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Case Studies

Convolutional Neural Networks

Outline

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    1. Using Open-Source Implementation
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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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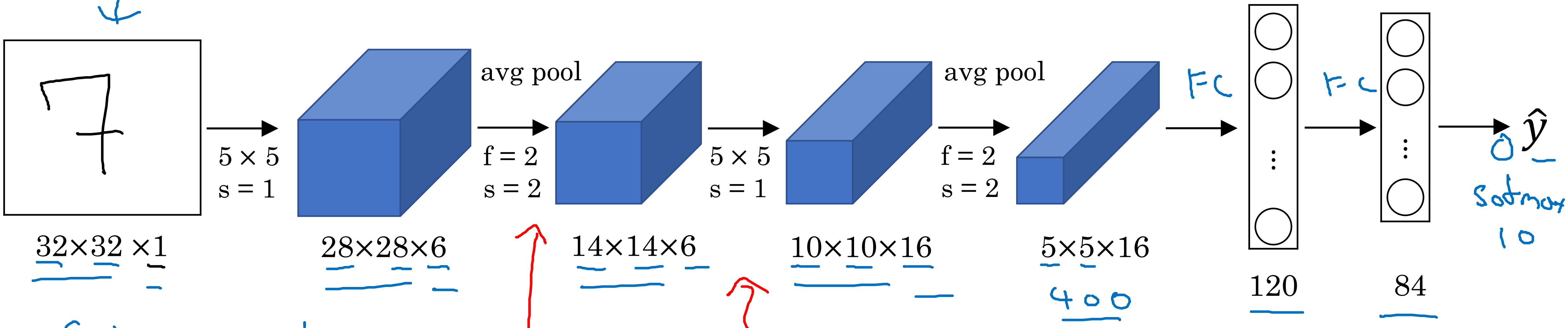
Case Studies

Classic networks

LeNet - 5



60K parameters

$n_H, n_W \downarrow$ $n_C \uparrow$

non-linearity after pooling

$n_H \times n_W \times n_C$ $f \times f \times n_C$

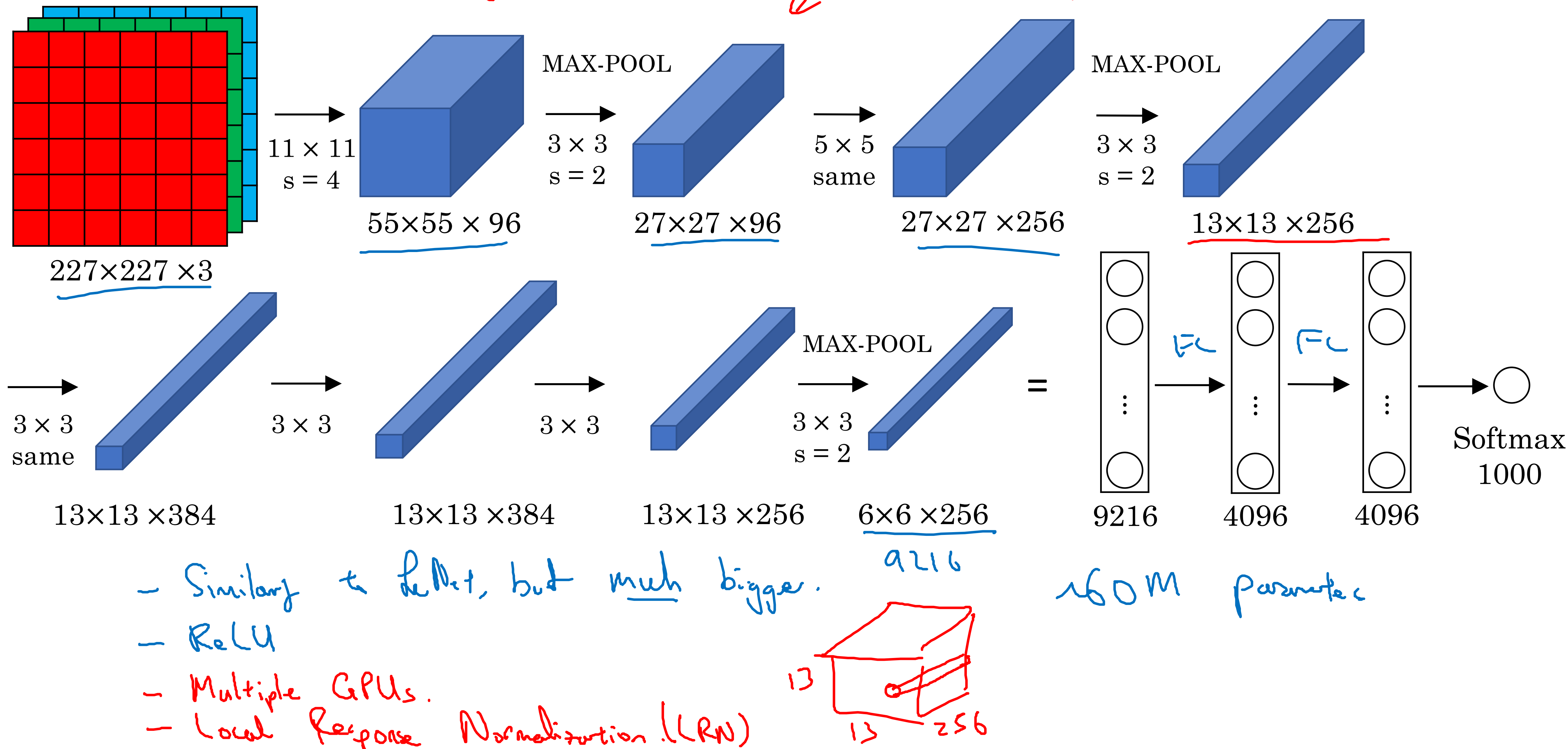
conv pool conv pool fc fc output

Advanced: sigmoid/tanh ReLU

II III.

