Paper Review

Deep Residual Learning for Image Recognition (2016 CVPR)

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Contents

Abstract

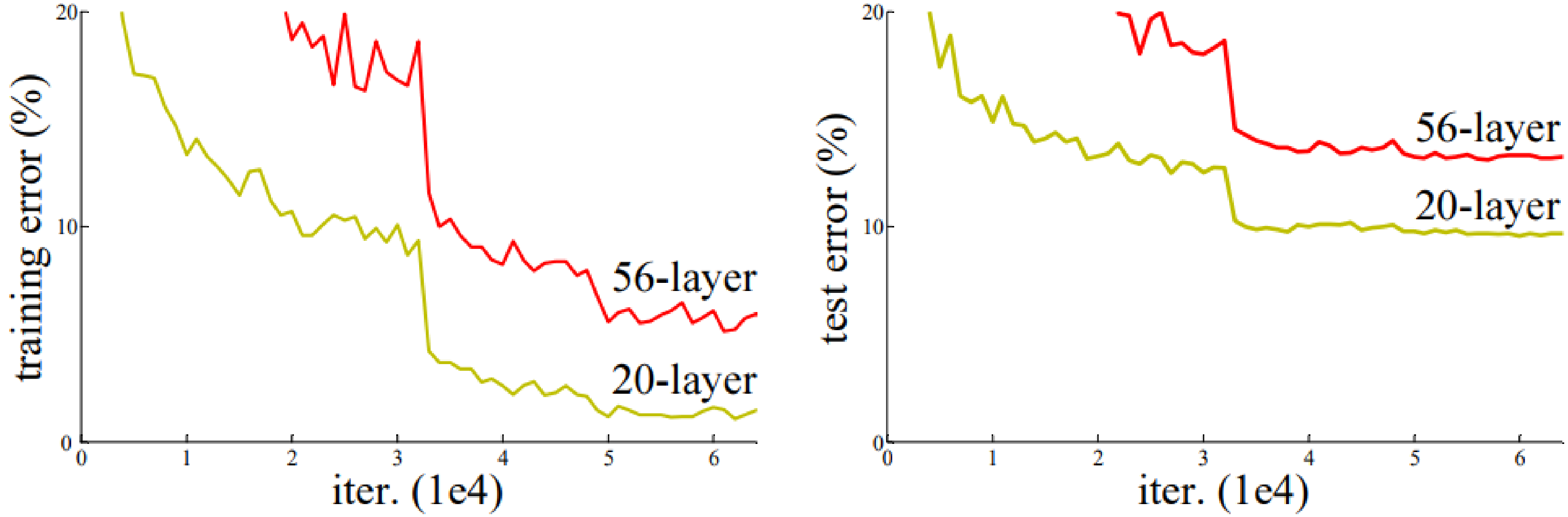

Figure 1. Training error (left) and test error (right) on CIFAR-10 with 20-layer and 56-layer "plain" networks. The deeper network has higher training error, and thus test error. Similar phenomena on ImageNet is presented in Fig. 4.

ResNet @ ILSVRC & COCO 2015 Competitions

1st places in all five main tracks

- ImageNet Classification : “Ultra-deep” 152-layer nets
- ImageNet Detection : 16% better than 2nd
- ImageNet Localization : 27% better than 2nd
- COCO Detection : 11% better than 2nd
- COCO Segmentation : 12% better than 2nd

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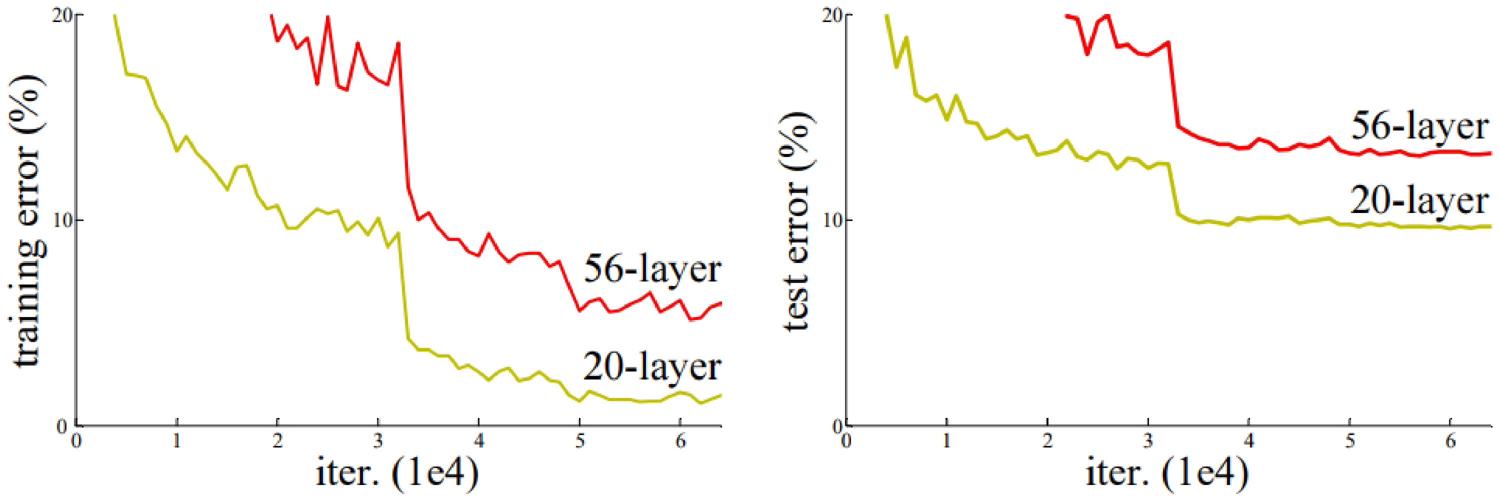

