Convolutional Neural Net Architectures

Materials from

- Intel Deep Learning https://www.intel.com/content/www/us/en/developer/learn/course-deep-learning.html
- Introduction to Neural Networks https://www.deeplearning.ai

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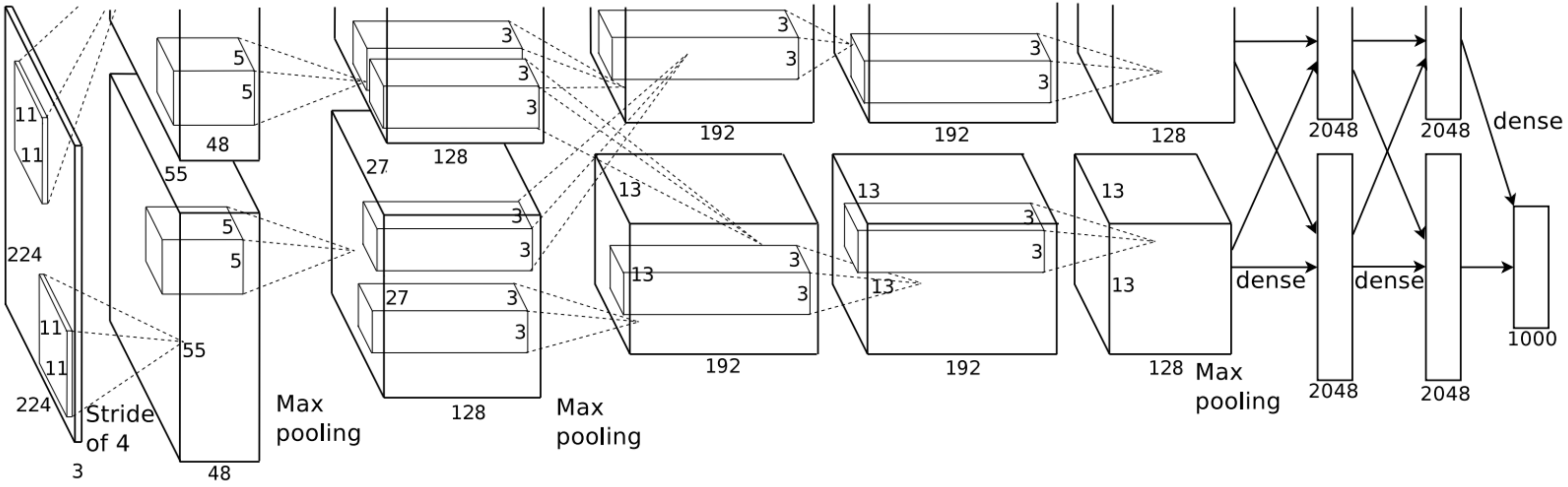
AlexNet

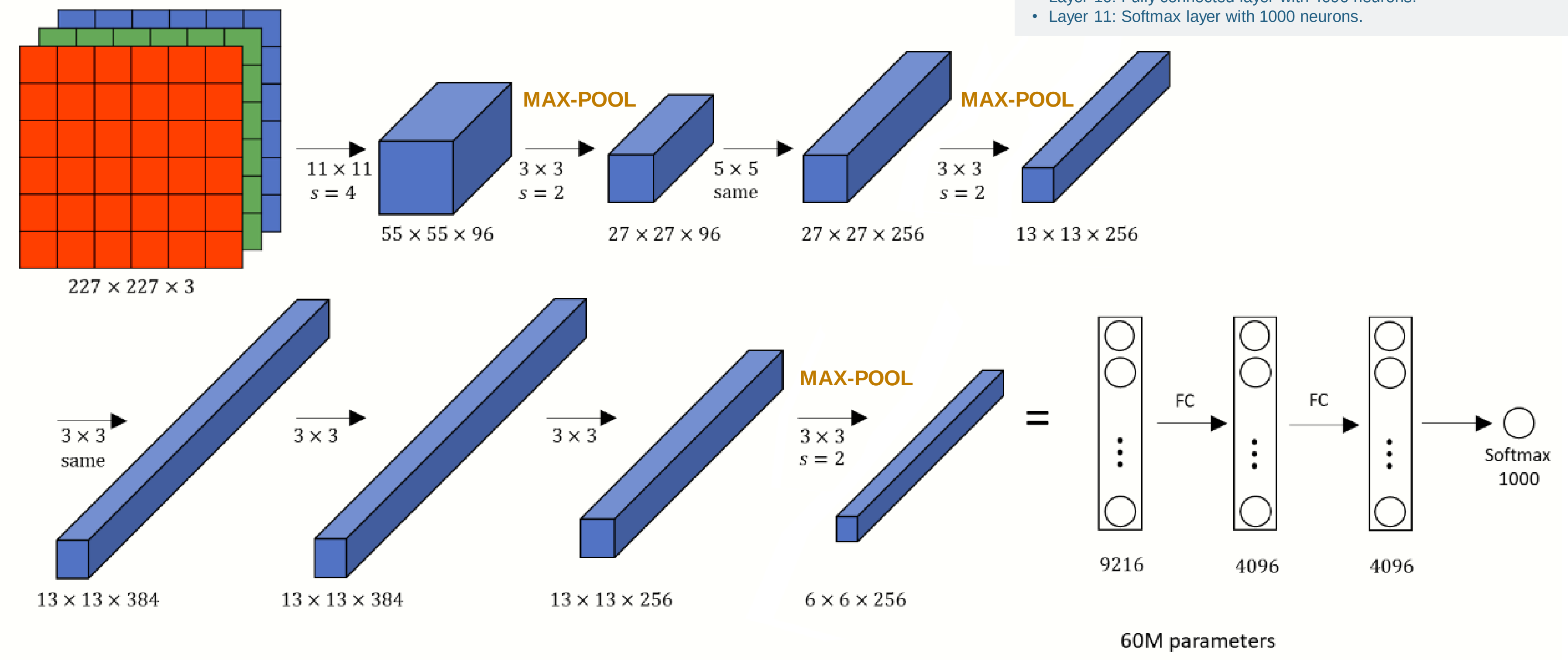
- Created in 2012 for the ImageNet Large Scale Visual Recognition Challenge (ILSVRC)
- Task: predict the correct label from among 1000 classes
- Dataset: around 1.2 million images
- Considered the “flash point” for modern deep learning
- Demolished the competition.
- Top 5 error rate of 15.3%
- Next best: 26.2%

AlexNet - Model Diagram



AlexNet - Model Diagram

- Layer 1: Convolutional layer with 96 filters of size 11x11 and a stride of 4.
- Layer 2: Max-pooling layer with a pooling size of 3x3 and a stride of 2.
- Layer 3: Convolutional layer with 256 filters of size 5x5 and a stride of 1.
- Layer 4: Max-pooling layer with a pooling size of 3x3 and a stride of 2.
- Layer 5: Convolutional layer with 384 filters of size 3x3 and a stride of 1.
- Layer 6: Convolutional layer with 384 filters of size 3x3 and a stride of 1.
- Layer 7: Convolutional layer with 256 filters of size 3x3 and a stride of 1.
- Layer 8: Max-pooling layer with a pooling size of 3x3 and a stride of 2.
- Layer 9: Fully connected layer with 4096 neurons.
- Layer 10: Fully connected layer with 4096 neurons.
- Layer 11: Softmax layer with 1000 neurons.



[Krizhevsky et al., 2012. ImageNet classification with deep convolutional neural networks]

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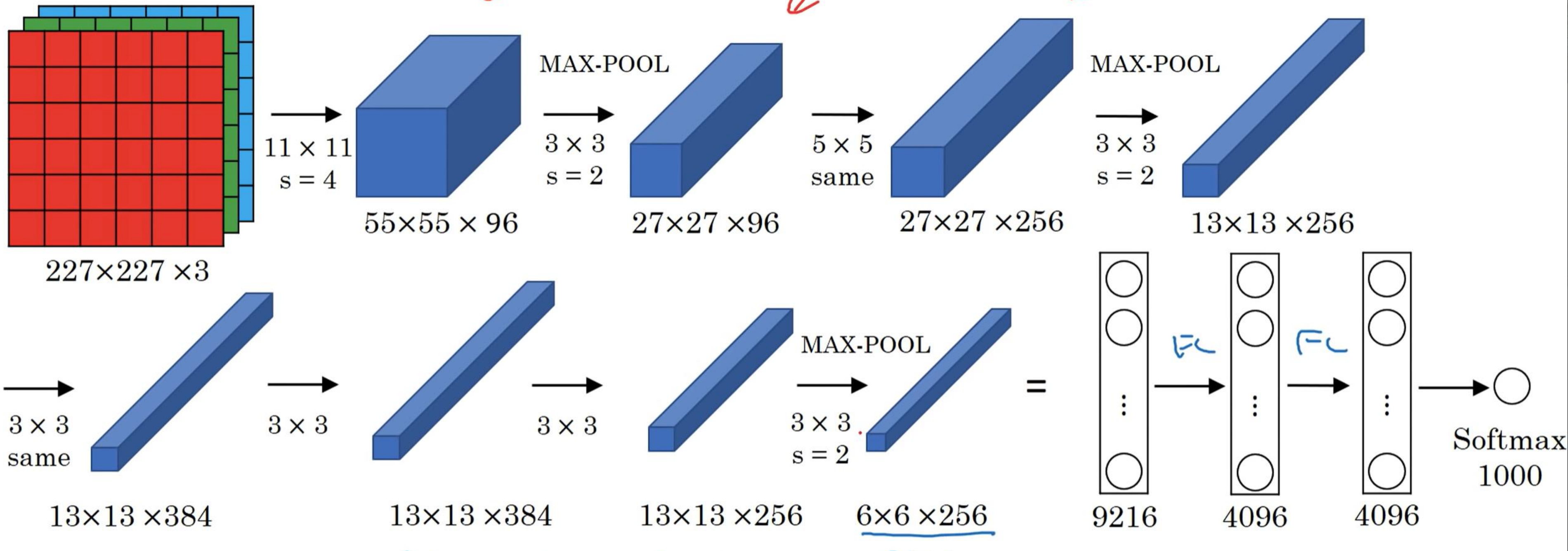
AlexNet



- Similar to LeNet, but much bigger. ~60M parameters
- ReLU
- Multiple GPUs.

[Krizhevsky et al., 2012. ImageNet classification with deep convolutional neural networks]

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AlexNet - Details

- They performed *data augmentation* for training
  - Includes Cropping, horizontal flipping, and other manipulations

- Basic Template:
  - Convolutions with ReLUs
  - Sometimes add maxpool after convolutional layer
  - Fully connected layers at the end before a softmax classifier

VGG

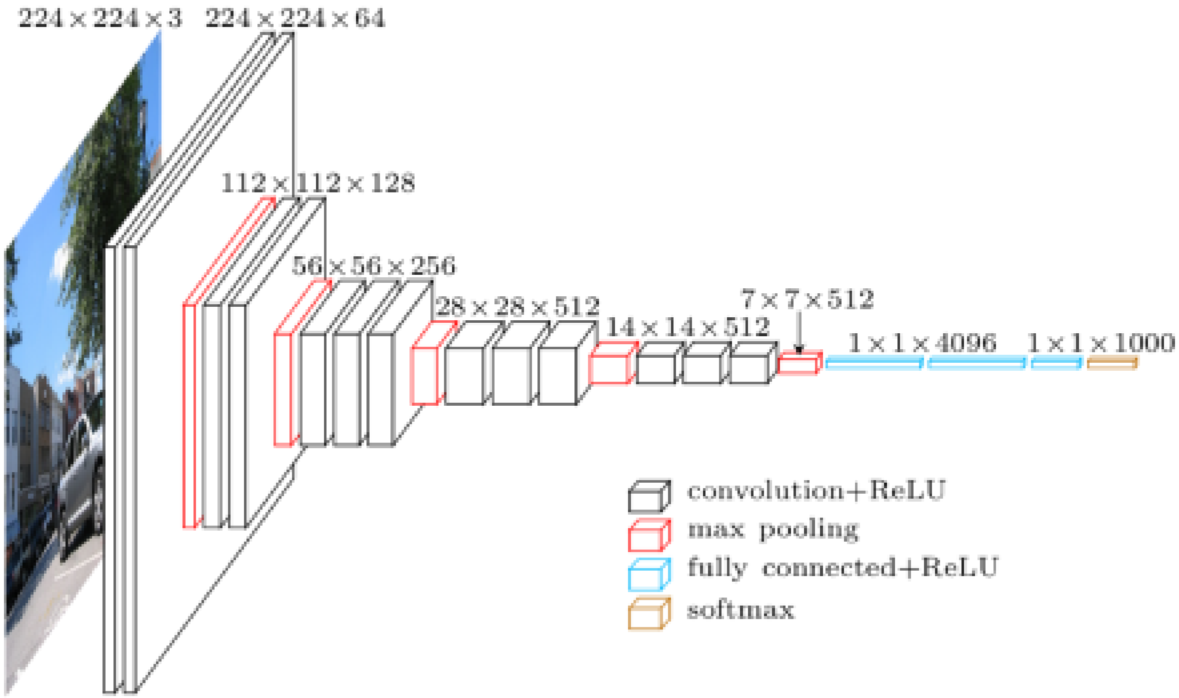
- Simplify Network Structure
- Achieved at error rate of 7.32%, Top 5 Recall in 2014
- Avoid Manual Choices of Convolution Size
- Very Deep Network with 3x3 Convolutions
- These “effectively” give rise to larger convolutions

