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# Case Studies

## Classic networks

# Outline

## Classic networks:

기본이면 (1980)

- LeNet-5 ←
- AlexNet ←
- VGG ←

ResNet (152)
다른 분야에도 유용

Inception

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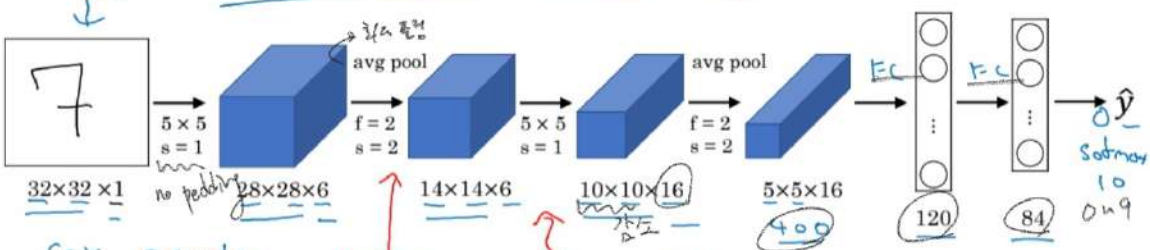
- 합성곱 신경망을 구축하기 위해서는 효율적인 신경망 구조를 살펴봐야 합니다. 하나의 컴퓨터 비전 작업에서 잘 작동한 구조가 다른 작업에도 유용하고 잘 작동
- 이후에 다룰 몇 개의 대표적인 신경망을 공부할 것입니다. 이것들은 꽤나 효과적인 신경망이고 몇몇 개념들은 현대 컴퓨터 비전의 기틀을 마련했습니다. 또한 다른 분야에도 적용할 수 있는 것들

# LeNet - 5




60K parameters.

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

non-linearity after pooling

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

conv pool conv pool fc fc output

Activation: Sigmoid/tanh ReLU 사용안함

II III

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

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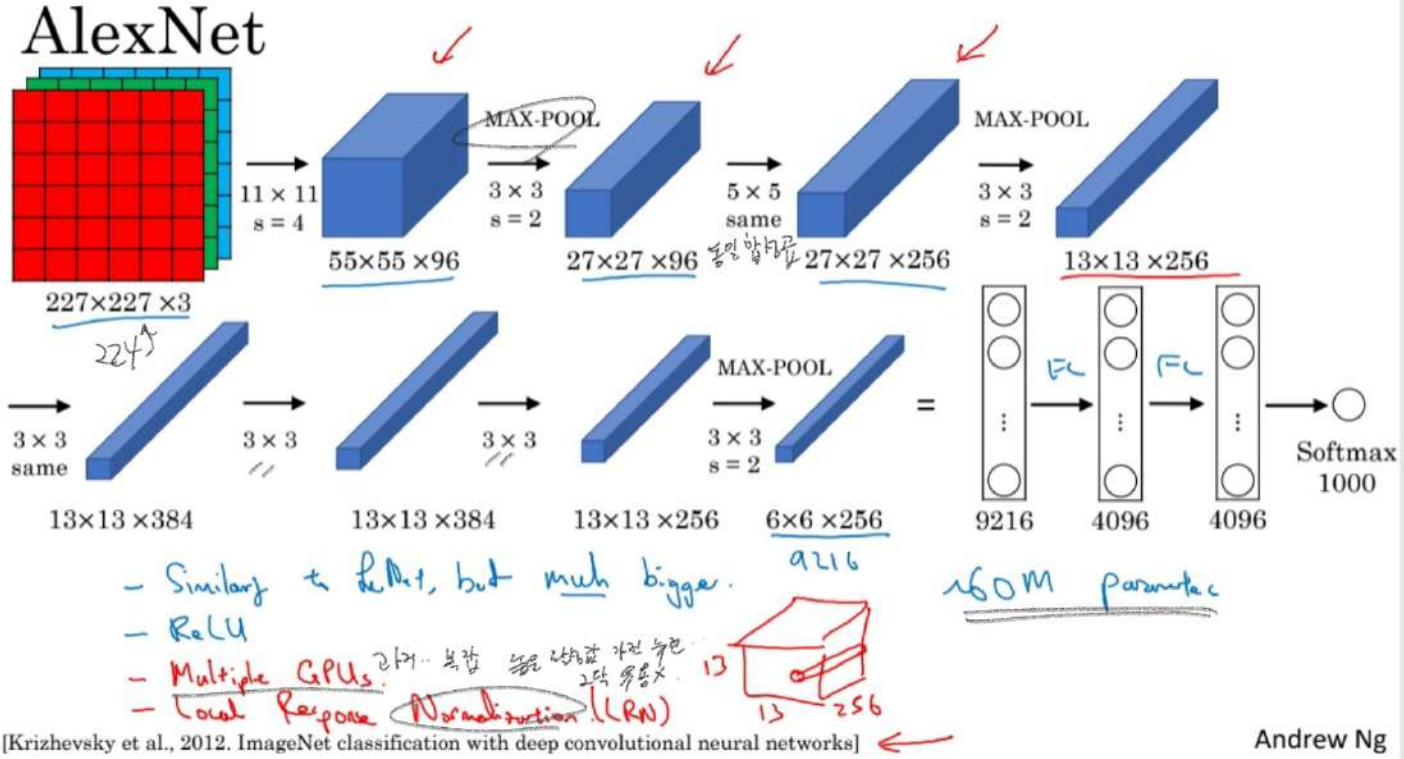
# AlexNet




