Chapter 4: Deep Learning- Case Study

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Case Studies

Convolutional Neural Networks

Outline

1. **Case studies**
    1. Why look at case studies?
    2. Classic Networks
    3. ResNets
    4. Why ResNets Work
    5. Networks in Networks and 1x1 Convolutions
    6. Inception Network Motivation
    7. Inception Network
2. **Practical advices for using ConvNets**
    1. Using Open-Source Implementation
    2. Transfer Learning
    3. Data Augmentation
    4. State of Computer Vision

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Case Studies

Why look at case studies?

Why look at case studies?

- We learned about the basic building blocks such as convolutional layers, proving layers and fully connected layers of conv nets.
- And one of the best ways for you to get intuition yourself is to see some of these examples.
- We'll first show you a few classic networks.
  - The LeNEt-5 network which came from, I guess, in 1980s,
  - AlexNet which is often cited and
  - The VGG (Visual Geometry Group) network and these are examples of pretty effective neural networks.
  - The ResNet neural network trained a very, very deep 152-layer neural network

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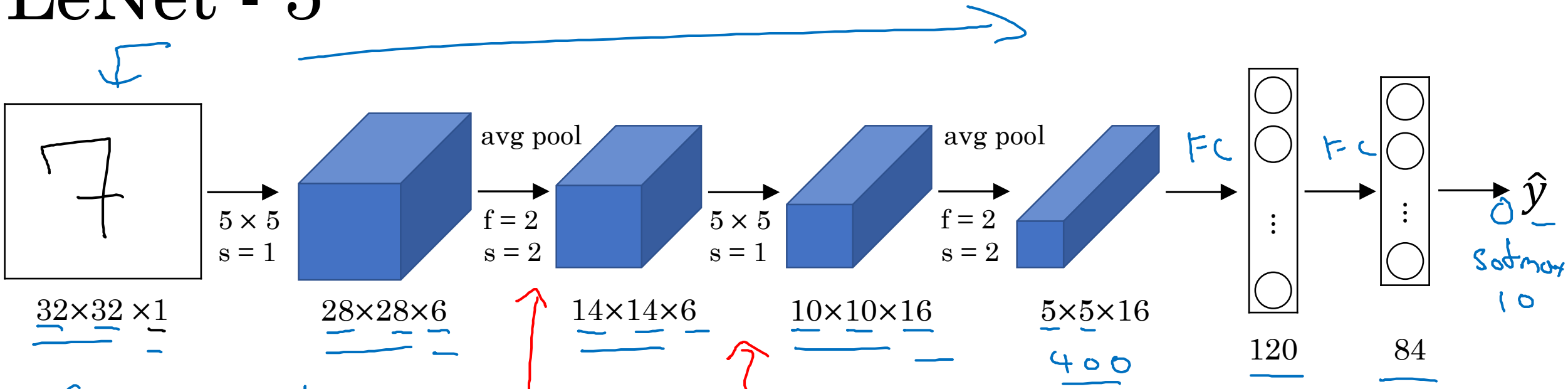
Case Studies

Classic networks

LeNet - 5



60k parameters.

$n_H, n_w \downarrow$ $n_c \uparrow$

Non-linearity after pooling

$n_{H} \times n_{w} \times n_c$ $f \times f \times n_c$

conv pool conv pool fc fc output

Advanced: sigmoid/tanh ReLU

II III

[LeCun et al., 1998. Gradient-based learning applied to document recognition]

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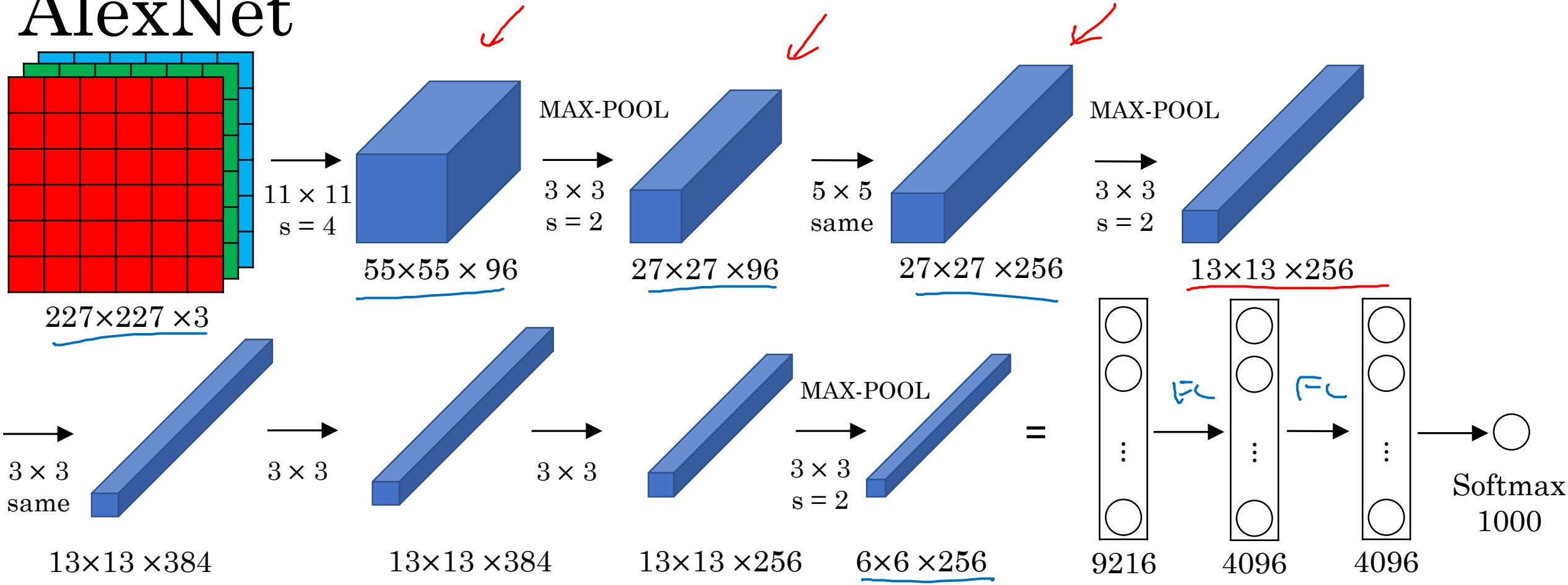
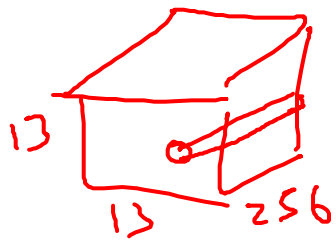
AlexNet



- Similar to LeNet, but much bigger.
- ReLU
- Multiple GPUs.
- Local Response Normalization (LRN)