Reference:

Very Deep Convolutional Networks for Large-Scale Image Recognition

Karen Simonyan and Andrew Zisserman, 2014

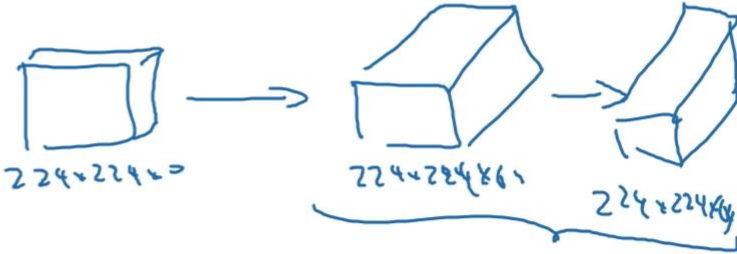
VGG-16 Diagram

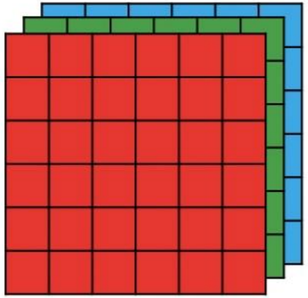


VGG - 16

VGG-19

CONV = 3×3 filter, s = 1, same   MAX-POOL = 2×2 , s = 2





224×224 ×3 $\xrightarrow[\times 2]{\text{[CONV 64]}}$ 224×224×64 $\xrightarrow{\text{POOL}}$ 112×112 ×64 $\xrightarrow[\times 2]{\text{[CONV 128]}}$ 112×112 ×128 $\xrightarrow{\text{POOL}}$ 56×56 ×128

$\xrightarrow[\times 3]{\text{[CONV 256]}}$ 56×56 ×256 $\xrightarrow{\text{POOL}}$ 28×28 ×256 $\xrightarrow[\times 3]{\text{[CONV 512]}}$ 28×28 ×512 $\xrightarrow{\text{POOL}}$ 14×14×512

$\xrightarrow[\times 3]{\text{[CONV 512]}}$ 14×14 ×512 $\xrightarrow{\text{POOL}}$ 7×7×512 $\longrightarrow$ FC 4096 $\longrightarrow$ FC 4096 $\longrightarrow$ Softmax 1000

$n_H, n_W \downarrow$ $n_c \uparrow$ ~138M

[Simonyan & Zisserman 2015. Very deep convolutional networks for large-scale image recognition]

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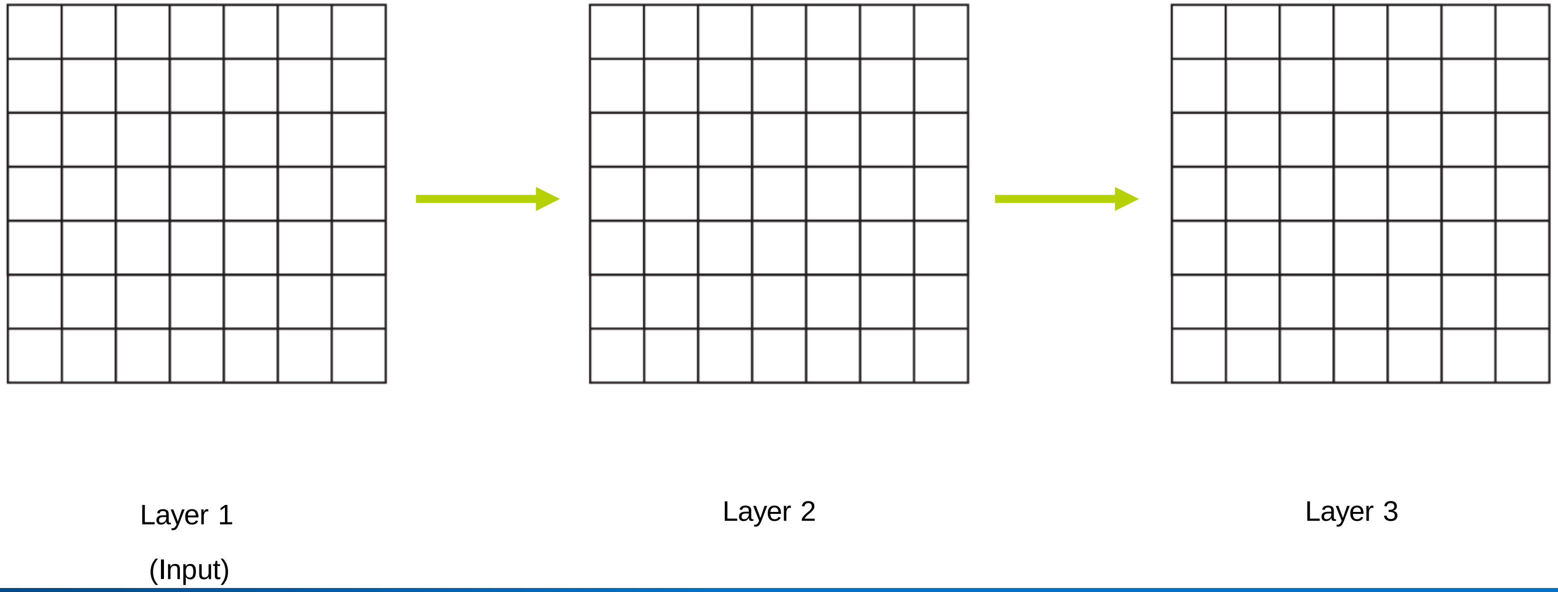
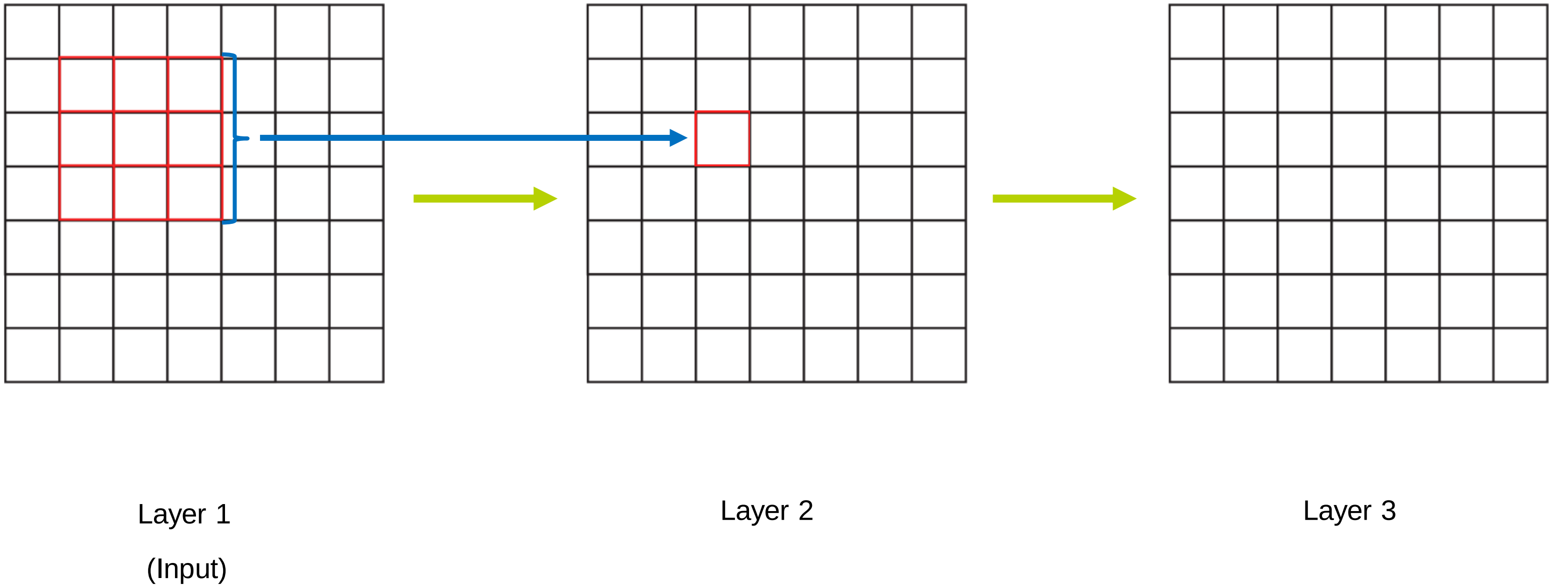
VGG



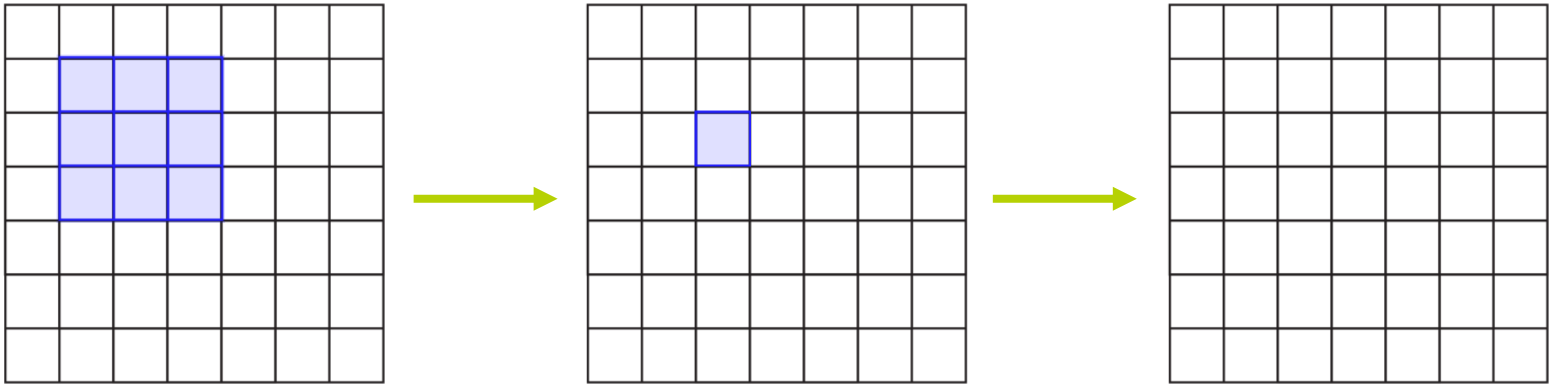
VGG



VGG

We can say that the “receptive field” of Layer 2 is 3x3

Each output has been influenced by a 3x3 patch of inputs



Layer 1

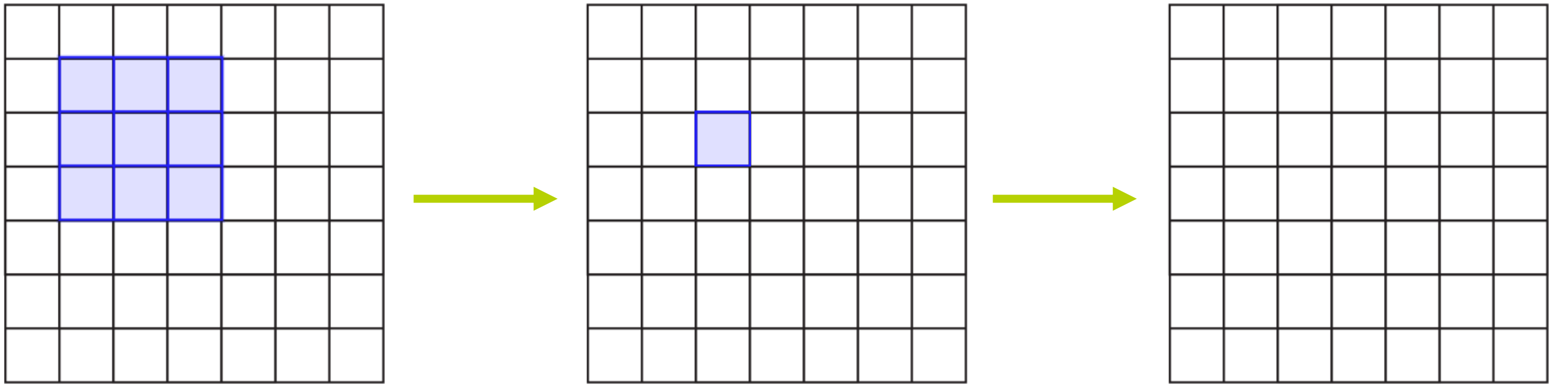
(Input)

Layer 2

Layer 3

VGG

What about on Layer 3?

