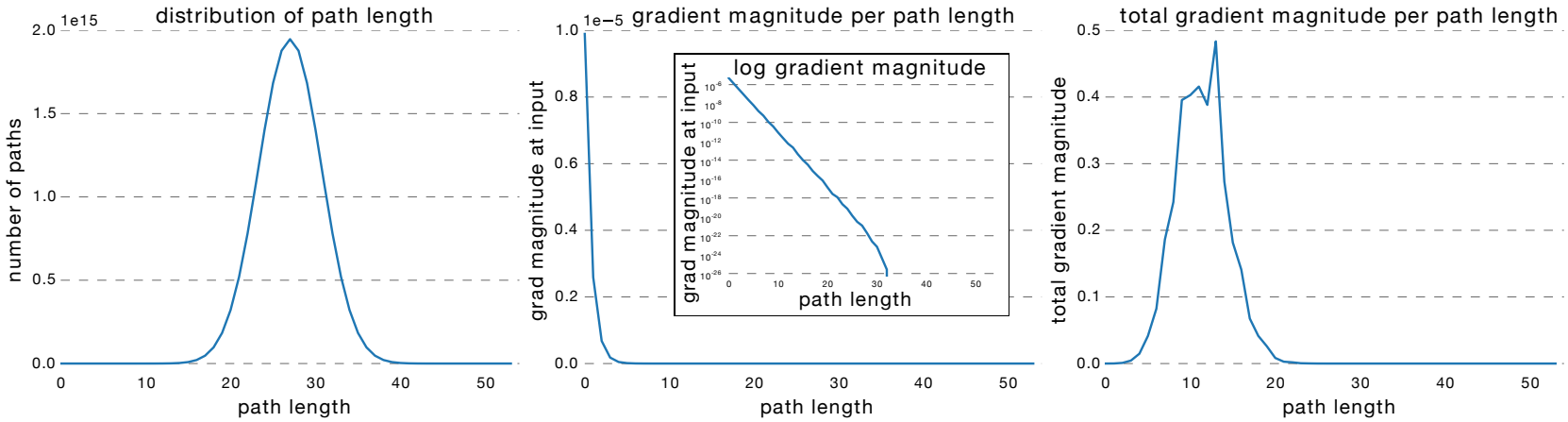


Figure 6: How much gradient do the paths of different lengths contribute in a residual network? To find out, we first show the distribution of all possible path lengths (a). This follows a Binomial distribution. Second, we record how much gradient is induced on the first layer of the network through paths of varying length (b), which appears to decay roughly exponentially with the number of modules the gradient passes through. Finally, we can multiply these two functions (c) to show how much gradient comes from all paths of a certain length. Though there are many paths of medium length, paths longer than $\sim$20 modules are generally too long to contribute noticeable gradient during training. This suggests that the effective paths in residual networks are relatively shallow.

ResNet [He et al., 2015]

Residual Networks Behave Like Ensembles of Relatively Shallow Networks [A. Veit et al., NIPS, 2016]

He's response in "Aggregated Residual Transformations for Deep Neural Networks"

Ensembling. Averaging a set of independently trained networks is an effective solution to improving accuracy [24], widely adopted in recognition competitions [33]. Veit *et al.* [40] interpret a single ResNet as an ensemble of shallower networks, which results from ResNet's *additive* behaviors [15]. Our method harnesses additions to aggregate a set of transformations. But we argue that it is imprecise to view our method as ensembling, because the members to be aggregated are trained jointly, not independently.

ResNet [He et al., 2015]

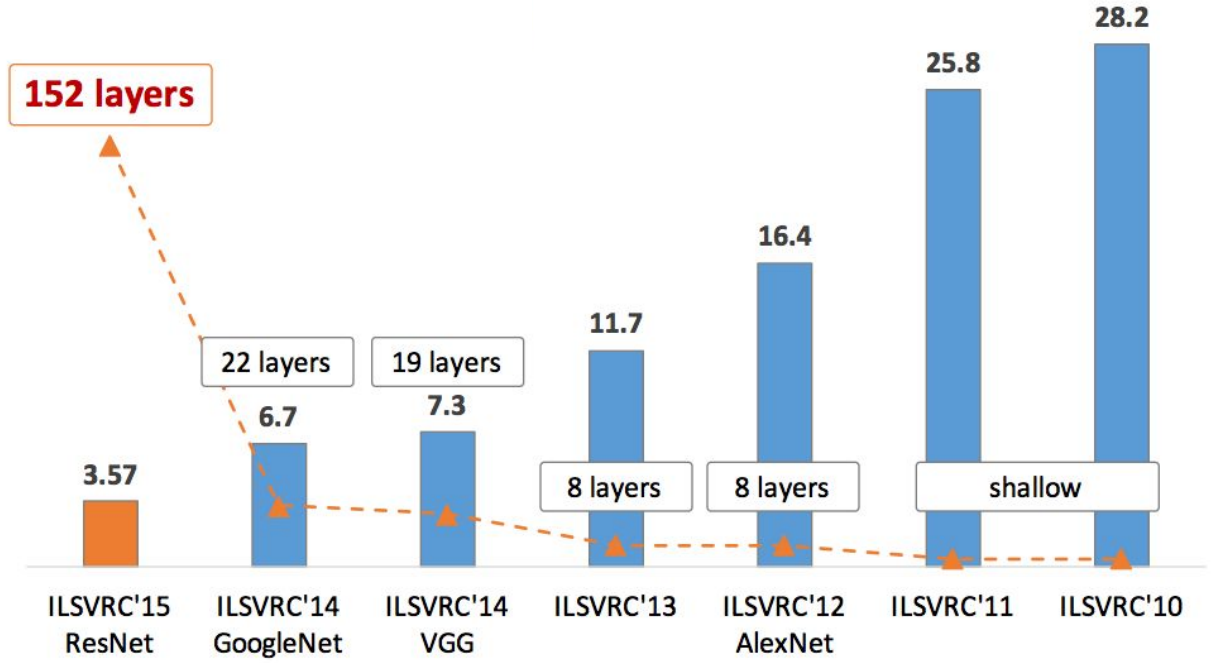
Experimental Results

- Able to train very deep networks without degrading (152 layers on ImageNet, 1202 on Cifar)
- Deeper networks now achieve lowing training error as expected
- Swept 1st place in all ILSVRC and COCO 2015 competitions

ILSVRC 2015 classification winner (3.6% top 5 error) -- better than "human performance"! (Russakovsky 2014)

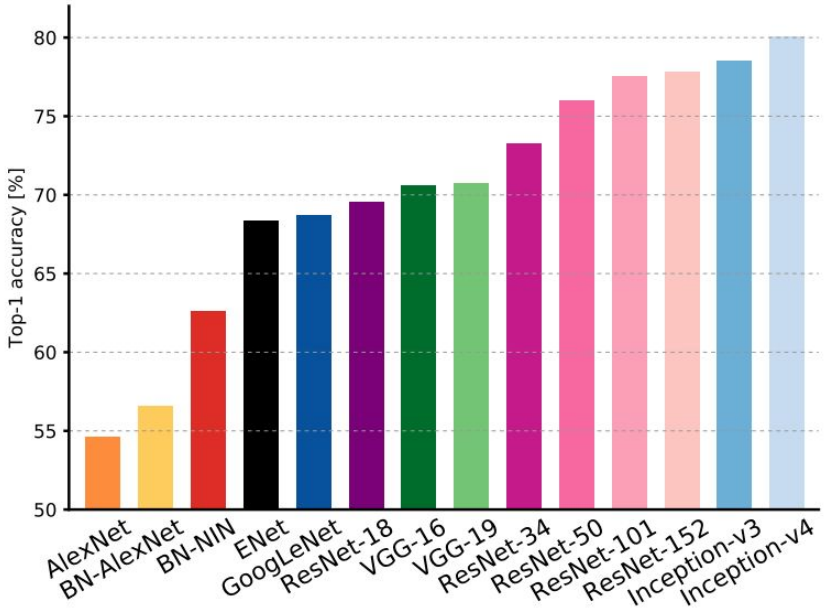
ResNet [He et al., 2015]

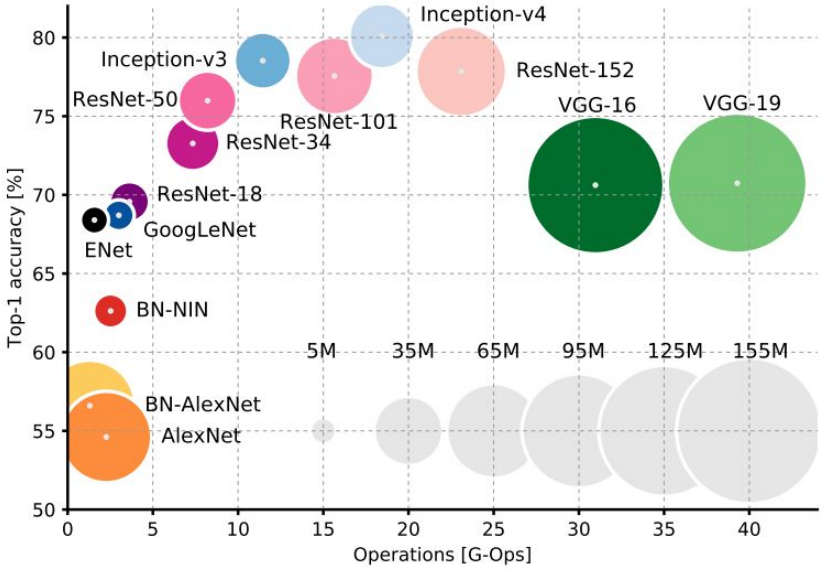
ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



Comparison

Comparing complexity...



