

Deep Residual Learning for Image Recognition (CVPR 2016)

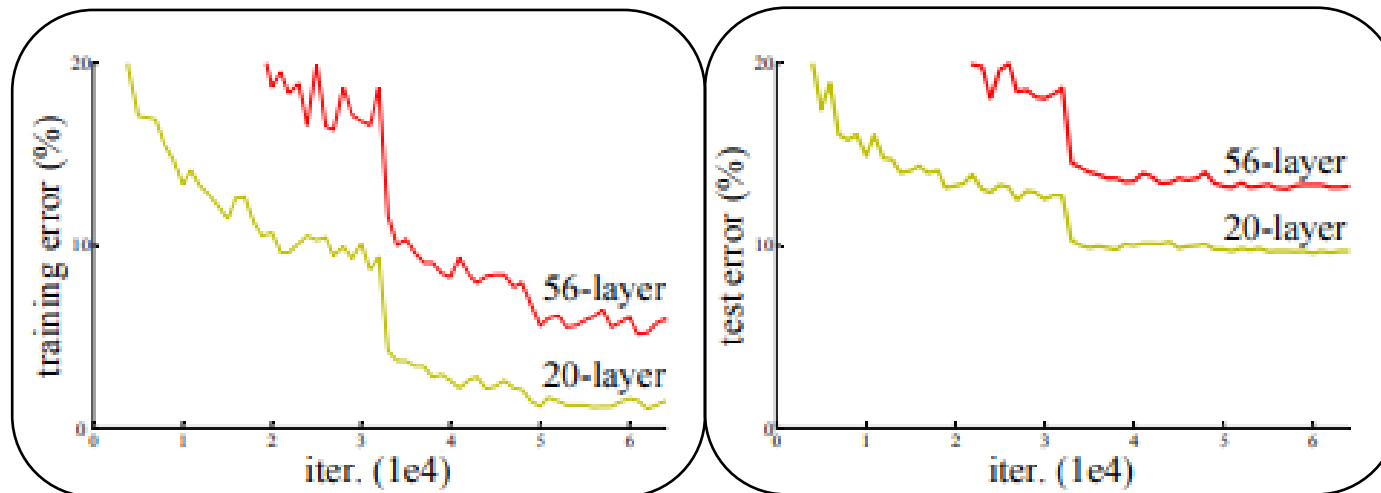
- 연구동기:

더 많은 layer를 쌓는 것(Network Depth)만큼 network 성능이 좋아지는가?

=> **Degradation problem** 발생 -> Overfitting? X, training error 증가

이러한 Degradation problem 발생을 해결하기 위해 **Residual** 학습을 제안.