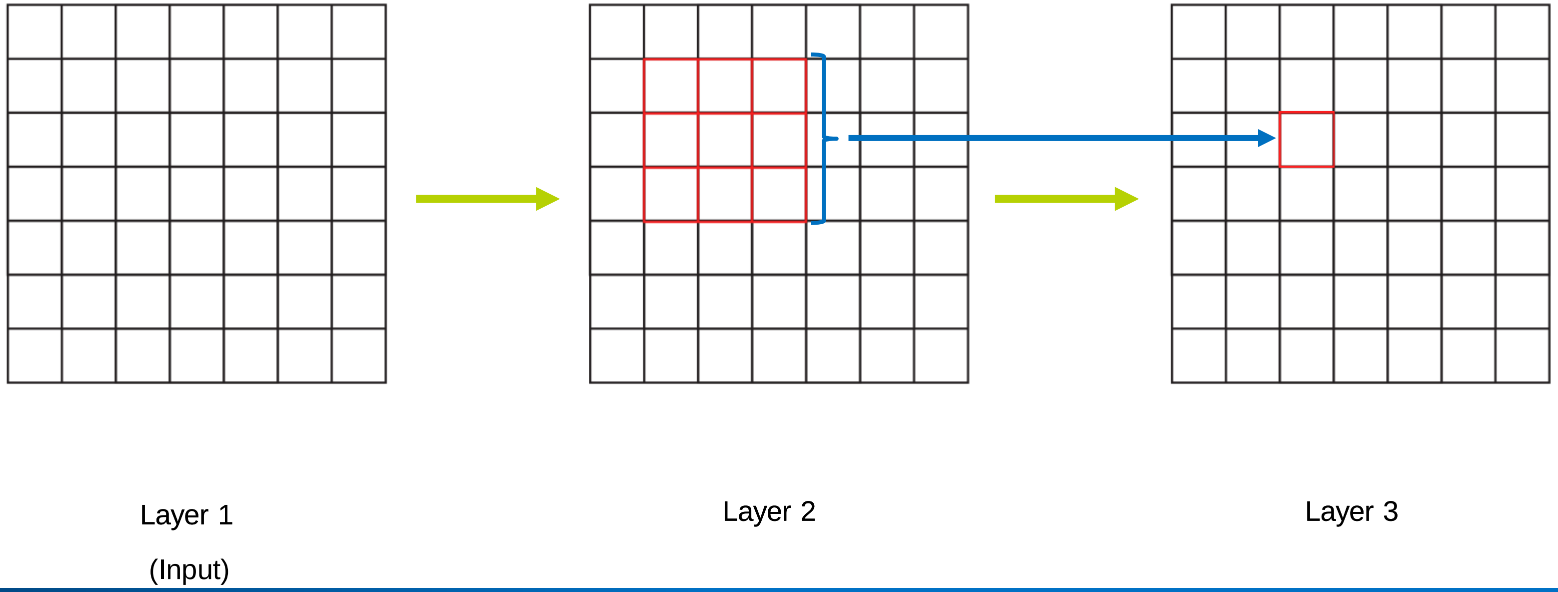


Layer 1 (Input) | Layer 2 | Layer 3

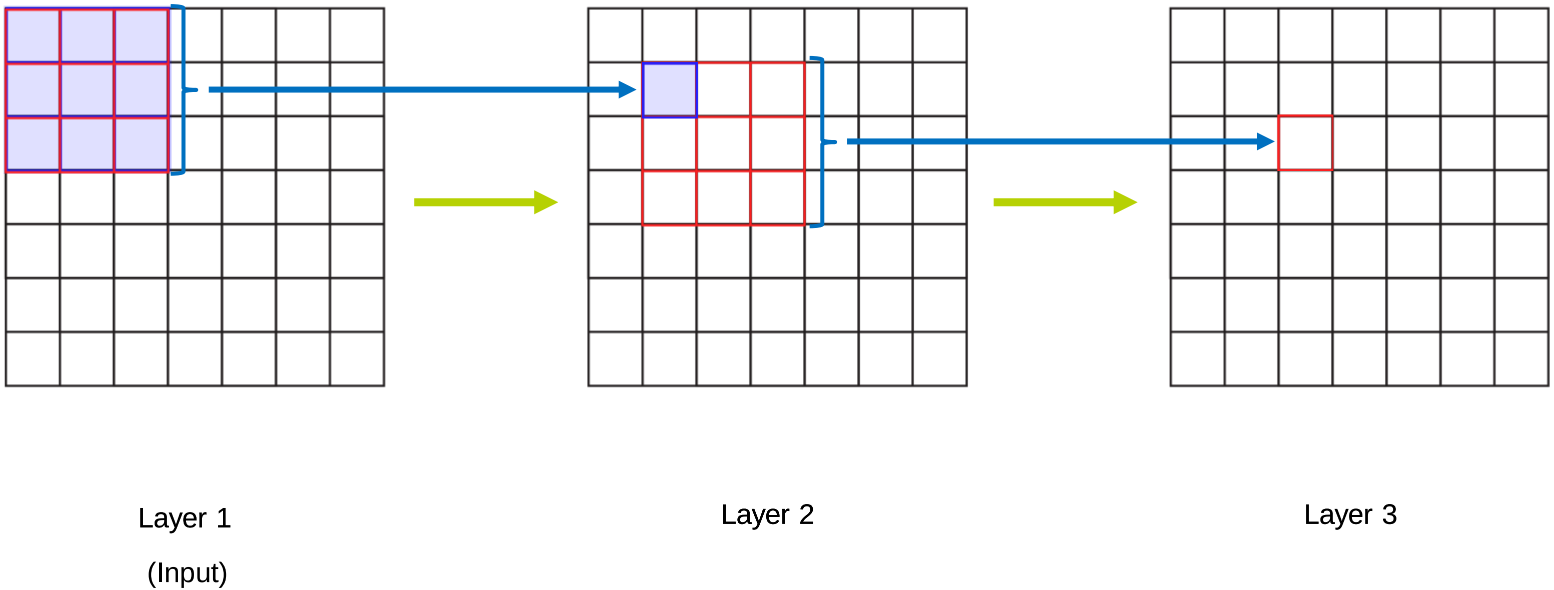
VGG

This output on Layer 3 uses a 3x3 patch from Layer 2

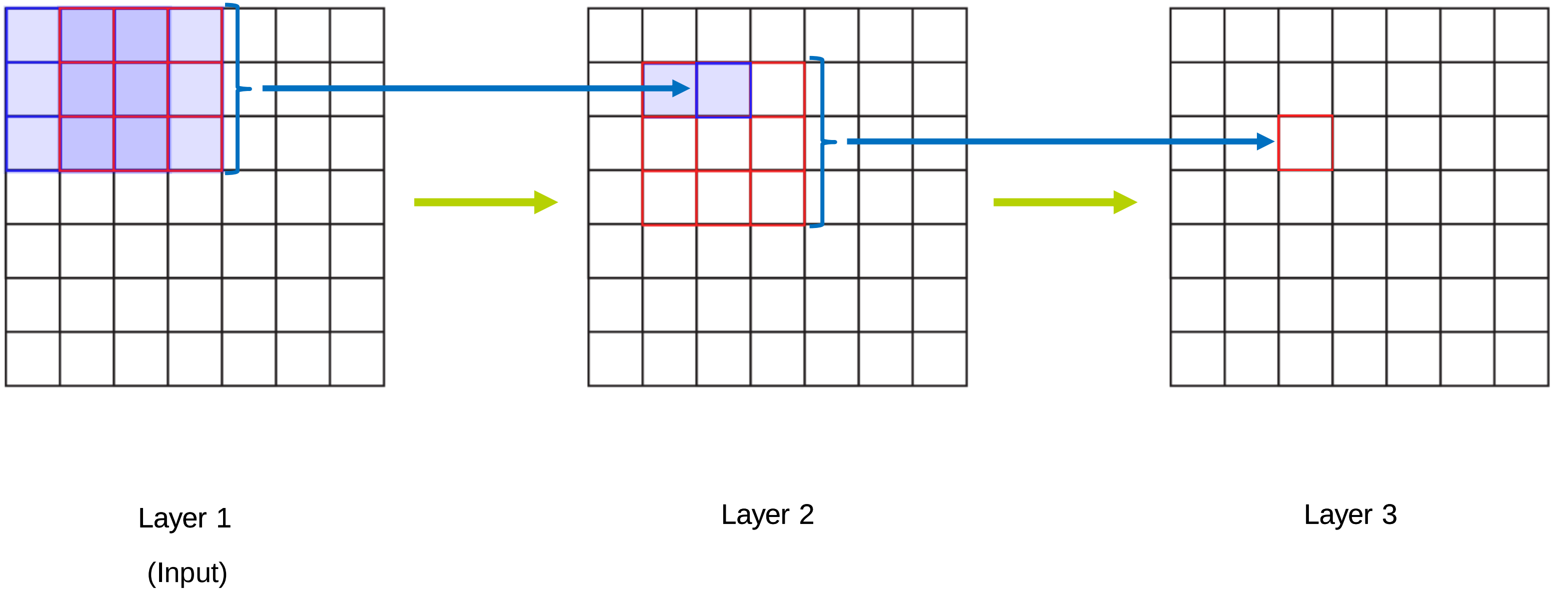
How much from Layer 1 does it use?