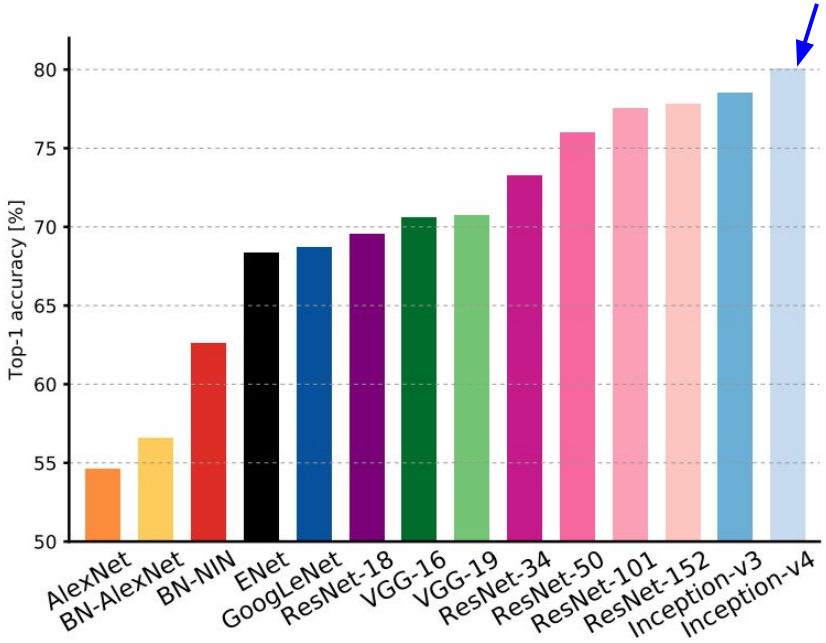


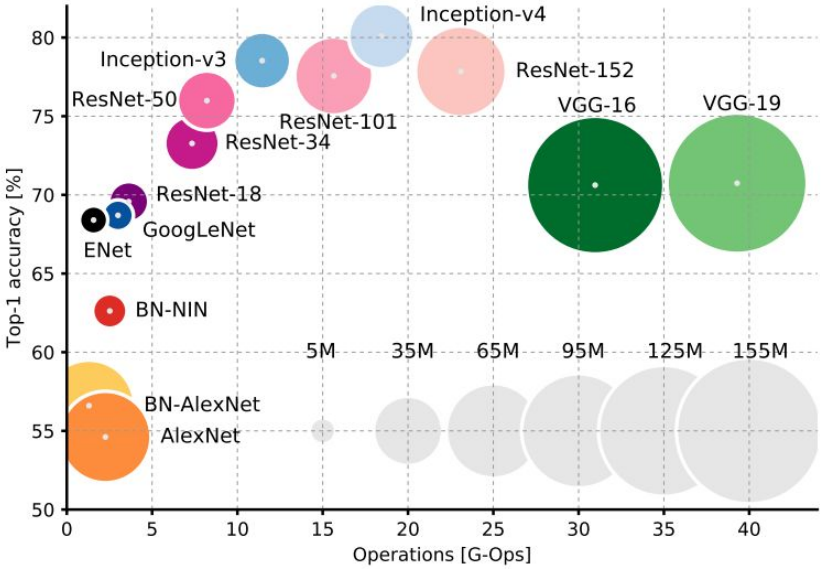
An Analysis of Deep Neural Network Models for Practical Applications, 2017.

Comparison

Comparing complexity...

Inception-v4: Resnet + Inception!





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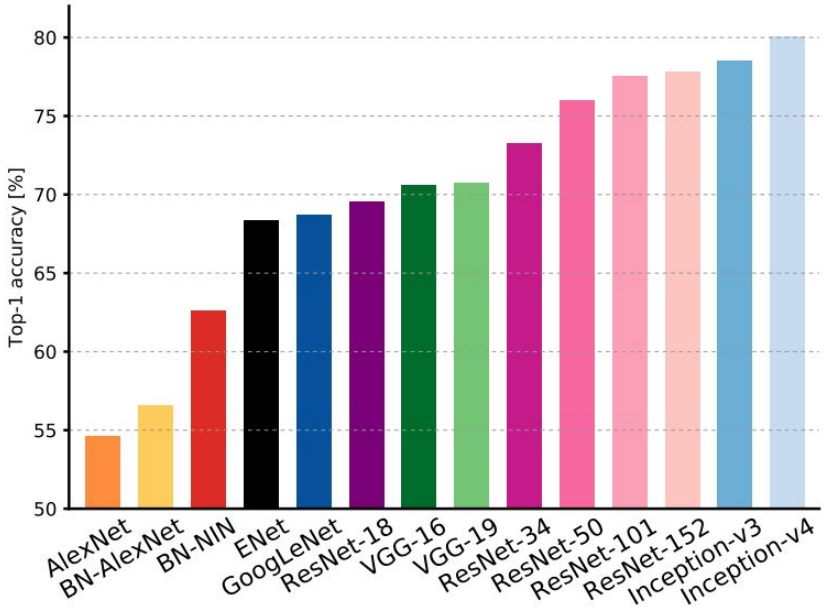
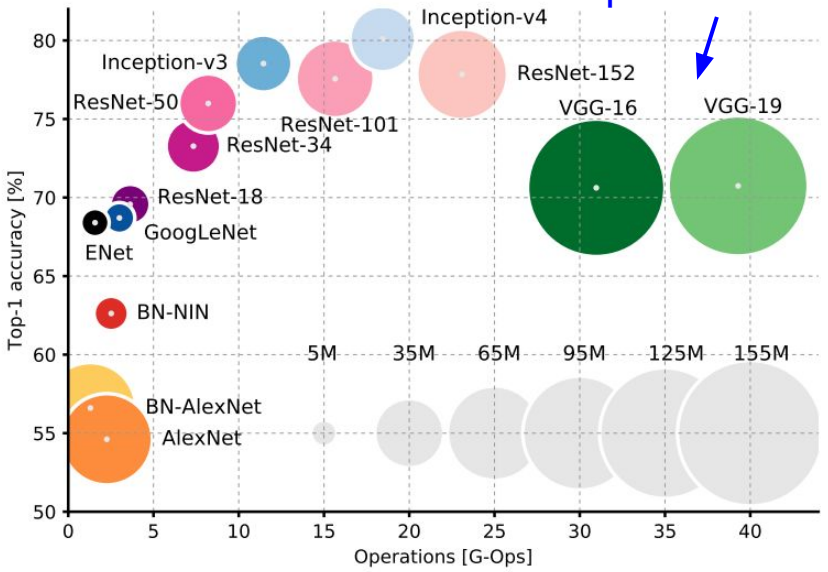


