StandAlone DeepLearning

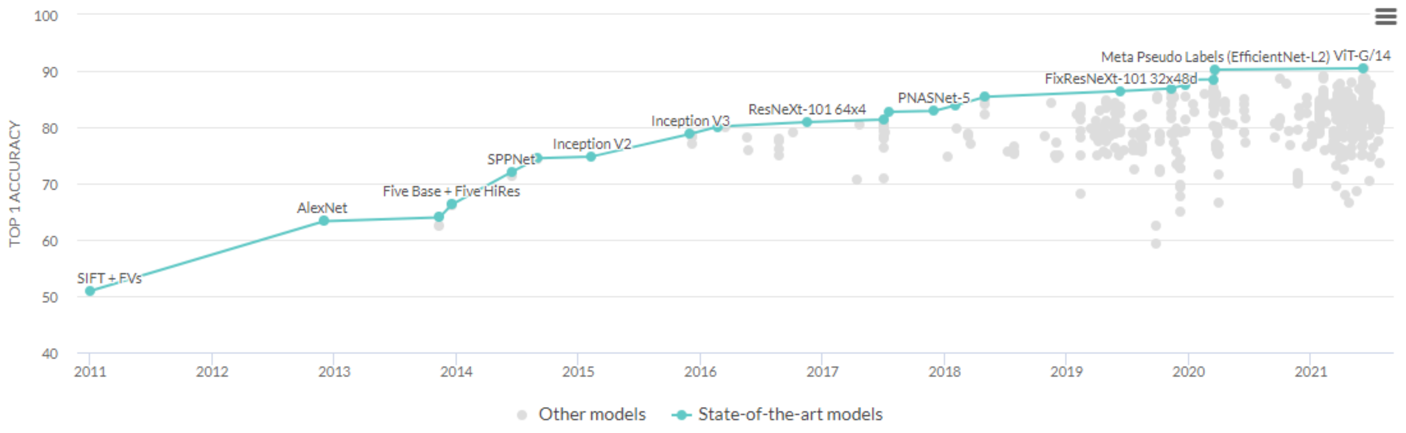
김영민

1. ImageNet Competition

Dataset

- 1000만장 이상의 이미지
- 1000개의 class
- 227 x 227 사이즈의 RGB 이미지

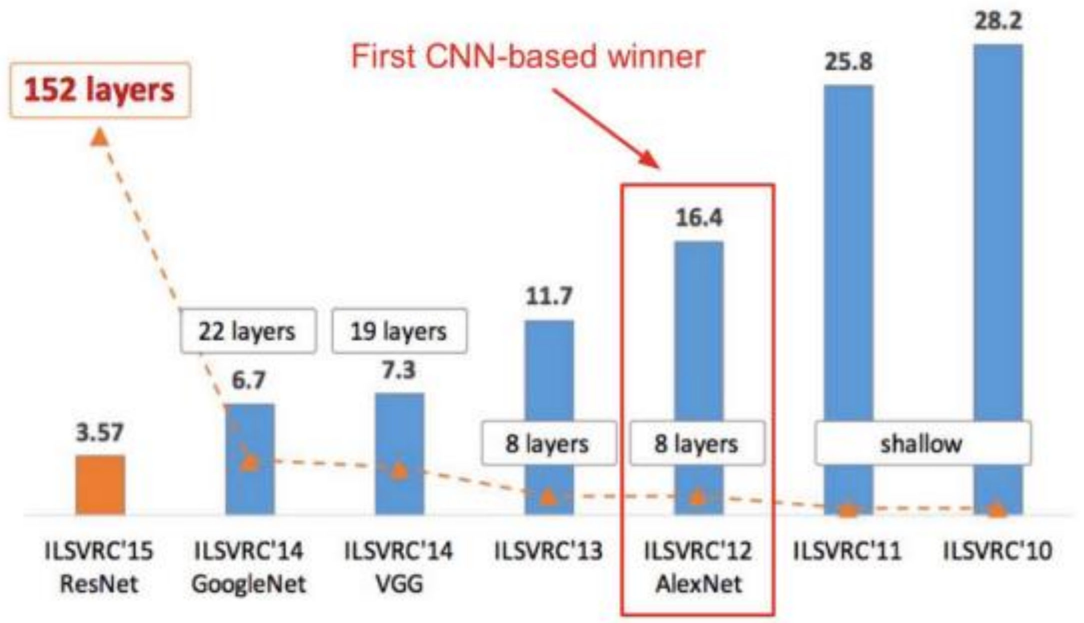
SOTA



2021 SOTA model = One of the ViT