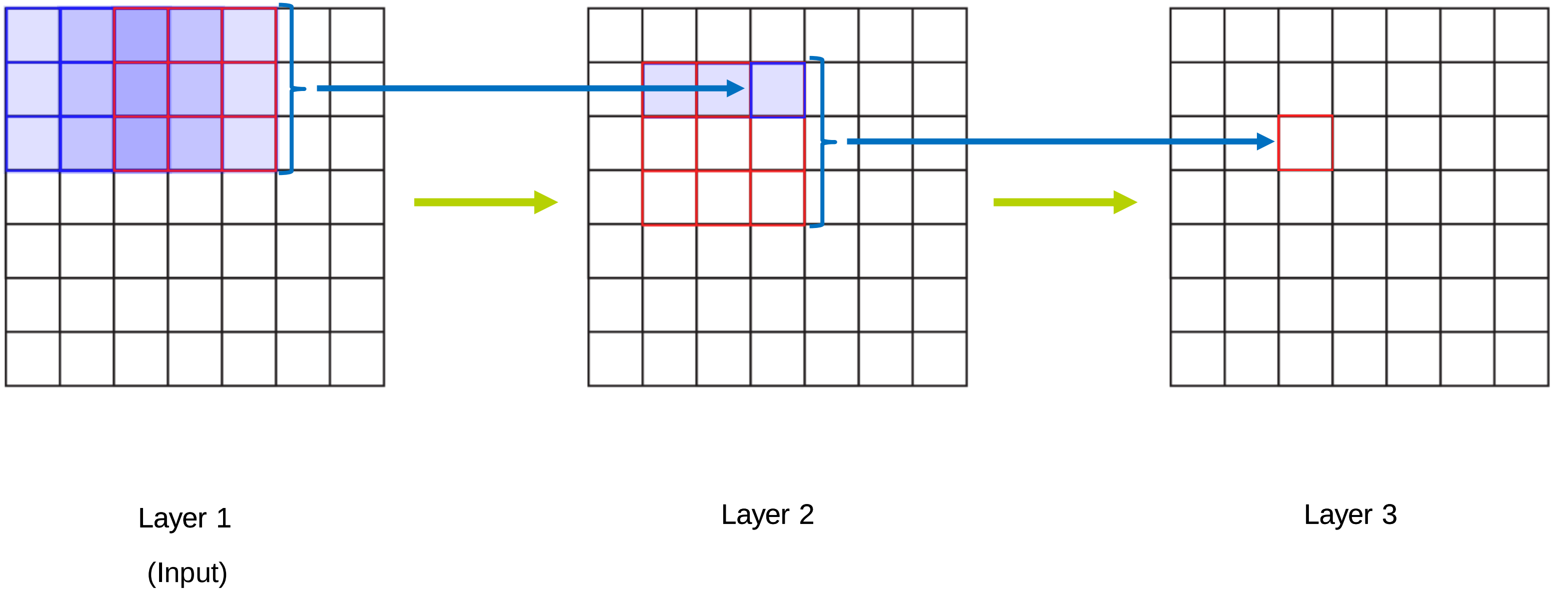
VGG



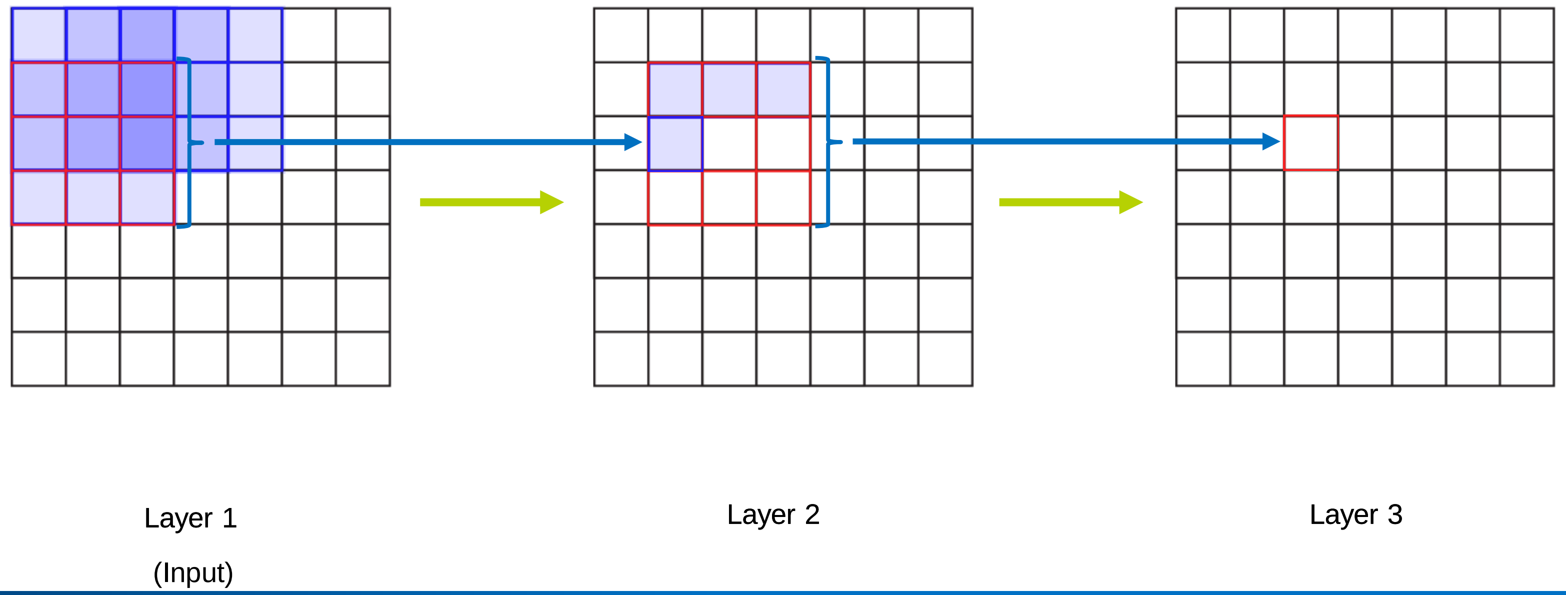
VGG



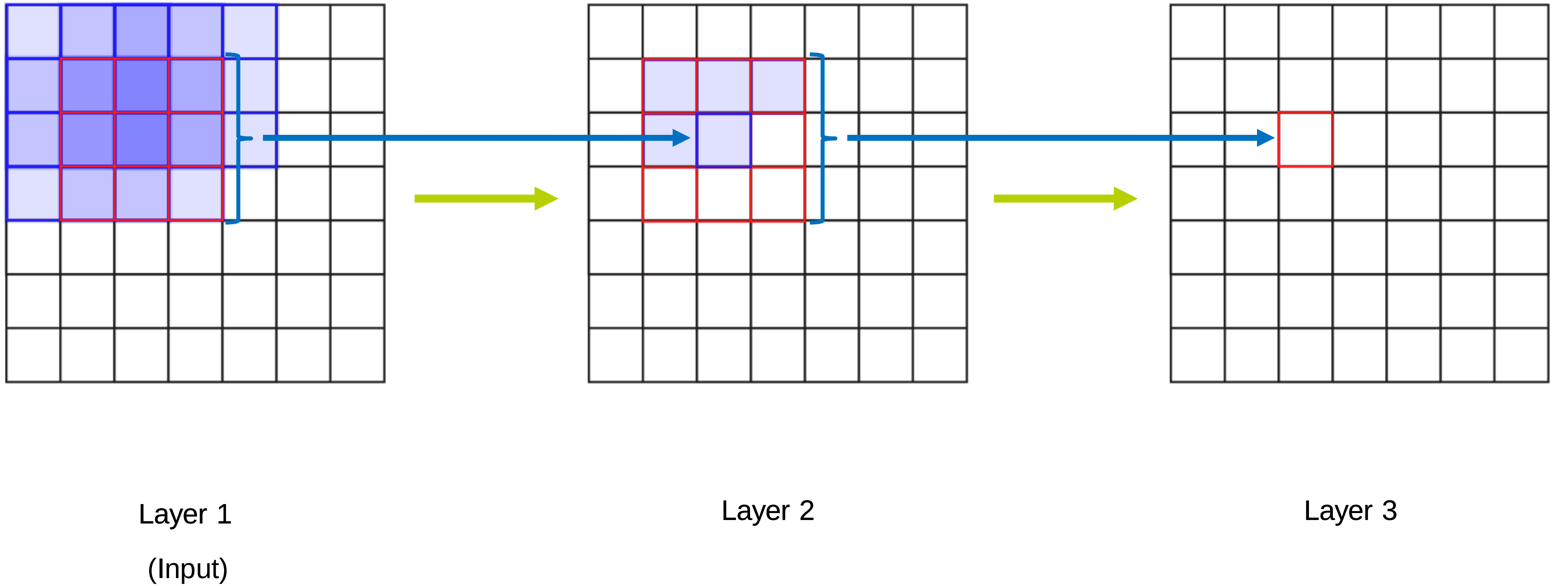
VGG



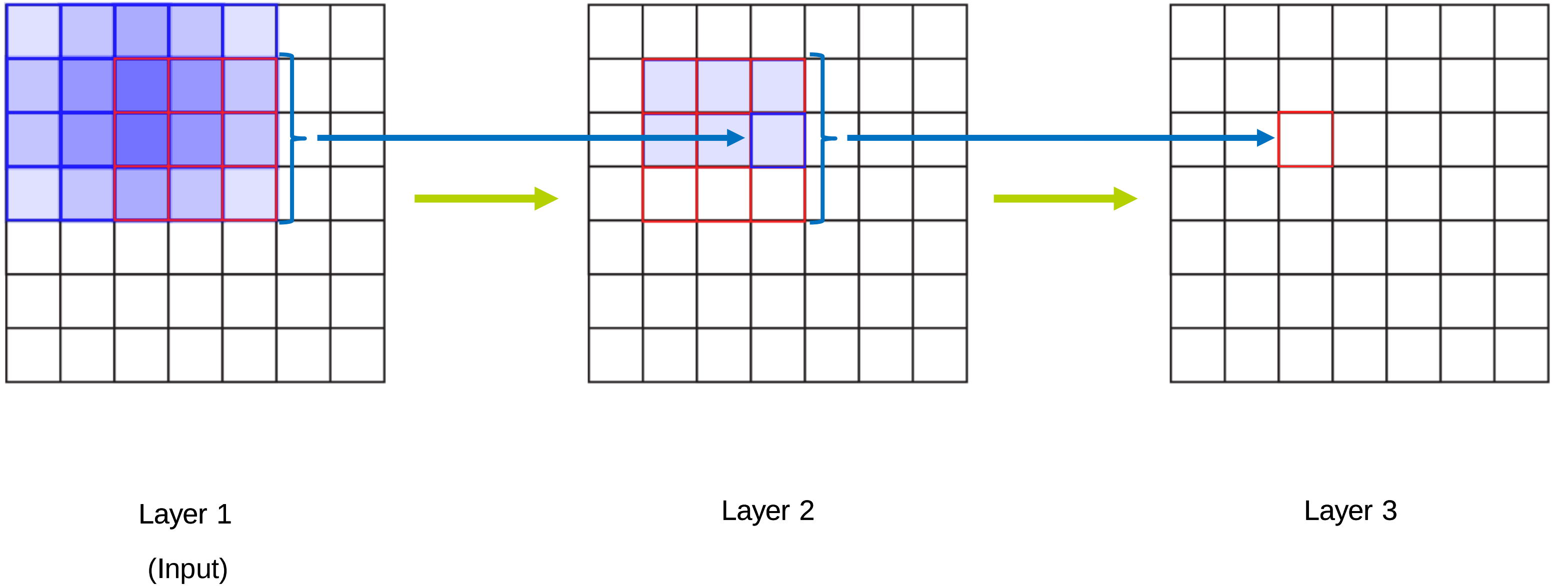
VGG



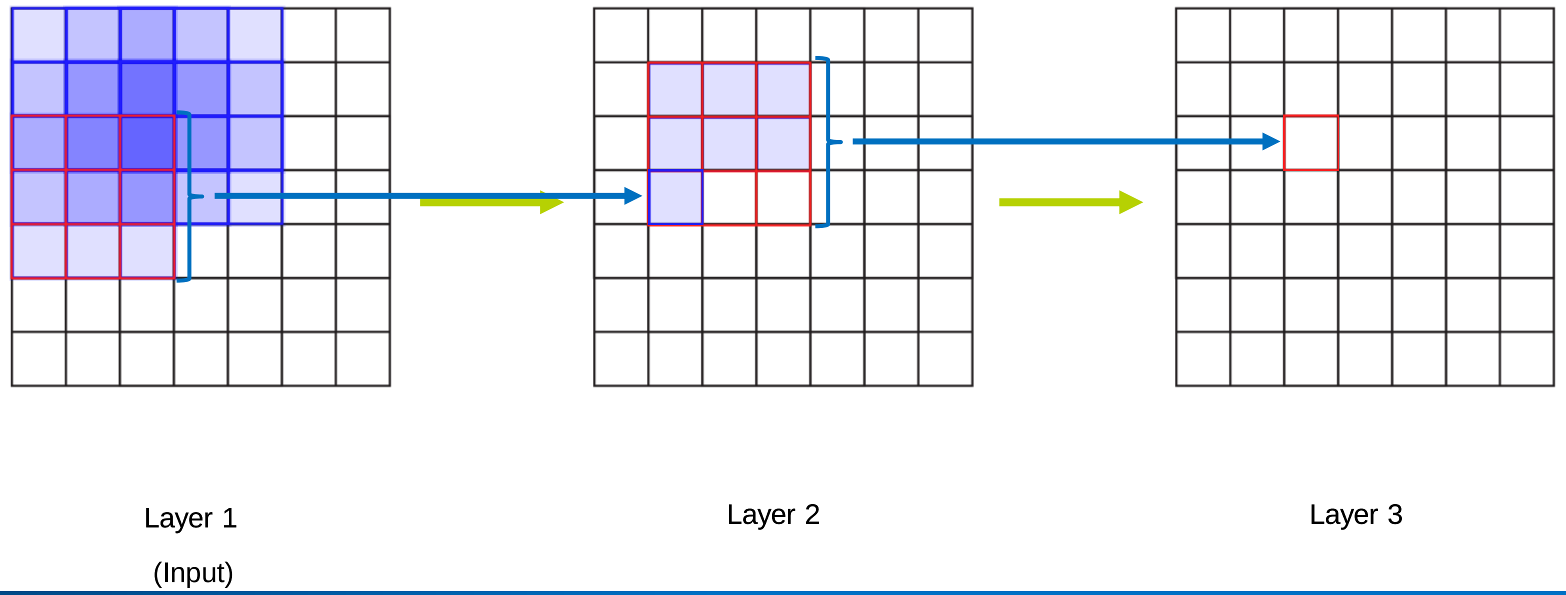
VGG



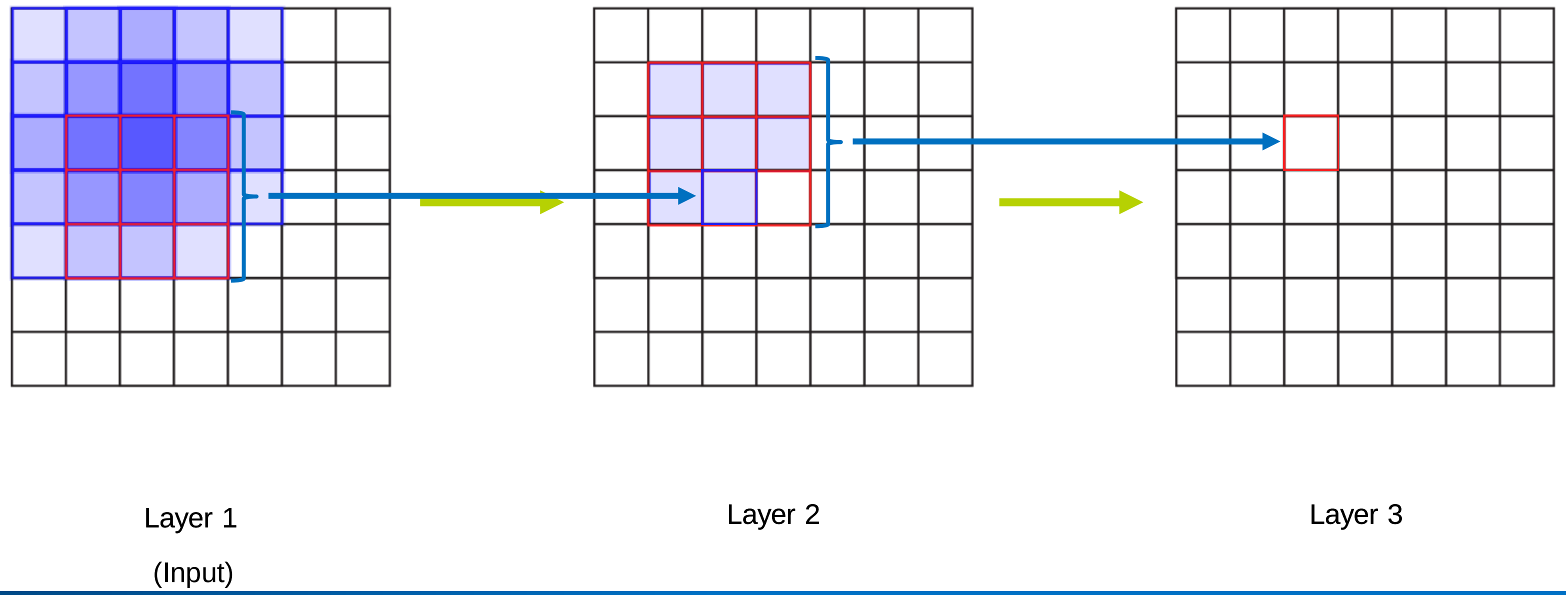
VGG



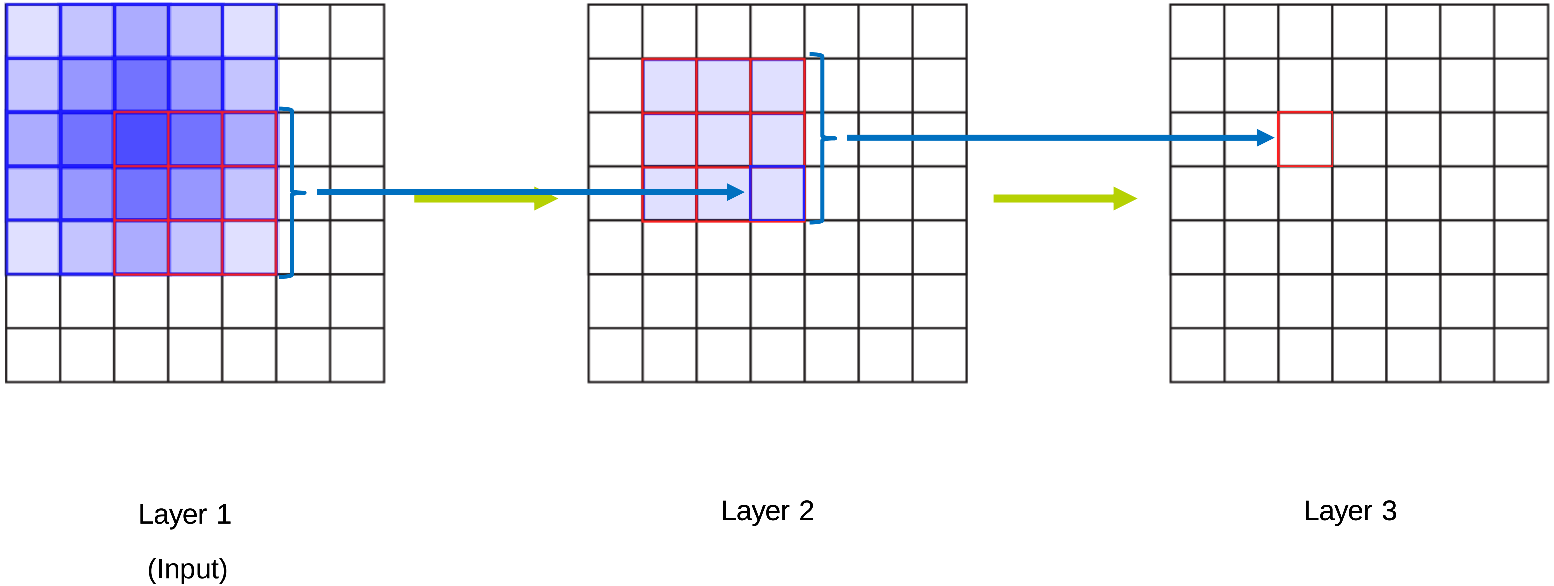
VGG



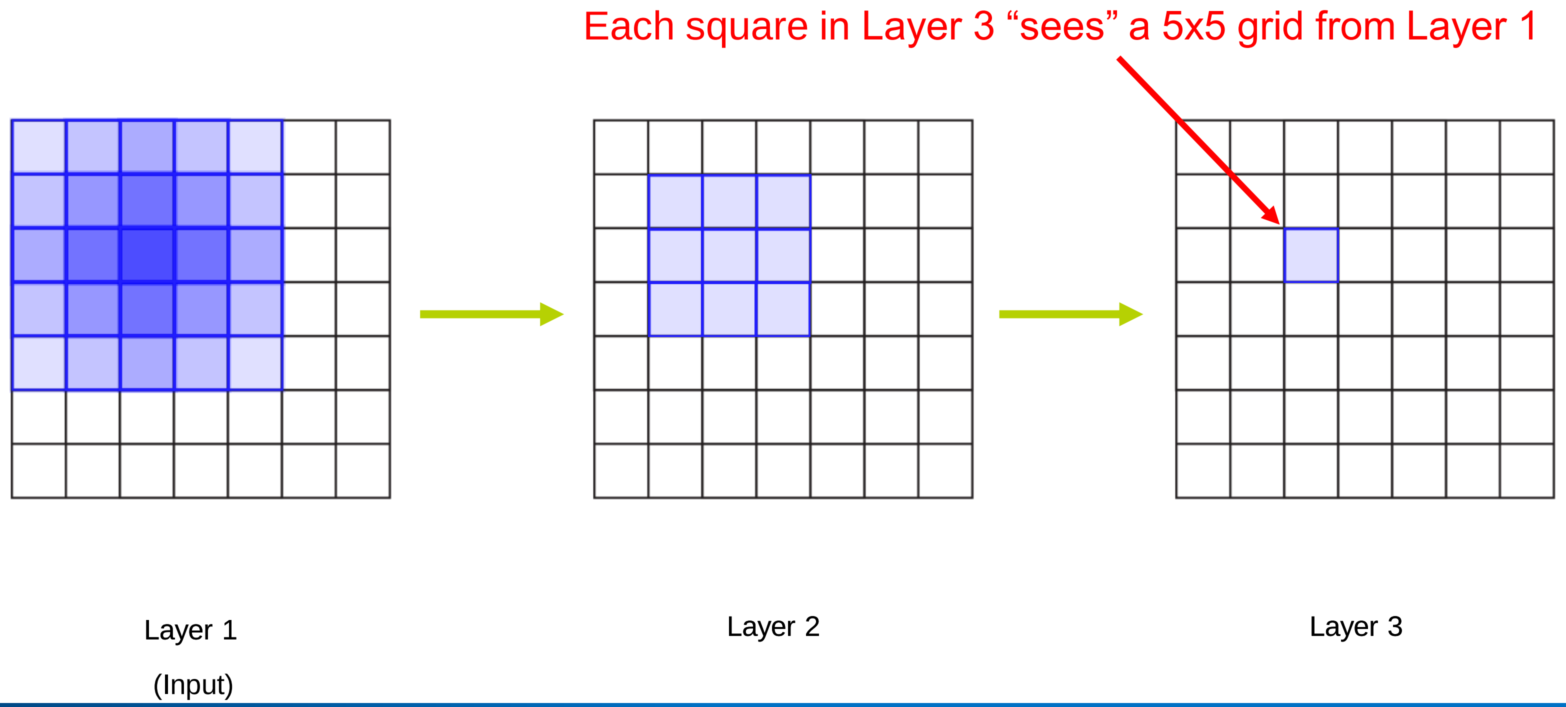
VGG



VGG



VGG


Each square in Layer 3 “sees” a 5x5 grid from Layer 1
Layer 1
(Input)
Layer 2
Layer 3

VGG

Two 3x3, stride 1 convolutions in a row → one 5x5

Three 3x3 convolutions → one 7x7 convolution

Benefit: fewer parameters