9216

60M parameters



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

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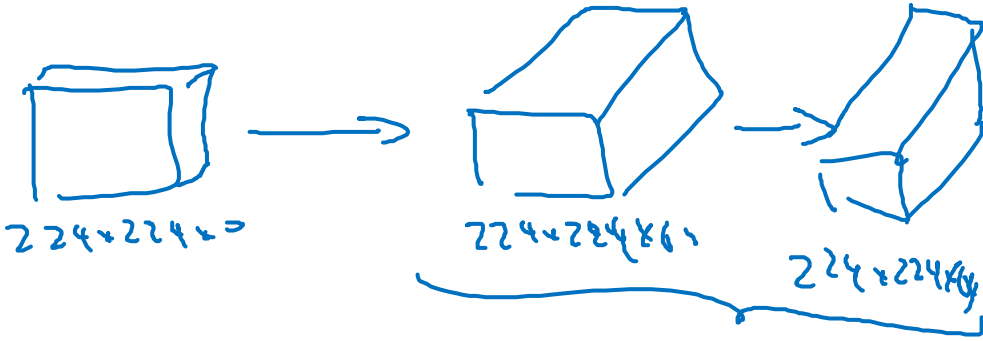
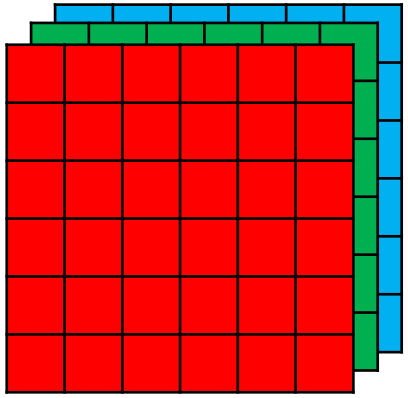
VGG - 16

VGG-19

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





224×224 ×3

→ [CONV 64] ×2 → 224×224×64 → POOL → 112×112 ×64 → [CONV 128] ×2 → 112×112 ×128 → POOL → 56×56 ×128

→ [CONV 256] ×3 → 56×56 ×256 → POOL → 28×28 ×256 → [CONV 512] × 3 → 28×28 ×512 → POOL → 14×14×512

→ [CONV 512] ×3 → 14×14 ×512 → POOL → 7×7×512 → FC 4096 → FC 4096 → 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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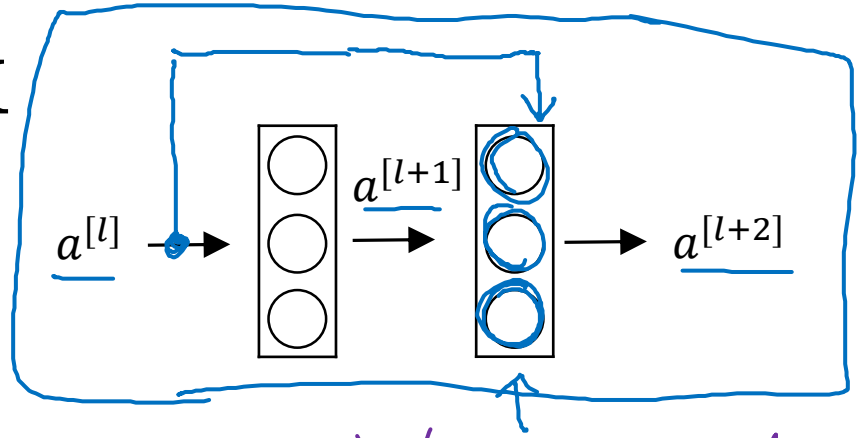
Case Studies

Residual Networks (ResNets)

Residual block



"short cut" / skip connection

$a^{[l]}$ → Linear → ReLU → $a^{[l+1]}$ → Linear → ReLU → $a^{[l+2]}$

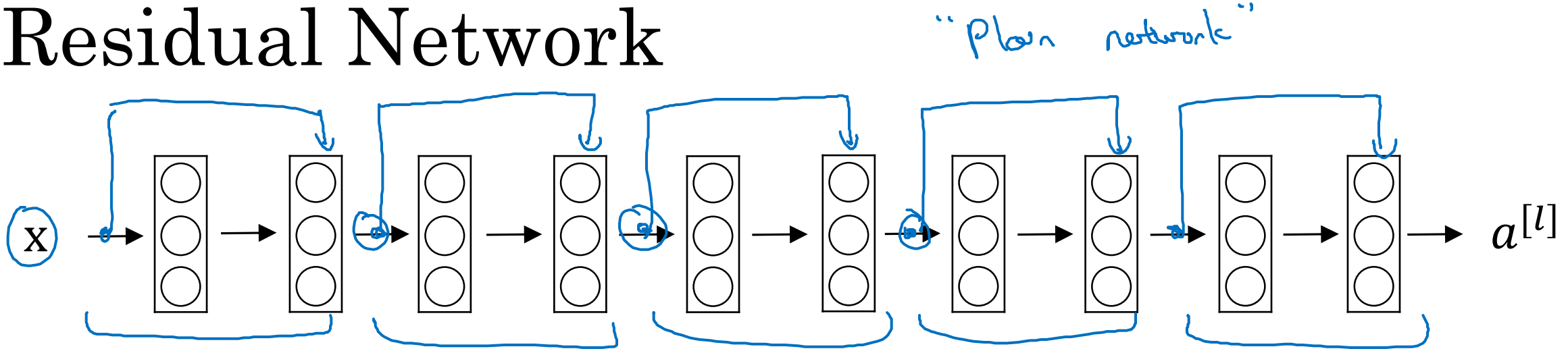
"main path"

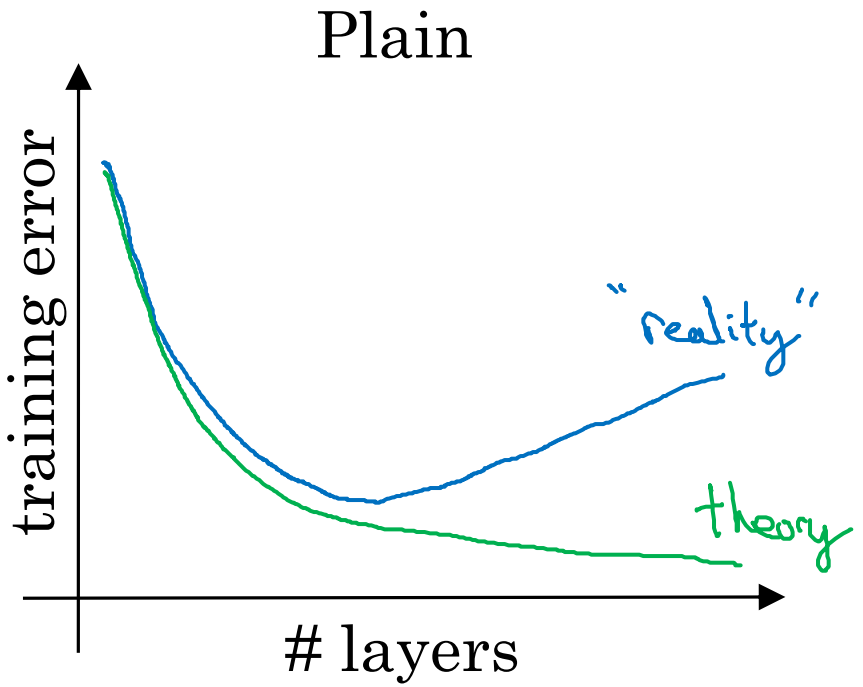
$$z^{[l+1]} = W^{[l+1]} a^{[l]} + b^{[l+1]} \qquad a^{[l+1]} = g(z^{[l+1]}) \qquad z^{[l+2]} = W^{[l+2]} a^{[l+1]} + b^{[l+2]} \qquad a^{[l+2]} = g(z^{[l+2]})$$