VGG: Highest memory, most operations



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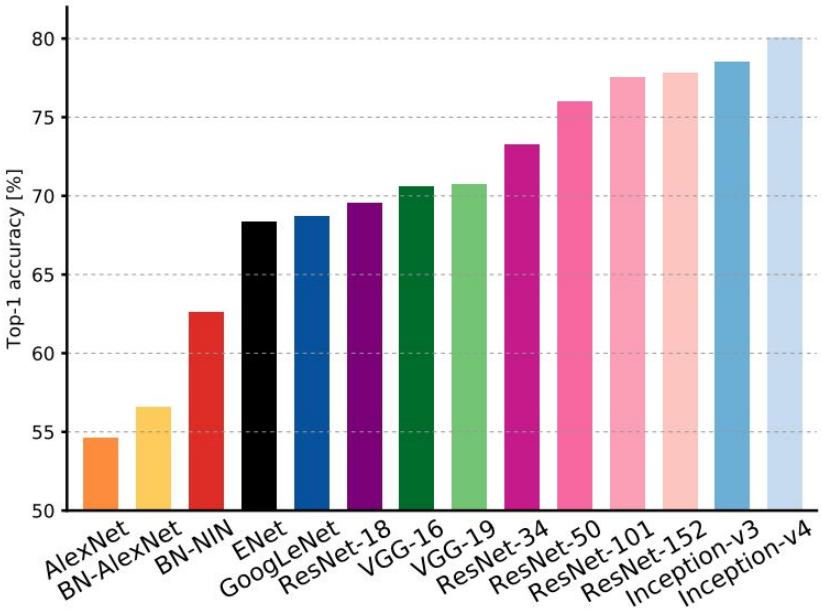
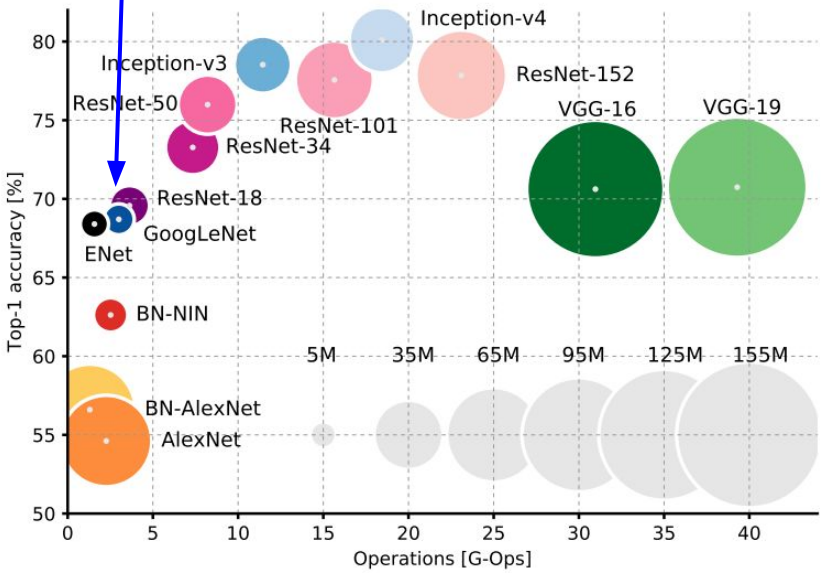


GoogLeNet:
most efficient



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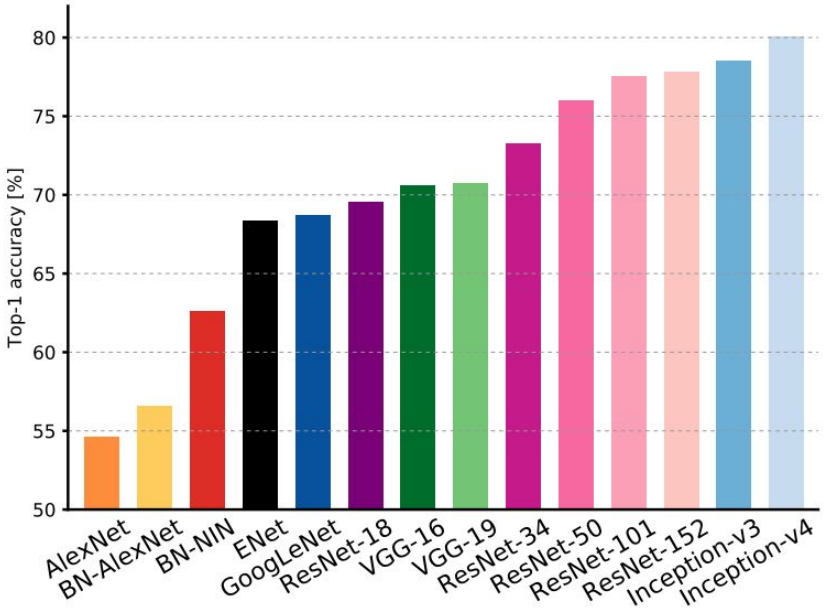
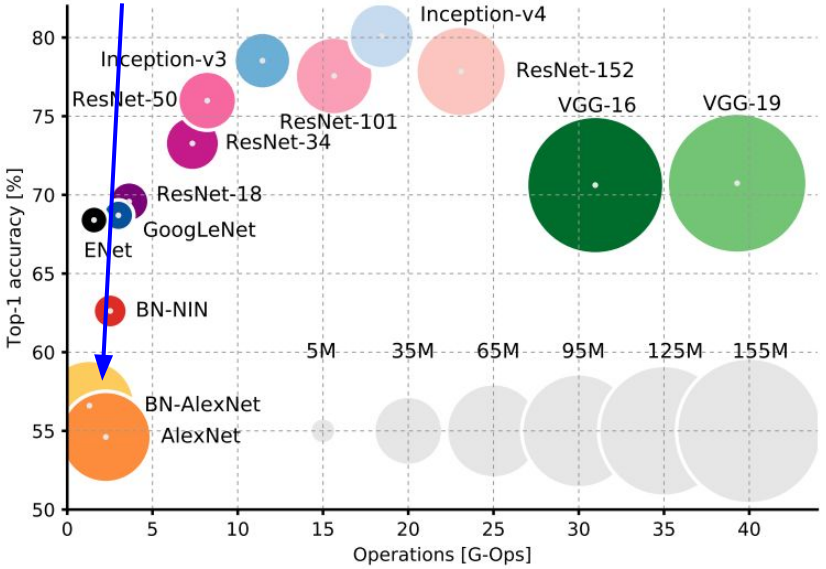


AlexNet:
Smaller compute, still memory heavy, lower accuracy



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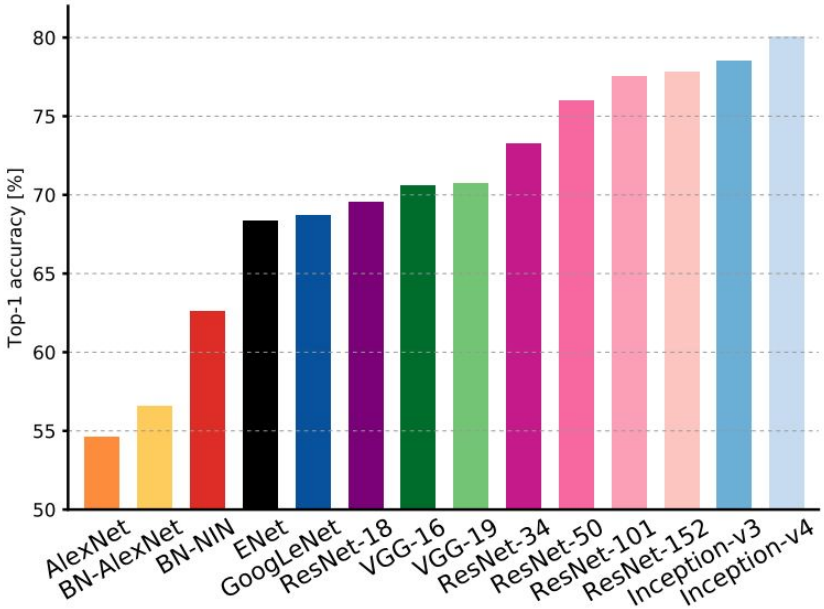
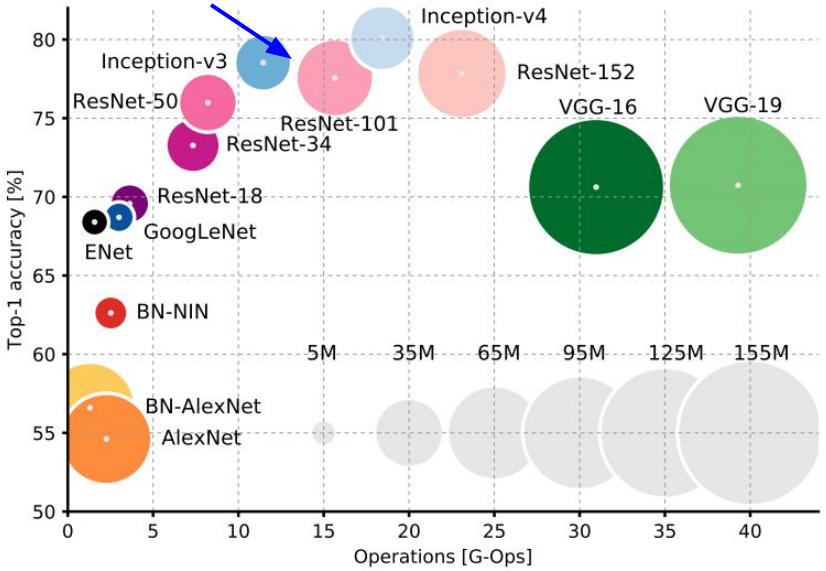