One 3x3 layer

$$3 \times 3 \times C = 9C$$

One 7x7 layer

$$7 \times 7 \times C = 49C$$

Three 3x3 layers

$$3 \times (9C) = 27C$$

$49C$ → $27C$ → ≈45% reduction!

VGG

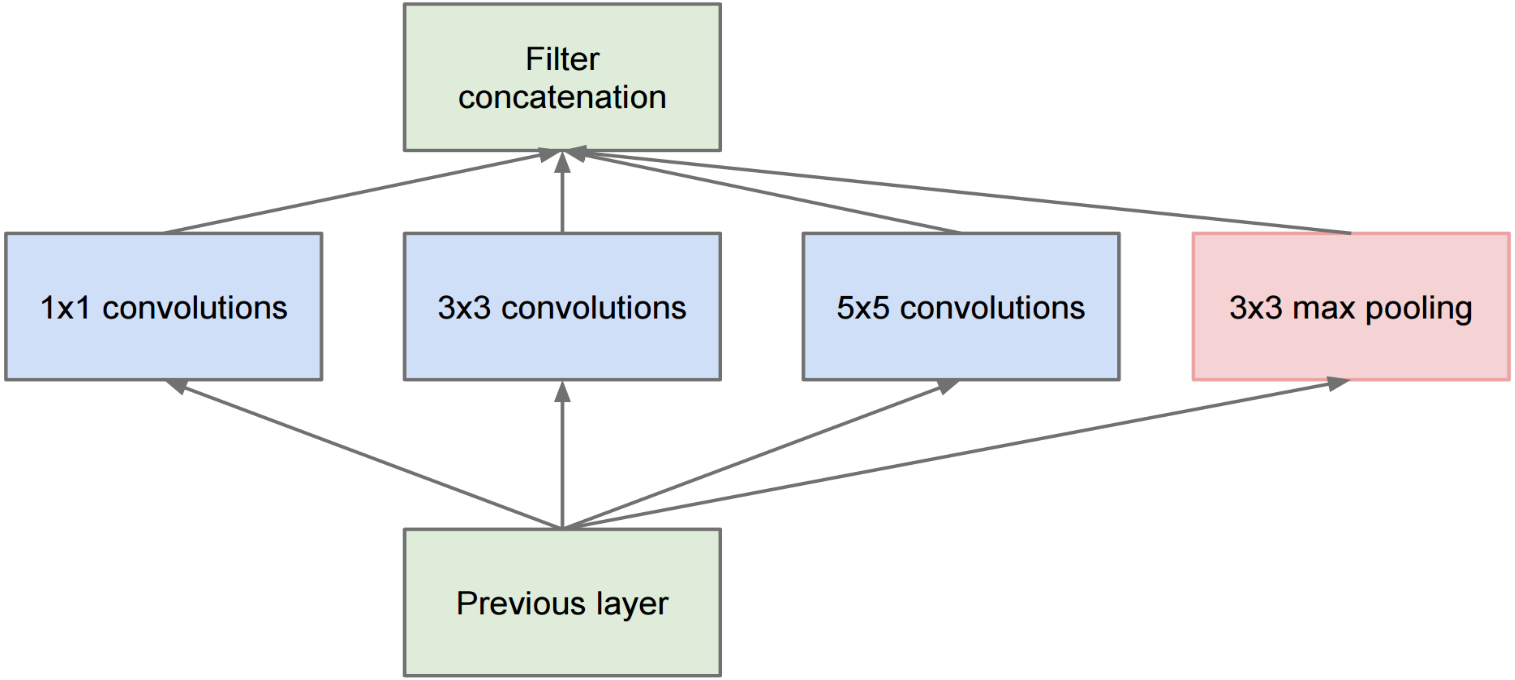
- One of the first architectures to experiment with many layers (More is better!)
- Can use multiple 3x3 convolutions to simulate larger kernels with fewer parameters
- VGGNet has a total of 138 million parameters, which is more than twice that of AlexNet
- Often used as a starting point for transfer learning because of its simple architecture
- Served as ”base model” for future works

