Convolutional Neural Network
-Advanced-

2017.08.05

최건호

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ImageNet Challenge

성능을 측정하려면 공통된 데이터와
성능 측정 메트릭이 필요

ImageNet Challenge

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Prof. Fei-Fei Li
B.S. in Physics from Princeton University.
Ph.D. degree from California Institute of Technology
Associate Professor, Stanford University
Google Cloud Chief Scientist AI/ML

ImageNet Challenge

https://www.ted.com/talks/fei_fei_li_how_we_re_teaching_computers_to_understand_pictures

ImageNet Challenge

IMAGENET

1.2 Million Images(1,200,000), 1000 Categories

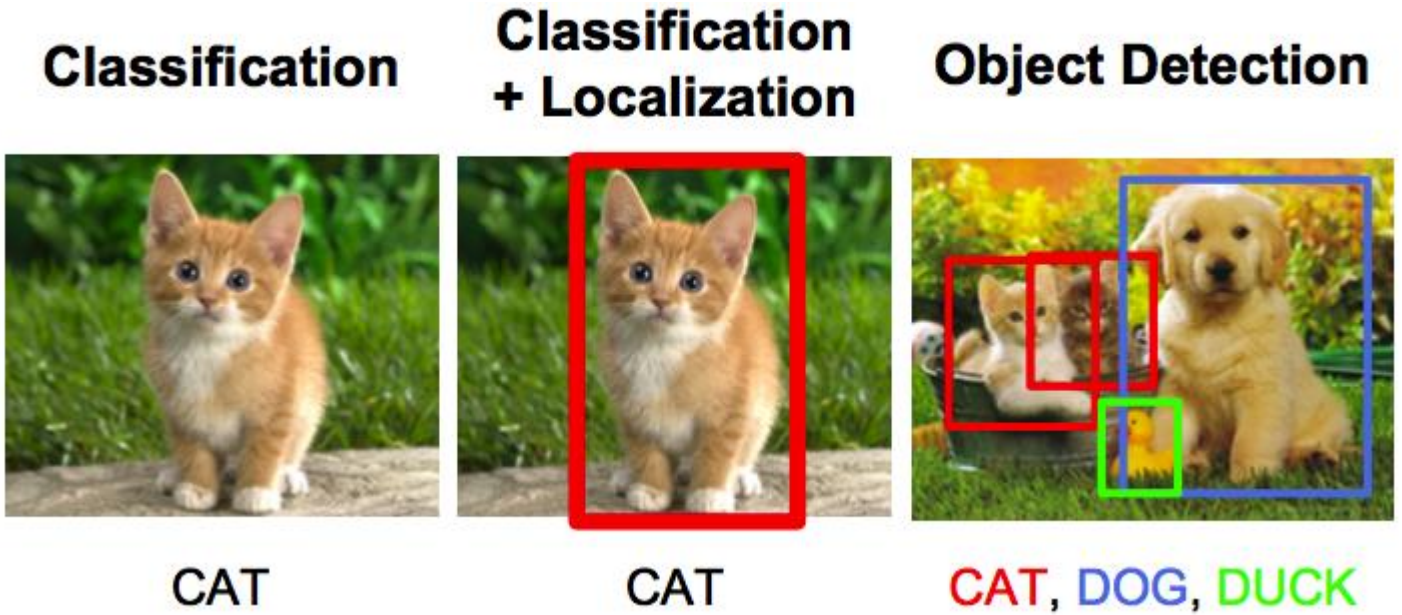
ImageNet Challenge

현재 14,197,122 Images

IMAGENET

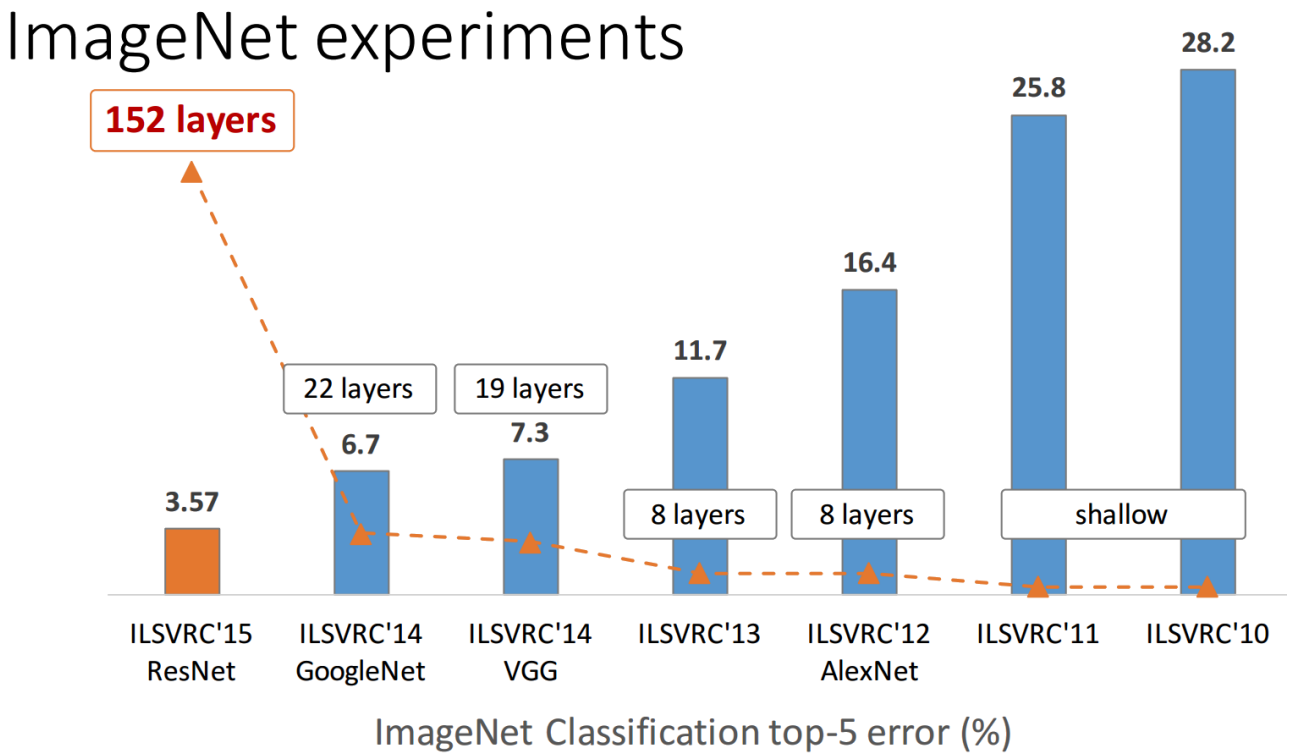
1.2 Million Images(1,200,000), 1000 Categories

ImageNet Challenge



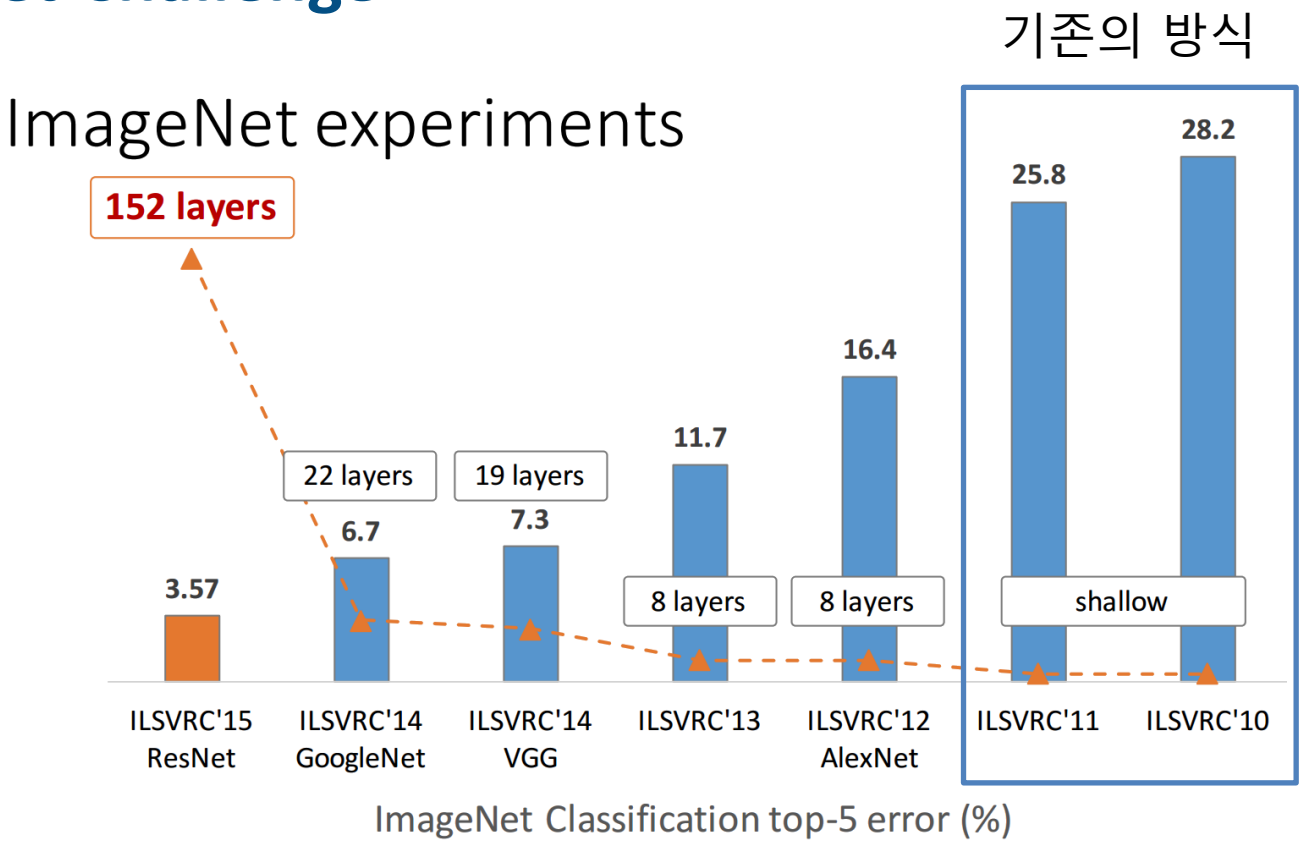
(출처:CS231n_lecture_slide)

ImageNet Challenge



(출처: Kaiming He "Deep residual learning for image recognition." ICML. 2016.)

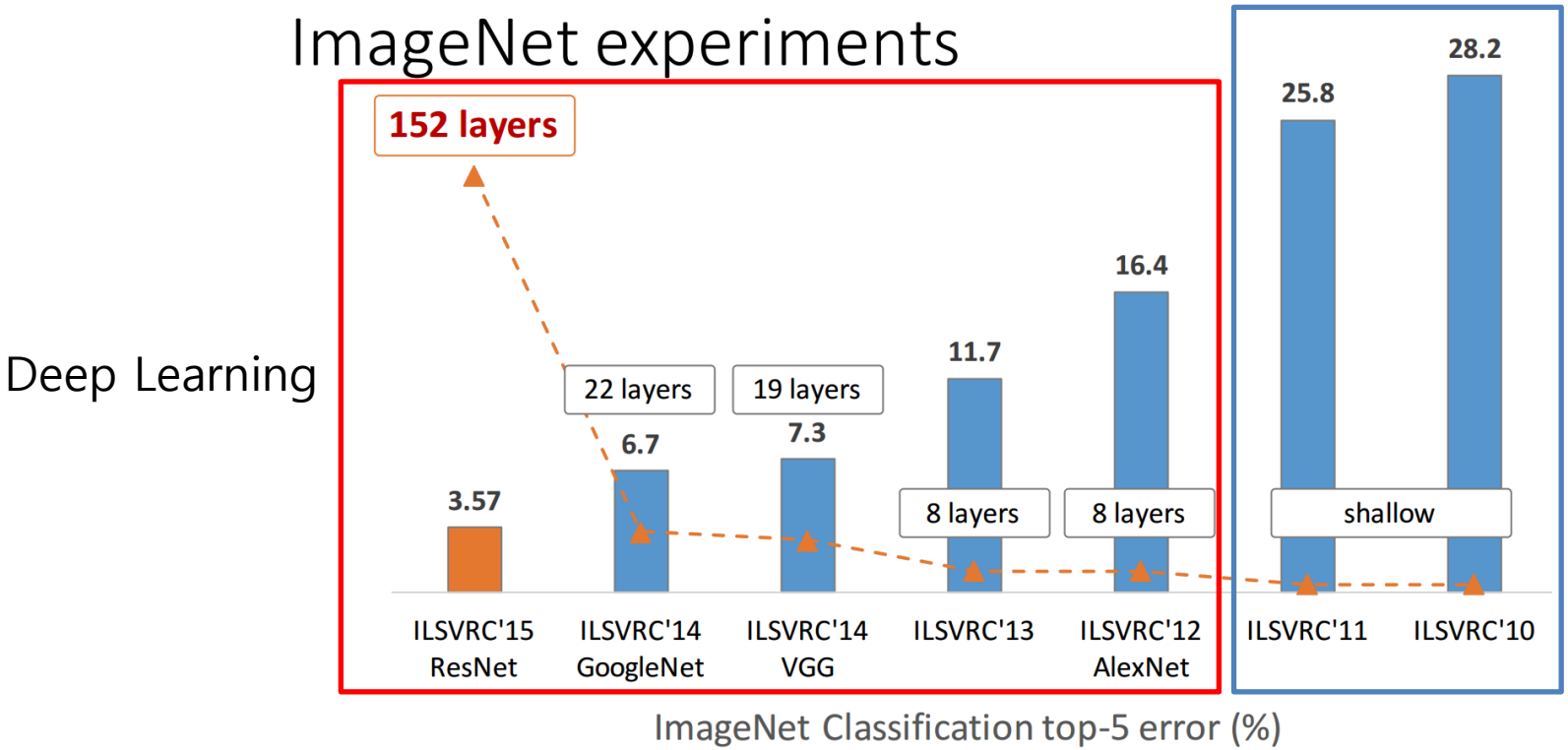
ImageNet Challenge



(출처: Kaiming He "Deep residual learning for image recognition." ICML. 2016.)

ImageNet Challenge

기존의 방식



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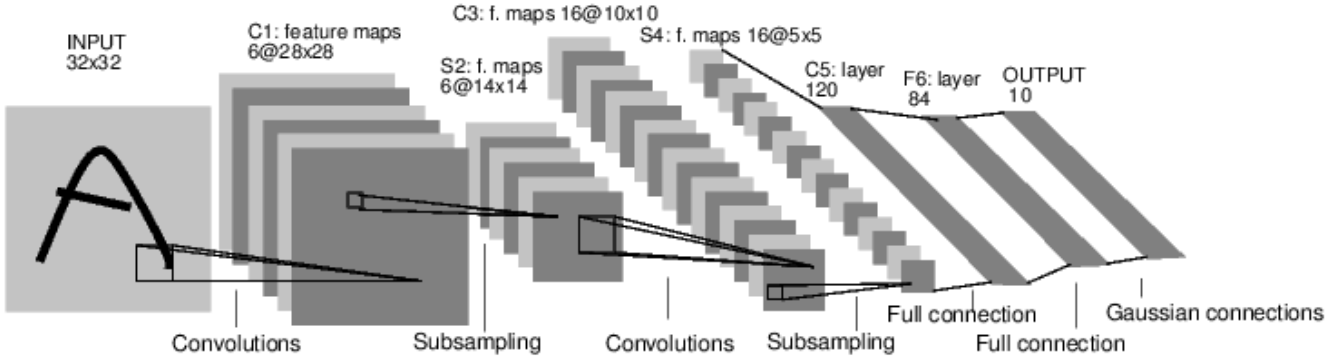
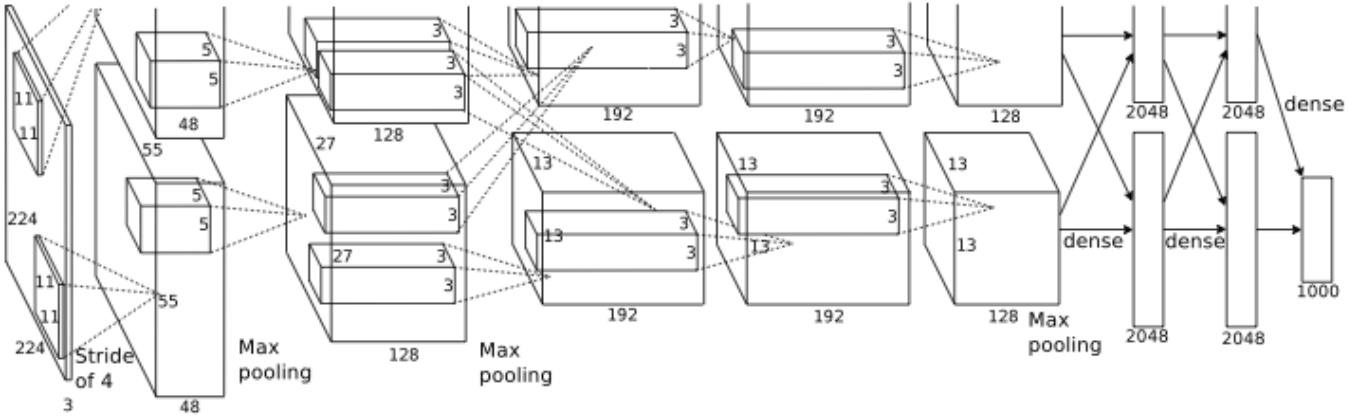
ImageNet Challenge

LeNet
(1998)



AlexNet
(2012)



ImageNet Challenge

AlexNet
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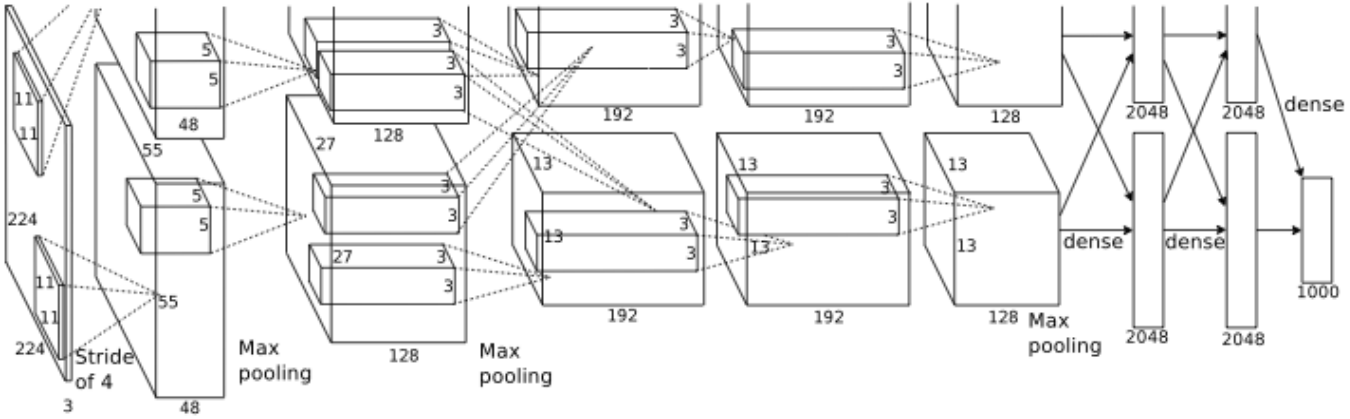

ImageNet Challenge

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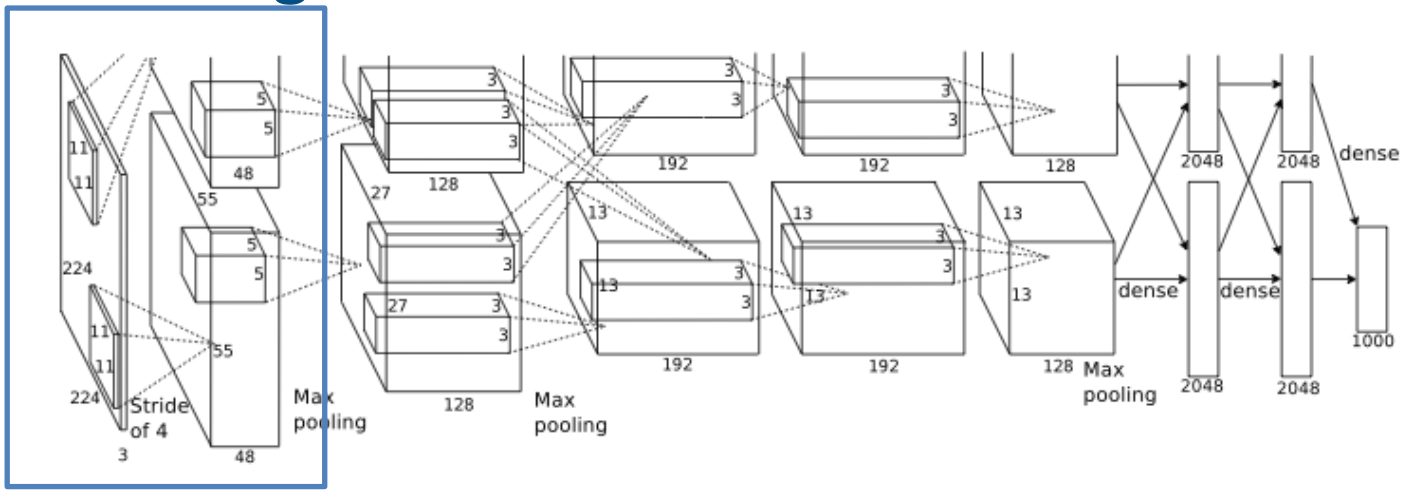
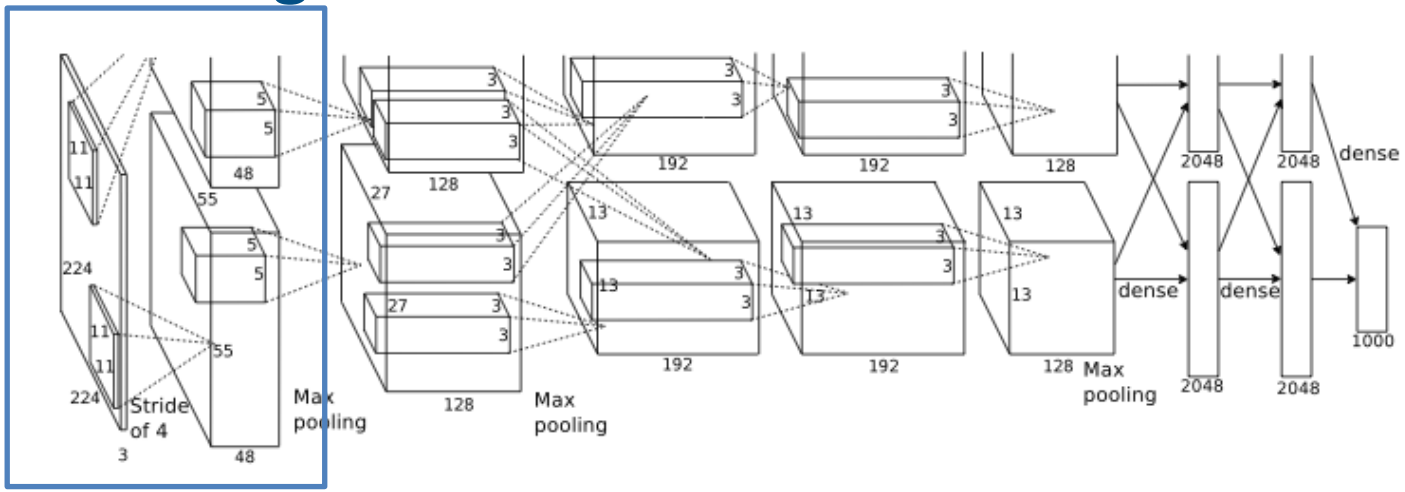


이 부분에 얼만큼의 파라미터가 생성될까?

ImageNet Challenge

AlexNet
(2012)

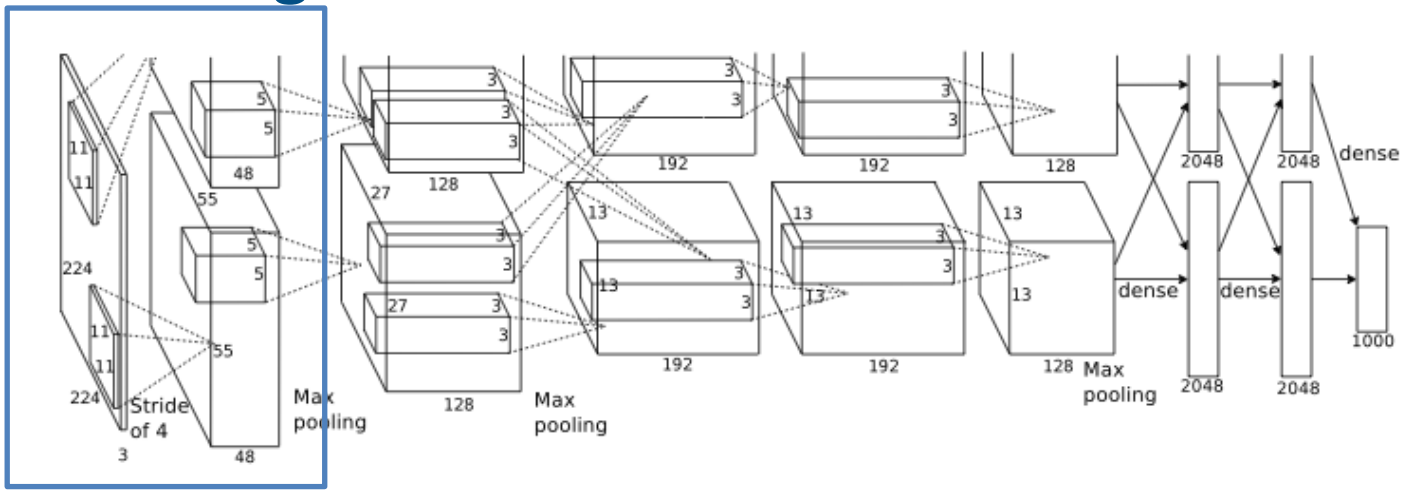


이 부분에 얼만큼의 파라미터가 생성될까?

Input: 224x224x3
Filter: 11x11
#Filter: 3 -> 96
Output: $floor[\frac{224-11}{4}+1]$

ImageNet Challenge

AlexNet
(2012)



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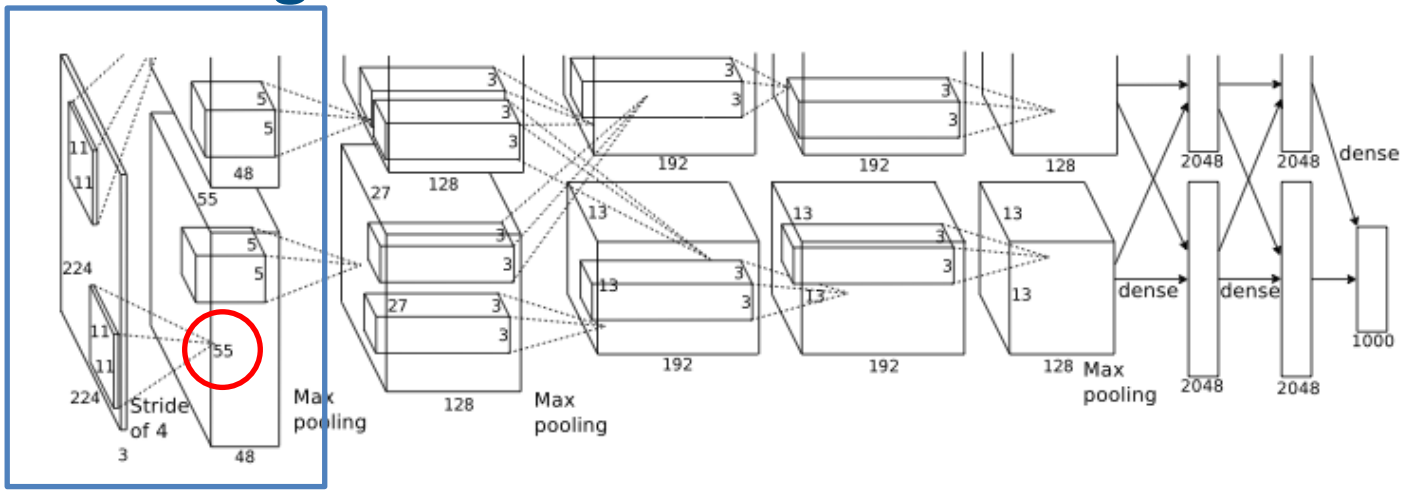
Input: 224x224x3
Filter: 11x11
#Filter: 3 -> 96
Output: $floor[\frac{224-11}{4}+1]=54$

ImageNet Challenge

AlexNet
(2012)



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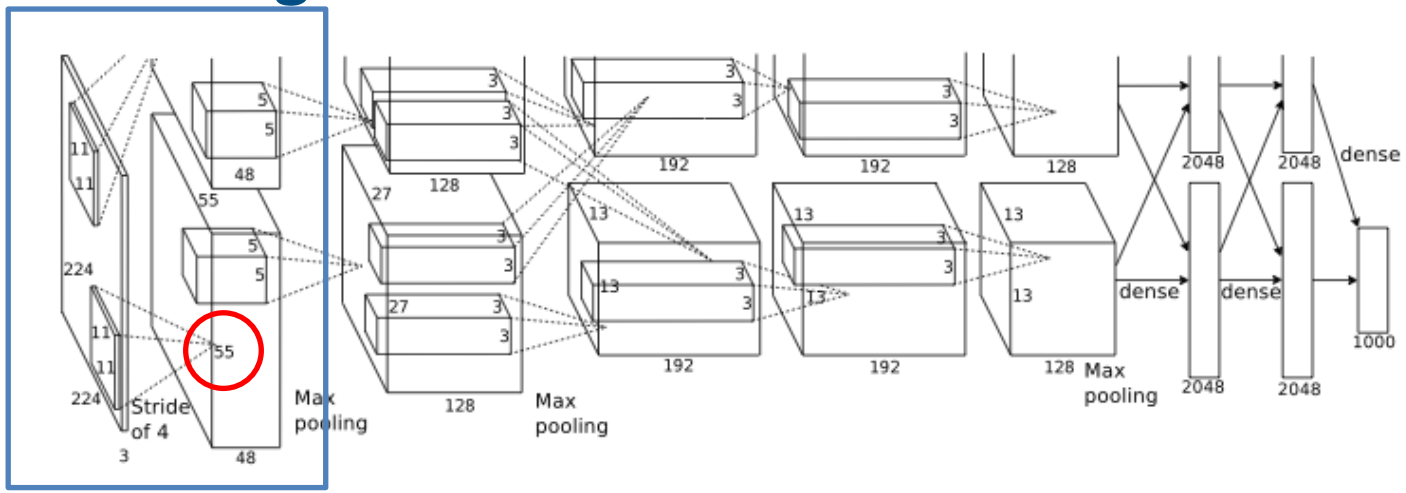
Input: 224x224x3
Filter: 11x11
#Filter: 3 -> 96
Output: $floor[\frac{224-11}{4}+1]$=54(???)

ImageNet Challenge

AlexNet
(2012)



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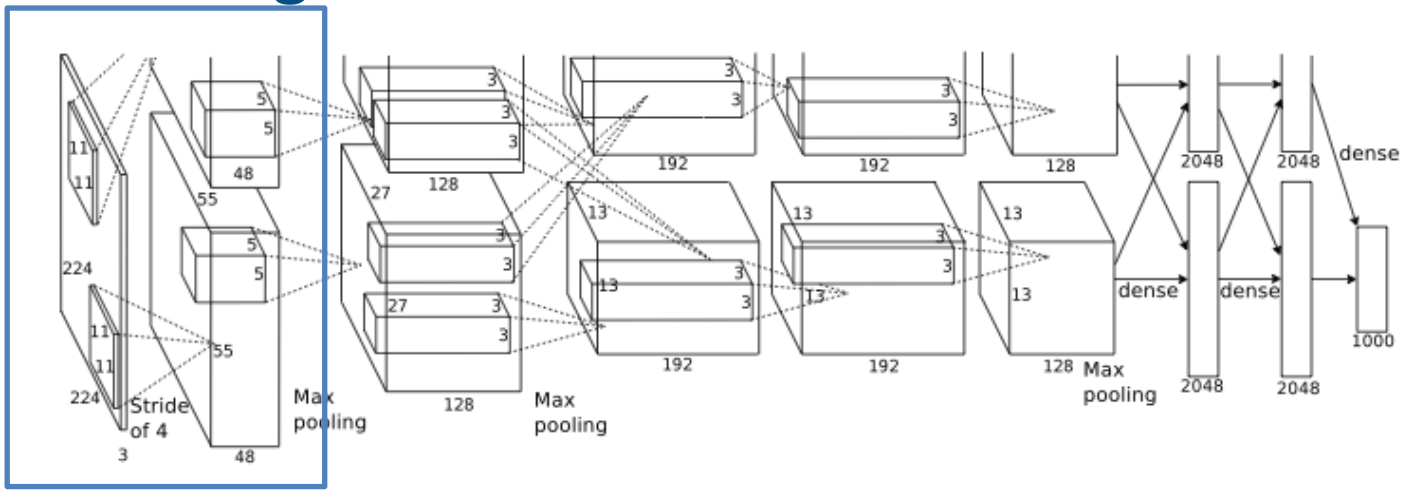
논문이 잘못했네..