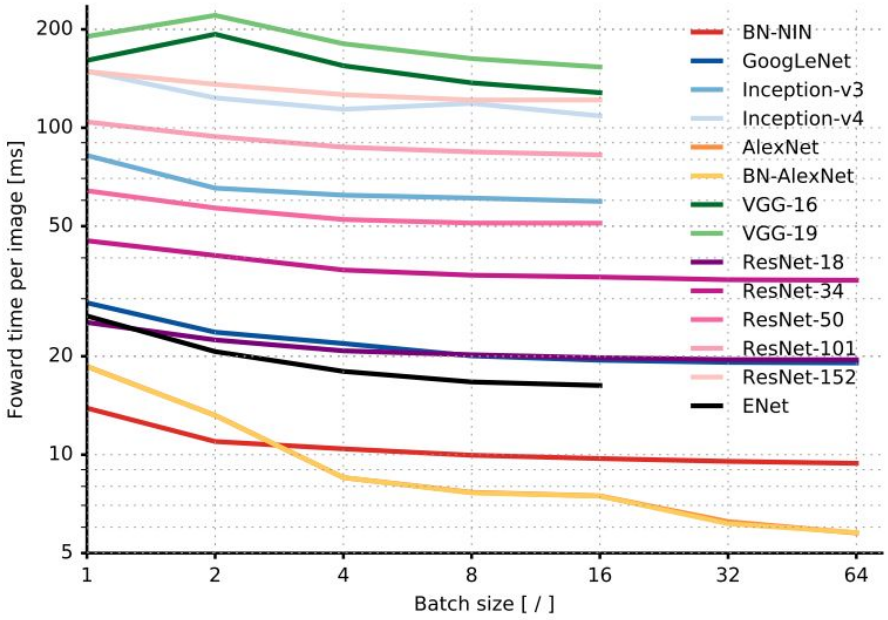
ResNet:
Moderate efficiency depending on model, highest accuracy

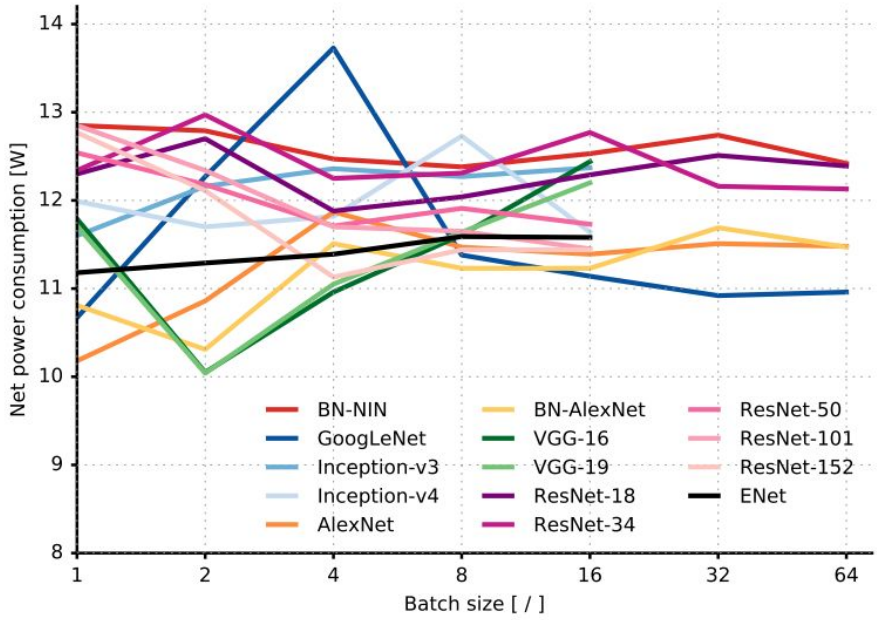


An Analysis of Deep Neural Network Models for Practical Applications, 2017.

Comparison

Forward pass time and power consumption





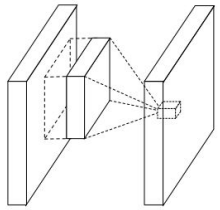
An Analysis of Deep Neural Network Models for Practical Applications, 2017.

Other Architectures to know

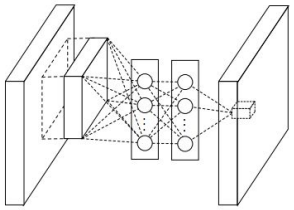
Network in Network (NiN)

[Lin et al. 2014]

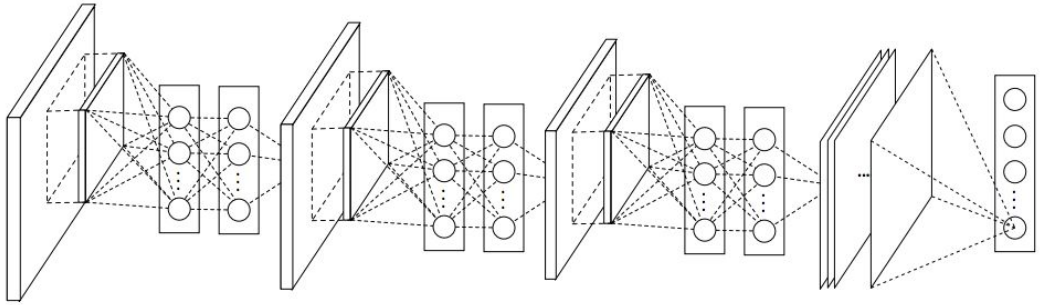
- Mlpconv layer with “micronetwork” within each conv layer to compute more abstract features for local patches
- Micronetwork uses multilayer perceptron (FC, i.e. 1x1 conv layers)
- Precursor to GoogLeNet and ResNet “bottleneck” layers
- Philosophical inspiration for GoogLeNet



(a) Linear convolution layer



(b) Mlpconv layer



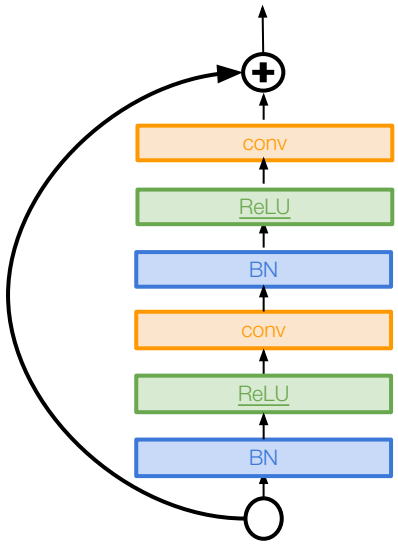
Other Architectures to know

Improving ResNets...

Identity Mappings in Deep Residual Networks

[He et al. 2016]

- Improved ResNet block design from creators of ResNet
- Creates a more direct path for propagating information throughout network (moves activation to residual mapping pathway)
- Gives better performance



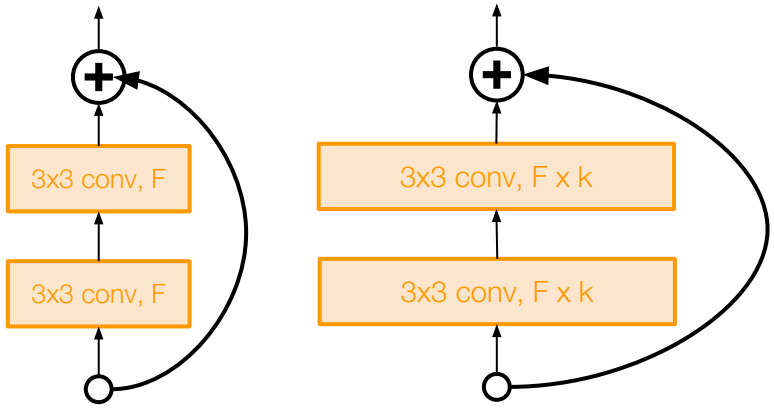
Other Architectures to know

Improving ResNets...

