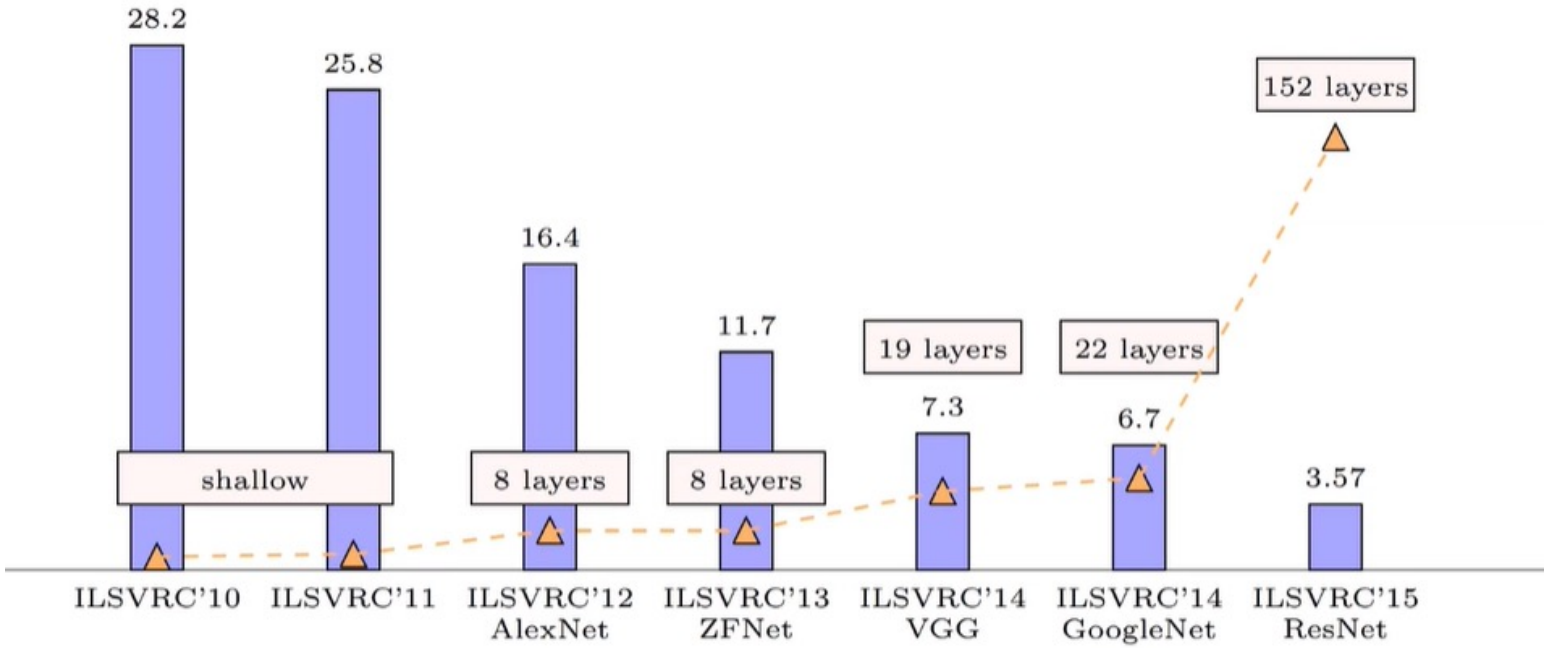
ResNet

에이아이스쿨(AISchool) 대표
양진호 (솔라리스)
http://aischool.ai
http://solarisailab.com

연도별 ILSVRC 대회 우승 모델들

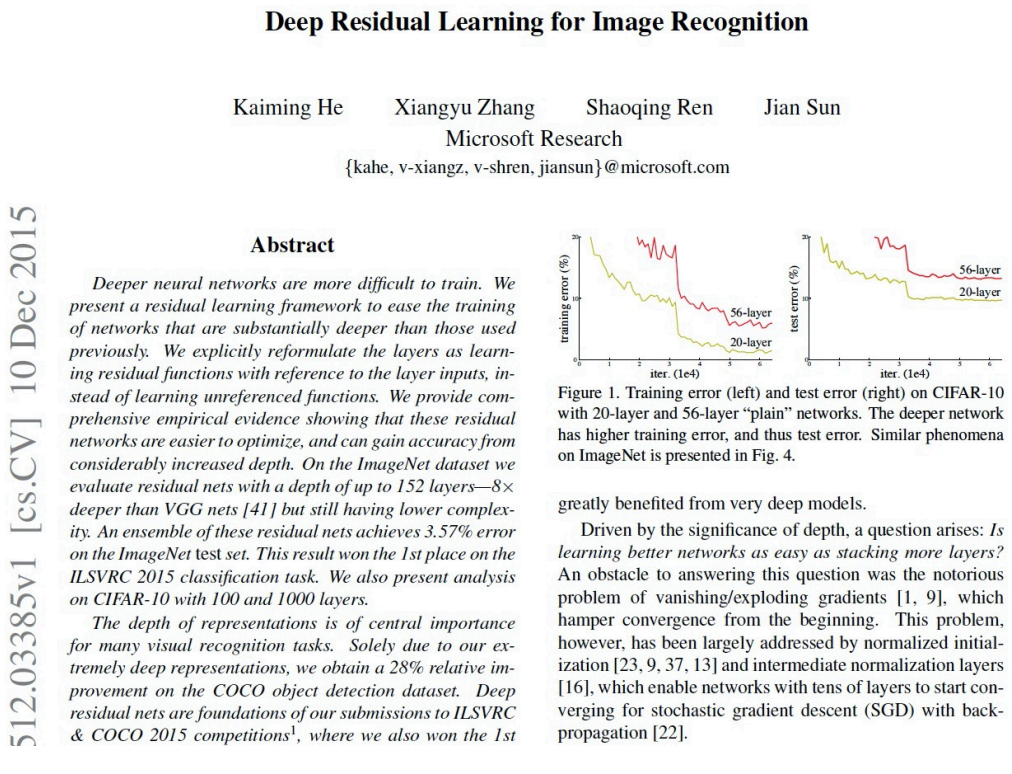
- ResNet은 Layer Depth를 기존 모델 대비 폭발적으로 늘리면서 큰 성능향상을 가져옴



Reference : https://medium.com/analytics-vidhya/7-cnn-architectures-evolved-from-2010-2015-fd5869bd744e

ResNet

- He, Kaiming, et al. "Deep residual learning for image recognition." Proceedings of the IEEE conference on computer vision and pattern recognition. 2016.
- https://arxiv.org/pdf/1512.03385.pdf
- **핵심 아이디어** : Degradation Problem을 해결하기 위한 residual block architecture를 제안하고 이의 정당성을 실험적으로 입증 함.



Deep Residual Learning for Image Recognition

Kaiming He Xiangyu Zhang Shaoqing Ren Jian Sun
Microsoft Research
{kahe, v-xiangz, v-shren, jiansun}@microsoft.com

Abstract

Deeper neural networks are more difficult to train. We present a residual learning framework to ease the training of networks that are substantially deeper than those used previously. We explicitly reformulate the layers as learning residual functions with reference to the layer inputs, instead of learning unreferenced functions. We provide comprehensive empirical evidence showing that these residual networks are easier to optimize, and can gain accuracy from considerably increased depth. On the ImageNet dataset we evaluate residual nets with a depth of up to 152 layers—8× deeper than VGG nets [41] but still having lower complexity. An ensemble of these residual nets achieves 3.57% error on the ImageNet test set. This result won the 1st place on the ILSVRC 2015 classification task. We also present analysis on CIFAR-10 with 100 and 1000 layers.

The depth of representations is of central importance for many visual recognition tasks. Solely due to our extremely deep representations, we obtain a 28% relative improvement on the COCO object detection dataset. Deep residual nets are foundations of our submissions to ILSVRC & COCO 2015 competitions[1], where we also won the 1st

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.

greatly benefited from very deep models.