ImageNet Challenge

AlexNet
(2012)

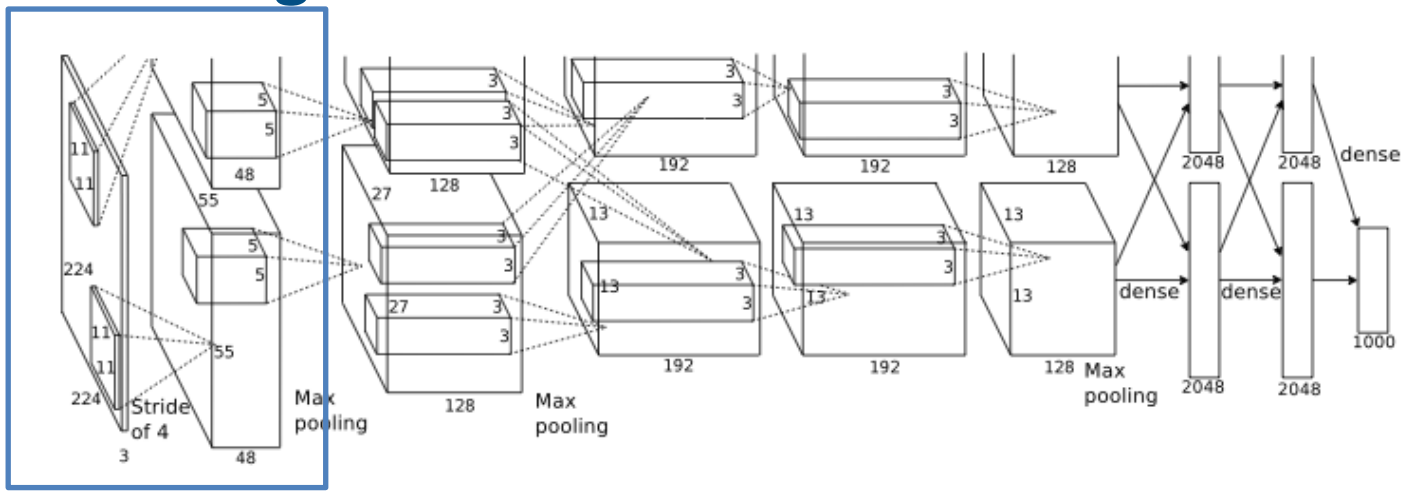


이 부분에 얼만큼의 파라미터가 생성될까?

Input: 227x227x3
Filter: 11x11
#Filter: 3 -> 96
Output: $floor[\frac{227-11}{4}+1]=55$

ImageNet Challenge

AlexNet
(2012)



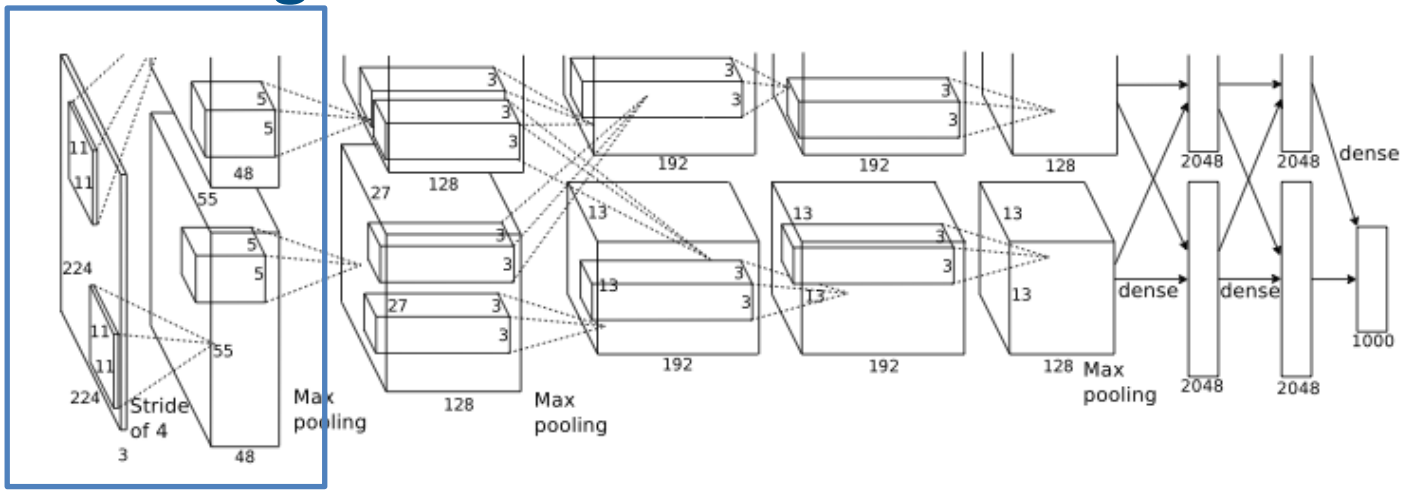
이 부분에 얼만큼의 파라미터가 생성될까?

필터 하나당 11x11x3+1=364

Input: 227x227x3
Filter: 11x11
#Filter: 3 -> 96
Output: $floor[\frac{227-11}{4}+1]=55$

ImageNet Challenge

AlexNet
(2012)



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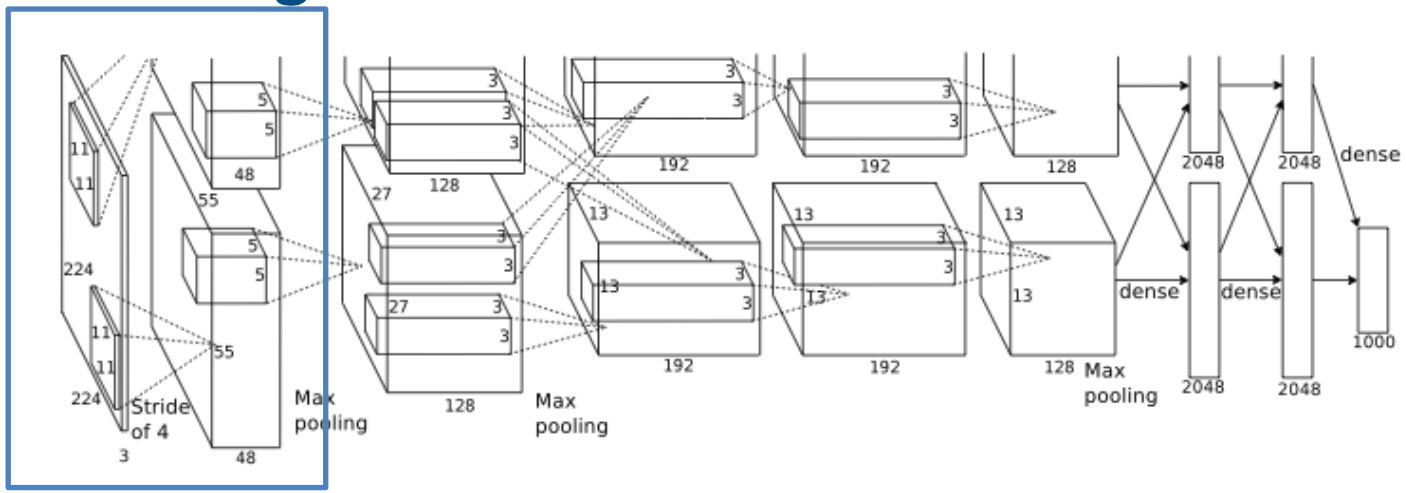
Input: 227x227x3
Filter: 11x11
#Filter: 3 -> 96
Output: $floor[\frac{227-11}{4}+1]=55$

필터 하나당 11x11x3+1=364
필터가 96개
결과적으로 364x96 = 34,944

ImageNet Challenge

AlexNet
(2012)



이 부분에 얼만큼의 파라미터가 생성될까?

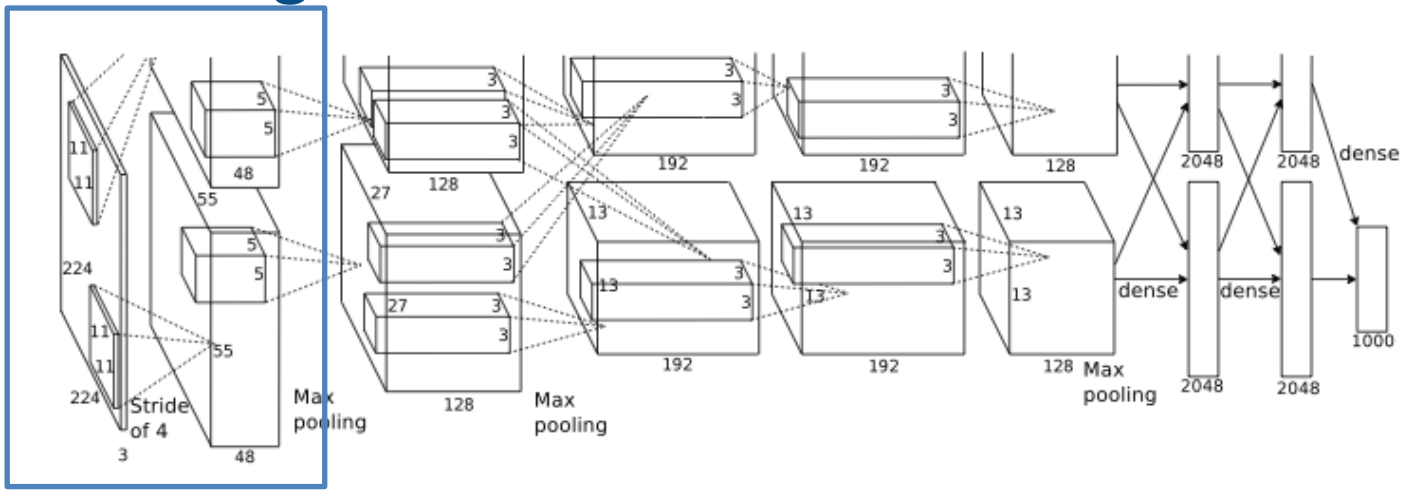
Input: 227x227x3
Filter: 11x11
#Filter: 3 -> 96
Output: $floor[\frac{227-11}{4}+1]$=55

필터 하나당 11x11x3+1=364
필터가 96개
결과적으로 364x96 = 34,944

output은 55x55x96 = 290,400

ImageNet Challenge

AlexNet
(2012)

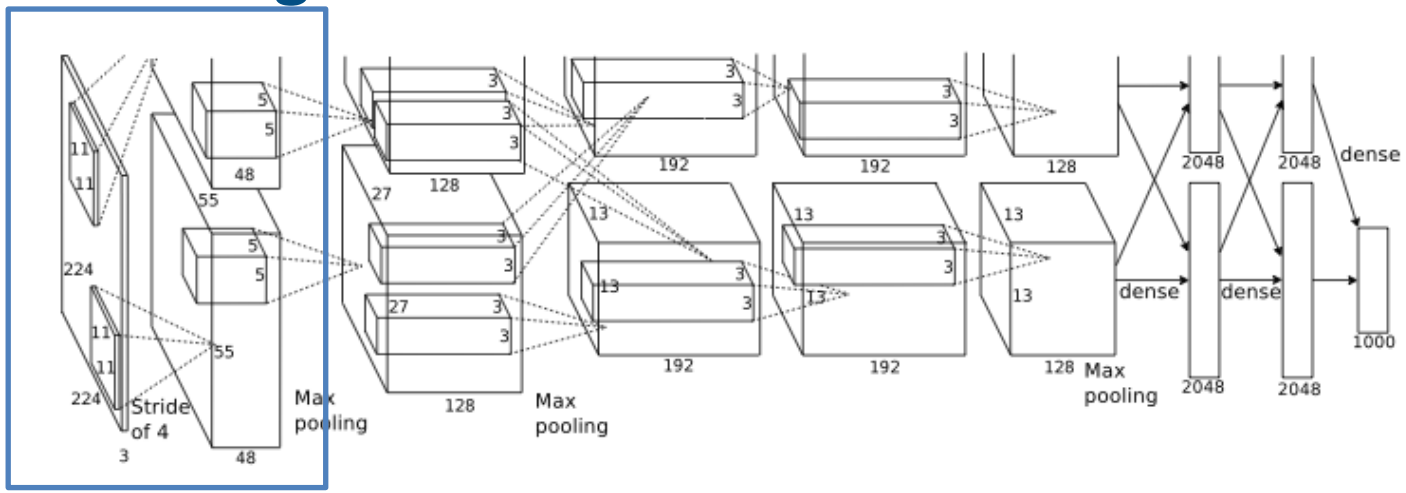


이 부분에 얼만큼의 파라미터가 생성될까? 34,944 + 290,400 = 325,344

Input: 227x227x3
Filter: 11x11
#Filter: 3 -> 96
Output: $floor[\frac{227-11}{4}+1]=55$

ImageNet Challenge

AlexNet
(2012)



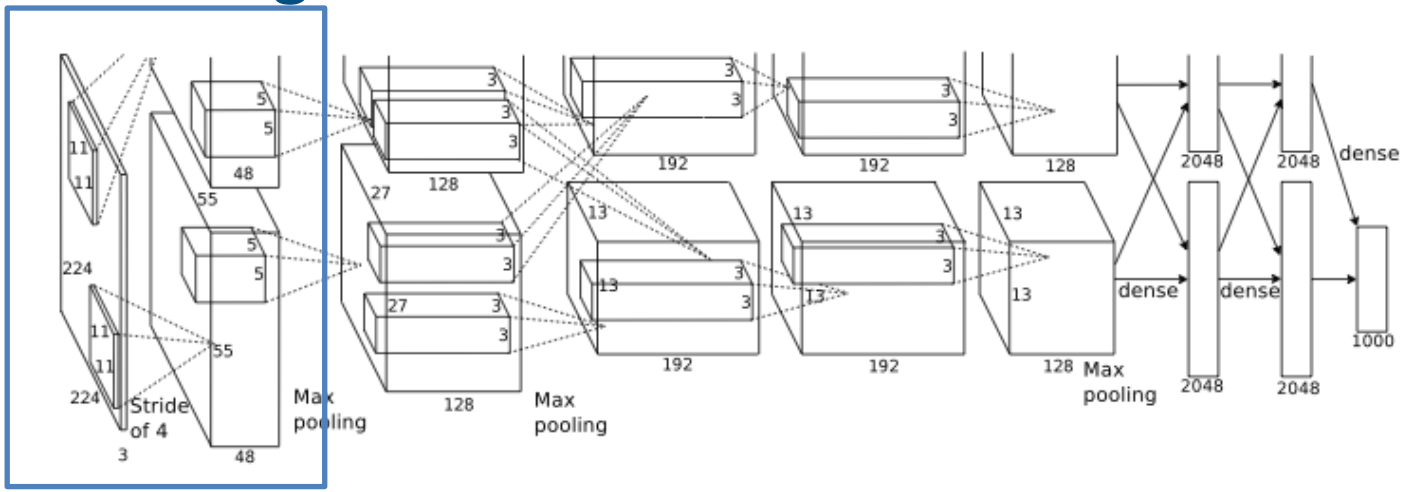
이 부분에 얼만큼의 파라미터가 생성될까?

34,944 + 290,400 = 325,344
기본형이 float32 = 4 byte

Input: 227x227x3
Filter: 11x11
#Filter: 3 -> 96
Output: $floor[\frac{227-11}{4}+1]=55$

ImageNet Challenge

AlexNet
(2012)



이 부분에 얼만큼의 파라미터가 생성될까?

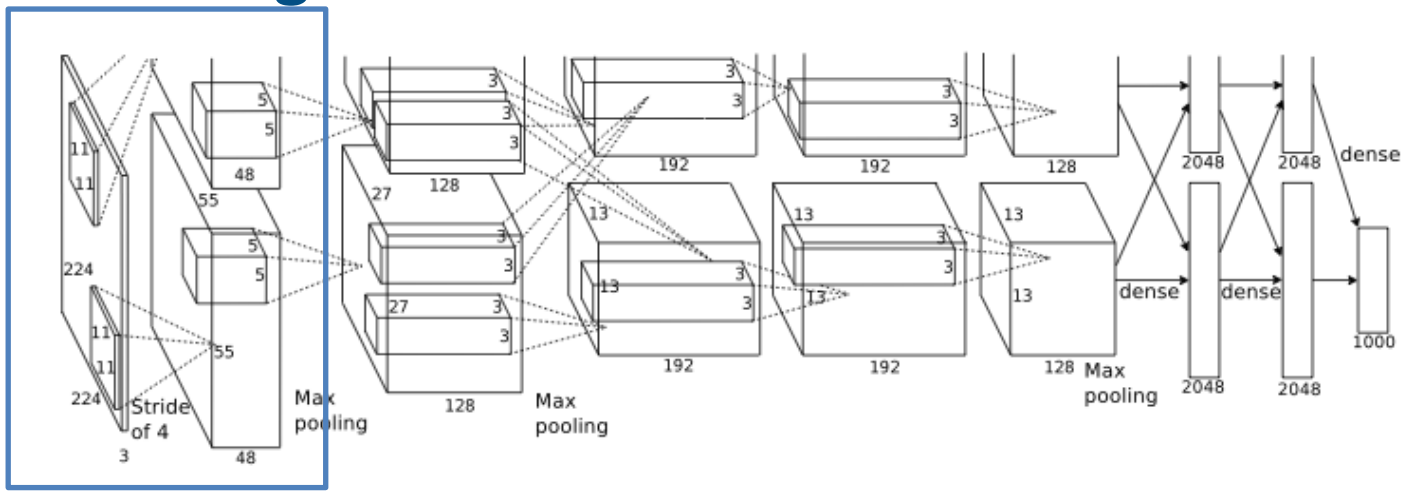
Input: 227x227x3
Filter: 11x11
#Filter: 3 -> 96
Output: $floor[\frac{227-11}{4}+1]=55$

34,944 + 290,400 = 325,344
기본형이 float32 = 4 byte

즉 325,344 x 4=1,301,376 byte

ImageNet Challenge

AlexNet
(2012)



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Input: 227x227x3
Filter: 11x11
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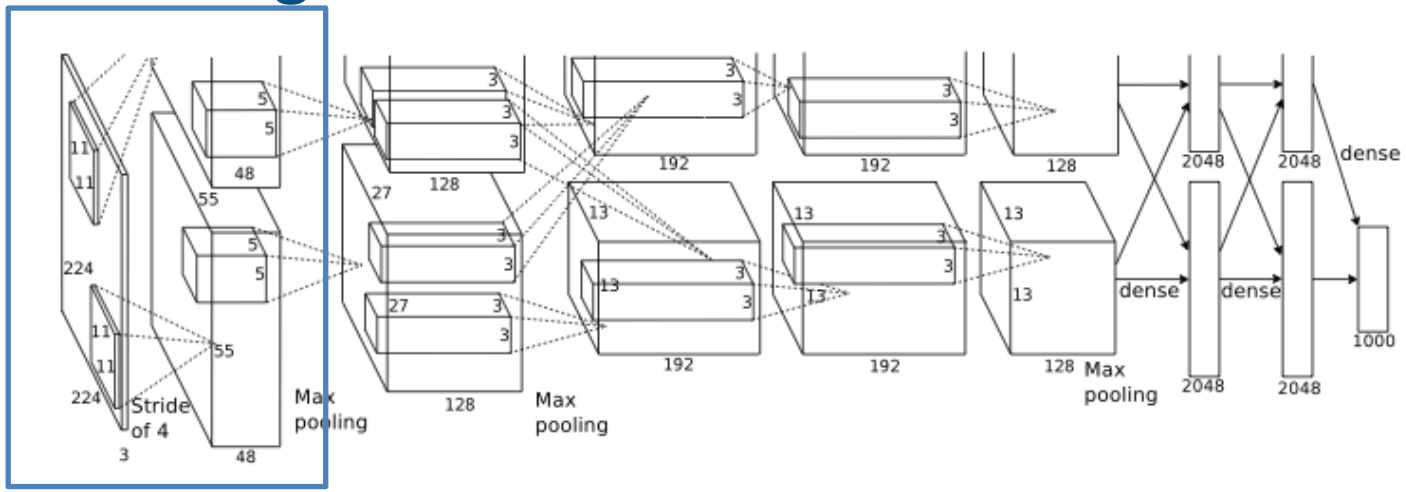
Output: $floor[\frac{227-11}{4}+1]=55$

34,944 + 290,400 = 325,344
기본형이 float32 = 4 byte

즉 325,344 x 4=1,301,376 byte
=1,301.376 KB

ImageNet Challenge

AlexNet
(2012)



이 부분에 얼만큼의 파라미터가 생성될까?

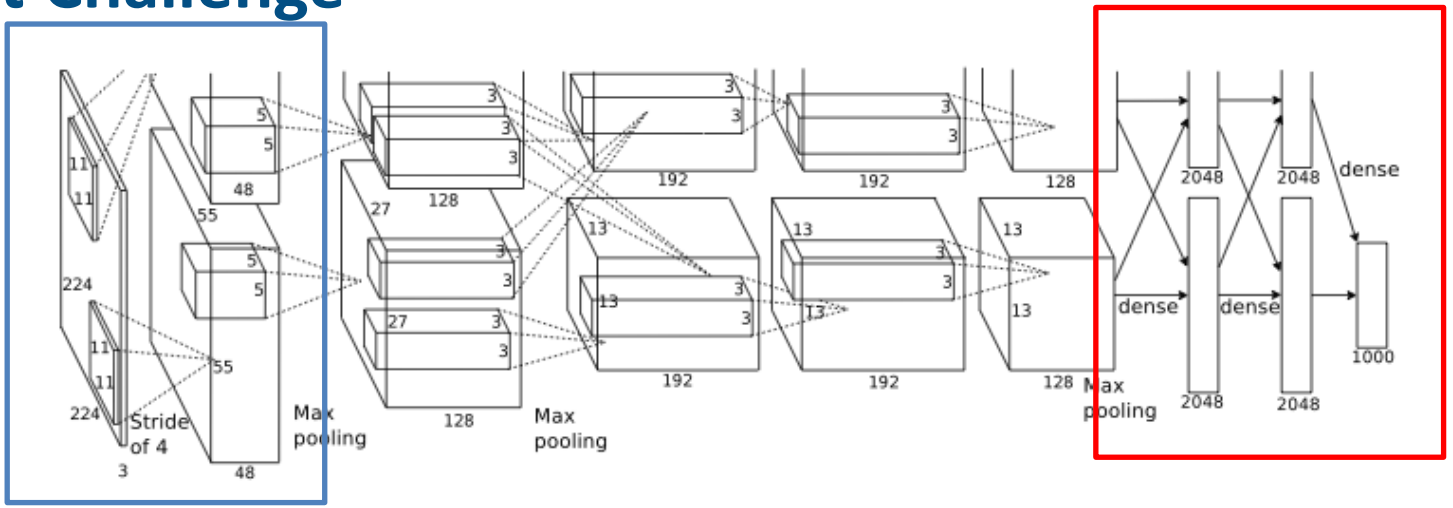
Input: 227x227x3
Filter: 11x11
#Filter: 3 -> 96
Output: $floor[\frac{227-11}{4}+1]=55$

34,944 + 290,400 = 325,344
기본형이 float32 = 4 byte

즉 325,344 x 4=1,301,376 byte
=1,301.376 KB
=1.3 MB

ImageNet Challenge

AlexNet
(2012)



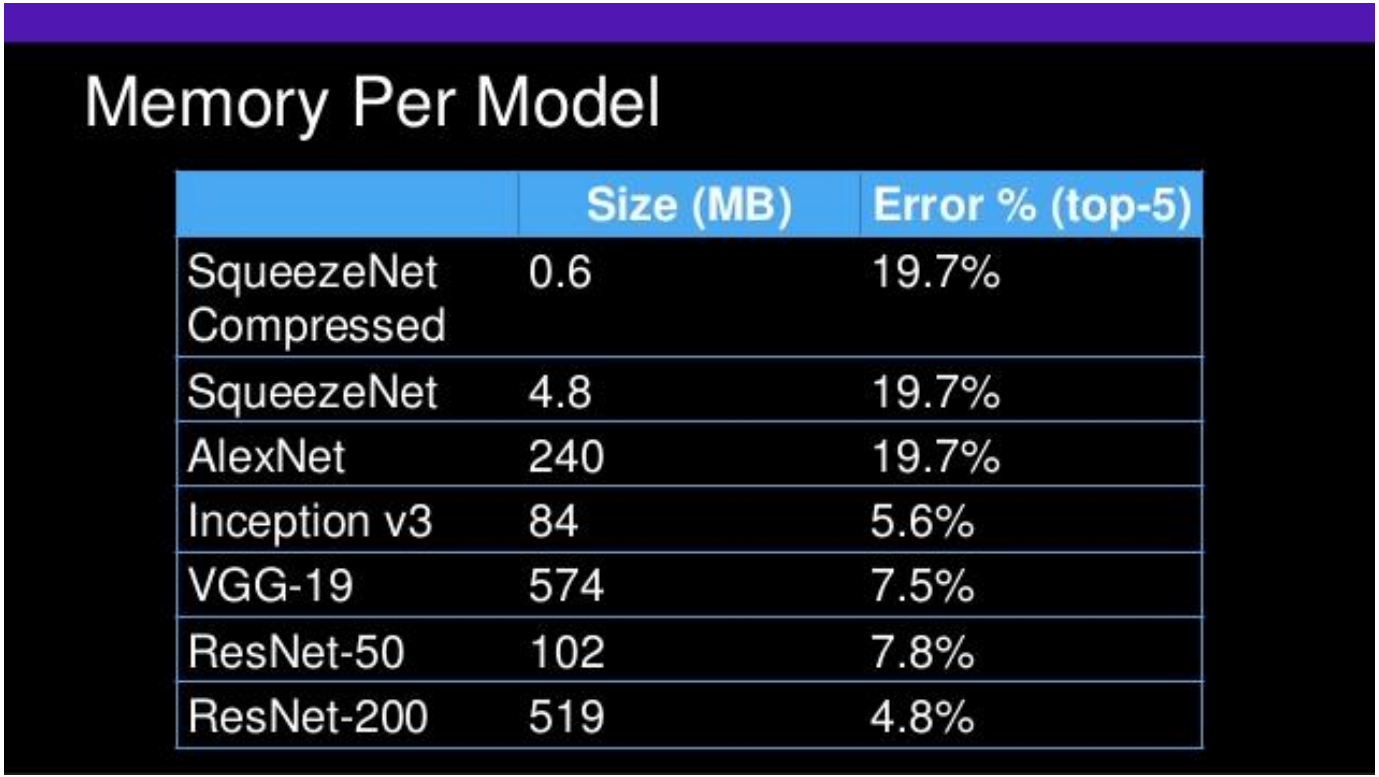
이 부분에 얼만큼의 파라미터가 생성될까?

Input: 13x13x256
Output: 4096 -> 4096 ->1000

13 x13 x 256= 43,264
43,264 x4096 +4096 =177,213,440
=177.2 MB

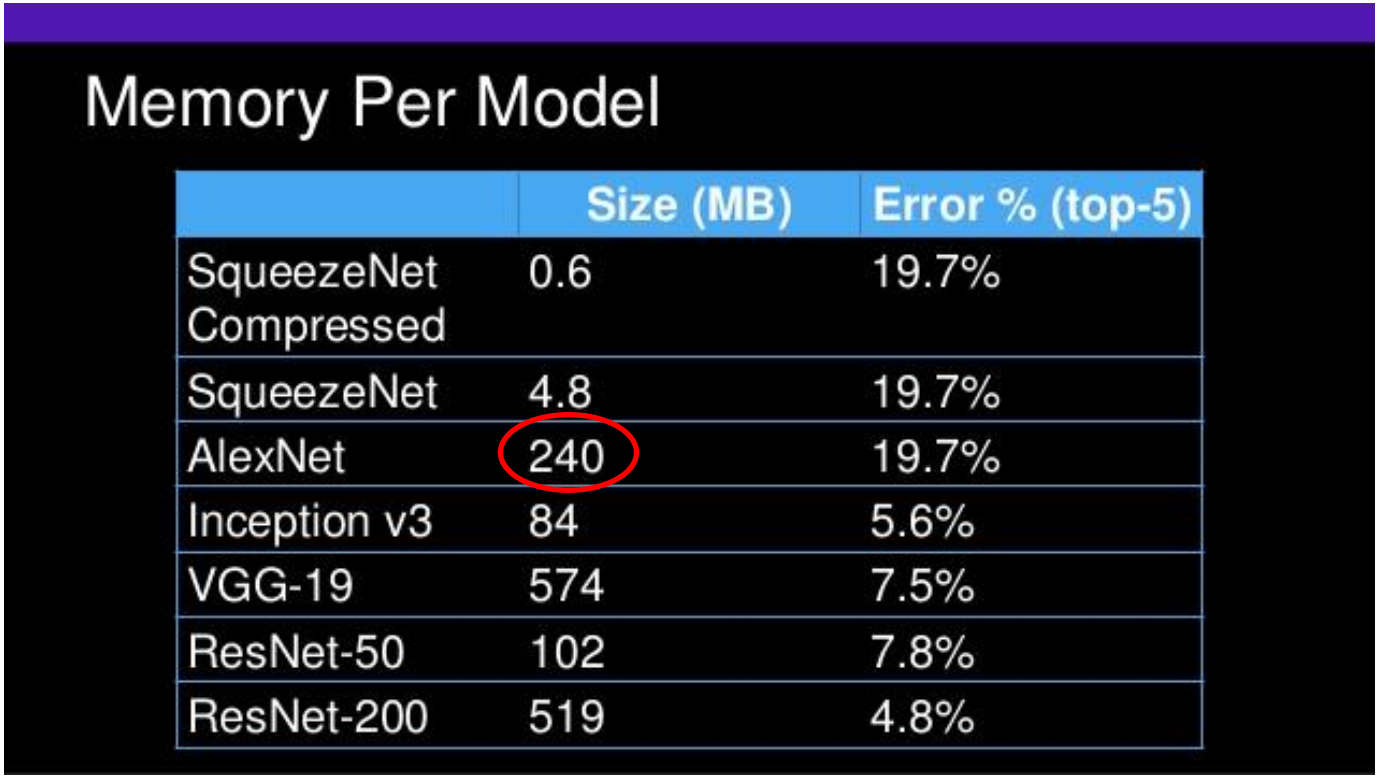
4096 x4096+4096 = 16,781,312
= 16.8 MB

ImageNet Challenge



(출처:AWS re:Invent 2016: Bringing Deep Learning to the Cloud with Amazon EC2 (CMP314)

ImageNet Challenge



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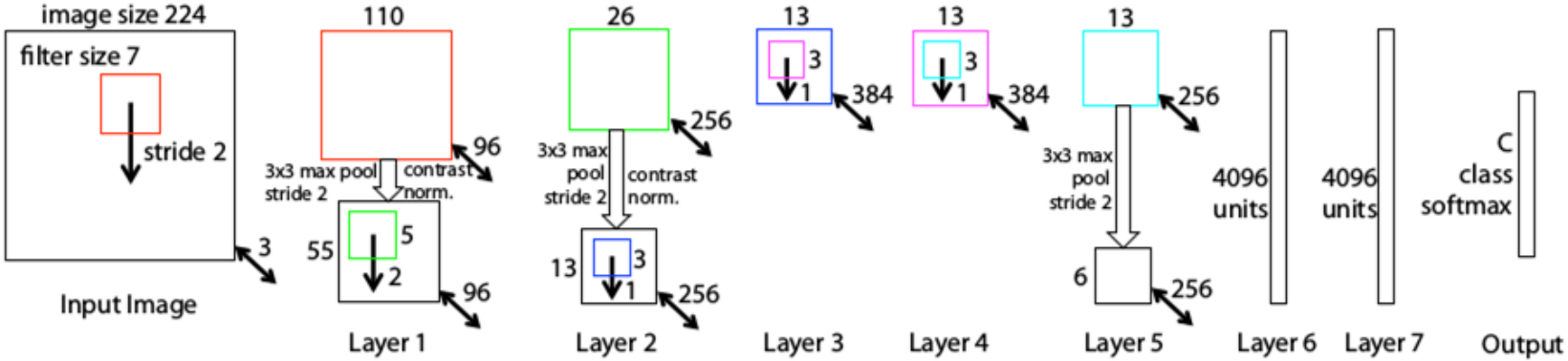
ImageNet Challenge

ZF Network(2013)



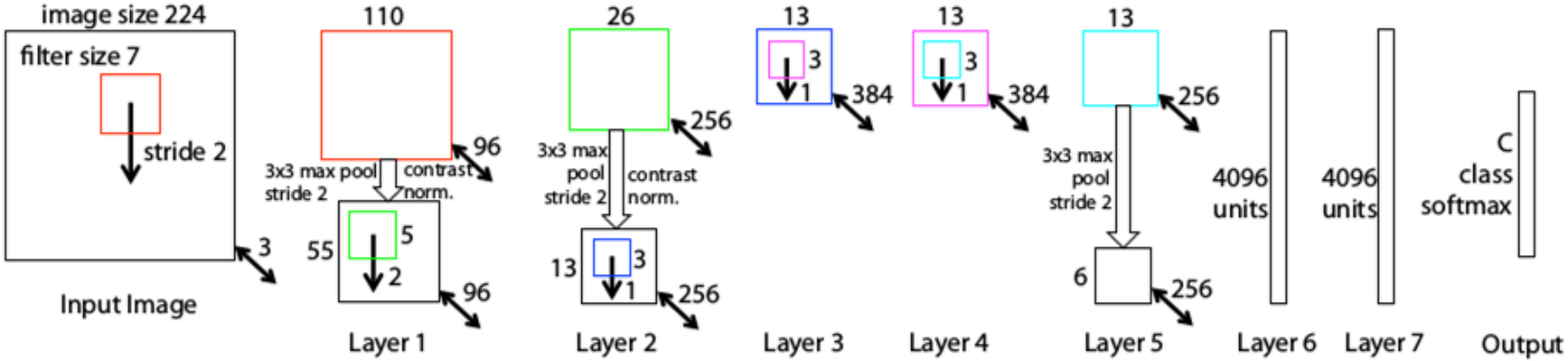
ZF Net Architecture

전체적 구조는 같음

(출처:https://arxiv.org/pdf/1311.2901.pdf)