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

60M parameters

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

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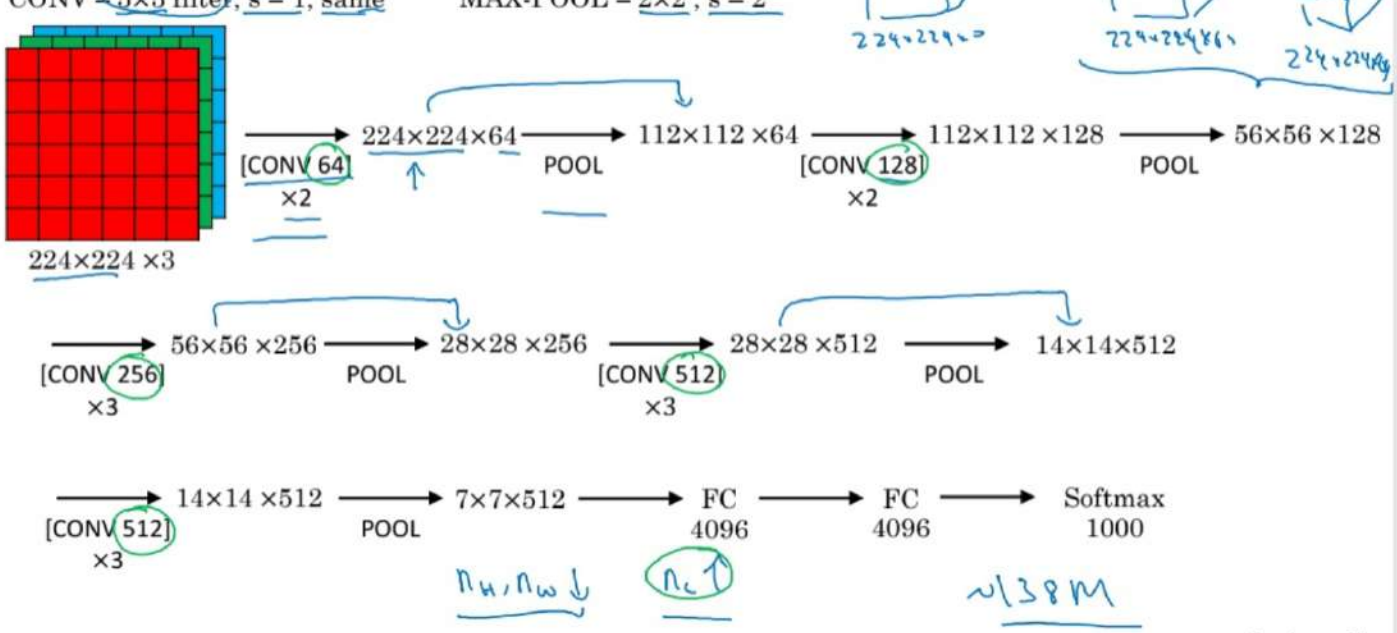
# VGG - 16

CONV = 3×3 filter, s = 1, same

MAX-POOL = 2×2 , s = 2




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

~138M

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

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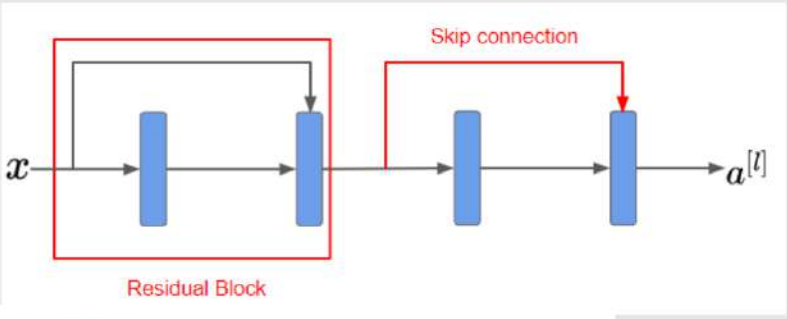
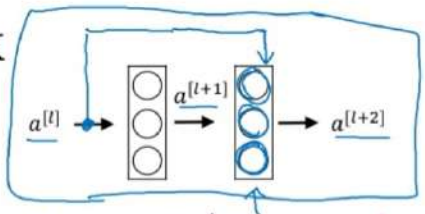
Case Studies