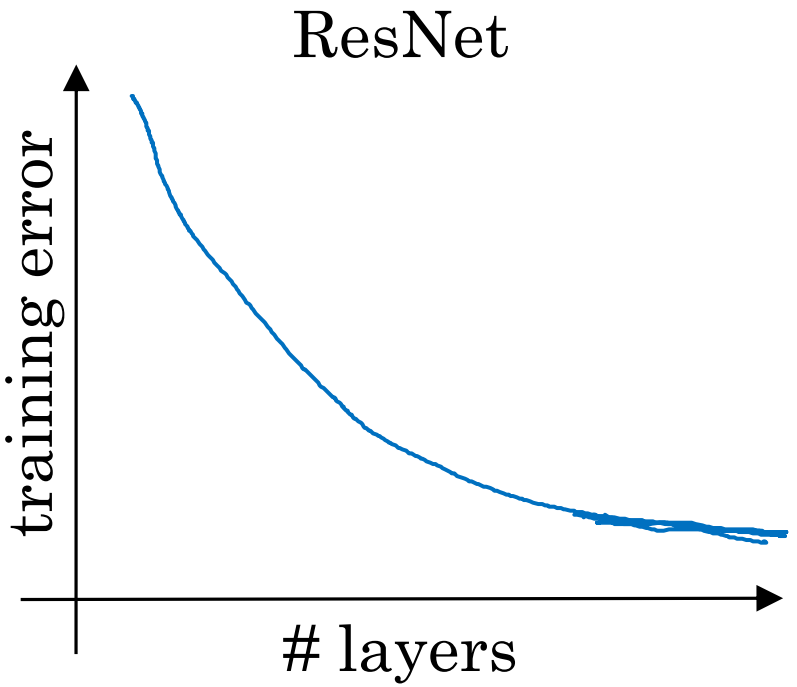
$$a^{[l+2]} = g(z^{[l+2]} + a^{[l]})$$

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

Residual Network







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

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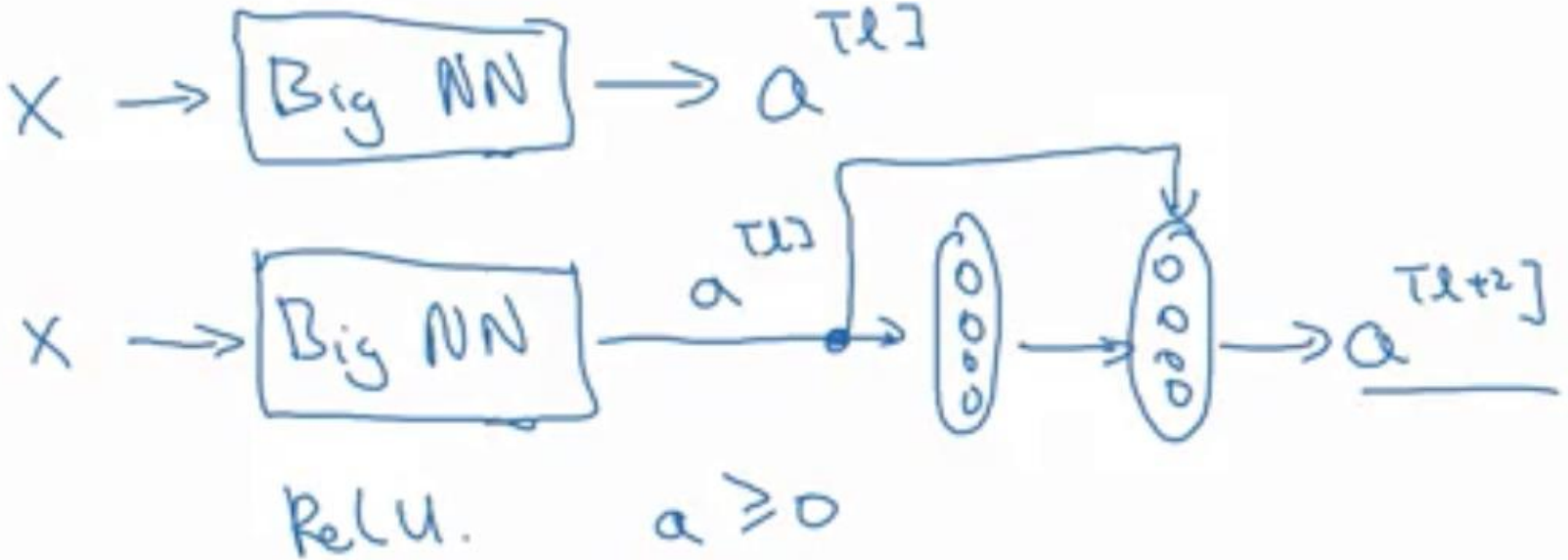
Case Studies

Why ResNets Work

Why do residual networks work?