ImageNet Challenge

ZF Network(2013)



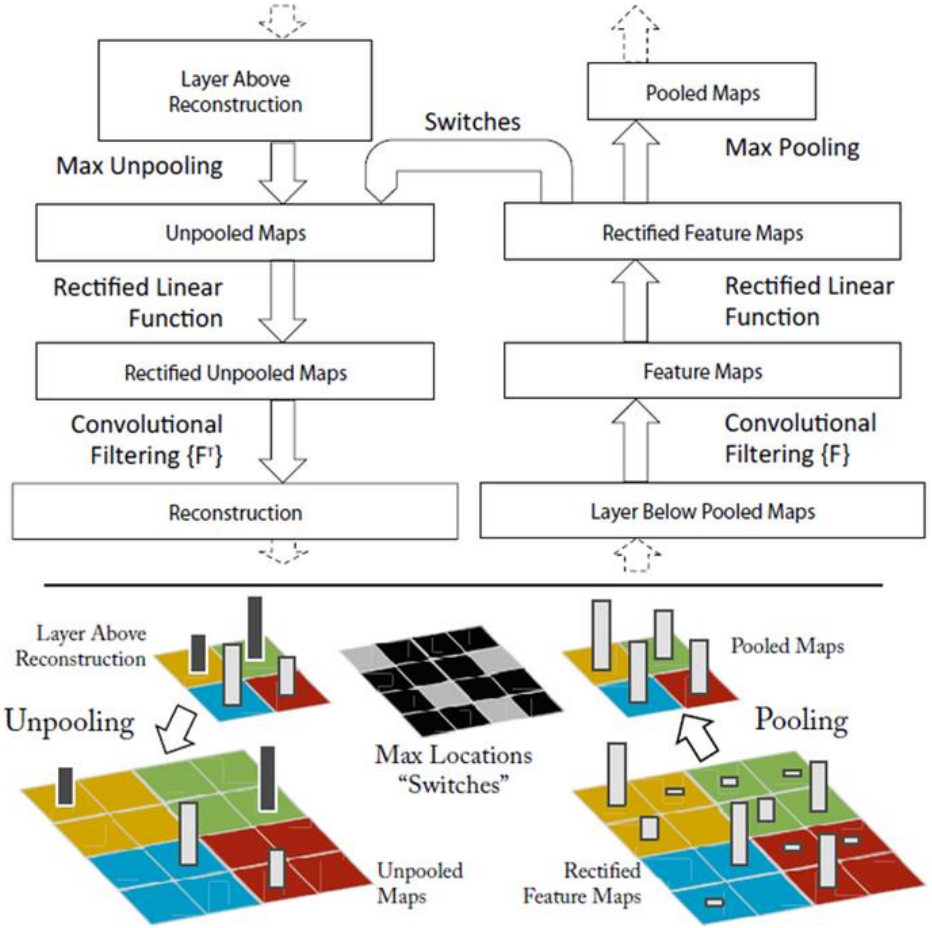
ZF Net Architecture

전체적 구조는 같음
ZF Net에서 배울 점은
CNN의 시각화

(출처:https://arxiv.org/pdf/1311.2901.pdf)

ImageNet Challenge

Convolution 연산을 역으로 진행하여 필터가 어떤 모양에 반응하는지 시각화



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ImageNet Challenge

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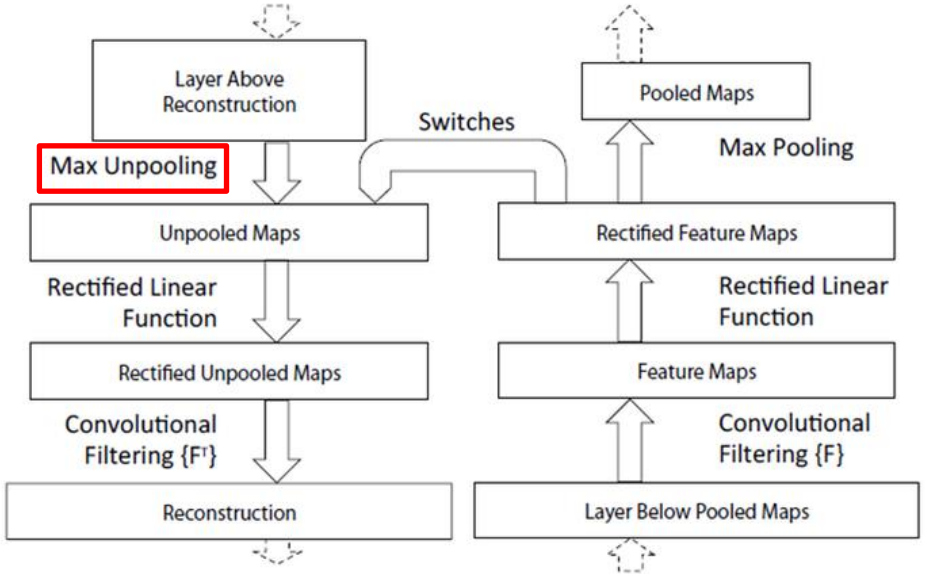
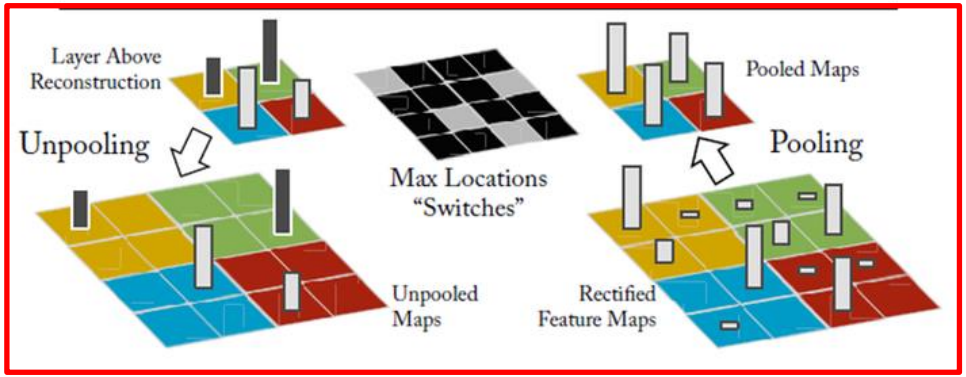
Max pooling은 Max였던 위치를 기억하여 그대로 확대





(출처:https://arxiv.org/pdf/1311.2901.pdf)

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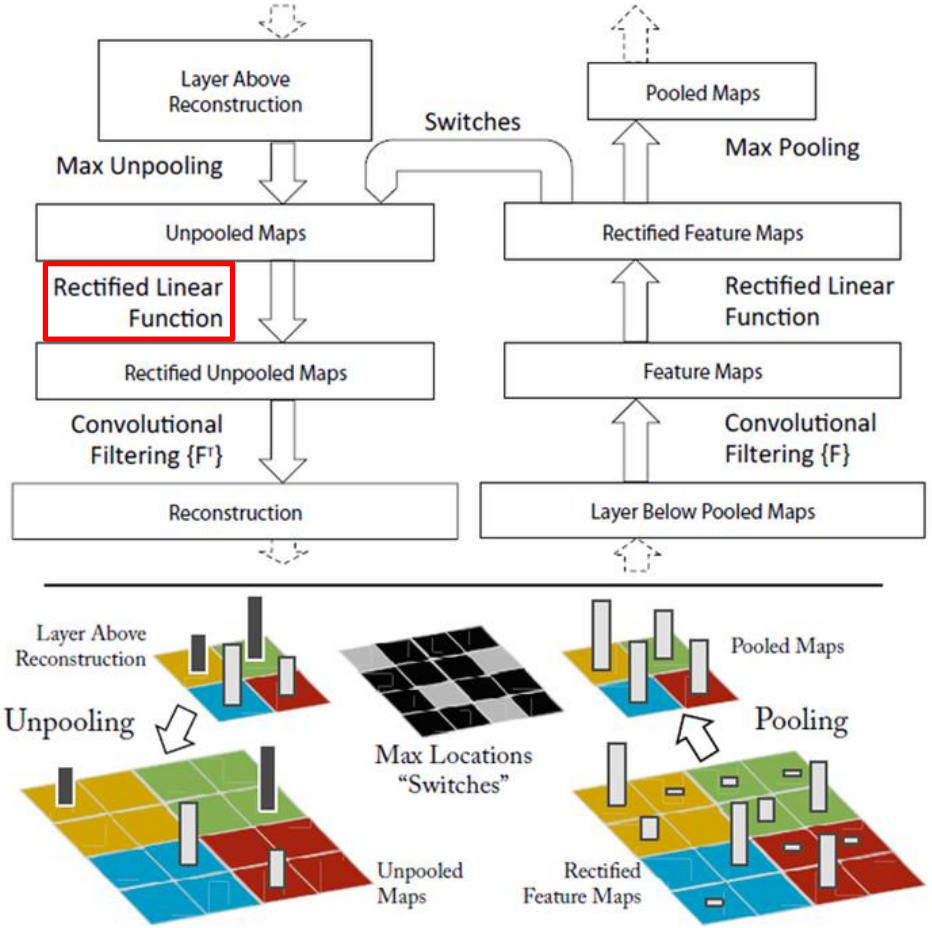
Rectified Linear Unit는 0이하의 숫자들이 문제가 되는데 연구에 의하면 시각화에 큰 영향이 없었다고 함



(출처:https://arxiv.org/pdf/1311.2901.pdf)

ImageNet Challenge

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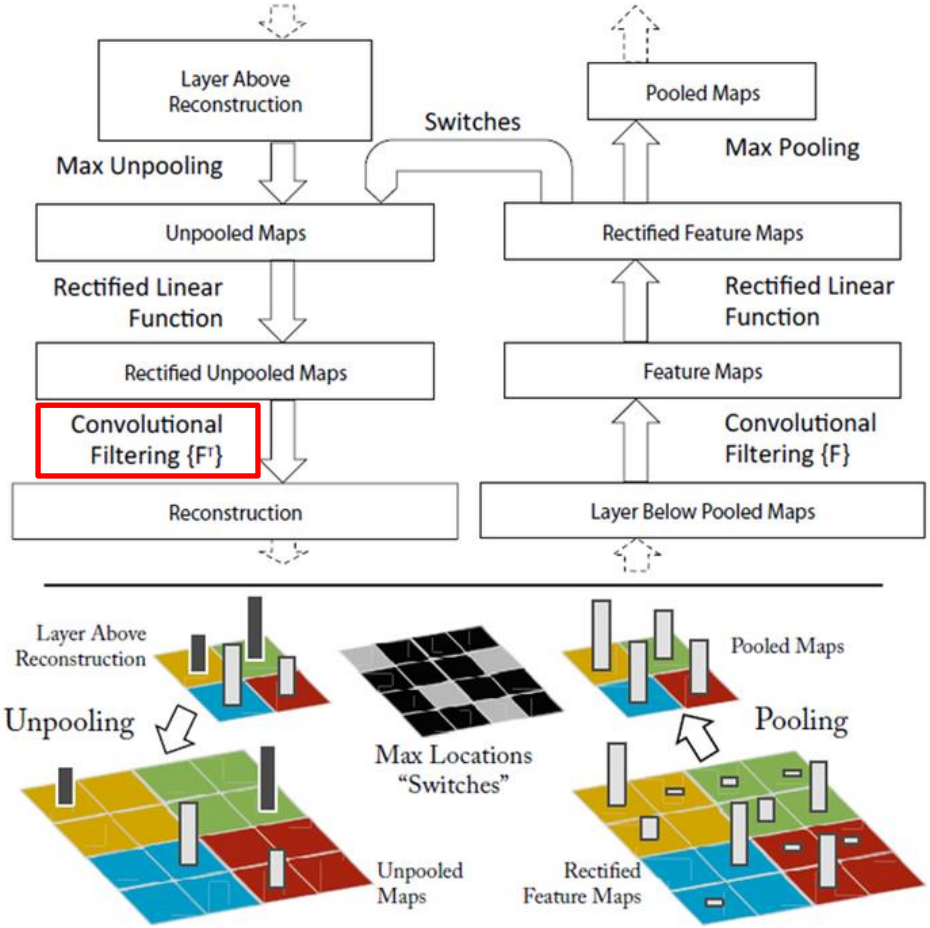
Convolution 연산은 weight 값을 알고 있으므로 그냥 역으로 연산



(출처:https://arxiv.org/pdf/1311.2901.pdf)

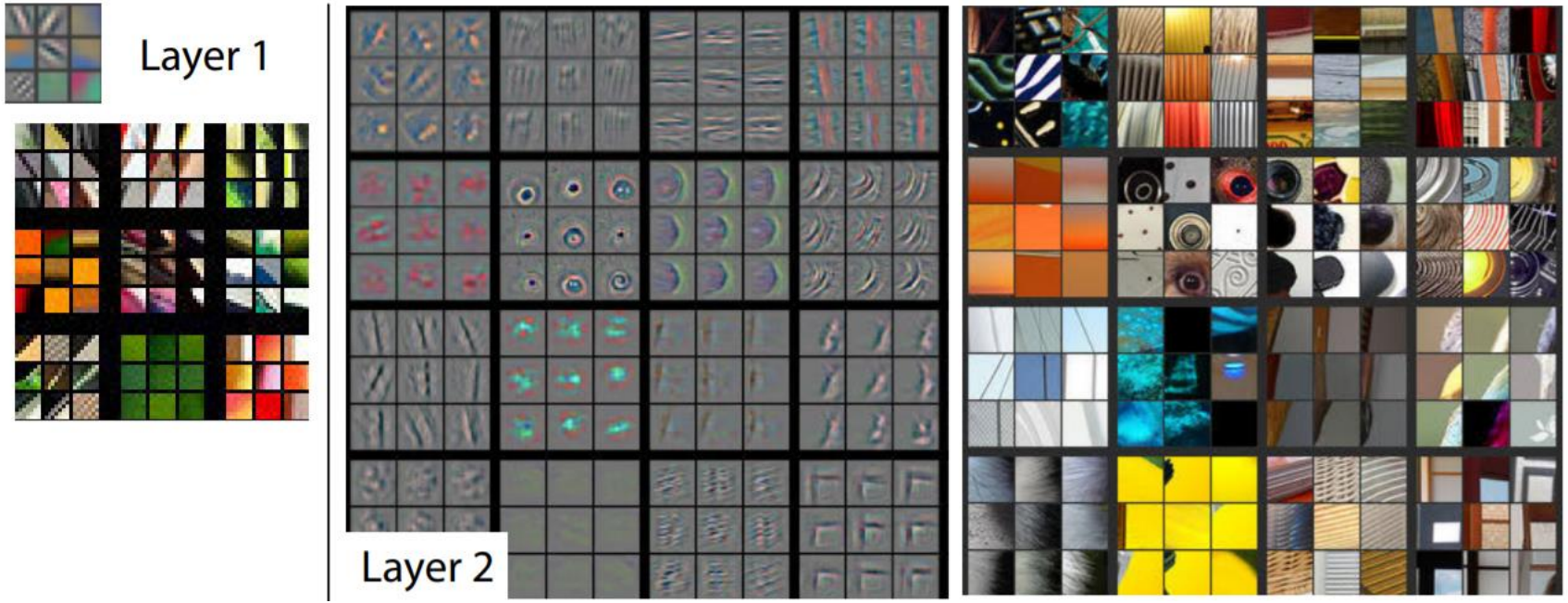
ImageNet Challenge

Layer 별로 필터 별로
강한 자극을 시각화 한 결과

(출처:https://arxiv.org/pdf/1311.2901.pdf)

ImageNet Challenge

Layer 별로 필터 별로
강한 자극을 시각화 한 결과



(출처:https://arxiv.org/pdf/1311.2901.pdf)

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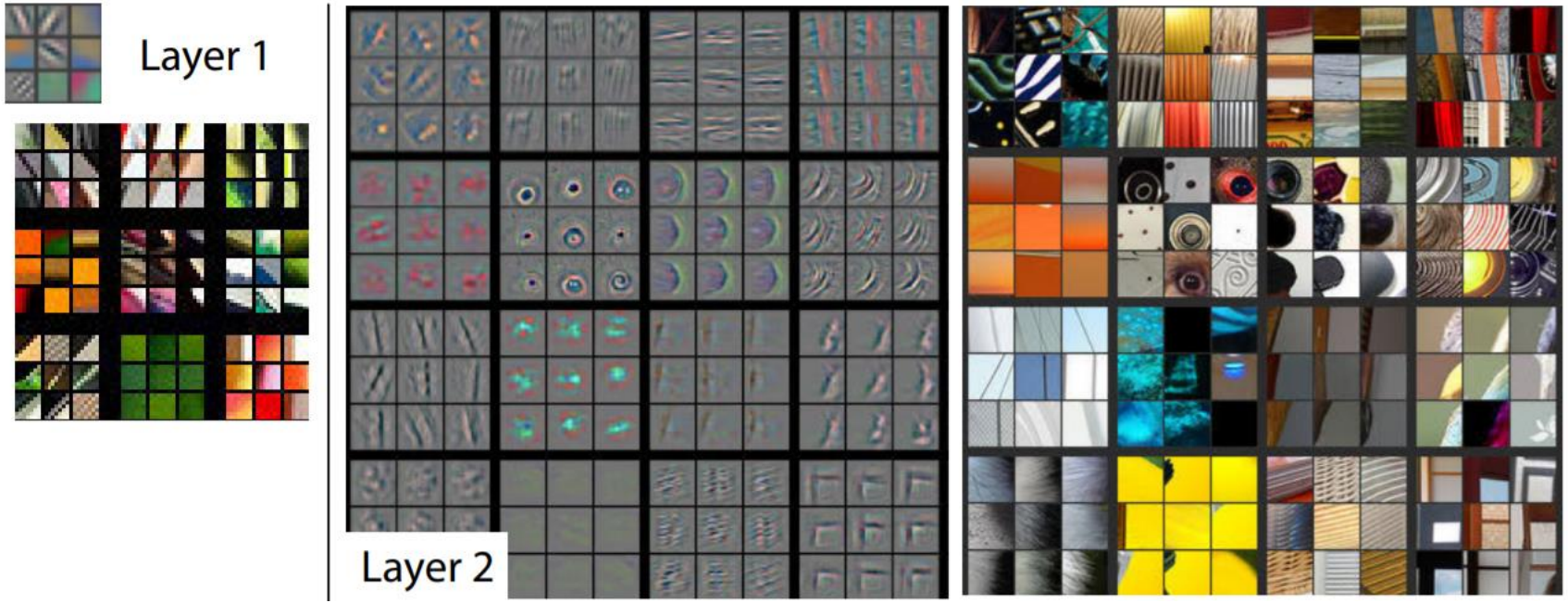
강한 자극을 시각화 한 결과



필터 별 자극

(출처:https://arxiv.org/pdf/1311.2901.pdf)

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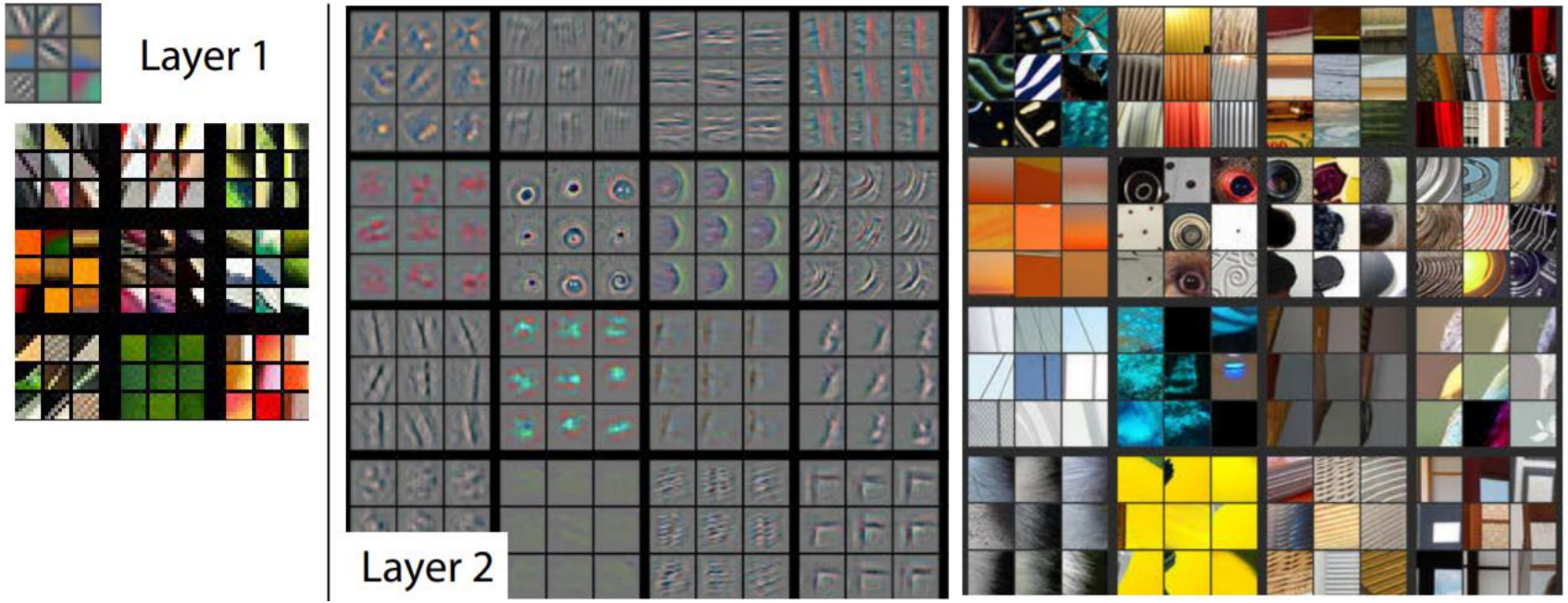


필터 별 자극

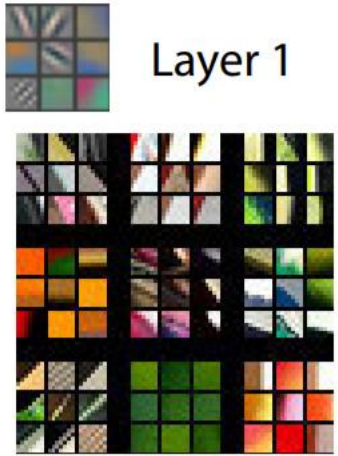
원본 이미지

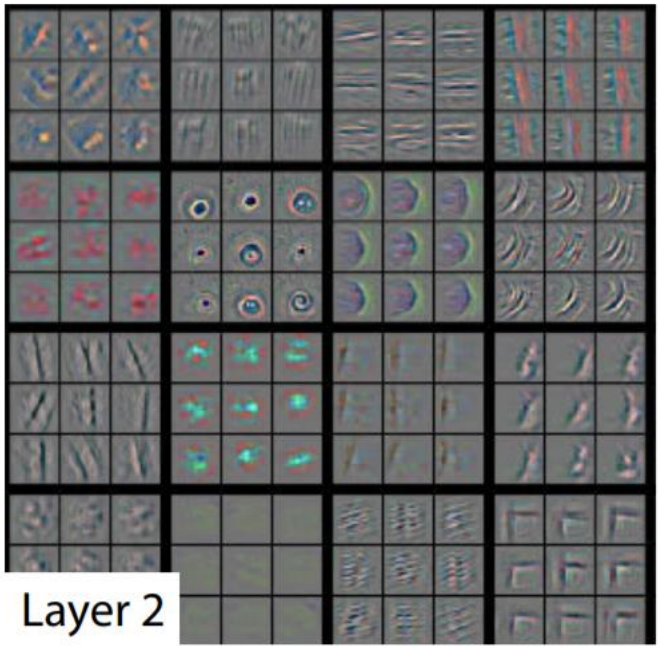
(출처:https://arxiv.org/pdf/1311.2901.pdf)

ImageNet Challenge

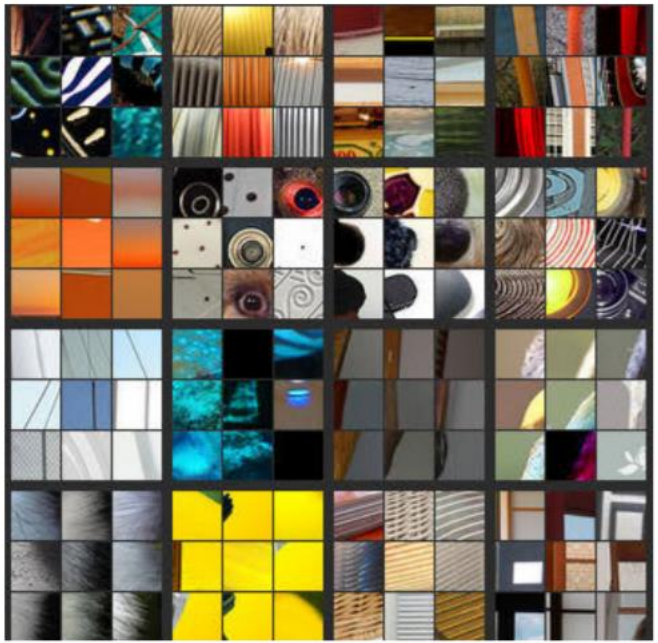
Layer 별로 필터 별로
강한 자극을 시각화 한 결과

단순한 선들





필터 별 자극



원본 이미지

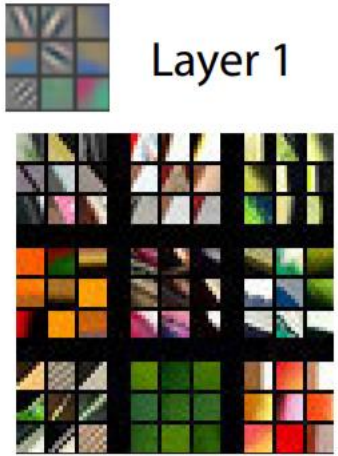
(출처:https://arxiv.org/pdf/1311.2901.pdf)

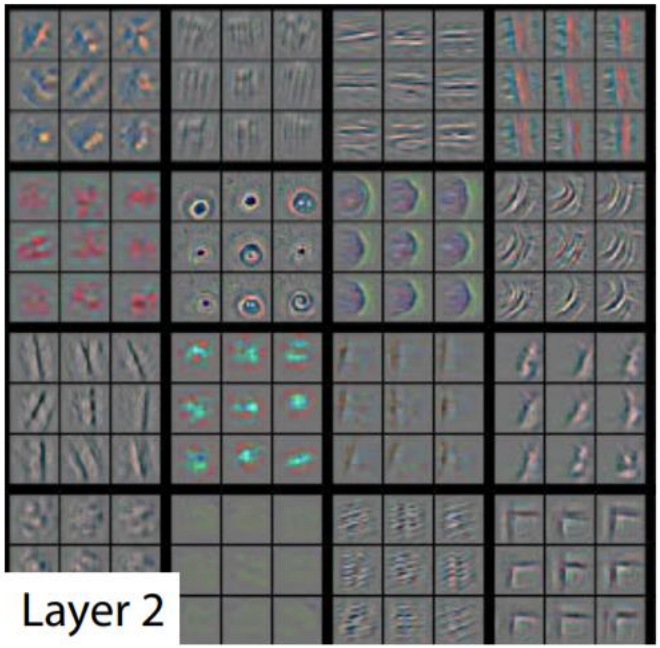
ImageNet Challenge

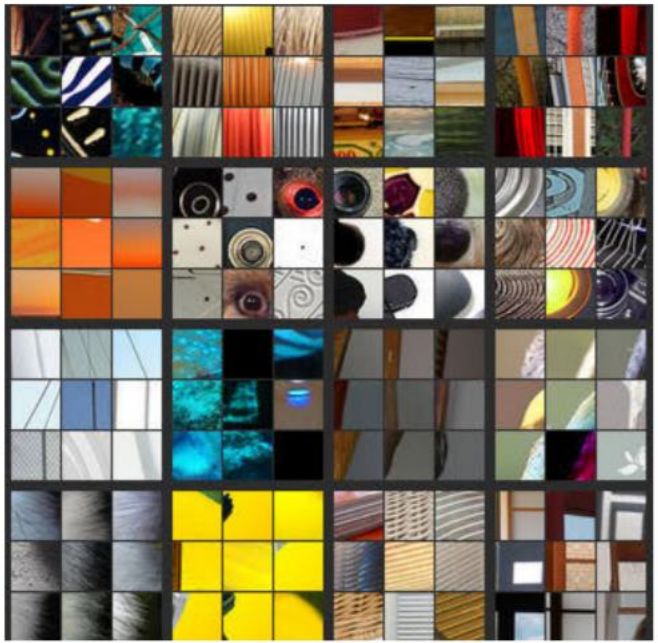
Layer 별로 필터 별로
강한 자극을 시각화 한 결과

단순한 선들

비교적 복잡







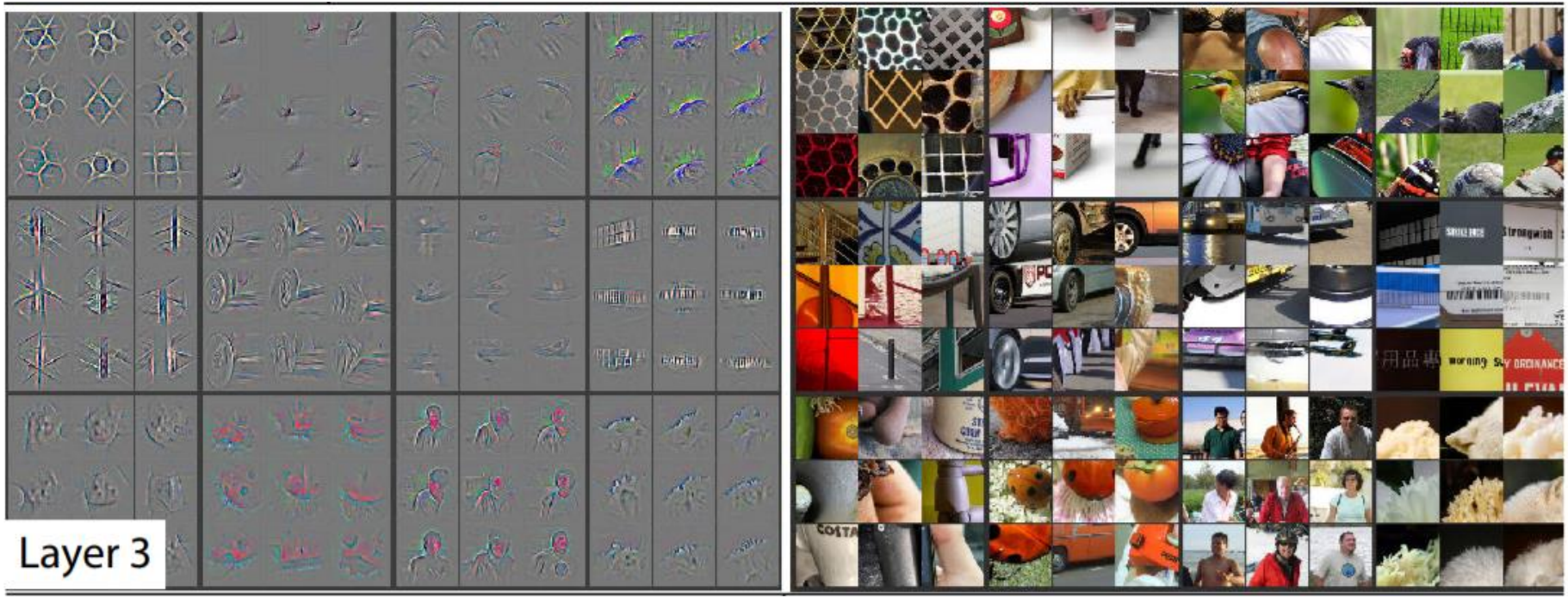
필터 별 자극

원본 이미지

(출처:https://arxiv.org/pdf/1311.2901.pdf)