# 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]

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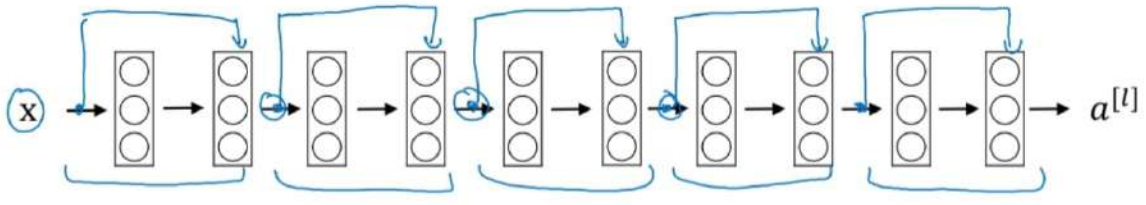
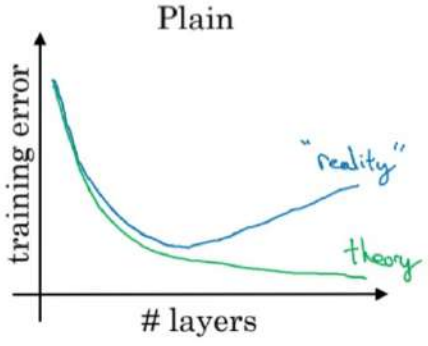
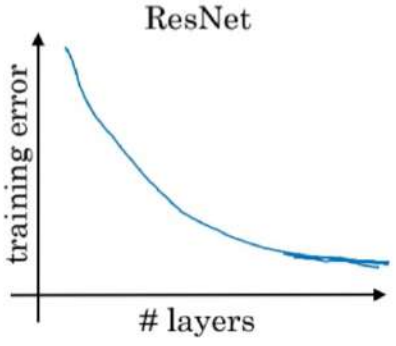
## Residual Network

"Plain network"




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

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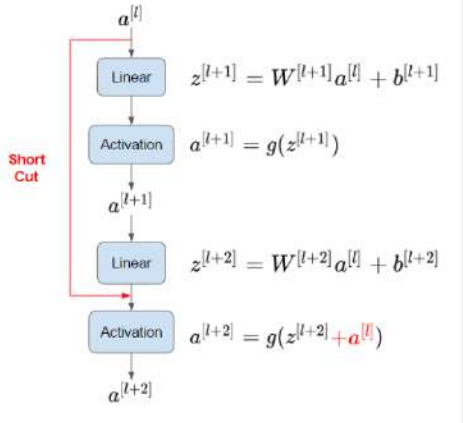
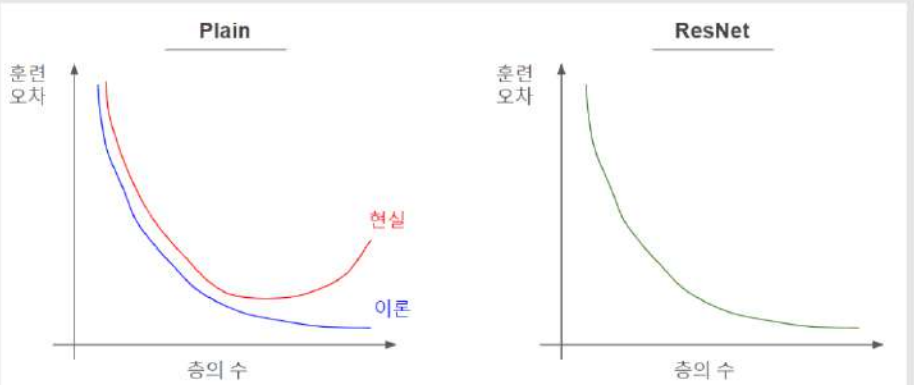
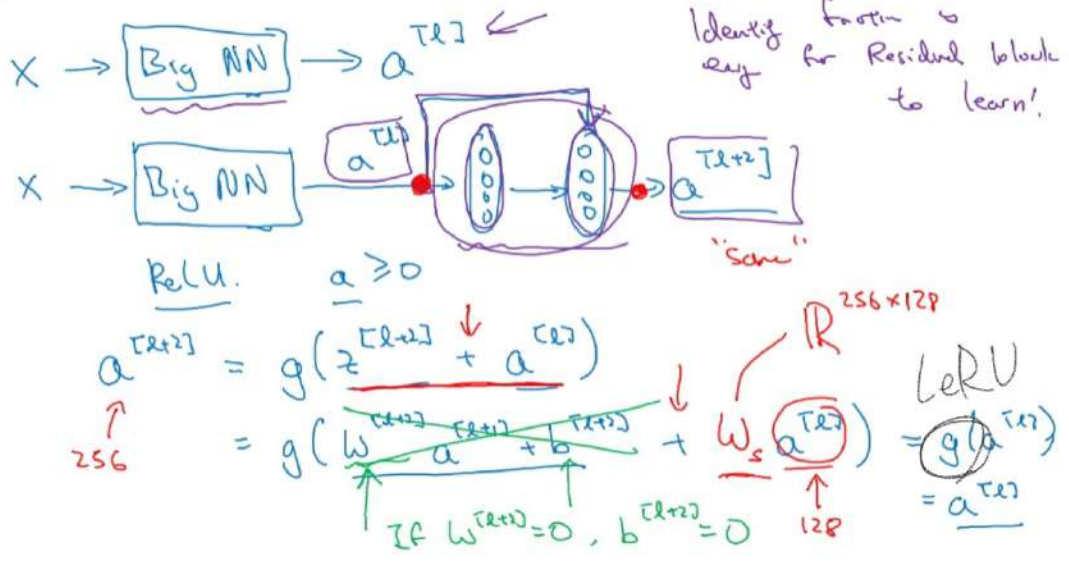