1. ImageNet Competition

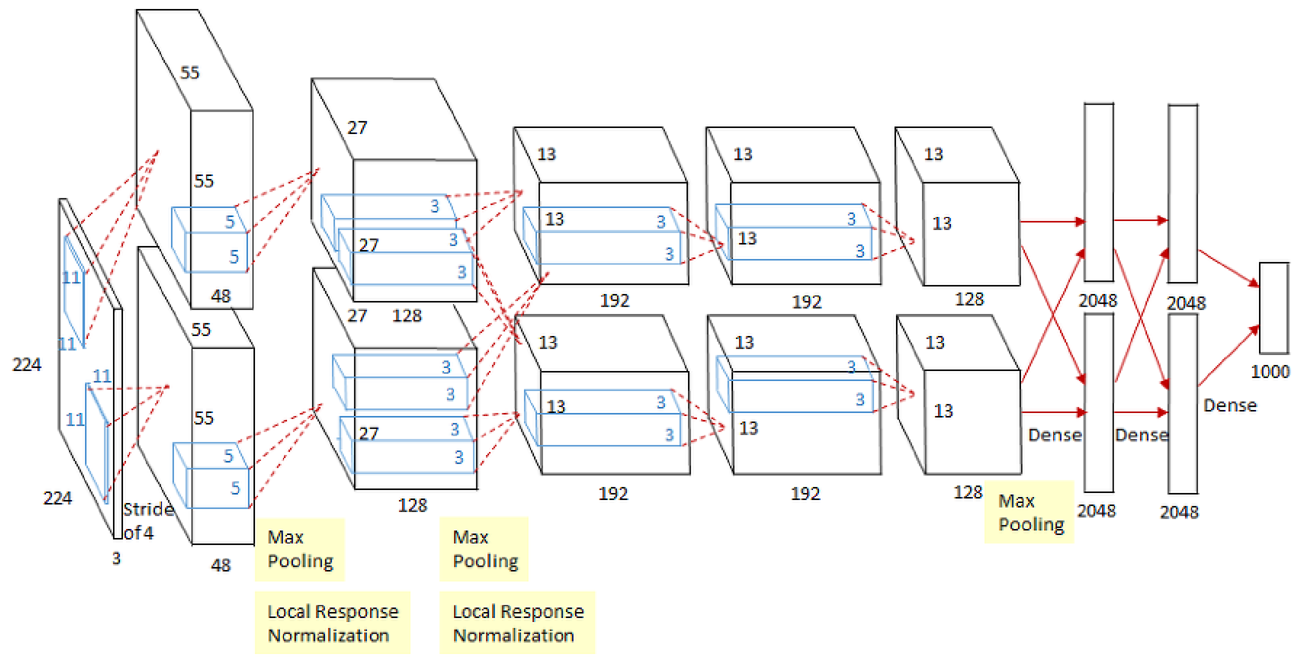
~2015



AlexNet -> VGG -> GoogleNet -> ResNet

2. AlexNet

Architecture



Acitvation Function = ReLU

Nomalization Layer 사용

Optimizer = SGD + Momentum(0.9)