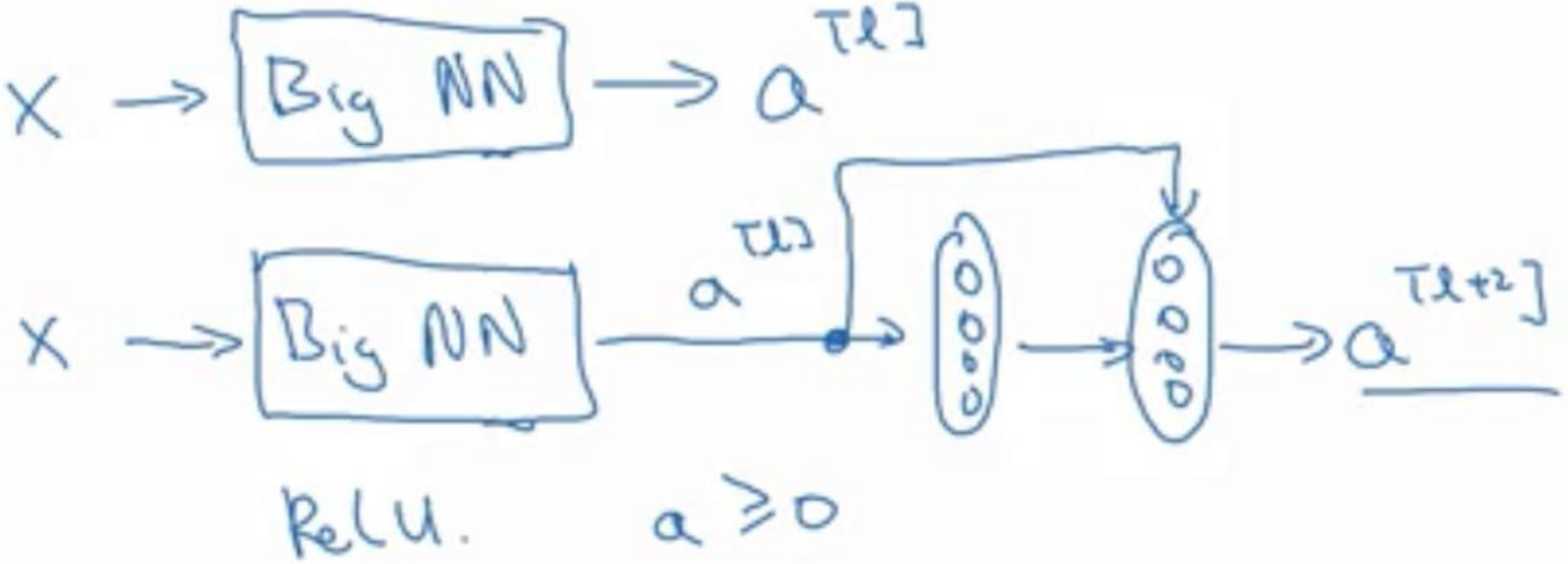


ReLU. $a \geq 0$

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

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

Why do residual networks work?