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

AlexNet



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

~60M parameters

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

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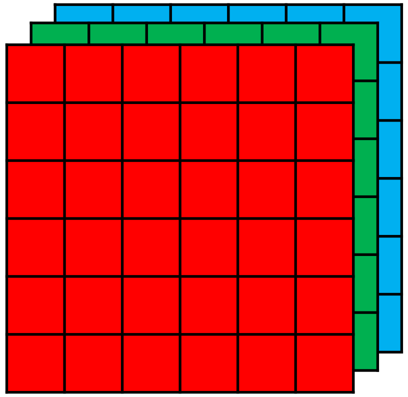
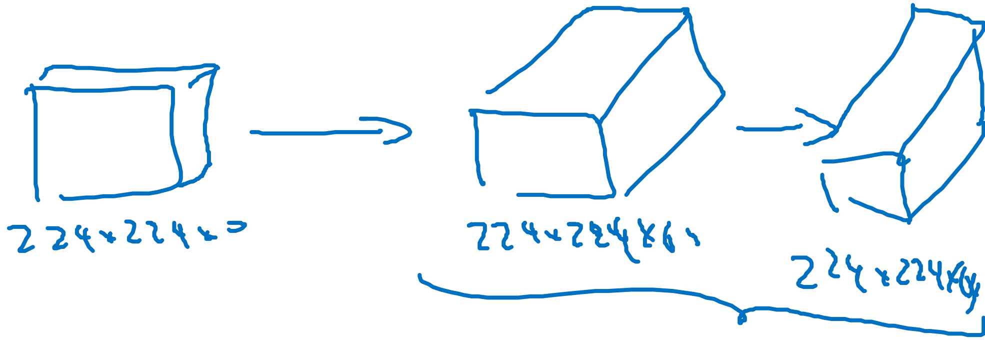
VGG - 16

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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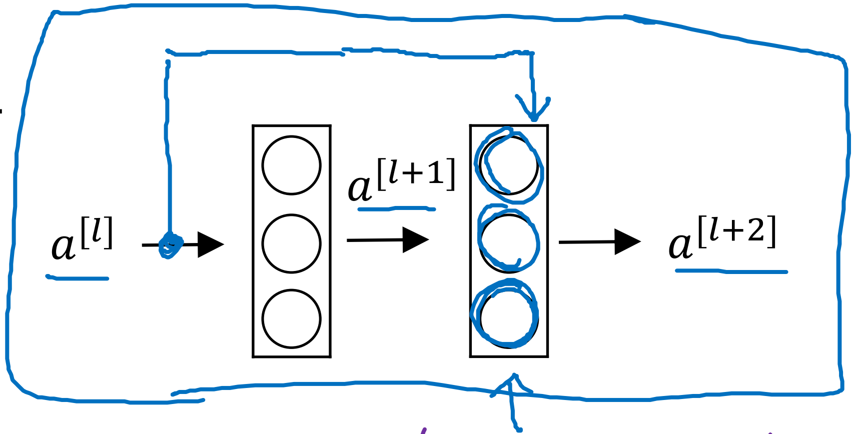
Case Studies

Residual Networks (ResNets)

Residual block



"short cut" / skip connection

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

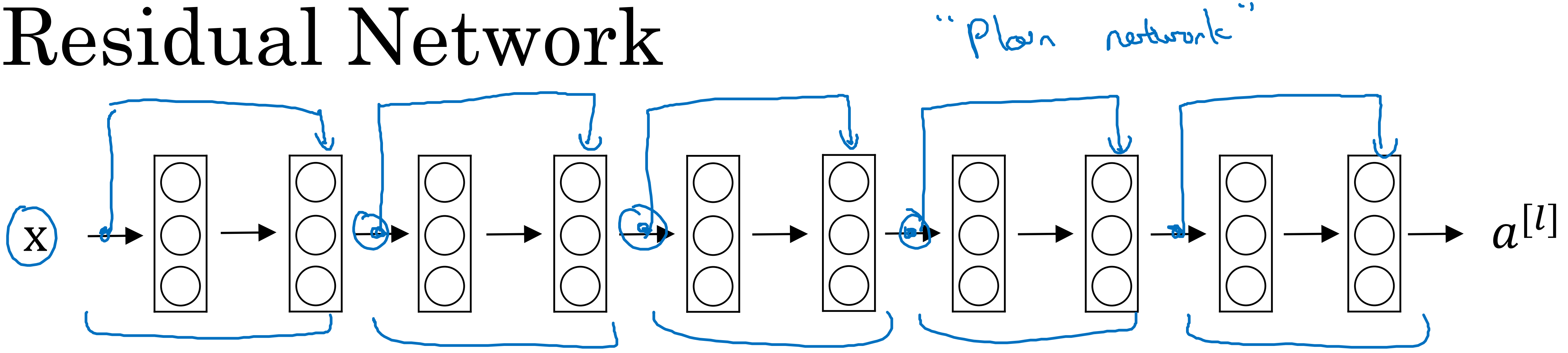
"main path"

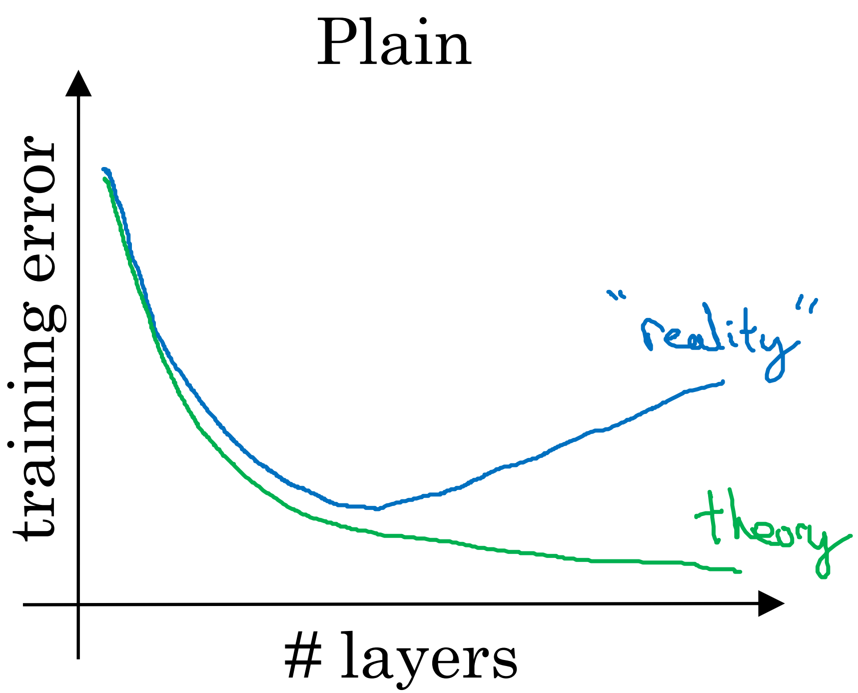
$z^{[l+1]} = W^{[l+1]} a^{[l]} + b^{[l+1]}$ $\quad a^{[l+1]} = g(z^{[l+1]})$ $\quad z^{[l+2]} = W^{[l+2]} a^{[l+1]} + b^{[l+2]}$ $\quad \boxed{\cancel{a^{[l+2]} = g(z^{[l+2]})}}$