Contribution

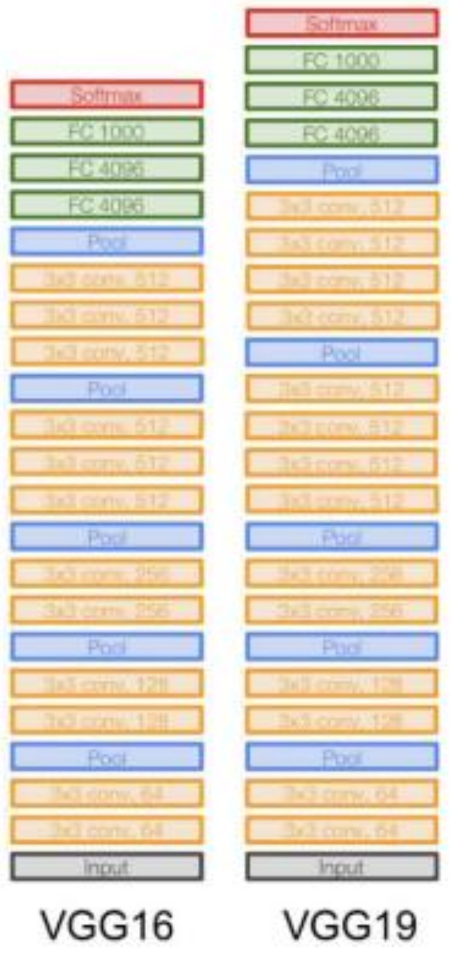
최초로 CNN을 사용하여 우승

최초로 ReLU 함수 사용

앙상블을 이용하여 성능 향상

3. VGGNet

Architecture



Contribution

작은 필터를 사용하여 층을 더 깊게 만듦

(AlexNet의 약 2배 Layer 사용)