ImageNet Challenge

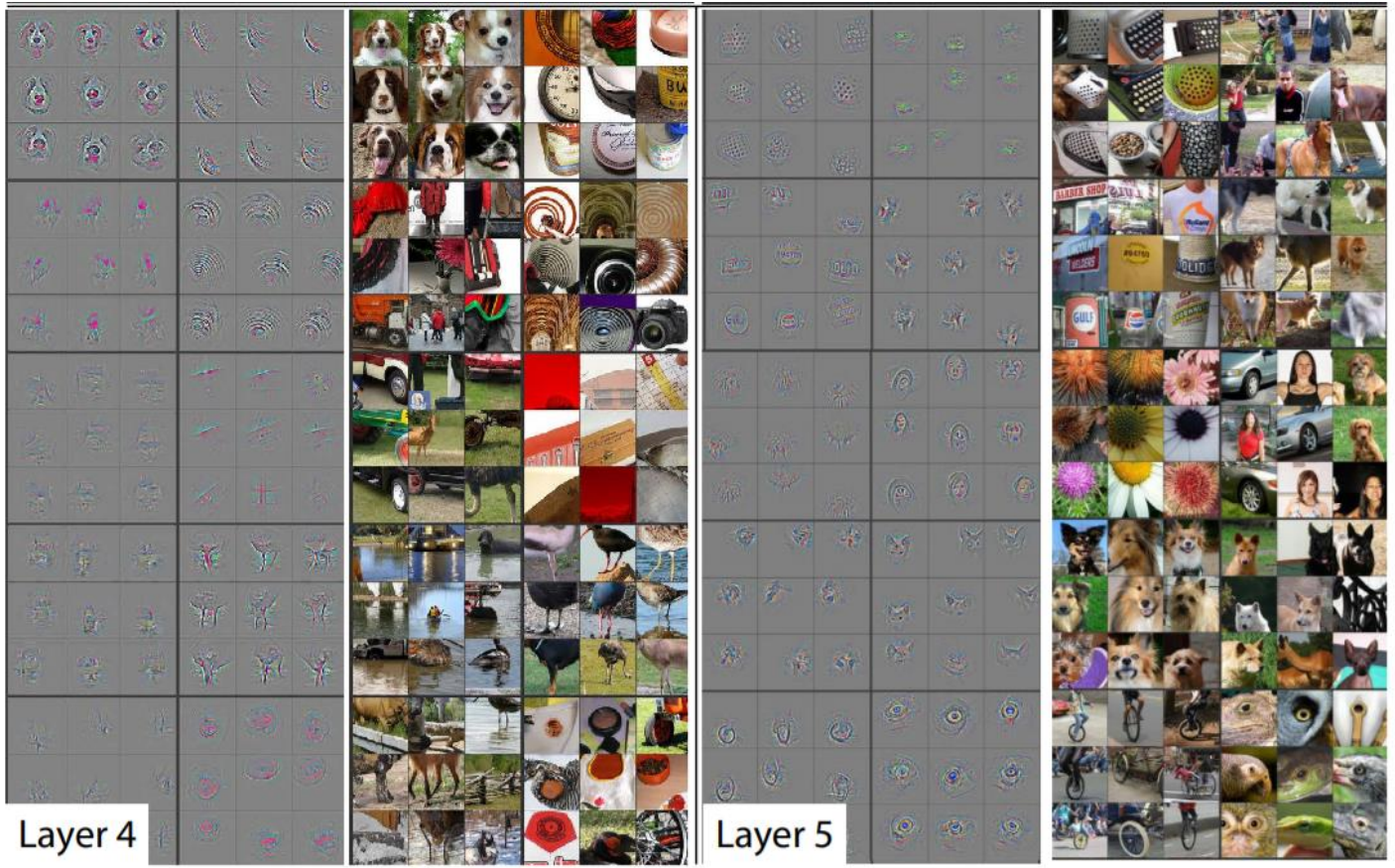
더 복잡



(출처:https://arxiv.org/pdf/1311.2901.pdf)

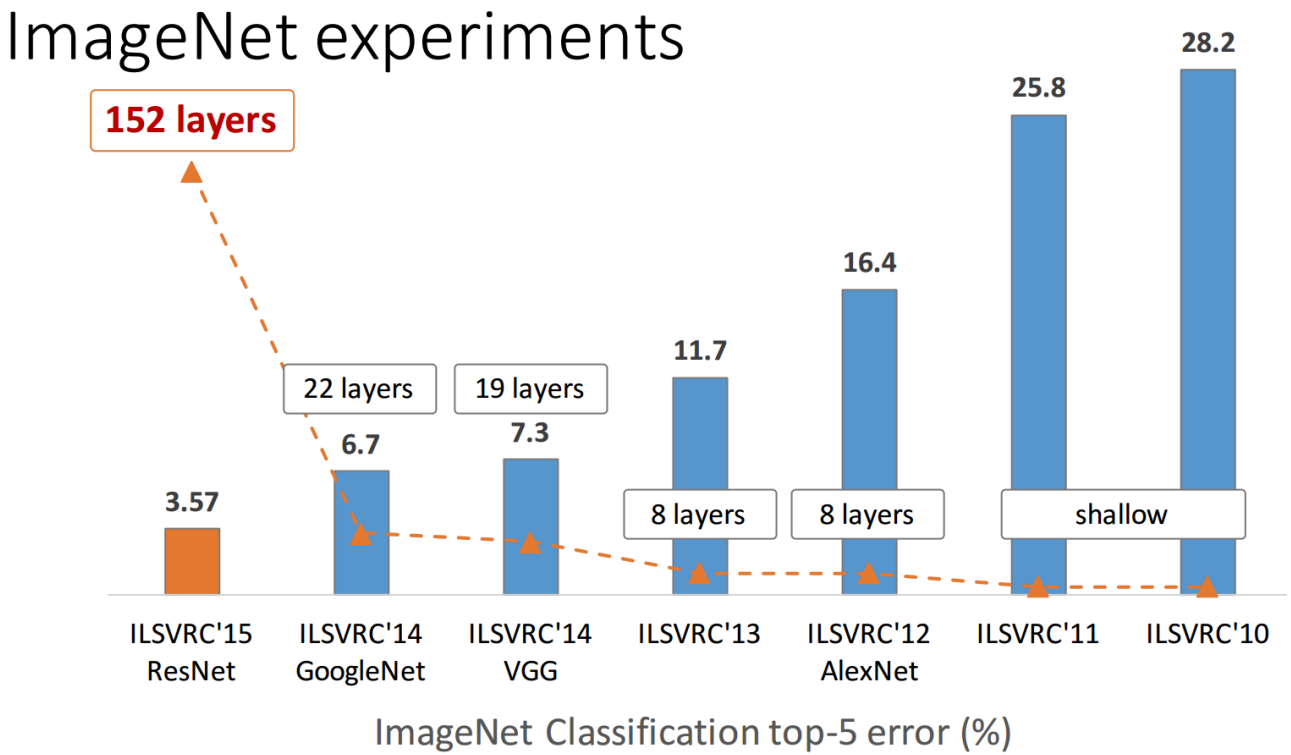
ImageNet Challenge

더욱 더 복잡

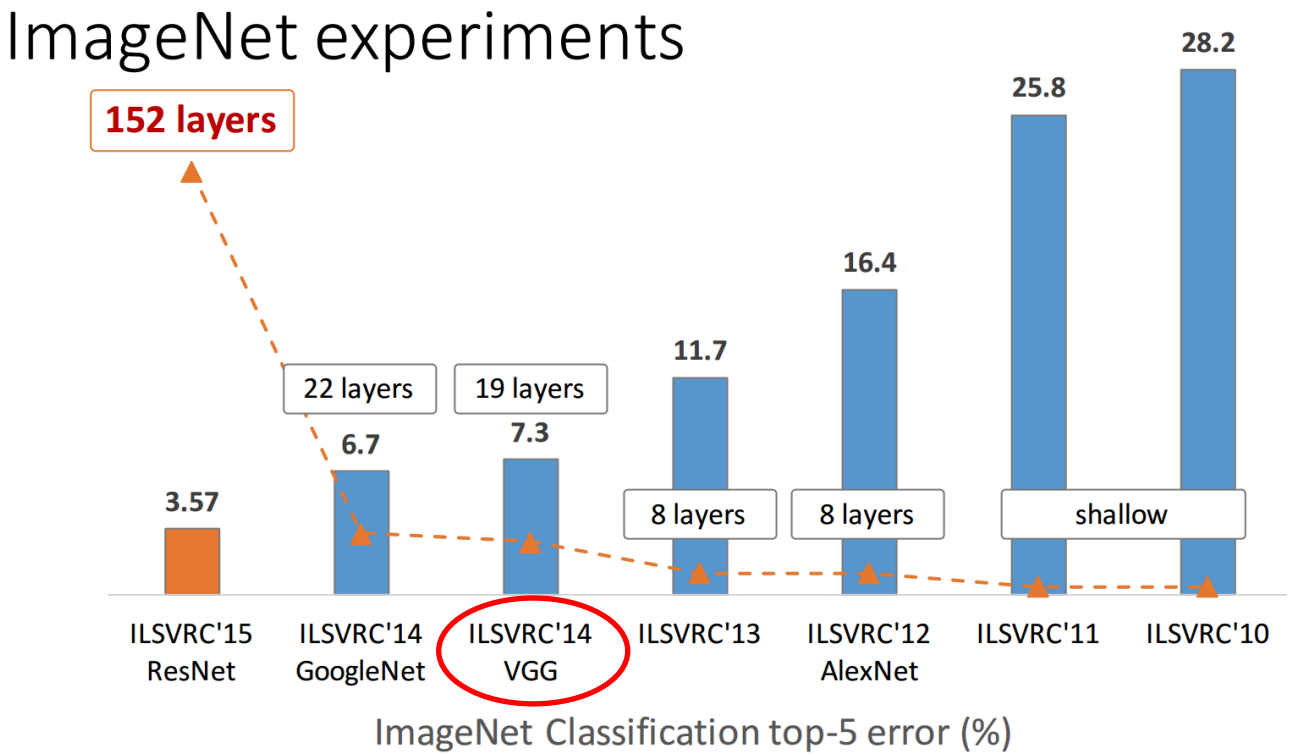


(출처:https://arxiv.org/pdf/1311.2901.pdf)

VGG Network


ImageNet experiments
152 layers
22 layers
19 layers
8 layers
8 layers
shallow
3.57
6.7
7.3
11.7
16.4
25.8
28.2
ILSVRC'15 ResNet
ILSVRC'14 GoogleNet
ILSVRC'14 VGG
ILSVRC'13
ILSVRC'12 AlexNet
ILSVRC'11
ILSVRC'10
ImageNet Classification top-5 error (%)

VGG Network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ILSVRC'13
ILSVRC'12 AlexNet
ILSVRC'11
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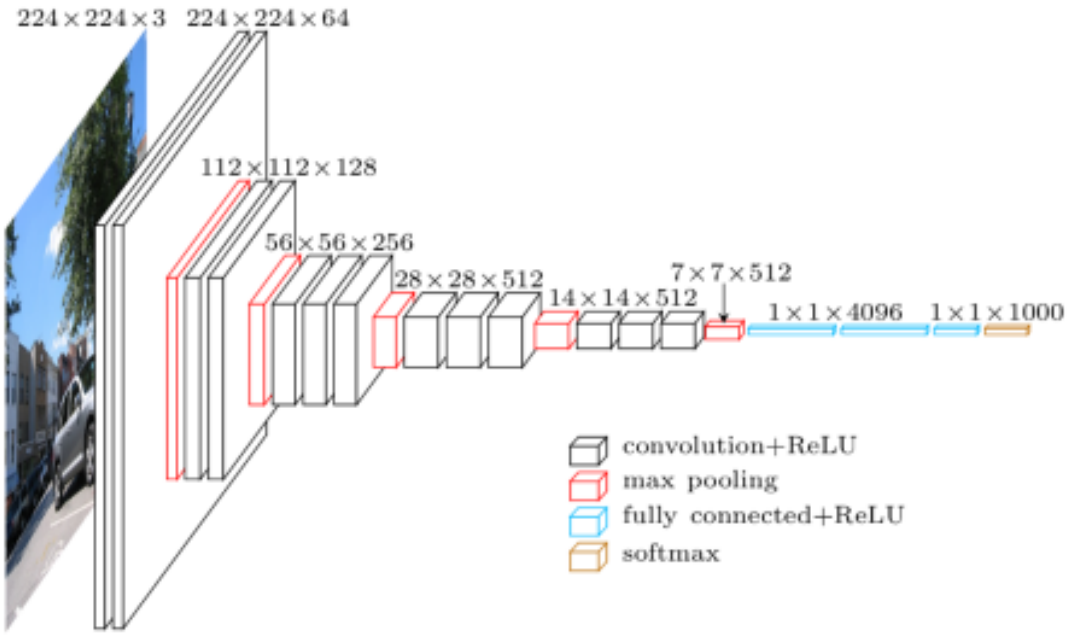
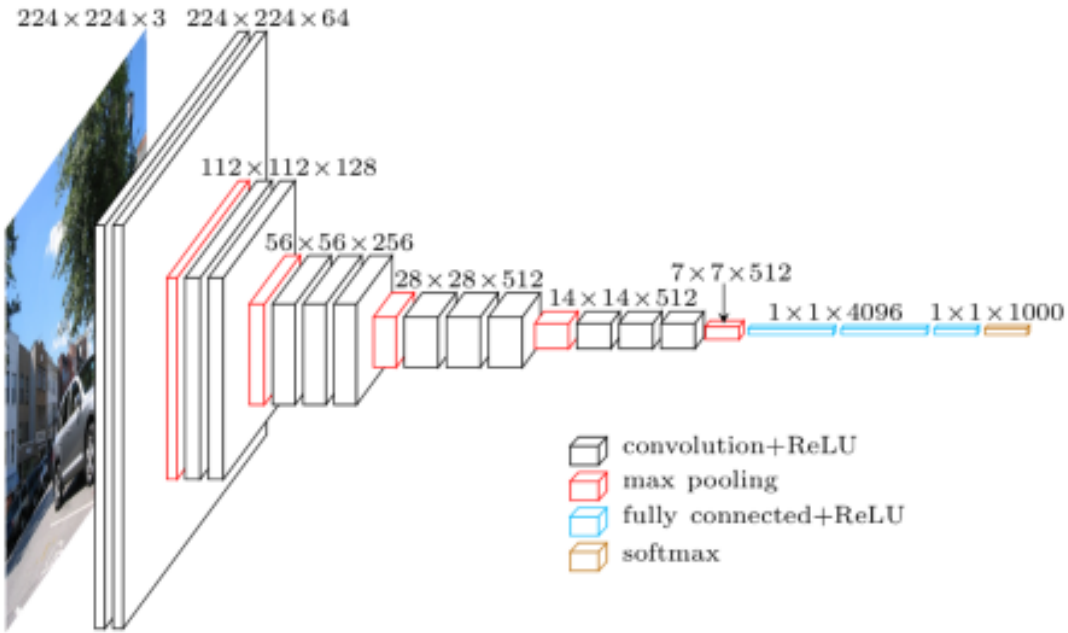
VGG Network



(출처:https://www.cs.toronto.edu/~frossard/post/vgg16/)

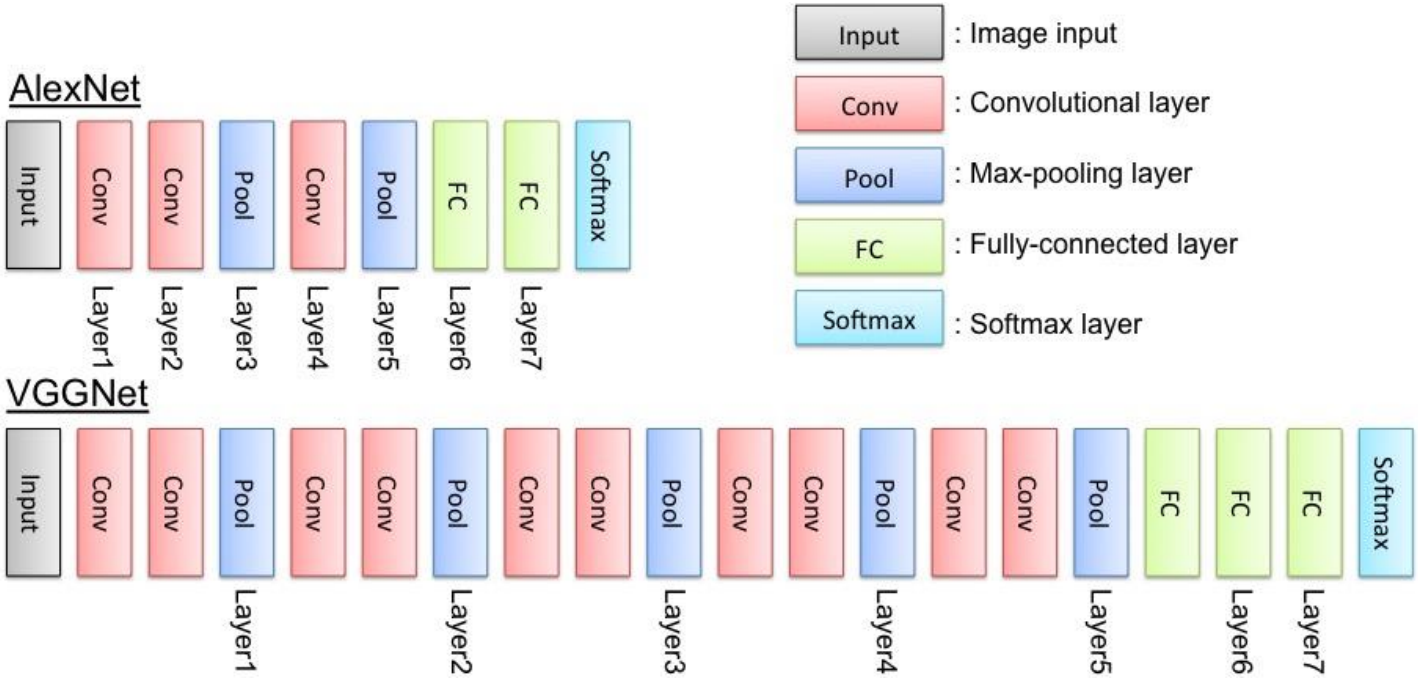
VGG Network



2014년 2위이지만 간단한 구조 때문에 오히려 더 많이 사용됨.

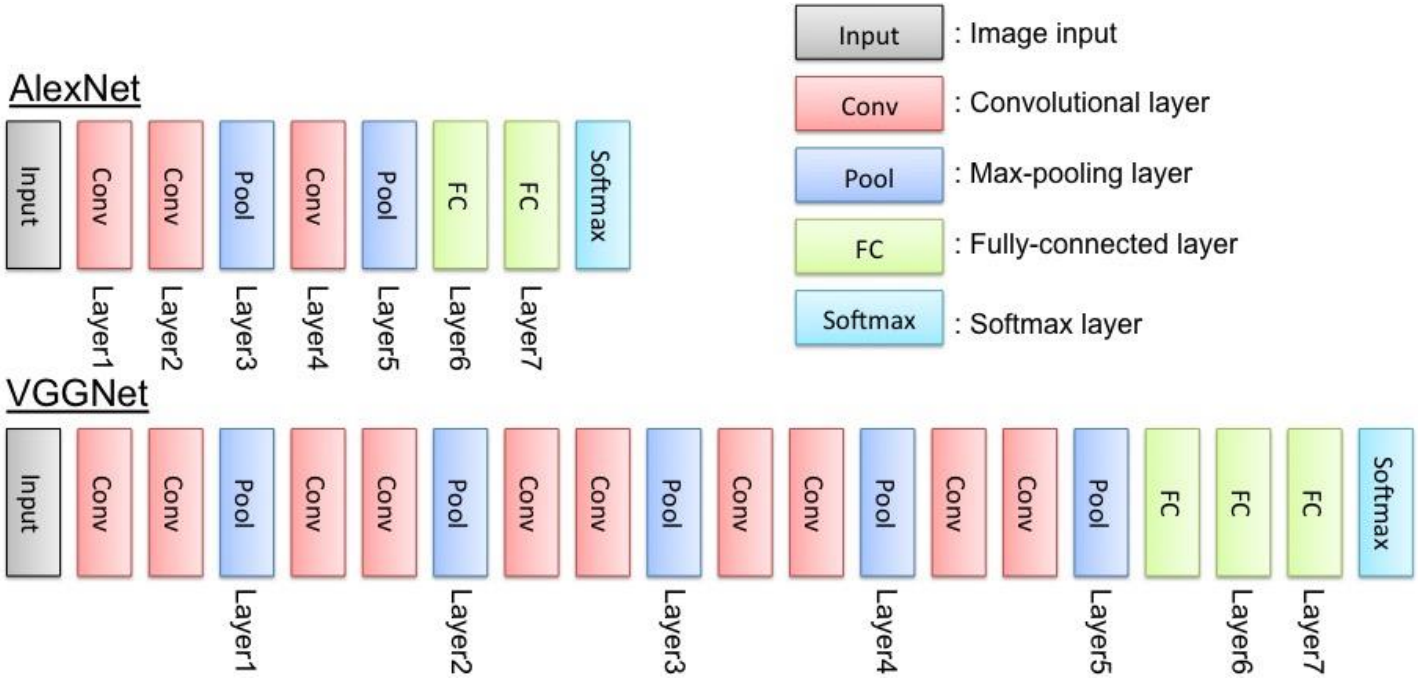
(출처:https://www.cs.toronto.edu/~frossard/post/vgg16/)

VGG Network



(출처: http://www.hirokatsukataoka.net/research/cnnfeatureevaluation/cnnfeatureevaluation.html)

VGG Network



그냥 단순히 망의 깊이를 늘린 것

(출처: http://www.hirokatsukataoka.net/research/cnnfeatureevaluation/cnnfeatureevaluation.html)

VGG Network

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

망의 깊이가 모델의 성능에 어떤 영향을 끼치는가?

(출처:https://arxiv.org/pdf/1409.1556.pdf)

VGG Network

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
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conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

망의 깊이가 모델의 성능에 어떤 영향을 끼치는가?

3가지만의 조합으로 모델 구성

(출처:https://arxiv.org/pdf/1409.1556.pdf)

VGG Network

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

망의 깊이가 모델의 성능에 어떤 영향을 끼치는가?

3가지만의 조합으로 모델 구성

- 3x3 convolution stride 1
- Max Pooling
- Fully Connected Layer

(출처:https://arxiv.org/pdf/1409.1556.pdf)

VGG Network

```
INPUT: [224x224x3]        memory:  224*224*3=150K   weights: 0
CONV3-64: [224x224x64]  memory:  224*224*64=3.2M   weights: (3*3*3)*64 = 1,728
CONV3-64: [224x224x64]  memory:  224*224*64=3.2M   weights: (3*3*64)*64 = 36,864
POOL2: [112x112x64]  memory:  112*112*64=800K   weights: 0
CONV3-128: [112x112x128]  memory:  112*112*128=1.6M   weights: (3*3*64)*128 = 73,728
CONV3-128: [112x112x128]  memory:  112*112*128=1.6M   weights: (3*3*128)*128 = 147,456
POOL2: [56x56x128]  memory:  56*56*128=400K   weights: 0
CONV3-256: [56x56x256]  memory:  56*56*256=800K   weights: (3*3*128)*256 = 294,912
CONV3-256: [56x56x256]  memory:  56*56*256=800K   weights: (3*3*256)*256 = 589,824
CONV3-256: [56x56x256]  memory:  56*56*256=800K   weights: (3*3*256)*256 = 589,824
POOL2: [28x28x256]  memory:  28*28*256=200K   weights: 0
CONV3-512: [28x28x512]  memory:  28*28*512=400K   weights: (3*3*256)*512 = 1,179,648
CONV3-512: [28x28x512]  memory:  28*28*512=400K   weights: (3*3*512)*512 = 2,359,296
CONV3-512: [28x28x512]  memory:  28*28*512=400K   weights: (3*3*512)*512 = 2,359,296
POOL2: [14x14x512]  memory:  14*14*512=100K   weights: 0
CONV3-512: [14x14x512]  memory:  14*14*512=100K   weights: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512]  memory:  14*14*512=100K   weights: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512]  memory:  14*14*512=100K   weights: (3*3*512)*512 = 2,359,296
POOL2: [7x7x512]  memory:  7*7*512=25K  weights: 0
FC: [1x1x4096]  memory:  4096  weights: 7*7*512*4096 = 102,760,448
FC: [1x1x4096]  memory:  4096  weights: 4096*4096 = 16,777,216
FC: [1x1x1000]  memory:  1000 weights: 4096*1000 = 4,096,000

TOTAL memory: 24M * 4 bytes ~= 93MB / image (only forward! ~*2 for bwd)
TOTAL params: 138M parameters
```

VGG Network

Memory Per Model

	Size (MB)	Error % (top-5)
SqueezeNet Compressed	0.6	19.7%
SqueezeNet	4.8	19.7%
AlexNet	240	19.7%
Inception v3	84	5.6%
VGG-19	574	7.5%
ResNet-50	102	7.8%
ResNet-200	519	4.8%

(출처:AWS re:Invent 2016: Bringing Deep Learning to the Cloud with Amazon EC2 (CMP314)

VGG Network

망이 깊을수록 성능이 좋다는 것은
알겠지만 효율이 그렇게 좋지는 않음

Memory Per Model

	Size (MB)	Error % (top-5)
SqueezeNet Compressed	0.6	19.7%
SqueezeNet	4.8	19.7%
AlexNet	240	19.7%
Inception v3	84	5.6%
VGG-19	574	7.5%
ResNet-50	102	7.8%
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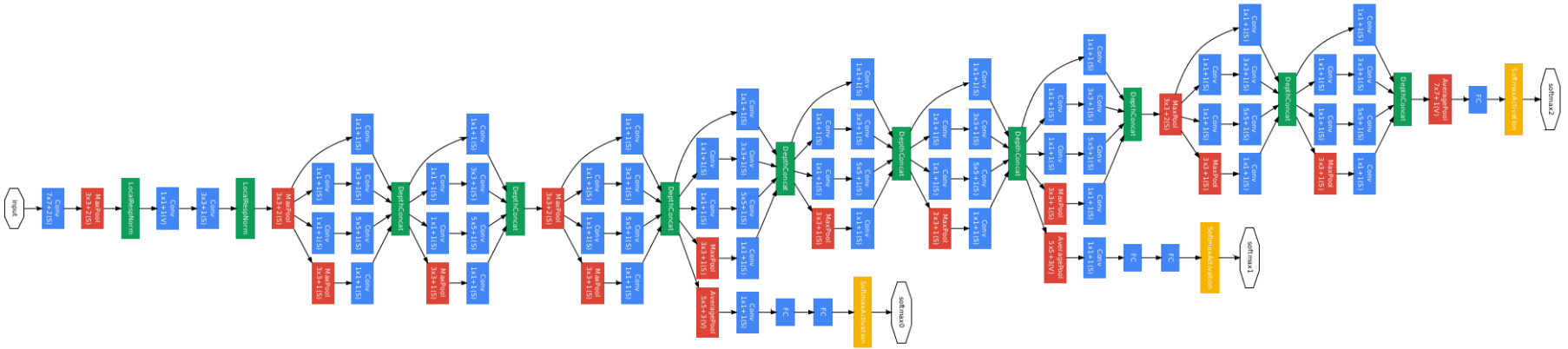
(출처:AWS re:Invent 2016: Bringing Deep Learning to the Cloud with Amazon EC2 (CMP314)

Google Network

Google Network

Inception Network

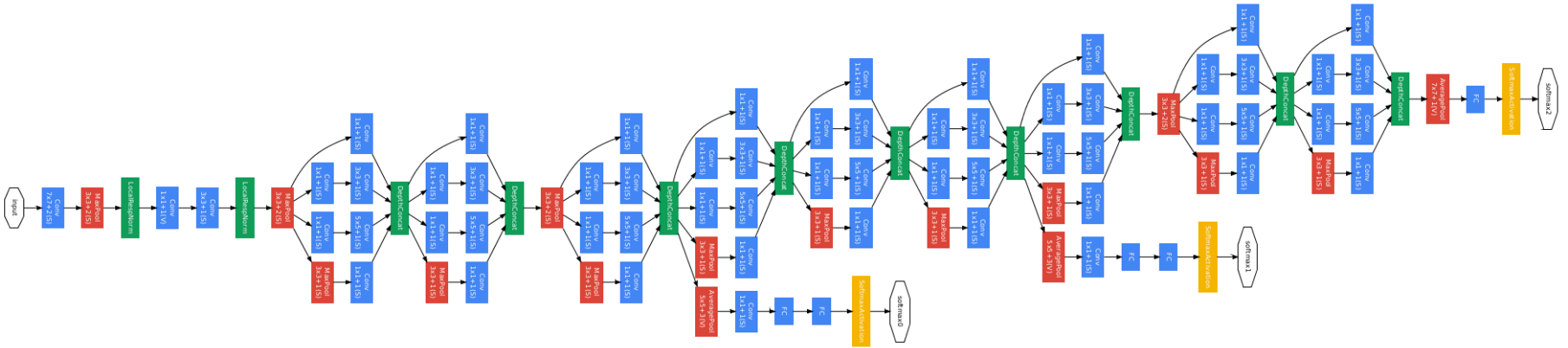
Google Network



(출처:https://arxiv.org/pdf/1409.4842.pdf)

Google Network

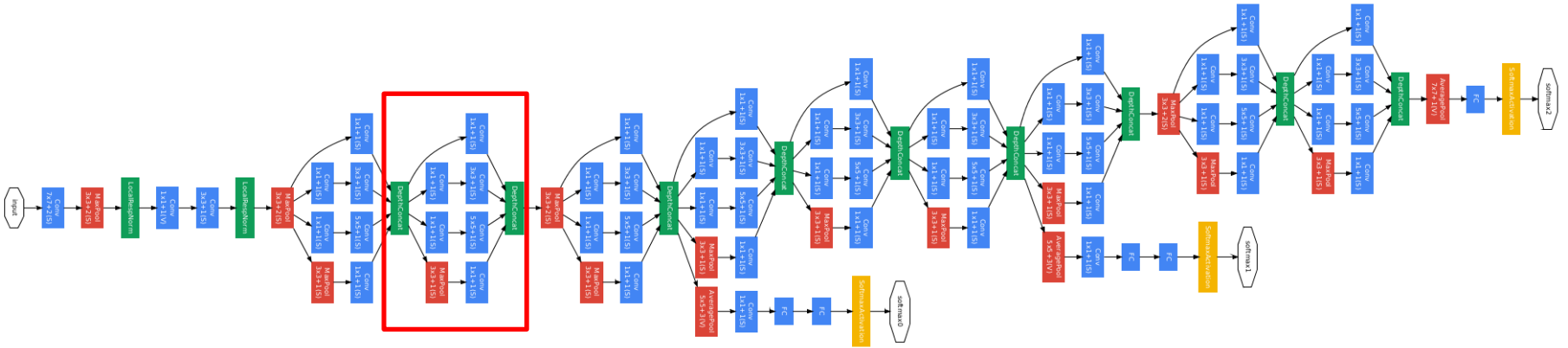
22 Layer



(출처:https://arxiv.org/pdf/1409.4842.pdf)

Google Network

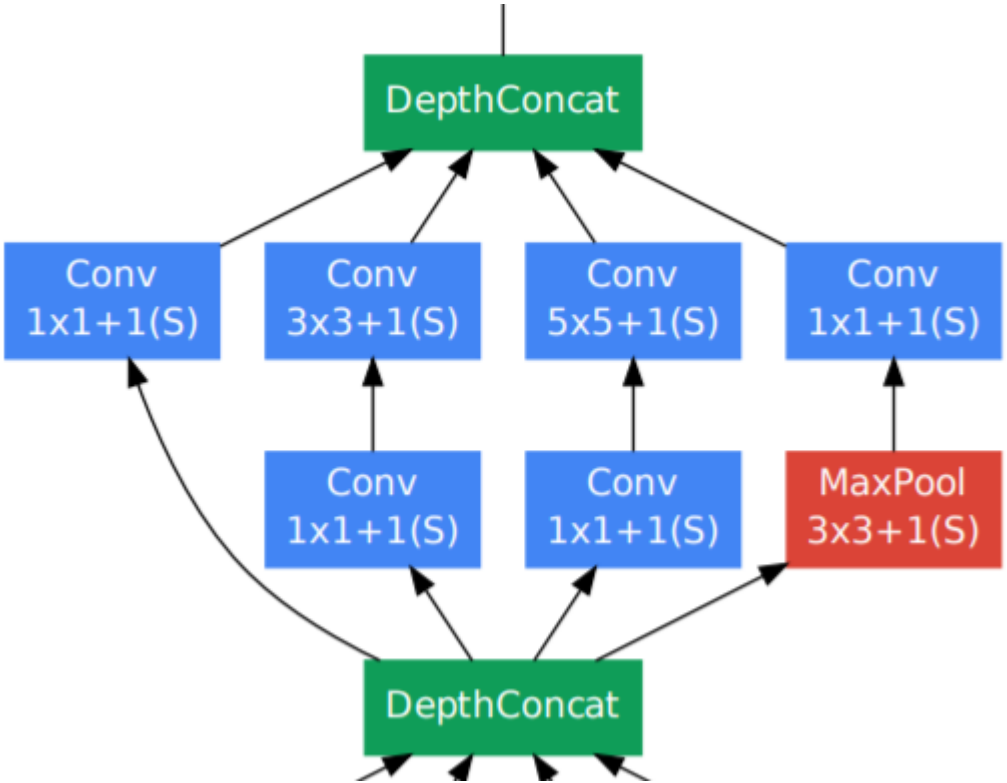
22 Layer



(출처:https://arxiv.org/pdf/1409.4842.pdf)

Google Network

s는 stride



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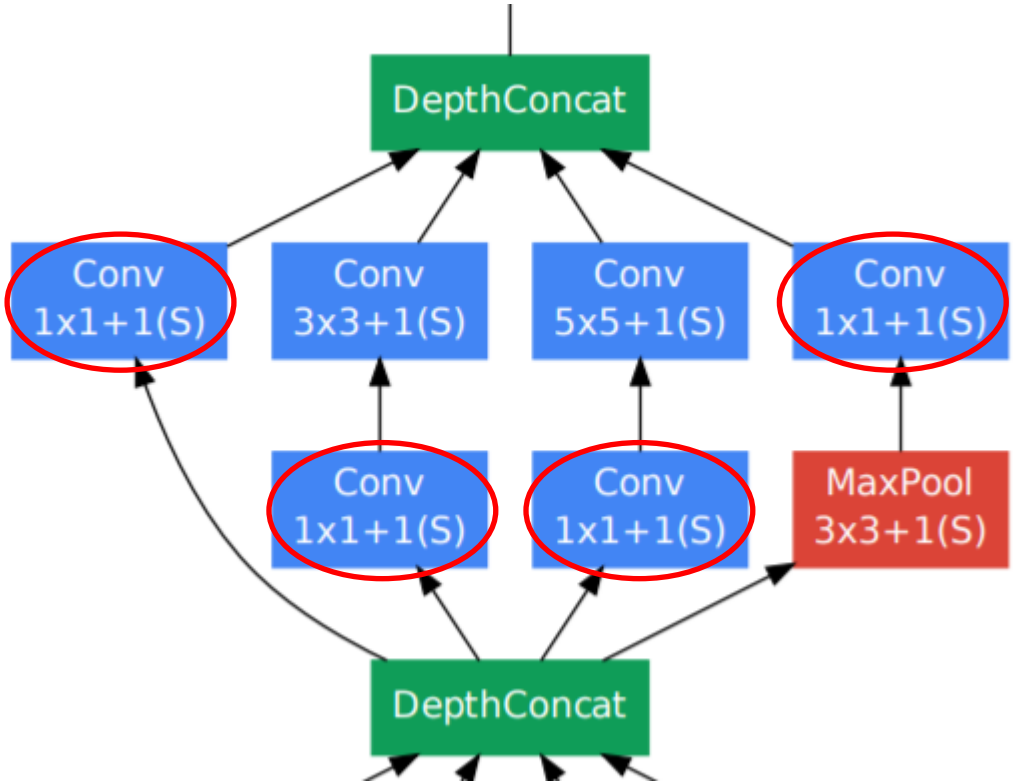
Google Network

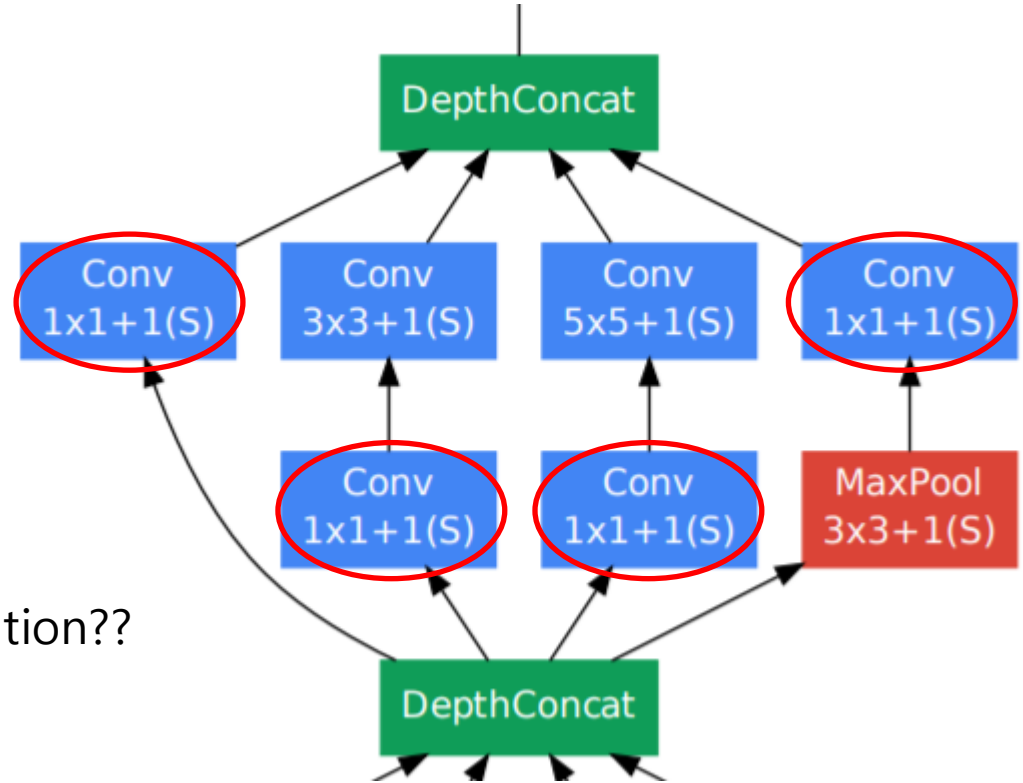
s는 stride



(출처:https://arxiv.org/pdf/1409.4842.pdf)

Google Network

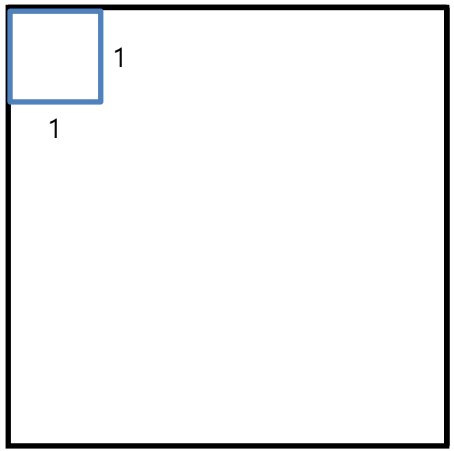
s는 stride



1x1 convolution??