<CIFAR-10 Training ,Test error>



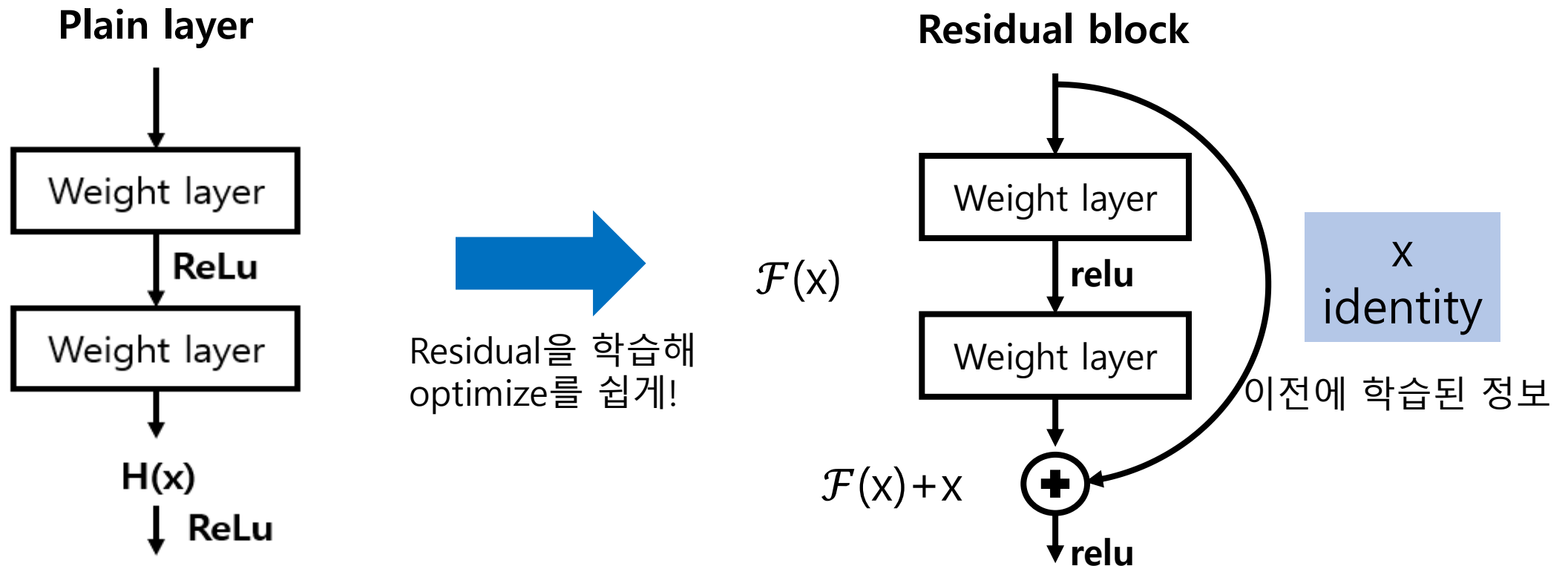
Degradation problem

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- **Method:**

Residual block이 기존의 mapping보다 optimize 하기 쉽다는 것을 가정

Residual method (gradient = 최소 1) + Shortcut connection (연산 간단화)



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- **Method:**

Residual block이 기존의 mapping보다 optimize 하기 쉽다는 것을 가정

문제: 기존의 mapping이 예측한 $H(x)$ 는 네트워크가 깊어질수록 **gradient vanishing** 현상 발생.

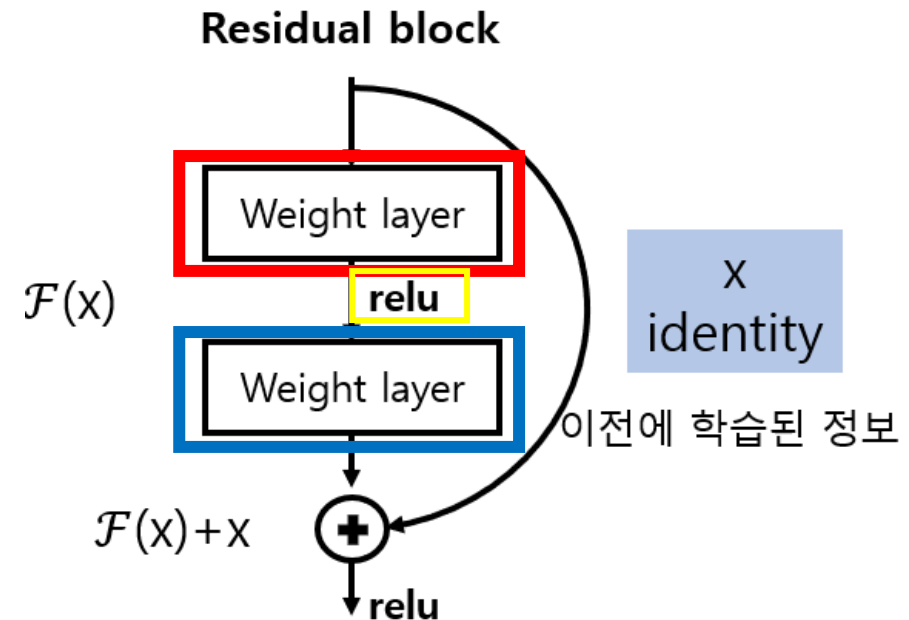
문제 해결: Residual block 은 $F(x)$ 가 0이 되도록 학습시키고 마지막에 x identity 를 더해 $H(x)$ 가 x 가 되도록 학습해 미분을 해도 x 자체는 미분값 1을 갖게 되어 최소 gradient=1