Wide Residual Networks

[Zagoruyko et al. 2016]

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



Basic residual block Wide residual block

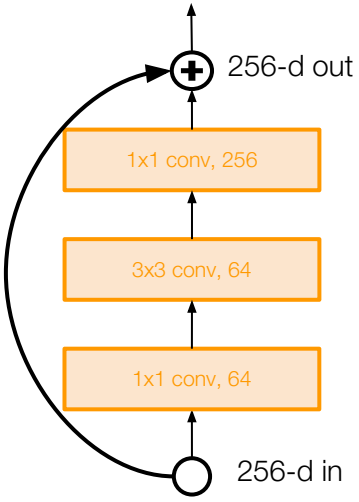
Other Architectures to know

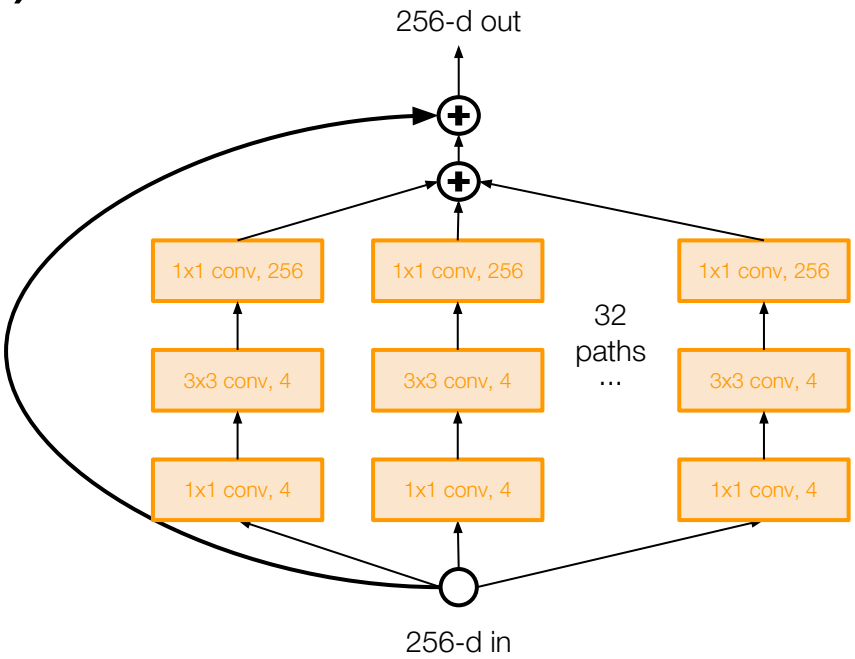
Improving ResNets...

Aggregated Residual Transformations for Deep Neural Networks (ResNeXt)

[Xie et al. 2016]

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





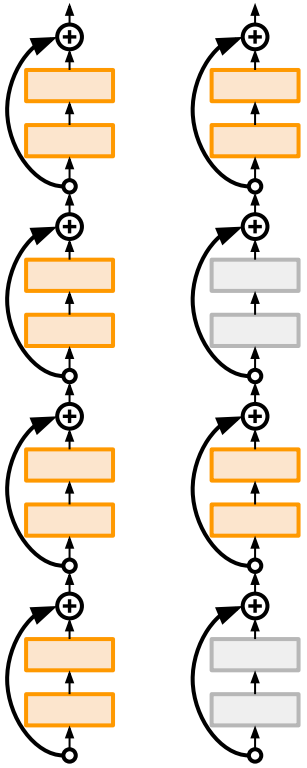
Other Architectures to know

Improving ResNets...

Deep Networks with Stochastic Depth

[Huang et al. 2016]

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



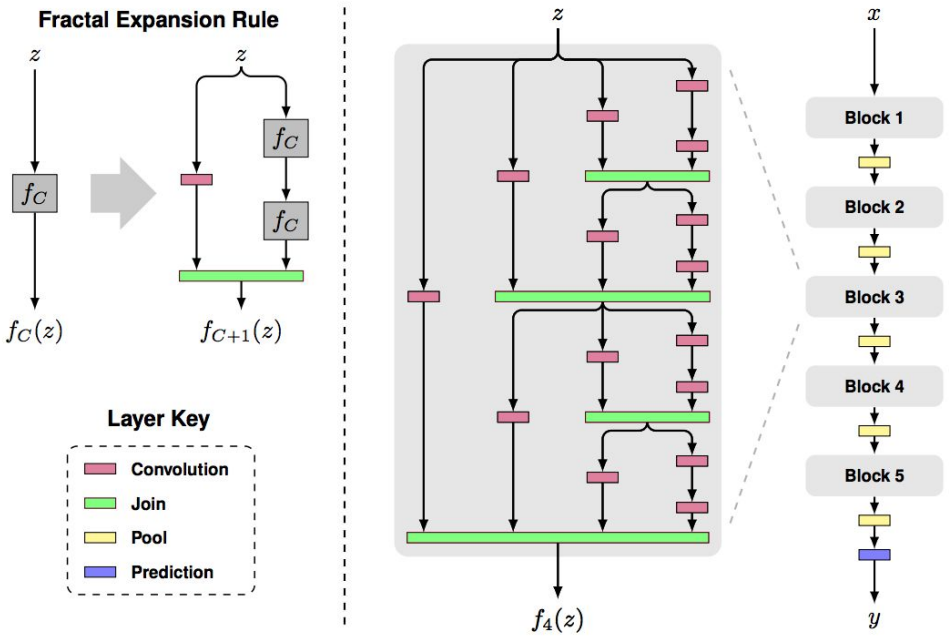
Other Architectures to know

Beyond ResNets...

FractalNet: Ultra-Deep Neural Networks without Residuals

[Larsson et al. 2017]

- Argues that key is transitioning effectively from shallow to deep and residual representations are not necessary
- Fractal architecture with both shallow and deep paths to output
- Trained with dropping out sub-paths
- Full network at test time



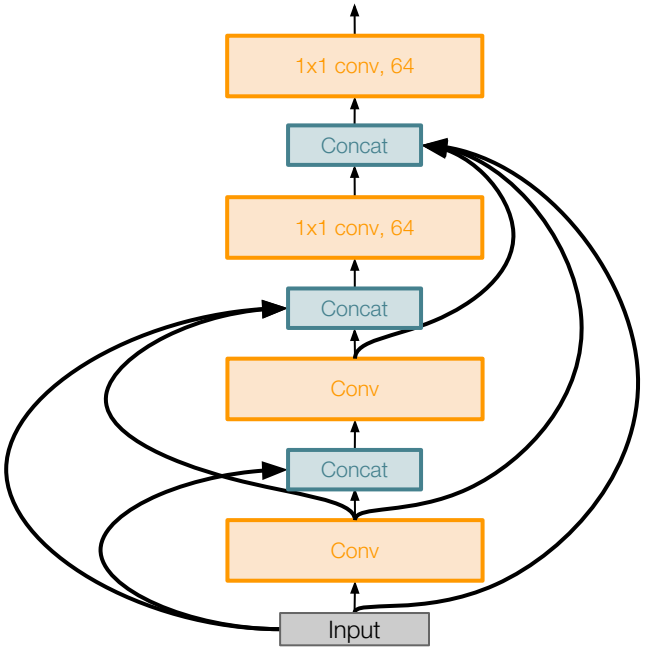
Other Architectures to know

Beyond ResNets...

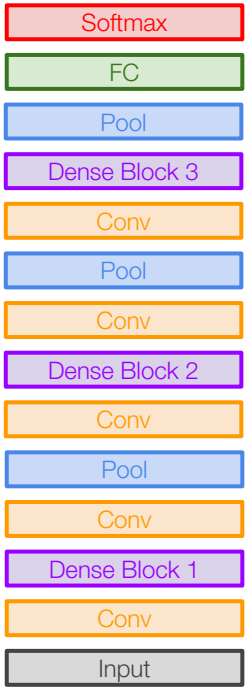
Densely Connected Convolutional Networks

[Huang et al. 2017]

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



Dense Block



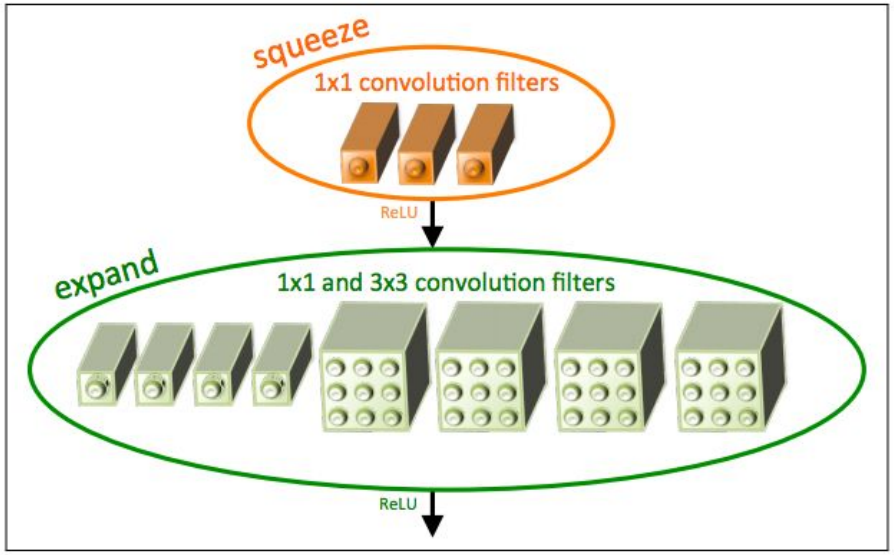
Other Architectures to know

Efficient networks...