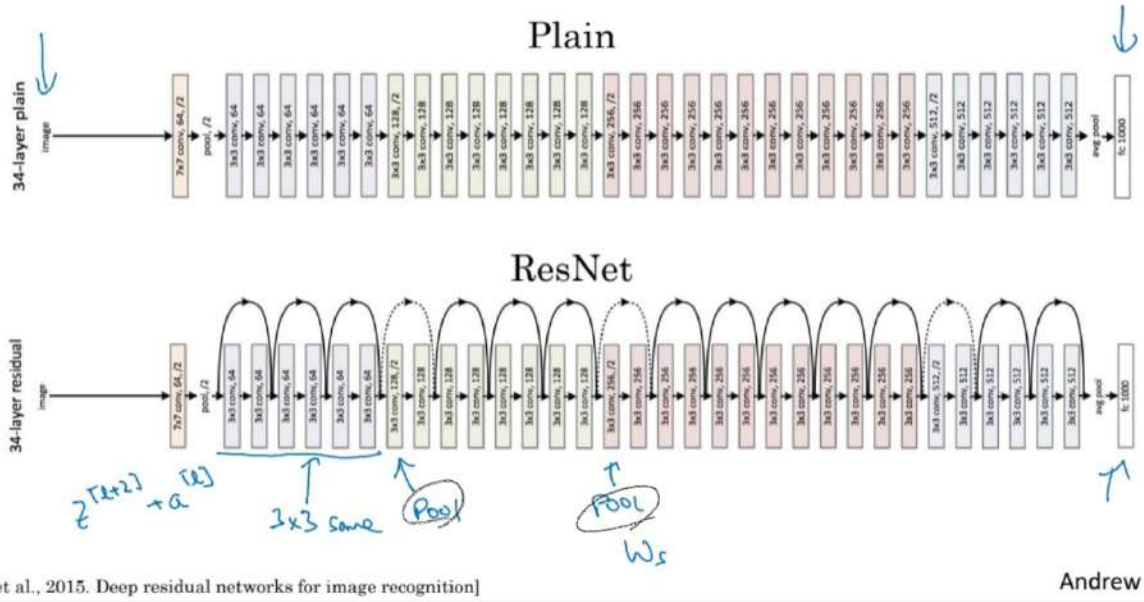



# Why ResNets work

## Why do residual networks work?




## ResNet




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

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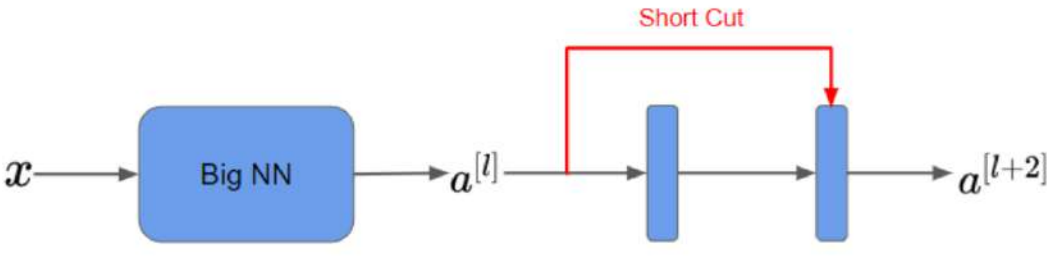


$$a^{[l+2]} = g(z^{[l+2]} + a^{[l]})$$
$$= g(W^{[l+2]} a^{[l+1]} + b^{[l+2]} + a^{[l]})$$