Inception

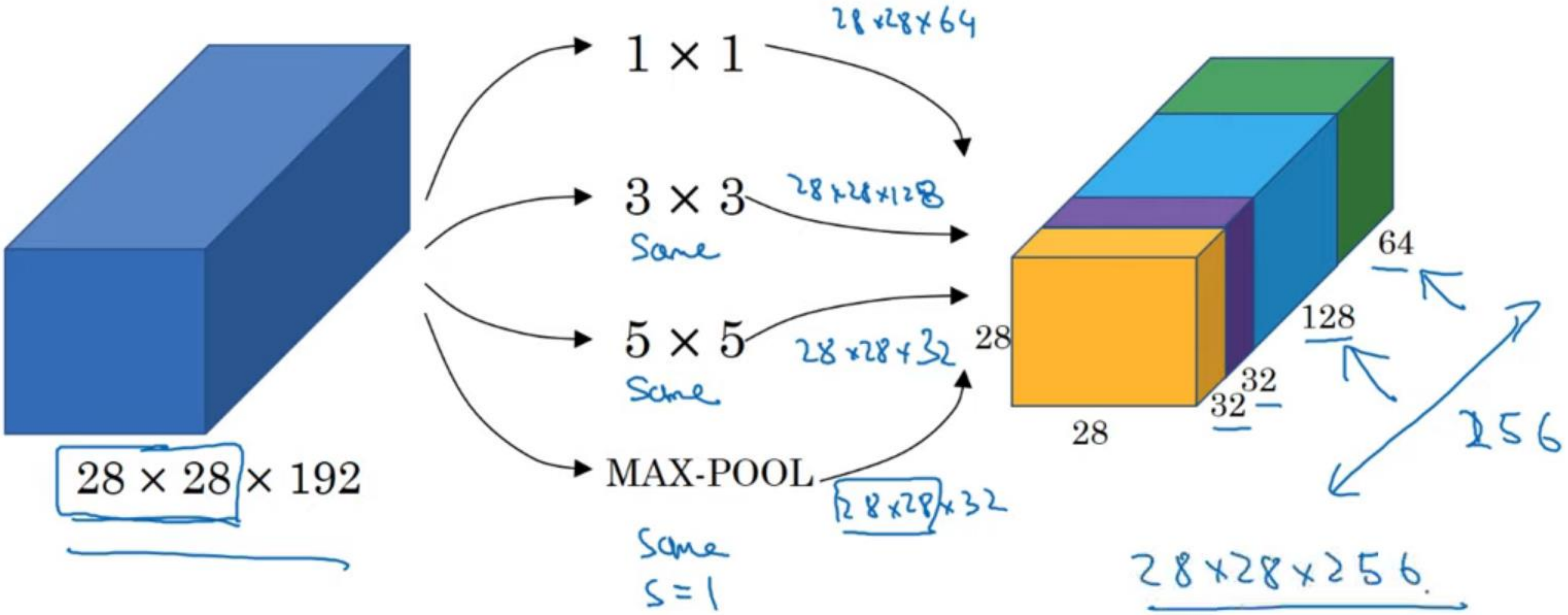
- Szegedy et al 2014
- Inception architecture-based GoogLeNet, was the winner of the 2014 ImageNet challenge, with a 6.7% top five error rate
- Idea: network would want to use different receptive fields
- Want computational efficiency
- Solution: Turn each layer into branches of convolutions
- Each branch handles smaller portion of workload
- Concatenate different branches at the end

Inception

Basic idea: replace single 3x3 convolutions with module

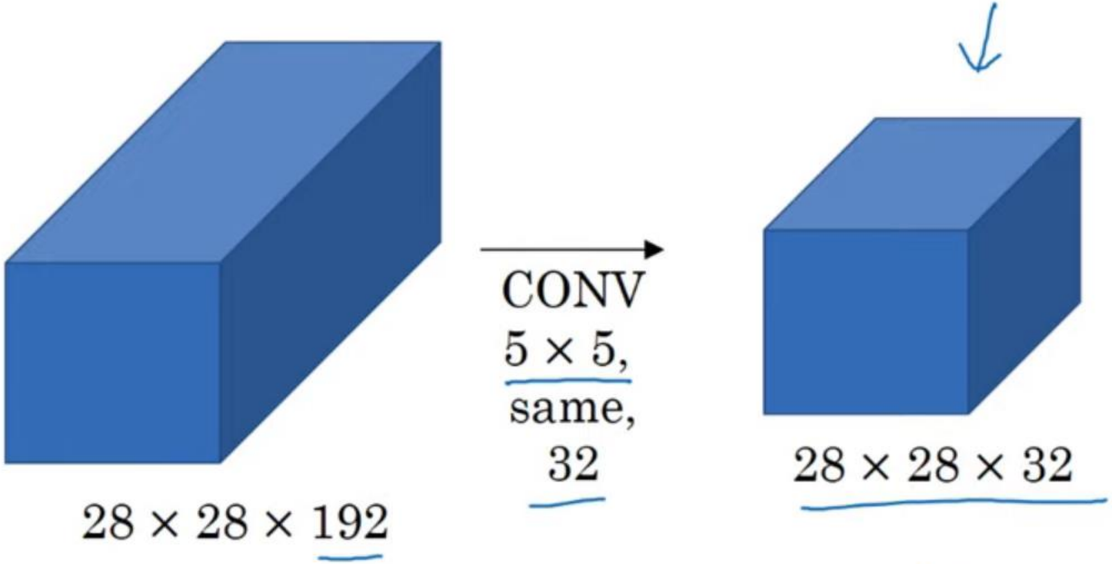


Motivation for inception network



[Szegedy et al. 2014. Going deeper with convolutions]

The problem of computational cost

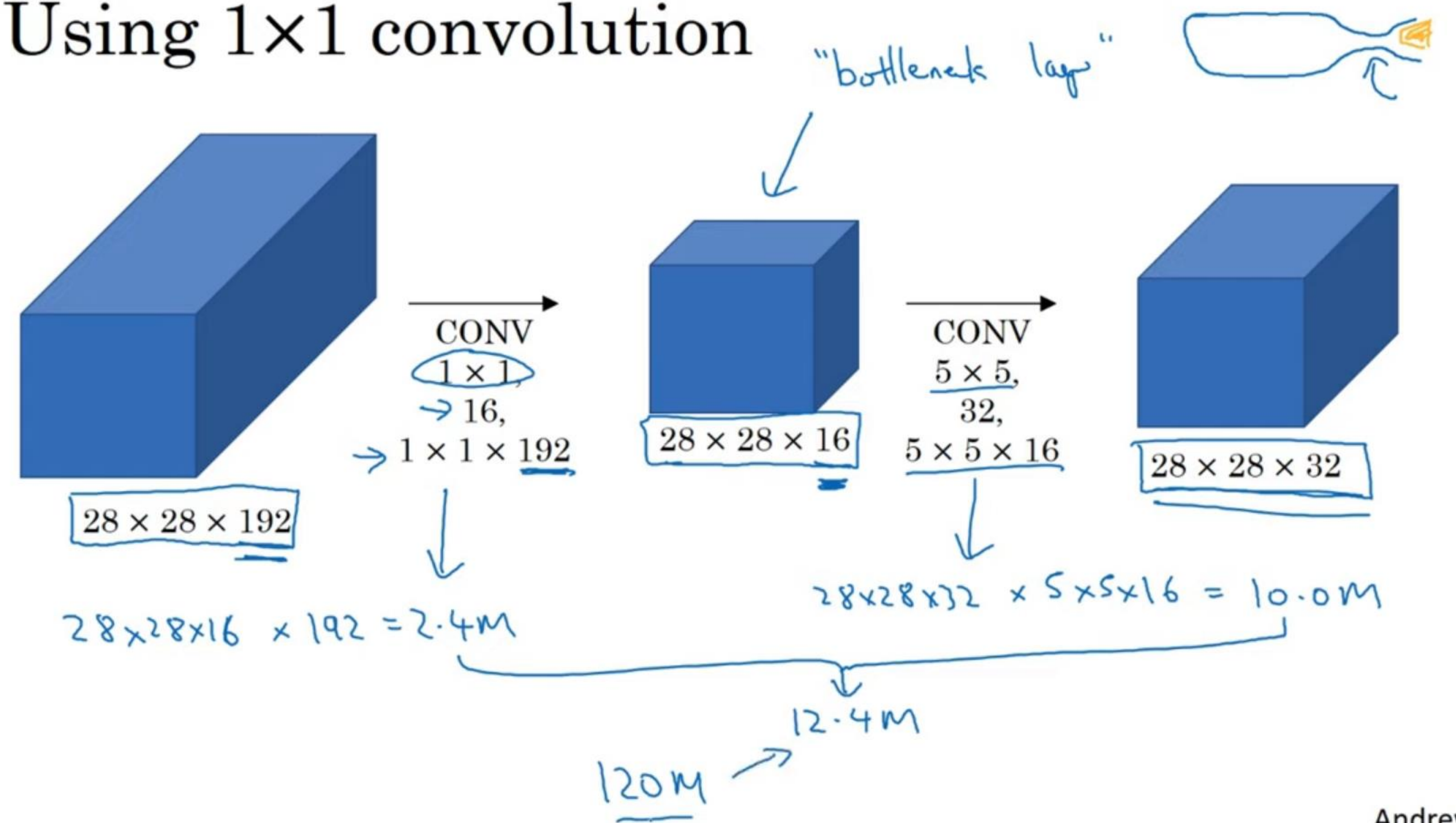


32 filters.

filters are 5×5×192 multiplications

28×28×32 × 5×5×192 = 120M

Using 1×1 convolution



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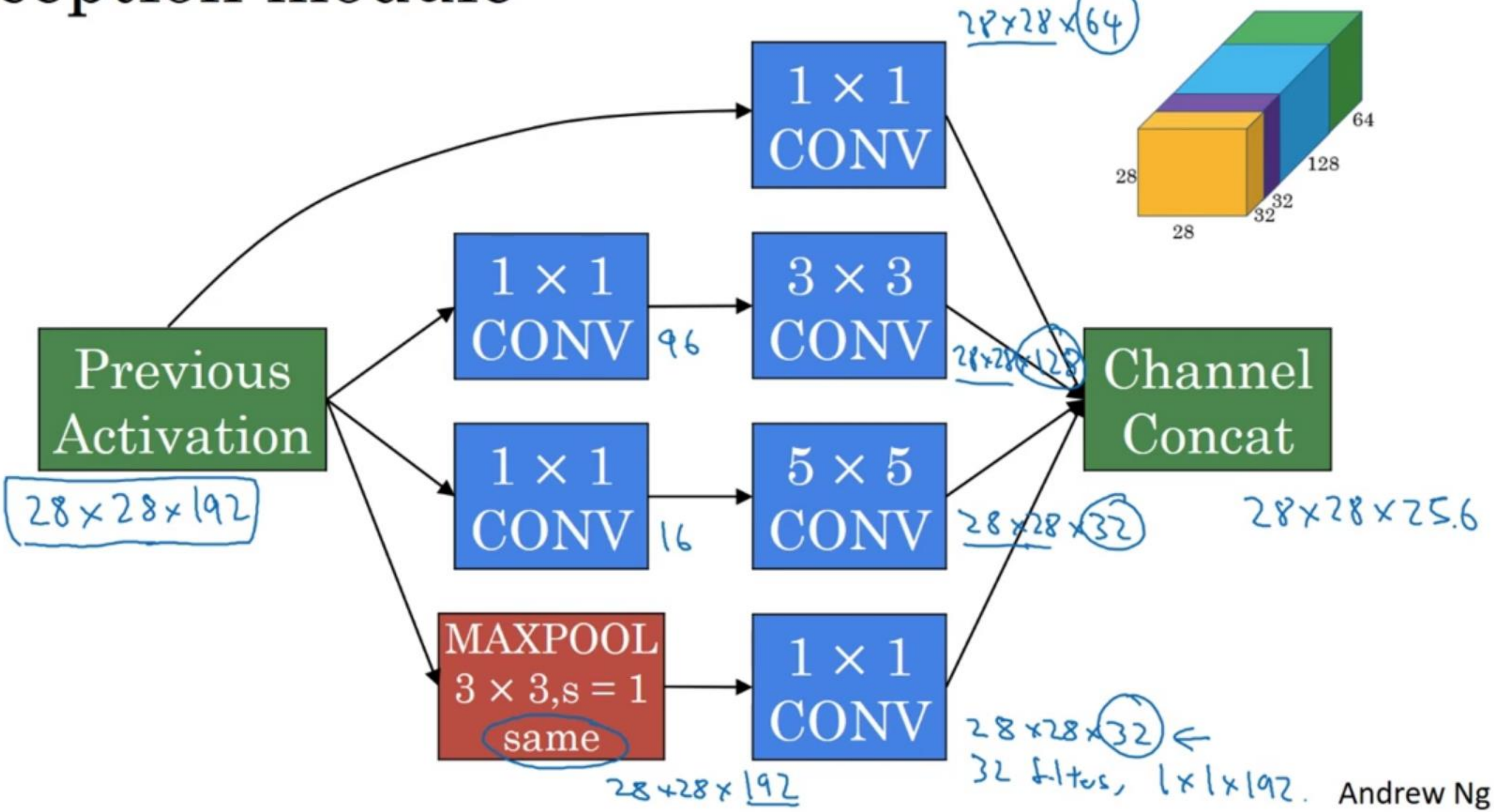
Inception module