↓

비선형성 ↑

Overfitting ↑

Number of Paramter ↓

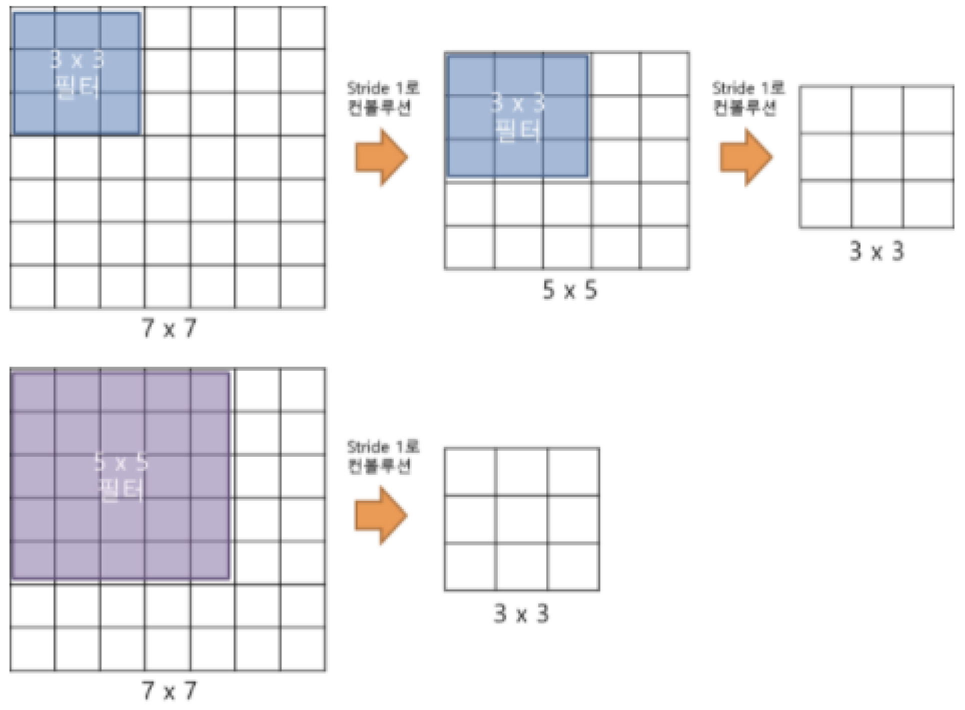
Future Work

VGG를 기반으로 한 많은 응용 연구 증가

3. VGGNet

Small Filter

3x3 filter 사용



7x7 Image -> 3x3 filter 2번 사용

파라미터 수 : 3x3 + 3x3 = 18

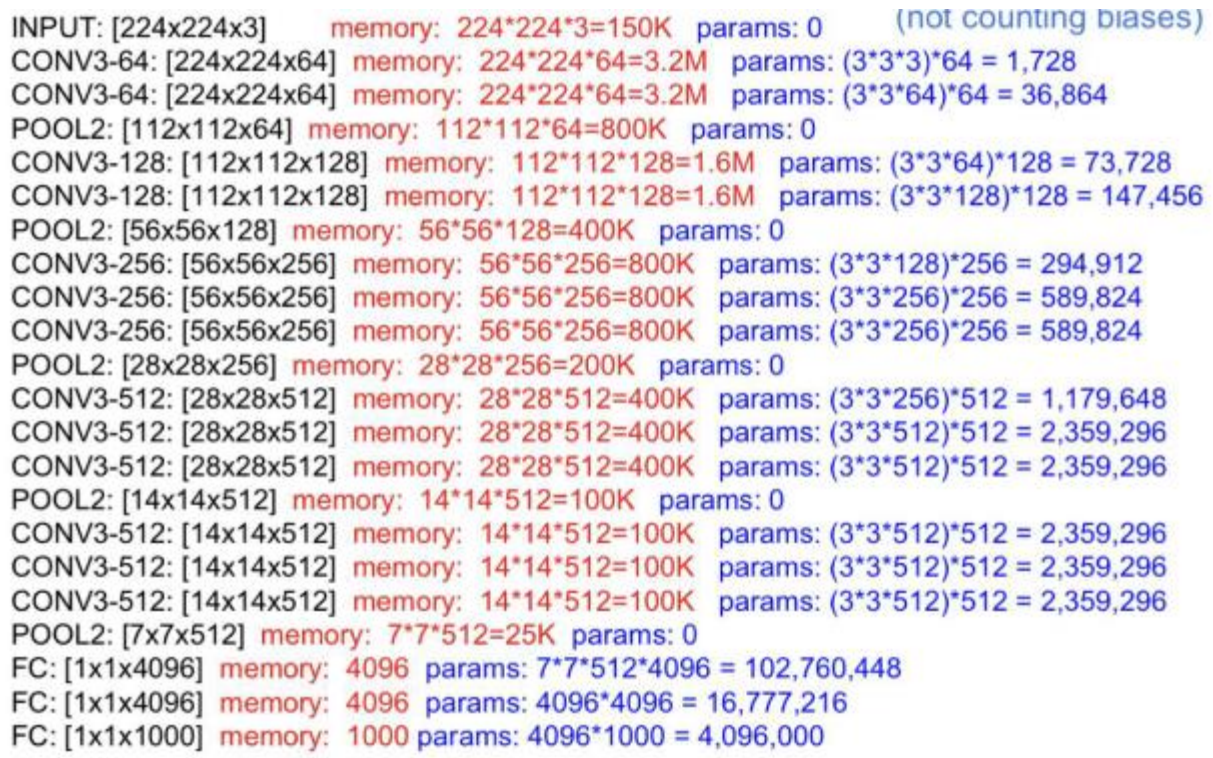
$\wedge$

7x7 Image -> 5x5 filter 1번 사용

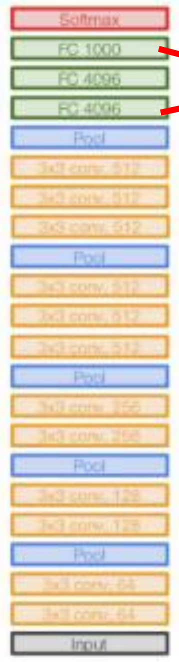
파라미터 수 : 5x5 = 25

3. VGGNet

VGG parameter



```
INPUT: [224x224x3]       memory:  224*224*3=150K   params: 0        (not counting biases)
CONV3-64: [224x224x64]  memory:  224*224*64=3.2M   params: (3*3*3)*64 = 1,728
CONV3-64: [224x224x64]  memory:  224*224*64=3.2M   params: (3*3*64)*64 = 36,864
POOL2: [112x112x64]  memory:  112*112*64=800K   params: 0
CONV3-128: [112x112x128]  memory:  112*112*128=1.6M   params: (3*3*64)*128 = 73,728
CONV3-128: [112x112x128]  memory:  112*112*128=1.6M   params: (3*3*128)*128 = 147,456
POOL2: [56x56x128]  memory:  56*56*128=400K   params: 0
CONV3-256: [56x56x256]  memory:  56*56*256=800K   params: (3*3*128)*256 = 294,912