Driven by the significance of depth, a question arises: *Is learning better networks as easy as stacking more layers?* An obstacle to answering this question was the notorious problem of vanishing/exploding gradients [1, 9], which hamper convergence from the beginning. This problem, however, has been largely addressed by normalized initialization [23, 9, 37, 13] and intermediate normalization layers [16], which enable networks with tens of layers to start converging for stochastic gradient descent (SGD) with backpropagation [22].

Degradation Problem

- 레이어가 깊어질수록 성능이 떨어지는 현상이 관찰된다. -> 하지만 이는 training error에서도 발생하는 현상이므로 overfitting 문제가 아니다.
- 저자들의 가설(hypothesis) : 더 깊은 레이어는 학습하기가 힘들다. 따라서 이는 optimization이 제대로 되지 않아서 발생하는 문제이다. (Degradation Problem)

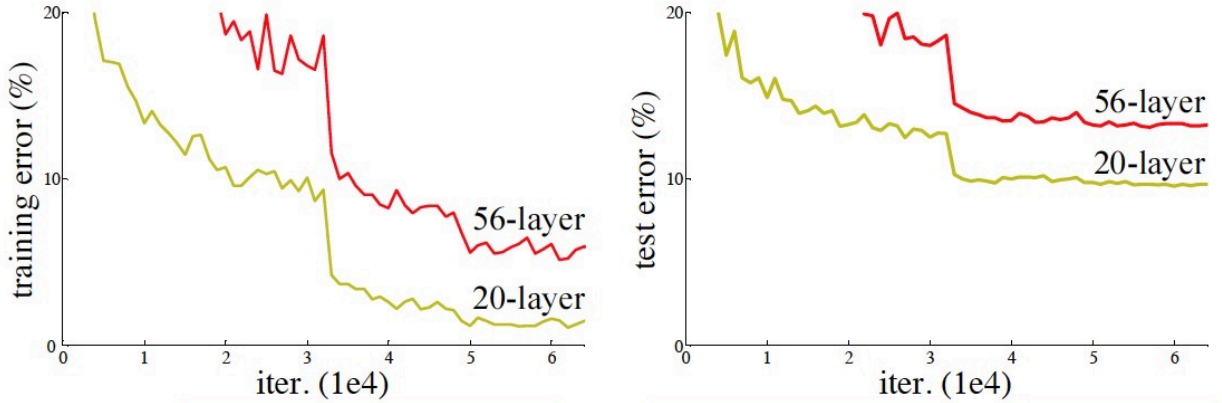


Figure 1. Training error (left) and test error (right) on CIFAR-10 with 20-layer and 56-layer "plain" networks. The deeper network has higher training error, and thus test error. Similar phenomena on ImageNet is presented in Fig. 4.

ResNet의 아이디어

- we explicitly let these layers fit a residual mapping.
- Formally, denoting the desired underlying mapping as H(x), we let the stacked nonlinear layers fit another mapping of F(x) := H(x)-x. The original mapping is recast into F(x)+x.
- We hypothesize that it is easier to optimize the residual mapping than to optimize the original, unreferenced mapping.