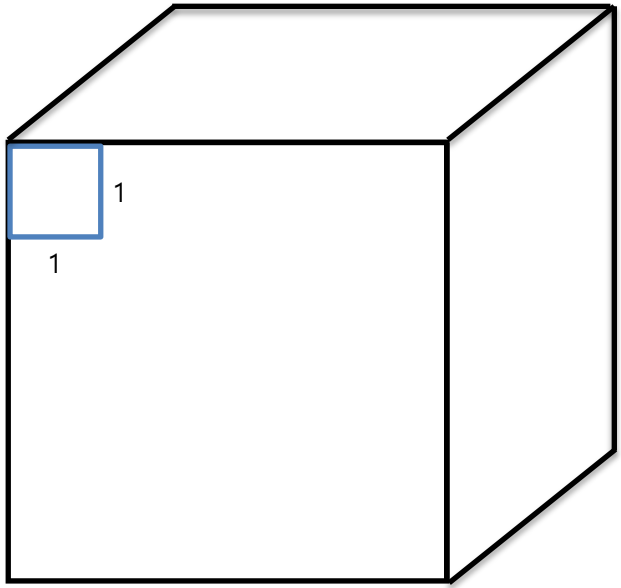
(출처:https://arxiv.org/pdf/1409.4842.pdf)

Google Network



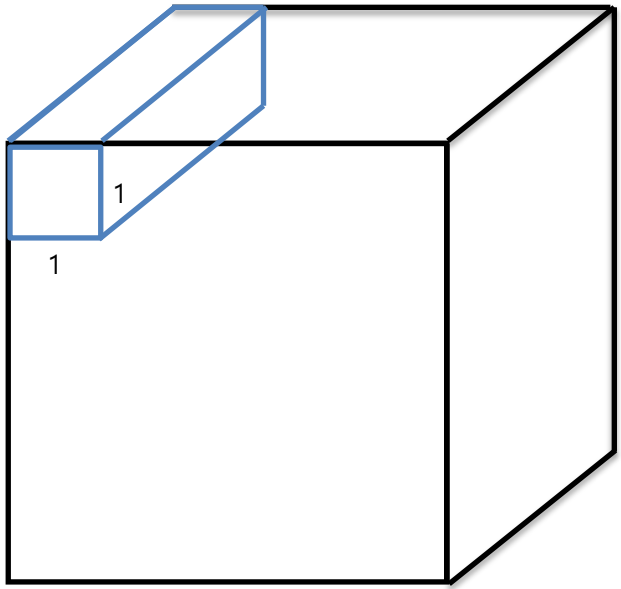
1x1 필터가 무슨 의미가 있지?

Google Network



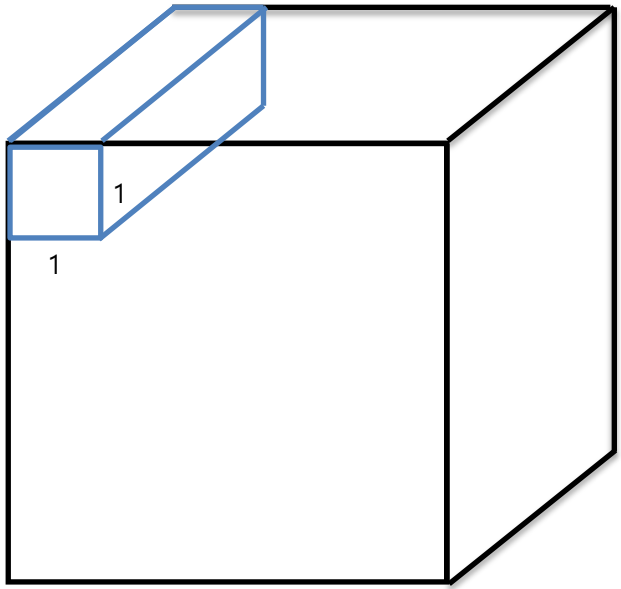
1x1 필터가 무슨 의미가 있지?

Google Network



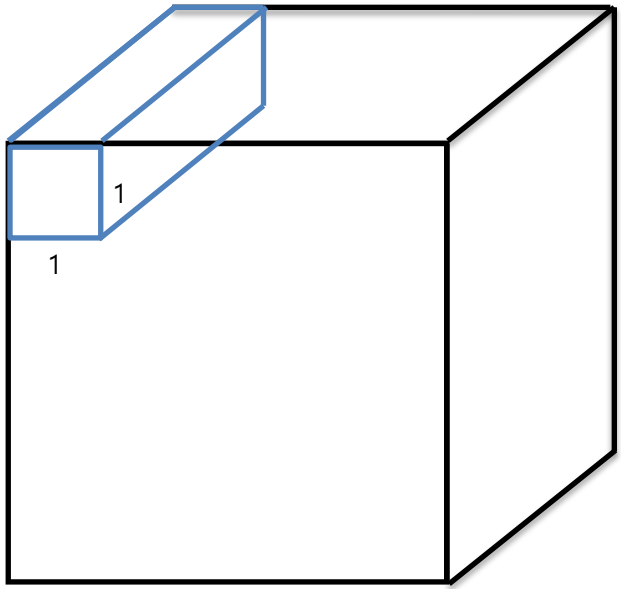
1x1 필터가 무슨 의미가 있지?

Google Network



1x1 convolution은 사실 각 채널을 node로 하는 Fully connected Network

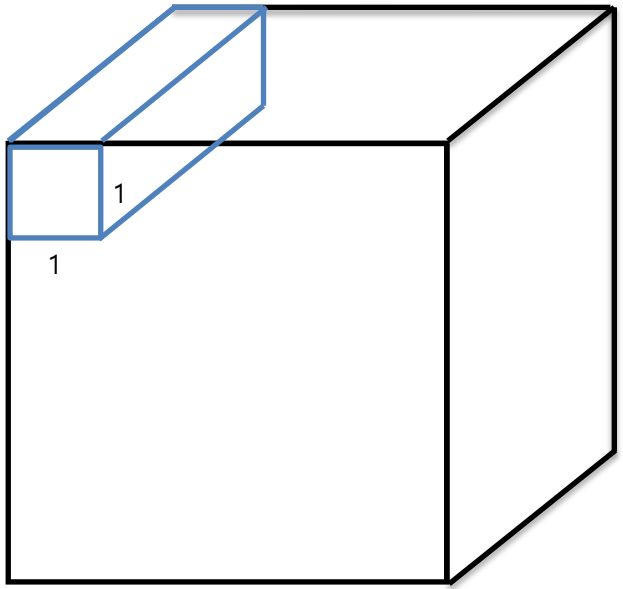
Google Network



1x1 convolution은 사실 각 채널을 node로 하는 Fully connected Network

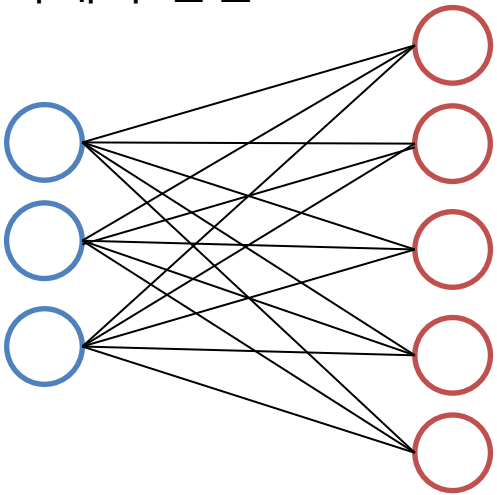
Input의 filter수가 3 output이 5이면 결국 아래와 같음

Google Network

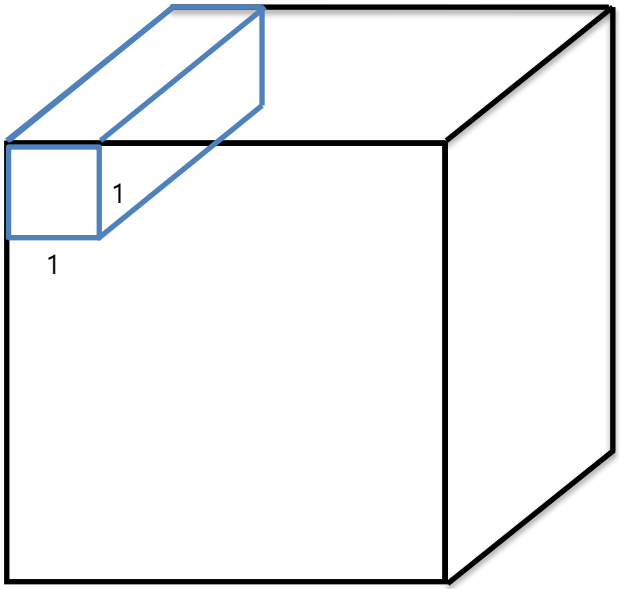


1x1 convolution은 사실 각 채널을 node로 하는 Fully connected Network

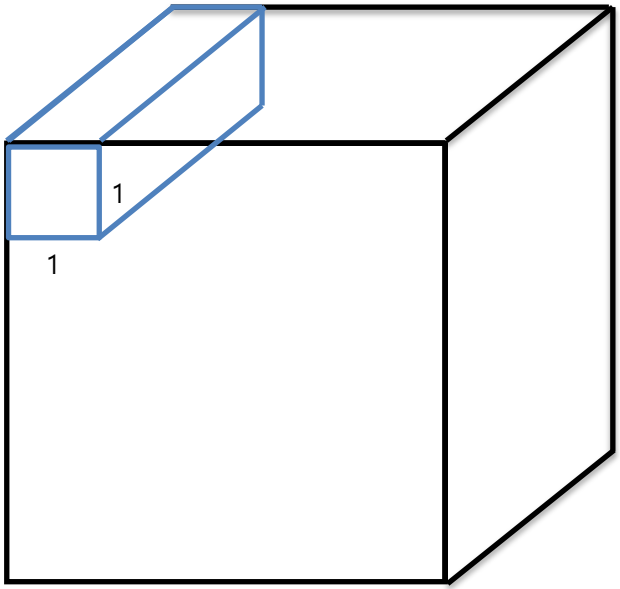
Input의 filter수가 3 output이 5이면 결국 아래와 같음



Google Network

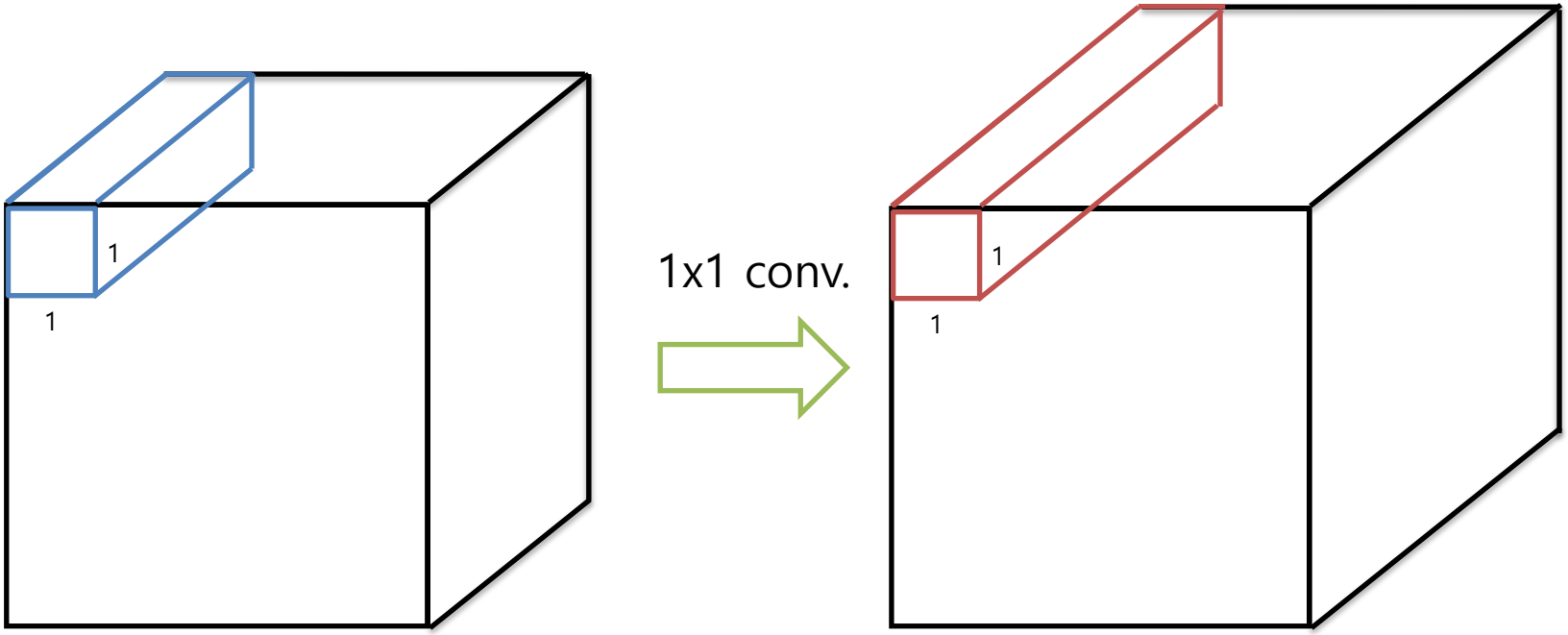


Google Network

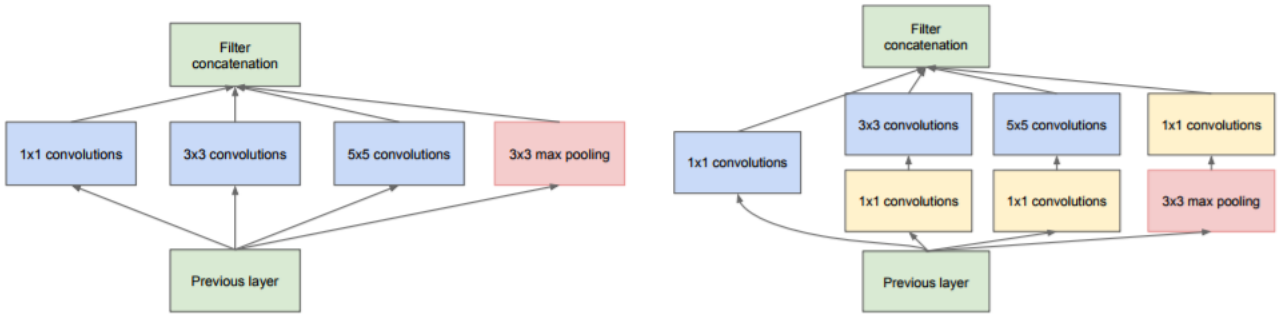


1x1 conv.

Google Network



Google Network



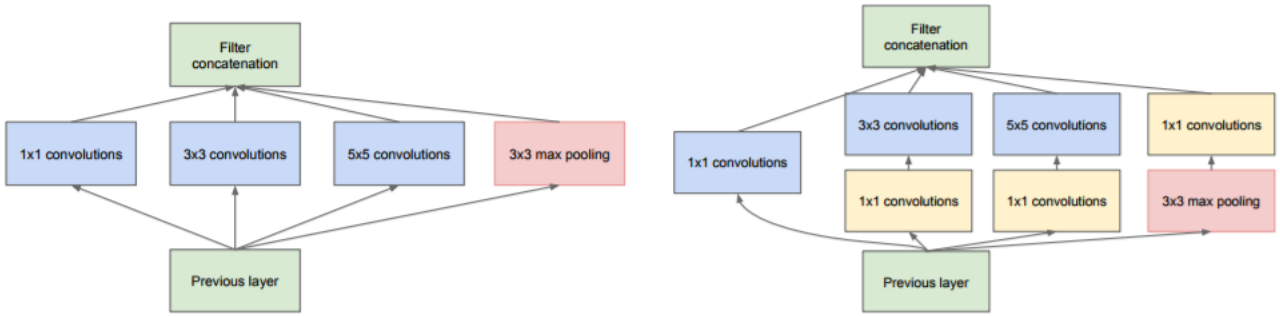
(a) Inception module, naïve version

(b) Inception module with dimension reductions

Figure 2: Inception module

(출처:https://arxiv.org/pdf/1409.4842.pdf)

Google Network



(a) Inception module, naïve version (b) Inception module with dimension reductions

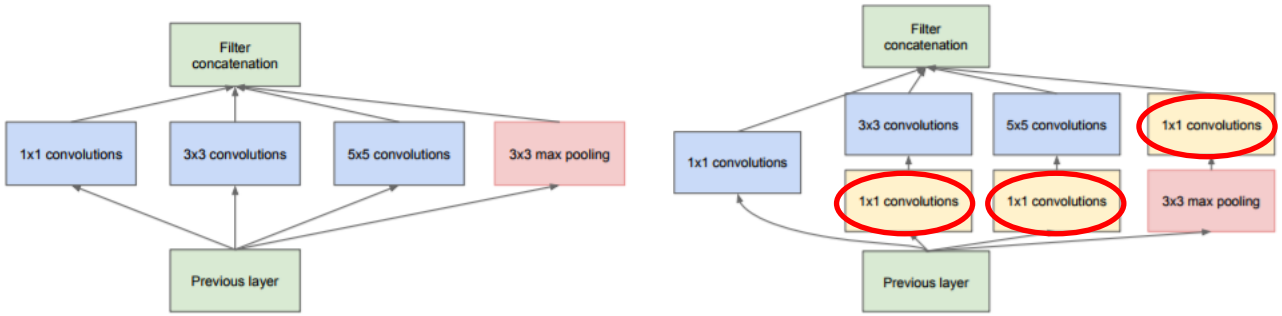
Figure 2: Inception module

하나의 input을 1x1, 3x3, 5x5, max pooling의
서로 다른 관점으로 보는 것

가까이, 중간, 멀리서 보는 거라고 생각하면 됨

(출처:https://arxiv.org/pdf/1409.4842.pdf)

Google Network



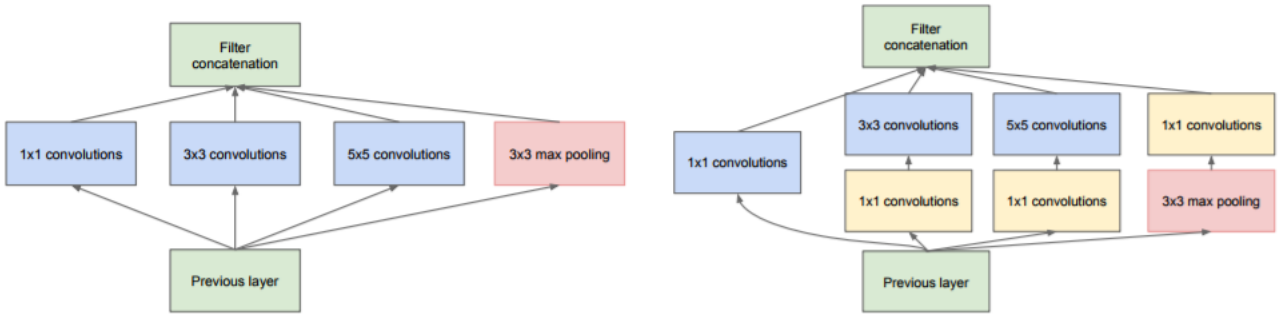
(a) Inception module, naïve version (b) Inception module with dimension reductions

Figure 2: Inception module

하지만 무언가 개선할 필요가 생겼고 그렇기 때문에 1x1 convolution을 사용하게 됨

(출처:https://arxiv.org/pdf/1409.4842.pdf)

Google Network



(a) Inception module, naïve version (b) Inception module with dimension reductions

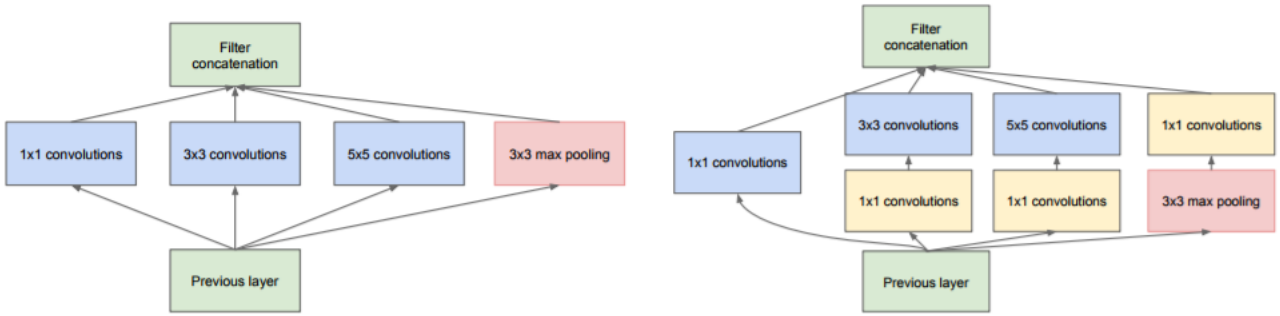
Figure 2: Inception module

하지만 무언가 개선할 필요가 생겼고 그렇기 때문에 1x1 convolution을 사용하게 됨

메모리!

(출처:https://arxiv.org/pdf/1409.4842.pdf)

Google Network



(a) Inception module, naïve version (b) Inception module with dimension reductions

Figure 2: Inception module

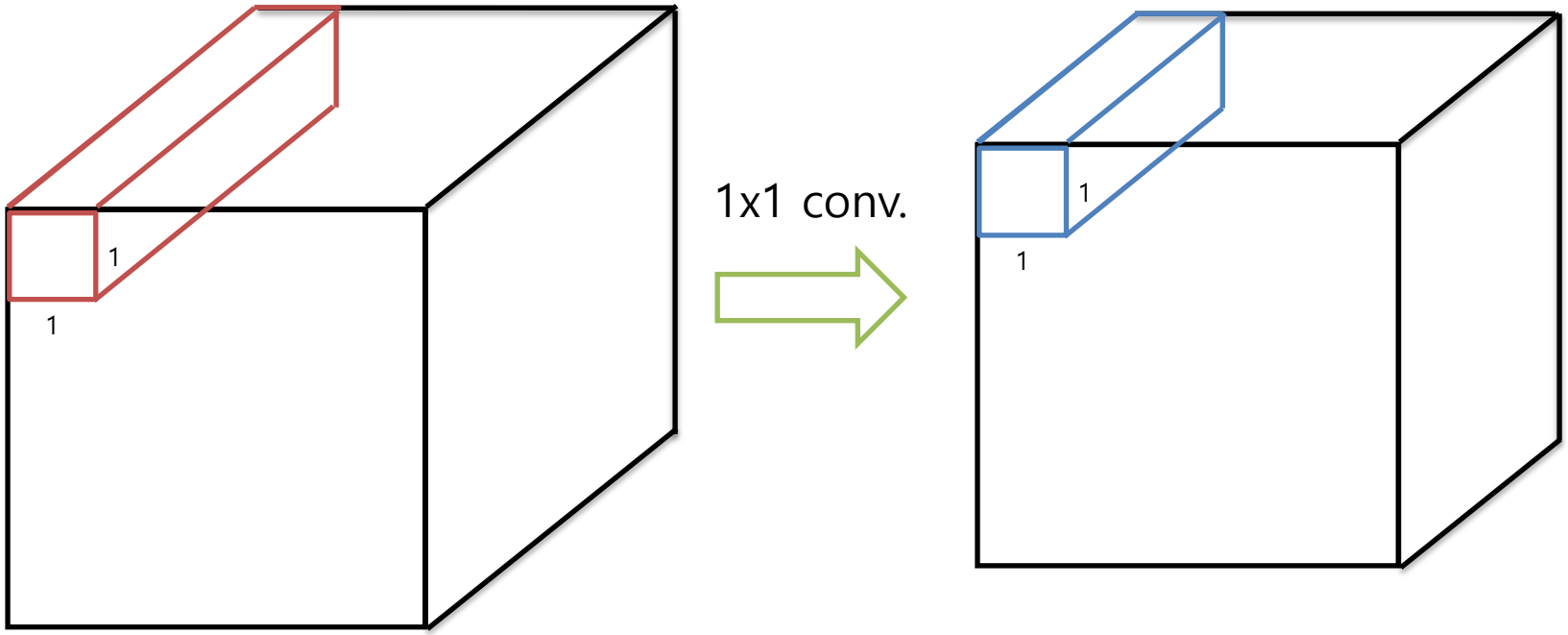
그렇다면 1x1 convolution은 어떻게 메모리 효율을 높이는가?

(출처:https://arxiv.org/pdf/1409.4842.pdf)

Google Network

(a) Inception module, naïve version (b) Inception module with dimension reductions

Figure 2: Inception module

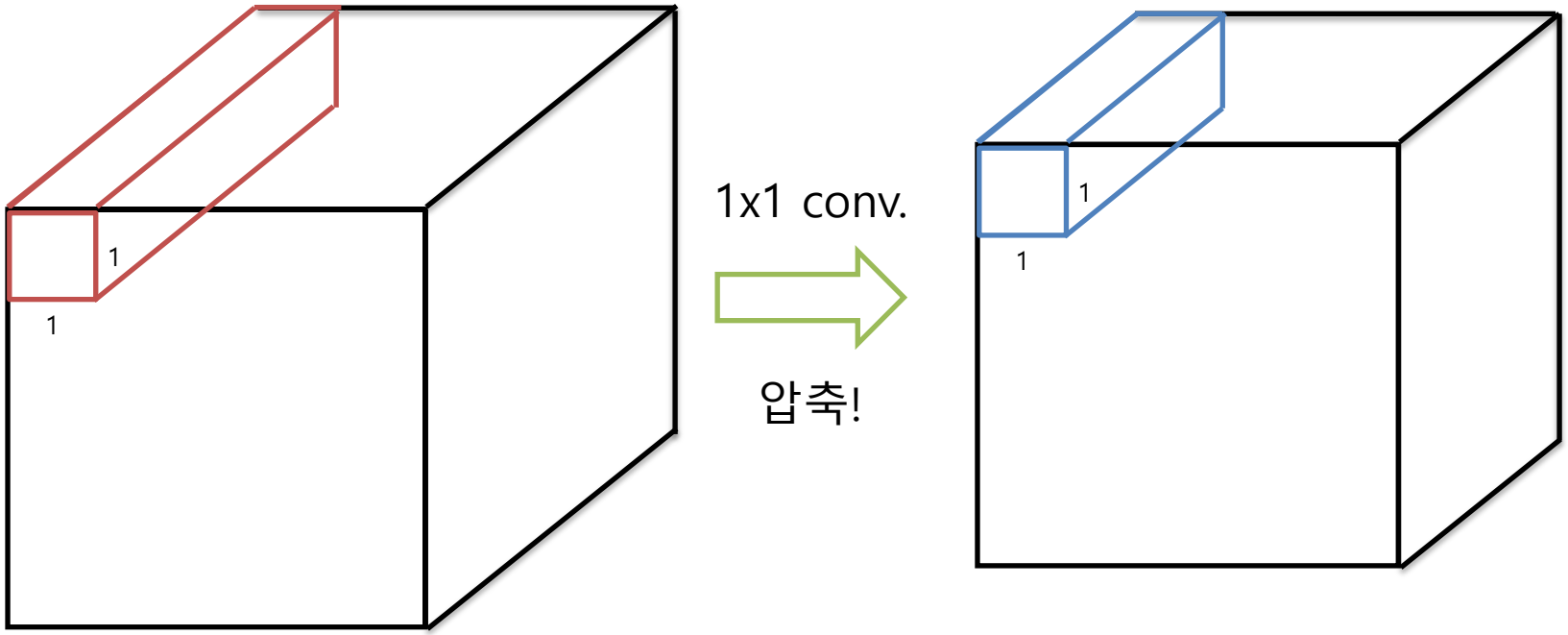


(출처:https://arxiv.org/pdf/1409.4842.pdf)

Google Network

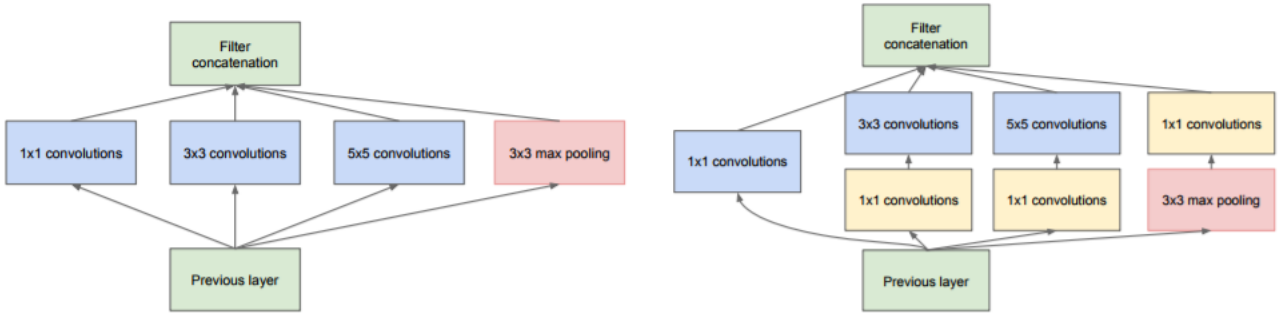
(a) Inception module, naïve version (b) Inception module with dimension reductions

Figure 2: Inception module



(출처:https://arxiv.org/pdf/1409.4842.pdf)

Google Network



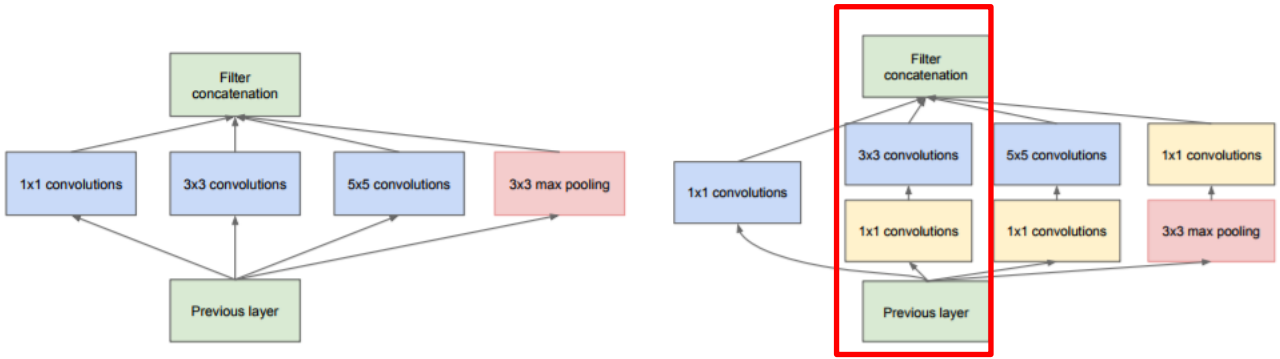
(a) Inception module, naïve version (b) Inception module with dimension reductions

Figure 2: Inception module

1x1 convolution으로 필터의 수를 줄이고 거기에다 3x3, 5x5 conv. 연산을 함으로써 결과적으로는 (a), (b)가 같은 결과를 내더라도 필요한 연산량과 메모리는 더 적다.

