Announcements, 2018-02-14

- HW #4 due tonight by 11:59pm uploaded to Gradescope.
- HW #5 will be uploaded by tomorrow night, and will be due Monday, 26 Feb 2018.
- We will aim to upload project guidelines shortly after the midterm.
- Midterm will be open book, open python / MATLAB, open CCLE (to get notes), but closed internet.

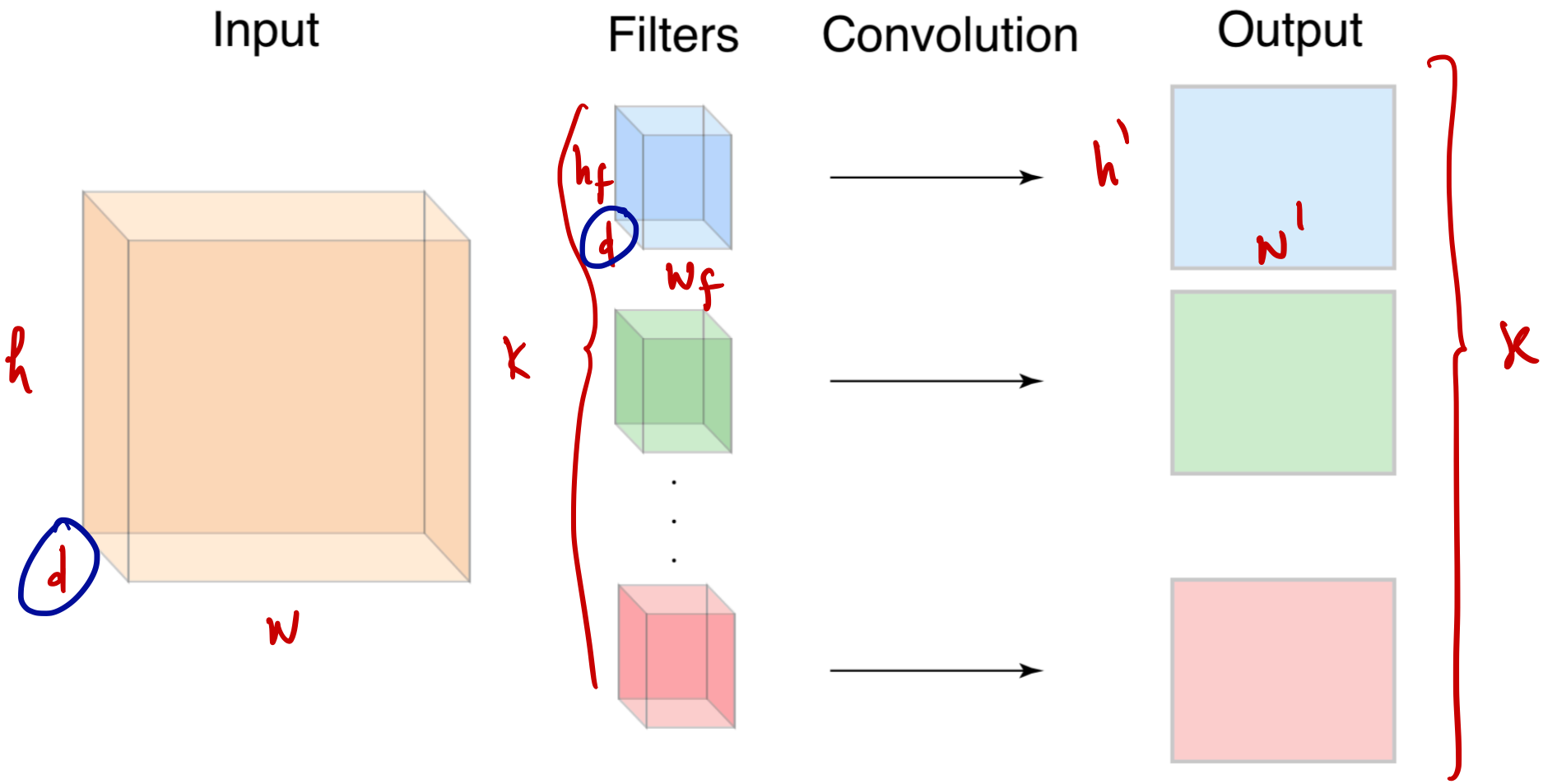
  Weds, Feb 21, 2018

  - This does not mean that the solutions to questions are exact statements that you will find in the book.
  - In particular, if you find yourself flipping through pages to find a sentence here or there, it's probably not a great use of time.
- We aim to upload some practice midterm questions to be posted on Saturday.

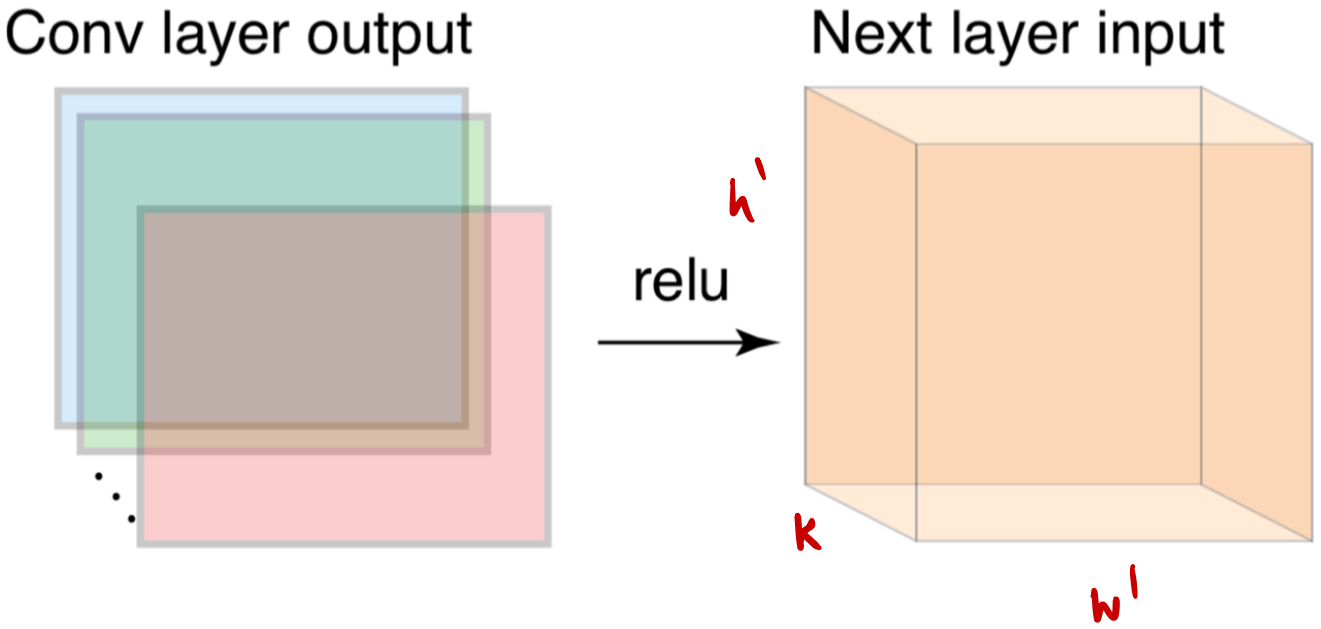
Recap: The convolutional layer of a CNN

Convolutional layer (cont.)

Now, we don't have just one filter in a convolutional layer, but multiple filters. We call each output (matrix) a slice.



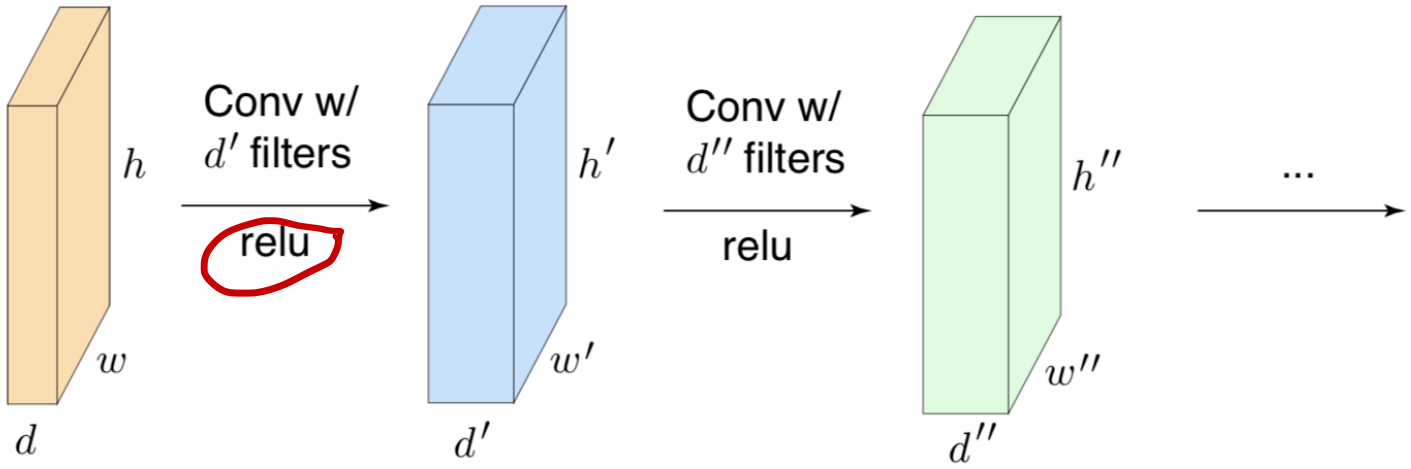
Recap: The convolutional layer of a CNN



Recap: The convolutional layer of a CNN

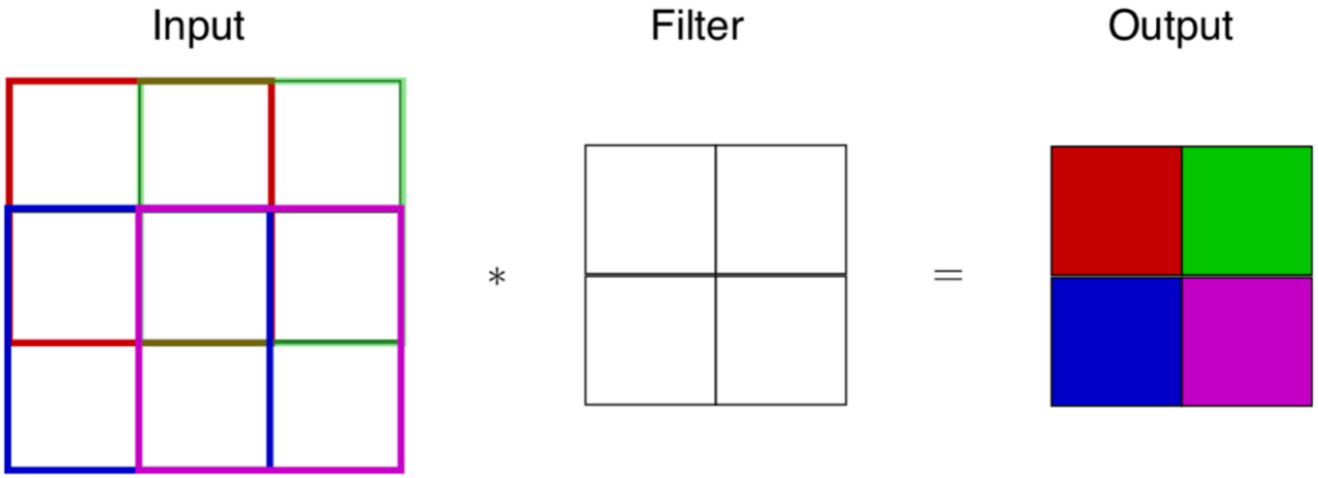
Composition of convolutional layers

These layers can then be composed, which comprise a large component of the CNN.



All convolutions in this class are valid convolutions

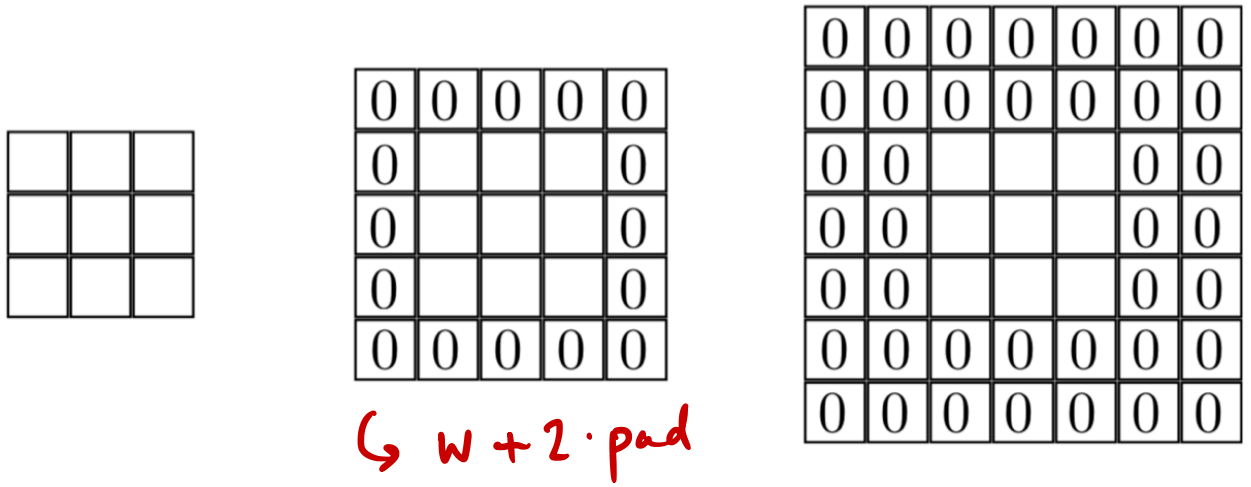
In this class, all convolutions will be valid convolutions. We explicitly specify the amount of zero padding when we need it.



Output size: $(w - w_f + 1, h - h_f + 1)$

Recap: convolutional padding

$\text{pad} = 0$ $\text{pad} = 1$ $\text{pad} = 2$



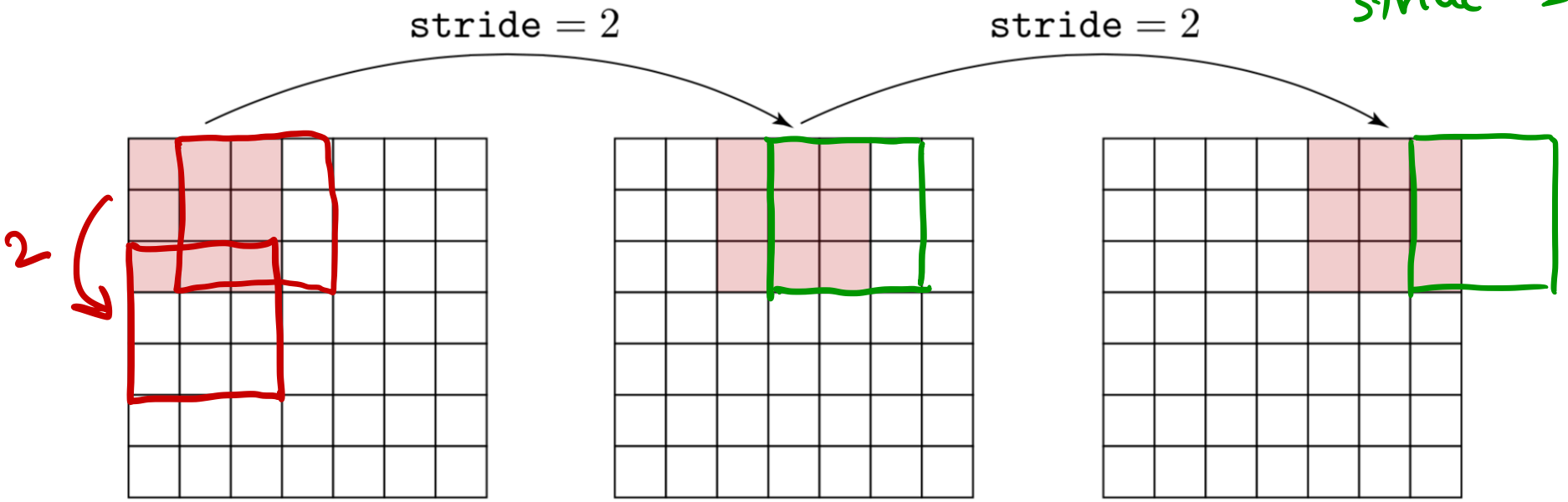
↳ $w + 2 \cdot \text{pad}$

The output of the convolution is now $(w - w_f + 1 + 2\text{pad}, h - h_f + 1 + 2\text{pad})$.

$w + 2 \cdot \text{pad} - w_f + 1$

Convolution stride

Another variable to control is the stride, which defines how much the filter moves in the convolution. For normal convolution, $\texttt{stride} = 1$, which denotes that the filter is dragged across every part of the input. Consider a 7×7 input with a 3×3 filter. If convolution is only applied where the kernel overlaps the input, the output is 5×5. With $\texttt{stride} = 2$, the output is 3×3.



Convolution stride (cont.)

The stride must be sensible. In the 7×7 input with 3×3 filter example, it is not correct to use $\texttt{stride} = 3$ as it is not consistent with input. However, one can zero-pad the input so that the stride is appropriate. The output size after accounting for stride and padding is:

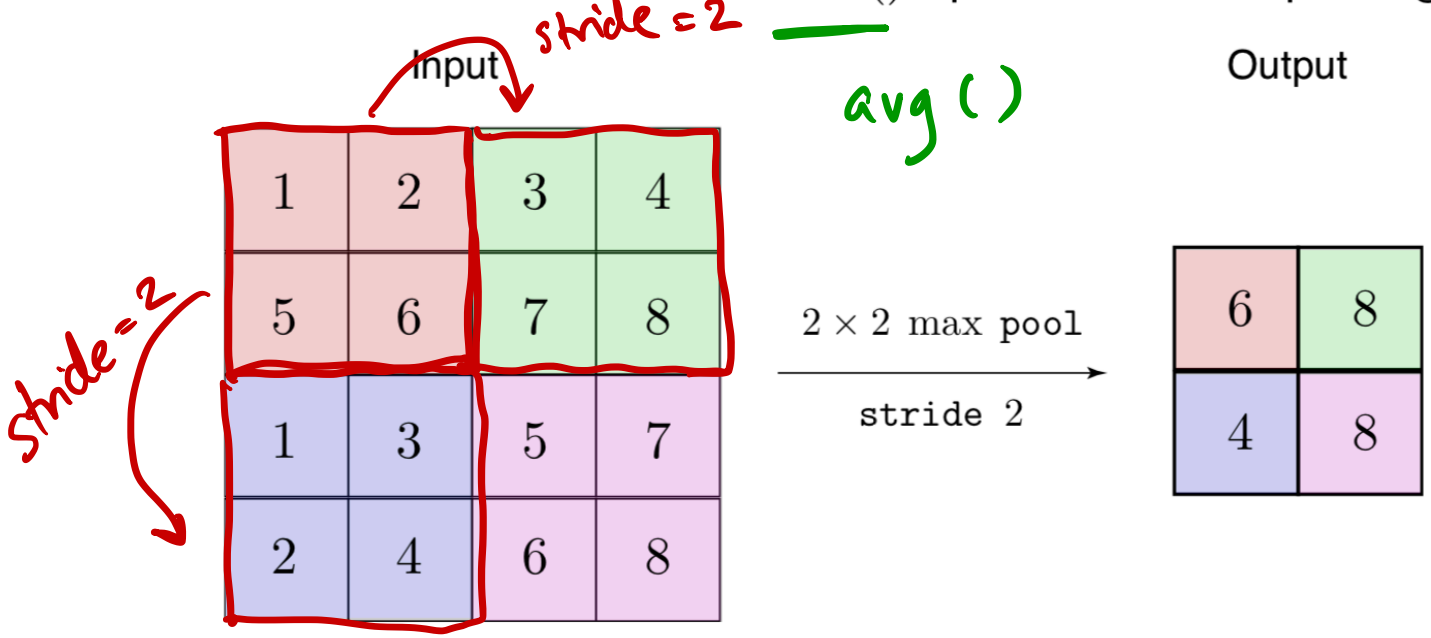
$$\left(\frac{w - w_f + 2\text{pad}}{\texttt{stride}} + 1, \frac{h - h_f + 2\text{pad}}{\texttt{stride}} + 1 \right)$$

Be careful when incorporating stride, as the data representation size will shrink in a divisive manner.

Pooling layer

CNNs also incorporate pooling layers, where an operation is applied to all elements within the filtering extent. This corresponds, effectively, to downsampling.

The pooling filter has width and height (w_p, h_p) and is applied with a given stride. It is most common to use the $\max()$ operation as the pooling operation.



Pooling layer (cont.)

A few notes on pooling layers.

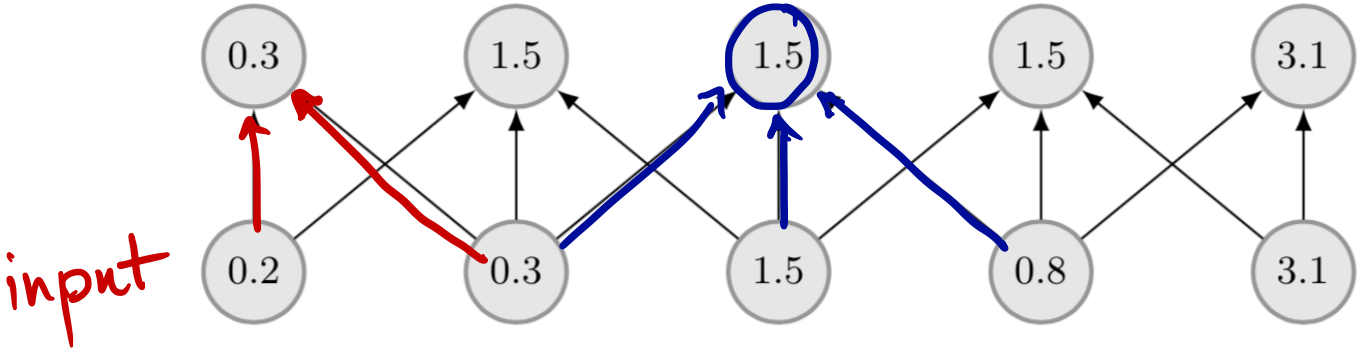
- The resulting output has dimensions

$$\left(\frac{w - w_p}{\texttt{stride}} + 1, \frac{h - h_p}{\texttt{stride}} + 1\right)$$

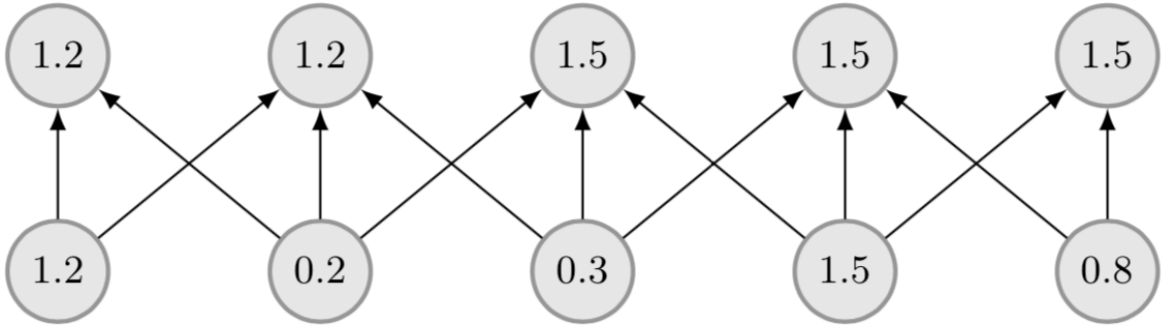
- Pooling layers introduce *no* additional parameters to the model.
- Pooling layers are intended to introduce small spatial invariances.

Pooling layer (cont.)

Invariance example:



Inputs shifted by 1. Five inputs change but only three outputs change.

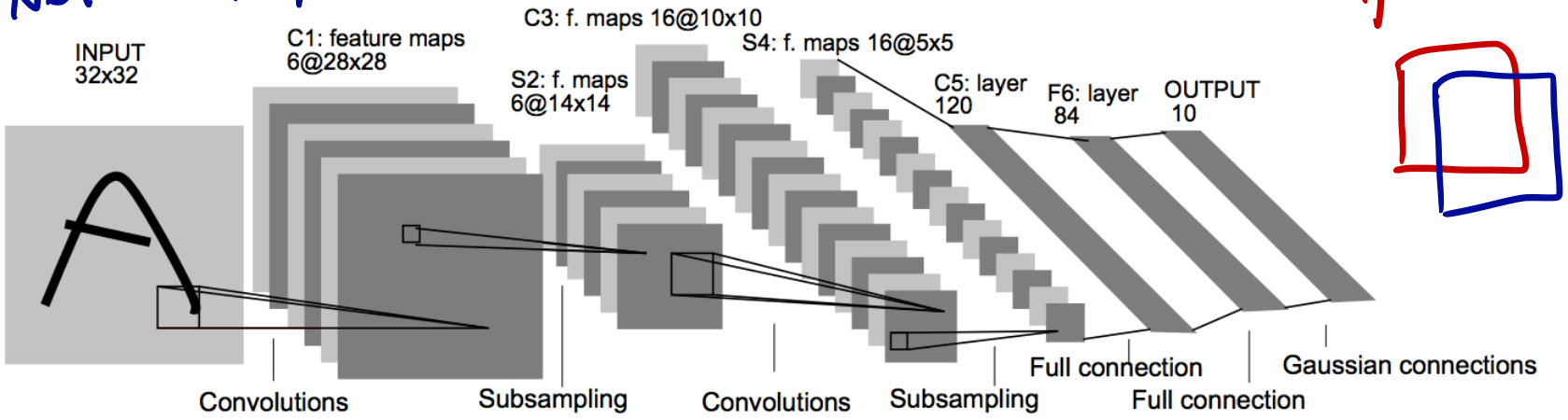


$\frac{W - W_p}{stride} + 1$

Sizing examples

LeNet 1998

$W - W_f + 1$



32x32

C1 contains six 5x5 conv filters. stride = 1, pad = 0

Size of feature maps at C1? $32 - 5 + 1 = 28$ $(28 \times 28 \times 6)$

Number of parameters in C1 layer? $(5 \times 5 + 1) \times 6 = 156$

S2 is a 2x2 pooling layer applied at stride 2.

Size of feature maps at S2? $(14 \times 14 \times 6)$

Number of parameters in S2 layer? 0

C3 contains sixteen 5x5 conv filters. $5 \times 5 \times 6$

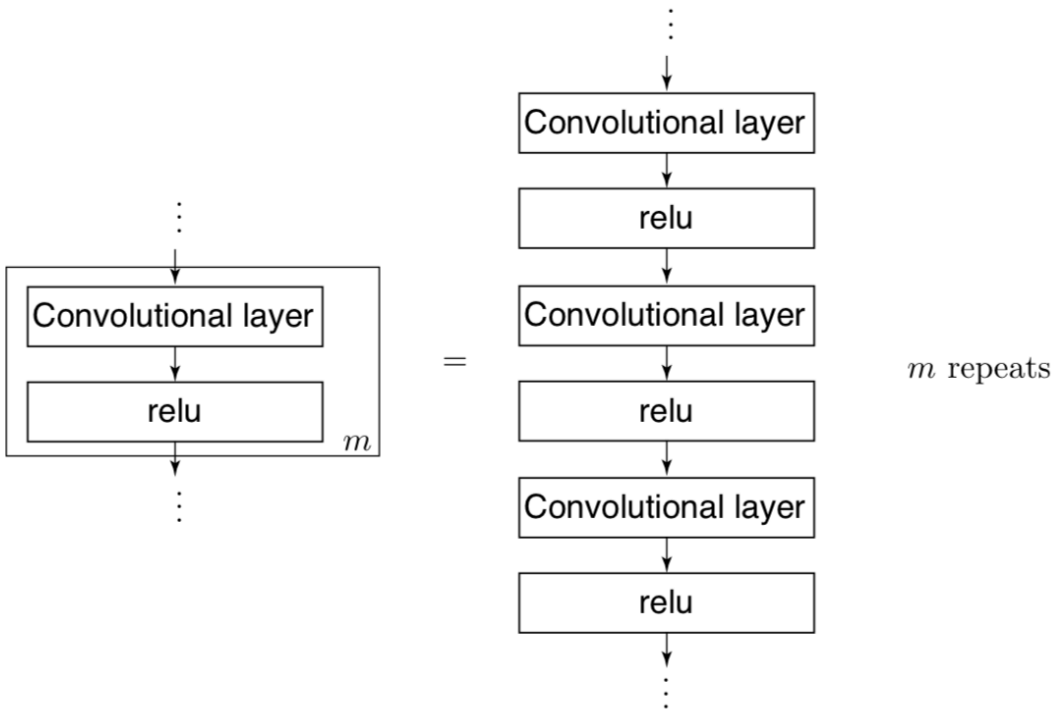
Size of feature maps at C3? $(10 \times 10 \times 16)$

Convolutional neural network architectures

Typically, convolutional neural networks are comprised of units that are composed of:

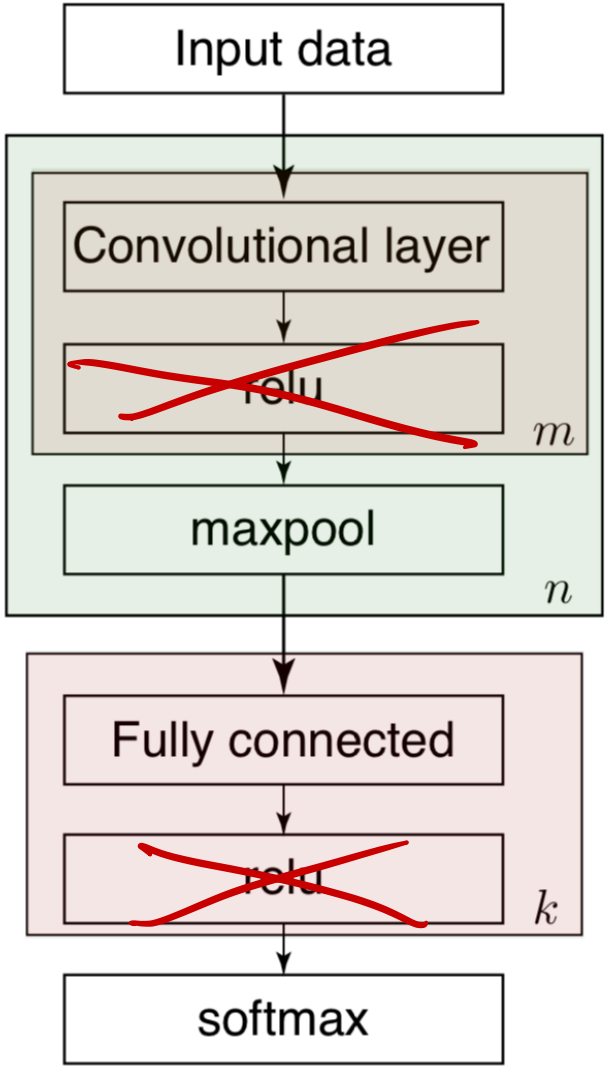
- Several paired convolutional-relu layers.
- Potentially one max pooling layer.