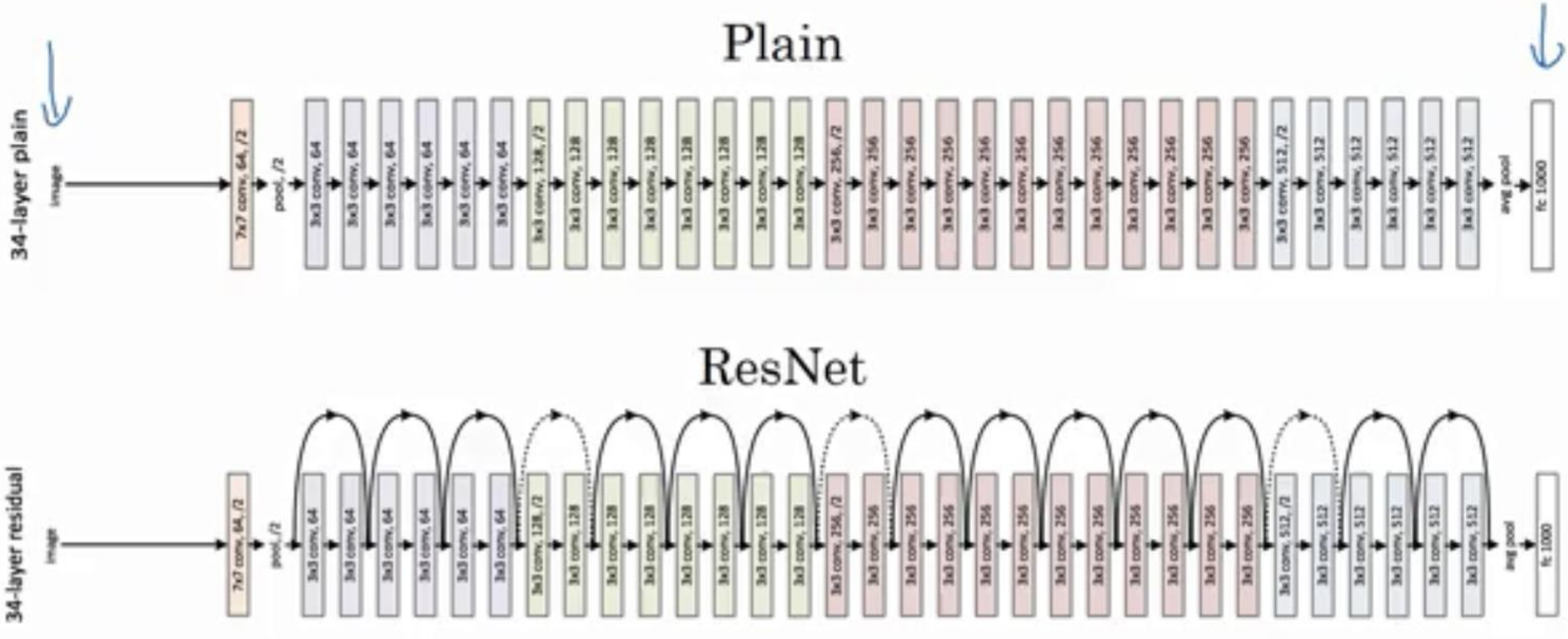
ReLU. $a \geq 0$

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

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

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

ResNet



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

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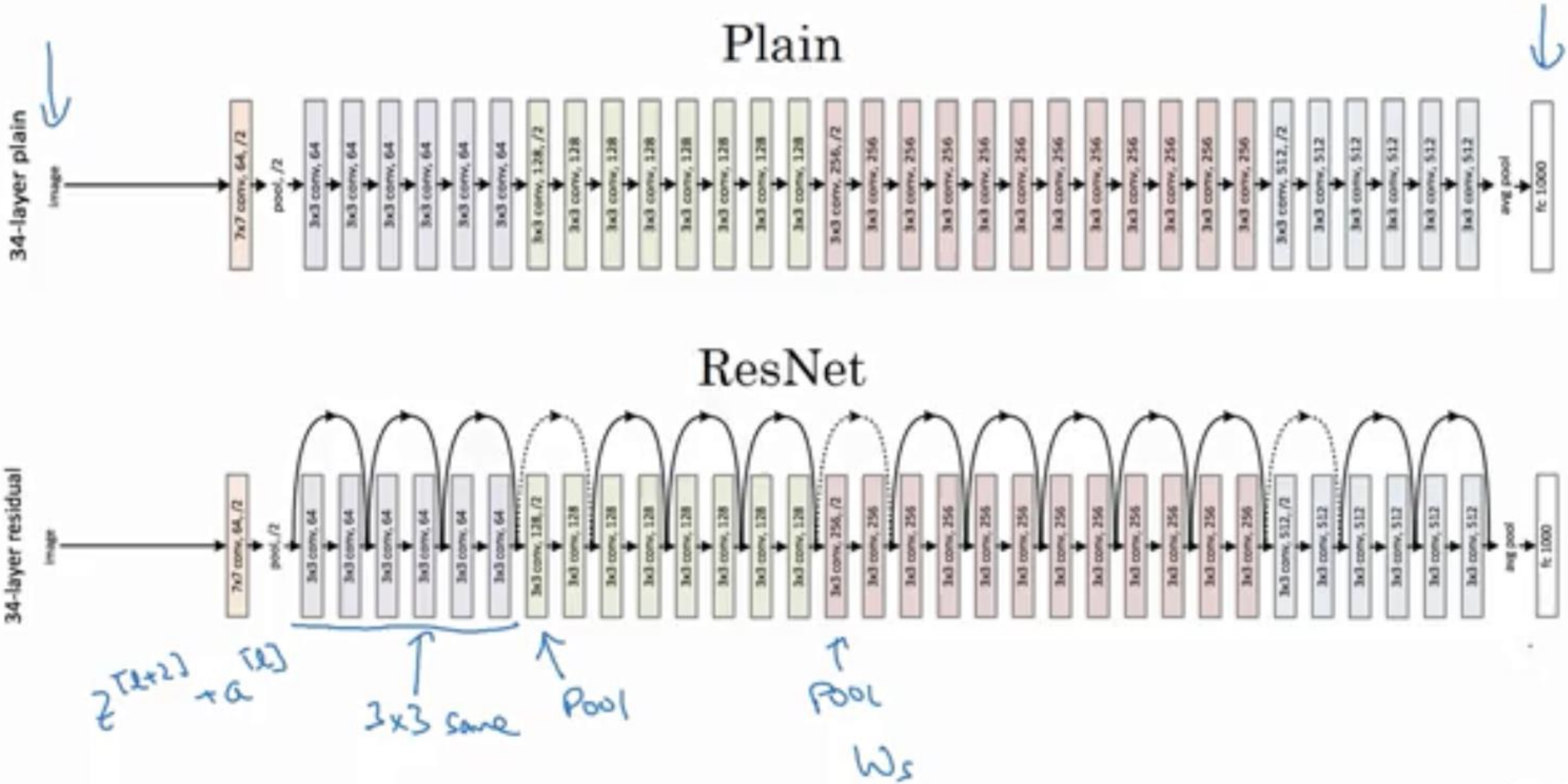
ResNet



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

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Case Studies

Network in Network and 1×1 convolutions

Why does a 1 × 1 convolution do?

1	2	3	6	5	8
3	5	5	1	3	4
2	1	3	4	9	3
4	7	8	5	7	9
1	5	3	7	4	8
5	4	9	8	3	5

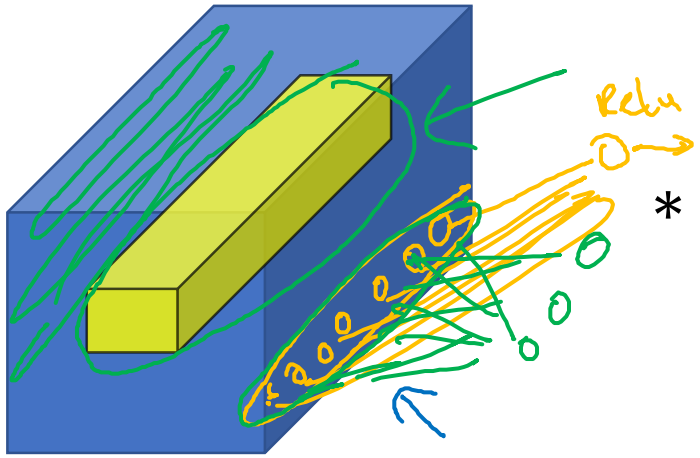
6 × 6 × 1

*

2

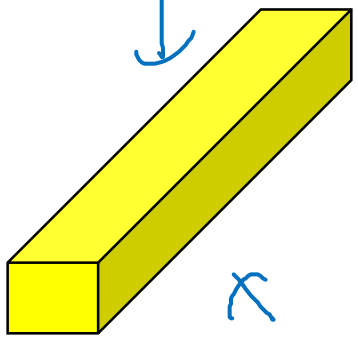
=

2	4	6	...		



6 × 6 × 32

*

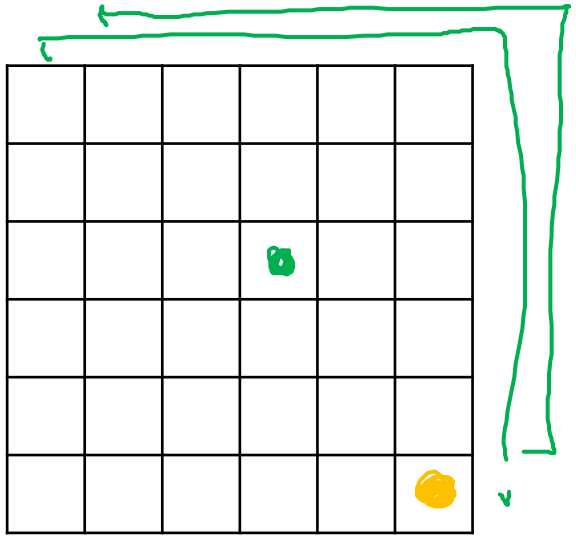


1 × 1 × 32

=

32 → # filters.

$n_c^{[l+1]}$



6 × 6 × # filters

ReLU

Network in Network

[Lin et al., 2013. Network in network]