$$\mathbf{y} = \mathcal{F}(\mathbf{x}, \{W_i\}) + \mathbf{x}. \qquad (1)$$

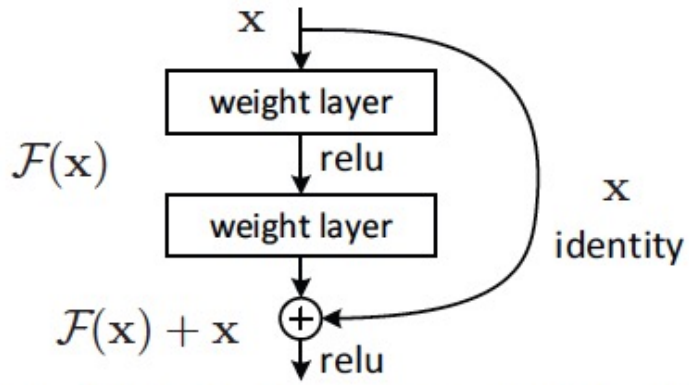
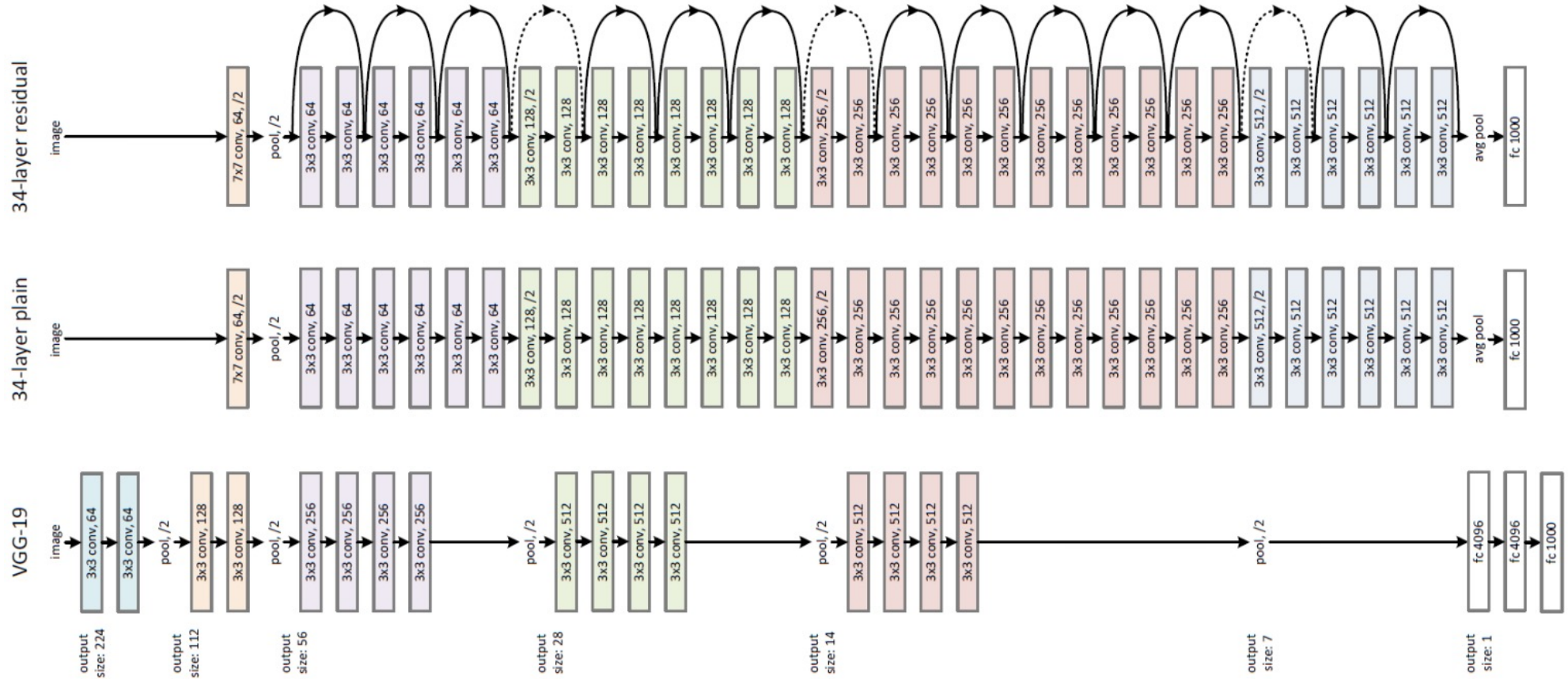


Figure 2. Residual learning: a building block.

ResNet의 아이디어

- 만약 VGG-19가 Optimal 구조라면 Shortcut 구간은 전부 Identity Mapping 형태로 진행될 것이다.



Reference : https://towardsdatascience.com/review-resnet-winner-of-ilsvrc-2015-image-classification-localization-detection-e39402bfa5d8

ResNet의 아이디어

- 차원이 변경되는 구간이라면 아래와 같이 2가지 옵션을 취할 수 있습니다.
- (A) 늘어난 차원만큼 Zero-Padding을 적용한다.
- (B) W_s 곱셈을 통해 차원 변경을 수행한 이후에 덧셈을 수행한다.

$$\mathbf{y} = \mathcal{F}(\mathbf{x}, \{W_i\}) + W_s\mathbf{x}. \qquad (2)$$

ImageNet Experiment Result

- ImageNet 실험 결과 ResNet Block이 의도한 대로 동작하는 바를 검증할 수 있었다.