These units are cascaded. Finally, a CNN may end with a fully connected-relu layer, followed by a softmax classifier. To illustrate this, we borrow the plate notation from graphical models, where:



Convolutional neural network architectures (cont.)

With this in mind, the following describes a fairly typical CNN architecture.



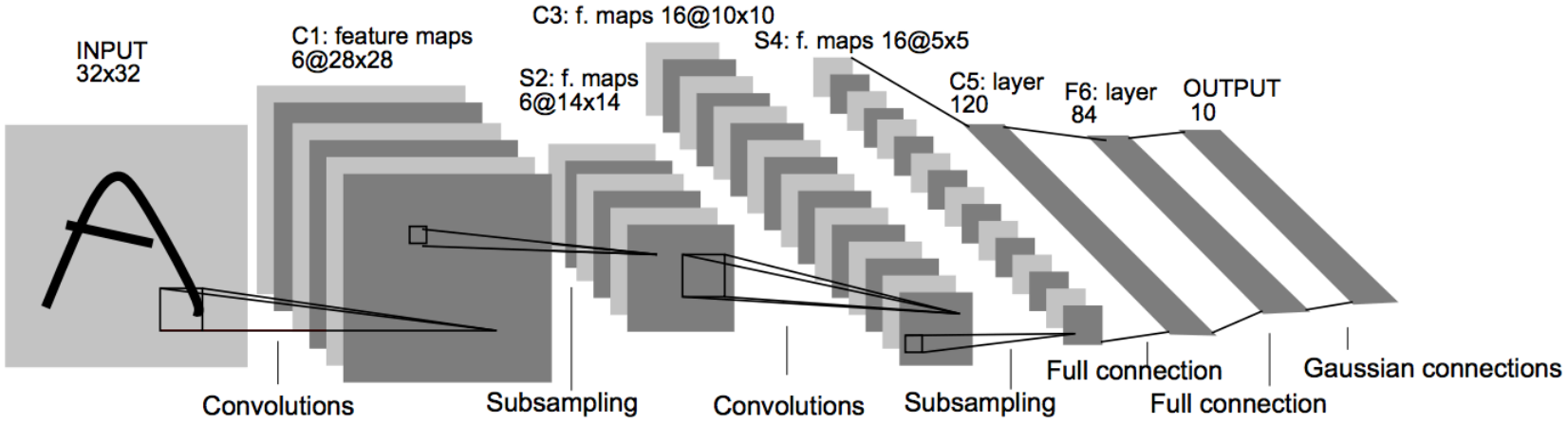
Case studies

To help get an intuition behind CNN's, we'll go over a few architectures that have been influential in recent years.

Case studies:

- LeNet (1998)
- AlexNet (2012)
- VGG (2013)
- GoogLeNet (2014)
- ResNet (2015)

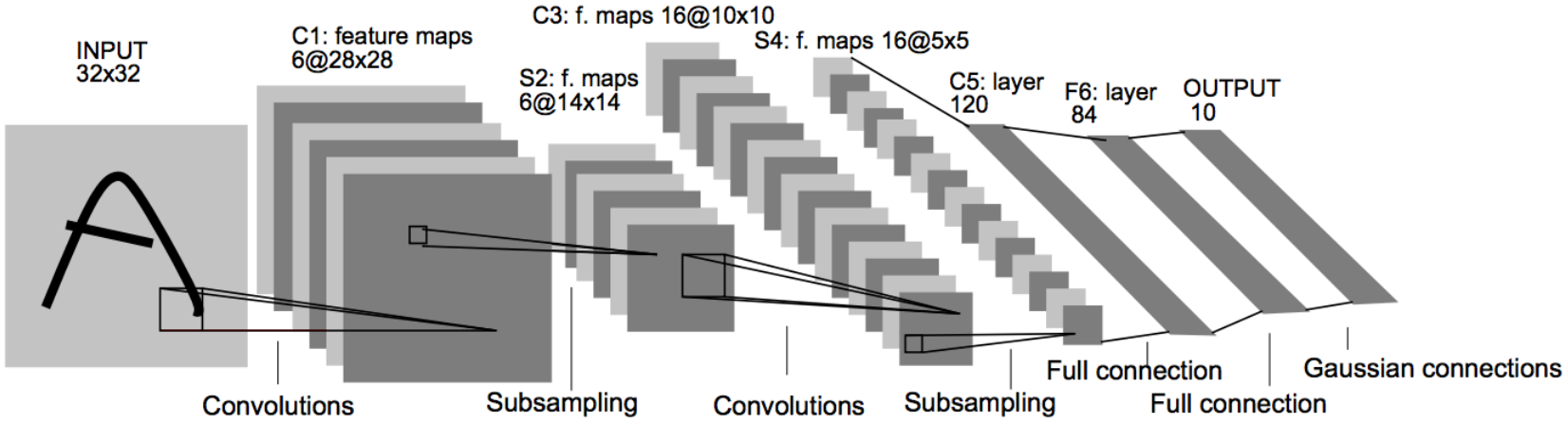
LeNet-5



LeCun et al., 1998.

Applied to handwriting recognition.

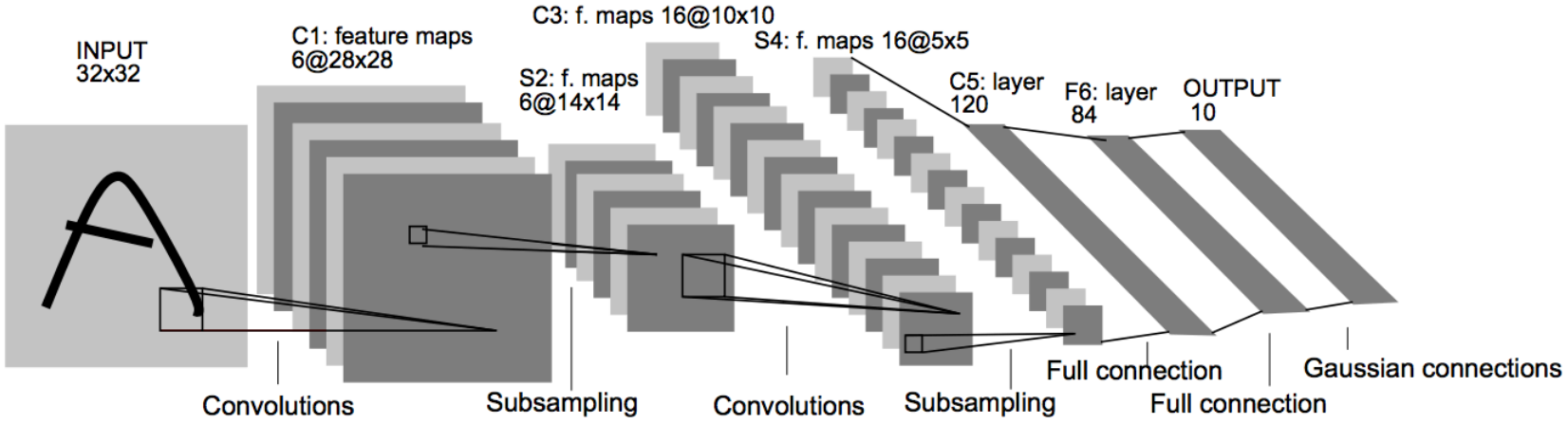
LeNet-5



LeCun et al., 1998.

Question: The input is 32x32. The first convolutional layer has 6 filters that are 5x5. What is the size of the output of the first convolutional layer?

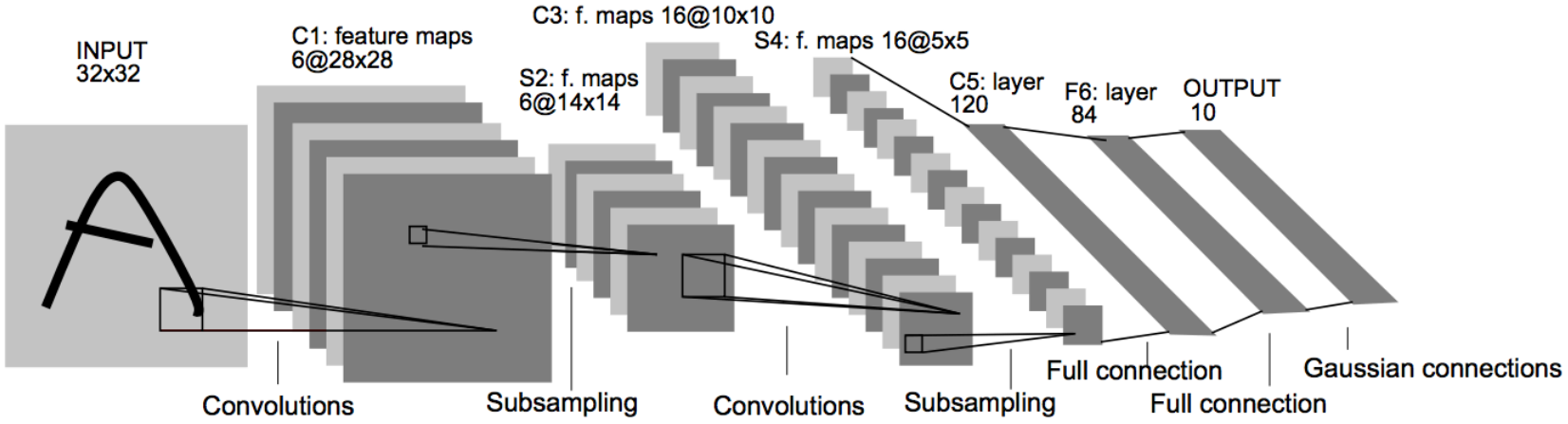
LeNet-5



LeCun et al., 1998.

Question: How many trainable parameters are there in the first convolutional layer?

LeNet-5



LeCun et al., 1998.

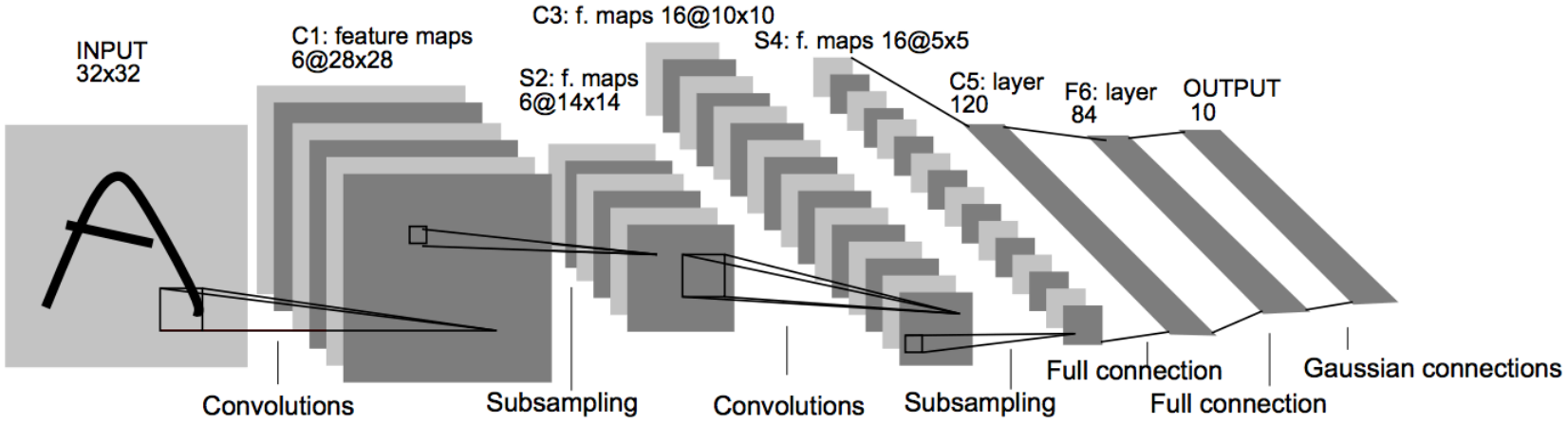
5x5 = 25 weights

Question: How many connections are there in the first convolutional layer?

$(28 \times 28 \times 5 \times 5 + 28 \times 28) \times 6$

$= 122,304$ connections

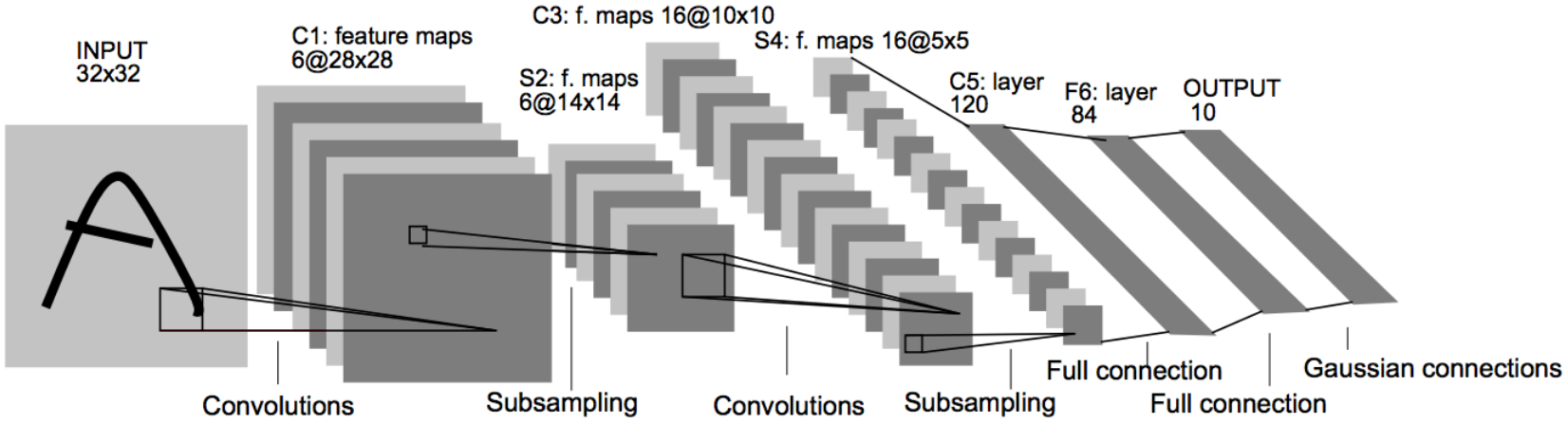
LeNet-5



7 total layers. Input is 32x32.

1. [28x28x6] **CONV**: 6 convolutional filters, 5x5 features, applied at stride 1.

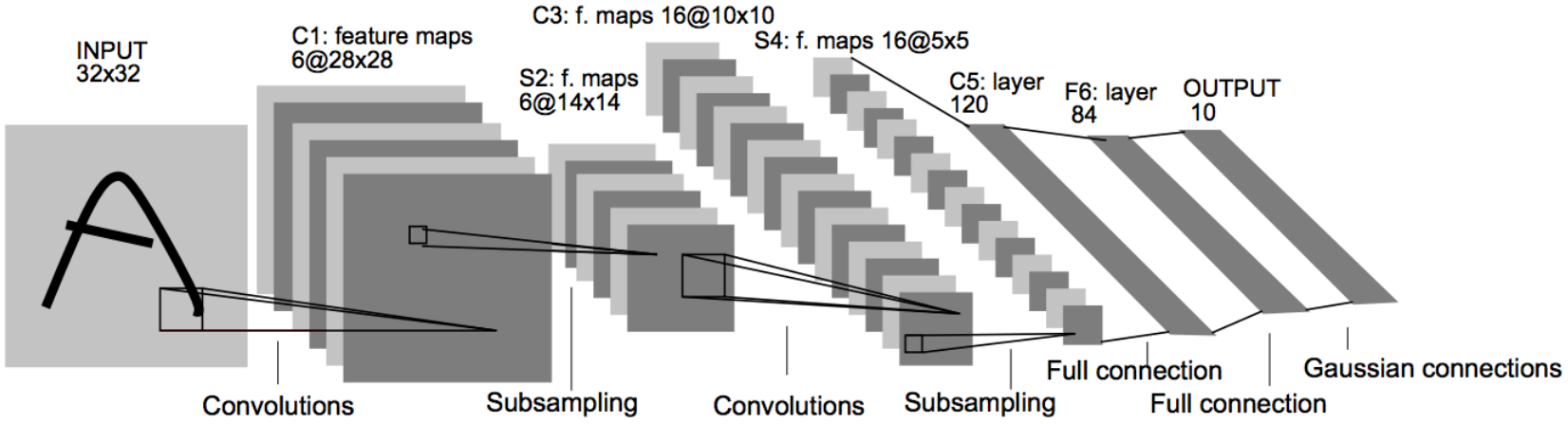
LeNet-5



LeCun et al., 1998.

Question: The second layer is a pooling layer with 2x2 filters applied at stride 2. What is the size at the output of this layer?

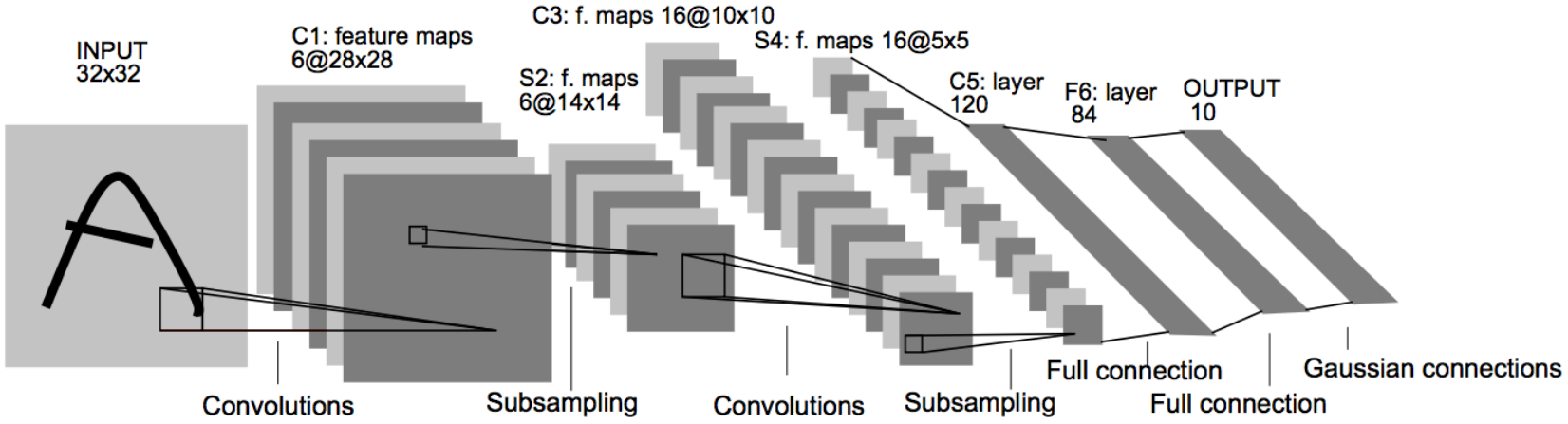
LeNet-5



7 total layers. Input is 32x32.

1. [28x28x6] **CONV**: 6 convolutional filters, 5x5 features, applied at stride 1.
2. [14x14x6] **POOL**: 2x2 pool with stride 2. (Adds all elems, multiplies them by trainable coefficient, then passes through sigmoid.)

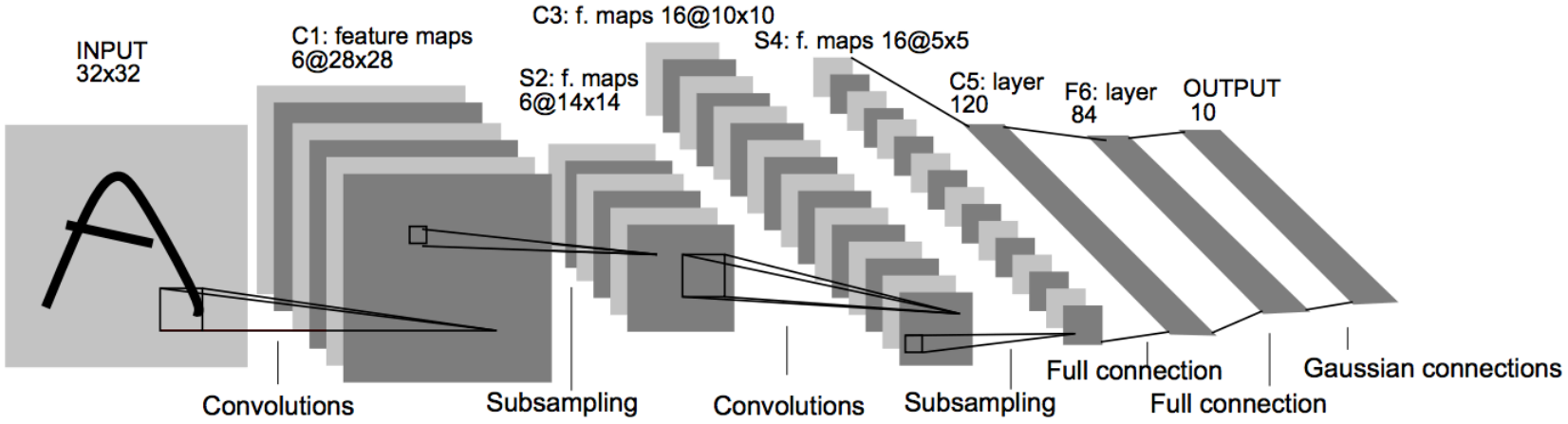
LeNet-5



8 total layers. Input is 32x32.

1. [28x28x6] **CONV**: 6 convolutional filters, 5x5 features, applied at stride 1.
2. [14x14x6] **POOL**: 2x2 pool with stride 2. (Adds all elems, multiplies them by trainable coefficient, then passes through sigmoid.)
3. [10x10x16] **CONV:** 16 convolutional filters, 5x5.
4. [5x5x16] **POOL**: 2x2 pool with stride 2.
5. [120] **CONV**: 120 5x5 convolutional filters.
6. [84] **FC**: FC layer: 84 x 120.
7. [10] **OUT:** MSE against a template for each digit.

LeNet-5

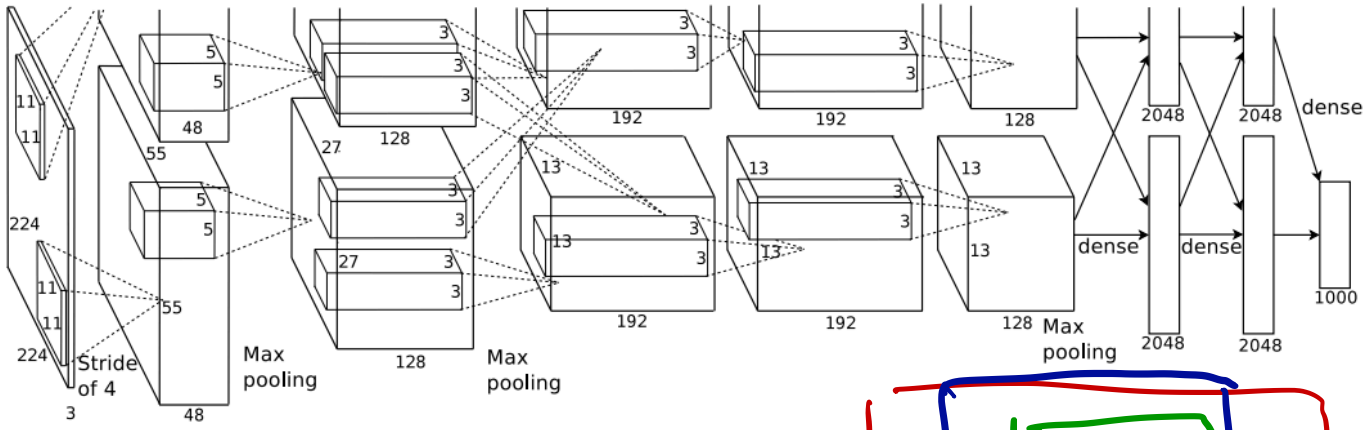


LeCun et al., 1998.

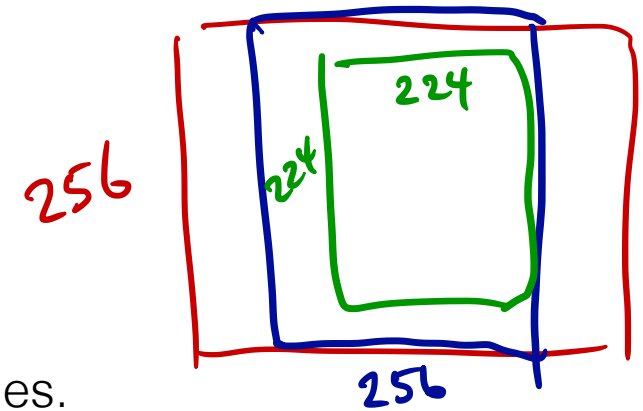
Overall architecture:

[CONV-POOL]x2 - CONV - FC - OUT

AlexNet



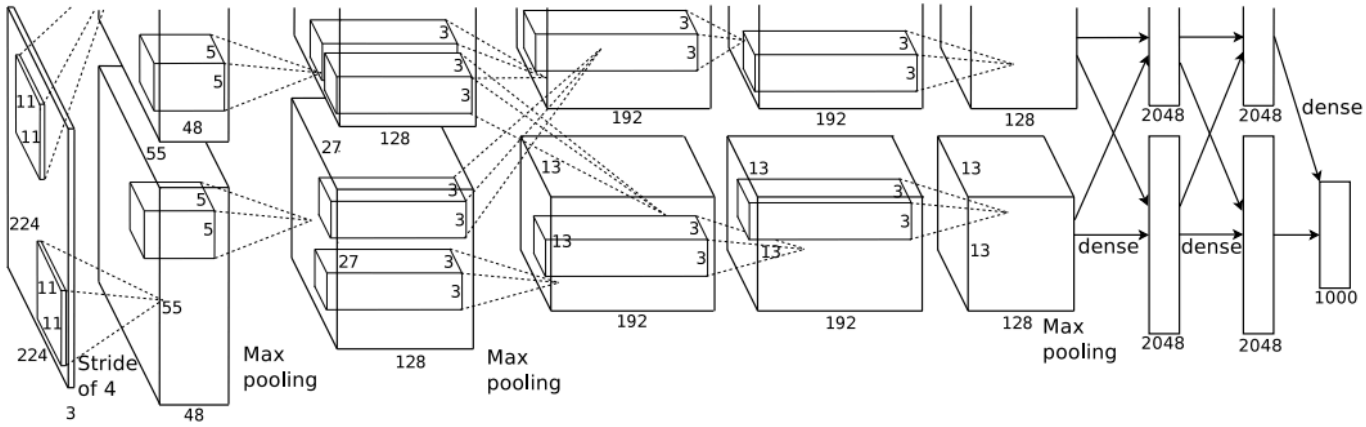
AlexNet, Krizhevsky et al., NIPS 2012.



Input processing:

- ImageNet has variable-sized images.
- Downsample or resize each image; given a rectangular image …
  - Crop so the shorter side is 256 pixels.
  - Crop out the central 256 x 256 pixels.
  - The actual input to the CNN is 224 x 224 x 3 after data augmentation.
    - However, the layer sizing doesn't quite work out, so we'll say it's 227x227x3.
- Subtracted the mean image over the training set from each pixel.