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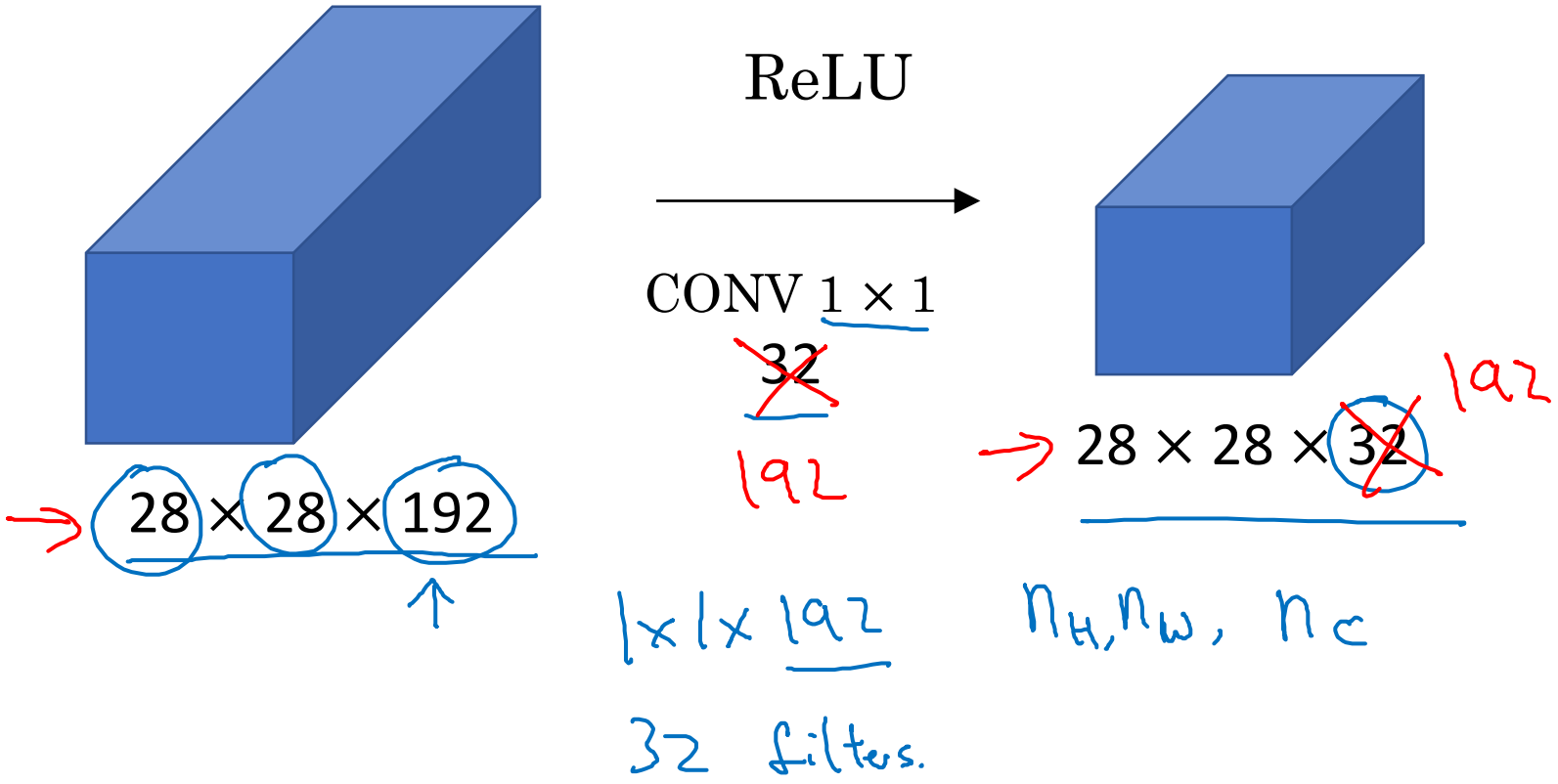
Using 1×1 convolutions



[Lin et al., 2013. Network in network]

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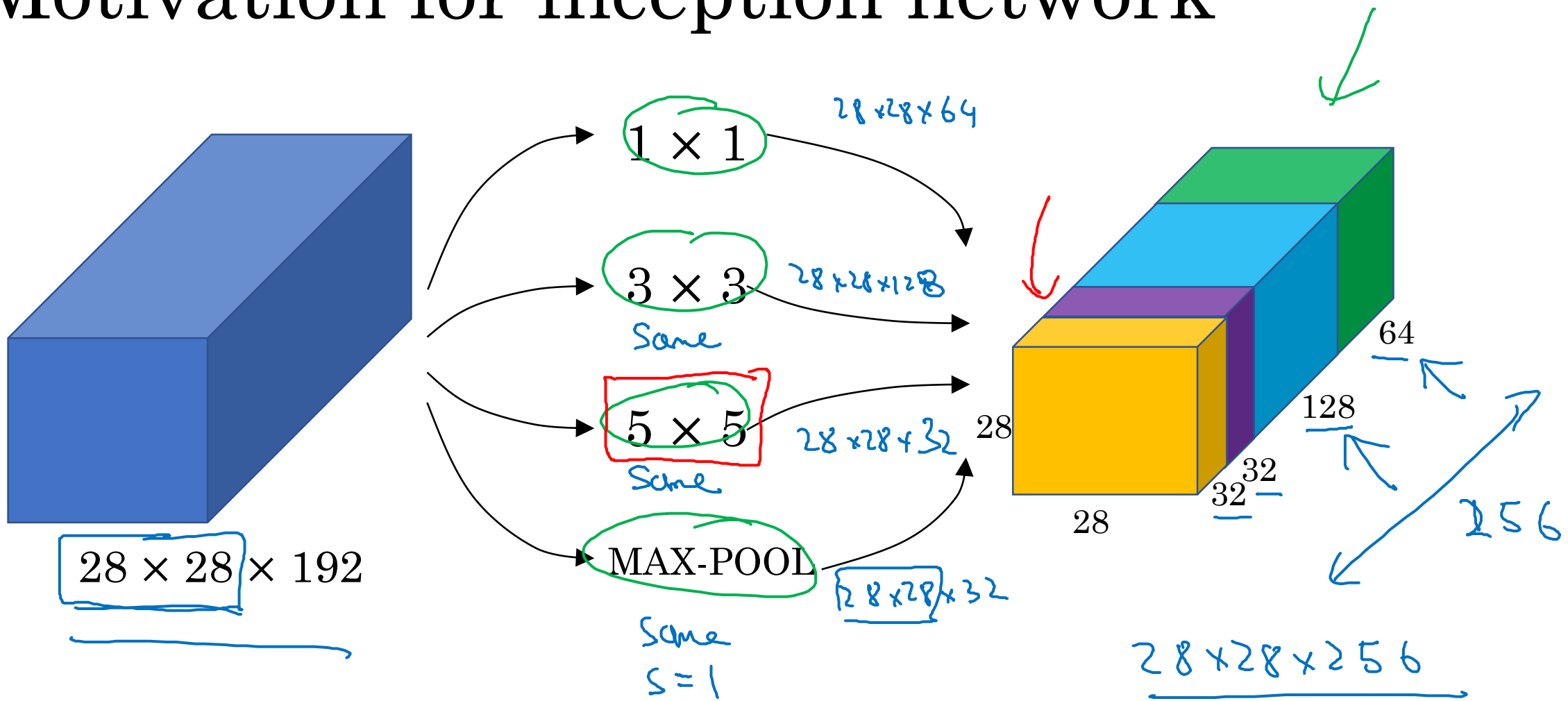
Case Studies