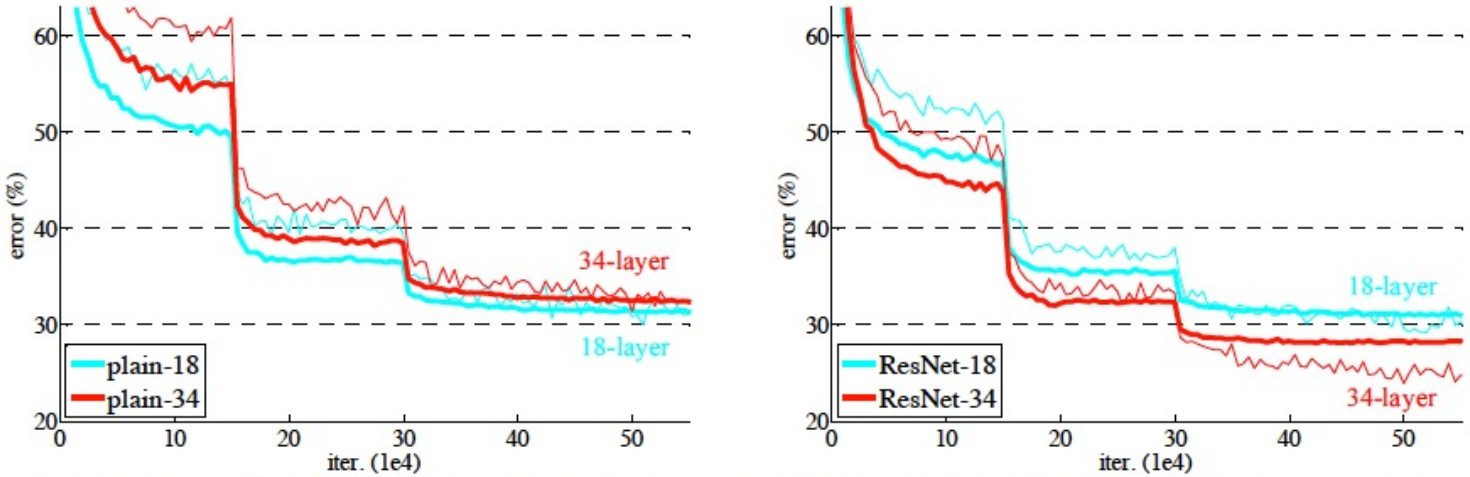


Figure 4. Training on **ImageNet**. Thin curves denote training error, and bold curves denote validation error of the center crops. Left: plain networks of 18 and 34 layers. Right: ResNets of 18 and 34 layers. In this plot, the residual networks have no extra parameter compared to their plain counterparts.

	plain	ResNet
18 layers	27.94	27.88
34 layers	28.54	**25.03**

Table 2. Top-1 error (%, 10-crop testing) on ImageNet validation. Here the ResNets have no extra parameter compared to their plain counterparts. Fig. 4 shows the training procedures.

Identity vs Projection Shortcuts.

- In Table 3 we compare three options:
- (A) zero-padding shortcuts are used for increasing dimensions, and all shortcuts are parameter-free (the same as Table 2 and Fig. 4 right);
- (B) projection shortcuts are used for increasing dimensions, and other shortcuts are identity; and
- (C) all shortcuts are projections.
- But the small differences among A/B/C indicate that projection shortcuts are not essential for addressing the degradation problem.
- So we do not use option C in the rest of this paper, to reduce memory/time complexity and model sizes.

model	top-1 err.	top-5 err.
VGG-16 [41]	28.07	9.33
GoogLeNet [44]	-	9.15
PReLU-net [13]	24.27	7.38
plain-34	28.54	10.02
ResNet-34 A	25.03	7.76
ResNet-34 B	24.52	7.46
ResNet-34 C	24.19	7.40
ResNet-50	22.85	6.71
ResNet-101	21.75	6.05
ResNet-152	**21.43**	**5.71**

Table 3. Error rates (%, **10-crop** testing) on ImageNet validation. VGG-16 is based on our test. ResNet-50/101/152 are of option B that only uses projections for increasing dimensions.