AlexNet

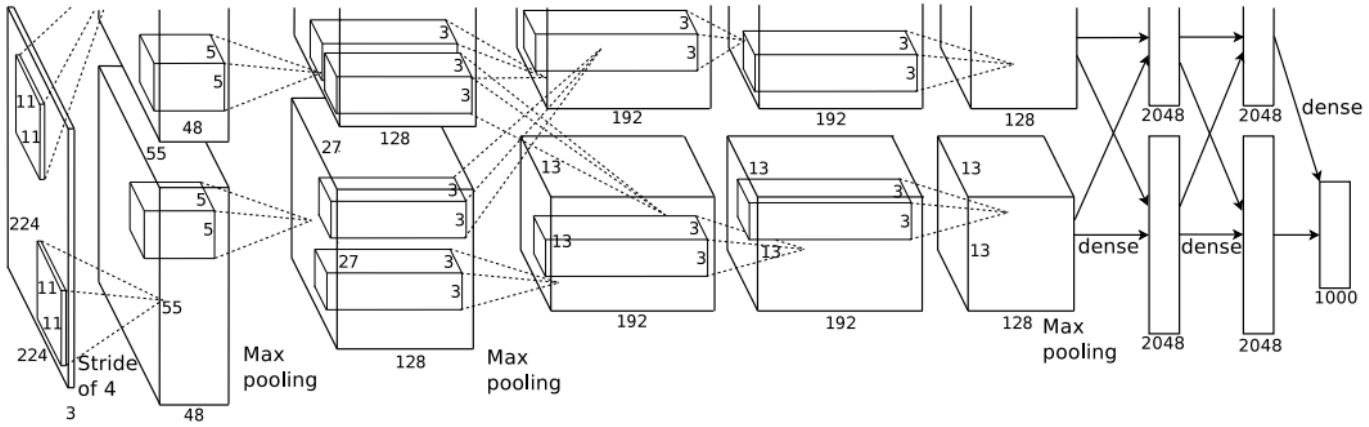


AlexNet, Krizhevsky et al., NIPS 2012.

Nonlinearity:

- Used the ReLU. It was faster than sigmoidal or tanh units.

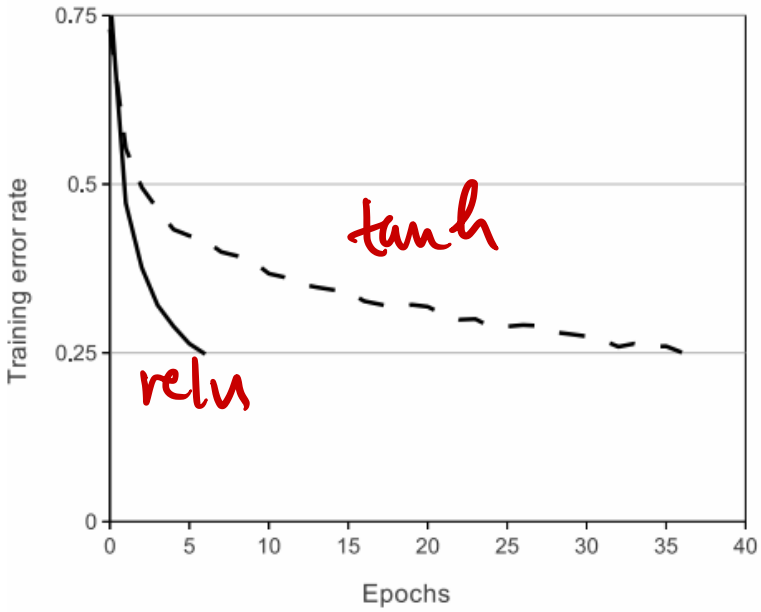
AlexNet



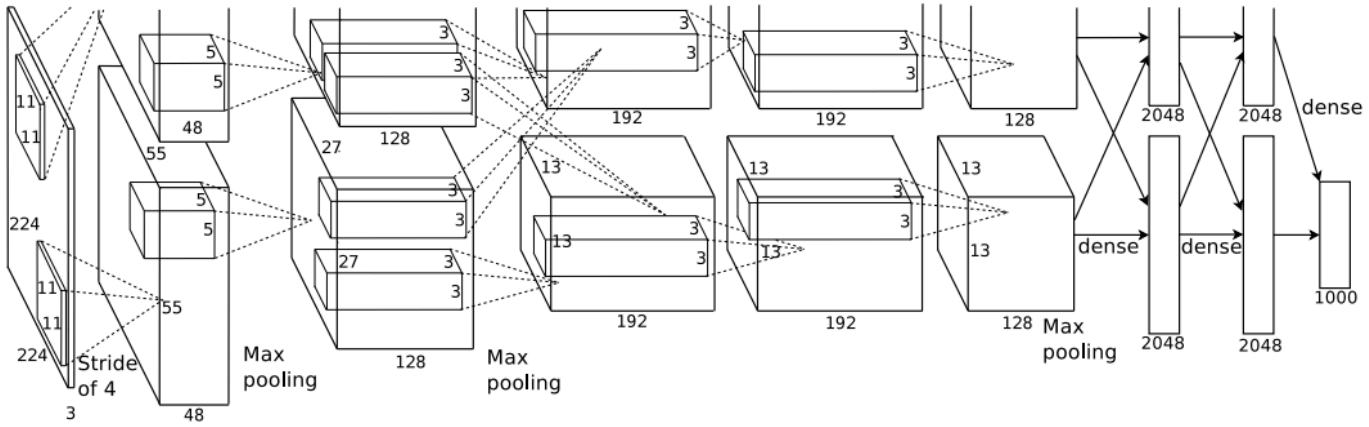
AlexNet, Krizhevsky et al., NIPS 2012.

Dotted line is tanh
Solid line is ReLU
Clearly ReLU resulted in more efficient training.

ReLU is at the output of every convolutional and fully-connected layer.



AlexNet

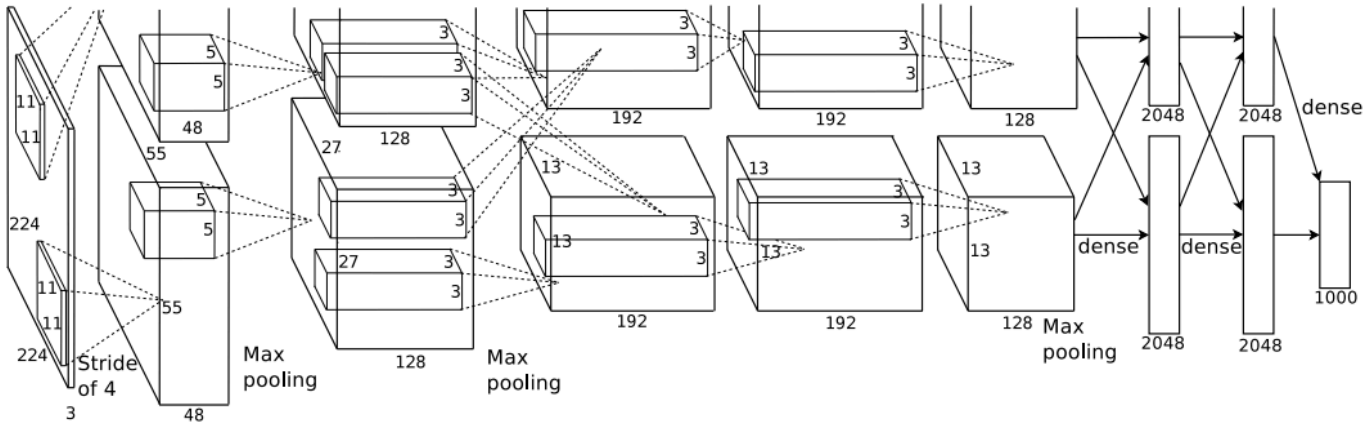


AlexNet, Krizhevsky et al., NIPS 2012.

Training on multiple GPUs.

- This is why the above image is cropped. Everything is replicated x2, and the two paths correspond to training on two GPU's.
- They trained on GPUs due to memory; they trained on 1.2 million images and they stored them on GPUs; each GPU had just 3 GB of memory.

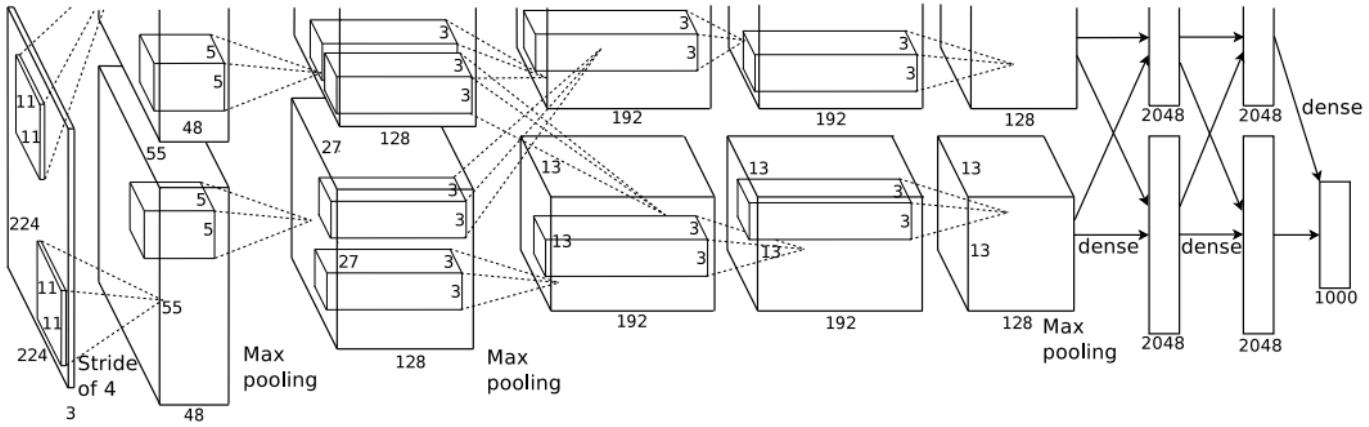
AlexNet



AlexNet, Krizhevsky et al., NIPS 2012.

- Local response normalization (not common anymore).
- Used pooling with overlapping (i.e., the stride was not the pool width).

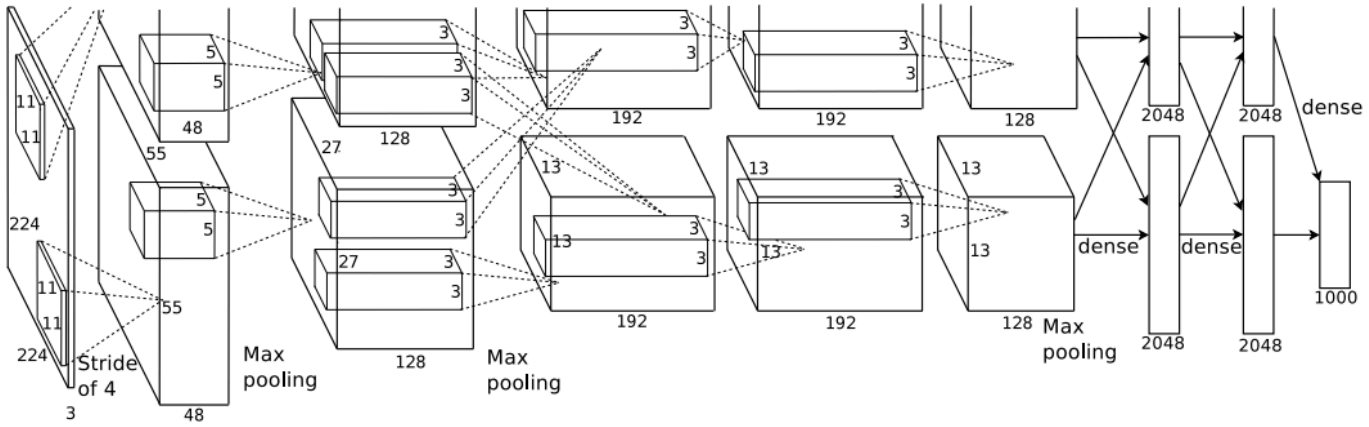
AlexNet



AlexNet, Krizhevsky et al., NIPS 2012.

- Data augmentation:
  - Image translations and horizontal reflections.
    - Extract out random 224 x 224 patches and their horizontal reflections.
    - At test time, extract 5 random 224 x 224 patches + reflections, and average the predictions of the 10 output softmax's. This avg'ing reduces error rate by ~1.5%.
  - Color augmentation: scale the PCs of the colors, capturing different levels of illumination and intensities.
    - Reduces the Top 1 error rate by 1%.
- Dropout with p = 0.5.
  - Substantially reduces overfitting; takes twice as long to train.

AlexNet



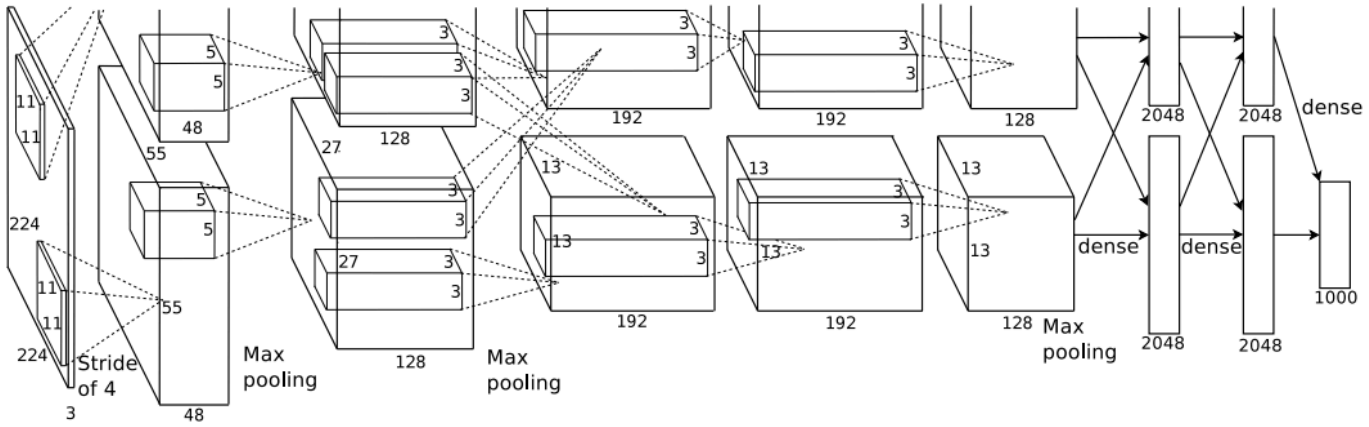
AlexNet, Krizhevsky et al., NIPS 2012.

- SGD with momentum and weight decay.
  - Batch size: 128, momentum: 0.9
  - Learning rate initialized to 0.01, manually decreased when validation error stopped improving.
  - L2 weight decay: 0.0005

$$v_{i+1} := 0.9 \cdot v_i - 0.0005 \cdot \epsilon \cdot w_i - \epsilon \cdot \left\langle \frac{\partial L}{\partial w}\Big|_{w_i} \right\rangle_{D_i}$$

$$w_{i+1} := w_i + v_{i+1}$$

AlexNet

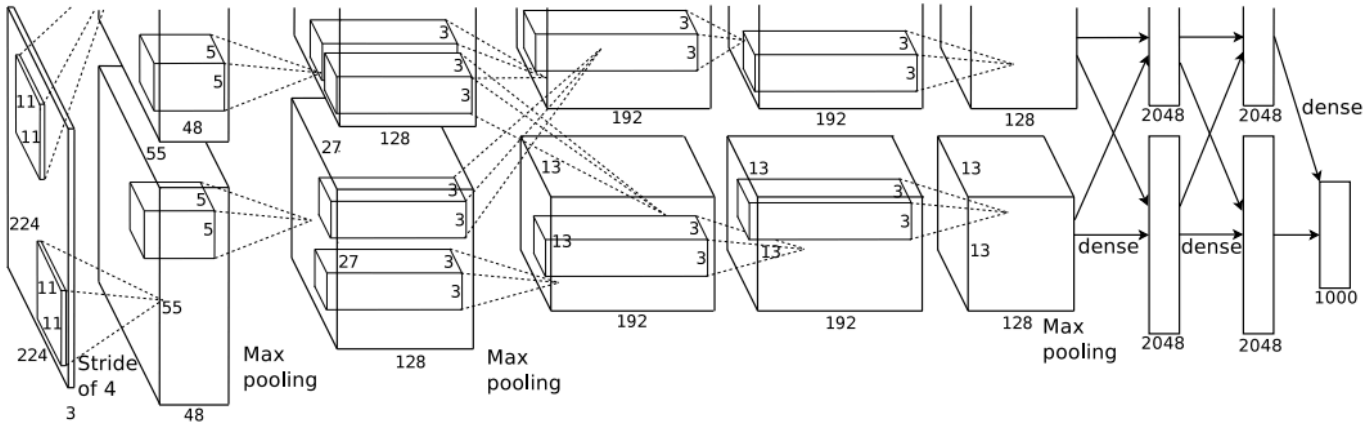


AlexNet, Krizhevsky et al., NIPS 2012.

- Training time: roughly five to six days on two GTX 580 GPUs.

reduced three times prior to termination. We trained the network for roughly 90 cycles through the training set of 1.2 million images, which took five to six days on two NVIDIA GTX 580 3GB GPUs.

AlexNet



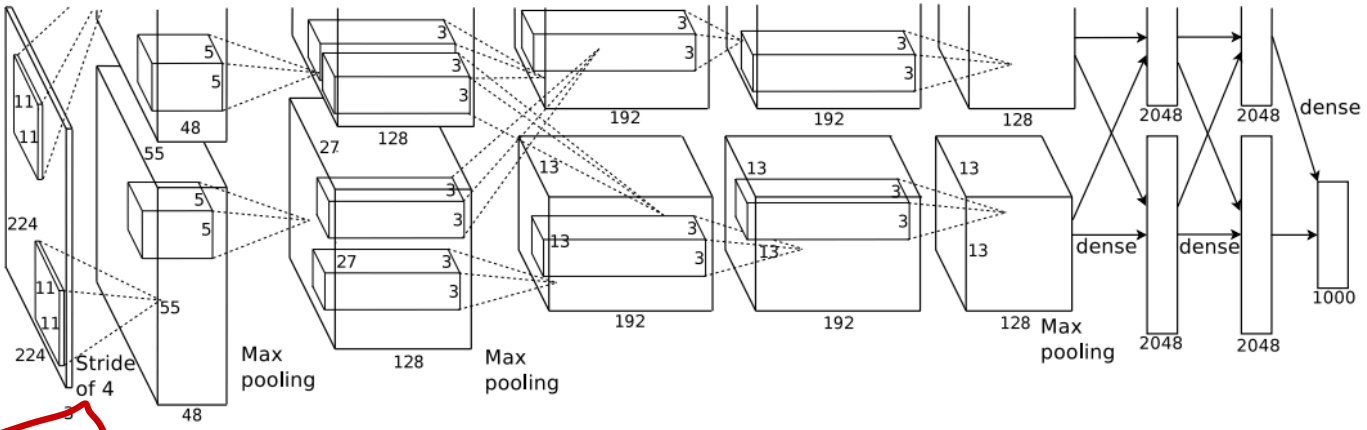
AlexNet, Krizhevsky et al., NIPS 2012.

- Averaged the output of multiple CNNs. Validation error of …
  - 1 CNN: 18.2%
  - 5 CNNs: 16.4%
  - 7 CNNs: 15.4% (was also pre-trained)

2%

1%

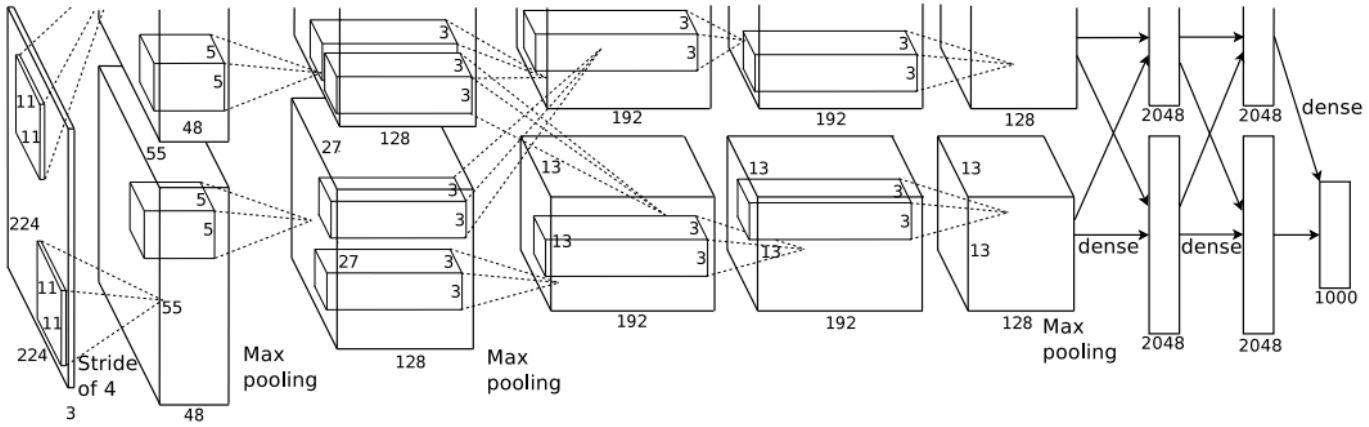
AlexNet



Top 1 error rate

Top 5 error rate

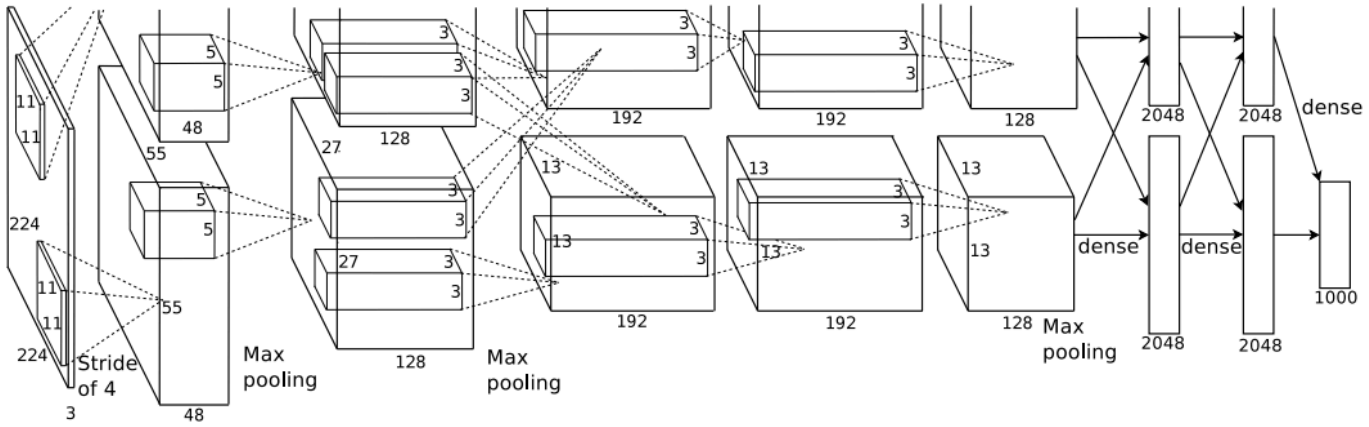
AlexNet



AlexNet, Krizhevsky et al., NIPS 2012.

- Importance of depth?
  - Validation error worsens by 2% by removing any middle layer.

AlexNet



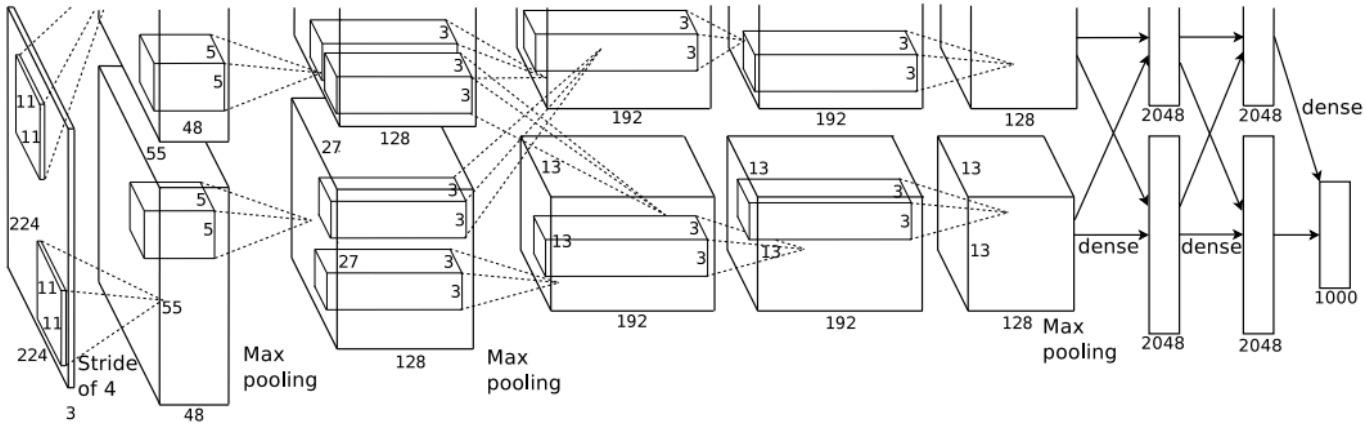
Architecture: 8 layers. Input is 227x227x3 (in paper, 224x224x3; numbers were changed so the operations work out).

Question: The input is 227x227x3. The first convolutional layer has 96 11x11 filters applied at stride 4. What is the output size?

$$\frac{227 - 11}{4} + 1 = 55$$

$(55 \times 55 \times 96)$

AlexNet

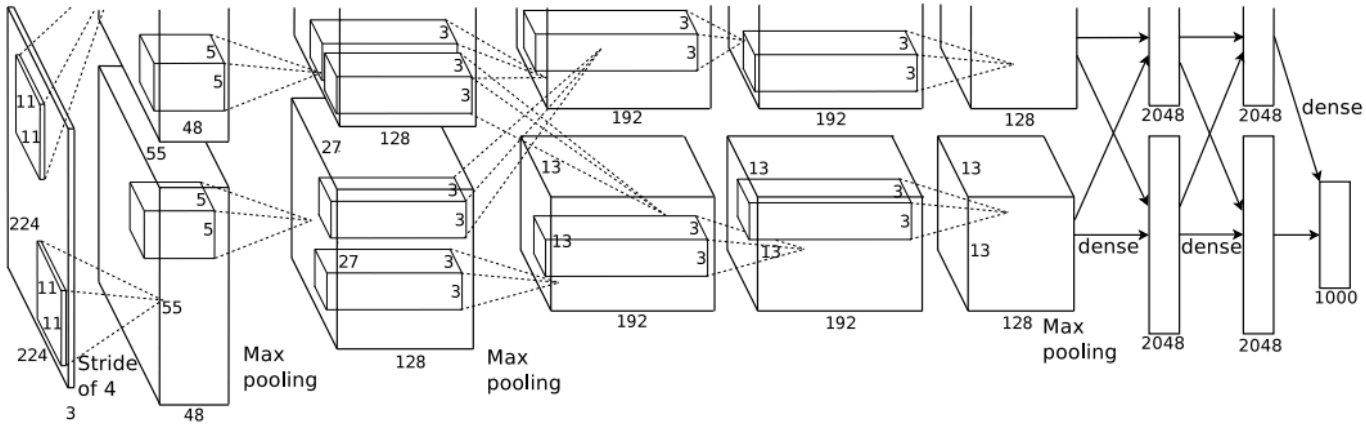


Architecture: 8 layers. Input is 227x227x3 (in paper, 224x224x3; numbers were changed so the operations work out).

Question: How many trainable parameters in the first convolutional layer? (Recall, 96 filters that are 11x11.)

$(11 \times 11 \times 3 + 1) \times 96 = 34,944$

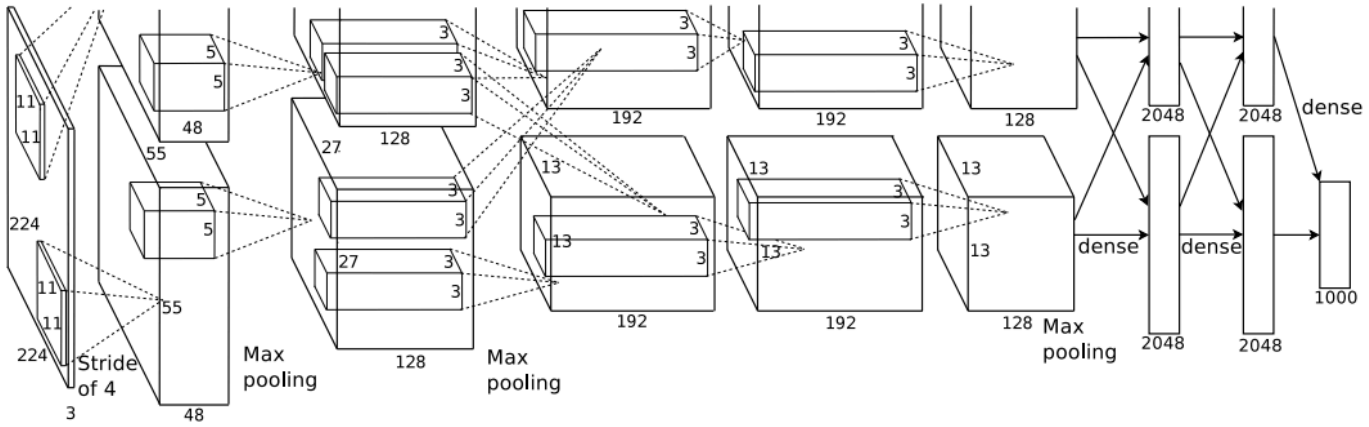
AlexNet



Architecture: 8 layers. Input is 227x227x3 (in paper, 224x224x3; numbers were changed so the operations work out).