(출처:https://arxiv.org/pdf/1409.4842.pdf)

Google Network



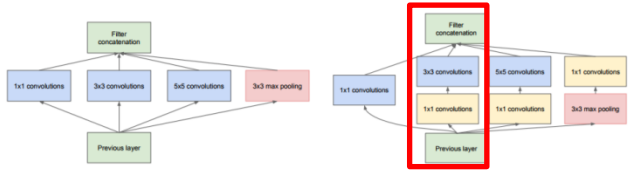
(a) Inception module, naïve version (b) Inception module with dimension reductions

Figure 2: Inception module

1x1 convolution으로 필터의 수를 줄이고 거기에다 3x3, 5x5 conv. 연산을 함으로써 결과적으로는 (a), (b)가 같은 결과를 내더라도 필요한 연산량과 메모리는 더 적다.

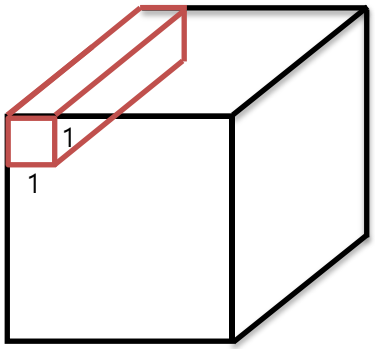
(출처:https://arxiv.org/pdf/1409.4842.pdf)

Google Network



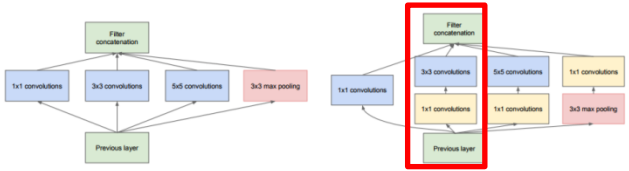
(a) Inception module, naïve version (b) Inception module with dimension reductions

Figure 2: Inception module



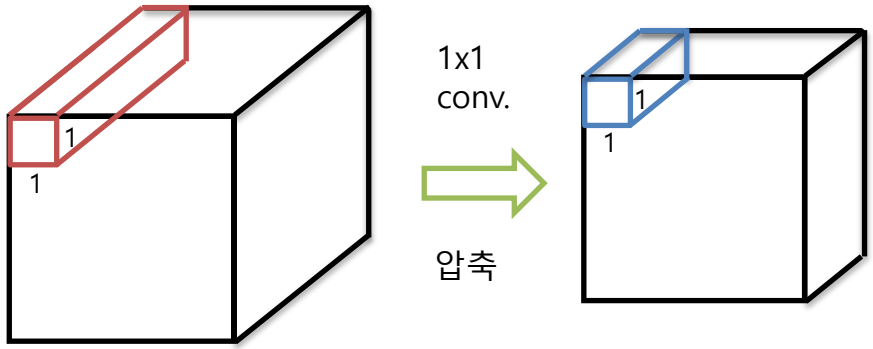
(출처:https://arxiv.org/pdf/1409.4842.pdf)

Google Network



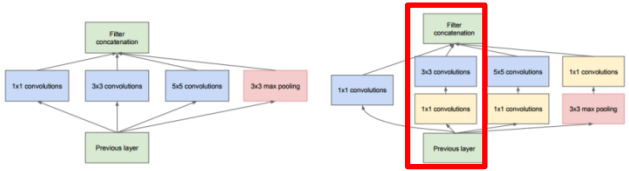
(a) Inception module, naïve version (b) Inception module with dimension reductions

Figure 2: Inception module



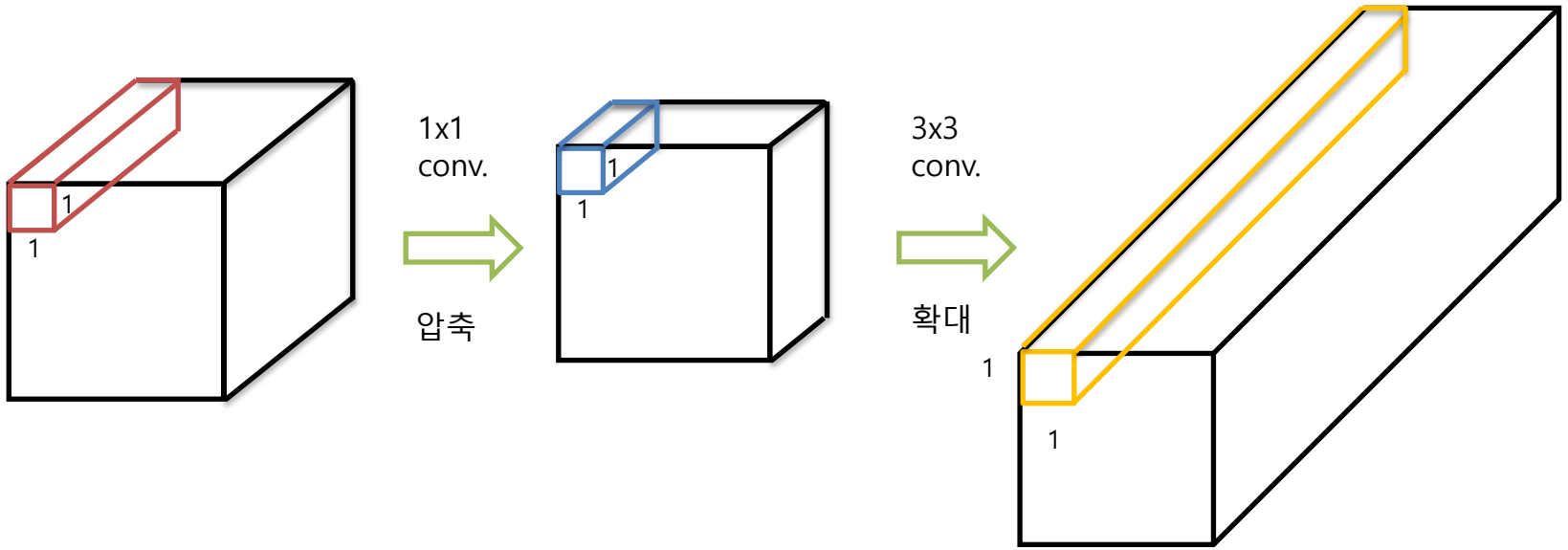
(출처:https://arxiv.org/pdf/1409.4842.pdf)

Google Network



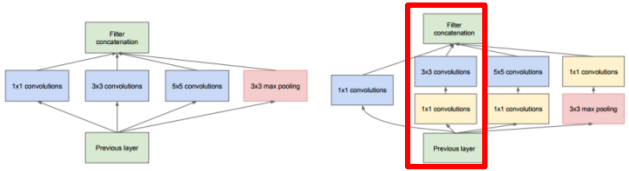
(a) Inception module, naïve version (b) Inception module with dimension reductions

Figure 2: Inception module



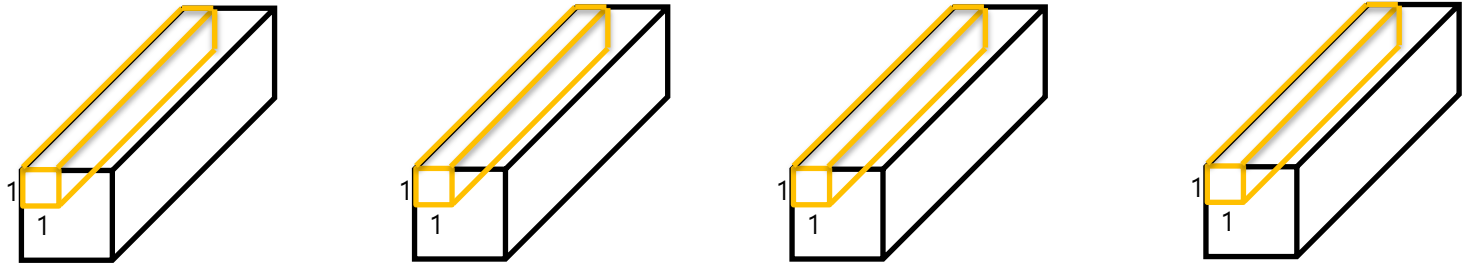
(출처:https://arxiv.org/pdf/1409.4842.pdf)

Google Network



(a) Inception module, naïve version (b) Inception module with dimension reductions

Figure 2: Inception module



1x1
conv.

5x5
conv.

1x1
conv.

3x3
conv.

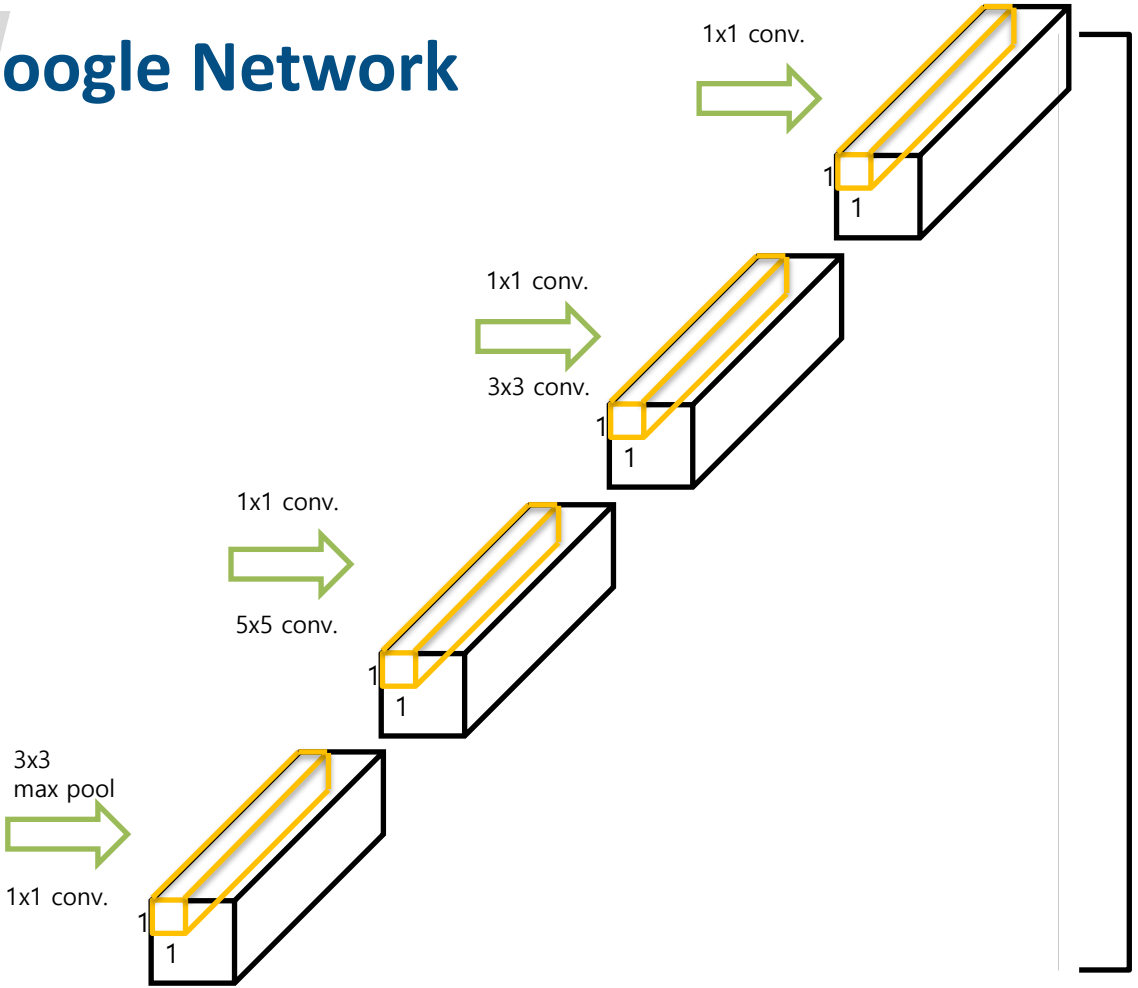
1x1
conv.

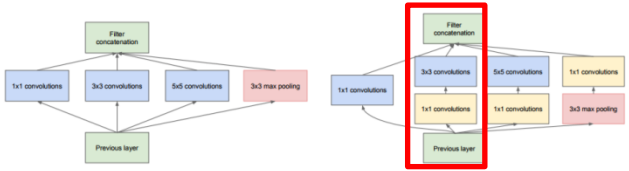
1x1
conv.

3x3
max pool

(출처:https://arxiv.org/pdf/1409.4842.pdf)

Google Network





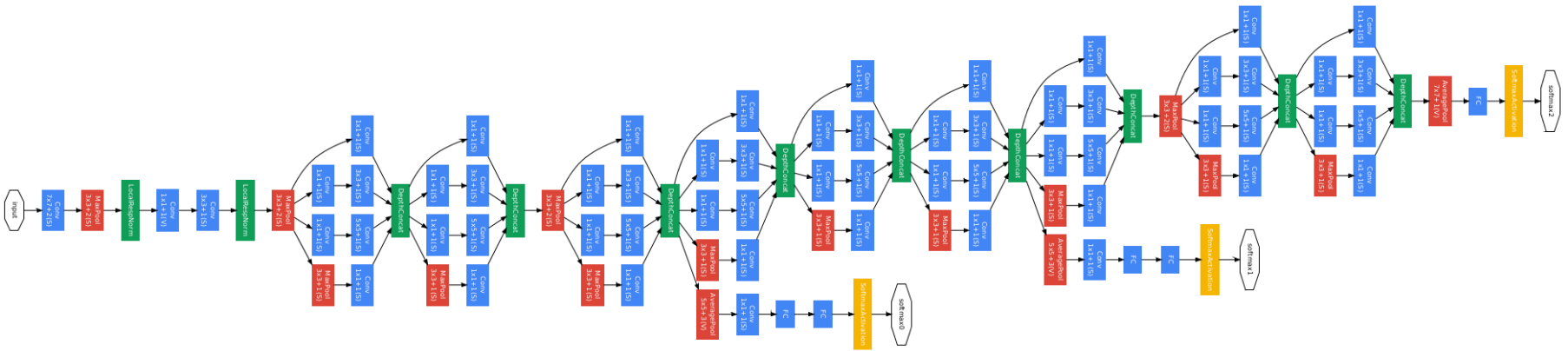
(a) Inception module, naïve version (b) Inception module with dimension reductions

Figure 2: Inception module

concatenate!

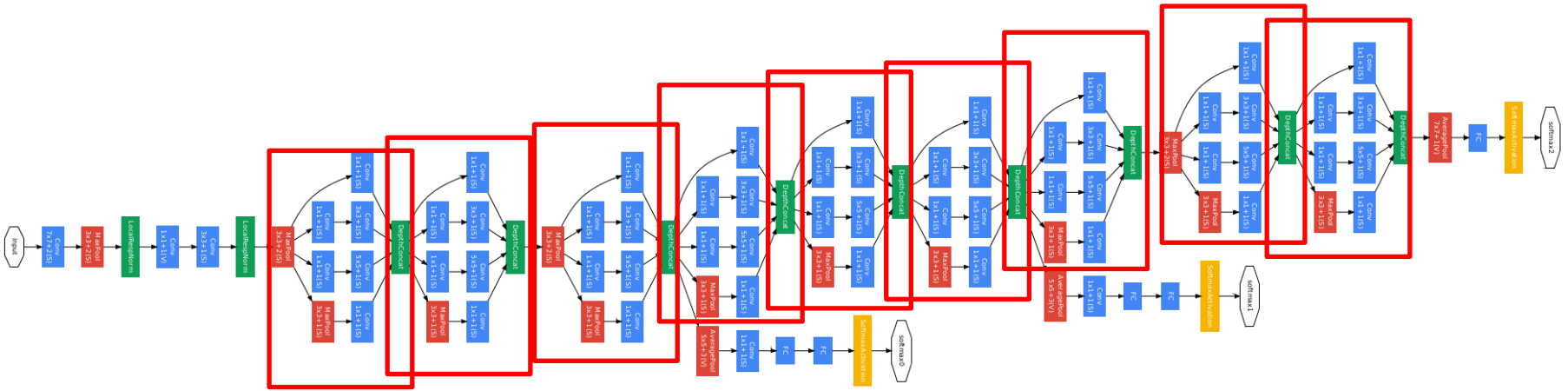
(출처:https://arxiv.org/pdf/1409.4842.pdf)

Google Network



(출처:https://arxiv.org/pdf/1409.4842.pdf)

Google Network



(출처:https://arxiv.org/pdf/1409.4842.pdf)

Google Network

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								

(출처:https://arxiv.org/pdf/1409.4842.pdf)

Google Network

Parameter만 보면 27MB

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
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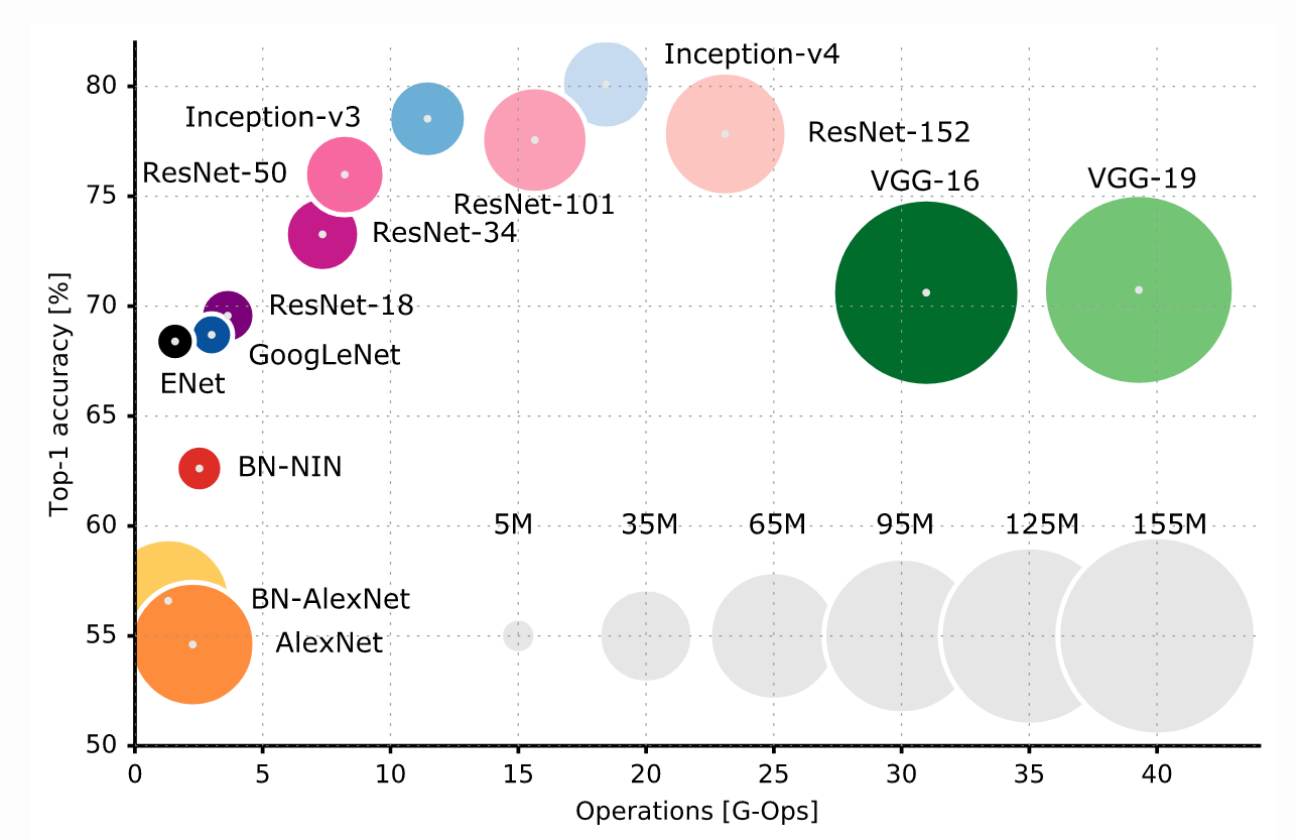
inception (4d)		14×14×528	2	112	144	288	32	64	64	580K	119M
inception (4e)		14×14×832	2	256	160	320	32	128	128	840K	170M
max pool	3×3/2	7×7×832	0								
inception (5a)		7×7×832	2	256	160	320	32	128	128	1072K	54M
inception (5b)		7×7×1024	2	384	192	384	48	128	128	1388K	71M
avg pool	7×7/1	1×1×1024	0								
dropout (40%)		1×1×1024	0								
linear		1×1×1000	1							1000K	1M
softmax		1×1×1000	0								

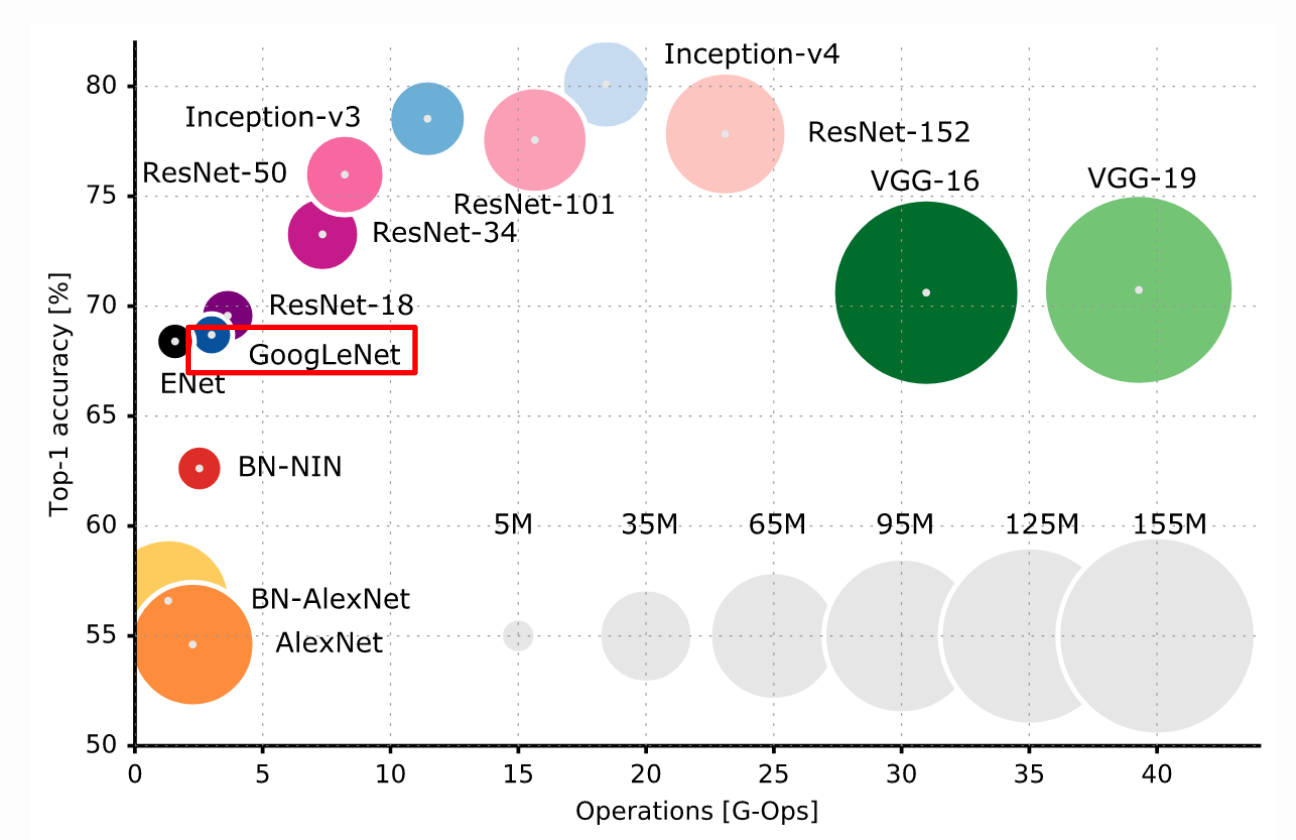
(출처:https://arxiv.org/pdf/1409.4842.pdf)

Google Network



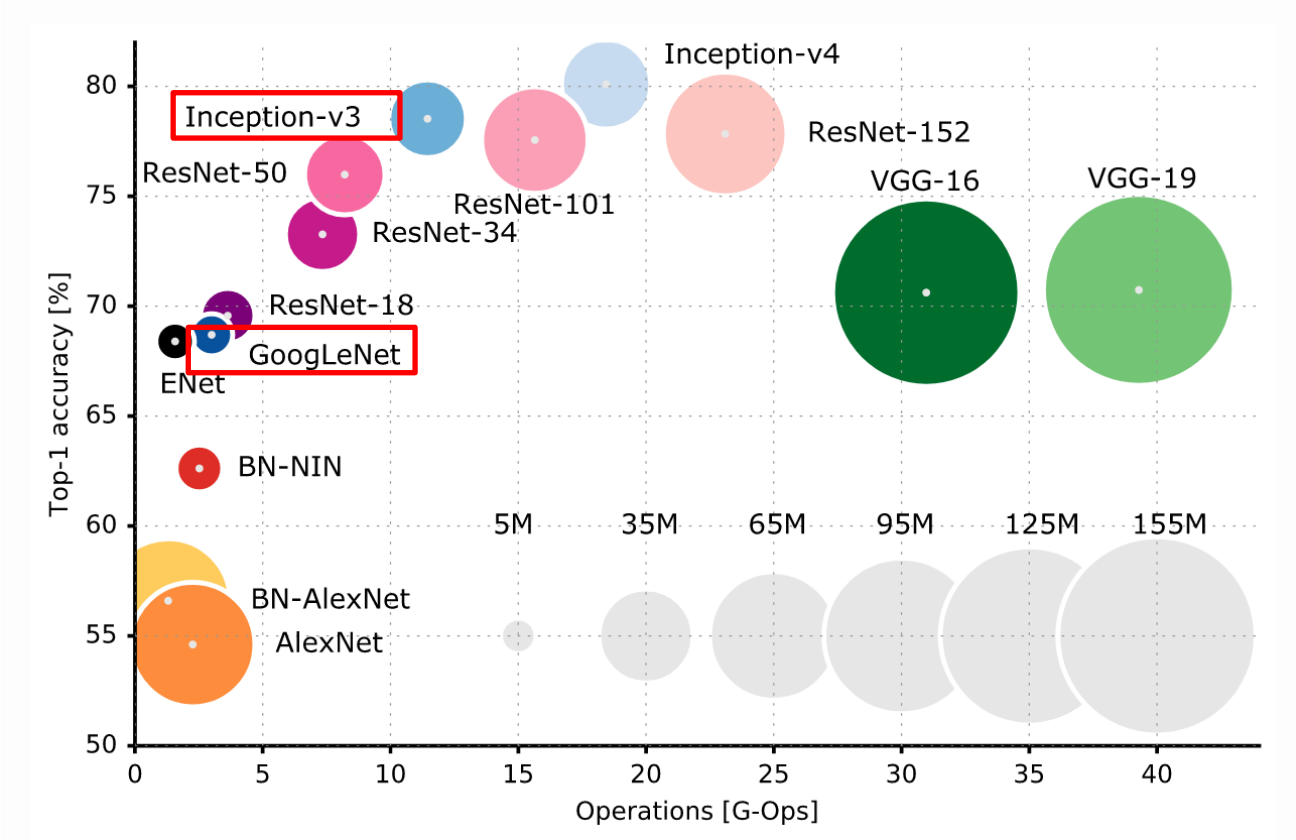
(출처: https://culurciello.github.io/tech/2016/06/20/training-enet.html)

Google Network



(출처: https://culurciello.github.io/tech/2016/06/20/training-enet.html)

Google Network



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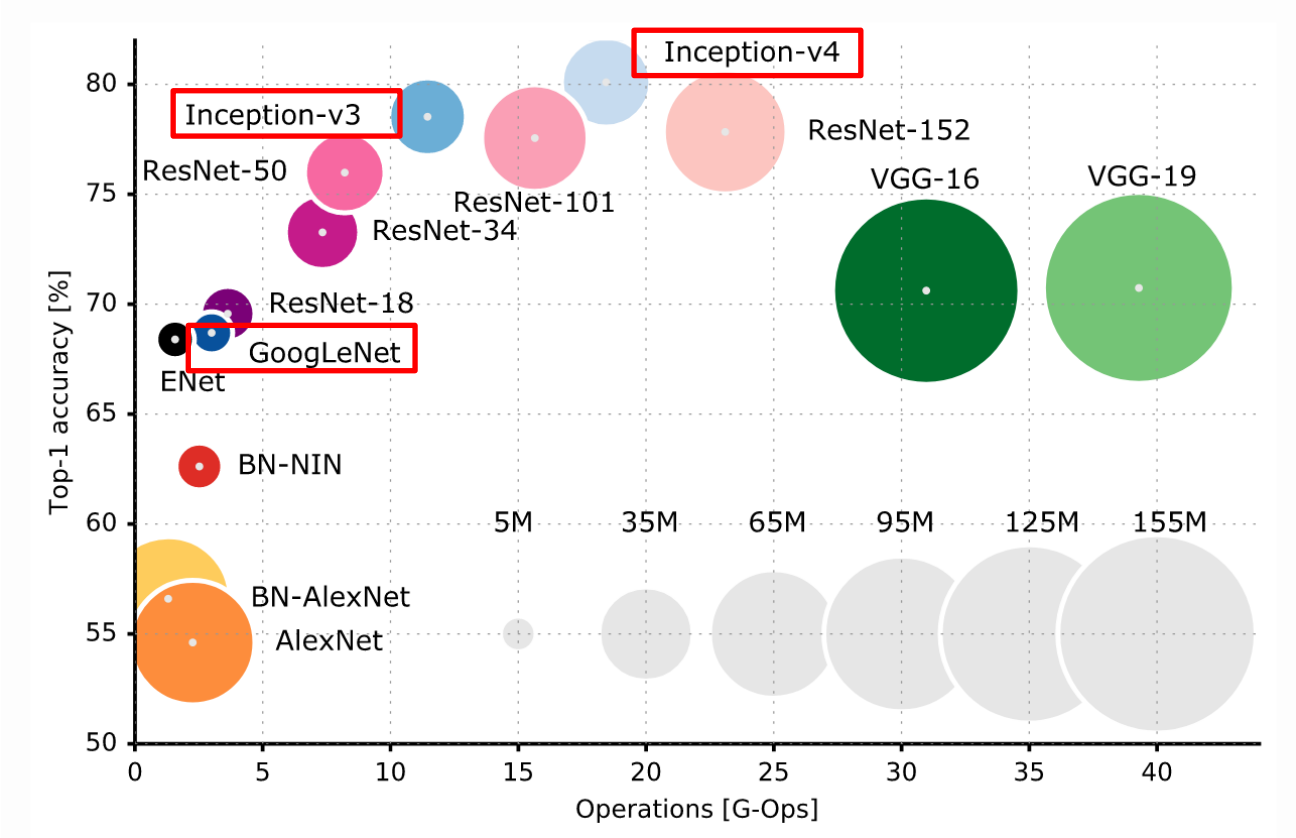
Google Network