Deeper Bottleneck Architectures.

- 1x1 Convolution을 이용해서 연산량을 줄인 디자인

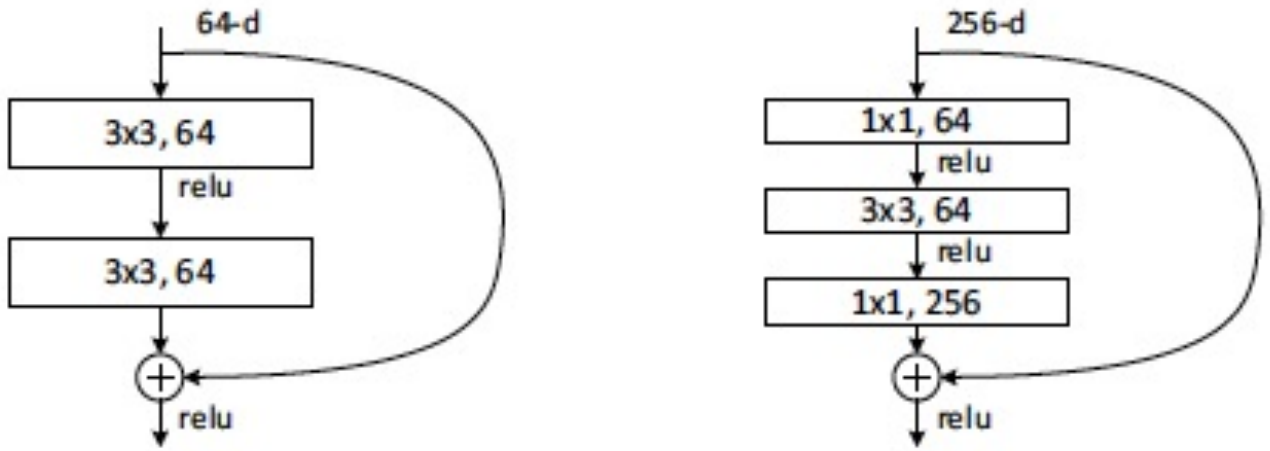


Figure 5. A deeper residual function $\mathcal{F}$ for ImageNet. Left: a building block (on 56×56 feature maps) as in Fig. 3 for ResNet-34. Right: a "bottleneck" building block for ResNet-50/101/152.

다양한 ResNet 구성 형태

- 다양한 Depth로 아래와 같이 ResNet을 구성할 수 있다.

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
		3×3 max pool, stride 2				
conv2_x	56×56	[3×3, 64; 3×3, 64] ×2	[3×3, 64; 3×3, 64] ×3	[1×1, 64; 3×3, 64; 1×1, 256] ×3	[1×1, 64; 3×3, 64; 1×1, 256] ×3	[1×1, 64; 3×3, 64; 1×1, 256] ×3
conv3_x	28×28	[3×3, 128; 3×3, 128] ×2	[3×3, 128; 3×3, 128] ×4	[1×1, 128; 3×3, 128; 1×1, 512] ×4	[1×1, 128; 3×3, 128; 1×1, 512] ×4	[1×1, 128; 3×3, 128; 1×1, 512] ×8
conv4_x	14×14	[3×3, 256; 3×3, 256] ×2	[3×3, 256; 3×3, 256] ×6	[1×1, 256; 3×3, 256; 1×1, 1024] ×6	[1×1, 256; 3×3, 256; 1×1, 1024] ×23	[1×1, 256; 3×3, 256; 1×1, 1024] ×36
conv5_x	7×7	[3×3, 512; 3×3, 512] ×2	[3×3, 512; 3×3, 512] ×3	[1×1, 512; 3×3, 512; 1×1, 2048] ×3	[1×1, 512; 3×3, 512; 1×1, 2048] ×3	[1×1, 512; 3×3, 512; 1×1, 2048] ×3
	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

Table 1. Architectures for ImageNet. Building blocks are shown in brackets (see also Fig. 5), with the numbers of blocks stacked. Down-sampling is performed by conv3_1, conv4_1, and conv5_1 with a stride of 2.