1. [55x55x96] **CONV**: 96 filters of size 11x11x3 with stride 4.

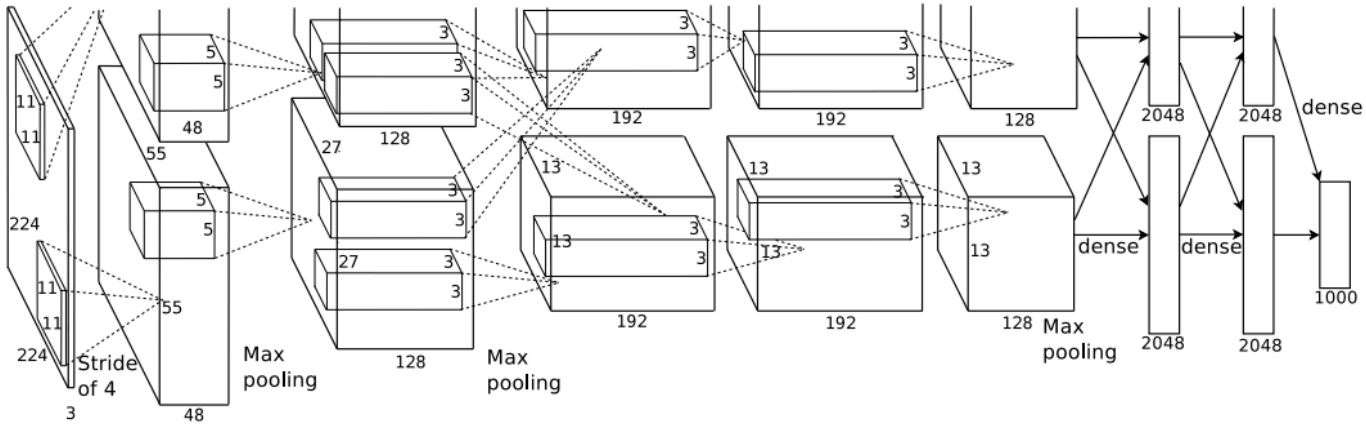
AlexNet



Architecture: 8 layers. Input is 227x227x3 (in paper, 224x224x3; numbers were changed so the operations work out).

Question: The output of the first convolutional layer is 55x55x96. The pooling layer is 3x3 filters applied at stride 2. What is the output size?

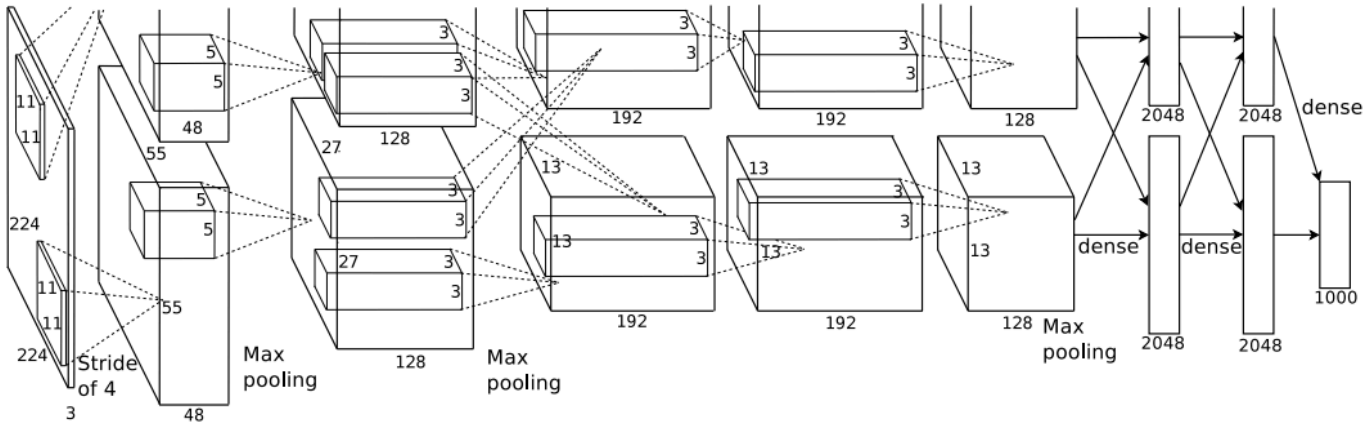
AlexNet



Architecture: 8 layers. Input is 227x227x3 (in paper, 224x224x3; numbers were changed so the operations work out).

Question: How many trainable parameters in the first pooling layer? (Recall, pool is with 3x3 filters at stride 2.)

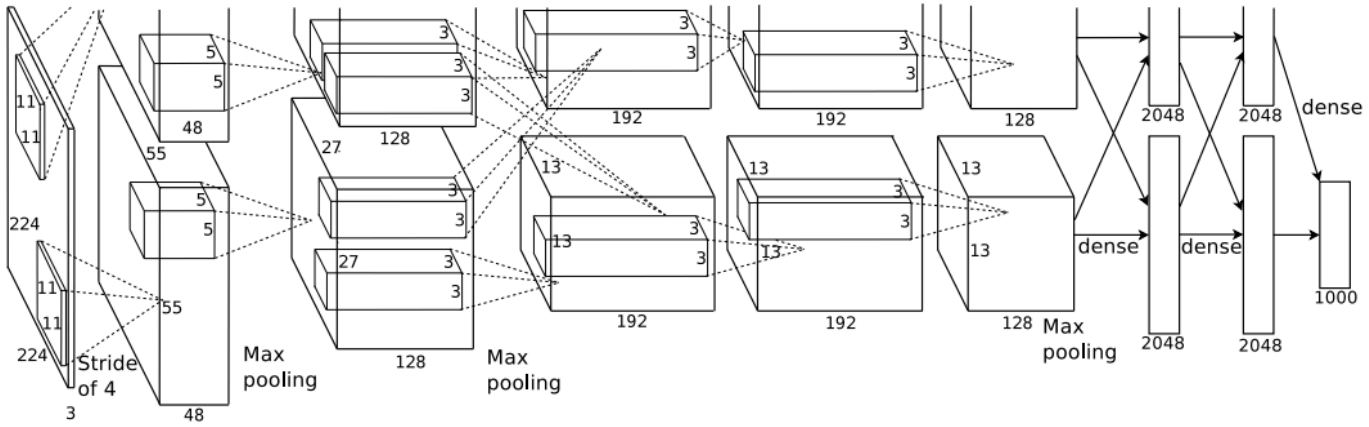
AlexNet



Architecture: 8 layers. Input is 227x227x3 (in paper, 224x224x3; numbers were changed so the operations work out).

1. [55x55x96] **CONV**: 96 filters of size 11x11x3 with stride 4.
2. [27x27x96] **POOL**: 3x3 filters with stride 2.
3. [27x27x96] **NORM**: normalization layer

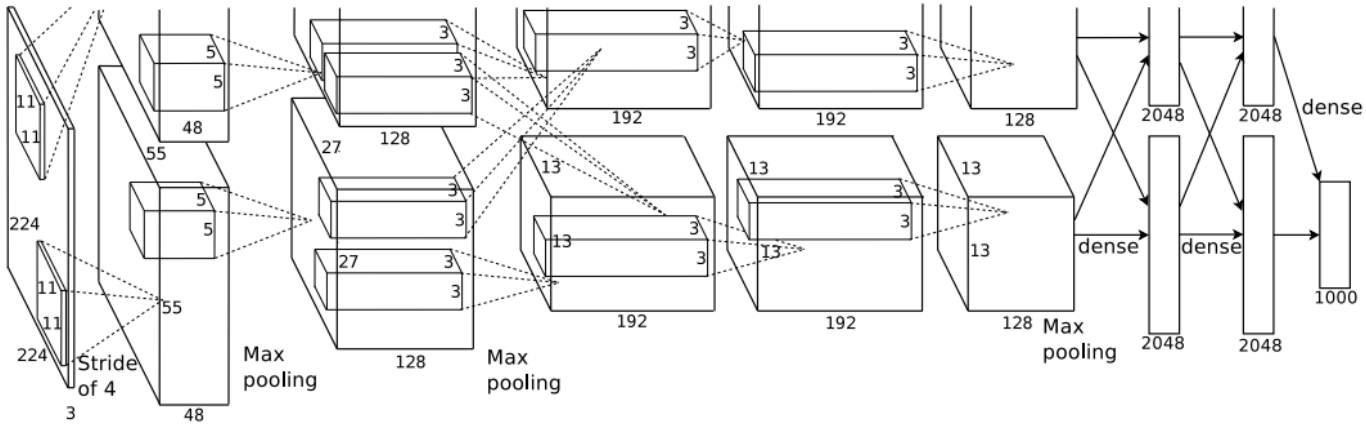
AlexNet



Architecture: 8 layers. Input is 227x227x3 (in paper, 224x224x3; numbers were changed so the operations work out).

Question: The input into the second convolutional layer is 27x27x96. The layer has 256 5x5 filters at stride 1 with pad 2. What is the output size?

AlexNet



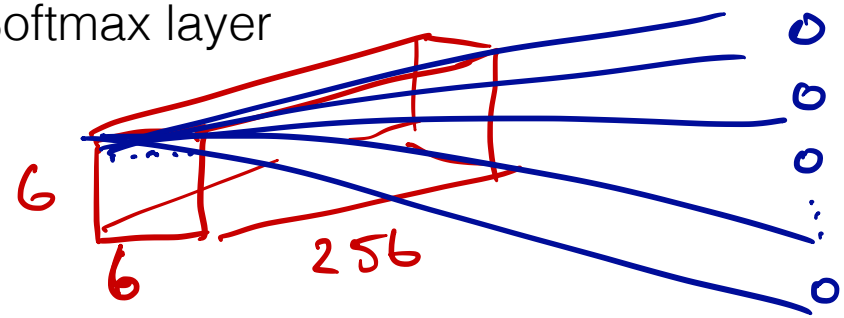
Architecture: 8 layers. Input is 227x227x3 (in paper, 224x224x3; numbers were changed so the operations work out).

1. [55x55x96] **CONV**: 96 filters of size 11x11x3 with stride 4.
2. [27x27x96] **POOL**: 3x3 filters with stride 2.
3. [27x27x96] **NORM**: normalization layer
4. [27x27x256] **CONV**: 256 filters of size 5x5x48 with stride 1, pad 2.
5. [13x13x256] **POOL**: 3x3 filters with stride 2.

AlexNet

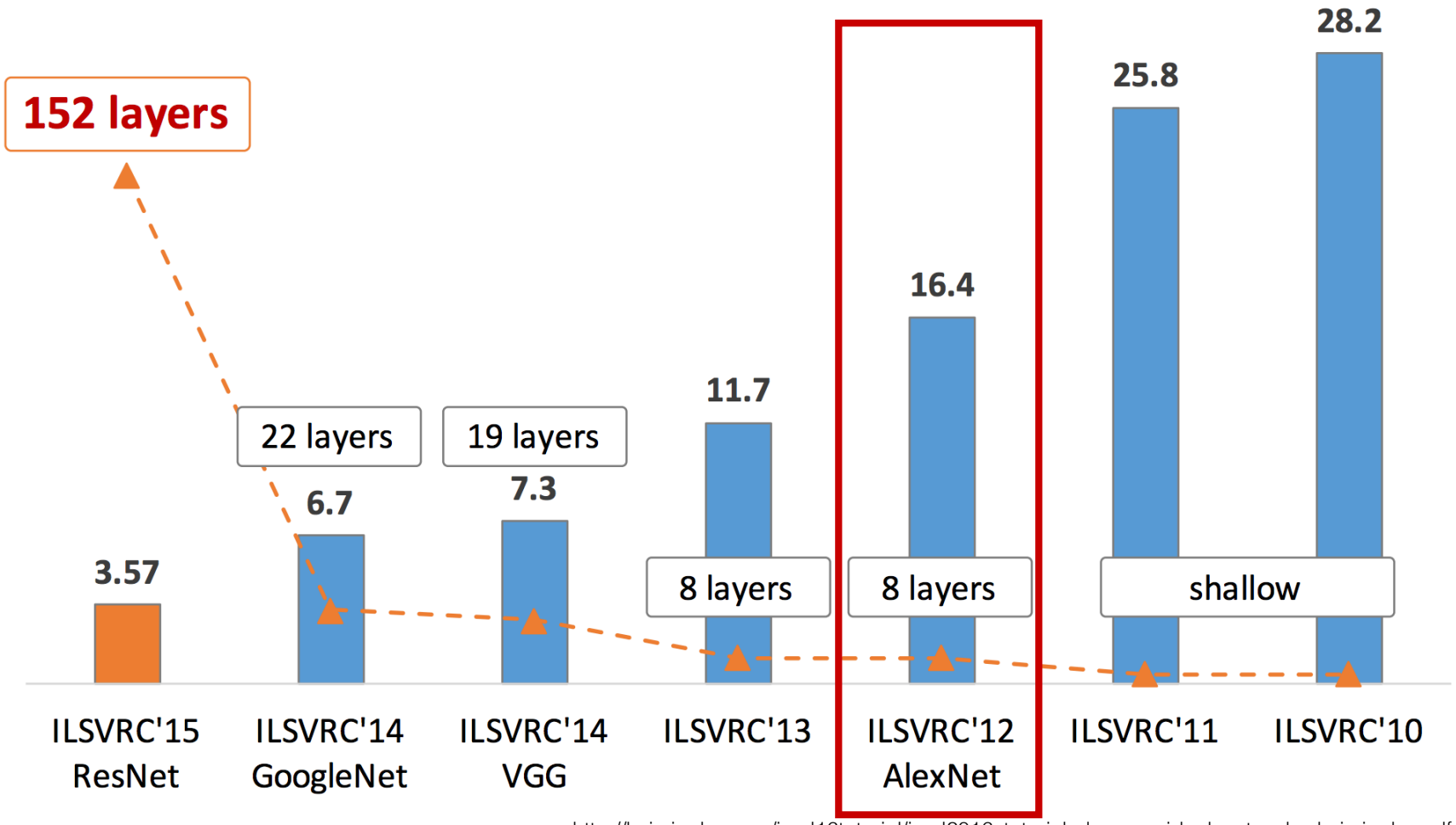
Architecture: 8 layers. Input is 227x227x3 (in paper, 224x224x3; numbers were changed so the operations work out).

1. [55x55x96] **CONV**: 96 filters of size 11x11x3 with stride 4.
2. [27x27x96] **POOL**: 3x3 filters with stride 2.
3. [27x27x96] **NORM**: normalization layer
4. [27x27x256] **CONV**: 256 filters of size 5x5x~~48~~ 96 with stride 1, pad 2.
5. [13x13x256] **POOL**: 3x3 filters with stride 2.
6. [27x27x96] **NORM**: normalization layer
7. [13x13x384] **CONV**: 384 filters of size 3x3 at stride 1, pad 1.
8. [13x13x384] **CONV**: 384 filters of size 3x3 at stride 1, pad 1.
9. [13x13x256] **CONV**: 256 filters of size 3x3 at stride 1, pad 1.
10. [6x6x256] **POOL**: 3x3 filters at stride 2.
11. [4096] **FC**: Fully connected layer with 4096 units
12. [4096] **FC**: Fully connected layer with 4096 units
13. [1000] **FC**: Fully connected layer with 1000 units (class scores).
14. [1000] **OUT**: Softmax layer



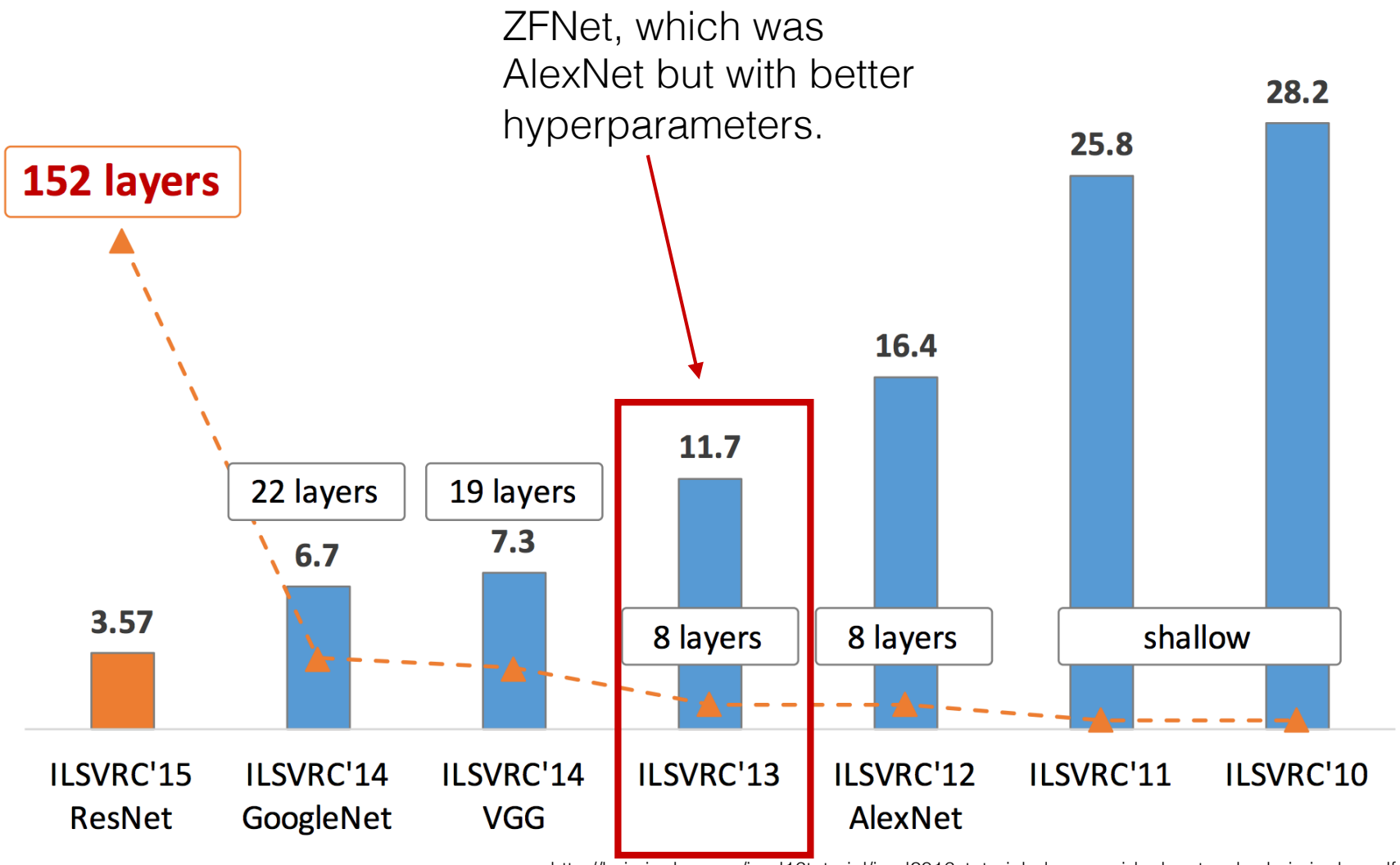
AlexNet in context

The number of layers refers to the number of convolutional or FC layers.



http://kaiminghe.com/icml16tutorial/icml2016_tutorial_deep_residual_networks_kaiminghe.pdf

ZFNet



http://kaiminghe.com/icml16tutorial/icml2016_tutorial_deep_residual_networks_kaiminghe.pdf

ZFNet

Zeiler & Fergus, arXiv 2013, “Visualizing and understand convolutional neural networks.”

- They introduced the deconvnet, which maps the output activations back to input pixels. This enables a visualization of features being captured by the convnets.

- With this, they made optimizations to AlexNet.

ZFNet

Differences between ZFNet and AlexNet:

- The first convolutional layer has 7x7 filters at stride 2 (AlexNet: 11x11 filters at stride 4).
- The third, fourth, and fifth convolutional layers have 512, 1024, and 512 filters (AlexNet: 384, 384, 256).

How big are these differences?

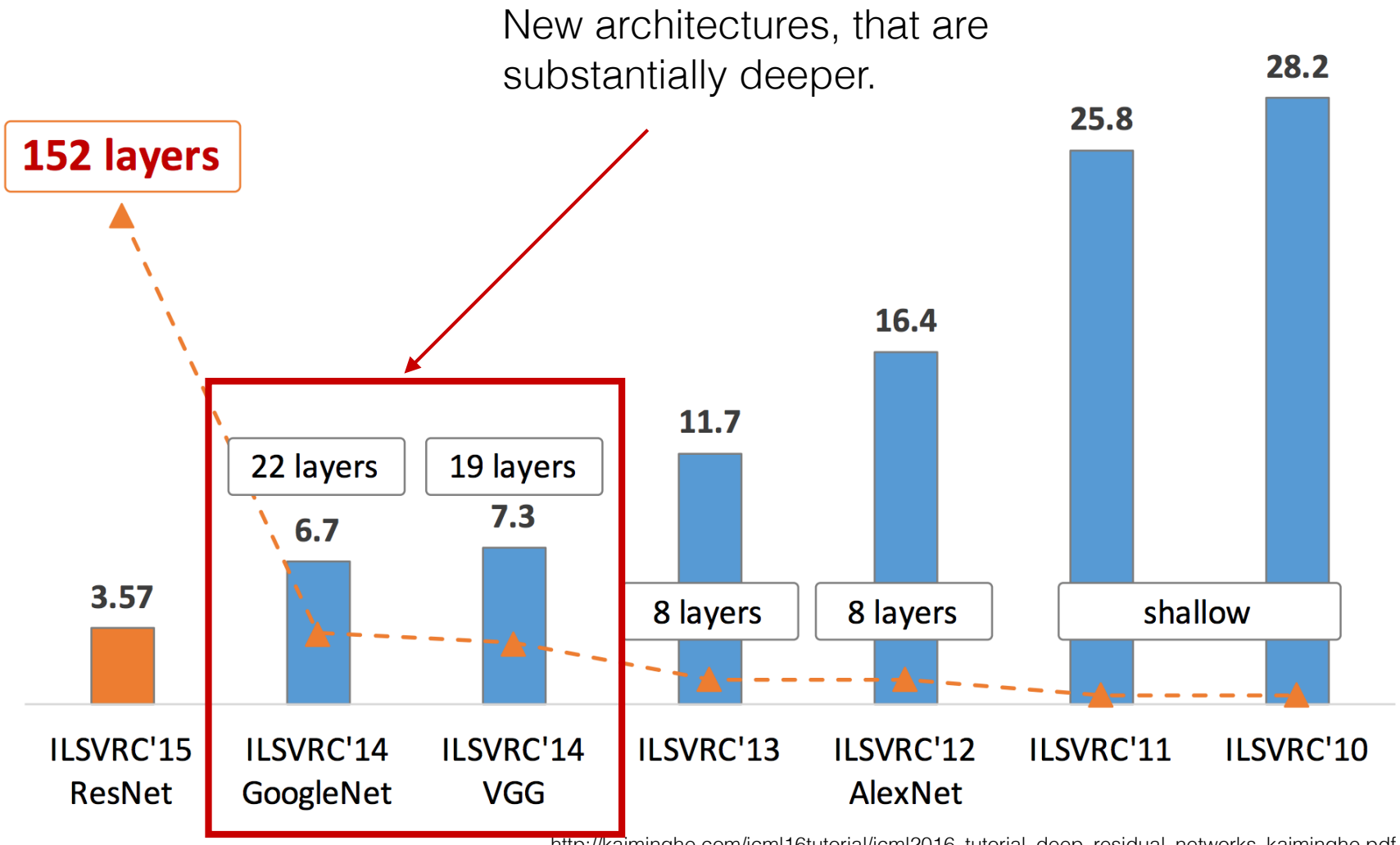
- Big!
- Dropped error rate from **16.4%** to **11.7%**.
- Measuring relative to zero error, this is approximately a 30% reduction in error.

What makes convolutional neural networks work better?

We'll unpack this more later on, but some observations from ZFNet are:

- Smaller filters applied at smaller strides appears to help (at least in early layers).
- Having more filters later on in deeper layers appears to help.

What about depth?



http://kaiminghe.com/icml16tutorial/icml2016_tutorial_deep_residual_networks_kaiminghe.pdf

VGGNet

From the Visual Geometry Group, Dept of Eng. Sci., Oxford, "Very Deep Convolutional Neural Networks for Large-Scale Image Recognition," Simonyan & Zisserman, arXiv 2014.

"Our main contribution is a thorough evaluation of networks of increasing depth using an architecture with very small (3×3) convolution filters, which shows that a significant improvement on the prior-art configurations can be achieved by pushing the depth to 16–19 weight layers."

Their approach: focus on a small convolutional filter (3x3) and extend the depth.

VGGNet

VGG Net:

Instead of 8 layers (AlexNet), VGGNet increased the network architecture to 16-19 layers.

ARCHITECTURE:

Input -> [CONVx2-POOL]x3 -> [CONVx3-POOL]x2 -> FC x 3 -> Softmax

All CONV filters are uniform: 3x3 with stride 1, pad 1
All POOL filters are uniform: 2x2 max pool with stride 2.

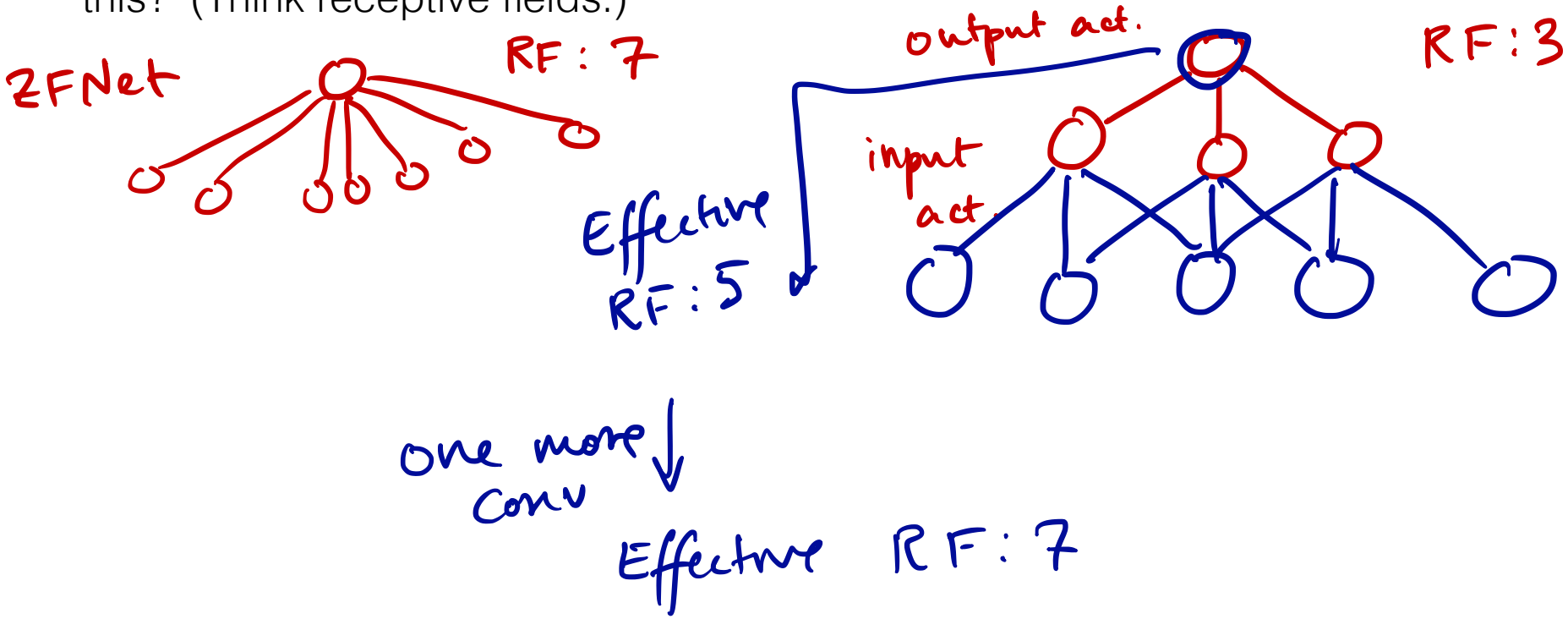
$W - 3 + 1 + 2 \cdot 1 = W$

Reduction from **11.7%** to **7.3%**, approximately a 40% reduction in error rate.

VGGNet

Small filters and depth:

What might be a con of using a small filter, and how does VGGNet address this? (Think receptive fields.)