SqueezeNet: AlexNet-level Accuracy With 50x Fewer Parameters and <0.5Mb Model Size

[Iandola et al. 2017]

- Fire modules consisting of a ‘squeeze’ layer with 1x1 filters feeding an ‘expand’ layer with 1x1 and 3x3 filters
- AlexNet level accuracy on ImageNet with 50x fewer parameters
- Can compress to 510x smaller than AlexNet (0.5Mb)



Summary

Case Studies

- AlexNet
- VGG
- GoogLeNet
- ResNet

Also....

- NiN (Network in Network)
- Wide ResNet
- ResNeXT
- Stochastic Depth
- DenseNet
- FractalNet
- SqueezeNet

Summary

- VGG, GoogLeNet, ResNet all in wide use, available in model zoos
- ResNet current best default
- Trend towards extremely deep networks
- Significant research centers around design of layer / skip connections and improving gradient flow
- Even more recent trend towards examining necessity of depth vs. width and residual connections

Deep networks, why and how

Why deep networks

Note that a shallow network with a single, huge, hidden layer is already a universal approximator

Why deep networks

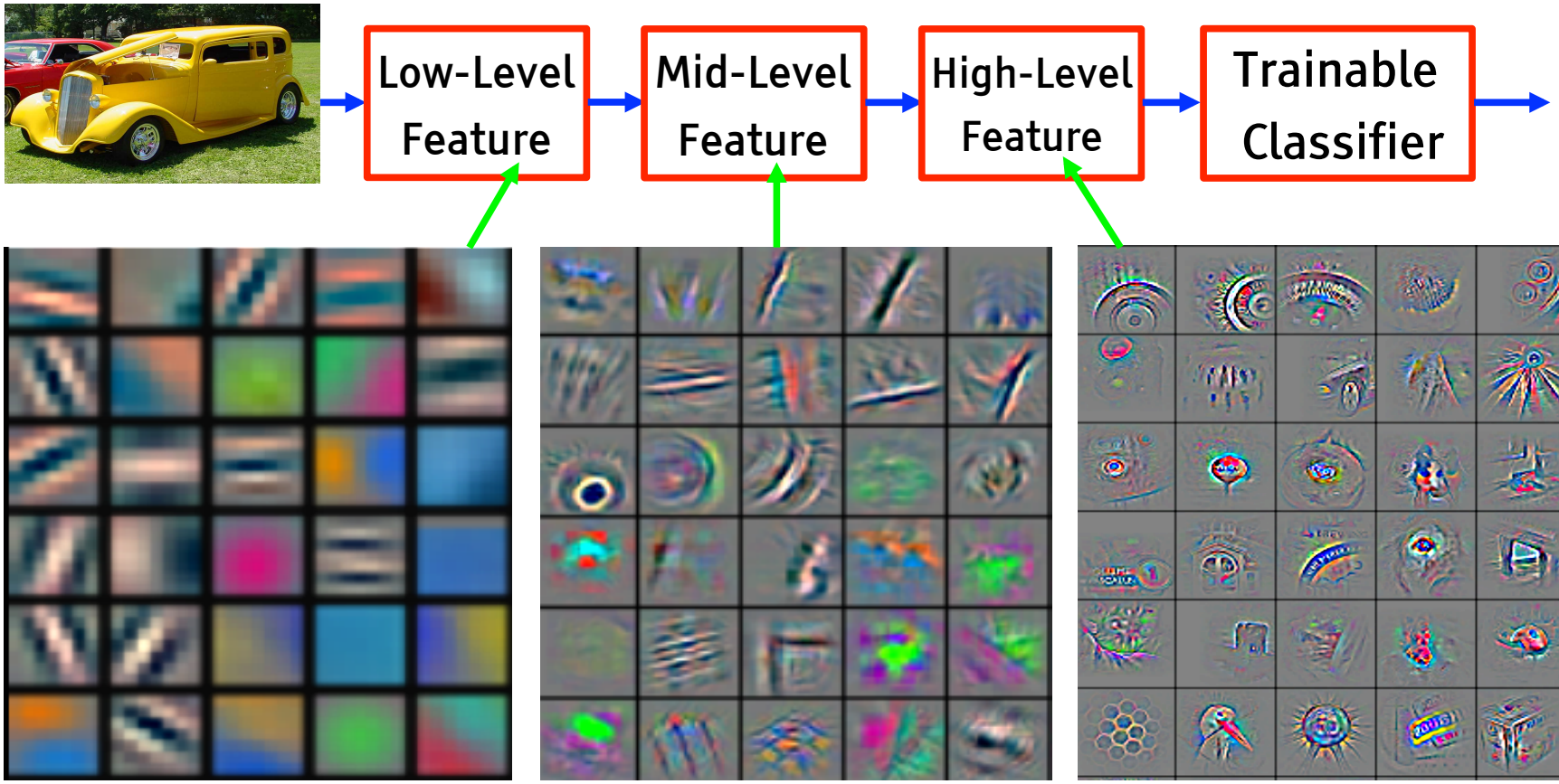
Note that a shallow network with a single, huge, hidden layer is already a universal approximator

The advantages of deeper networks:

1. Additional prior: compositionality is useful to describe the world around us efficiently
2. Exponential expressiveness of deep networks

The advantage of deep networks

1. Additional prior: compositionality is useful to describe the world around us efficiently



The advantage of deep networks

2. Exponential expressiveness of deep networks

Some functions compactly represented with k layers may require exponentially many more parameters with 2 layers

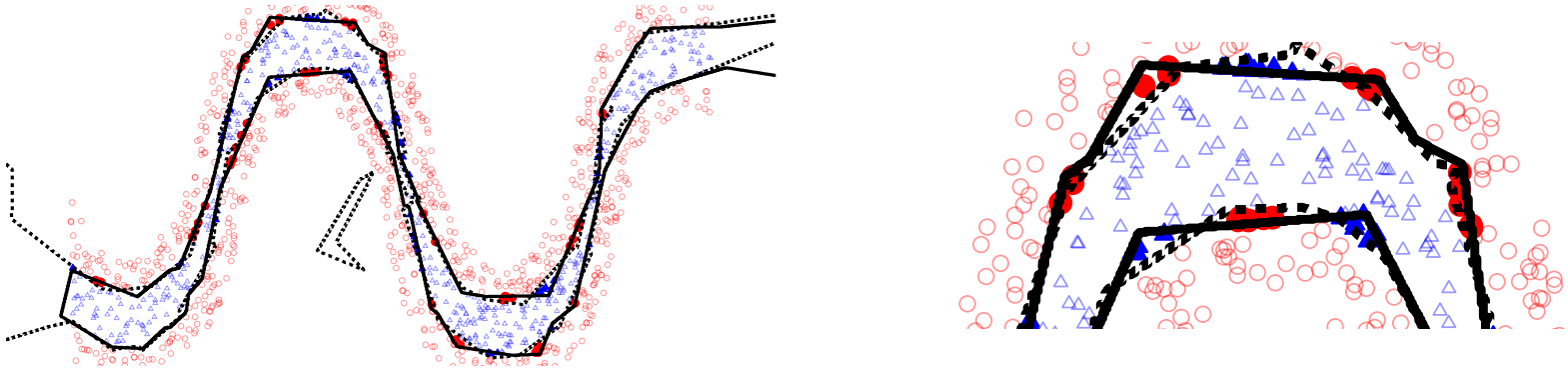


Figure 1: Binary classification using a shallow model with 20 hidden units (solid line) and a deep model with two layers of 10 units each (dashed line). The right panel shows a close-up of the left panel. Filled markers indicate errors made by the shallow model.

But deep networks are hard to train

Problem1: Vanishing/exploding gradients

- Phenomenon: the gradient of early layers become extremely small or large
- When: hamper convergence from the beginning
- Reason: multiplication of several parameters
- How to avoid:
  - Recurrent networks use the same parameter at each time step, hence gives rise to especially pronounced difficulties. Let's discuss next time.
  - Feed-forward networks do not use the same parameters at each layer, and this problem has been largely addressed by normalized initialization and intermediate normalization layers (e.g., batch normalization).