CONV3-256: [56x56x256]  memory:  56*56*256=800K   params: (3*3*256)*256 = 589,824
CONV3-256: [56x56x256]  memory:  56*56*256=800K   params: (3*3*256)*256 = 589,824
POOL2: [28x28x256]  memory:  28*28*256=200K   params: 0
CONV3-512: [28x28x512]  memory:  28*28*512=400K   params: (3*3*256)*512 = 1,179,648
CONV3-512: [28x28x512]  memory:  28*28*512=400K   params: (3*3*512)*512 = 2,359,296
CONV3-512: [28x28x512]  memory:  28*28*512=400K   params: (3*3*512)*512 = 2,359,296
POOL2: [14x14x512]  memory:  14*14*512=100K   params: 0
CONV3-512: [14x14x512]  memory:  14*14*512=100K   params: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512]  memory:  14*14*512=100K   params: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512]  memory:  14*14*512=100K   params: (3*3*512)*512 = 2,359,296
POOL2: [7x7x512]  memory:  7*7*512=25K  params: 0
FC: [1x1x4096]  memory:  4096  params: 7*7*512*4096 = 102,760,448
FC: [1x1x4096]  memory:  4096  params: 4096*4096 = 16,777,216
FC: [1x1x1000]  memory:  1000 params: 4096*1000 = 4,096,000
```