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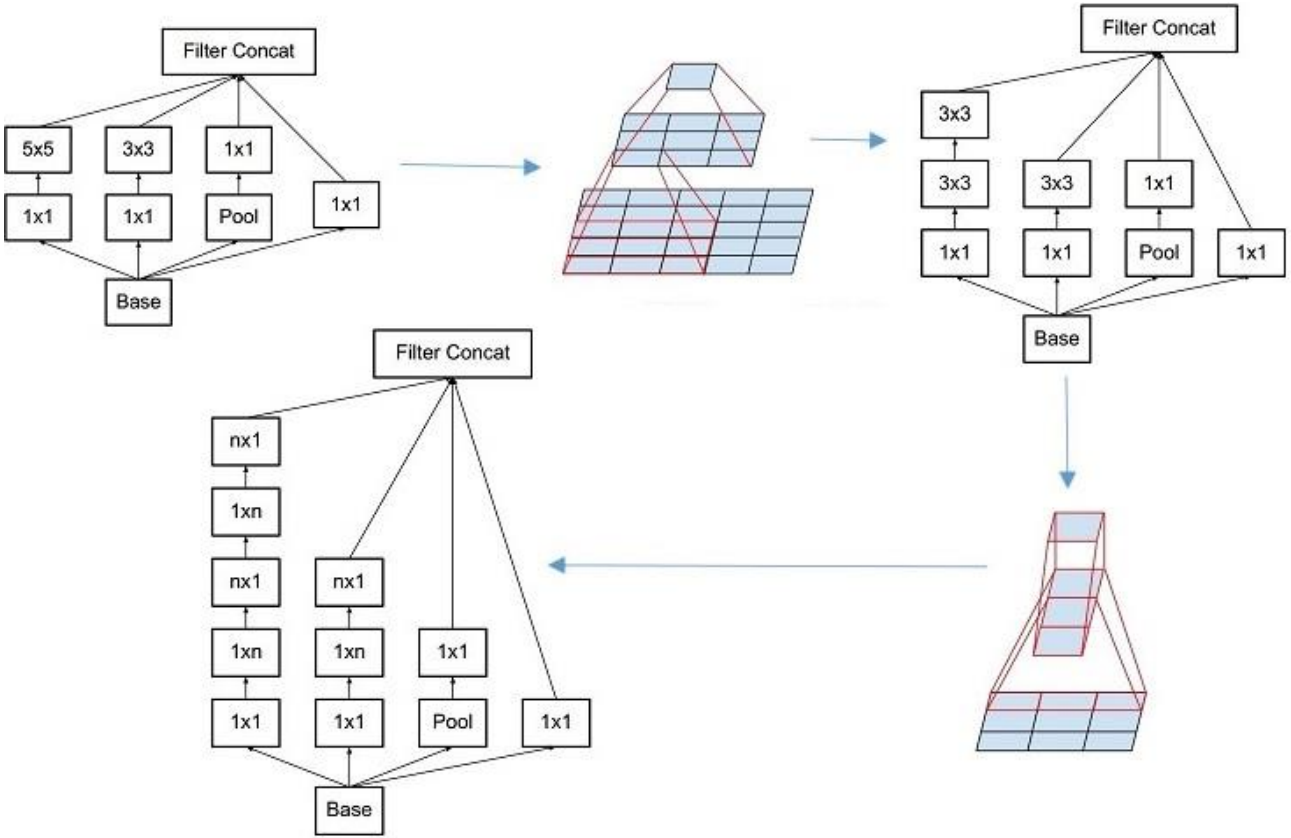
Google Network

Inception v1 -> v2
Convolution Factorization

(출처: https://arxiv.org/pdf/1512.00567v3.pdf)

Google Network

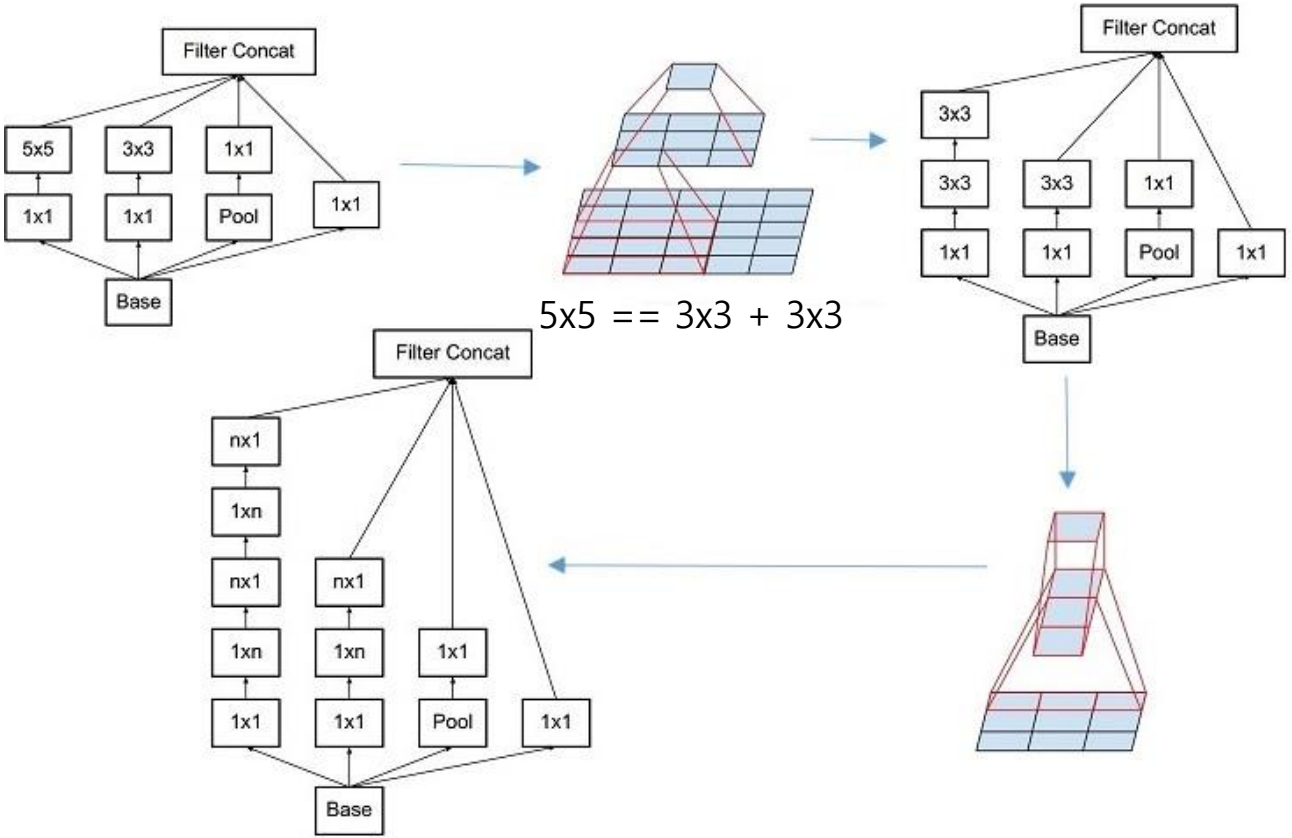
Inception v1 -> v2
Convolution Factorization



(출처: https://arxiv.org/pdf/1512.00567v3.pdf)

Google Network

Inception v1 -> v2
Convolution Factorization



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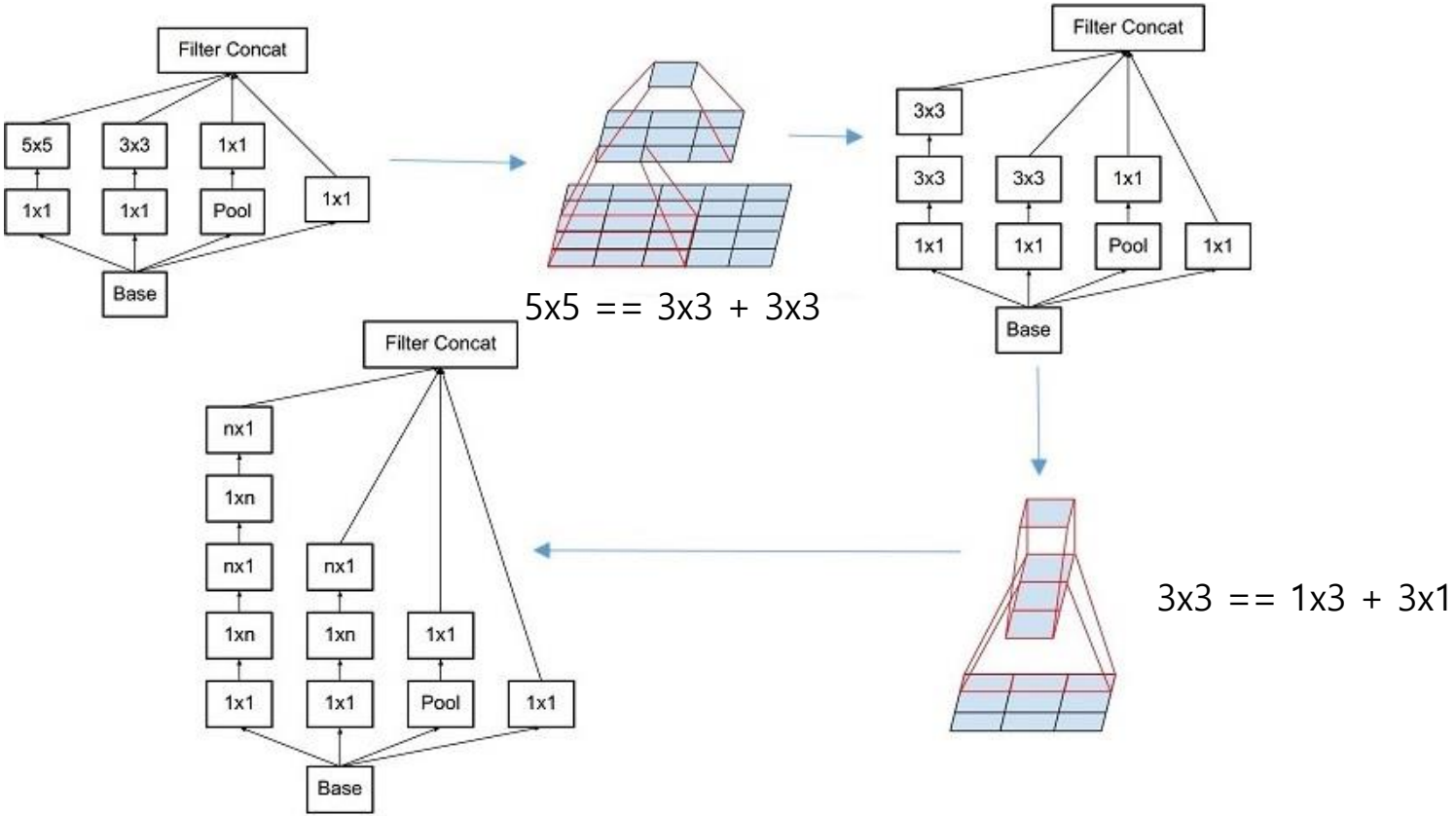

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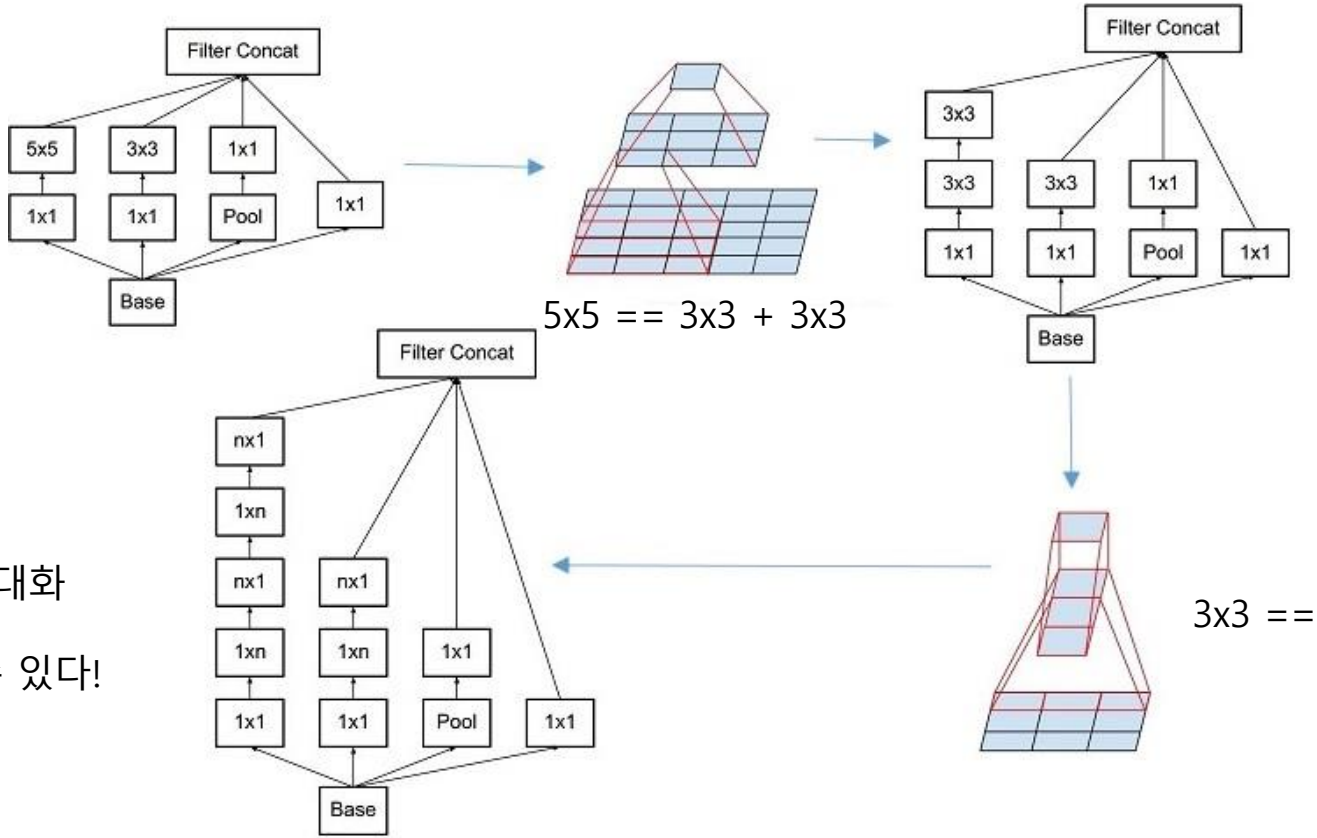

메모리 효율 극대화

더 깊이 쌓을 수 있다!

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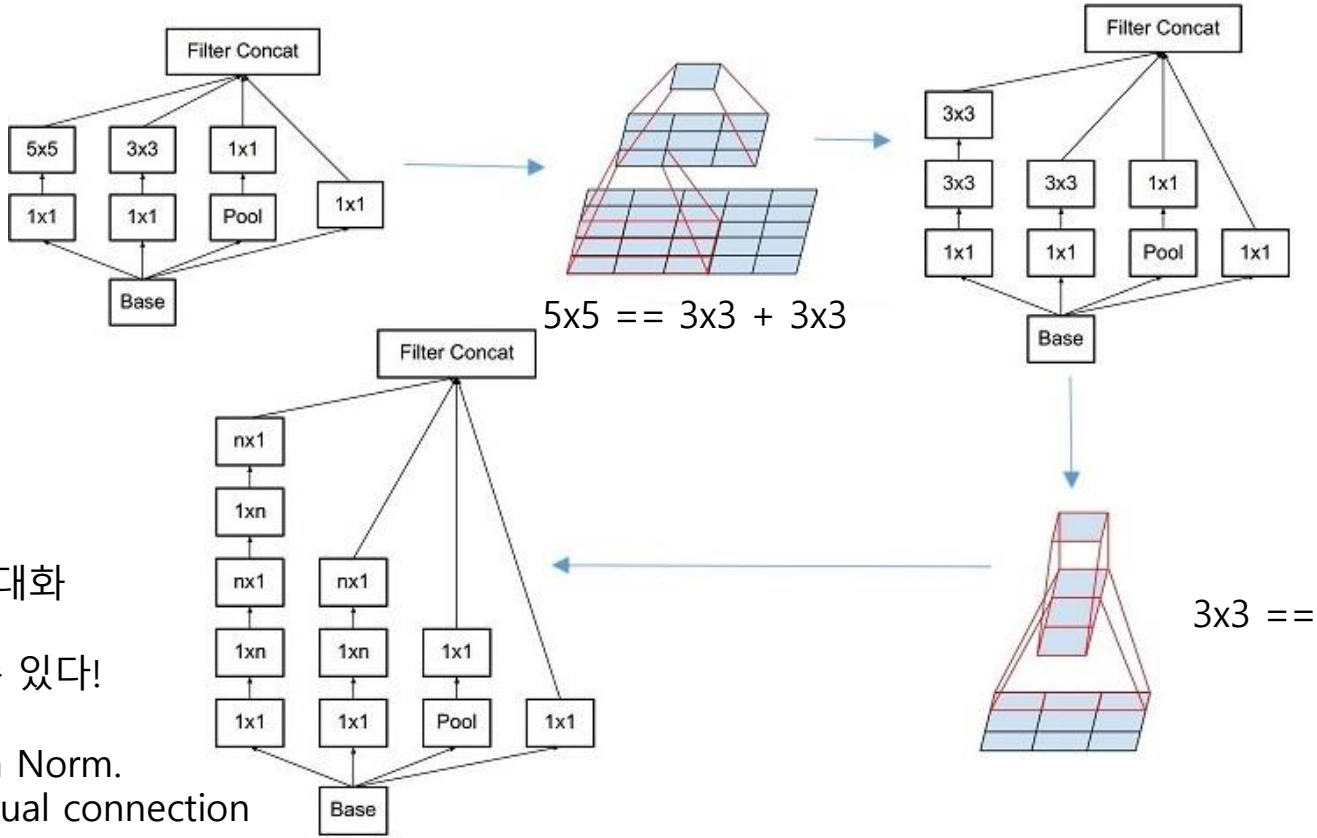


메모리 효율 극대화

더 깊이 쌓을 수 있다!

v2->v3는 Batch Norm.
v3->v4는 Residual connection

(출처: https://arxiv.org/pdf/1512.00567v3.pdf)

Residual Network

2014년 모델들을 보고 든 생각

Residual Network

2014년 모델들을 보고 든 생각

보아하니 깊어지면 깊어질수록 성능이 올라가는데 지금보다 더 쌓으면 어떻게 될까?

Residual Network

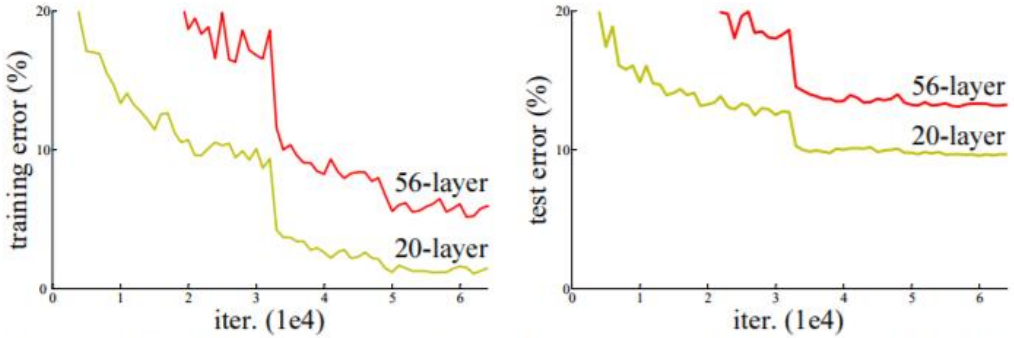
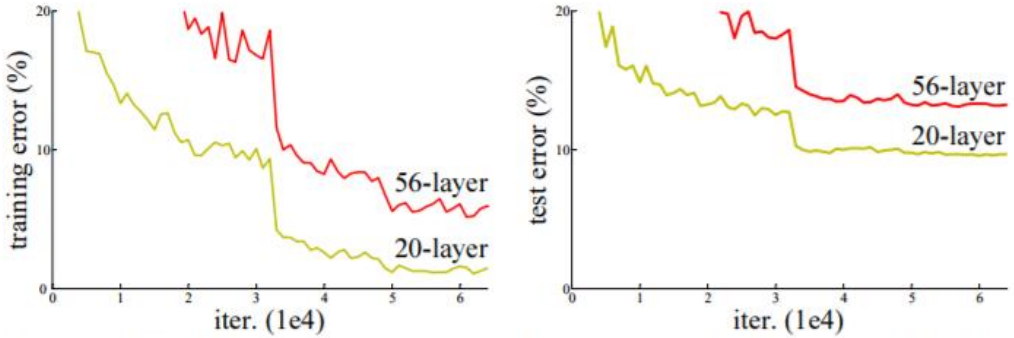


Figure 1. Training error (left) and test error (right) on CIFAR-10 with 20-layer and 56-layer "plain" networks. The deeper network has higher training error, and thus test error. Similar phenomena on ImageNet is presented in Fig. 4.

(출처: https://arxiv.org/abs/1512.03385)

Residual Network



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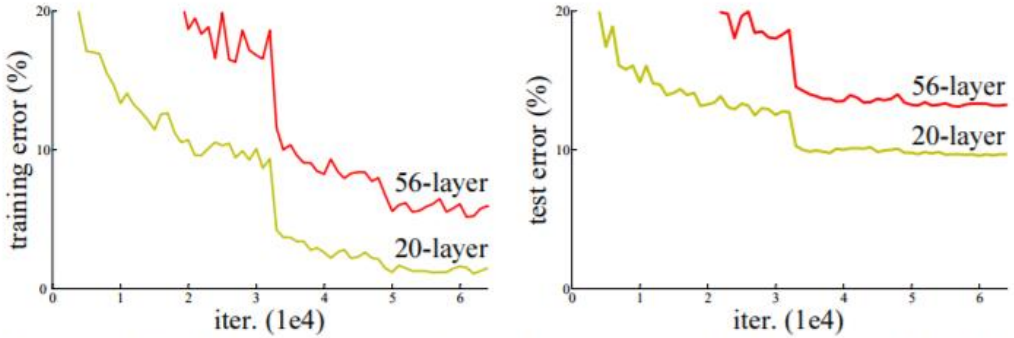
무작정 깊다고 더 좋아지는 건 아니다. 또한 training error와 test error 둘 다 높은 것은 아예 학습이 잘 안 되었음을 의미함

(출처: https://arxiv.org/abs/1512.03385)

Residual Network



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(출처: https://arxiv.org/abs/1512.03385)

Residual Network

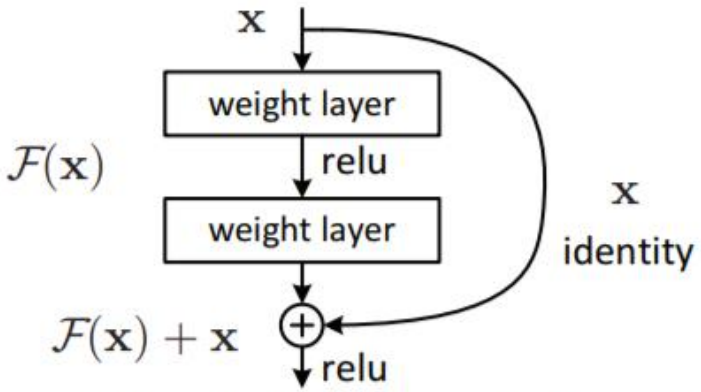


Figure 2. Residual learning: a building block.

(출처: https://arxiv.org/abs/1512.03385)

Residual Network

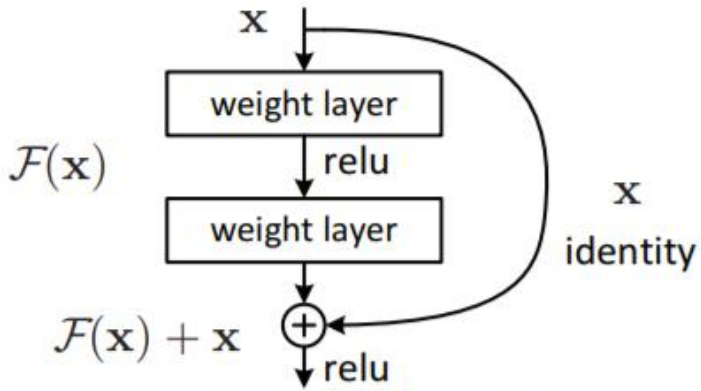
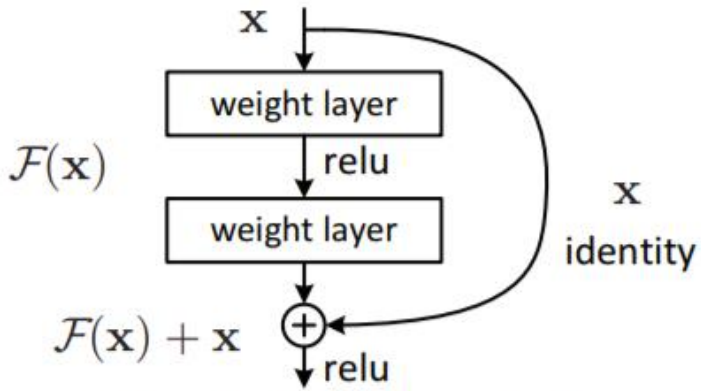


Figure 2. Residual learning: a building block.

ResNet 저자들이 생각해 낸 것이 Residual Learning
하지만 이전에 없던 완전 새로운 것은 아니고 identity mapping, shortcut connection 등의 비슷한 아이디어가 있었음.

(출처: https://arxiv.org/abs/1512.03385)

Residual Network



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-> 과연 좋을까?

(출처: https://arxiv.org/abs/1512.03385)

Residual Network

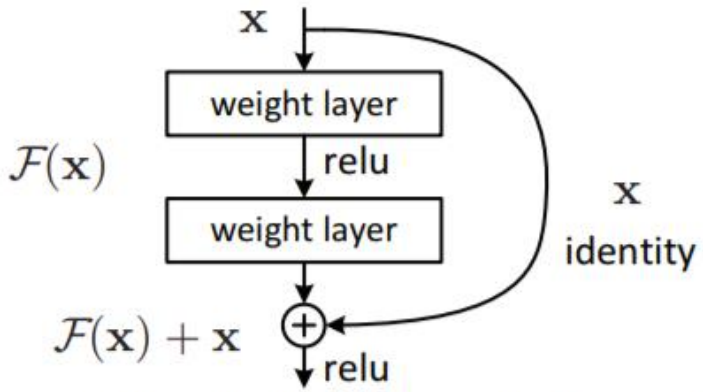
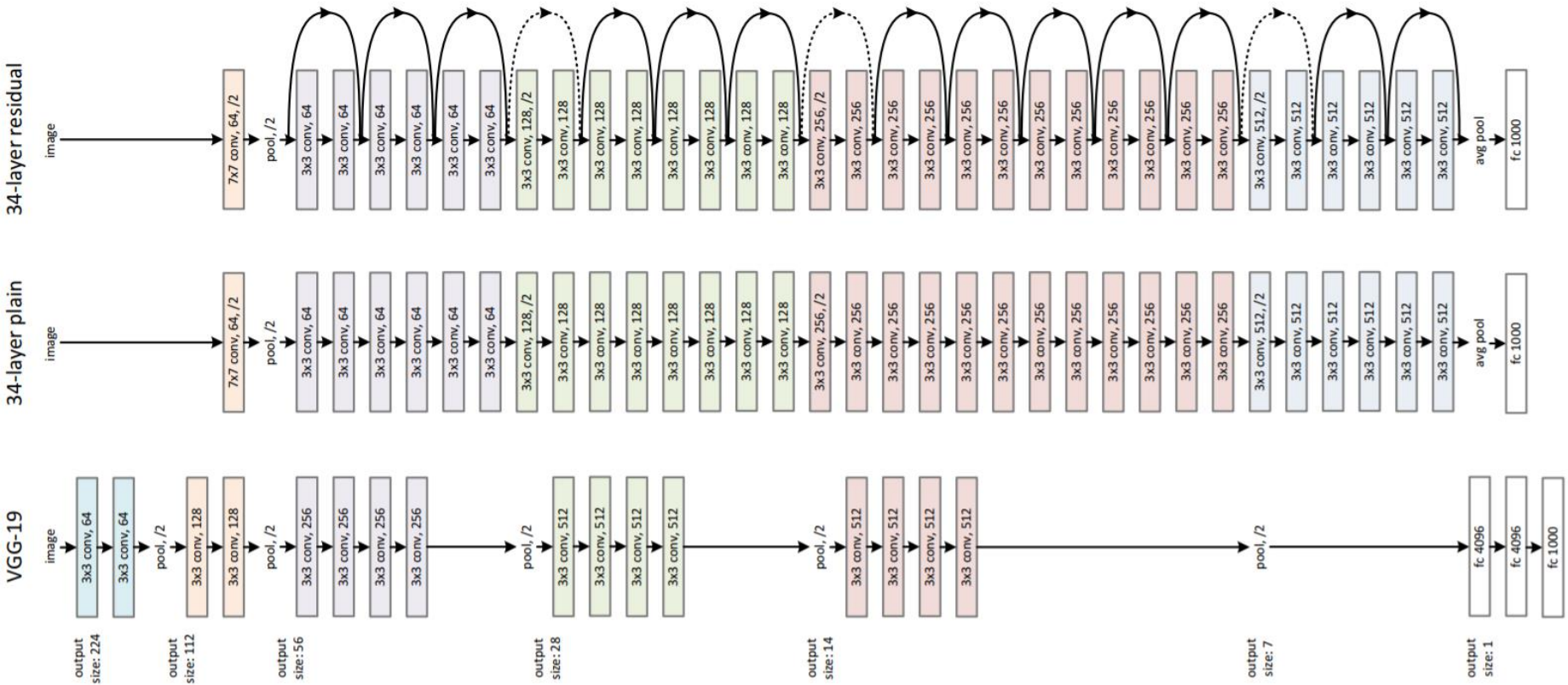


Figure 2. Residual learning: a building block.

직관적으로 생각해보면 초반에 뽑힌 단순한 형태들이 residual connection 없이 넘어가면 마지막 단에서는 복잡한 feature만을 가지고 판단해야 했다. 하지만 사실 단순하게 생각할수록 쉽게 풀리는 문제도 있듯이 앞 단의 비교적 간단한 feature 정보도 추가로 넘겨줌으로써 모델이 깊어지더라도 잘 판단할 수 있을 것

(출처: https://arxiv.org/abs/1512.03385)

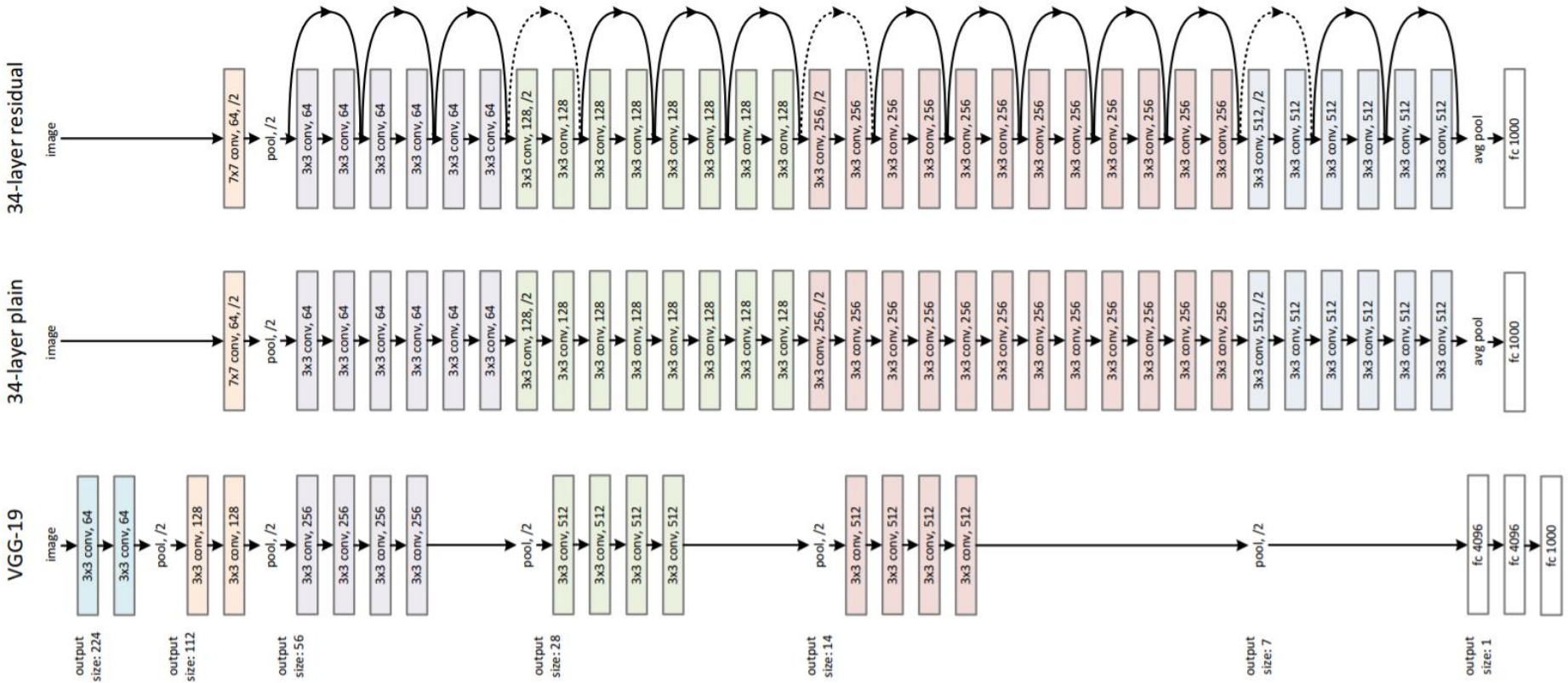
Residual Network



(출처: https://arxiv.org/abs/1512.03385)

Residual Network

점선은 convolution 연산 stride 2로 이미지가 작아졌을 때 맞춰주는 residual connection



(출처: https://arxiv.org/abs/1512.03385)

Residual Network

Plain Network

Residual Network

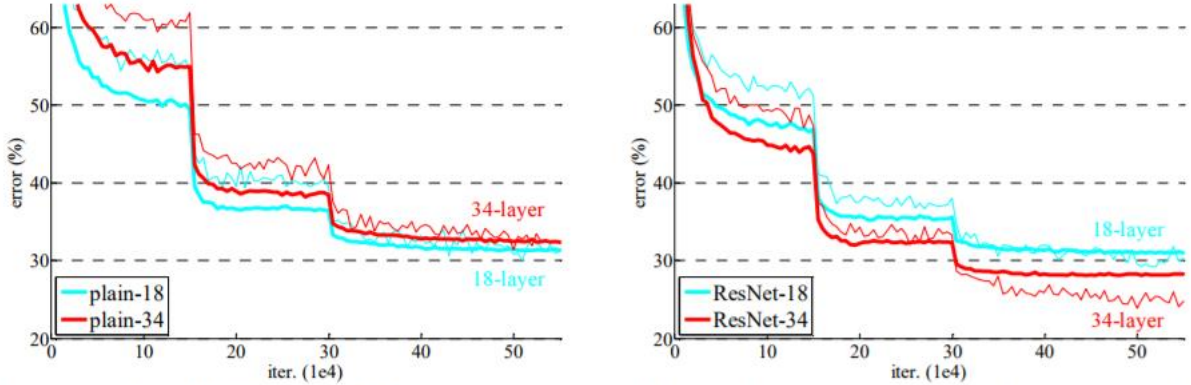


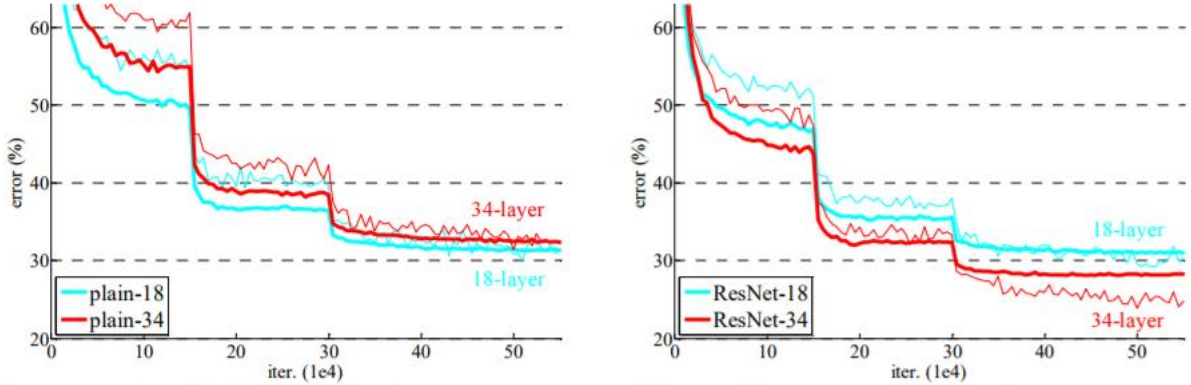
Figure 4. Training on **ImageNet**. Thin curves denote training error, and bold curves denote validation error of the center crops. Left: plain networks of 18 and 34 layers. Right: ResNets of 18 and 34 layers. In this plot, the residual networks have no extra parameter compared to their plain counterparts.