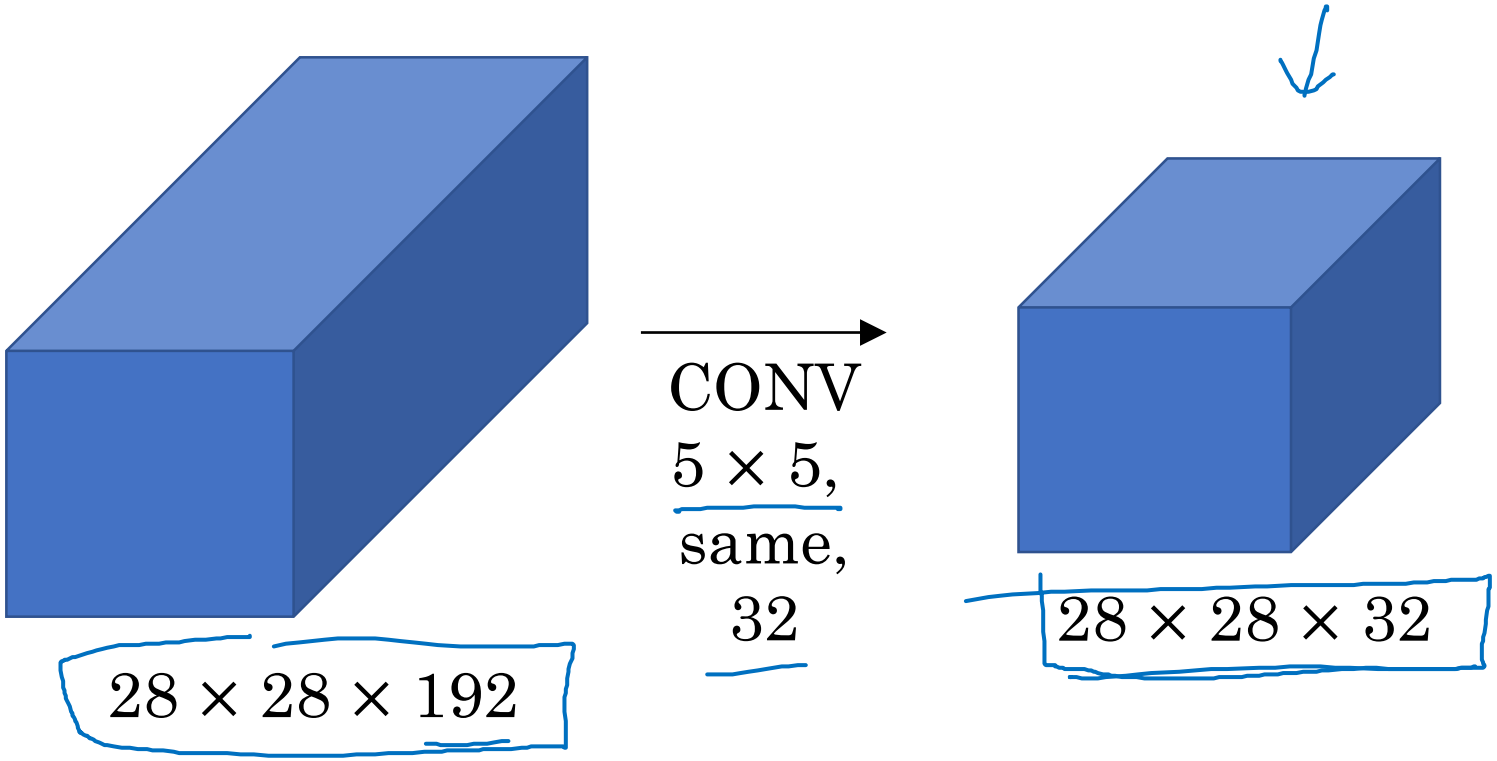
Inception network motivation

Motivation for inception network



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

The problem of computational cost

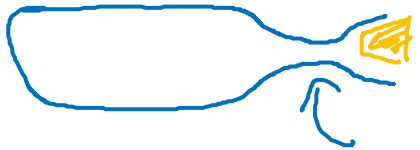


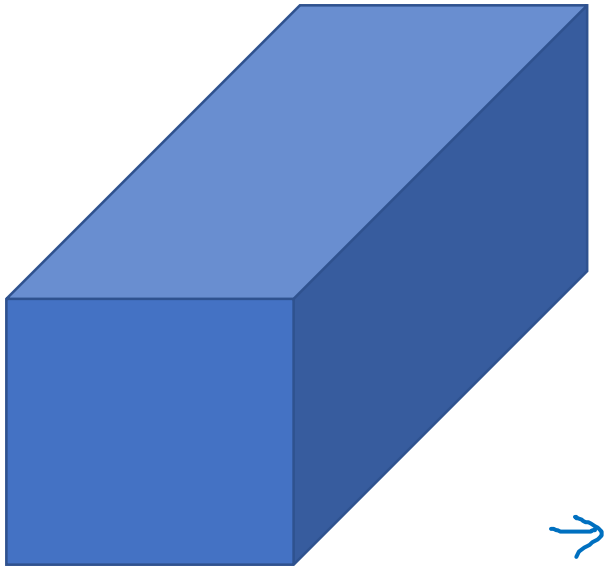
32 filters. filter one 5×5×192.

28×28×32 × 5×5×192 = 120M.

Using 1×1 convolution

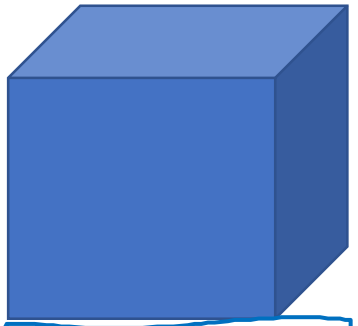
"bottleneck layer"