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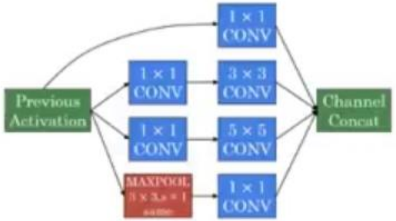
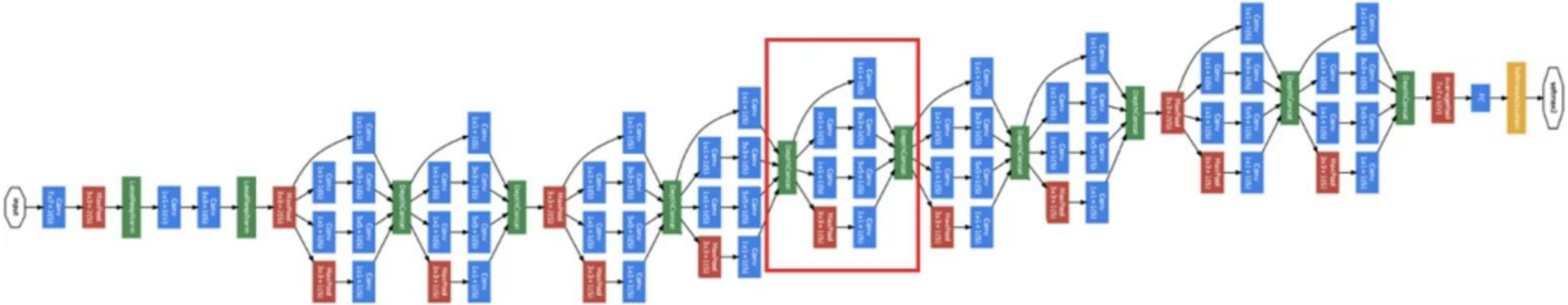
Inception network





[Szegedy et al., 2014, Going Deeper with Convolutions]

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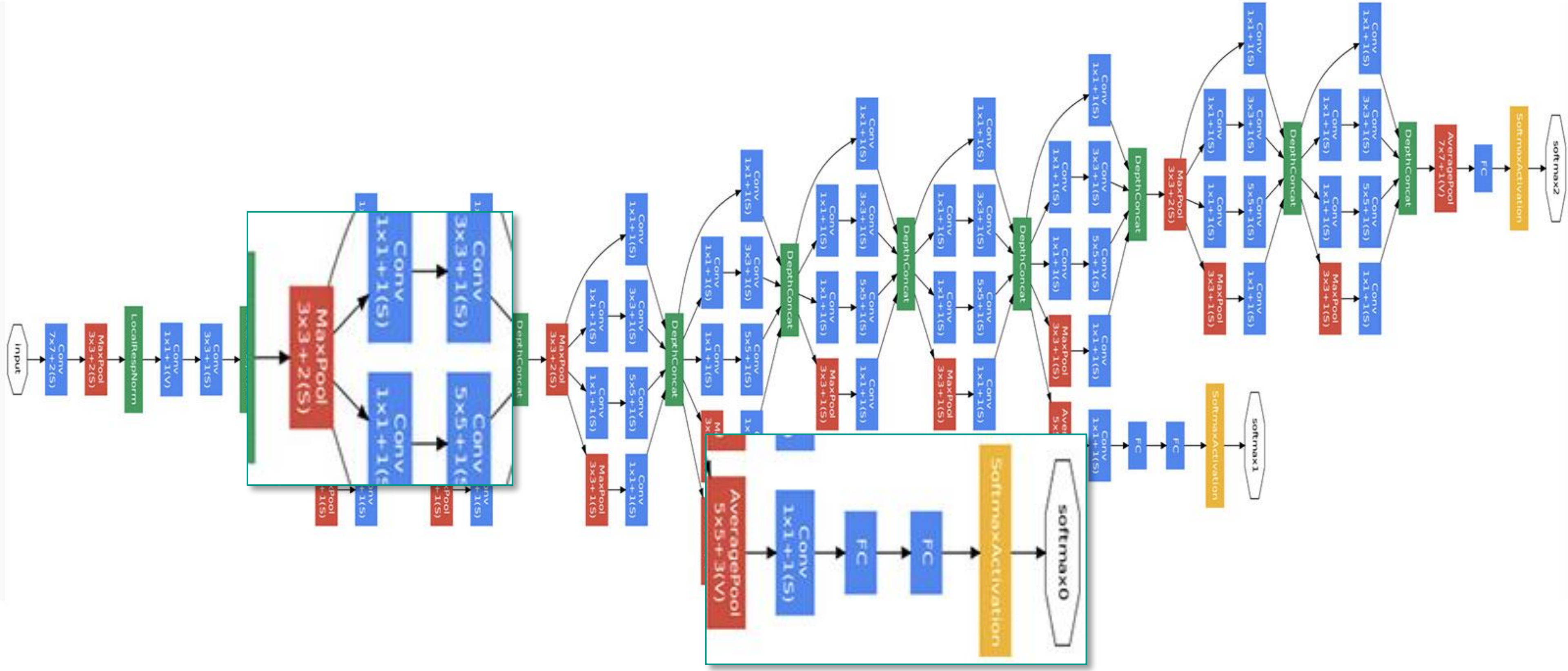
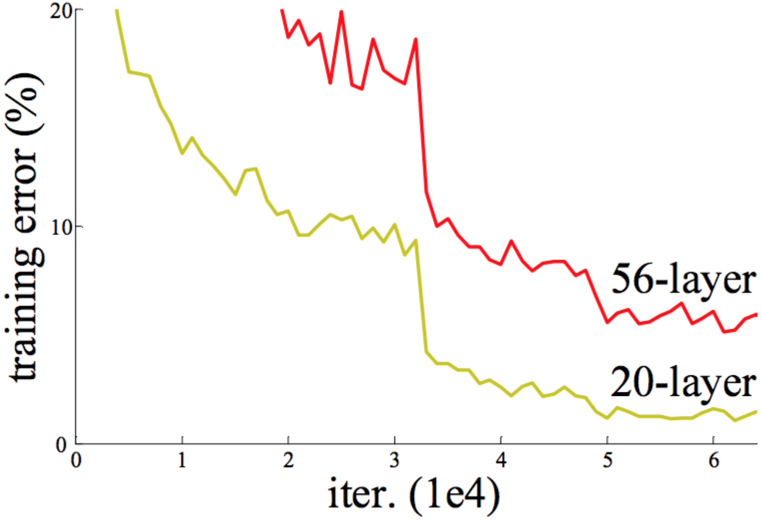
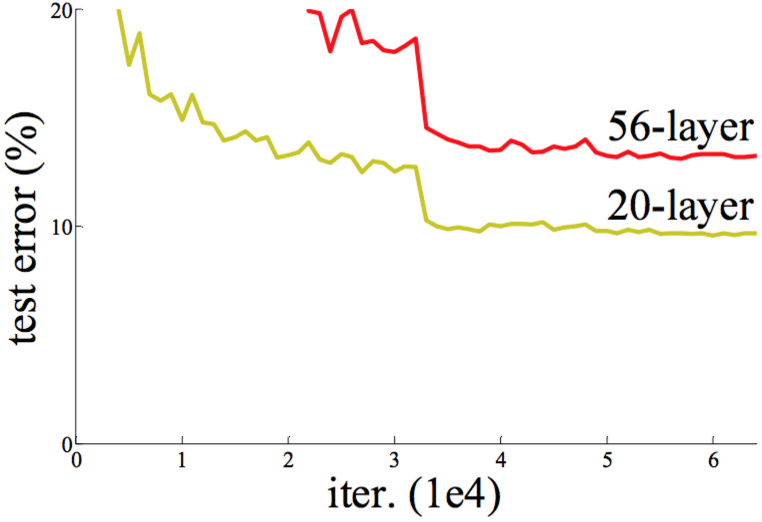


input
MaxPool 3x3+2(S)
Conv 1x1+1(S)
Conv 3x3+1(S)
Conv 5x5+1(S)
DepthConcat
AveragePool 5x5+3(V)
FC
SoftmaxActivation
softmax0
softmax1
softmax2

ResNet - Motivation

Issue: Deeper Networks performing worse on **training** data!
(as well as test data)



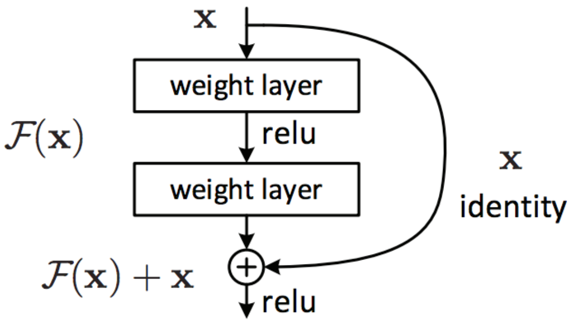


ResNet

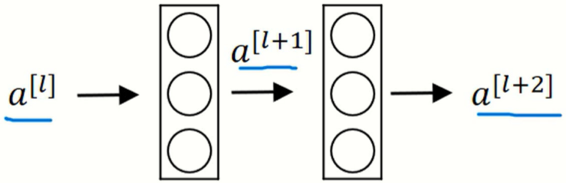
- Surprising because deeper networks should overfit more.
- So what's happening?
- Early layers of Deep Networks are very slow to adjust.
- Analogous to "Vanishing Gradient" issue.
- In theory, should be able to just have an "identity" transformation that makes the deeper network behave like a shallower one

ResNet

- Assumption: best transformation over multiple layers is close to $\mathcal{F}(x) + x$
- x → input to series of layers
- $\mathcal{F}(x)$ → function represented by several layers (such as convs)
- Enforce this by adding "shortcut connections"
- Add the inputs from an earlier layer to the output of current layer



Residual block



$a^{[l]} \rightarrow$ Linear $\rightarrow$ ReLU $\xrightarrow{a^{[l+1]}}$ Linear $\rightarrow$ ReLU $\rightarrow a^{[l+2]}$

$z^{[l+1]} = W^{[l+1]} a^{[l]} + b^{[l+1]}$ $\quad a^{[l+1]} = g(z^{[l+1]})$ $\quad z^{[l+2]} = W^{[l+2]} a^{[l+1]} + b^{[l+2]}$ $\quad a^{[l+2]} = g(z^{[l+2]})$

[He et al., 2015. Deep residual networks for image recognition]

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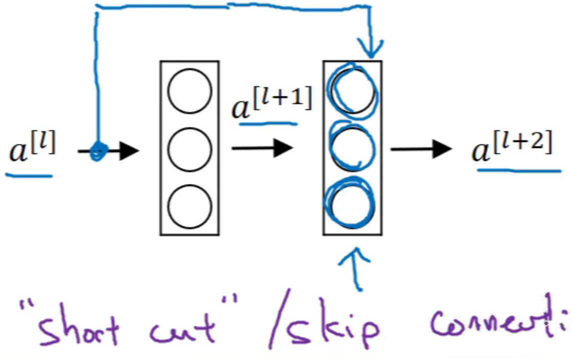
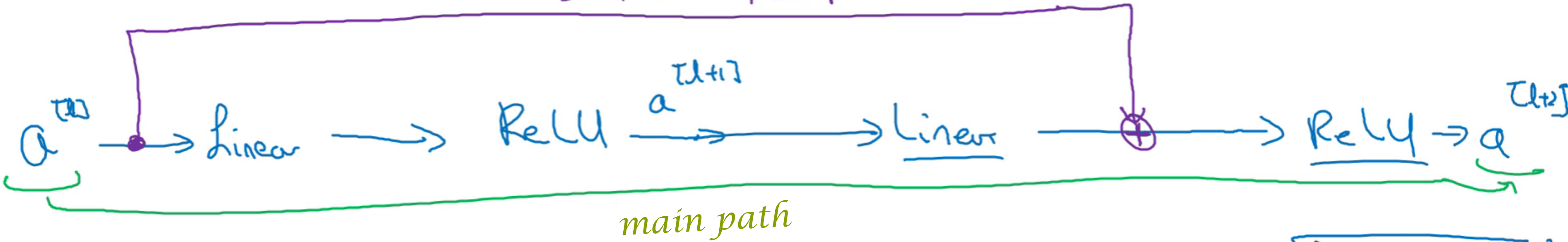
Residual block





$z^{[l+1]} = W^{[l+1]} a^{[l]} + b^{[l+1]}$ $\quad a^{[l+1]} = g(z^{[l+1]})$ $\quad z^{[l+2]} = W^{[l+2]} a^{[l+1]} + b^{[l+2]}$ $\quad \boxed{\cancel{a^{[l+2]} = g(z^{[l+2]})}}$

$$a^{[l+2]} = g\left(z^{[l+2]} + a^{[l]}\right)$$

[He et al., 2015. Deep residual networks for image recognition]

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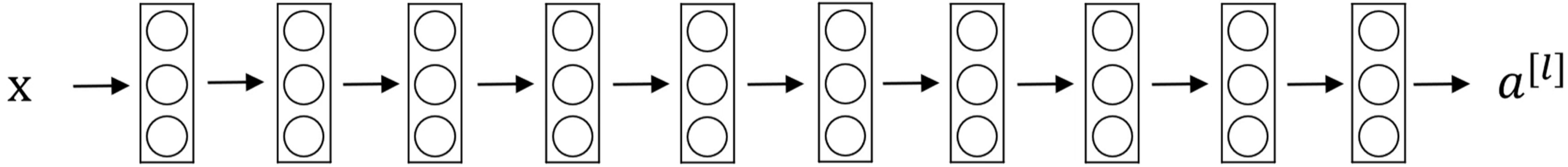
Residual Network

plain network



[He et al., 2015. Deep residual networks for image recognition]