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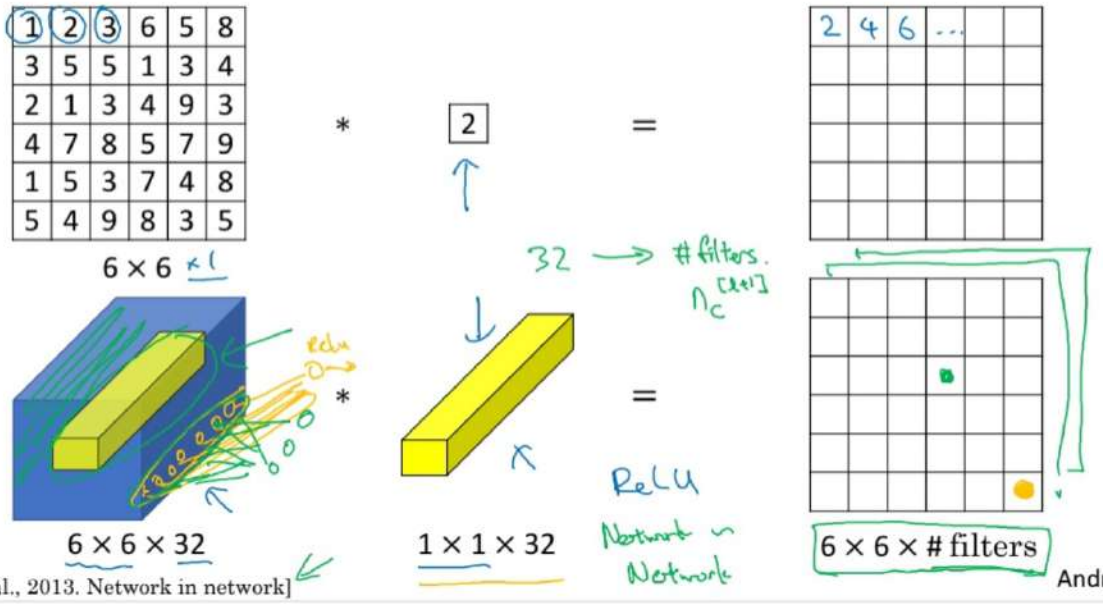
Case Studies

Network in Network and 1×1 convolutions

1x1 합성곱 연산을 통해 비선형성을 하나 더 추가해 복합한 함수를 학습 시킬 수 있고, 채널수를 조절

## Why does a 1 × 1 convolution do?




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

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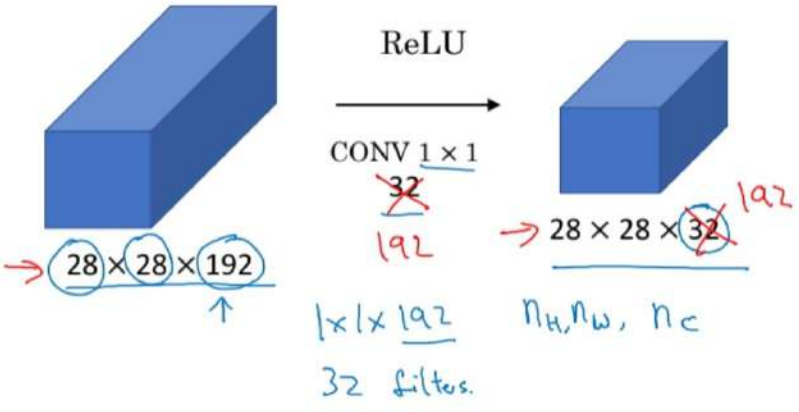
## Using 1×1 convolutions




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

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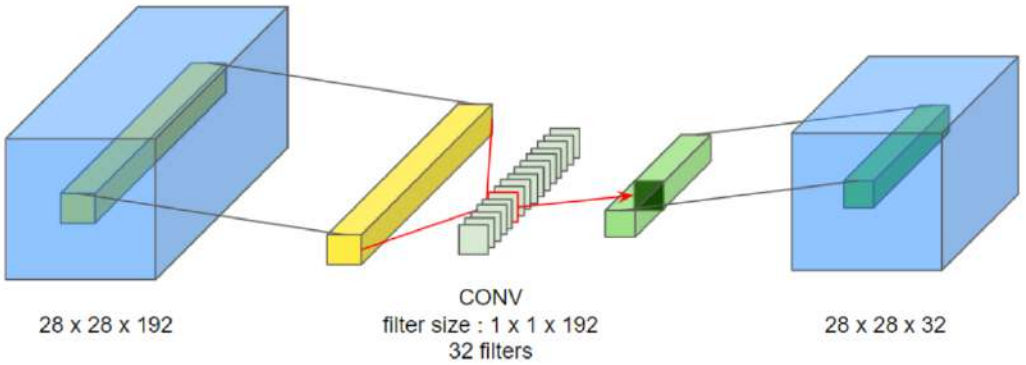