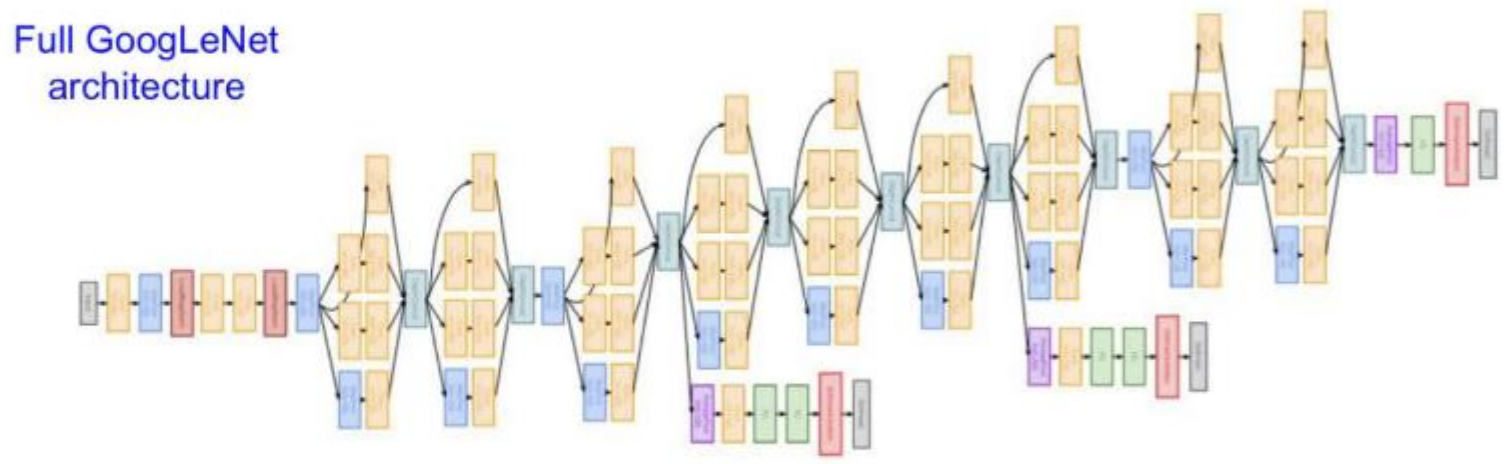
VGG16

Fully Connected Layer

Parameter 수 급격하게 증가

4. GoogleNet

GoogleNet Architecture

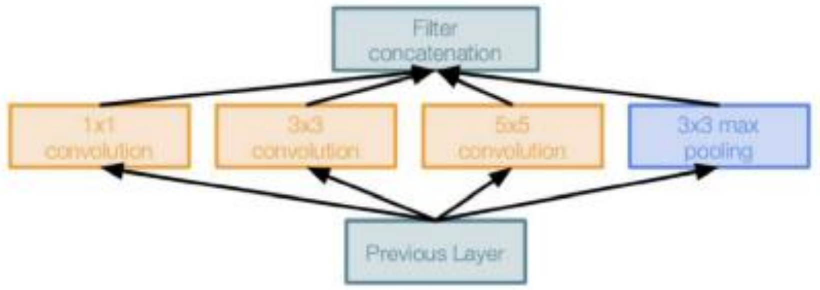


Contribution

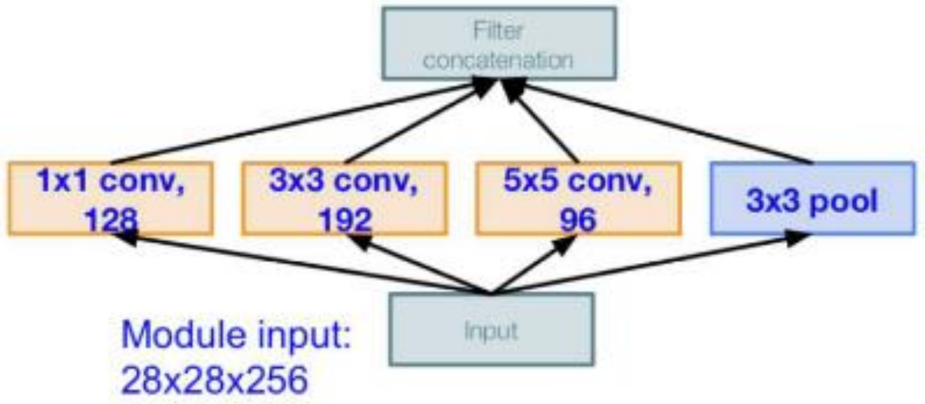
More Deeper than VGG19	22 Layer > 19Layer(VGG)
Use Inception Module	1x1 filter 사용
Fewer Paramter	Under 5M parameter