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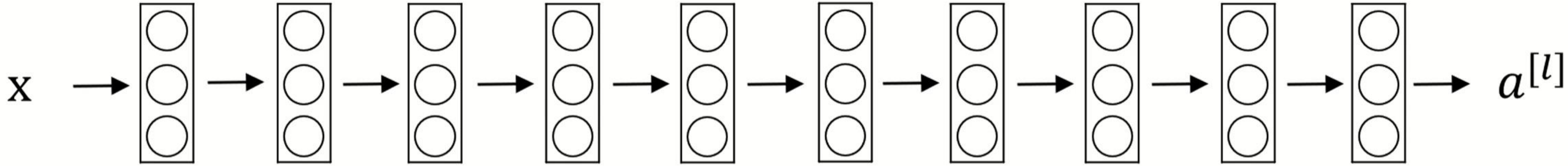
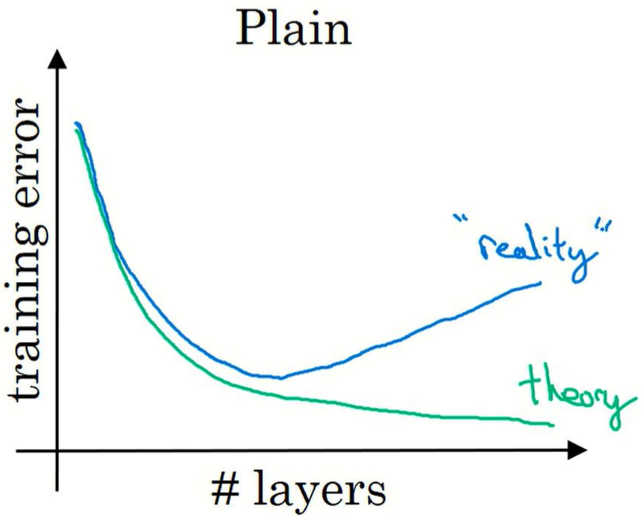
Residual Network

plain network

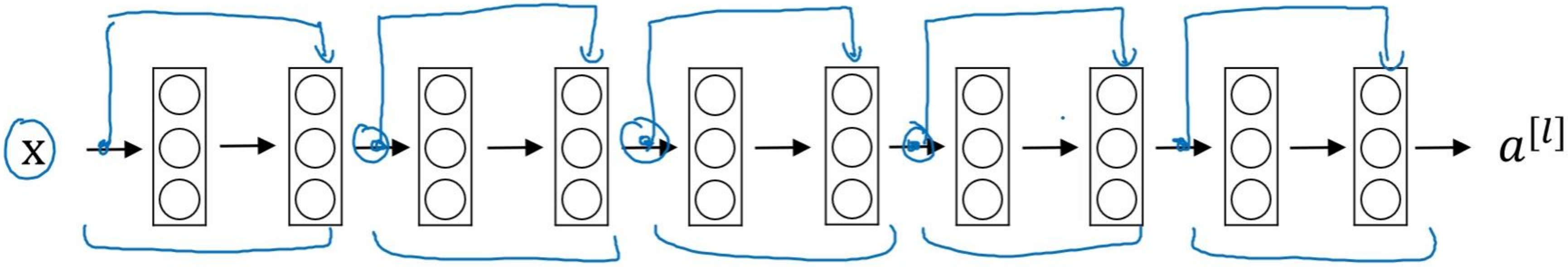


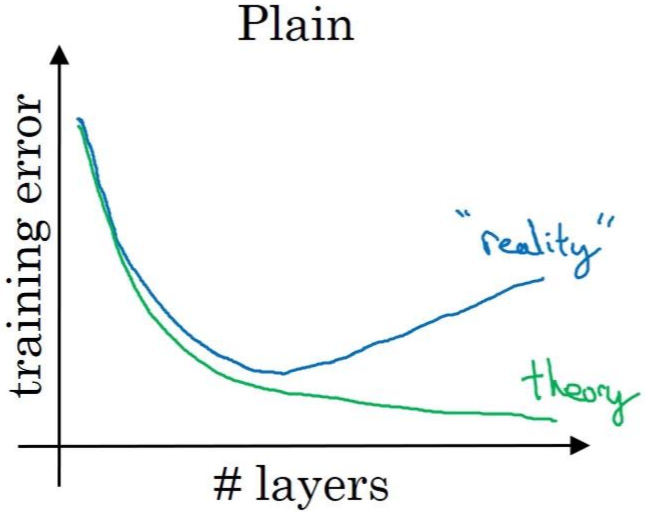


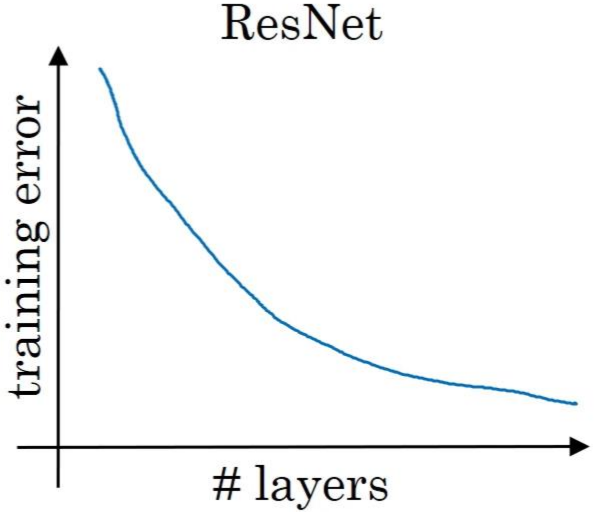
[He et al., 2015. Deep residual networks for image recognition]

Residual Network

with residual blocks

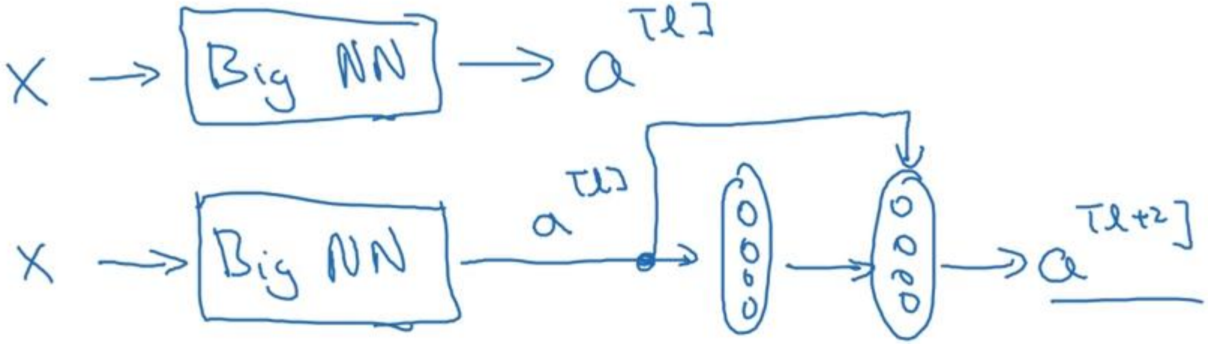






[He et al., 2015. Deep residual networks for image recognition]

Why do residual networks work?



ReLU. $a \geq 0$

$$a^{[l+2]} = g(\underline{z^{[l+2]}} + \underline{a^{[l]}})$$

$$= g(\underline{W^{[l+2]} a^{[l+1]} + b^{[l+2]}} + a^{[l]}$$

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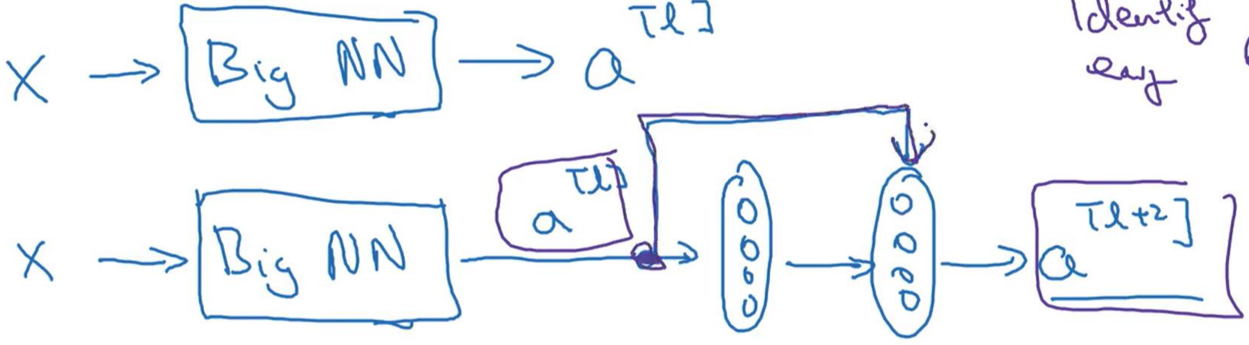
Why do residual networks work?



Identity function is easy for Residual block to learn!

ReLU. $a \geq 0$

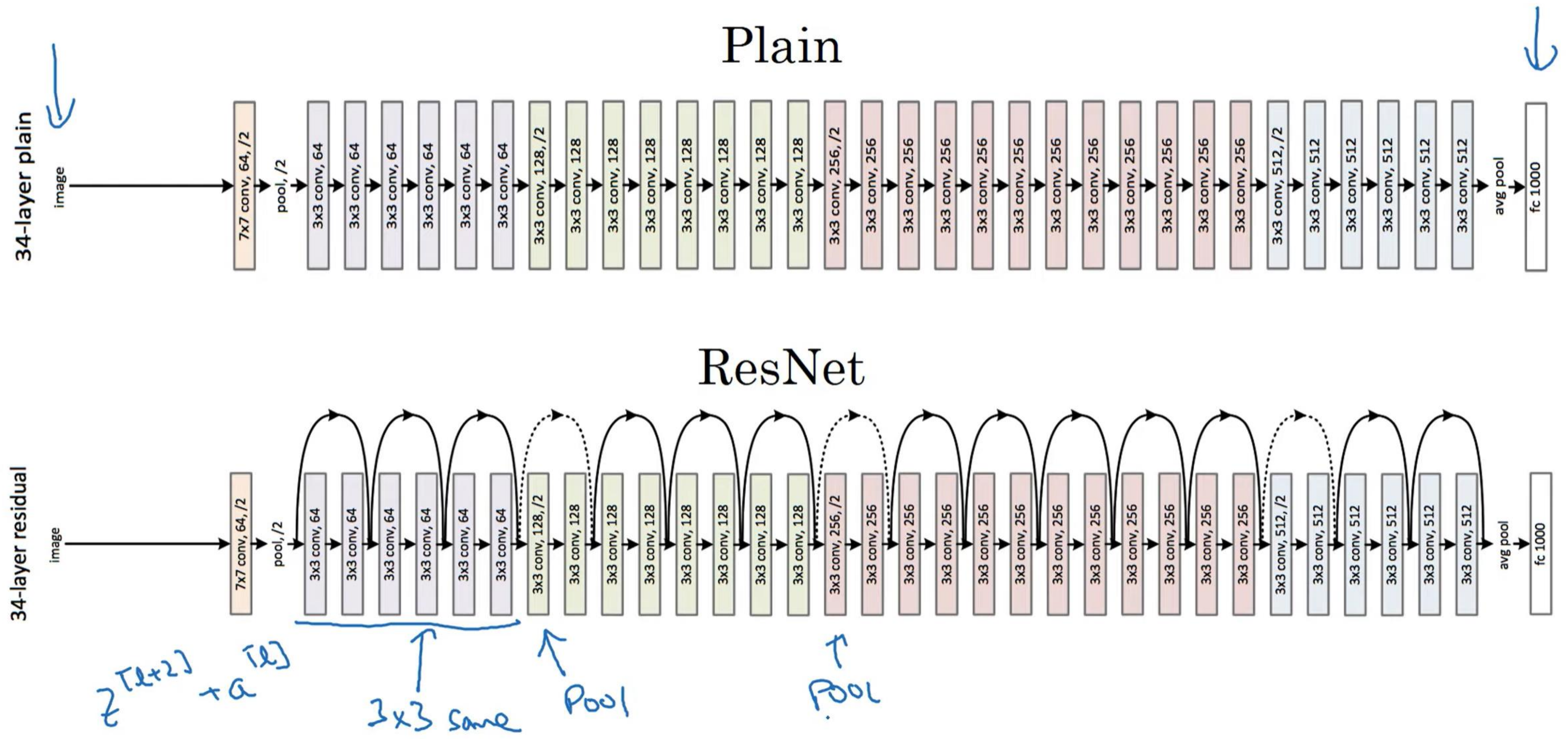
$$a^{[l+2]} = g(z^{[l+2]} + a^{[l]})$$

$$= g(\cancel{W^{[l+2]} a^{[l+1]} + b^{[l+2]}} + a^{[l]}) = g(a^{[l]})$$

$$= a^{[l]}$$

If $W^{[l+2]} = 0$, $b^{[l+2]} = 0$

ResNet



[He et al., 2015. Deep residual networks for image recognition]

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ResNet

- ResNet uses 152 layers and achieved 3.6% top five error to win the 2015 ImageNet competition.
- This exceeds average human ability.
- ResNet was faster to train than VGGNet, which has only 20 layers.

Software