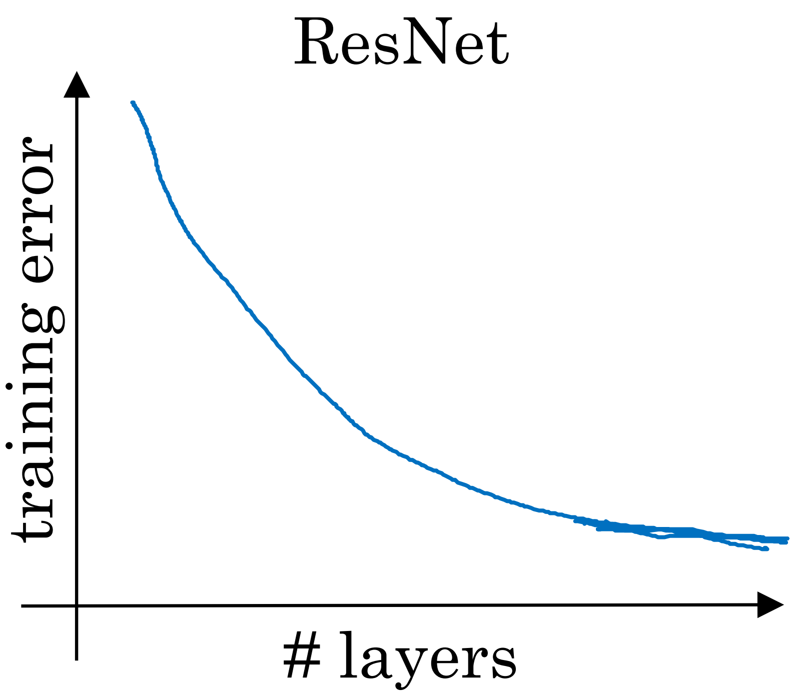
$$a^{[l+2]} = g\left(z^{[l+2]} + a^{[l]}\right)$$

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

Residual Network







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

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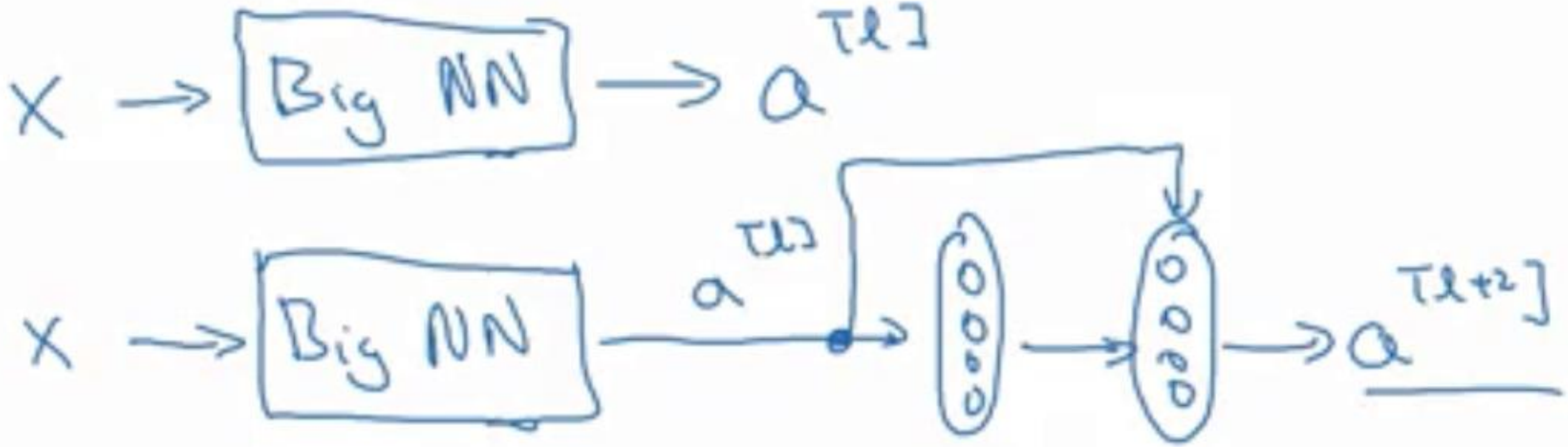
Case Studies

Why ResNets Work

Why do residual networks work?



ReLU. $a \geq 0$

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

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

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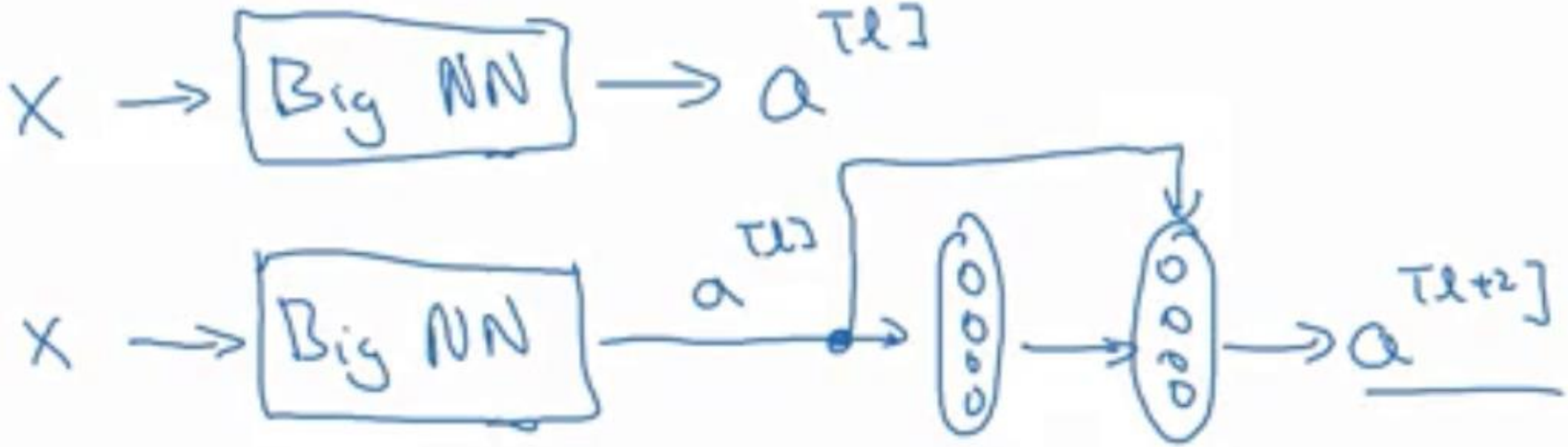
Why do residual networks work?