VGGNet

Small filters and depth:

Why might this turn into a good thing? (w.r.t. receptive fields)

VGGNet

Small filters and depth:

Which has more parameters? One 7x7 CONV layer or three 3x3 stacked CONV layers?

input: depth = C_{in}

output: C_{out} filters

$(7 \times 7 \times C_{in}) C_{out}$

$49 C^2$

stack 3x3

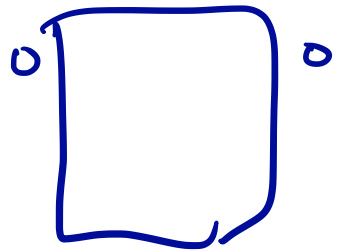
$3 \times (3 \times 3 \times C_{in}) \cdot C_{out}$

$27 C^2$

VGGNet

Small filters and depth:

What is a potential con of using small filters and more layers?



7x7

W - 7 + 1

<

3 x 3

(W - 3 + 1)

W - Wf + 1 + 2·pad

(W - 4, h - 4)

(W, h)

conv

(W, h)

conv

(W, h)

VGGNet

INPUT	[224x224x3]
CONV (64)	[224x224x64]
CONV (64)	[224x224x64]
POOL	[112x112x64]
CONV (128)	[112x112x128]
CONV (128)	[112x112x128]
POOL	[56x56x128]
CONV (256)	[56x56x256]
CONV (256)	[56x56x256]
CONV (256)	[56x56x256]
POOL	[28x28x256]
CONV (512)	[28x28x512]
CONV (512)	[28x28x512]
CONV (512)	[28x28x512]
POOL	[14x14x512]
CONV (512)	[14x14x512]
CONV (512)	[14x14x512]
CONV (512)	[14x14x512]
POOL	[7x7x512]
FC	[1x1x4096]
FC	[1x1x4096]
FC	[1x1x1000]

Each # is 4 bytes

VGGNet

INPUT	[224x224x3]	224*224*3	~ 150K
CONV (64)	[224x224x64]	224*224*64	~ 3.2M
CONV (64)	[224x224x64]	224*224*64	~ 3.2M
POOL	[112x112x64]	112*112*64	~ 800K
CONV (128)	[112x112x128]	112*112*128	~ 1.6M
CONV (128)	[112x112x128]	112*112*128	~ 1.6M
POOL	[56x56x128]	56*56*128	~ 400K
CONV (256)	[56x56x256]	56*56*256	~ 800K
CONV (256)	[56x56x256]	56*56*256	~ 800K
CONV (256)	[56x56x256]	56*56*256	~ 800K
POOL	[28x28x256]	28*28*256	~ 200K
CONV (512)	[28x28x512]	28*28*512	~ 400K
CONV (512)	[28x28x512]	28*28*512	~ 400K
CONV (512)	[28x28x512]	28*28*512	~ 400K
POOL	[14x14x512]	14*14*512	~ 100K
CONV (512)	[14x14x512]	14*14*512	~ 100K
CONV (512)	[14x14x512]	14*14*512	~ 100K
CONV (512)	[14x14x512]	14*14*512	~ 100K
POOL	[7x7x512]	7*7*512	~ 25K
FC	[1x1x4096]		4096
FC	[1x1x4096]		4096
FC	[1x1x1000]		1000

24M → 96 MB

224 x 224 x 3

VGGNet

No biases

INPUT	[224x224x3]	224*224*3	~ 150K	0
CONV (64)	[224x224x64]	224*224*64	~ 3.2M	(3*3*3)*64 = 1,728
CONV (64)	[224x224x64]	224*224*64	~ 3.2M	(3*3*64)*64 = 36,864
POOL	[112x112x64]	112*112*64	~ 800K	0
CONV (128)	[112x112x128]	112*112*128	~ 1.6M	(3*3*64)*128 = 73,728
CONV (128)	[112x112x128]	112*112*128	~ 1.6M	(3*3*128)*128 = 147,456
POOL	[56x56x128]	56*56*128	~ 400K	0
CONV (256)	[56x56x256]	56*56*256	~ 800K	(3*3*128)*256 = 294,912
CONV (256)	[56x56x256]	56*56*256	~ 800K	(3*3*256)*256 = 589,824
CONV (256)	[56x56x256]	56*56*256	~ 800K	(3*3*256)*256 = 589,824
POOL	[28x28x256]	28*28*256	~ 200K	0
CONV (512)	[28x28x512]	28*28*512	~ 400K	(3*3*256)*512 = 1,179,648
CONV (512)	[28x28x512]	28*28*512	~ 400K	(3*3*512)*512 = 2,359,296
CONV (512)	[28x28x512]	28*28*512	~ 400K	(3*3*512)*512 = 2,359,296
POOL	[14x14x512]	14*14*512	~ 100K	0
CONV (512)	[14x14x512]	14*14*512	~ 100K	(3*3*512)*512 = 2,359,296
CONV (512)	[14x14x512]	14*14*512	~ 100K	(3*3*512)*512 = 2,359,296
CONV (512)	[14x14x512]	14*14*512	~ 100K	(3*3*512)*512 = 2,359,296
POOL	[7x7x512]	7*7*512	~ 25K	0
FC	[1x1x4096]		4096	7*7*512*4096 = 102,760,448
FC	[1x1x4096]		4096	4096*4096 = 16,777,216
FC	[1x1x1000]		1000	4096*1000 = 4,096,000

~122M

138 M parameters

VGGNet

Some observations:

- Total memory: 24M * 4 bytes = 96MB for one forward pass.
- Total parameters: 138M parameters
- A lot of the network parameters are in the fully connected layer.

VGGNet

Number of layers

A - 11
B - 13
C - 16
D - 16
E - 19

ConvNet config. (Table 1)	smallest image side		top-1 val. error (%)	top-5 val. error (%)
	train (S)	test (Q)		
B	256	224,256,288	28.2	9.6
C	256	224,256,288	27.7	9.2
	384	352,384,416	27.8	9.2
	[256; 512]	256,384,512	26.3	8.2
D	256	224,256,288	26.6	8.6
	384	352,384,416	26.5	8.6
	[256; 512]	256,384,512	**24.8**	**7.5**
E	256	224,256,288	26.9	8.7
	384	352,384,416	26.7	8.6
	[256; 512]	256,384,512	**24.8**	**7.5**

13
16
16
19

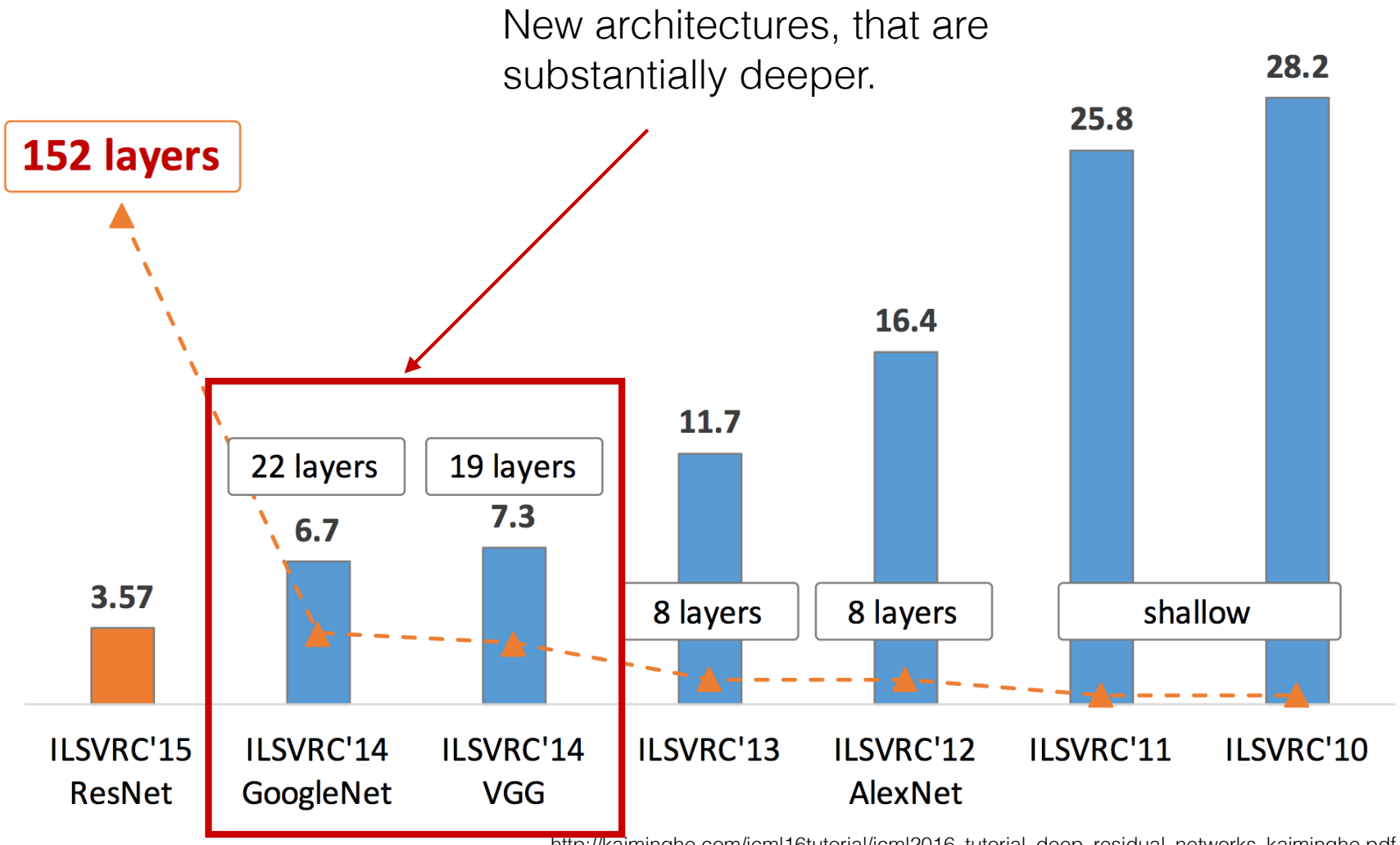
Simonyan et al., arXiv 2014

VGGNet

Other implementation notes about VGGNet.

- Input is 224x224 RGB image that has global mean-subtraction.
- They disposed of the local response normalization (LRN) layers from AlexNet, as they found they did not increase performance but consumed more memory & computation.
- Batch size 256, SGD + momentum 0.9.
- L2 penalty of 5e-4.
- Dropout for first two FC layers.
- Learning rate adjusted as in AlexNet.
- In initialization, they randomized a shallower network and then used the weights there as the initial weights for deeper networks.
  - But later on they found out the Xavier initialization was fine.
- Also performed the horizontal flipping, random crops, and RGB shifting that Krizhevsky and others used.
- Training took 2-3 weeks on a 4 GPU machine.
- Their submission averaged the output of 7 nets.

What about depth?



http://kaiminghe.com/icml16tutorial/icml2016_tutorial_deep_residual_networks_kaiminghe.pdf

GoogLeNet

From Szegedy et al., IEEE CVPR 2014.

The main take-home points of the GoogLeNet:

- 22 layers (deeper)
- Introduces the “Inception” module
- Gets rid of fully connected layers.
- Has only 5 million parameters, which is about 12x less than AlexNet and 27x less than VGGNet.
- Also tries to keep computational budget down.
  - “… so that the [sic] they do not end up to be a purely academic curiosity…”
- Won ImageNet top 5 error (w/ error rate 6.7%).

GoogLeNet

Going deeper requires more parameters, and more computational expense.

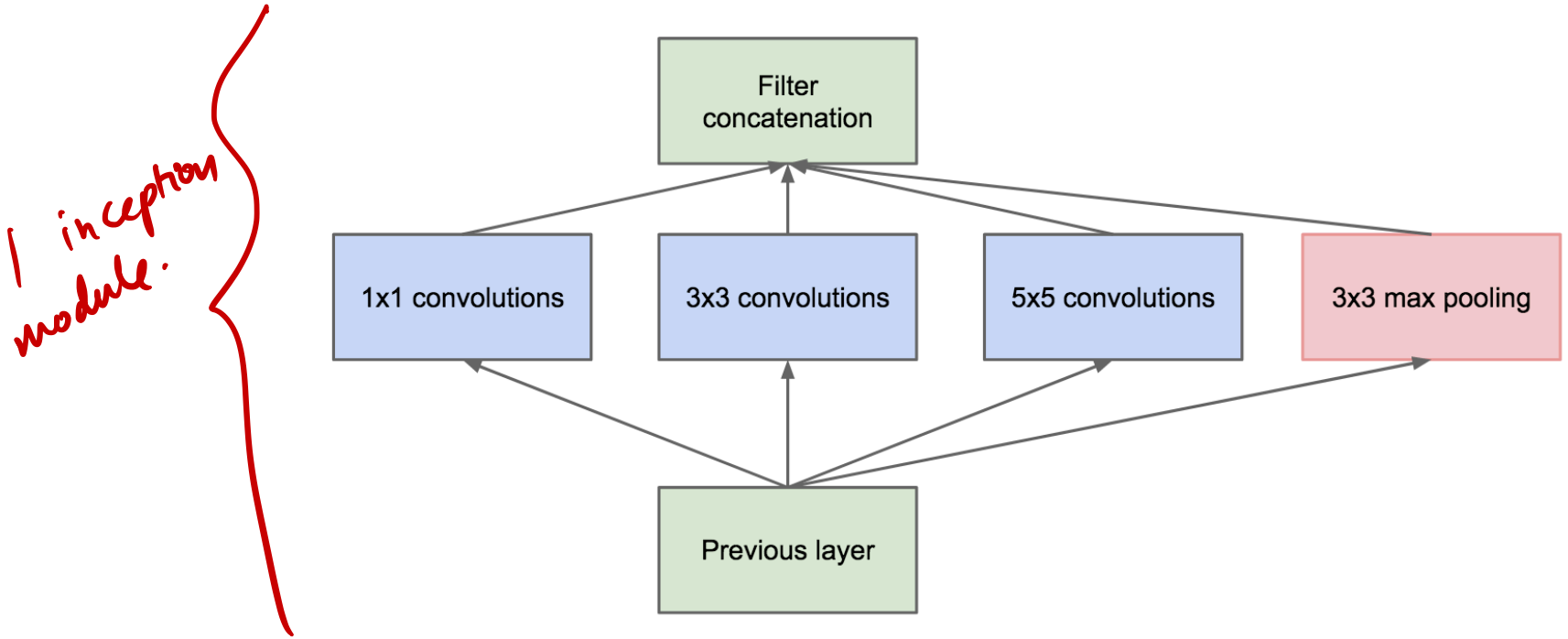
Is there a way to address this?

GoogLeNet: the inception module.

GoogLeNet

They leverage an idea called “network-in-network.”

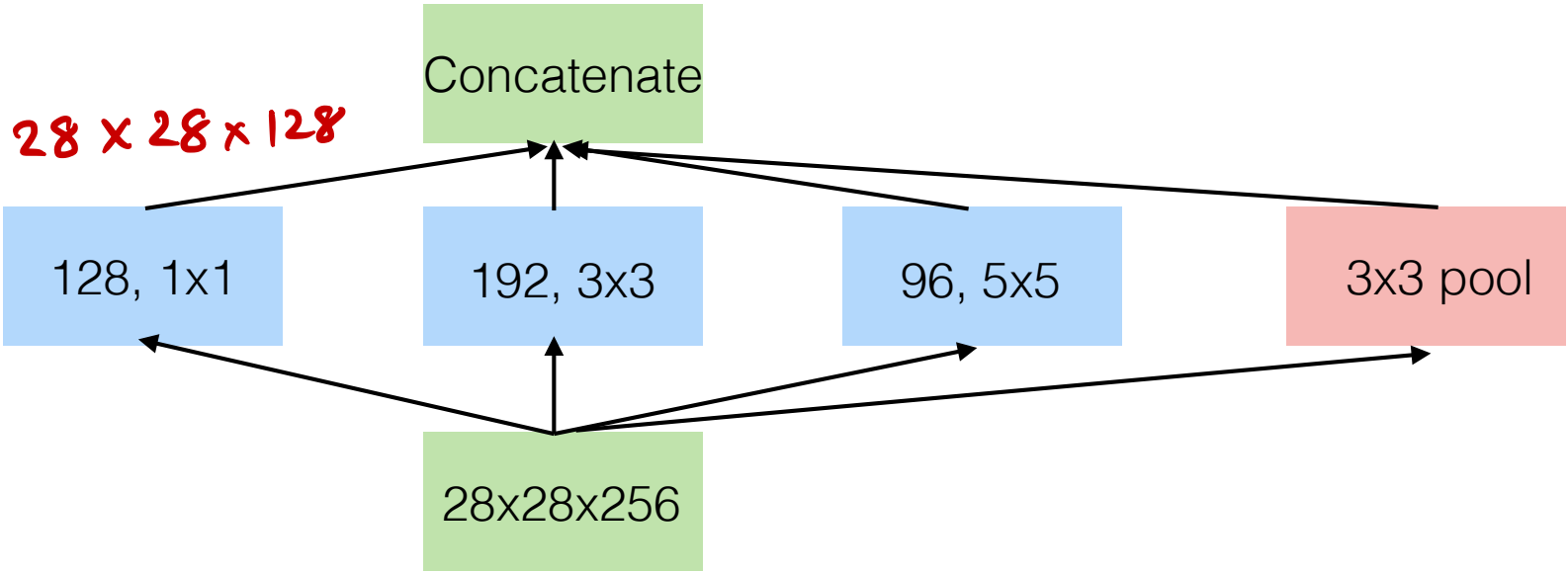
Naive inception module:



GoogLeNet

They leverage an idea called “network-in-network.”

Naive inception module:

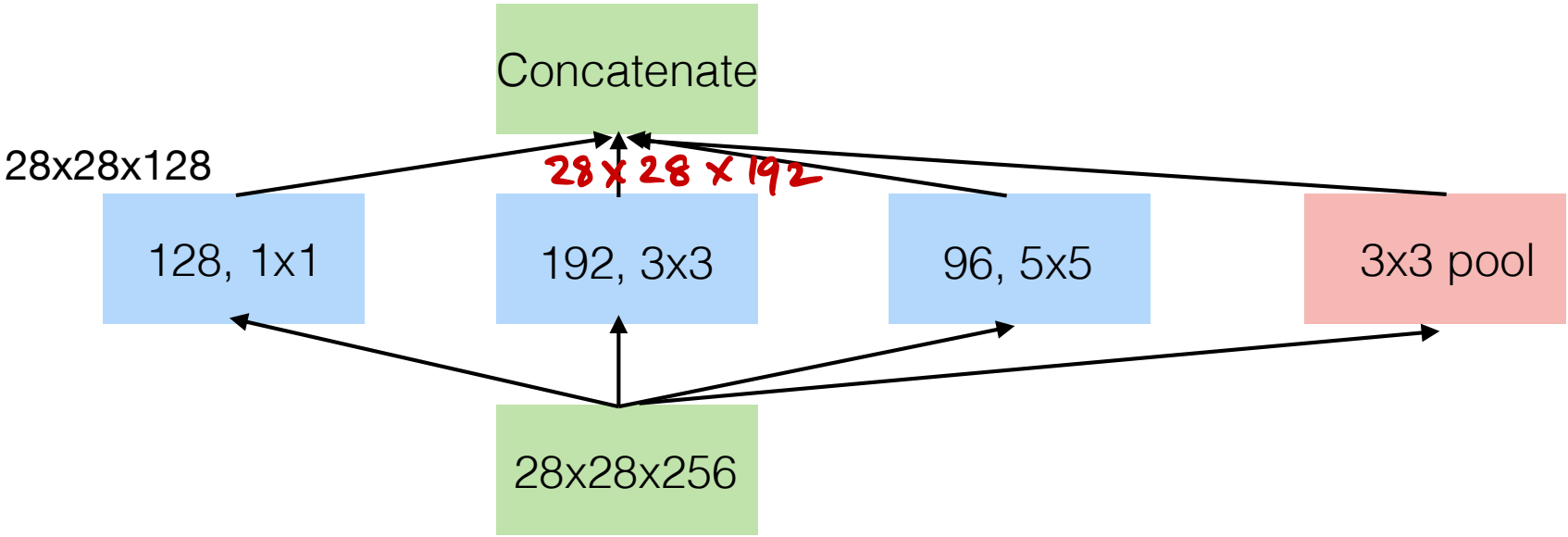


What is the size of the output of the 128 1x1 convolutions?

GoogLeNet

They leverage an idea called “network-in-network.”

Naive inception module:



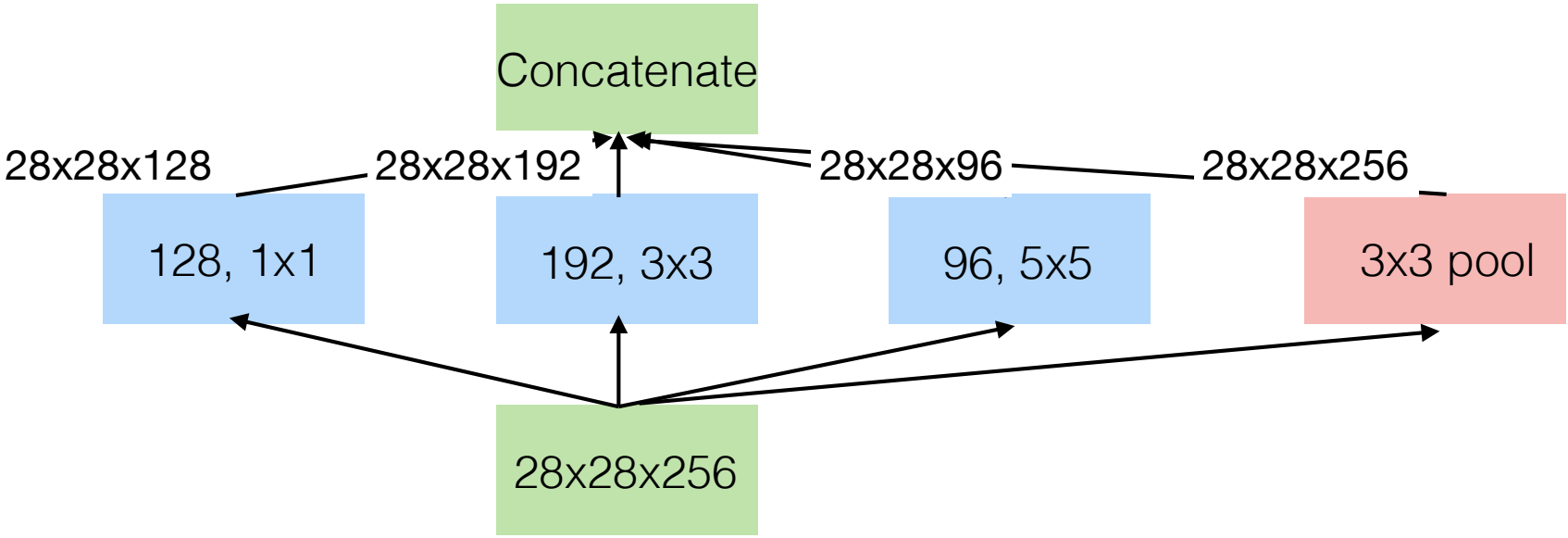
What padding do we need to keep the output size consistent for the 192 3x3 convolutional filters?

pad = 1

GoogLeNet

They leverage an idea called “network-in-network.”

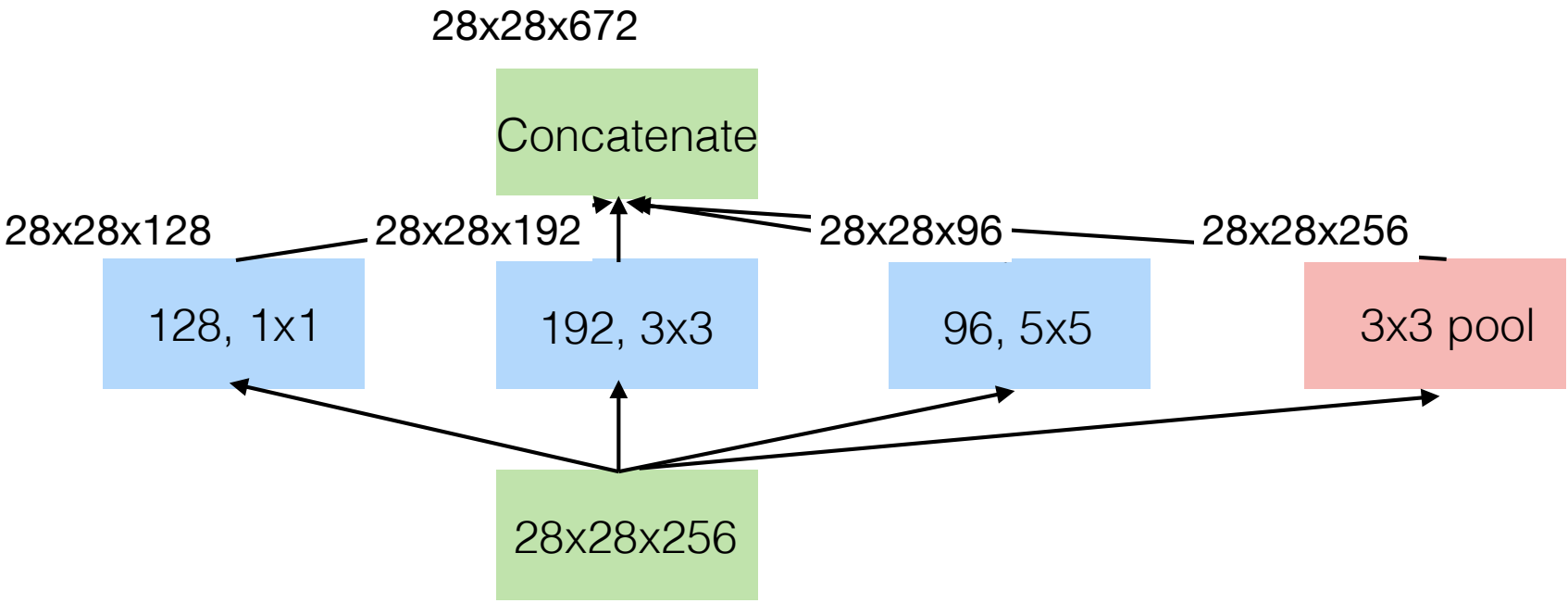
Naive inception module:



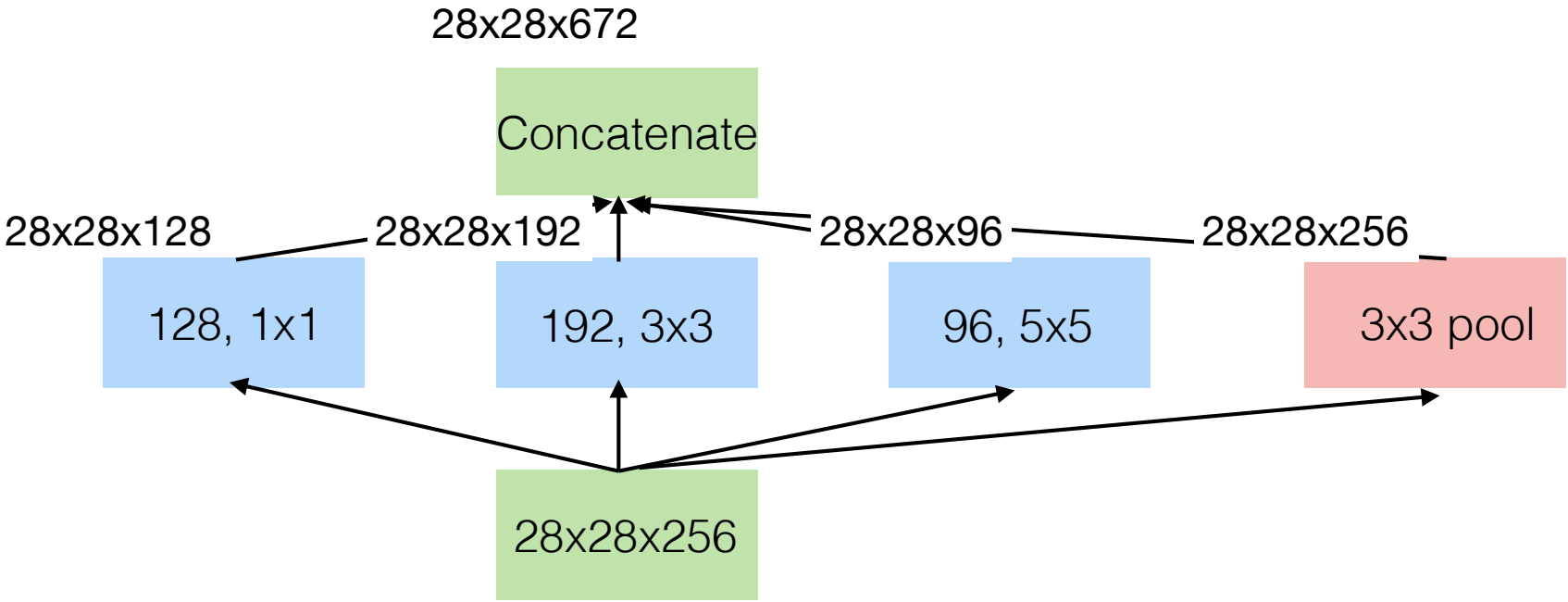
GoogLeNet

They leverage an idea called “network-in-network.”