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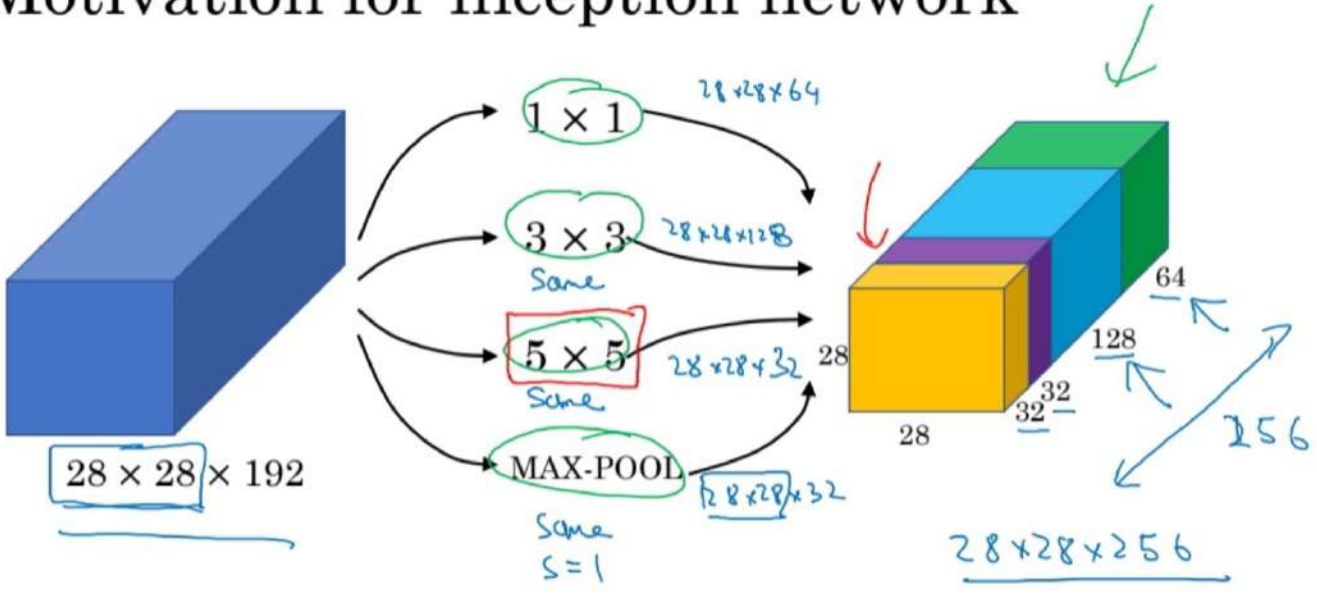
Case Studies

Inception network

# Motivation for inception network




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

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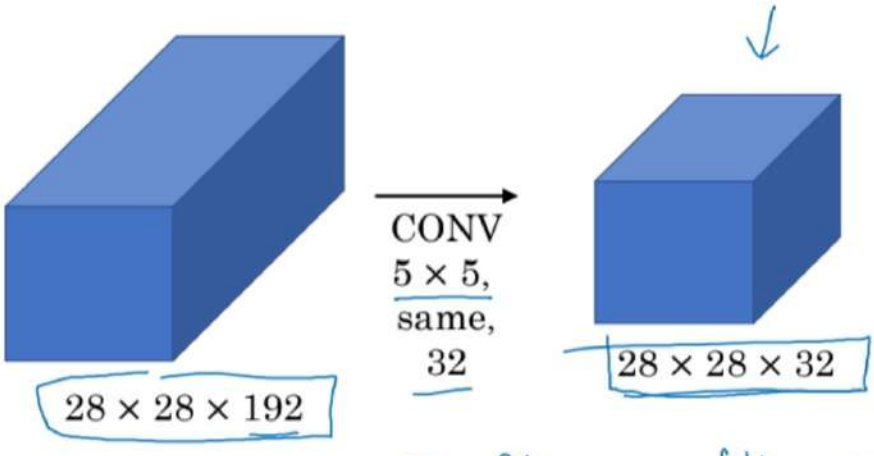
# The problem of computational cost




32 filters. filter one 5×5×192.

28×28×32 × 5×5×192 = 120M. 계산비용↑

1x1 합성곱으로 해결

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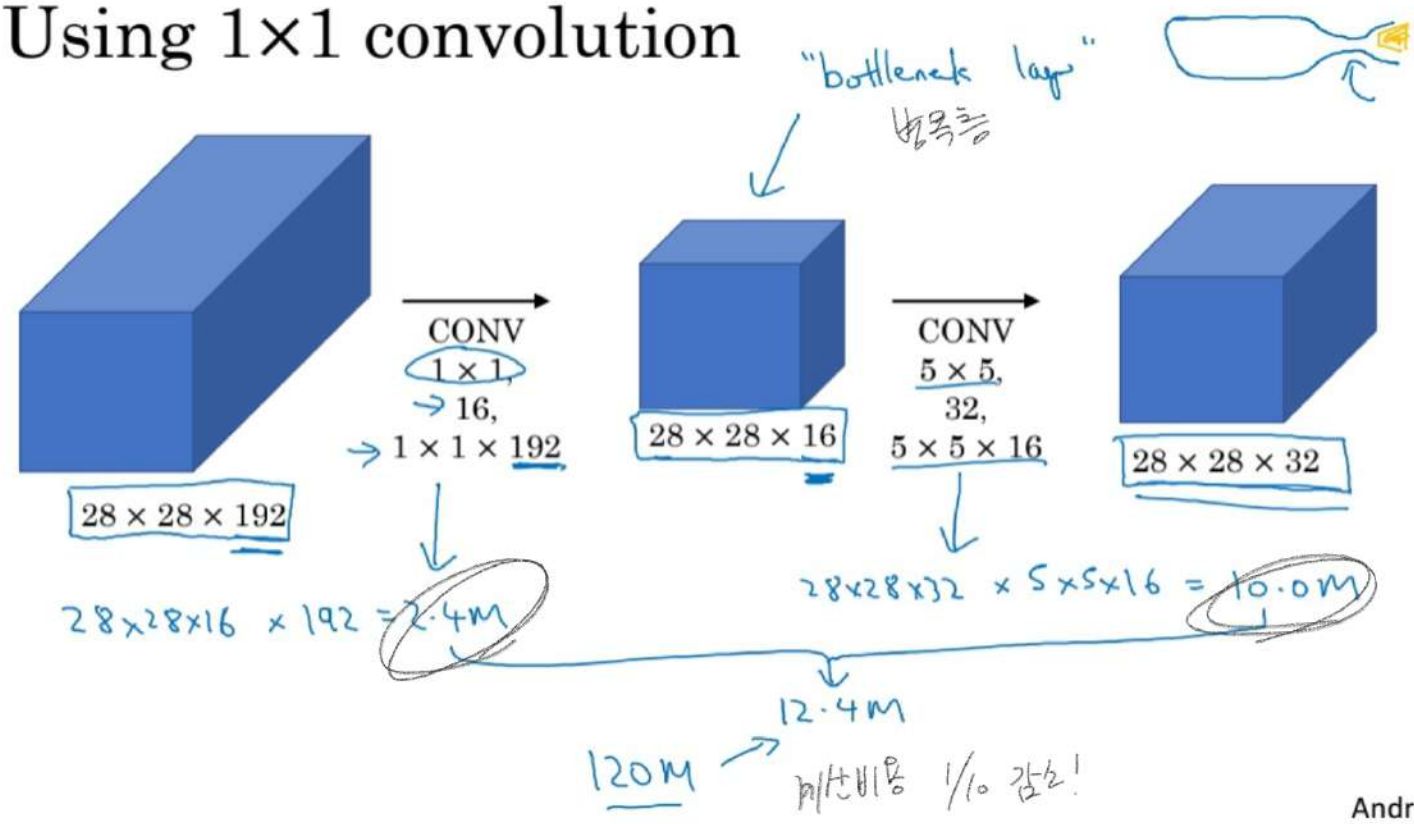
# Using 1×1 convolution