다른 방법과의 비교

- 다음과 같이 ResNet이 더높은 정확도를 보여줌을 알 수 있다.

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.

CIFAR-10 Experiment Result

- ImageNet 실험 결과 ResNet Block이 의도한 대로 동작하는 바를 검증할 수 있었다.
- But there are still open problems on such aggressively deep models. The testing result of this 1202-layer network is worse than that of our 110-layer network, although both have similar training error. We argue that this is because of overfitting.

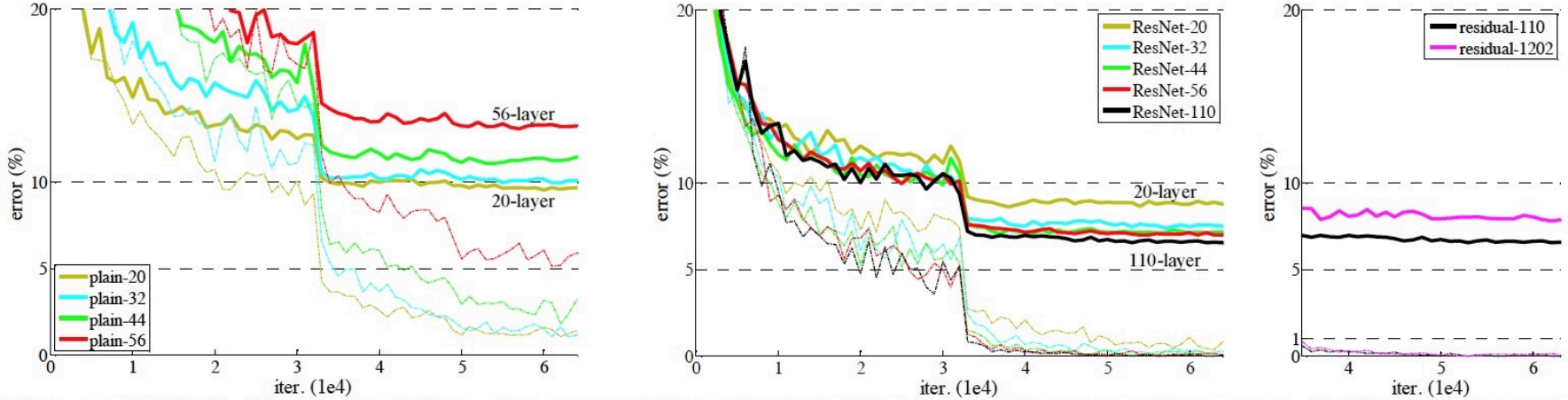


Figure 6. Training on **CIFAR-10**. Dashed lines denote training error, and bold lines denote testing error. **Left**: plain networks. The error of plain-110 is higher than 60% and not displayed. **Middle**: ResNets. **Right**: ResNets with 110 and 1202 layers.

Object Detection 문제에 대한 ResNet 응용

- Faster R-CNN의 Backbone을 VGG-16에서 ResNet으로 바꿨을 경우에 대한 성능비교 분석

training data	07+12	07++12
test data	VOC 07 test	VOC 12 test
VGG-16	73.2	70.4
ResNet-101	**76.4**	**73.8**

Table 7. Object detection mAP (%) on the PASCAL VOC 2007/2012 test sets using **baseline** Faster R-CNN. See also Table 10 and 11 for better results.

metric	mAP@.5	mAP@[.5, .95]
VGG-16	41.5	21.2
ResNet-101	**48.4**	**27.2**

Table 8. Object detection mAP (%) on the COCO validation set using **baseline** Faster R-CNN. See also Table 9 for better results.

RestNet의 의의

- Identity Mapping을 추가한 Shortcut을 추가함으로써 Layer Depth를 획기적으로 늘리는 창의적인 아이디어를 제안함
- 이후 100-depth 이상의 깊은 CNN 모델 시대를 여는 시초가 됨

Thank you!