(출처: https://arxiv.org/abs/1512.03385)

Residual Network

Plain Network

Residual Network



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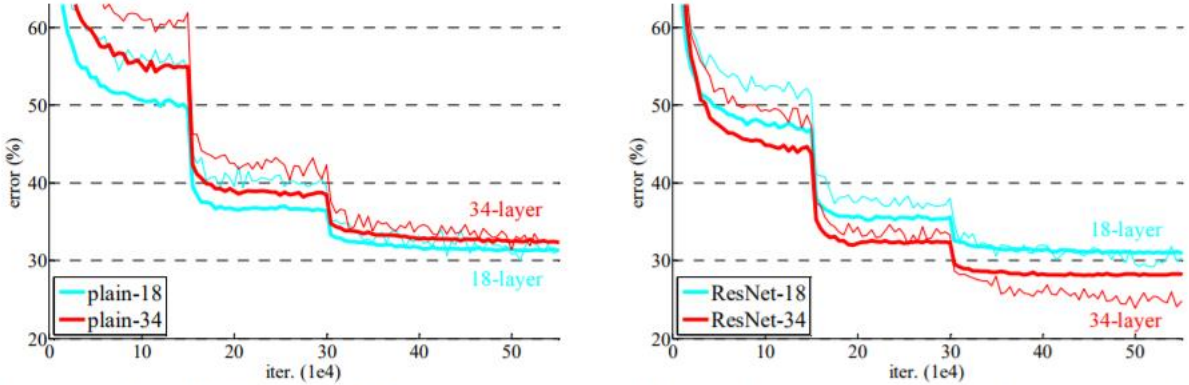
18 layer는 별 차이가 없었지만
34 layer는 눈에 띄게 성능이 더 좋다

(출처: https://arxiv.org/abs/1512.03385)

Residual Network

Plain Network

Residual Network



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34 layer는 눈에 띄게 성능이 더 좋다
-> 그렇다면 이번엔 어디까지 깊어질 수 있을까?

(출처: https://arxiv.org/abs/1512.03385)

Residual Network

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times23$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

(출처: https://arxiv.org/abs/1512.03385)

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conv5_x	7×7	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$
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(출처: https://arxiv.org/abs/1512.03385)

Residual Network

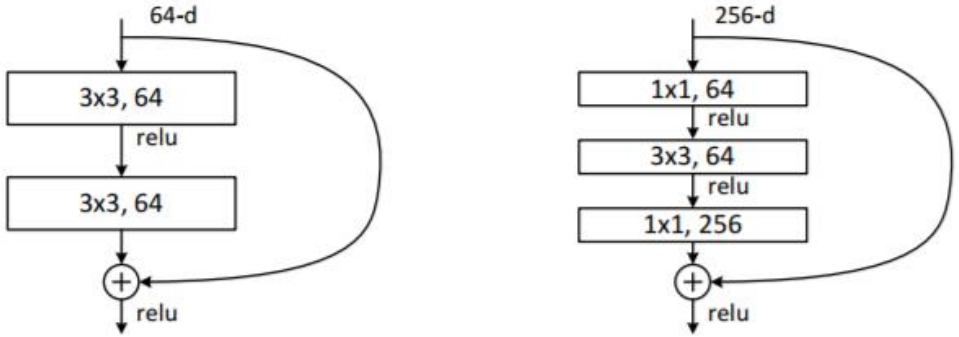
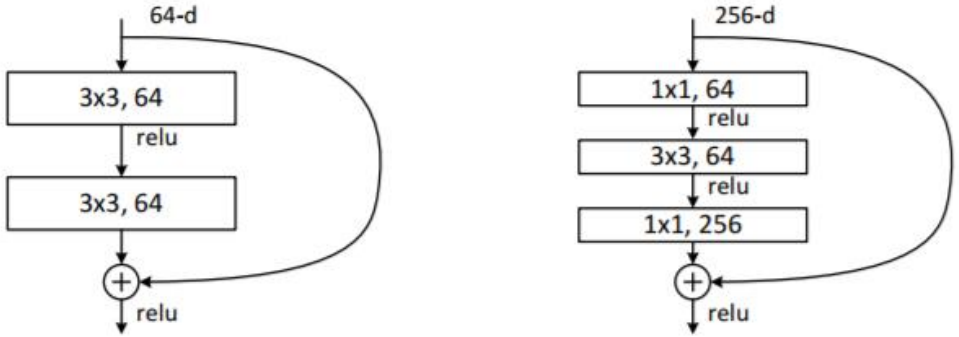


Figure 5. A deeper residual function $\mathcal{F}$ for ImageNet. Left: a building block (on 56×56 feature maps) as in Fig. 3 for ResNet-34. Right: a "bottleneck" building block for ResNet-50/101/152.

(출처: https://arxiv.org/abs/1512.03385)

Residual Network



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ResNet 역시 깊어질수록 연산량과 메모리 문제 때문에 1x1 convolution을 도입하여 압축한 상태로 feature를 뽑고 다시 확장하는 "Bottleneck"을 도입함

(출처: https://arxiv.org/abs/1512.03385)

Residual Network

method	top-1 err.	top-5 err.
VGG [41] (ILSVRC'14)	-	8.43†
GoogLeNet [44] (ILSVRC'14)	-	7.89
VGG [41] (v5)	24.4	7.1
PReLU-net [13]	21.59	5.71
BN-inception [16]	21.99	5.81
ResNet-34 B	21.84	5.71
ResNet-34 C	21.53	5.60
ResNet-50	20.74	5.25
ResNet-101	19.87	4.60
ResNet-152	**19.38**	**4.49**

Table 4. Error rates (%) of **single-model** results on the ImageNet validation set (except † reported on the test set).

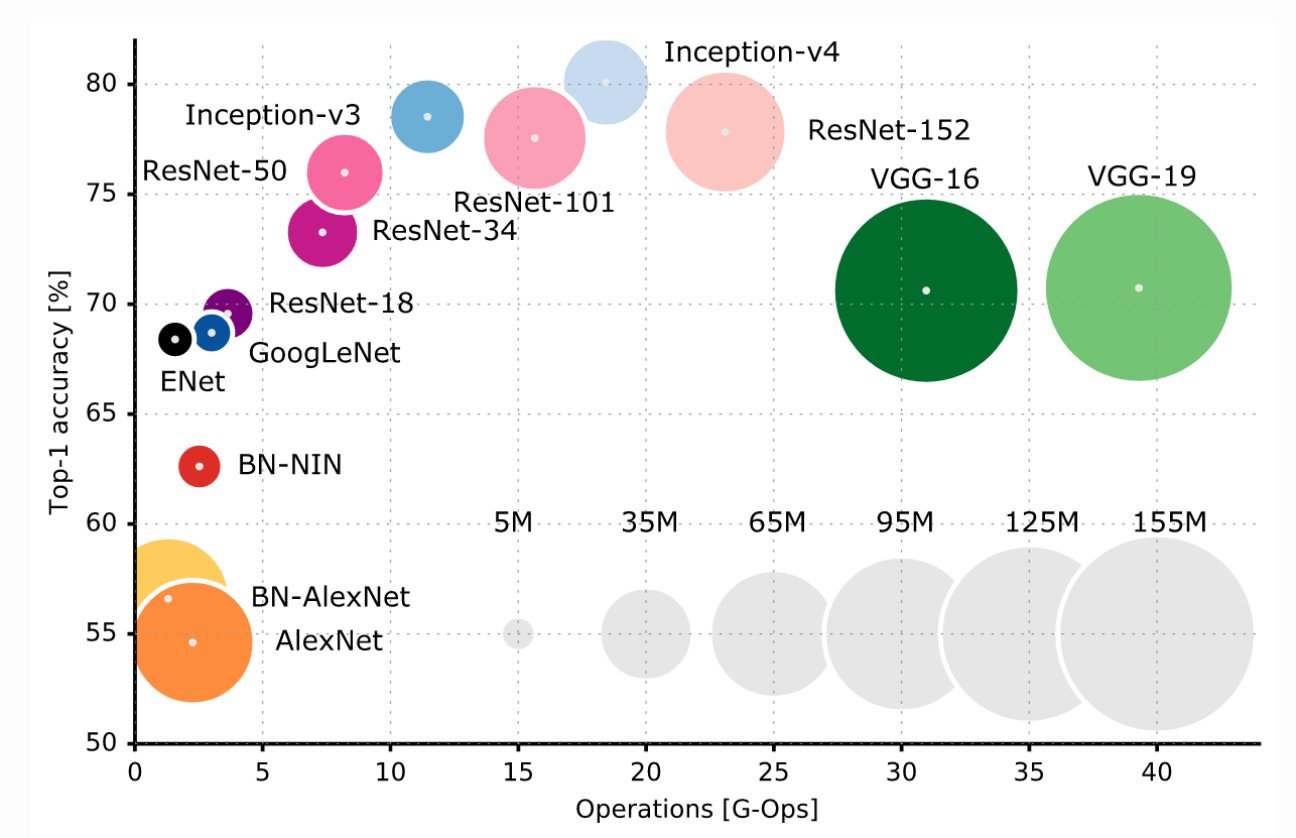
method	top-5 err. (**test**)
VGG [41] (ILSVRC'14)	7.32
GoogLeNet [44] (ILSVRC'14)	6.66
VGG [41] (v5)	6.8
PReLU-net [13]	4.94
BN-inception [16]	4.82
ResNet (ILSVRC'15)	**3.57**

Table 5. Error rates (%) of **ensembles**. The top-5 error is on the test set of ImageNet and reported by the test server.

다른 모델들을 제치고 ImageNet Challenge 1위

(출처: https://arxiv.org/abs/1512.03385)

Residual Network



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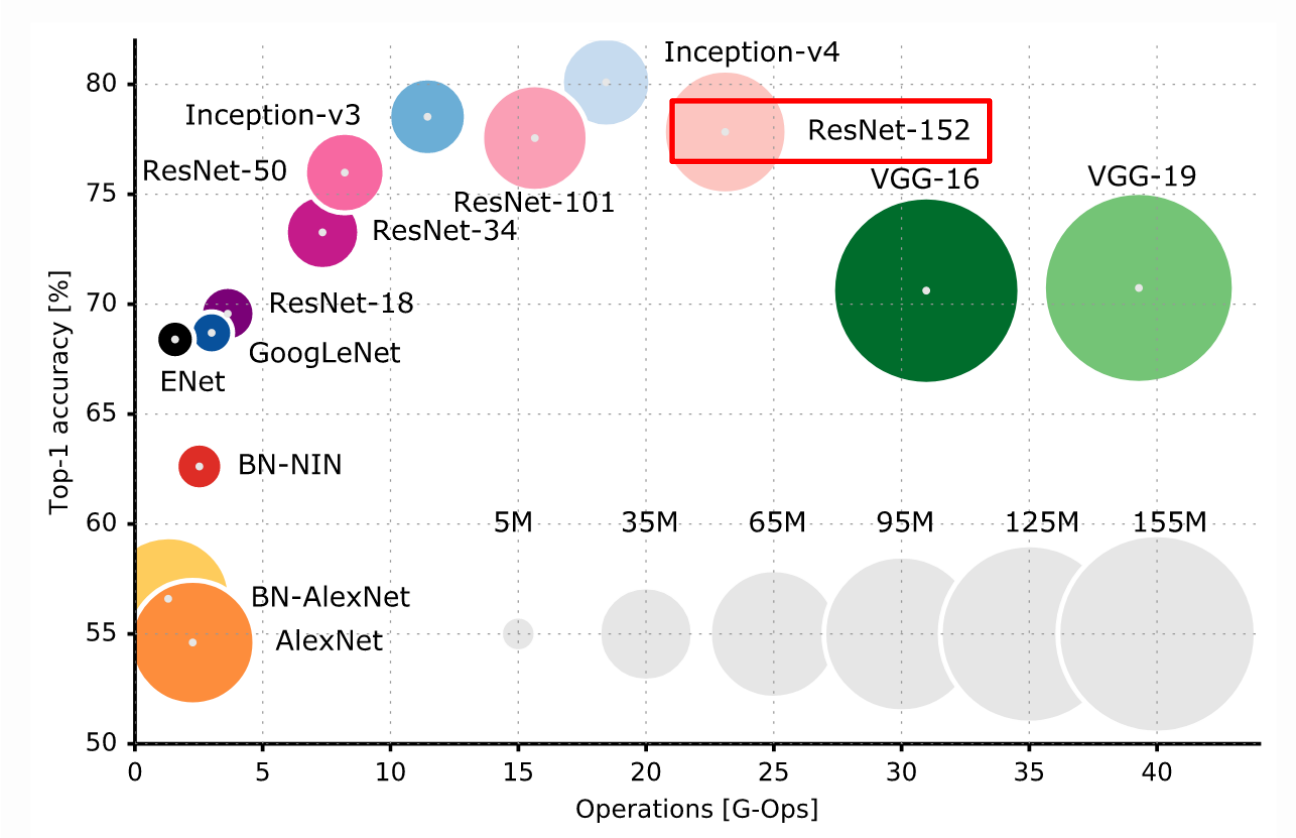
Residual Network



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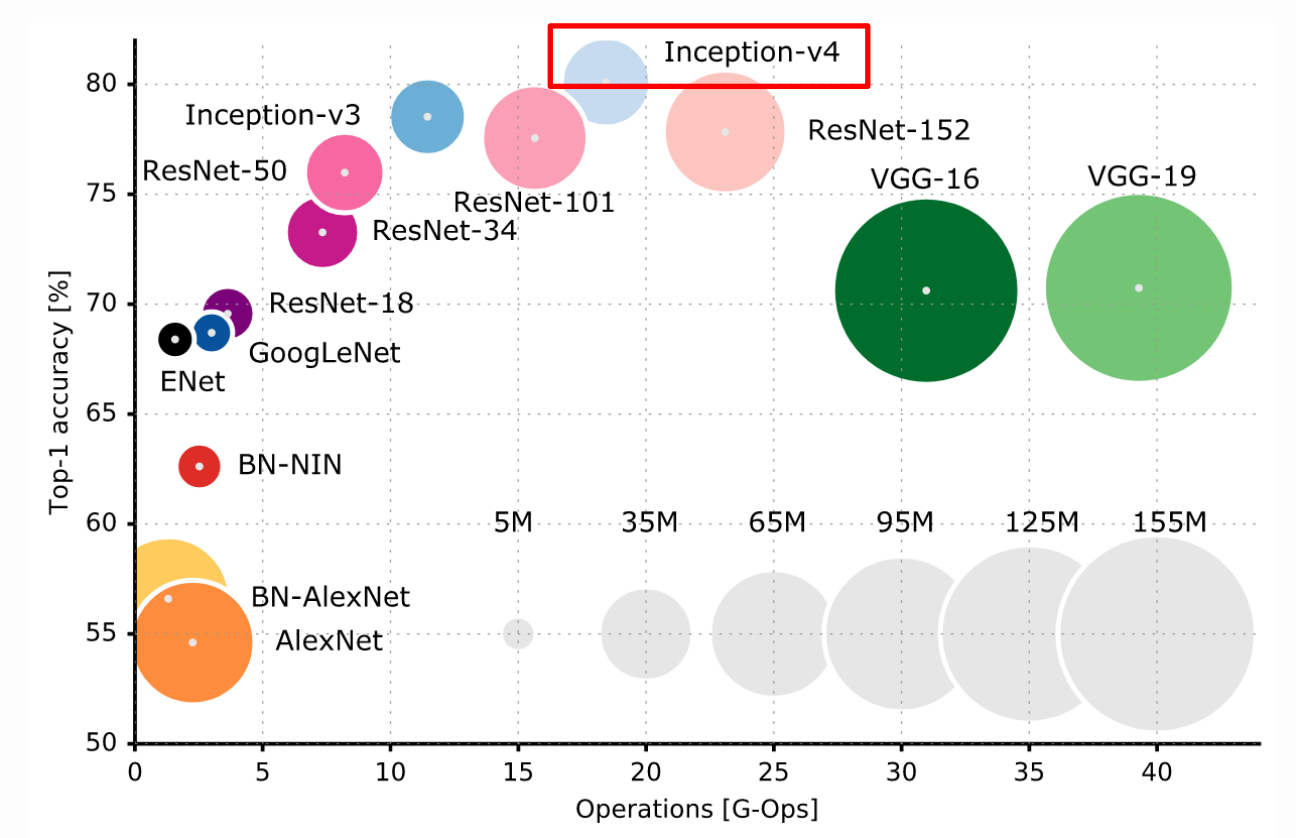
Residual Network



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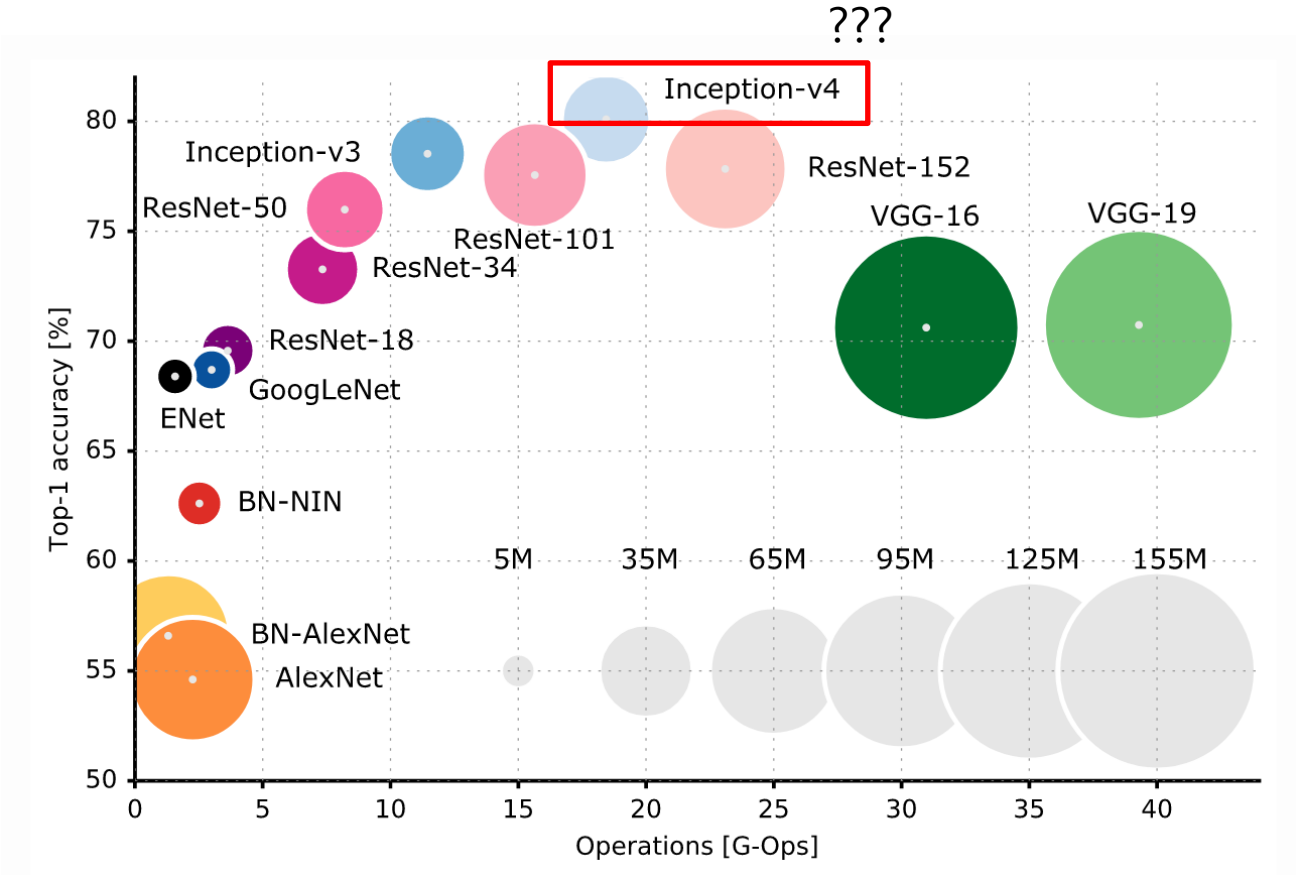
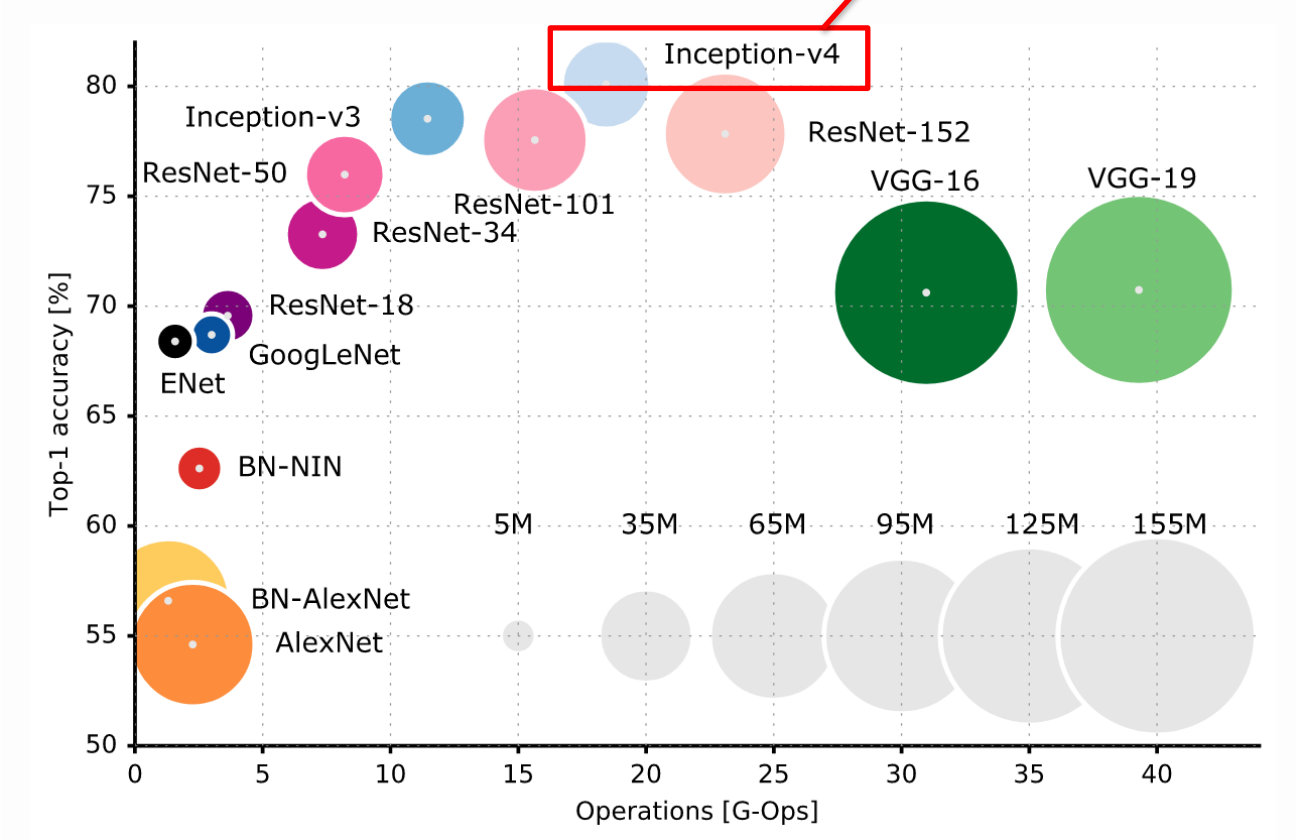
Residual Network



(출처: https://arxiv.org/abs/1512.03385)

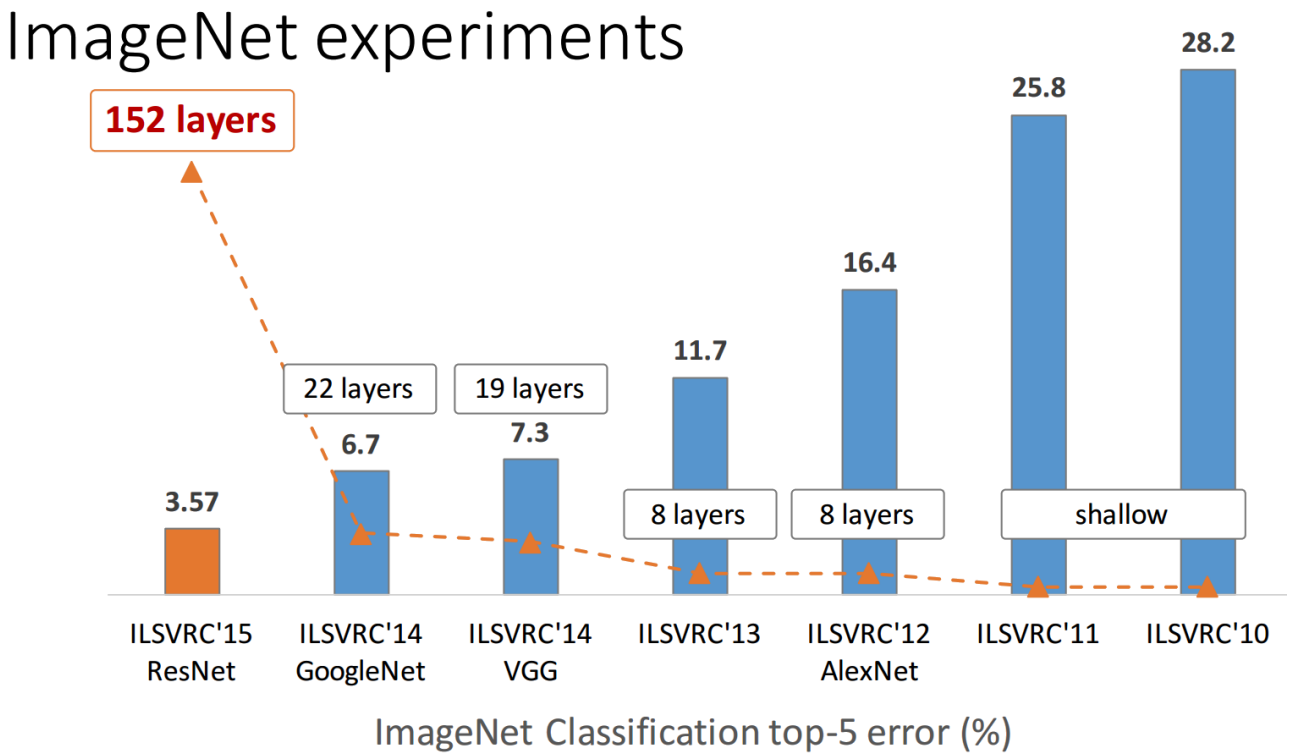
Residual Network

Inception + Residual + BN



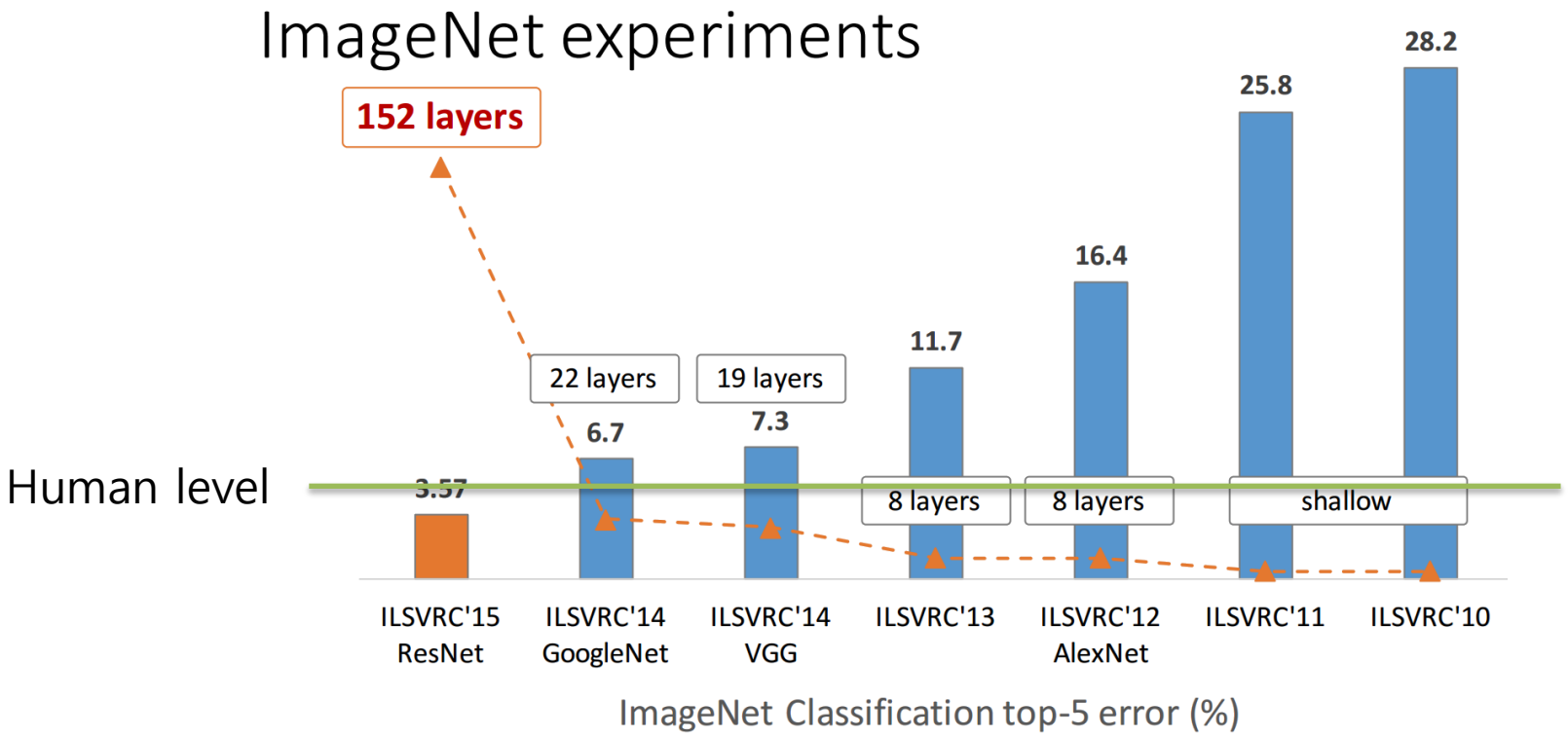
(출처: https://arxiv.org/abs/1512.03385)

Residual Network



(출처: Kaiming He "Deep residual learning for image recognition." ICML. 2016.)

Residual Network



(출처: Kaiming He "Deep residual learning for image recognition." ICML. 2016.)

Q&A