But deep networks are hard to train

Problem2: Degradation problem

- Phenomenon: with the network depth increasing, accuracy gets saturated and then degrades rapidly.
- When: after deeper networks are able to start converging
- Reason: long-range dependency
- How to avoid:
  - adding extra copies of the output that are attached to the intermediate hidden layers of the network, as in GoogLeNet
  - adding skip connections between layers reduce the length of the shortest path from the lower layer's parameters to the output, as in ResNet

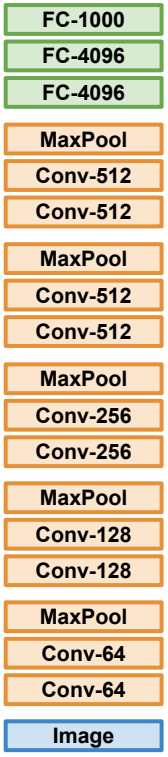
Transfer Learning with CNNs

Transfer learning with CNNs

Transfer Learning with CNNs

Donahue et al, “DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition”, ICML 2014
Razavian et al, “CNN Features Off-the-Shelf: An Astounding Baseline for Recognition”, CVPR Workshops 2014

1. Train on Imagenet



Transfer learning with CNNs

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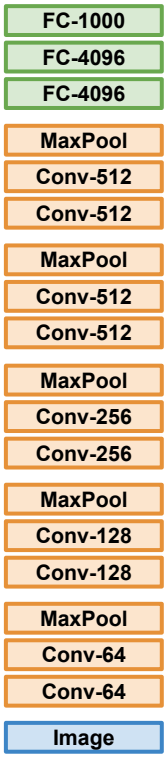
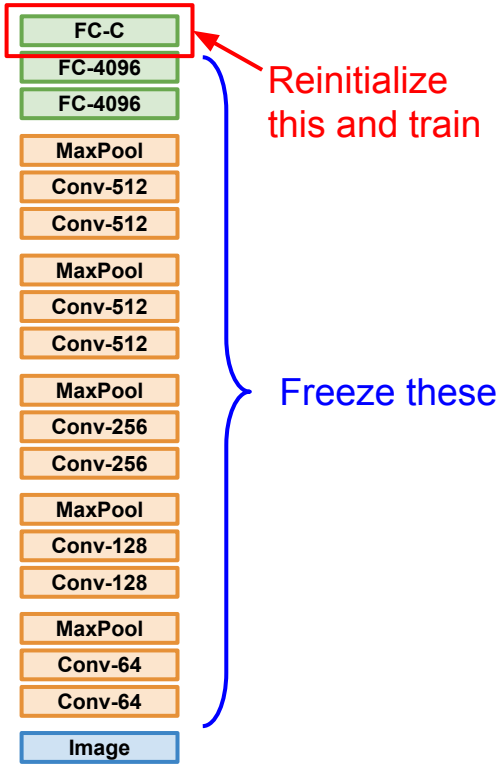


2. Small Dataset (C classes)



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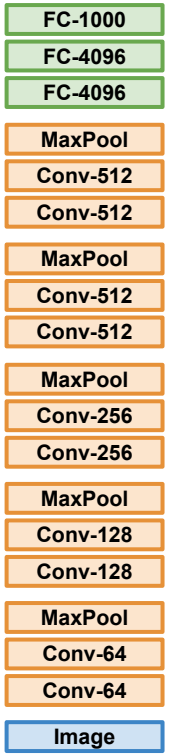

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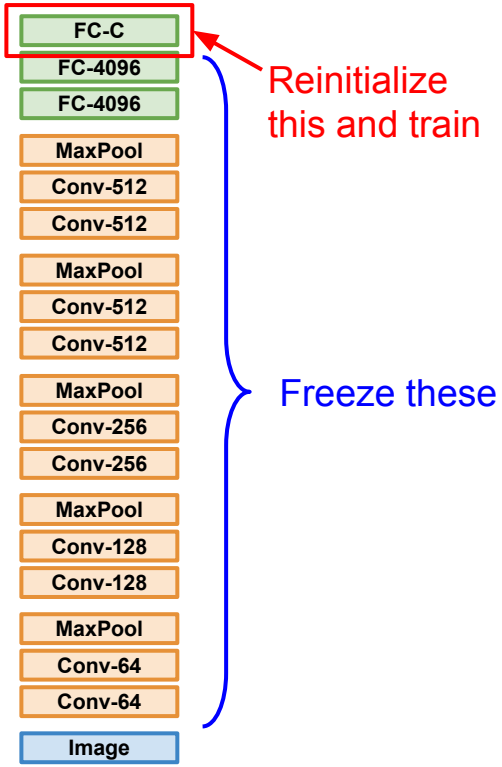
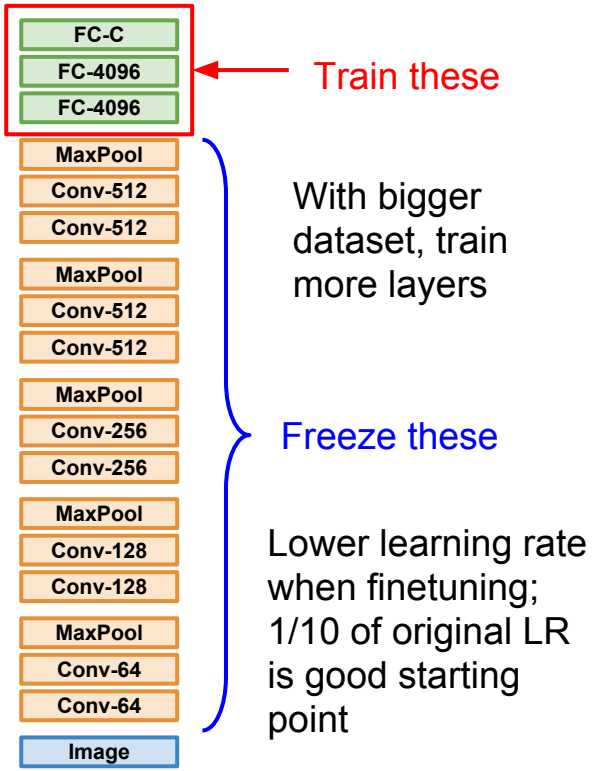
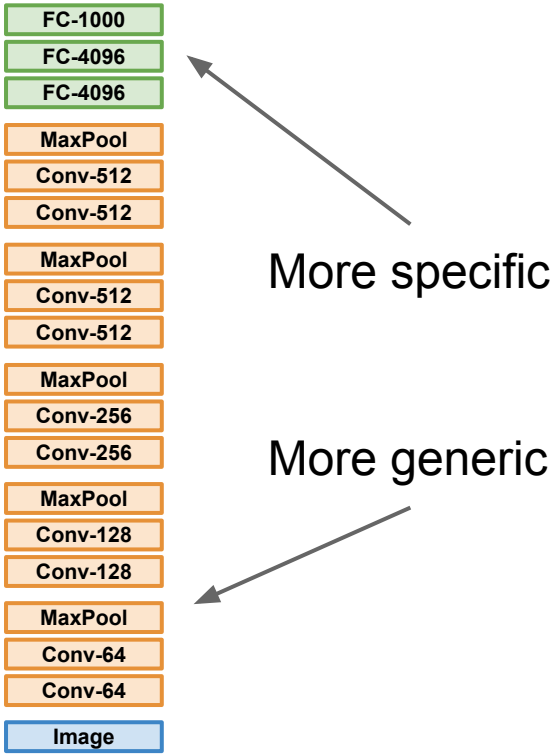


3. Bigger dataset

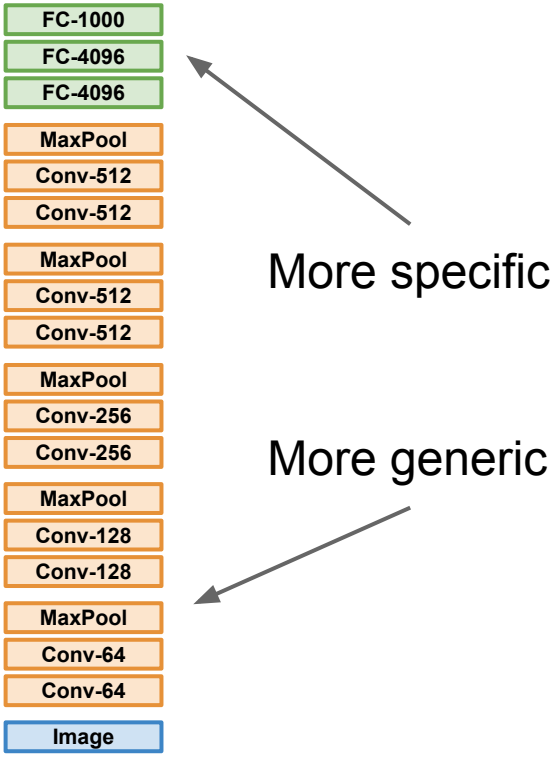


Transfer learning with CNNs



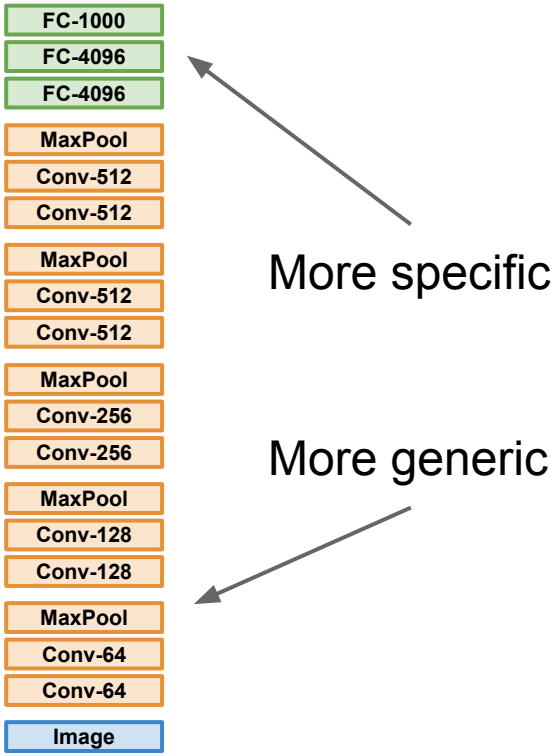
	very similar dataset	very different dataset
very little data	?	?
quite a lot of data	?	?