Naive inception module:



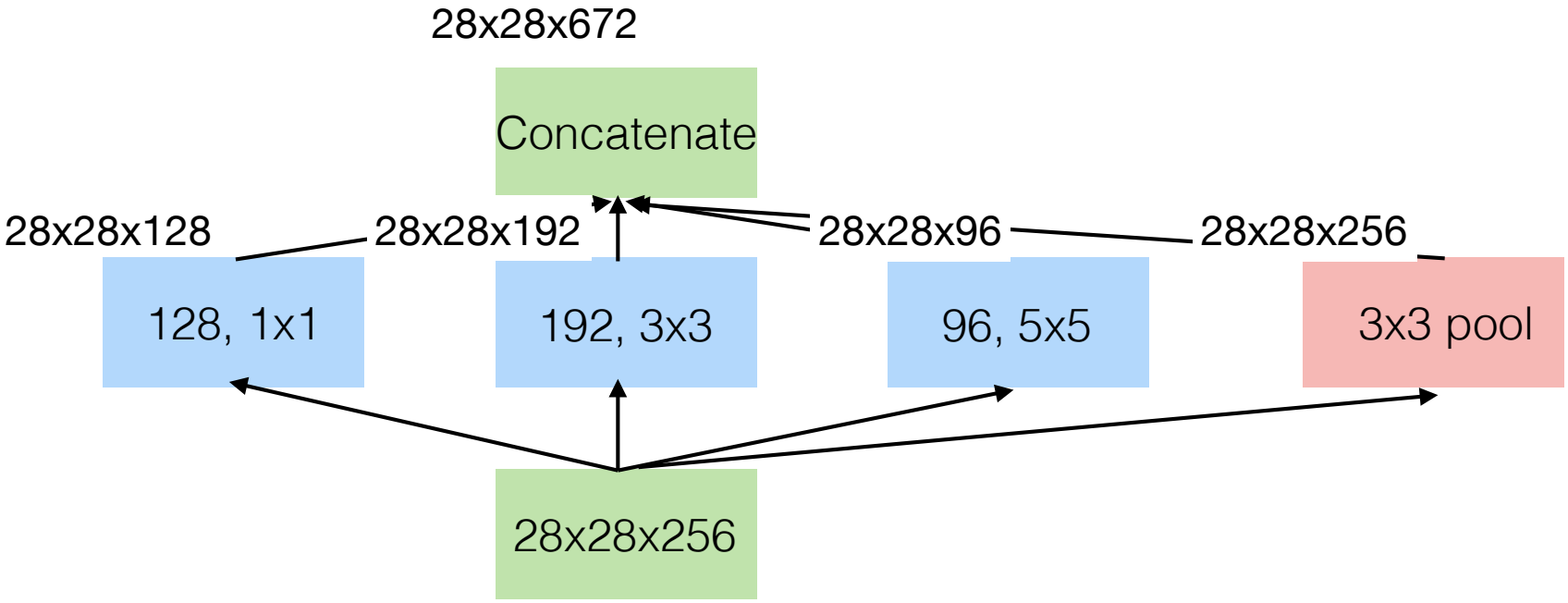
GoogLeNet



With this architecture, can the concatenated output ever have smaller depth (3rd dimension) than the input?

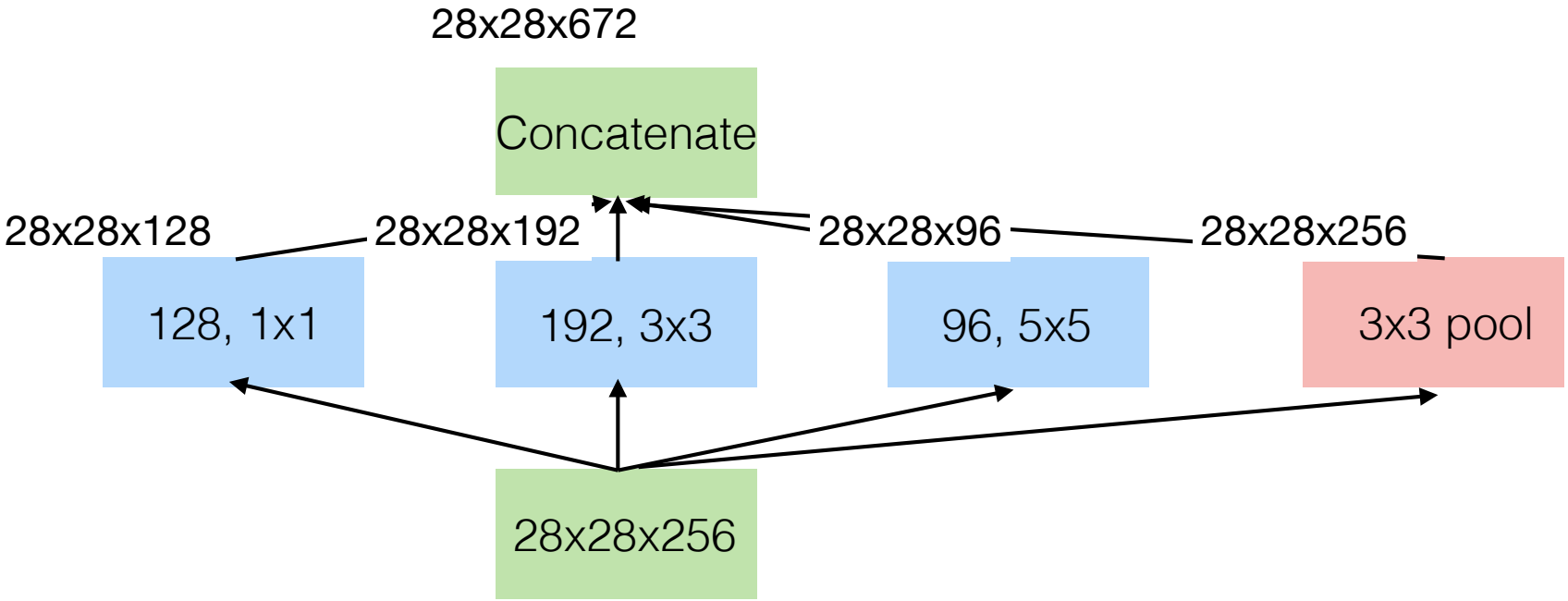
will grow the feature maps

GoogLeNet



How many operations are there in this layer?

GoogLeNet



How many operations are there in this layer?

1x1x128 conv: 28*28*256*1*1*128 = 25,690,112

3x3x192 conv: 28*28*256*3*3*192 = 356,816,512

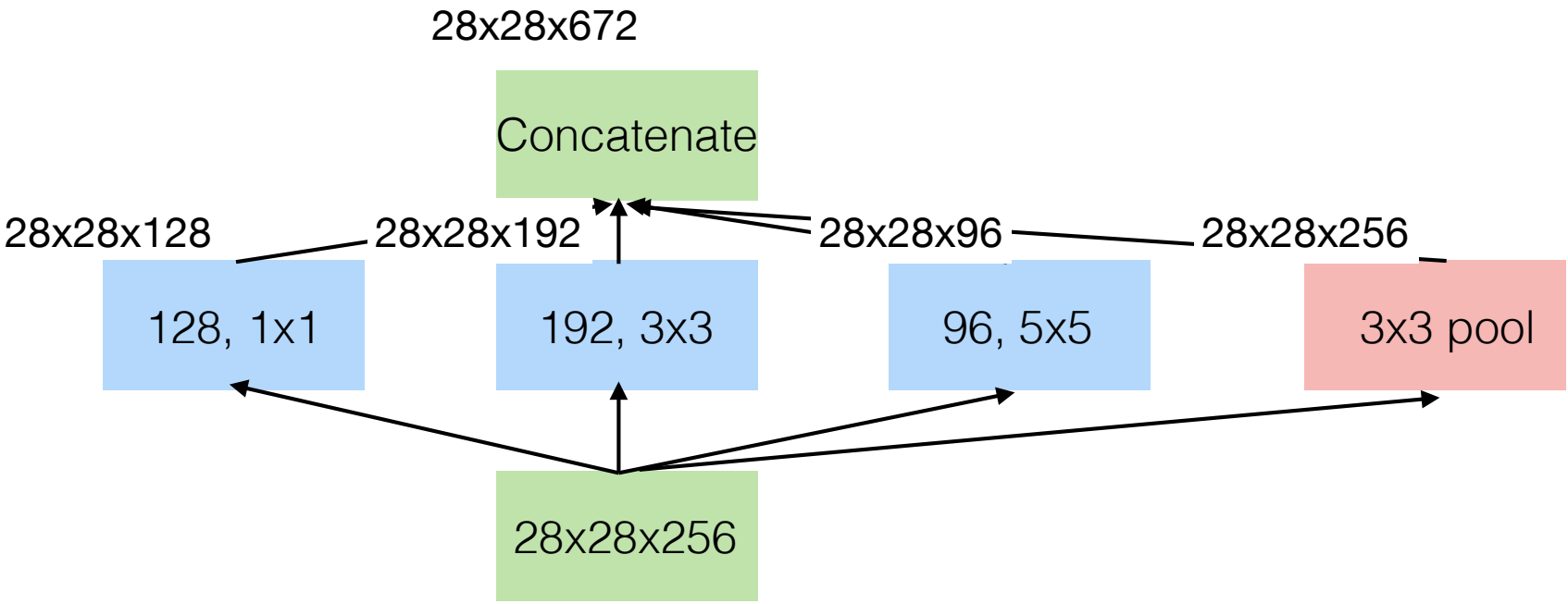
5x5x96 conv: 28*28*256*5*5*96 = 481,689,600

SUM = 864,196,224

GoogLeNet

To address this, in GoogLeNet, 1x1xF convolutional layers are added, that reduce the number of feature maps to substantially reduce the number of operations.

Question: Say F = 64. Where should we put these convolutional layers?



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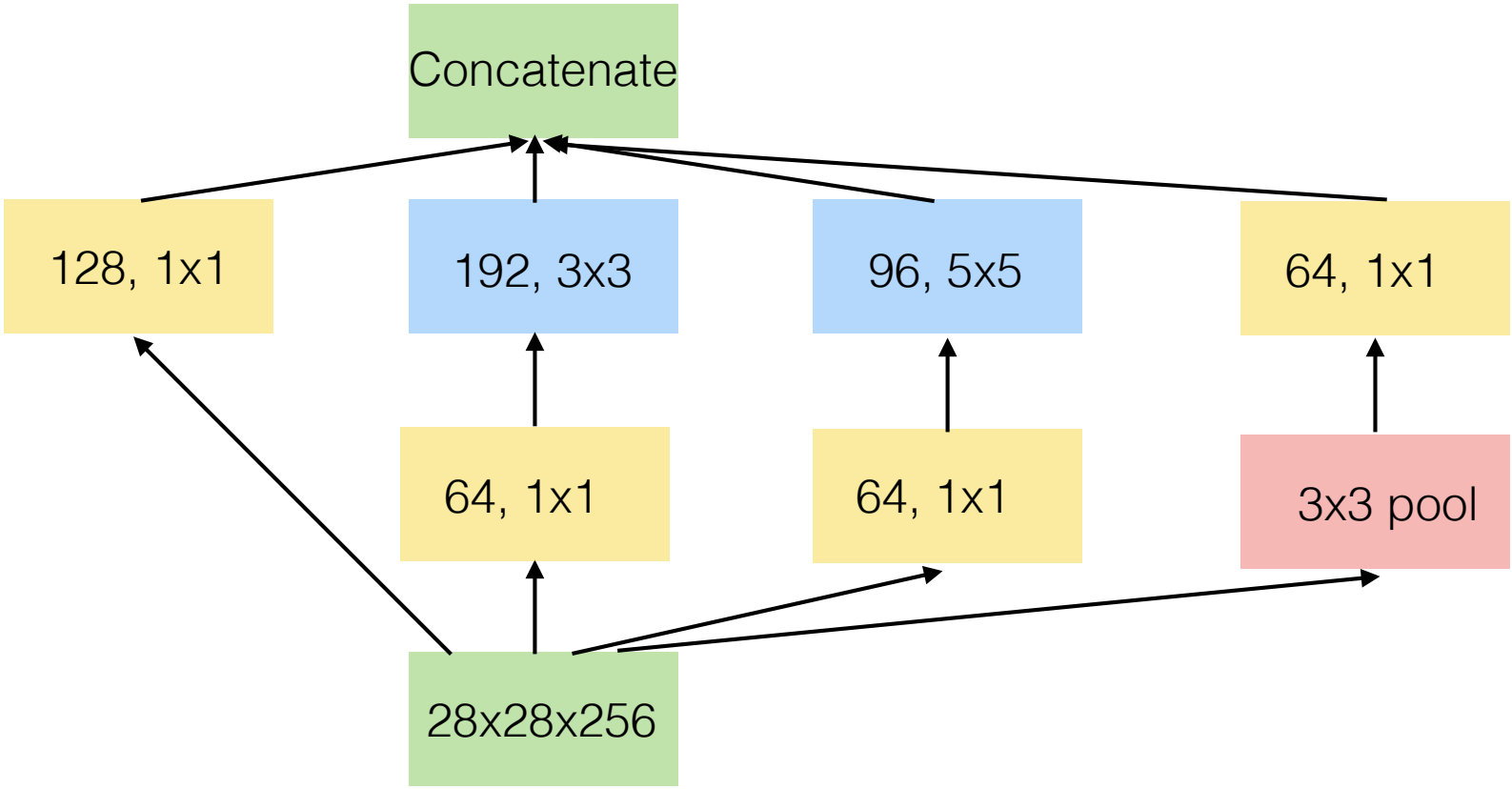

GoogLeNet

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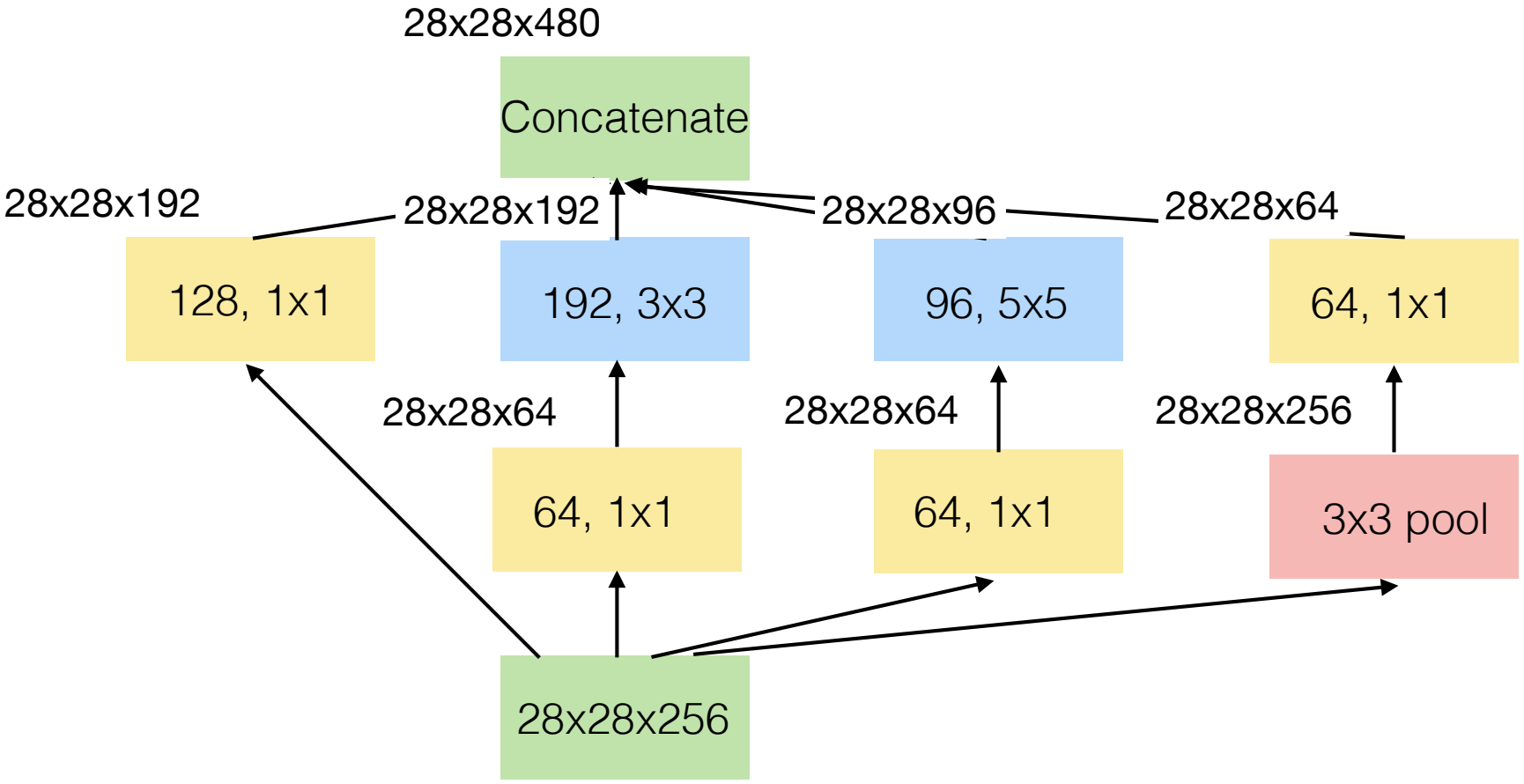


GoogLeNet

How many operations?

1x1x128 conv: 28*28*256*1*1*128 = 25,690,112
1x1x64 conv: 28*28*256*1*1*64 = 12,845,056
1x1x64 conv: 28*28*256*1*1*64 = 12,845,056
1x1x64 conv: 28*28*256*1*1*64 = 12,845,056
3x3x192 conv: 28*28*64*3*3*192 = 86,704,128
5x5x96 conv: 28*28*64*5*5*96 = 120,422,400

SUM: 271,351,808

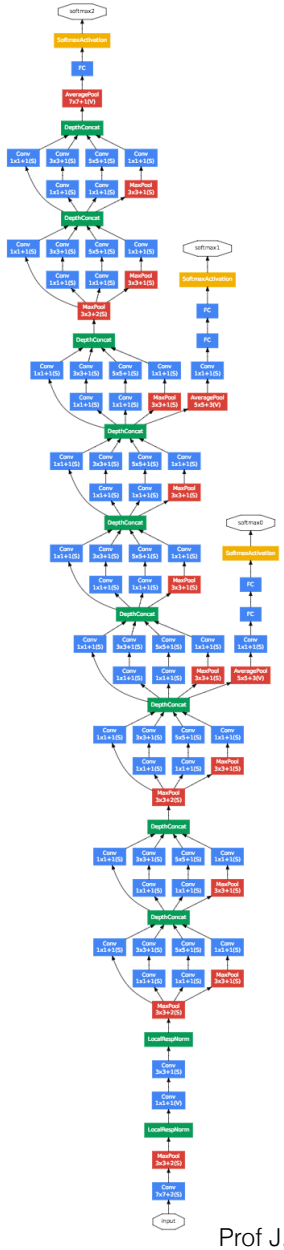
These 1x1 convolutions reduce the amount of computation by almost 4x in this example.

Is information lost in these 1x1x64 convolutions?

GoogLeNet

GoogLeNet architecture.

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								



GoogLeNet

	Num layers
Convolution	1
Max pool	
Convolution (2x)	2
Max pool	
Inception (2x)	4
Max pool	
Inception (5x)	10
Max pool	
Inception (2x)	4
Avg pool	
FC (dropout)	1
Softmax	

Total layers: 22

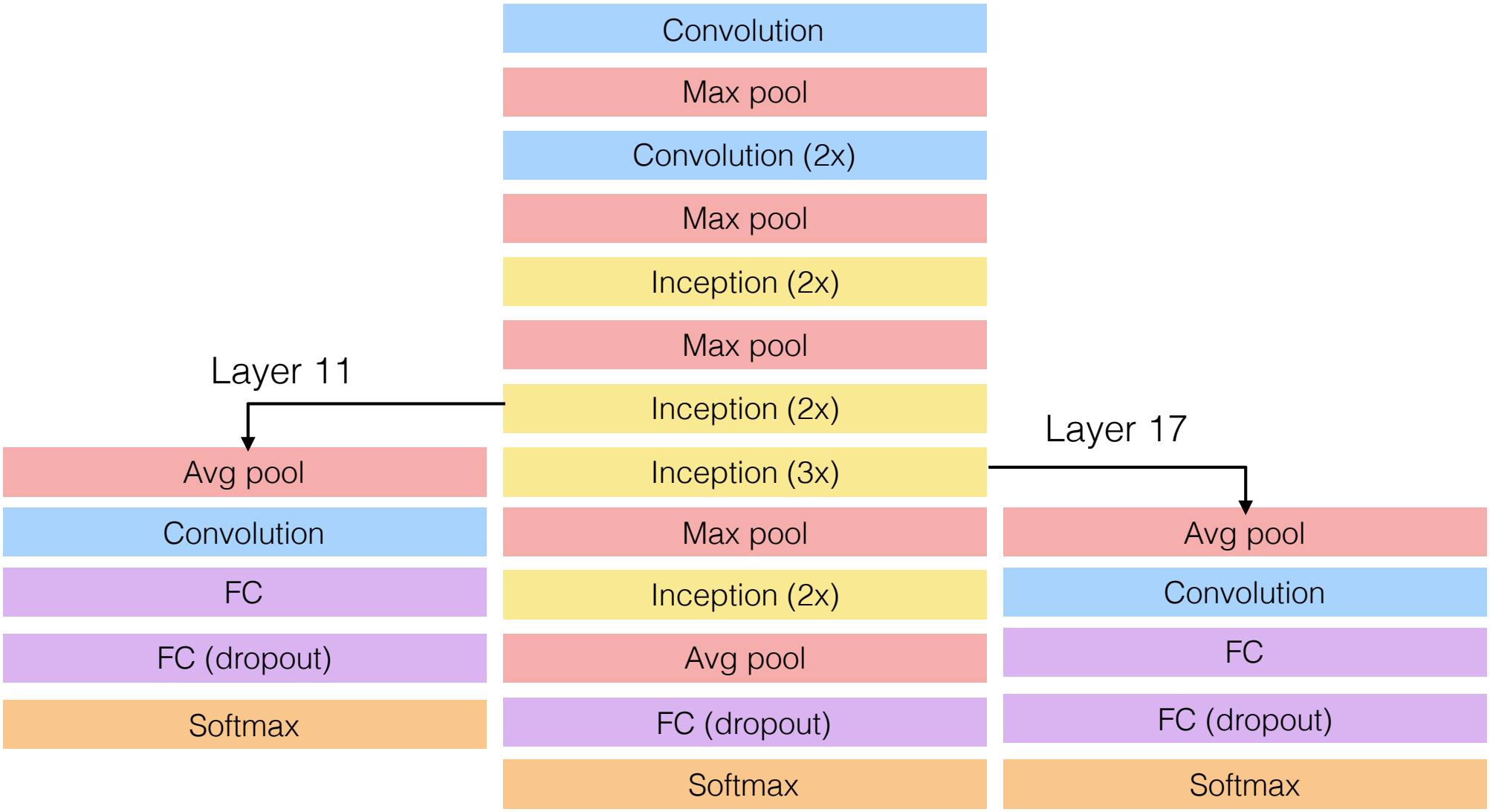
GoogLeNet

	Num layers
Convolution	1
Max pool	
Convolution (2x)	2
Max pool	
Inception (2x)	4
Max pool	
Inception (5x)	10
Max pool	
Inception (2x)	4
Avg pool	
FC (dropout)	1
Softmax	

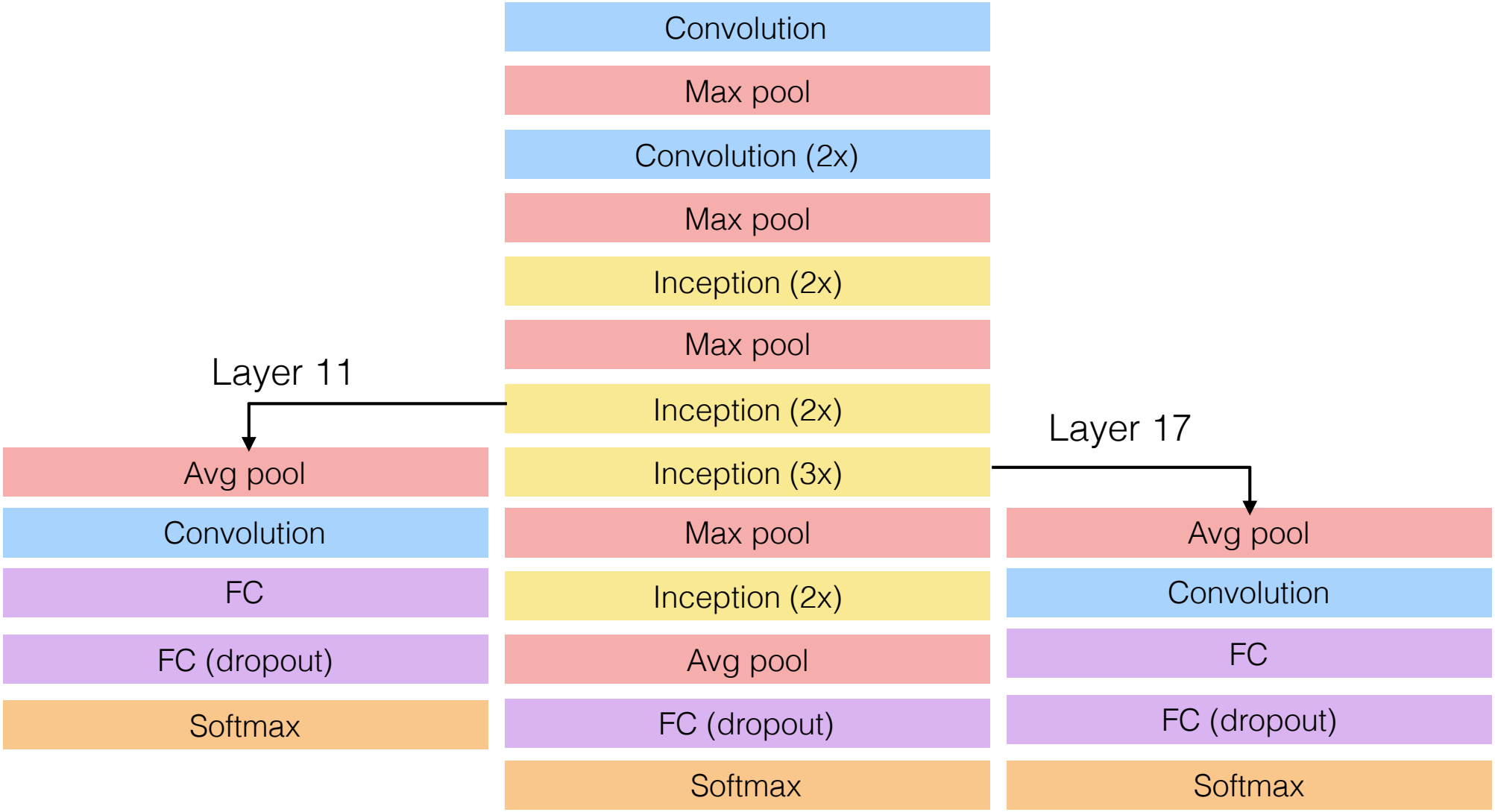
Total layers: 22

What might be a concern about this architecture?