4. GoogleNet

Inception Module



Naive Inception module



1x1 filter 128개 = 28x28x128x1x1x256 = 25,690,112

3x3 filter 192개 = 28x28x192x3x3x256 = 346,816,512

5x5 filter 96개 = 28x28x96x5x5x256 = 481,689,600

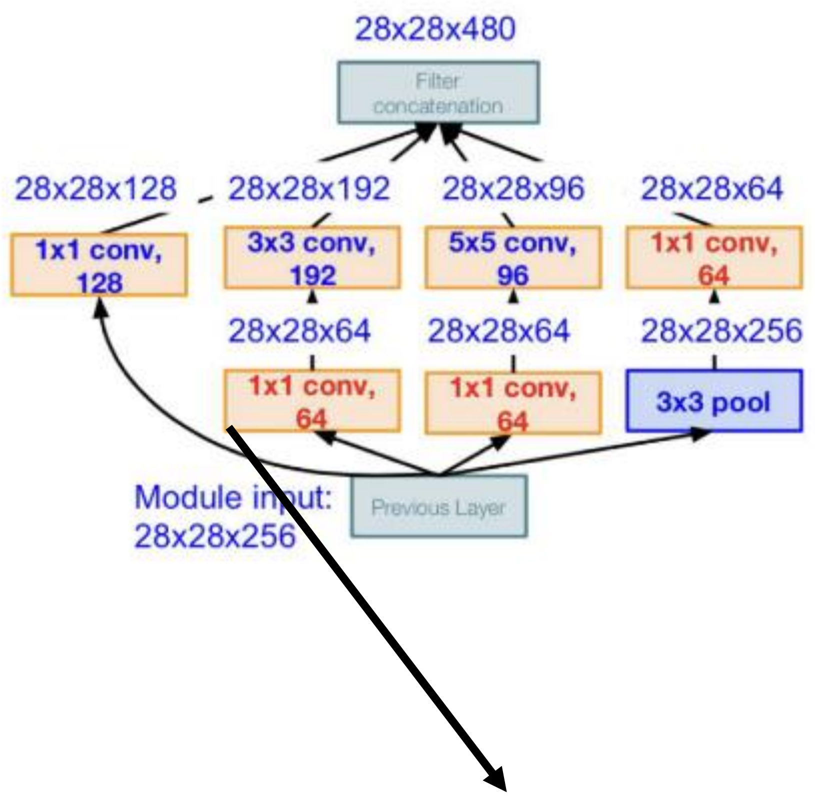
MaxPooling = 28x28x256 = 200,704

Total

854,396,939 paramter

4. GoogleNet

Efficient Inception Module



BottleNeck Layer

1x1 filter 128개 = 28x28x128x1x1x256 = 25,690,112

1x1 filter 64개 = 28x28x64x1x1x256 = 12,845,056

1x1 filter 64개 = 28x28x64x1x1x256 = 12,845,056

3x3 filter 192개 = 28x28x192x3x3x64 = 86,704,128

5x5 filter 96개 = 28x28x96x5x5x64 = 120,422,400

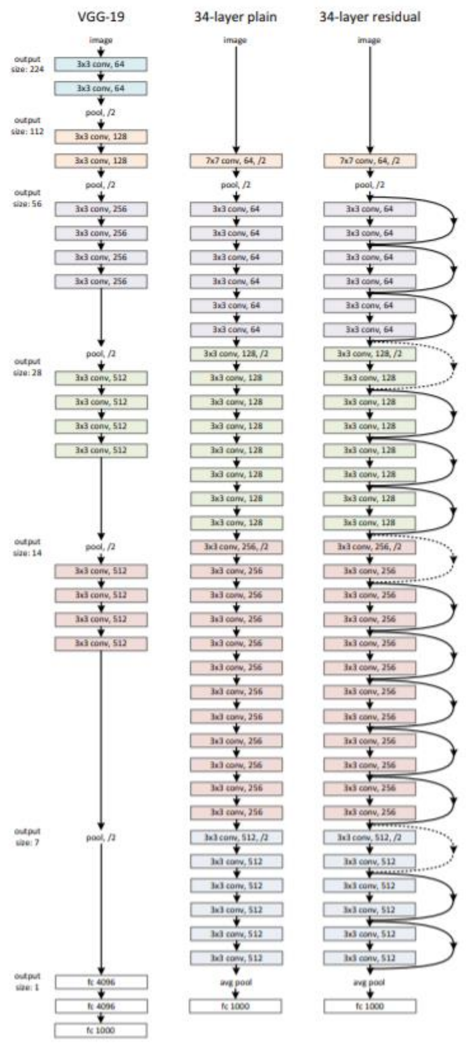
1x1 filter 64개 = 28x28x64x1x1x256 = 12,845,056