Transfer learning with CNNs



	very similar dataset	**very different dataset**
very little data	Use Linear Classifier on top layer	?
quite a lot of data	Finetune a few layers	?

Transfer learning with CNNs

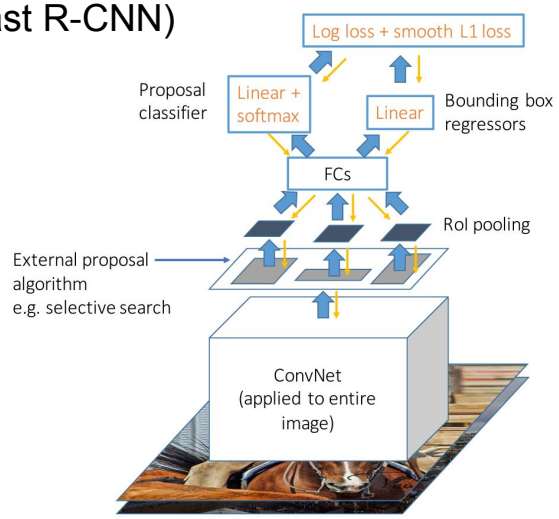


	very similar dataset	**very different dataset**
very little data	Use Linear Classifier on top layer	You're in trouble… Try linear classifier from different stages
quite a lot of data	Finetune a few layers	Finetune a larger number of layers

Transfer learning with CNNs

Transfer learning with CNNs is pervasive…
(it's the norm, not an exception)

Object Detection
(Fast R-CNN)



Girshick, "Fast R-CNN", ICCV 2015
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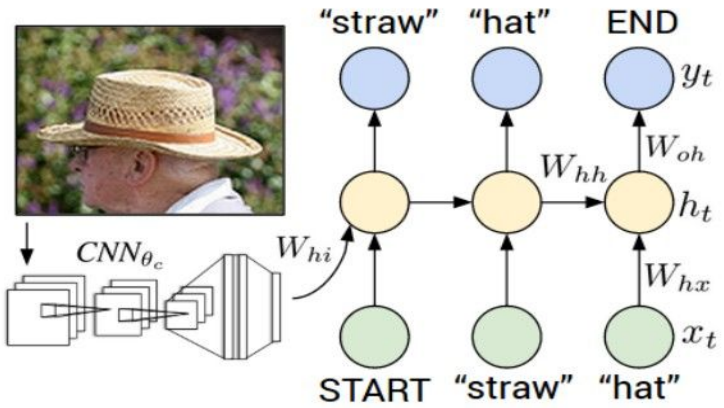
Image Captioning: CNN + RNN



Karpathy and Fei-Fei, "Deep Visual-Semantic Alignments for Generating Image Descriptions", CVPR 2015
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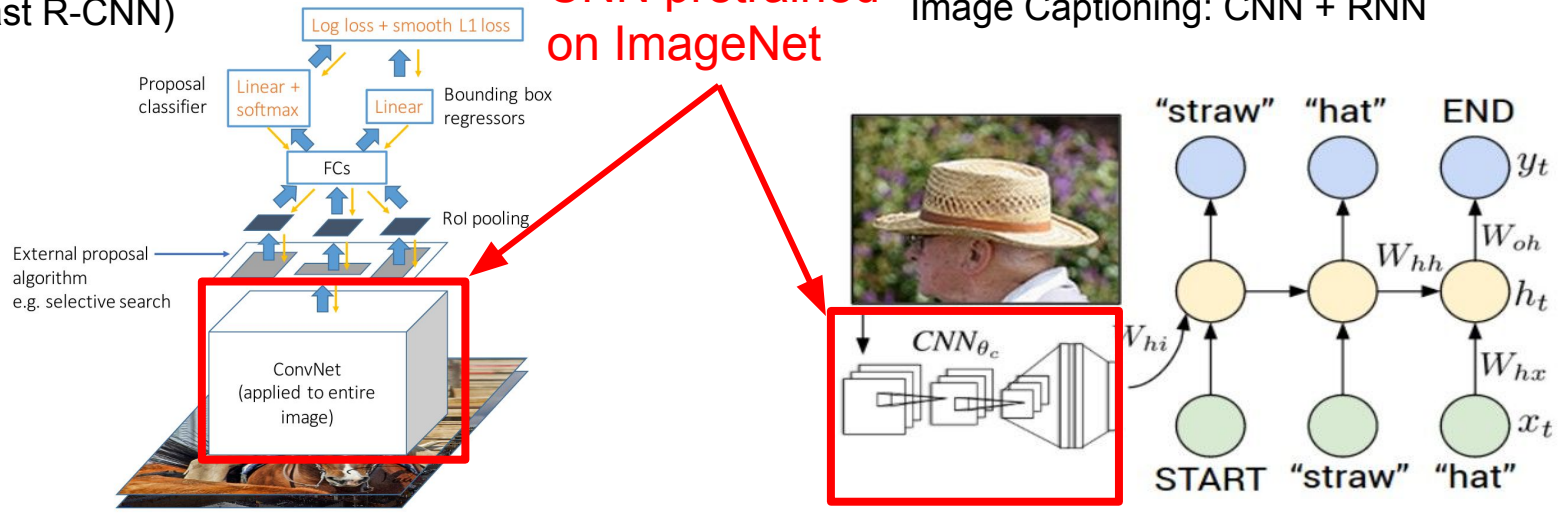
Transfer learning is pervasive

Object Detection
(Fast R-CNN)

CNN pretrained
on ImageNet

Image Captioning: CNN + RNN



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Transfer learning is pervasive

Object Detection
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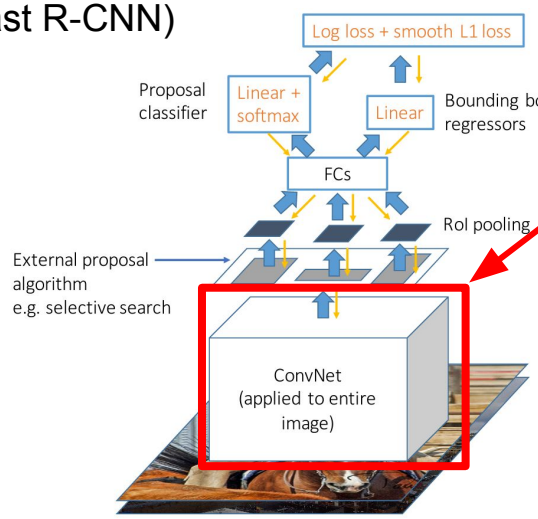
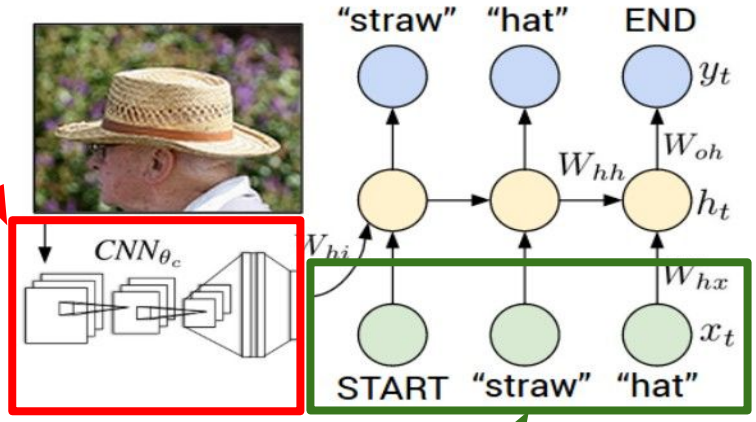


CNN pretrained on ImageNet

Image Captioning: CNN + RNN



Word vectors pretrained with word2vec

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