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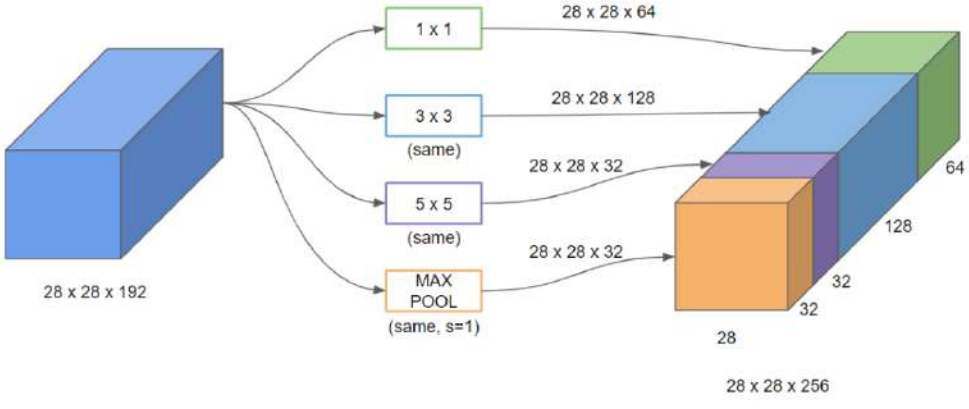


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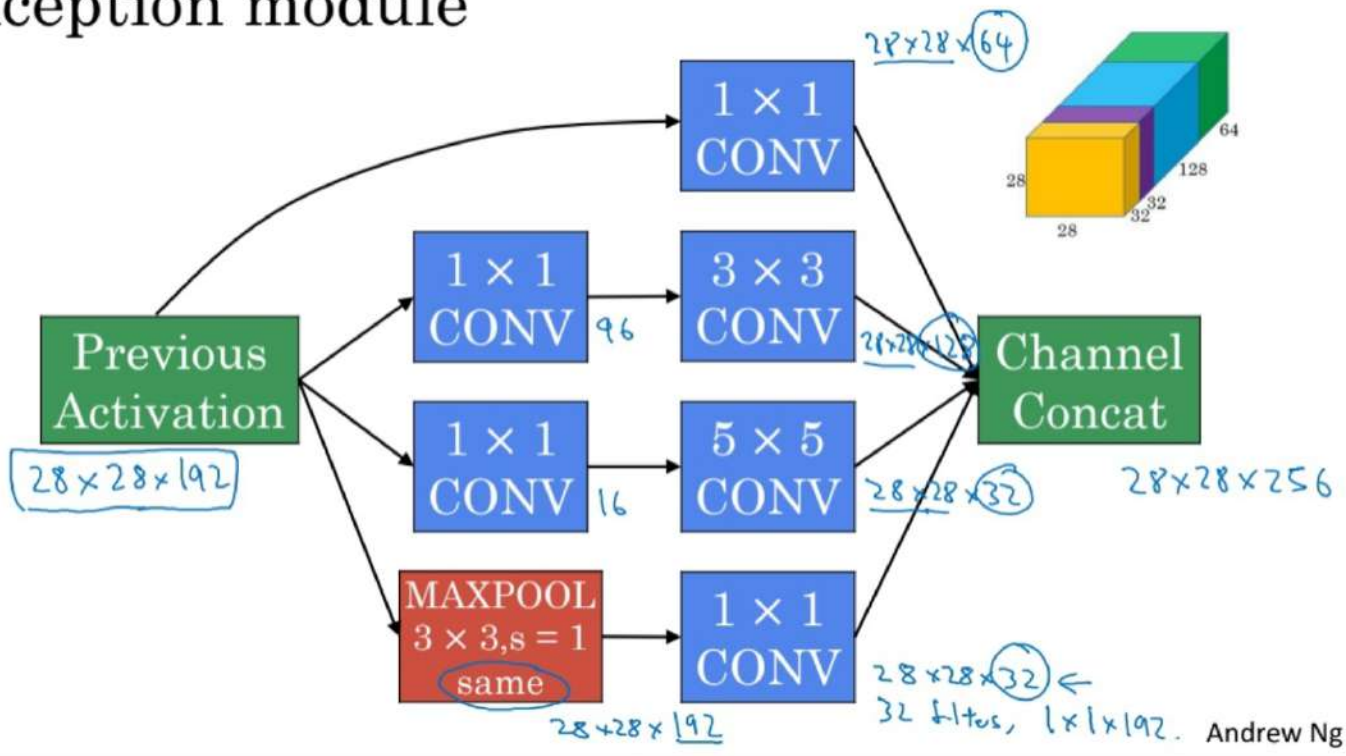
# Inception module