$$\begin{aligned} H(x) &= F(x) + id(x) \\ &= F(x) + x \end{aligned}$$

$$F = W_2 \sigma(W_1 x)$$

$$y = F(x, \{W_i\}) + \underline{W_s x}$$

Shortcut connection

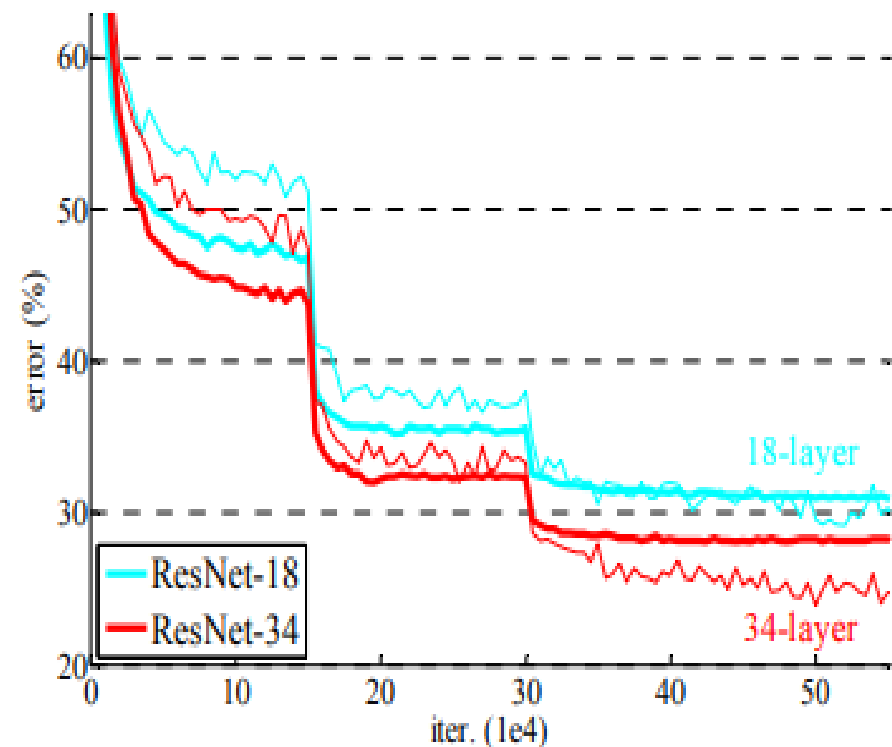
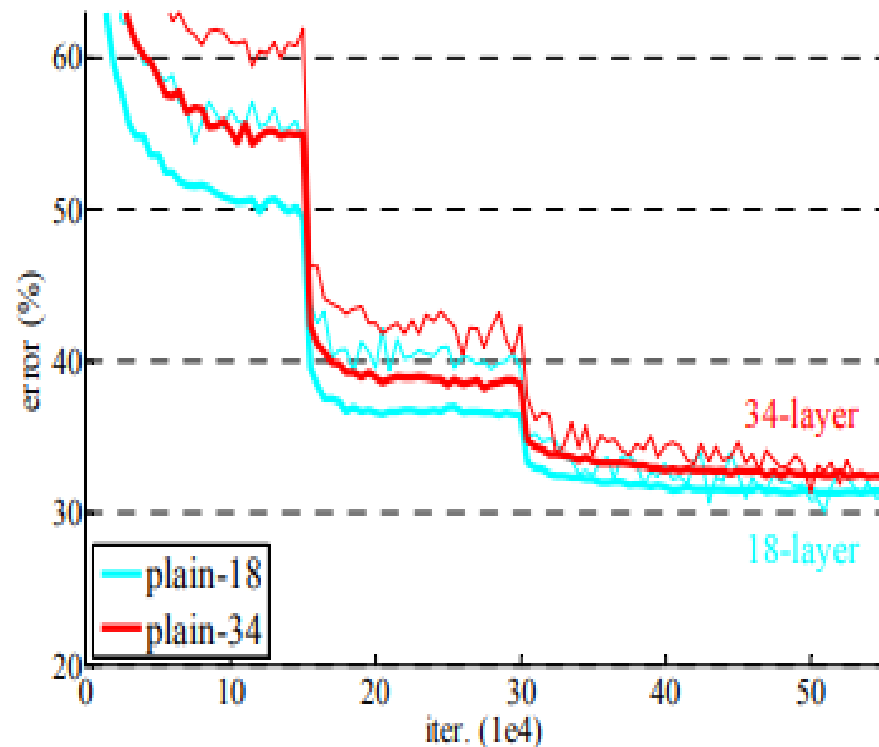


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Experiment:

Network depth가 깊어져도 성능의 향상 (Degradation을 적절히 조절)

Training Error in Plain Network and ResNet



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Experiment: 네트워크가 과도하게 깊어지면 성능이 감소하는 문제 발생.

Top-1 error on ImageNet Validation
: Plain layer vs ResNet

	plain	ResNet
18 layers	27.94	27.88
34 layers	28.54	25.03

Top-1, Top-5 error on ImageNet Validation
: single-model

method	top-1 err.	top-5 err.
VGG [40] (ILSVRC'14)	-	8.43 [†]
GoogLeNet [43] (ILSVRC'14)	-	7.89
VGG [40] (v5)	24.4	7.1
PReLU-net [12]	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

Top-5 error on ImageNet Test
: Ensembles

method	top-5 err. (test)
VGG [40] (ILSVRC'14)	7.32
GoogLeNet [43] (ILSVRC'14)	6.66
VGG [40] (v5)	6.8
PReLU-net [12]	4.94
BN-inception [16]	4.82
ResNet (ILSVRC'15)	3.57

error rate(%) on CIFAR-10
: Residual-110 vs Residual-1202