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

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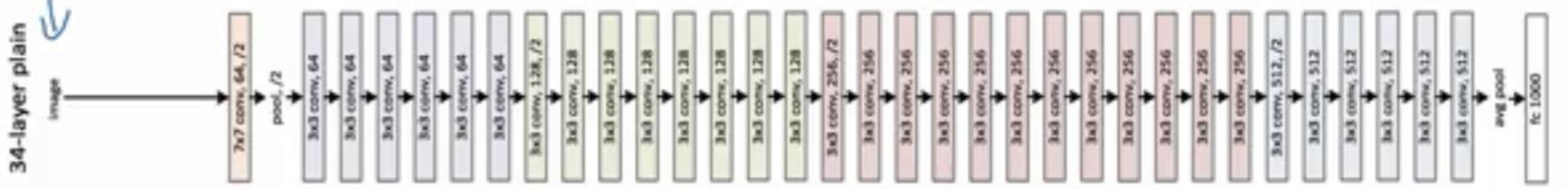
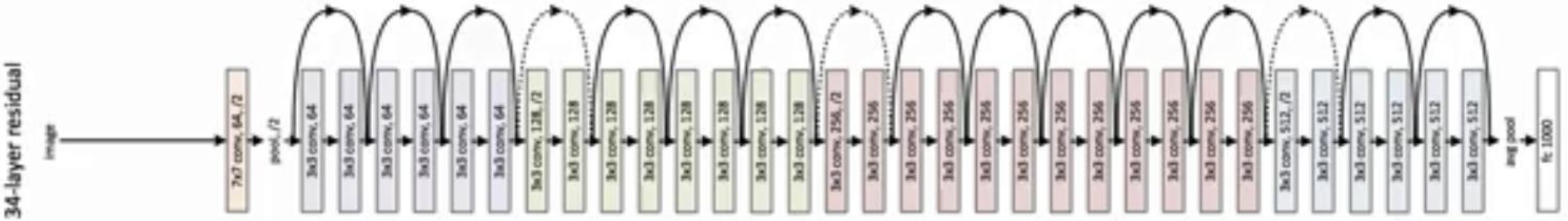
ResNet

Plain



ResNet



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

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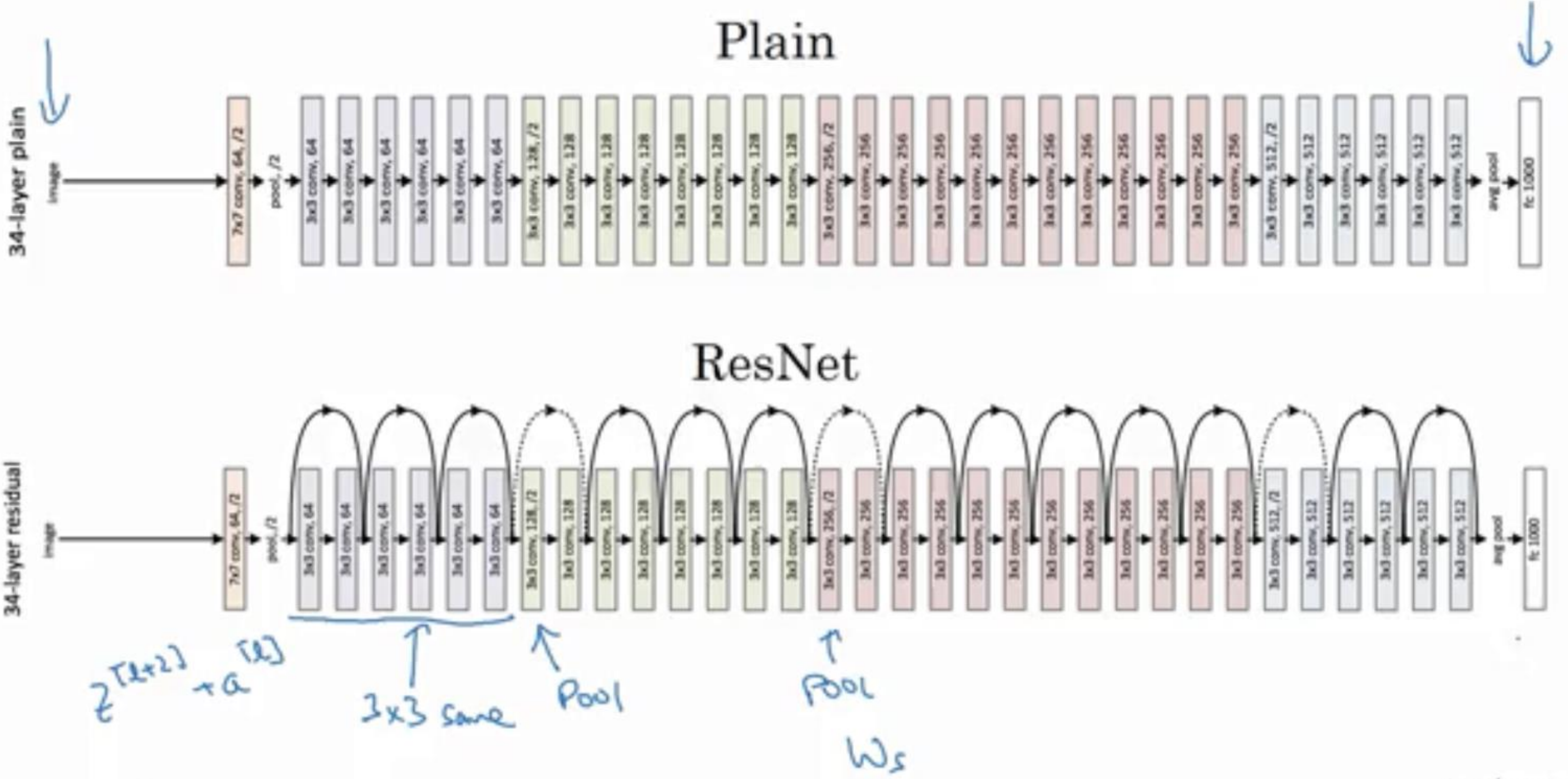
ResNet



[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

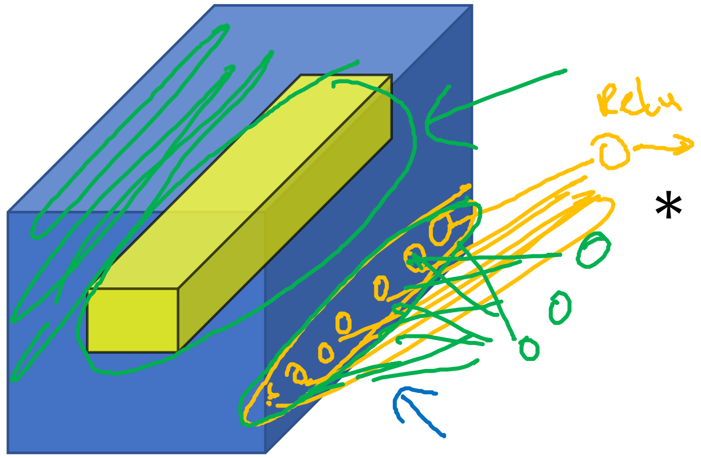
6 × 6 × 1

$*$ $\boxed{2}$ $=$

2	4	6	...		