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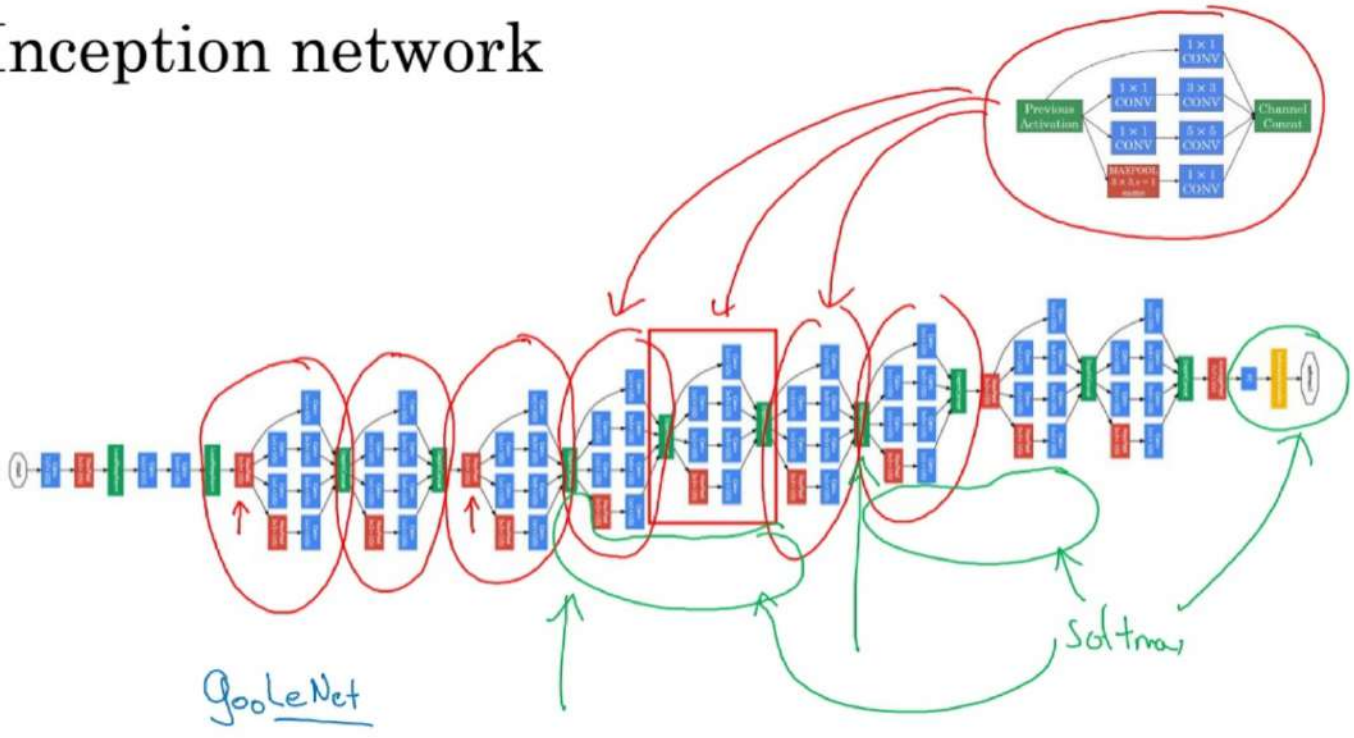
# Inception network




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

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중간 중간에 차원을 바꾸기 위한 최대 풀링층을 포함해서 여러개의 인셉션 블록이 계속 반복