GoogLeNet


Convolution
Max pool
Convolution (2x)
Max pool
Inception (2x)
Max pool
Inception (2x)
Inception (3x)
Max pool
Inception (2x)
Avg pool
FC (dropout)
Softmax
Layer 11
Avg pool
Convolution
FC
FC (dropout)
Softmax
Layer 17
Avg pool
Convolution
FC
FC (dropout)
Softmax

GoogLeNet



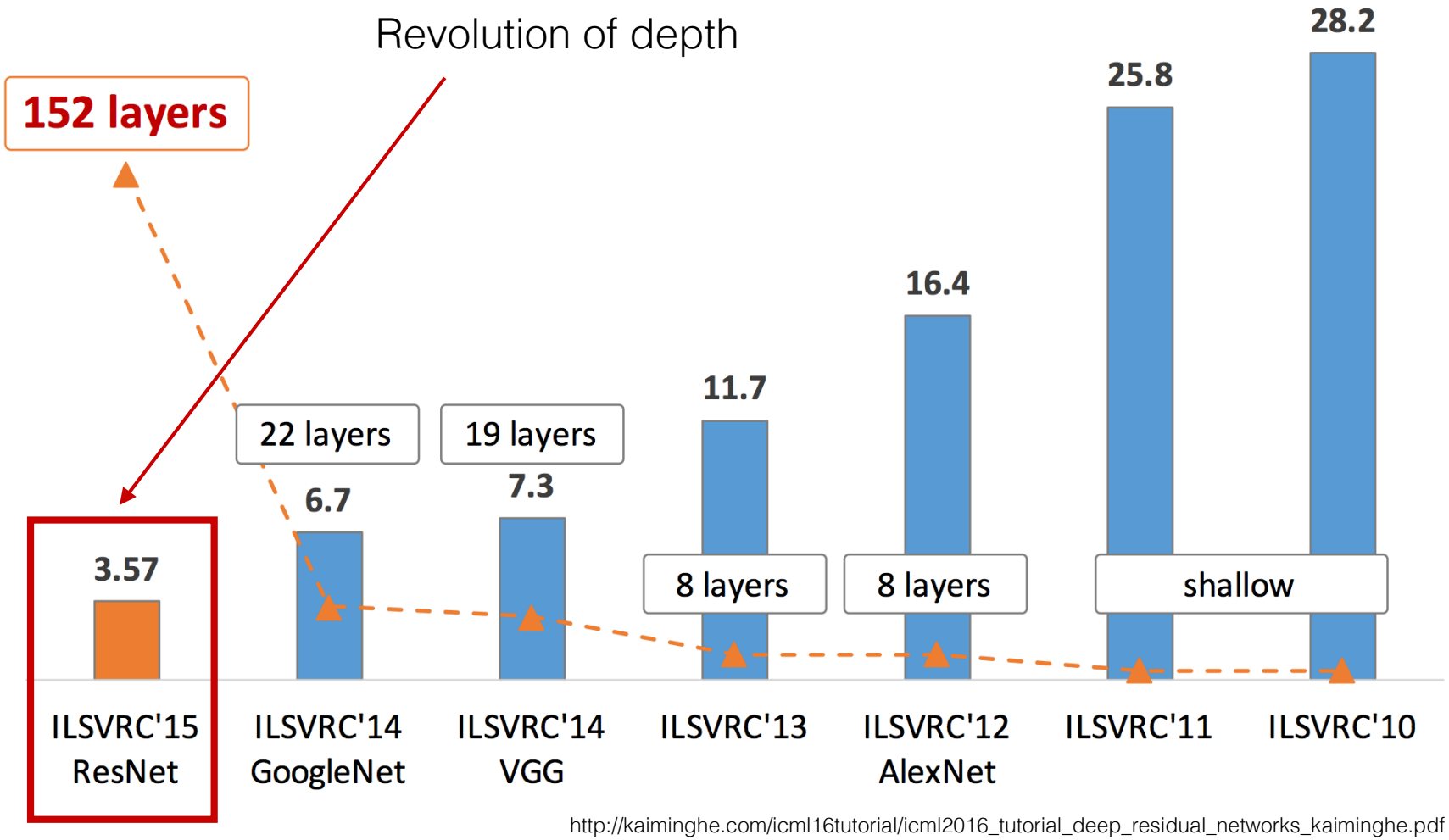
Later work showed auxiliary classifiers had a minor effect (0.5%) and you only need one of them. They're discarded at inference. Their loss is multiplied by 0.3.

GoogLeNet

Other details:

- SGD with 0.9 momentum.
- Decrease learning rate by 4% every 8 epochs.
- Image size patches from 8 to 100% of the area, having aspect ratios 3x4 or 4x3. Used 144 crops per image.
- Other “photometric” operations.
- Averaged results of 7 GoogLeNets.
- Did not use GPUs (!)
- Again, 12x less params than AlexNet. Won ILSVRC ’14. (6.7% top 5 error.)

ResNet

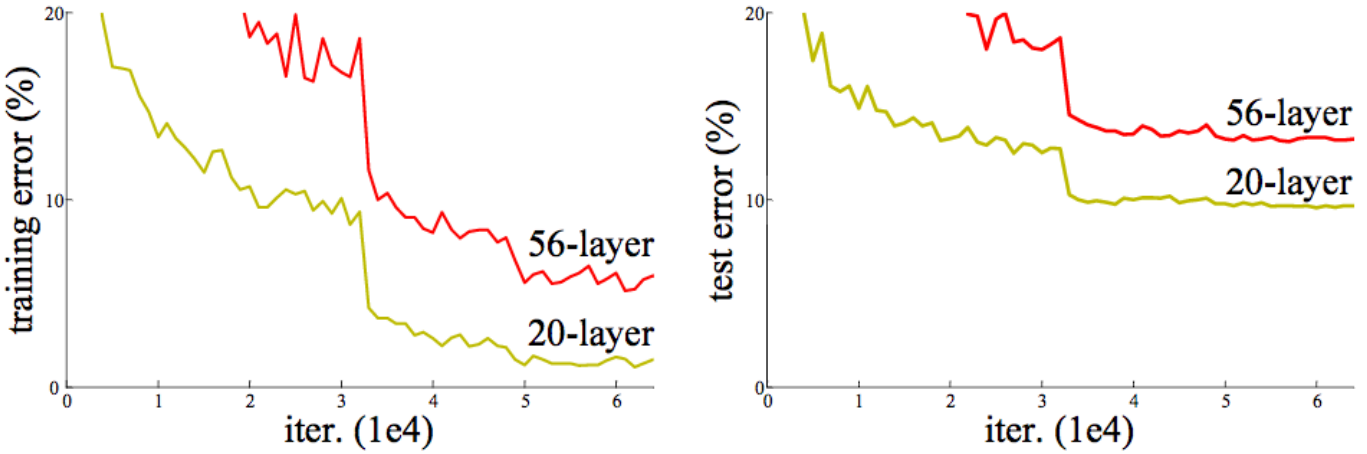


http://kaiminghe.com/icml16tutorial/icml2016_tutorial_deep_residual_networks_kaiminghe.pdf

ResNet

Idea so far:

- AlexNet and ZFNet were 8 layers.
- VGG Net was 16-19 layers.
- GoogLeNet was 22 layers?
- Why not just keep adding layers?



He et al., 2016

ResNet

This result is non-intuitive. (Why?)

ResNet

The degradation problem suggests that the solvers might have difficulties in approximating identity mappings by multiple nonlinear layers. With the residual learning re-formulation, if identity mappings are optimal, the solvers may simply drive the weights of the multiple nonlinear layers toward zero to approach identity mappings.

- He et al., 2016

ResNet

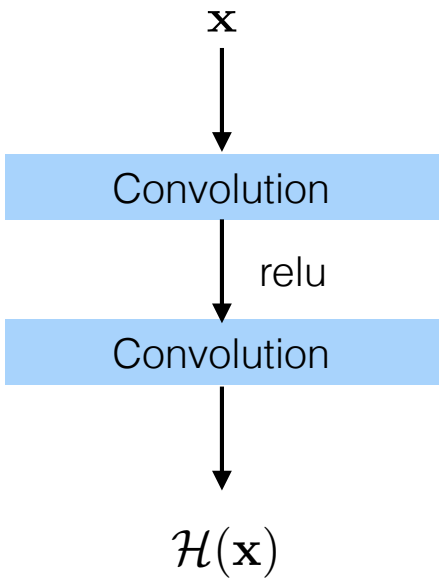
In real cases, it is unlikely that identity mappings are optimal, but our reformulation may help to precondition the problem. If the optimal function is closer to an identity mapping than to a zero mapping, it should be easier for the solver to find the perturbations with reference to an identity mapping, than to learn the function as a new one.

- He et al., 2016

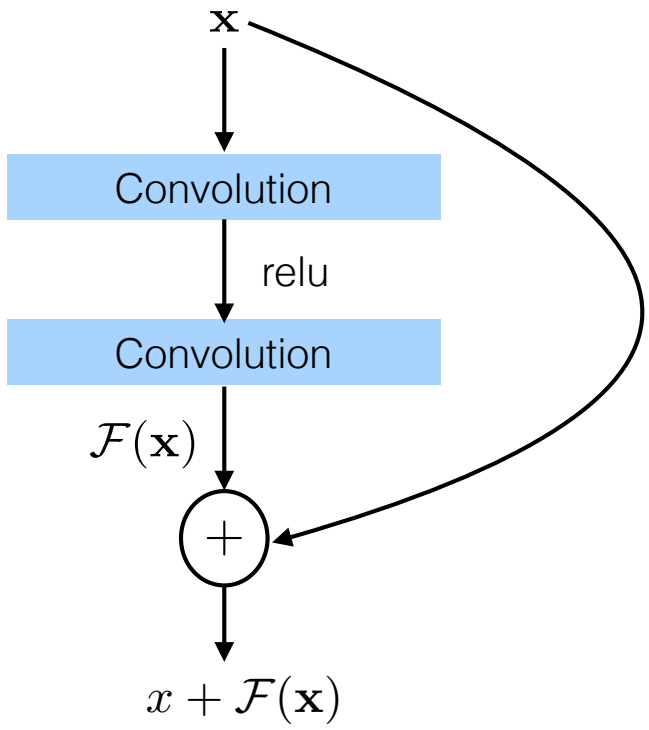
ResNet

The main idea of the ResNet architecture is to facilitate the network training by causing each layer to learn a residual to add to the input.

Normal architecture



ResNet architecture



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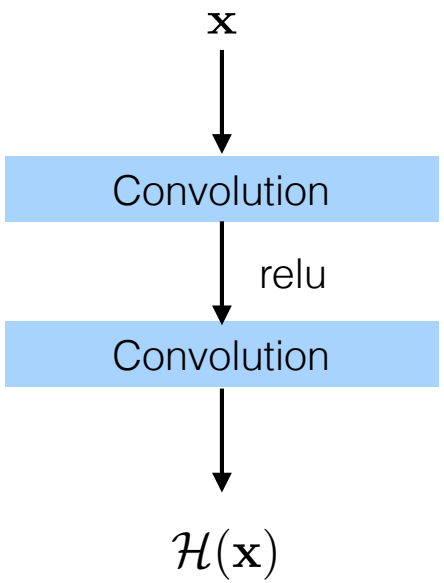
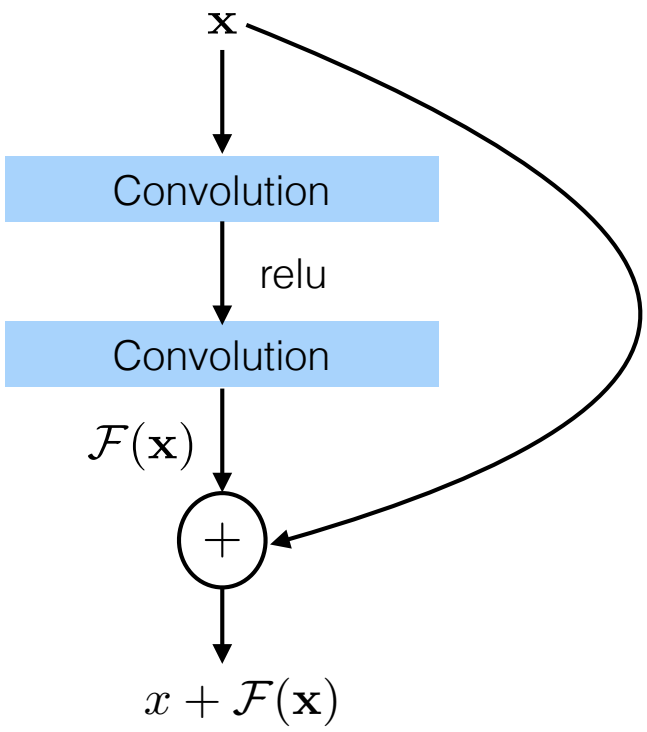


ResNet architecture



Residual layers are used to fit $\mathcal{F}(\mathbf{x}) \approx \mathcal{H}(\mathbf{x}) - \mathbf{x}$

To make dimensions work out, sometimes a linear mapping is used: $\mathbf{W}_s\mathbf{x}$

Feature maps are added by doing 1x1 convolutions or padding.

ResNet

"We hypothesize that it is easier to optimize the residual mapping than to optimize the original, unreferenced mapping."

"To the extreme, if an identity mapping were optimal, it would be easier to push the residual to zero than to fit an identity mapping by a stack of nonlinear layers."

(He et al., 2016)

ResNet

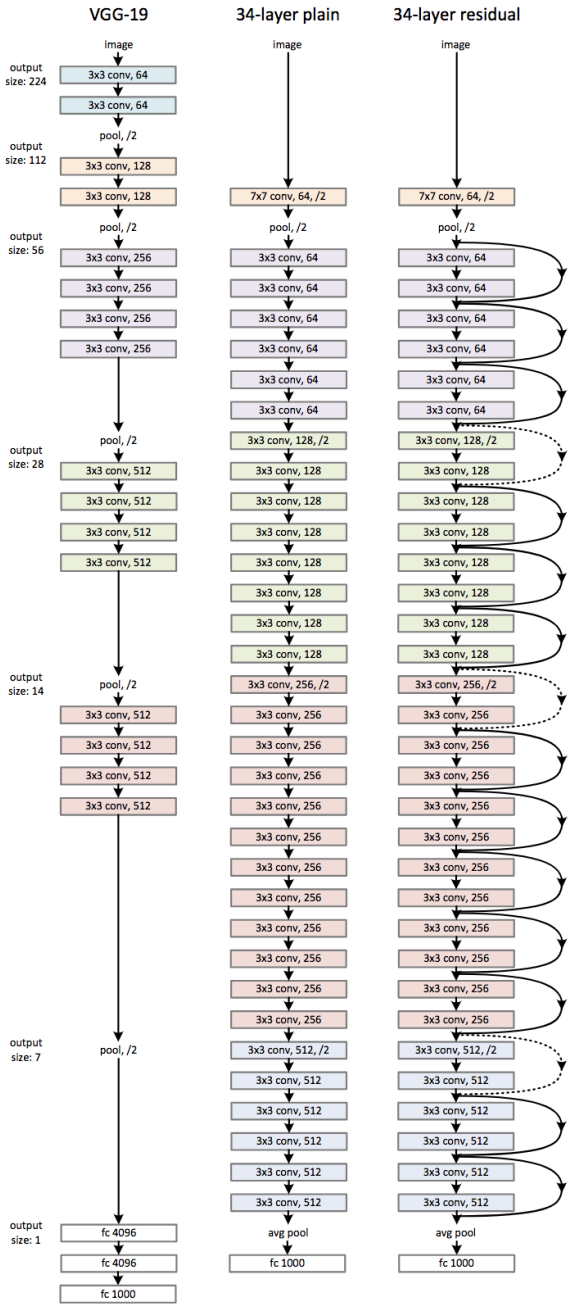
Network architecture:

- They follow the design rules of VGG Net.
  - All conv layers are 3x3 filters with the same number of filters.
  - If the feature map size is halved, the number of filters is doubled so that the computational complexity in each layer is the same.
  - The output ends with average pooling and then a FC 1000 layer to a Softmax.
- Conv layers are residual network layers.

Other notes:

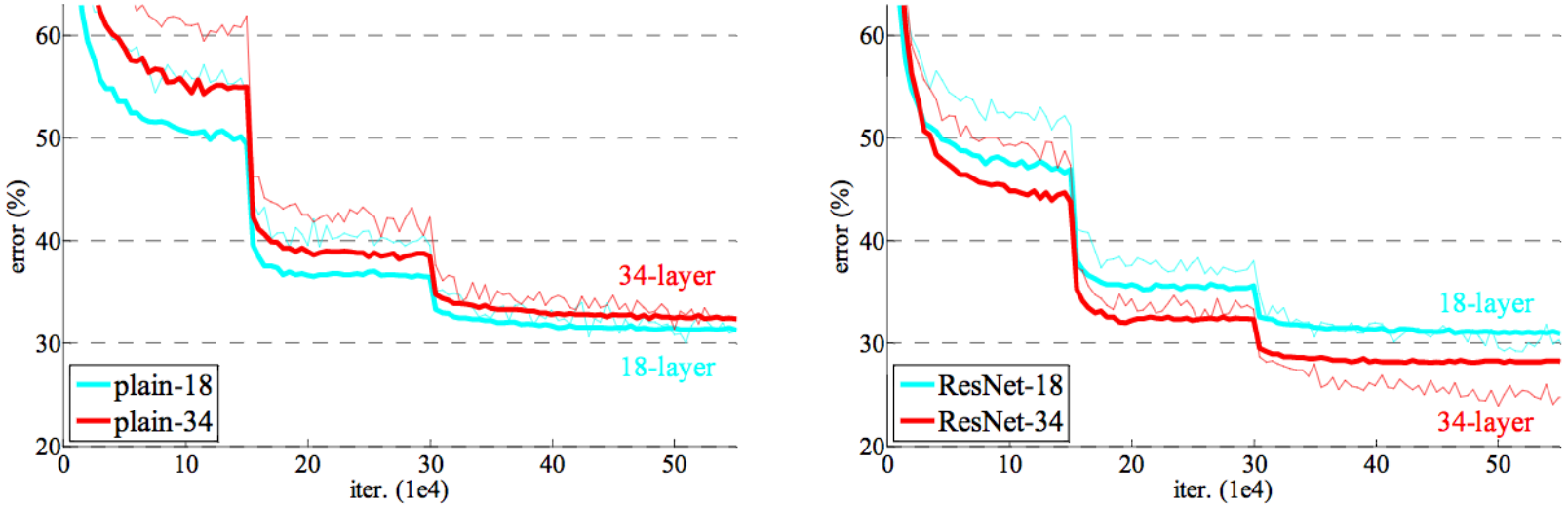
- They performed data augmentation (image scaling, different crops)
- SGD with momentum 0.9, with mini batch size 256.
- L2 regularization with weight 0.0001
- Learning rate starts off at 0.1 and is decreased by an order of magnitude when the error plateaus.
- No dropout.

ResNet



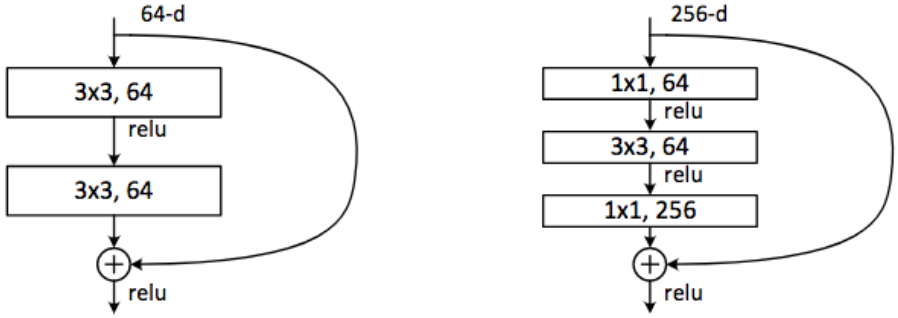
He et al., 2016

ResNet



He et al., 2016

For deeper networks, use an idea similar to inception:



He et al., 2016

ResNet

CIFAR-10 performance:

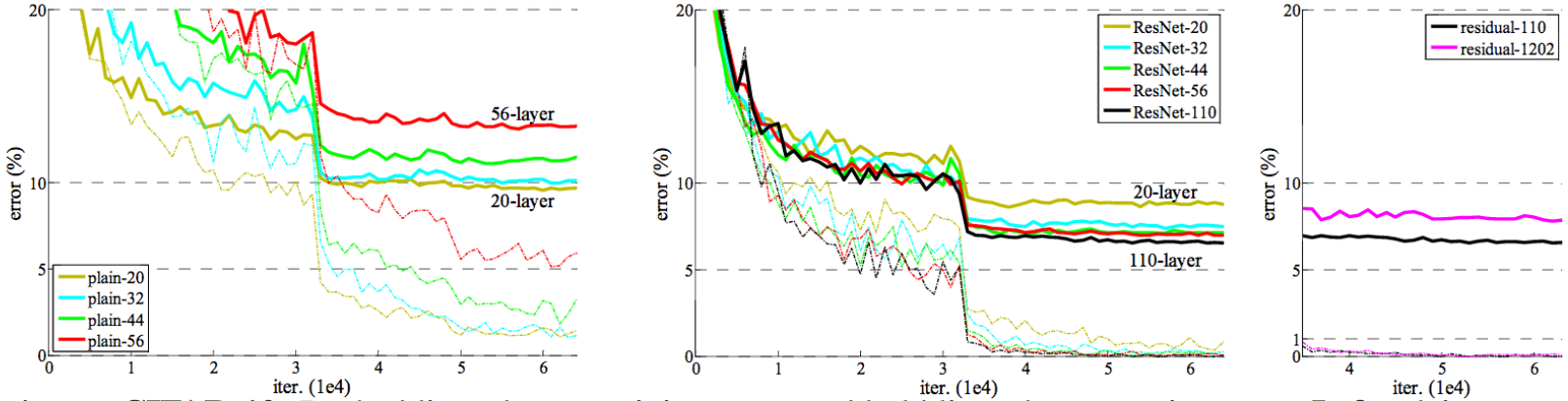
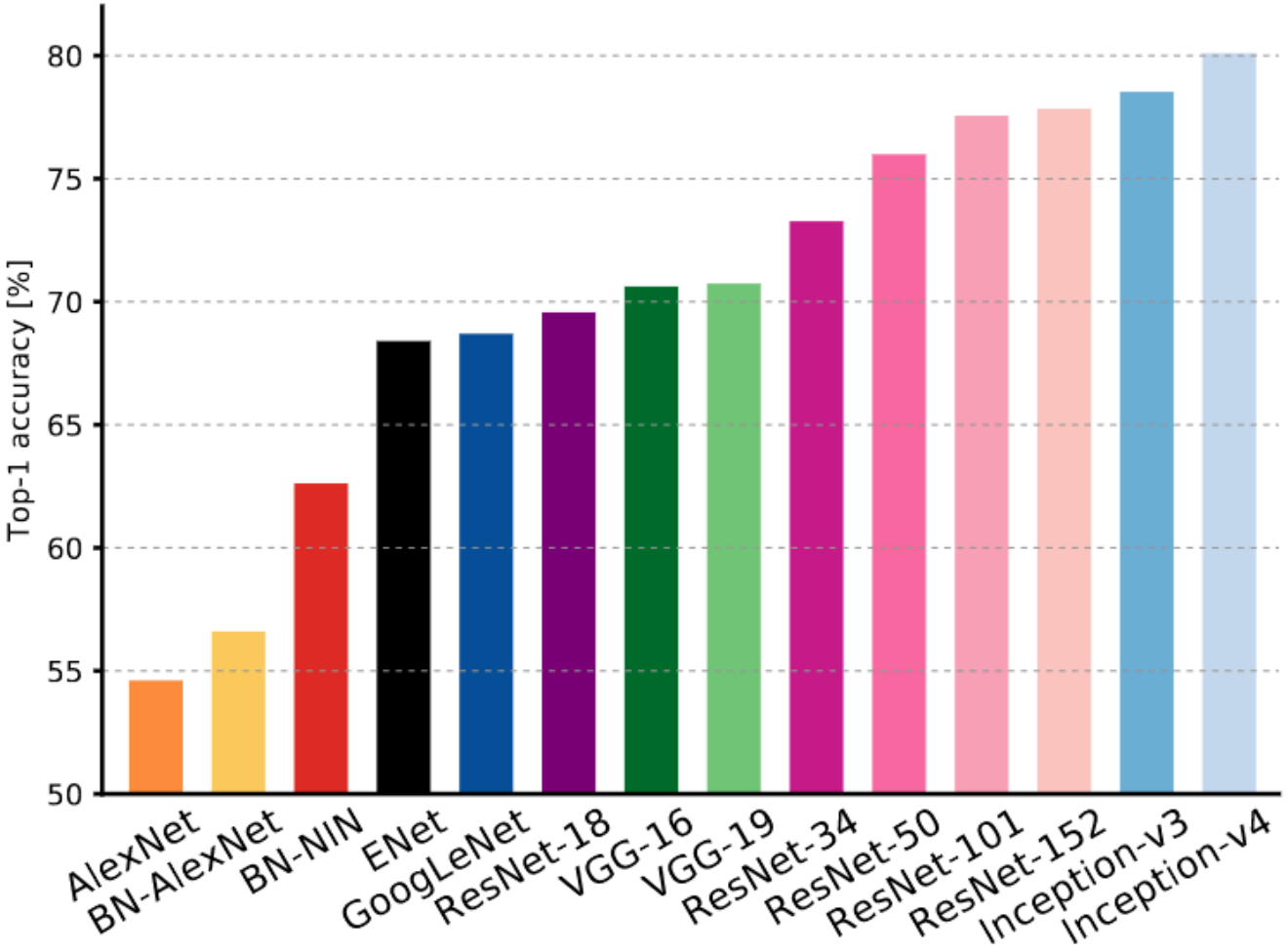


Figure 6. Training on **CIFAR-10**. Dashed lines denote training error, and bold lines denote testing error. **Left**: plain networks. The error of plain-110 is higher than 60% and not displayed. **Middle**: ResNets. **Right**: ResNets with 110 and 1202 layers.