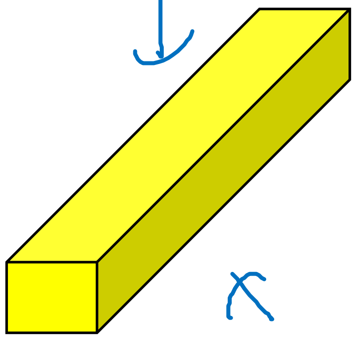
32 → # filters.

$n_c^{[l+1]}$



6 × 6 × 32

$*$

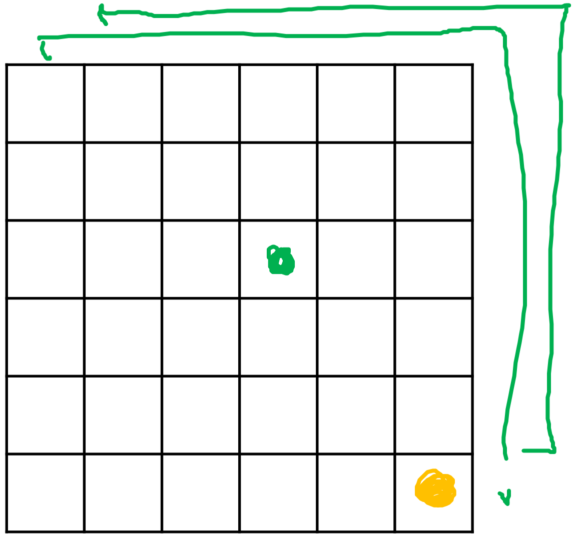


1 × 1 × 32

$=$

ReLU

Network in Network



6 × 6 × # filters

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

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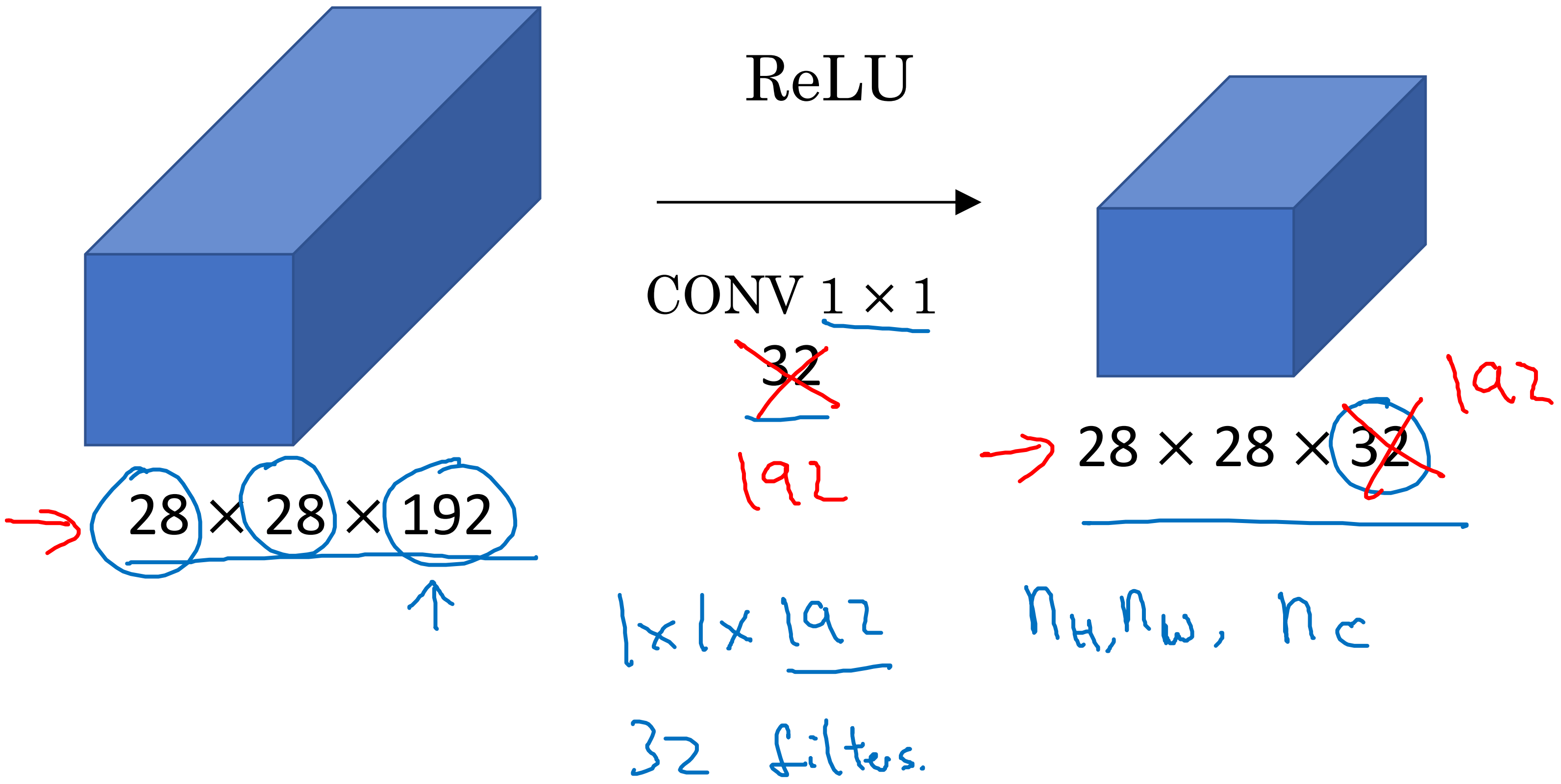
Using 1×1 convolutions