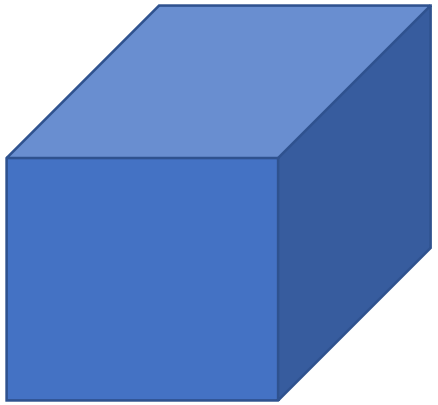
28 × 28 × 192

CONV
1 × 1,
16,
1 × 1 × 192



28 × 28 × 16

CONV
5 × 5,
32,
5 × 5 × 16



28 × 28 × 32

28×28×16 × 192 = 2.4M

28×28×32 × 5×5×16 = 10.0M

12.4M

120M

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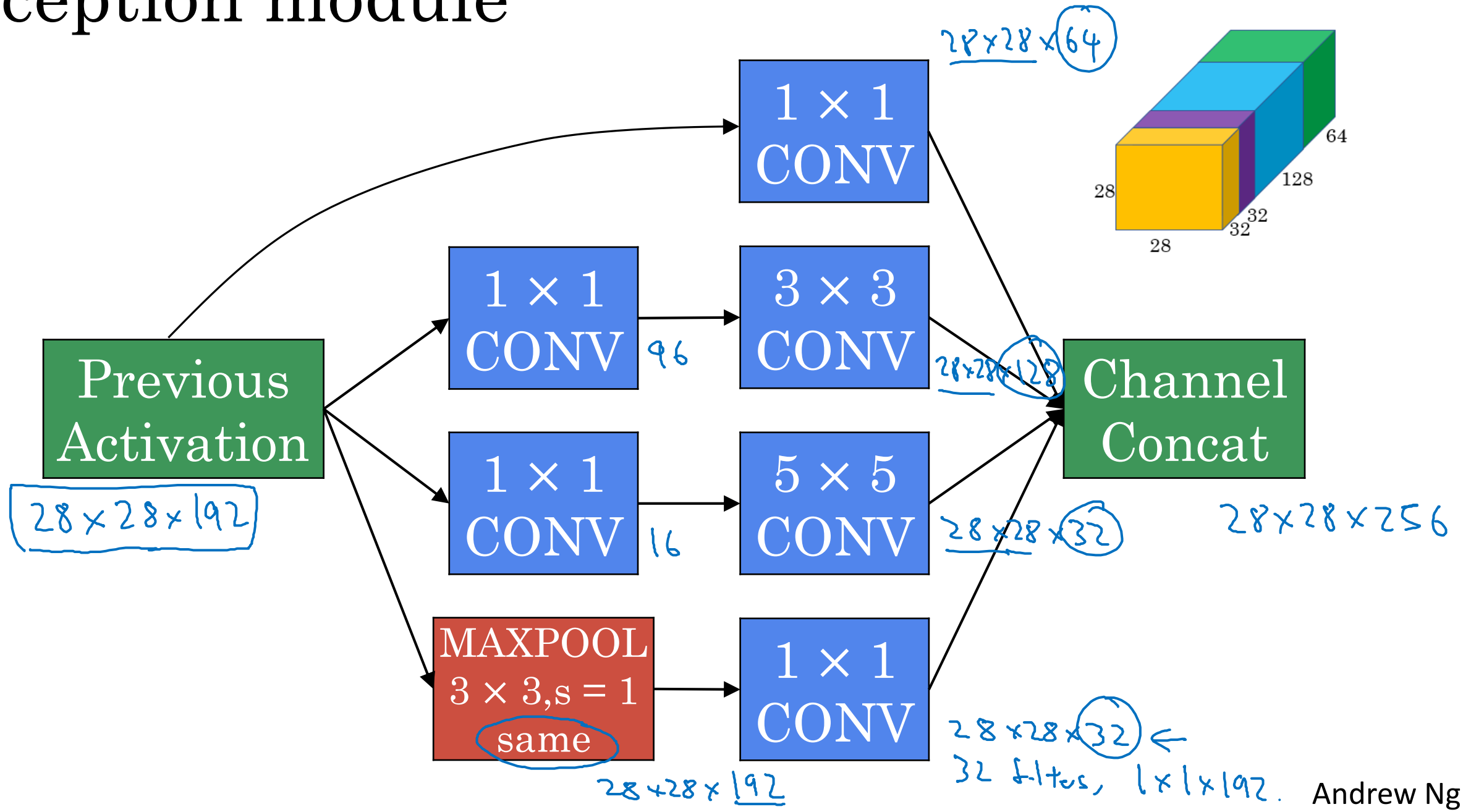
Case Studies

Inception network

Inception module



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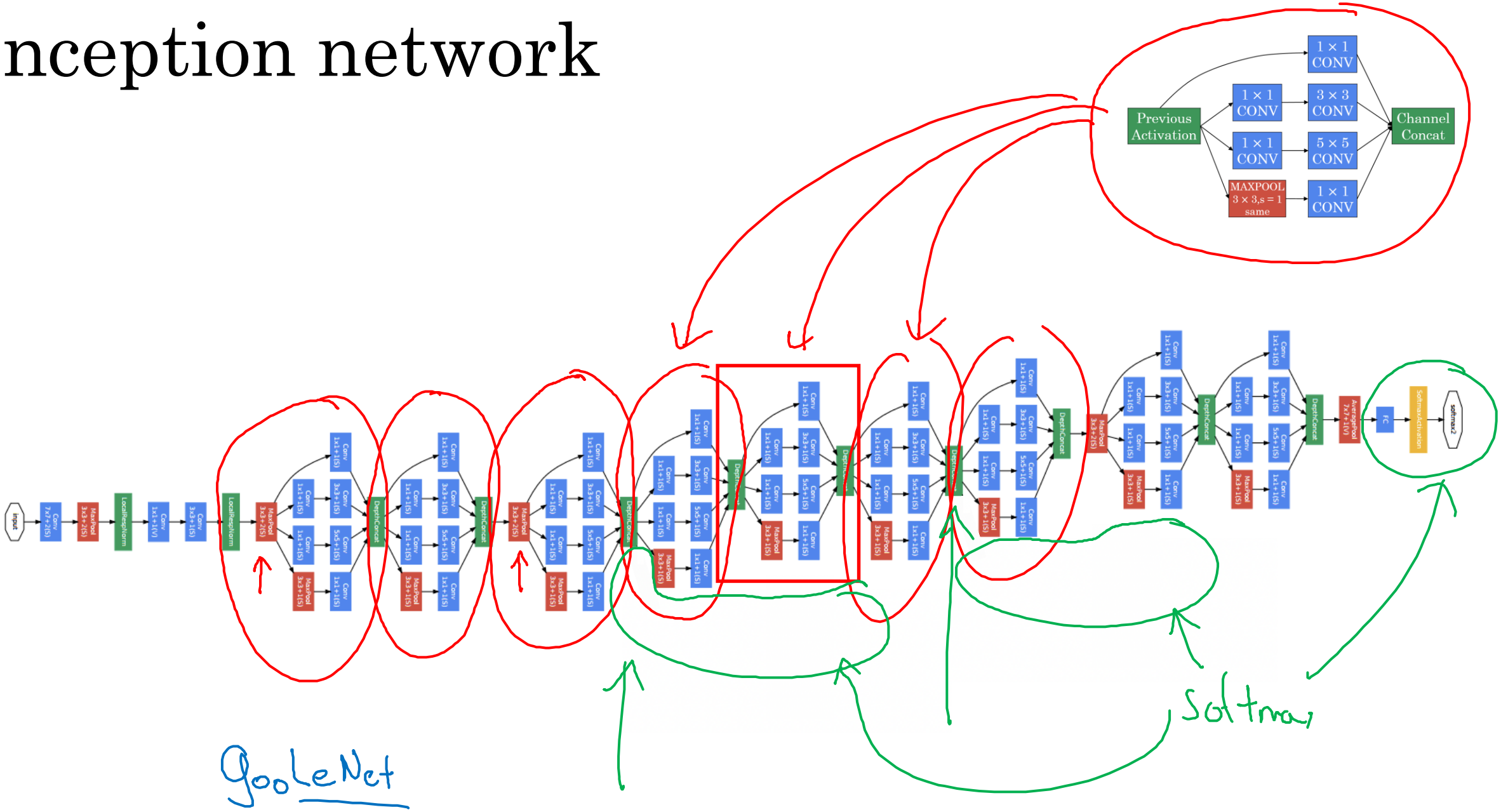
Inception network



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

http://knowyourmeme.com/memes/we-need-to-go-deeper