Total

계산기 다시 paramter

5. ResNet

Architecture



Contribution

More Deeper Layer → 152 Layer

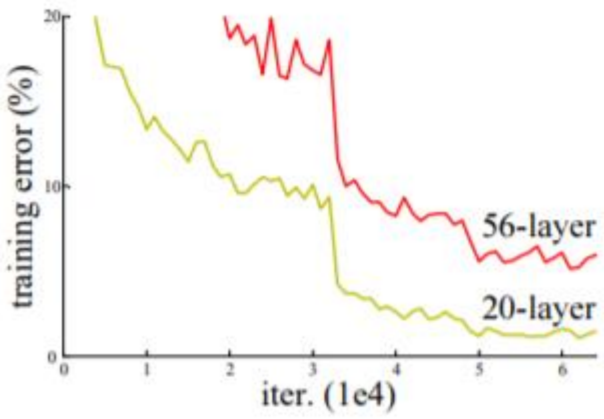
Skip Connection

Solution of Degradation Problem

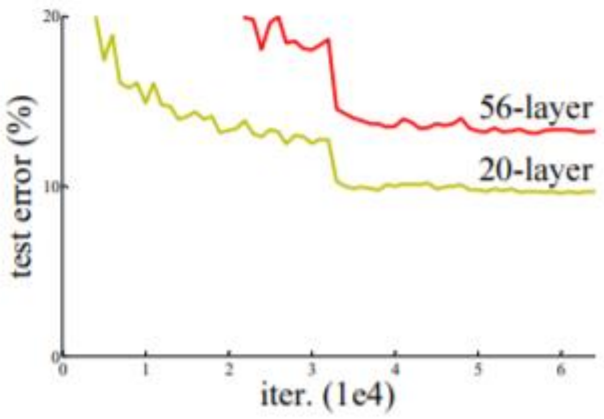
→ VGG Based

5. ResNet

Degradation



Train error rate



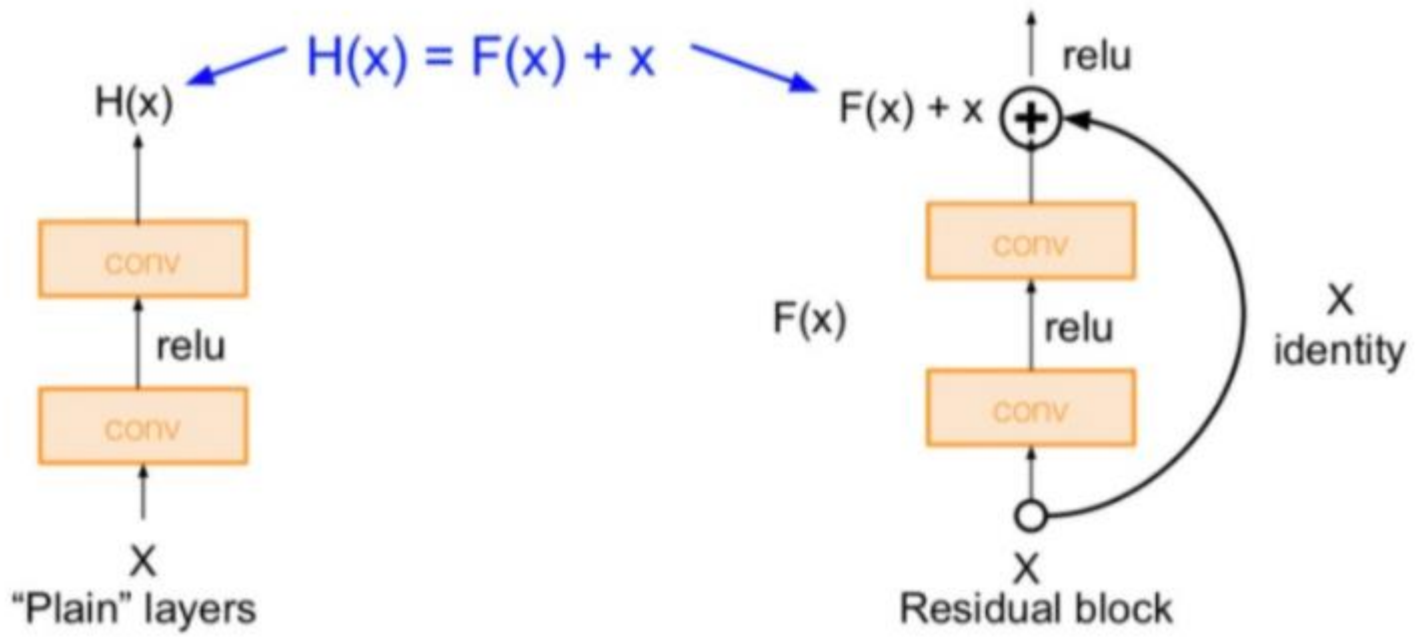
Test error rate

Overfitting	Train 성능 ⬆	Test 성능 ⬇
Degradation	Train 성능 ⬇	Test 성능 ⬇

What is Solution? → Residual Learning

5. ResNet

Skip Connection = ShortCut Connection 한 개 이상의 layer를 skip 하는 것



여러 비선형 Layer들이 복잡한 함수이고
Identity mapping이 최적이라면

H(x)를 mapping 시키는 것 보다
잔차인 F(x)=0으로 만드는 것이 더 쉽다

Plain Layers $H(x) = F(x) + x$

Residual Layers $F(x) = H(x) - x$

$H(x): Original\ mapping$

$F(x): Residual$

$x: Input$