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

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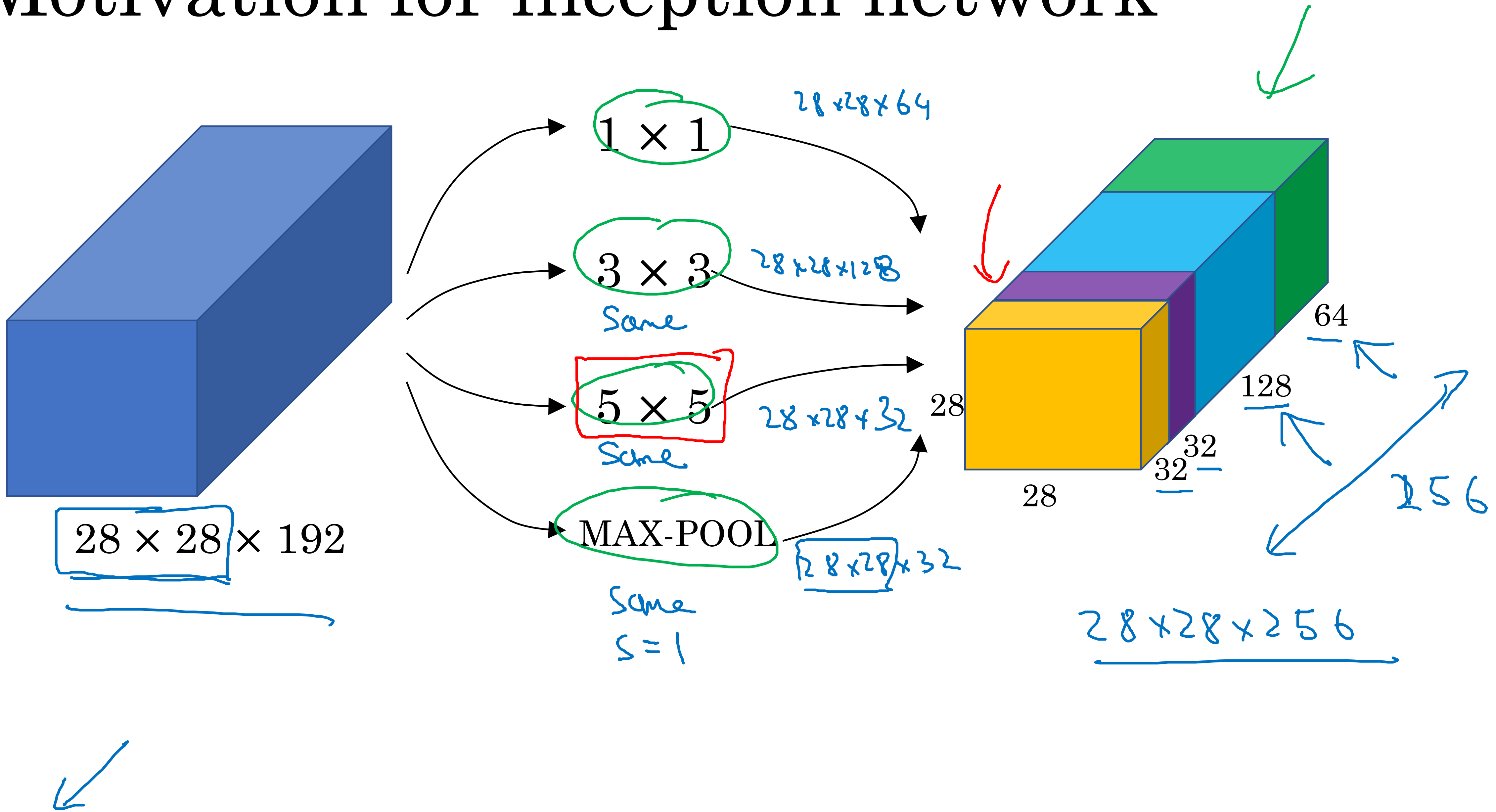
Case Studies