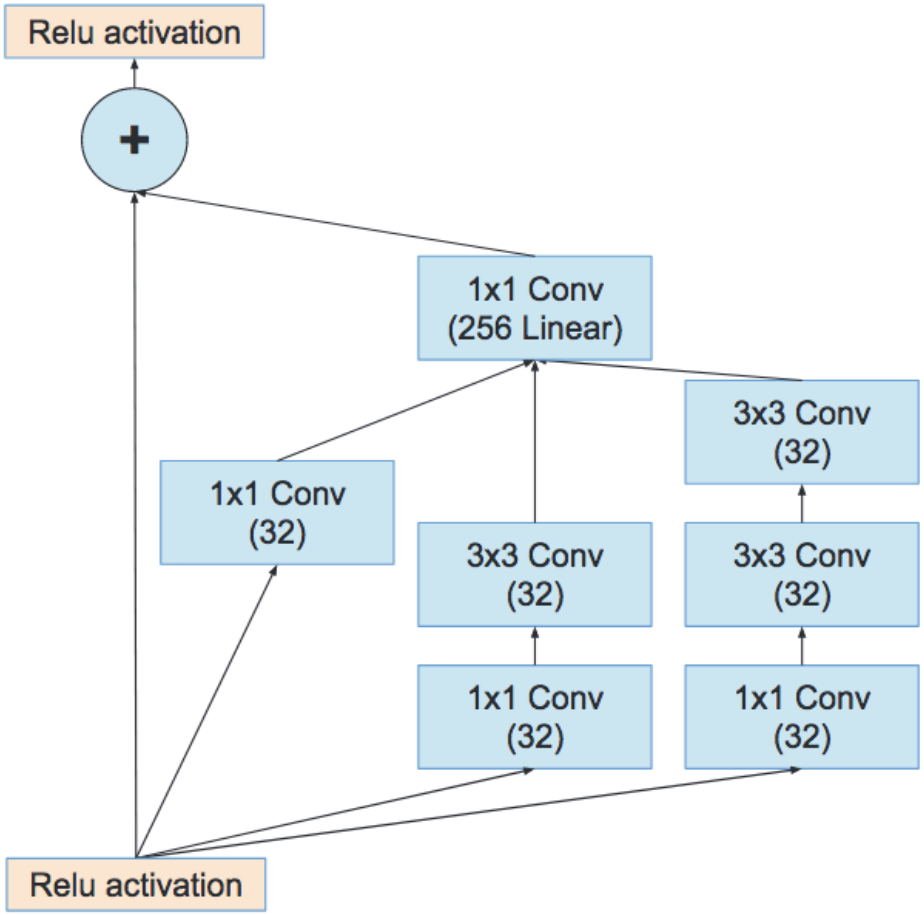
He et al., 2016

An overall view of architectures



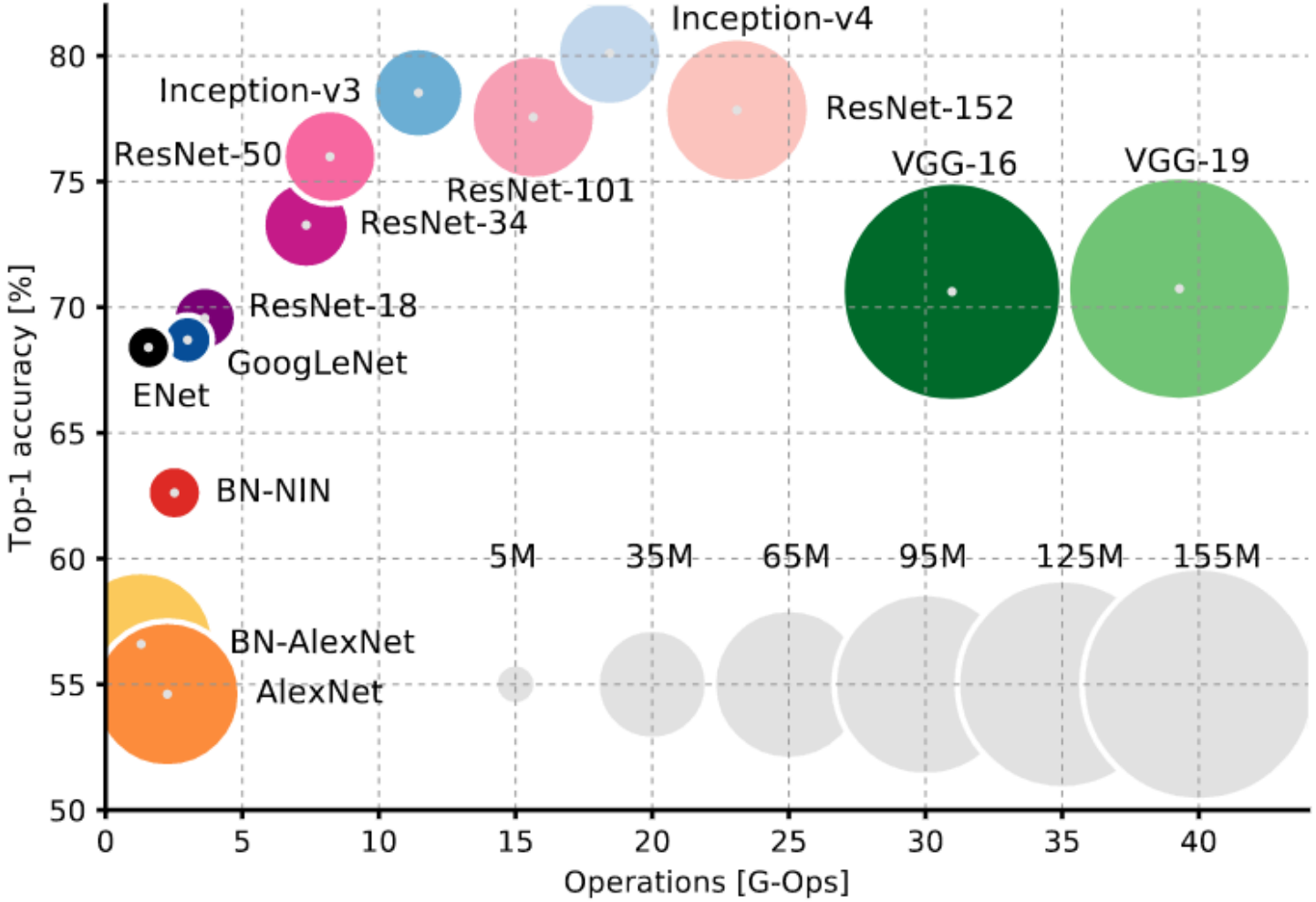
Canziani et al., 2017

Inception-v4



Szegedy et al., 2017

An overall view of architectures



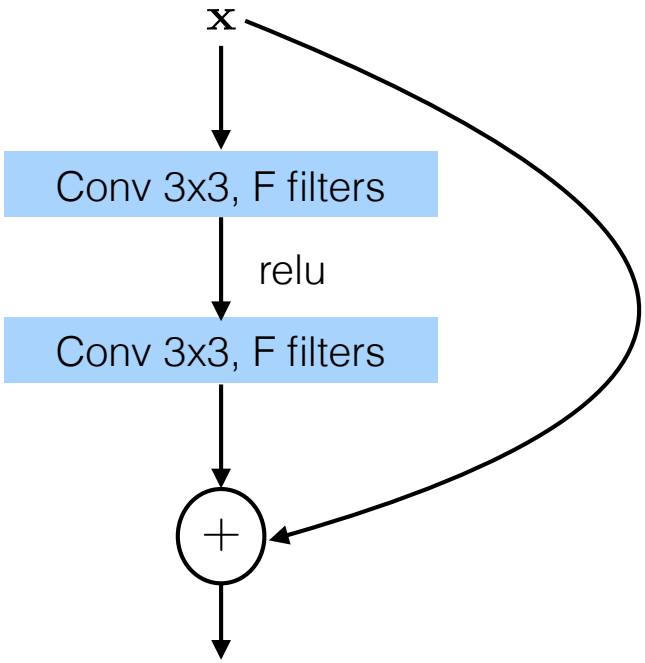
Canziani et al., 2017

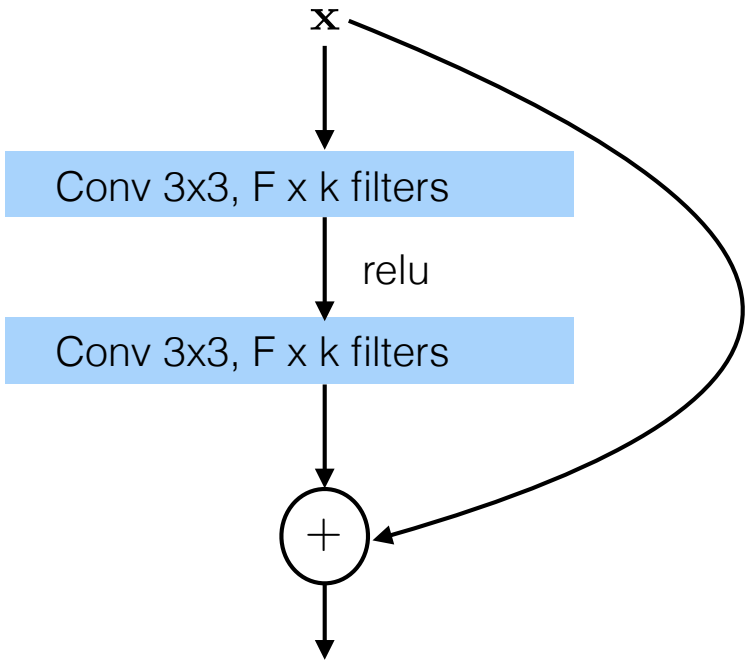
ResNets were 2015. What's been going on since then?

ImageNet errors continue to get lower and lower. Here are some architectures that have been developed since the ResNet. A lot of them are modifications on top of ResNet.

Wide ResNets

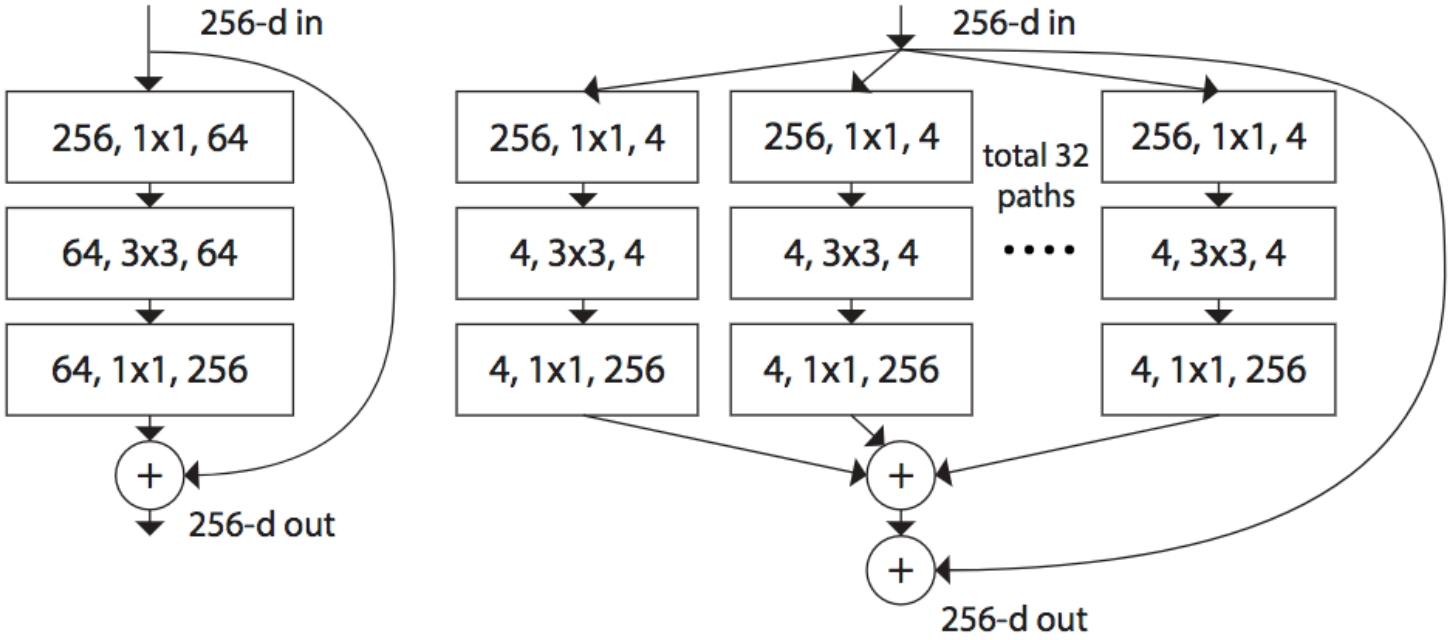
ResNets and Wide ResNets





ResNeXt (ImageNet 2016 2nd place)

ResNeXt.



Xie et al., 2017

ResNeXt (ImageNet 2016 2nd place)

ResNeXt.

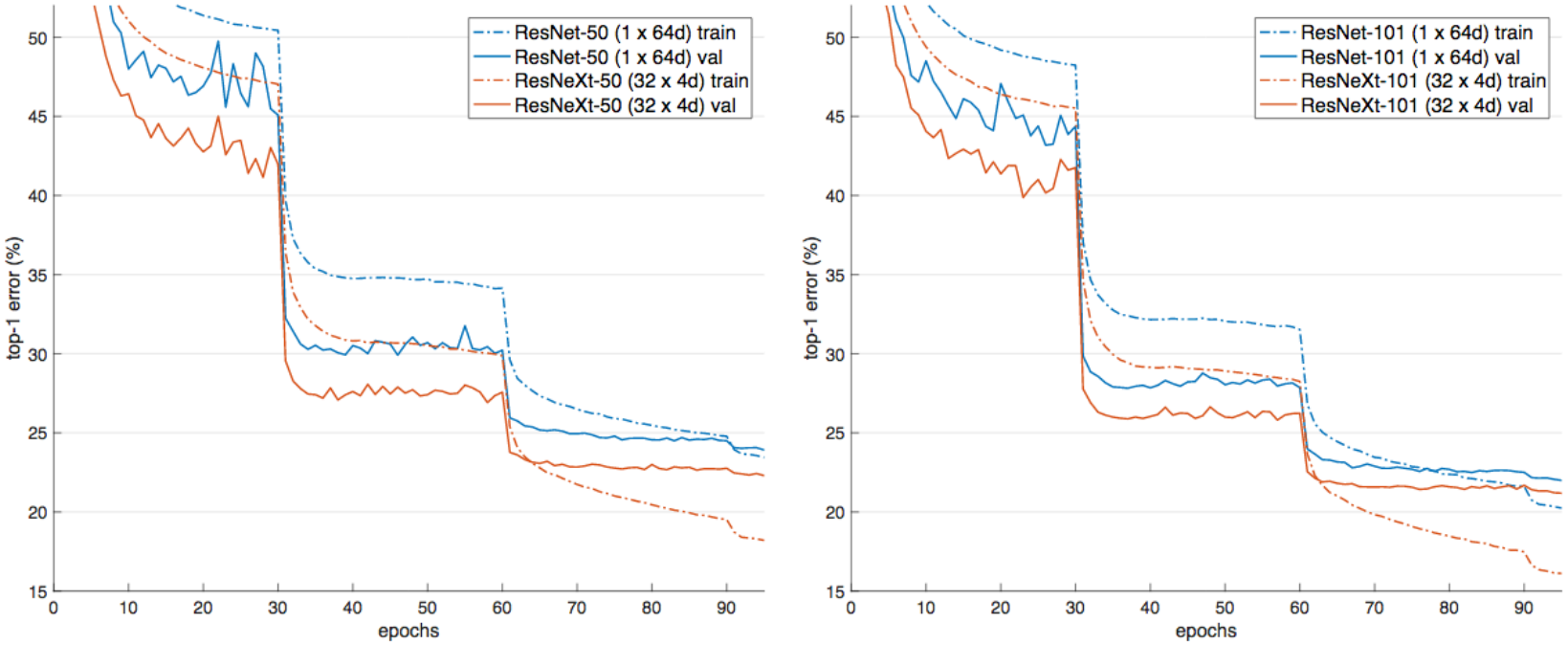
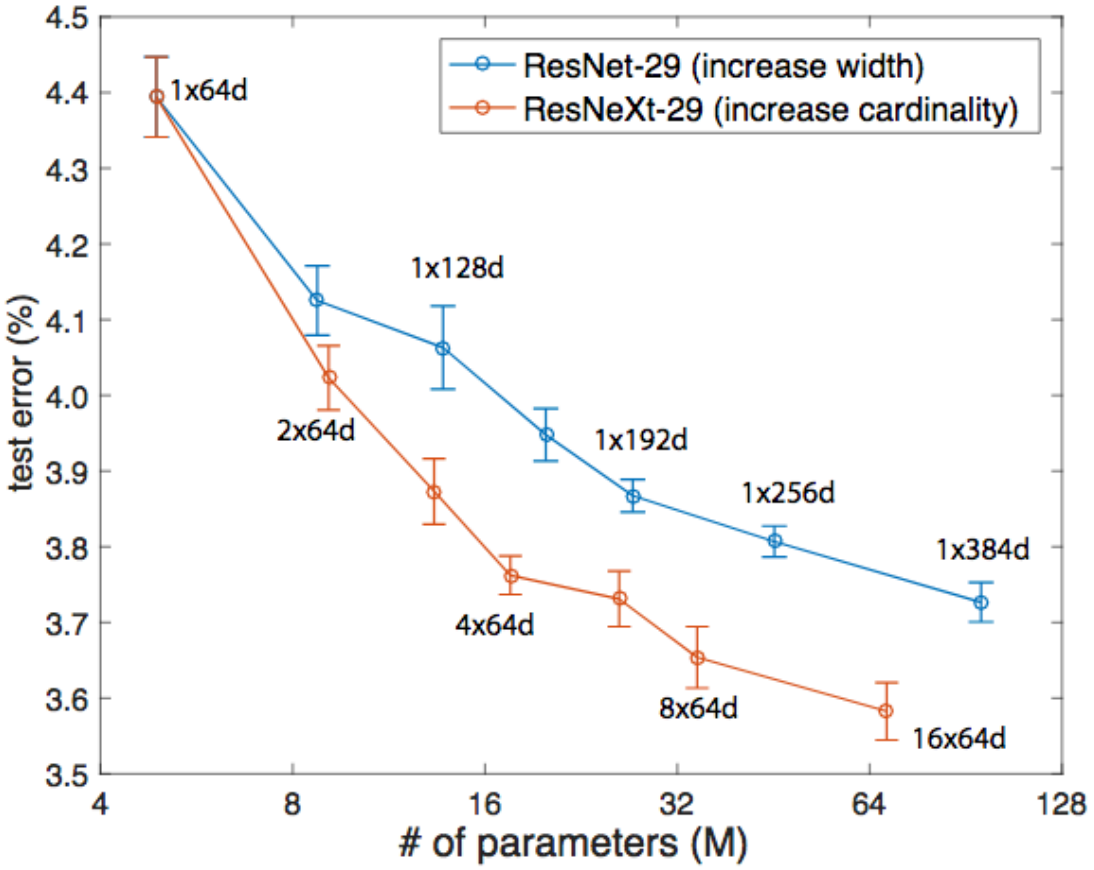


Figure 5. Training curves on ImageNet-1K. (**Left**): ResNet/ResNeXt-50 with preserved complexity (~4.1 billion FLOPs, ~25 million parameters); (**Right**): ResNet/ResNeXt-101 with preserved complexity (~7.8 billion FLOPs, ~44 million parameters).

Xie et al., 2017

ResNeXt (ImageNet 2016 2nd place)

Better than simply increasing width.



Xie et al., 2017

Stochastic depth

Randomly dropout modules of the ResNet.

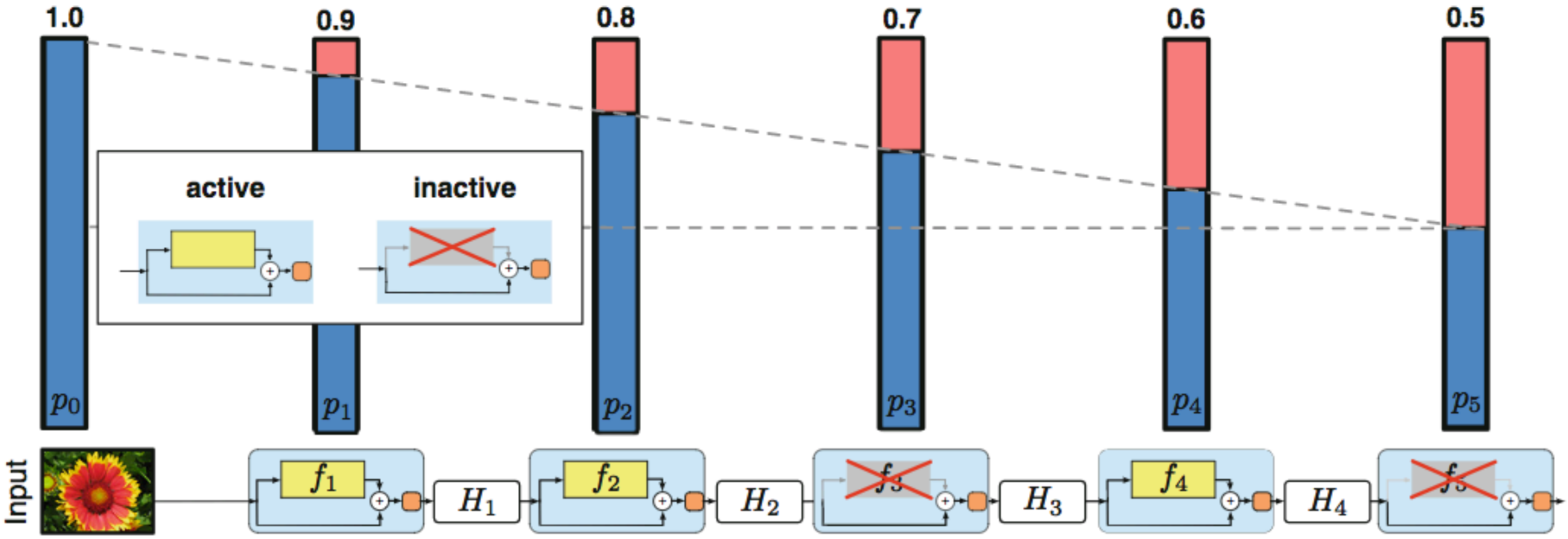


Fig. 2. The linear decay of p_ℓ illustrated on a ResNet with stochastic depth for $p_0 = 1$ and $p_L = 0.5$. Conceptually, we treat the input to the first ResBlock as H_0, which is always active.

Huang et al., 2016

Stochastic depth

Randomly dropout modules of the ResNet.

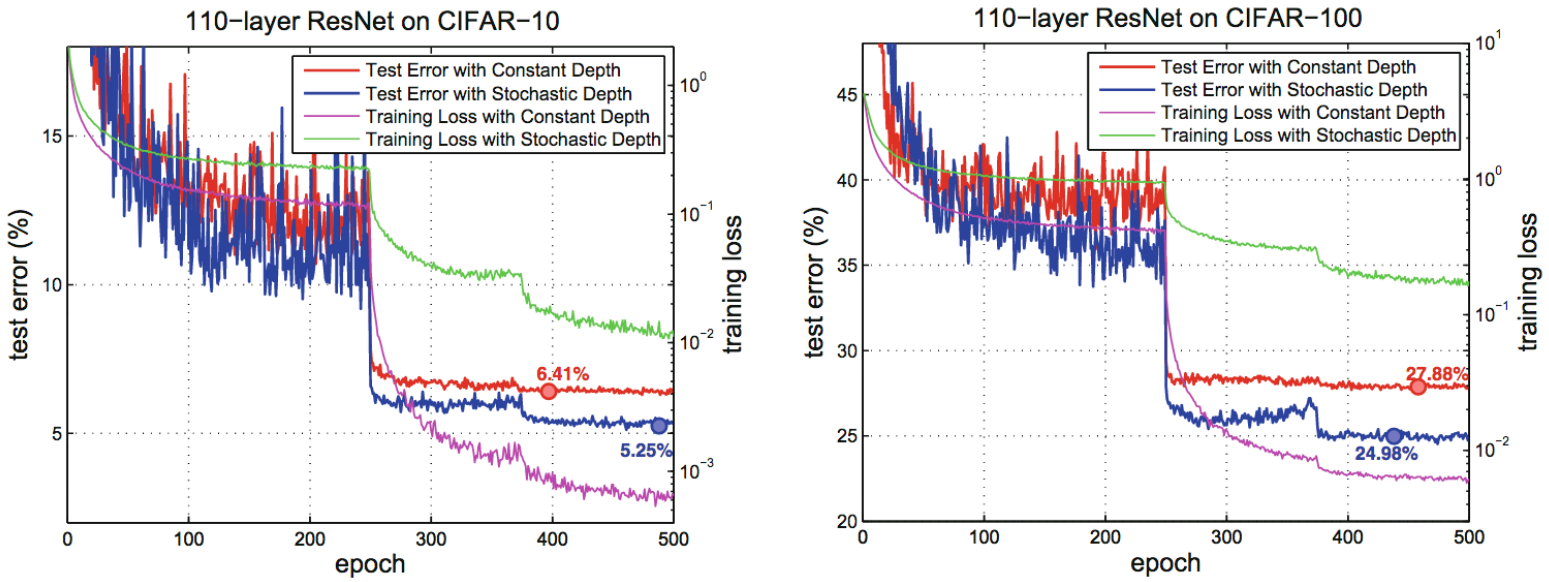


Fig. 3. Test error on CIFAR-10 (*left*) and CIFAR-100 (*right*) during training, with data augmentation, corresponding to results in the first two columns of Table 1.

Huang et al., 2016

Fractal Nets

"…thereby demonstrating that ***residual representations may not be fundamental to the success of extremely deep convolutional neural networks. Rather, the key may be the ability to transition, during training, from effectively shallow to deep.****"*

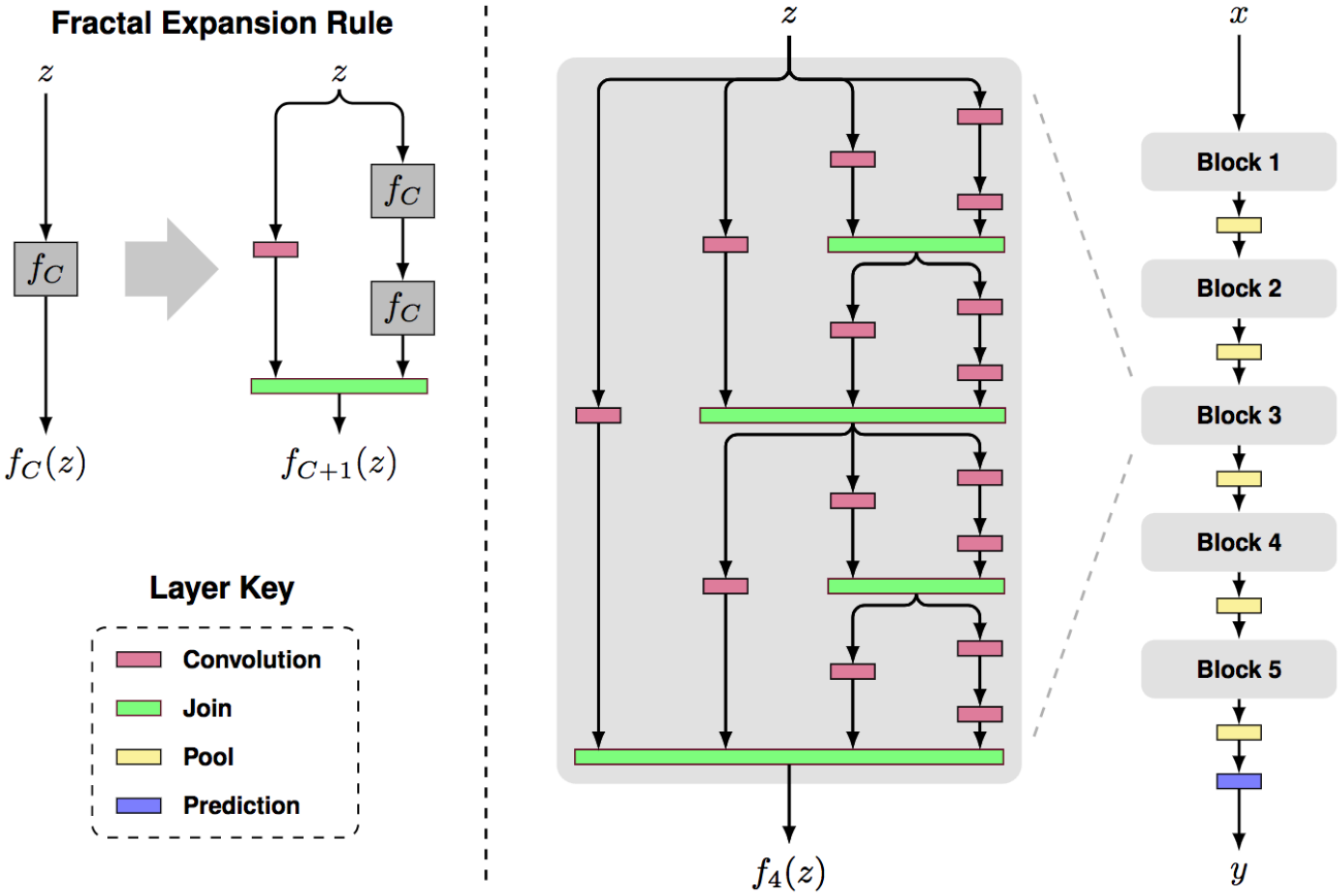
Larsson et al., 2017

Regarding ResNet:

First, the objective changes to learning residual outputs, rather than unreferenced absolute mappings. Second, these networks exhibit a type of deep supervision (Lee et al., 2014), as near-identity layers effectively reduce distance to the loss. ***He et al. (2016a) speculate that the former, the residual formulation itself, is crucial.***

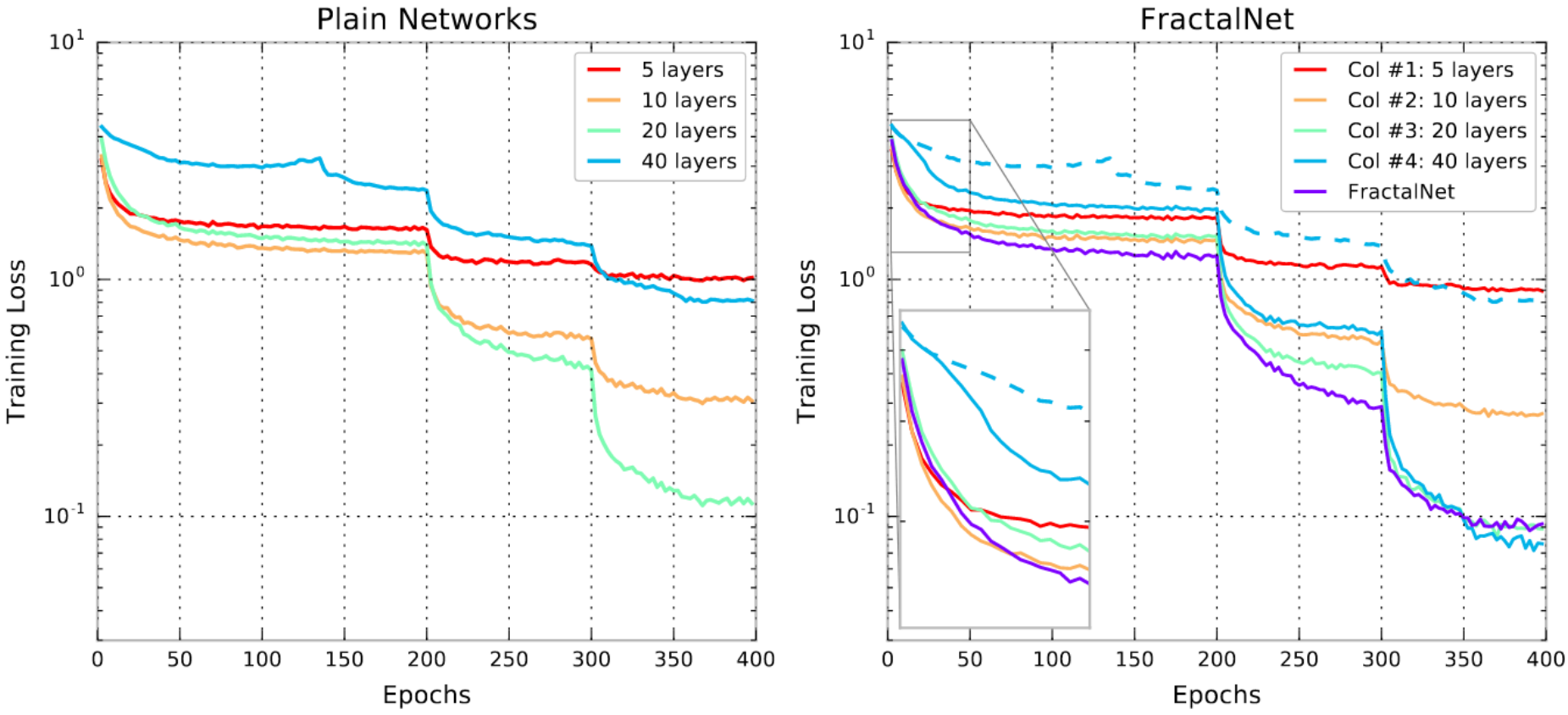
Larsson et al., 2017

Fractal Nets



Larsson et al., 2017

Fractal Nets



Larsson et al., 2017

Take home points

For convolutional neural networks:

- Architecture can play a key role in the performance of the network.
- There is evidence that deeper and wider (i.e., more feature maps) result in better performance.
- Going deeper helps to a point; beyond that, new architectures have to be considered (like the ResNet).
- It appears that what is key about these different architectures is that they reduce the *effective depth* of the network, i.e., they shorten the longest path from the output loss to the network input. This helps to avoid the fundamental problem of deep learning.