Inception network motivation

Motivation for inception network



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

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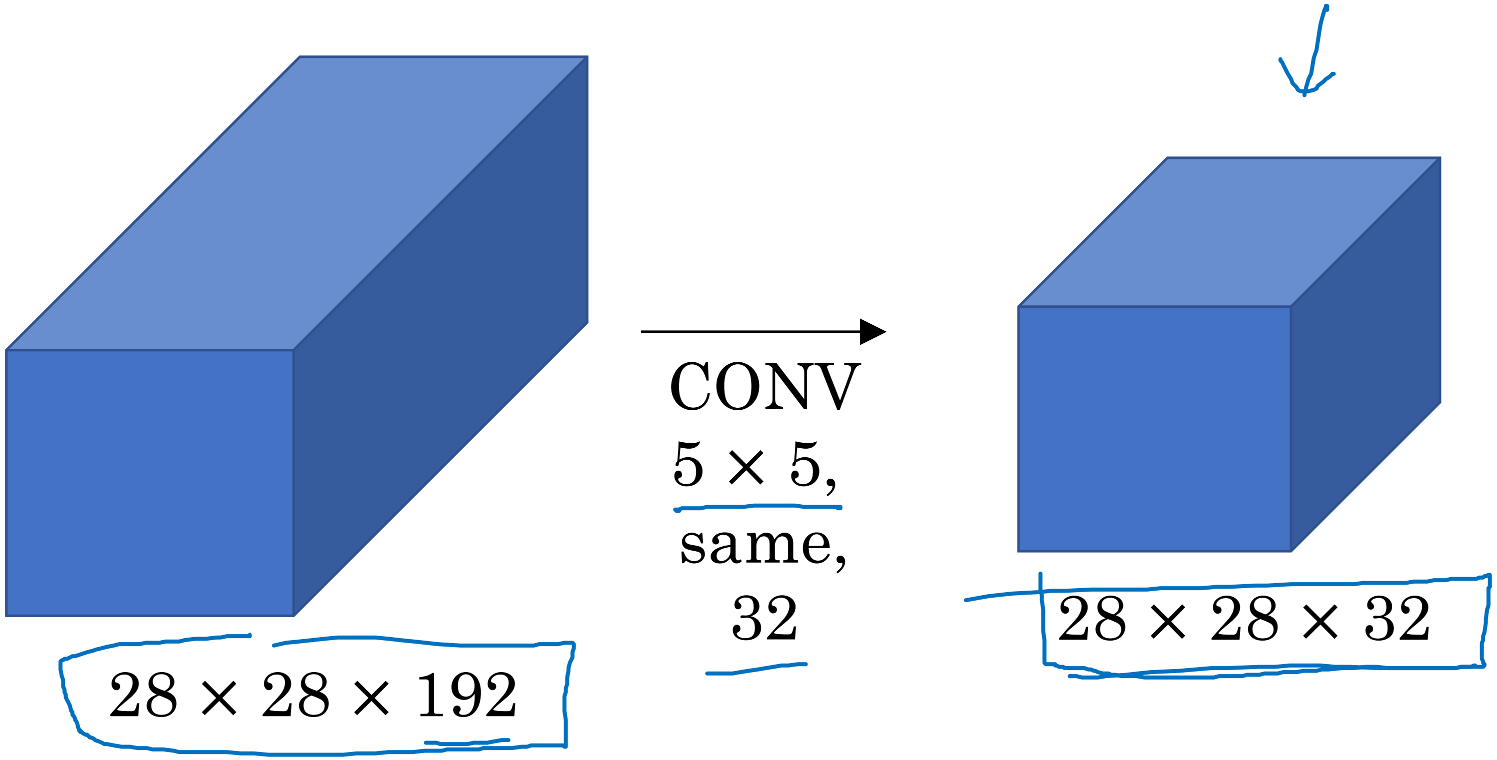
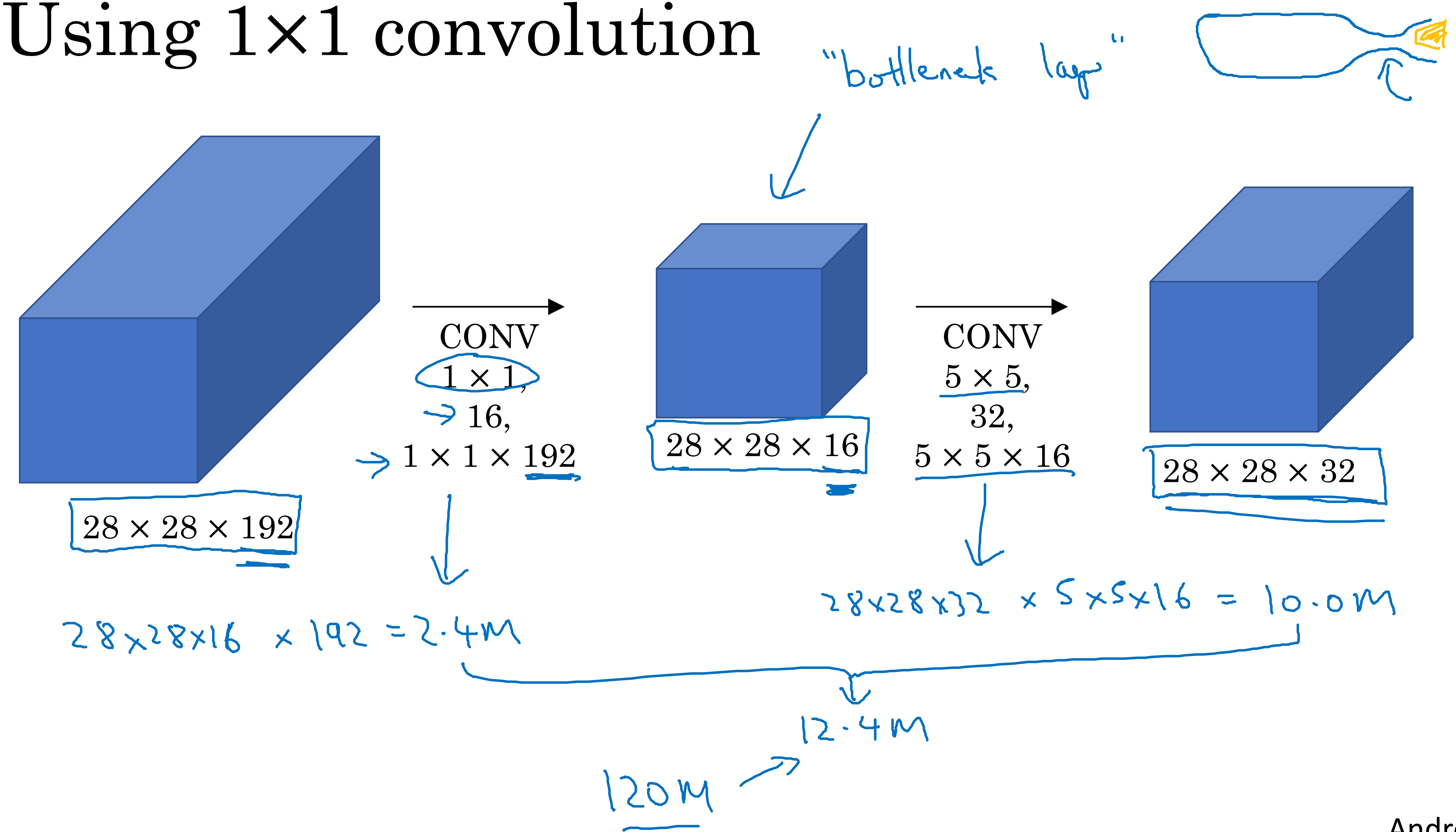
The problem of computational cost



32 filters. filters are $5 \times 5 \times 192$.

$28 \times 28 \times 32 \times 5 \times 5 \times 192 = 120M$.

Using 1×1 convolution



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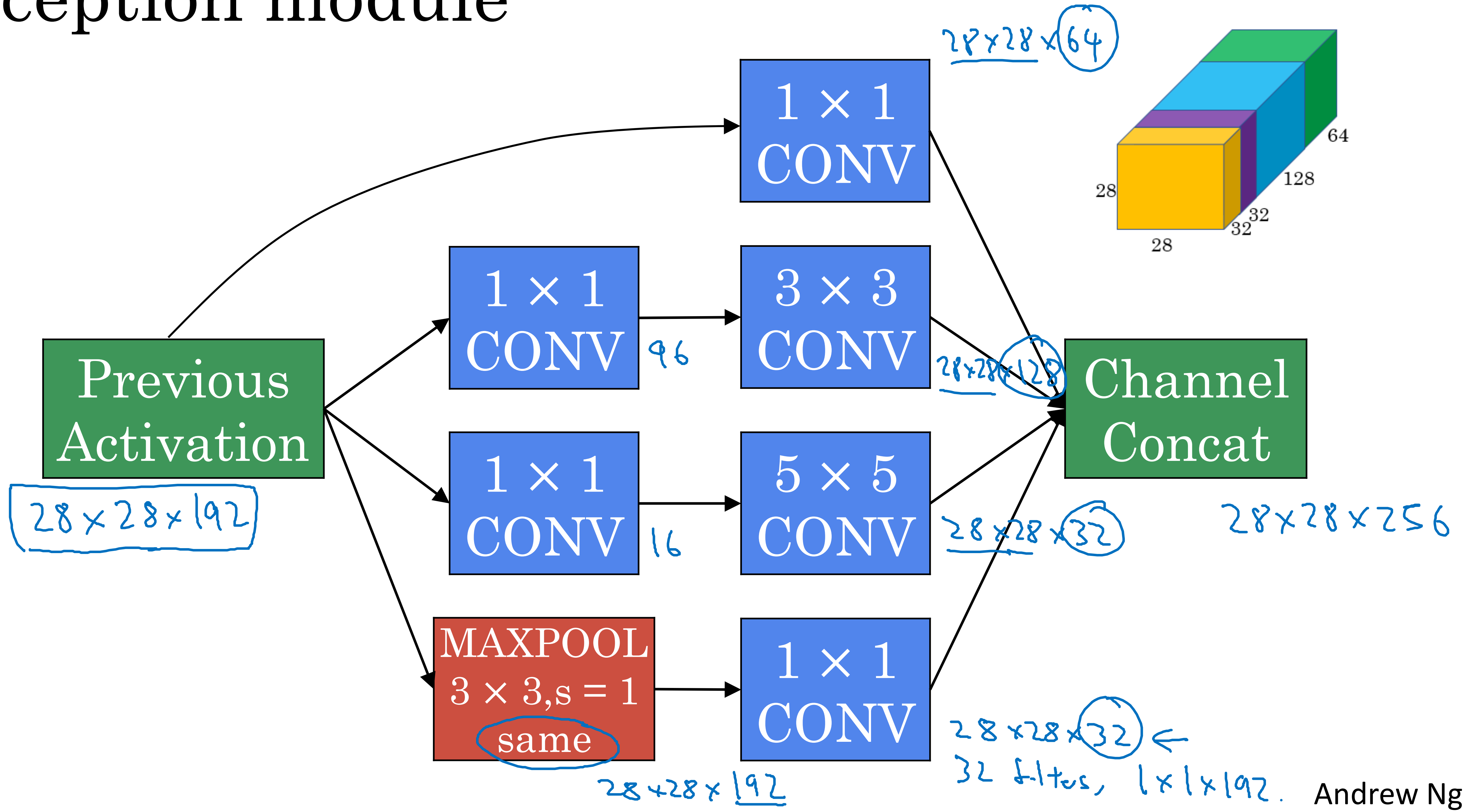
Case Studies

Inception network

Inception module



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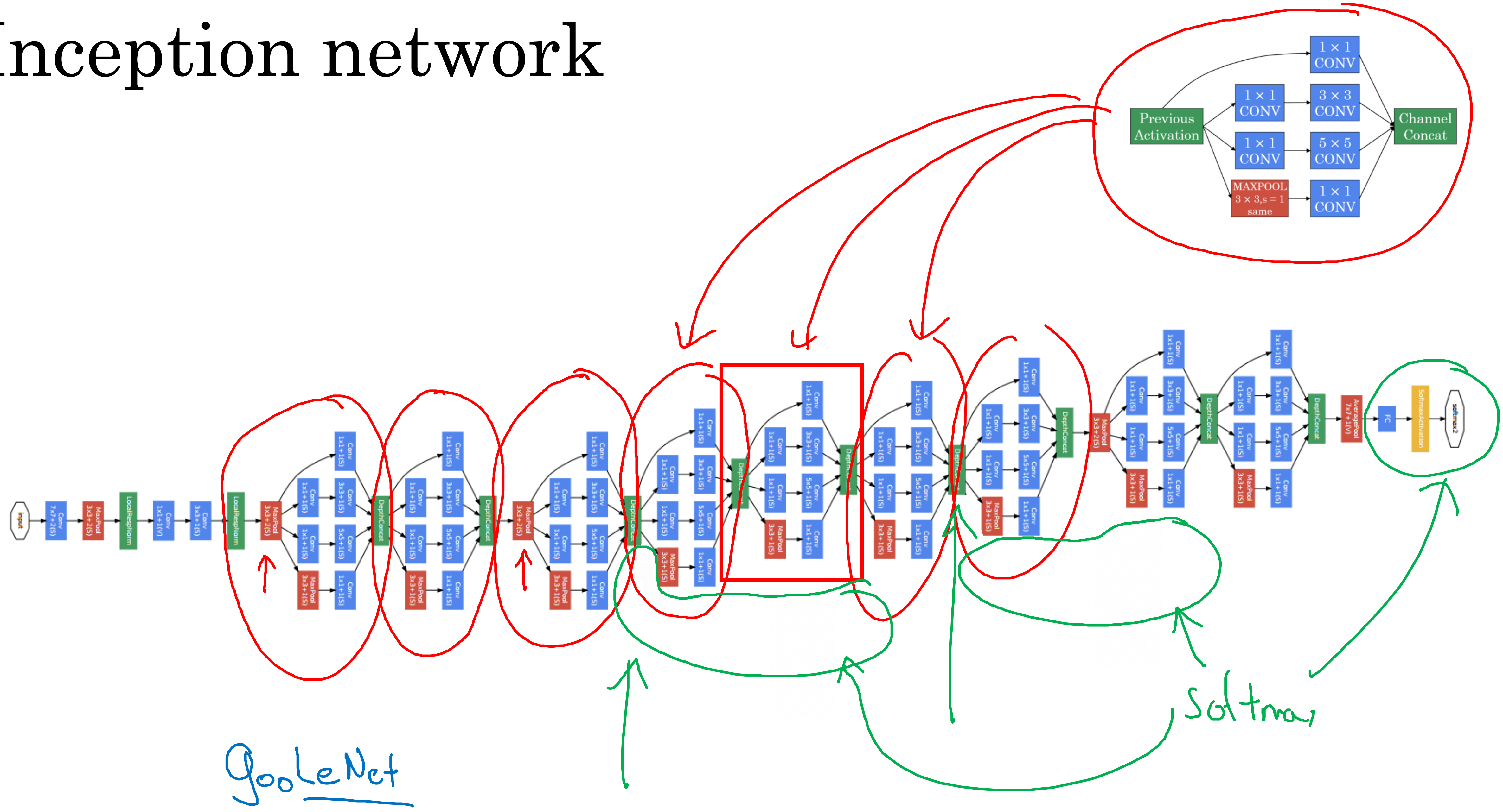
Inception network



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

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

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