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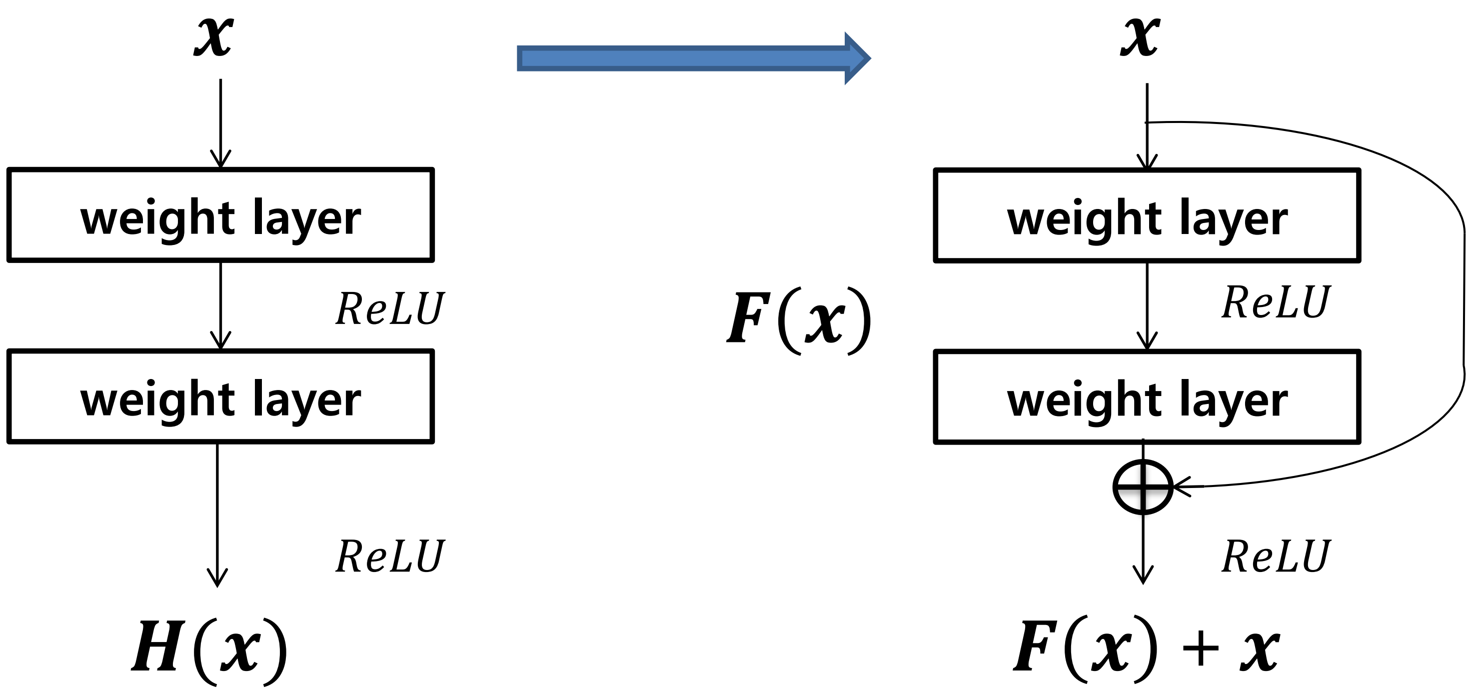
Introduction

$$F(x) := H(x) - x$$



Plain Net **Residual block**

Related Work

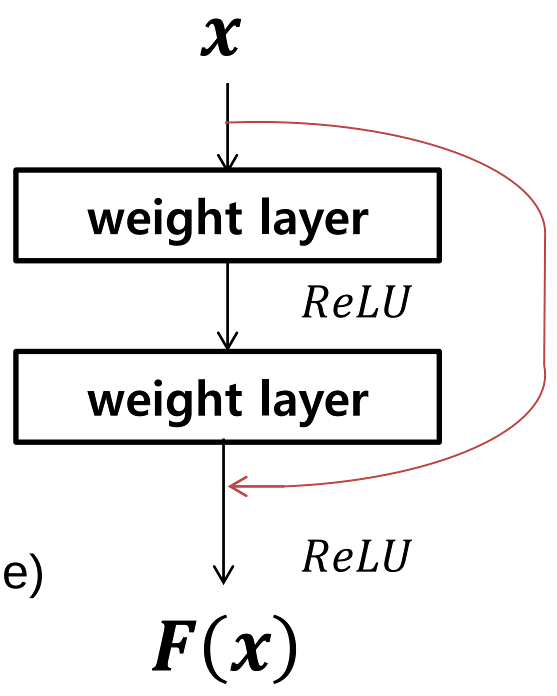
Shortcut Connection (Skip Connection)

GoogleNet vs ResNet

- Low parameter
- Not required Auxillary Classifier separately.

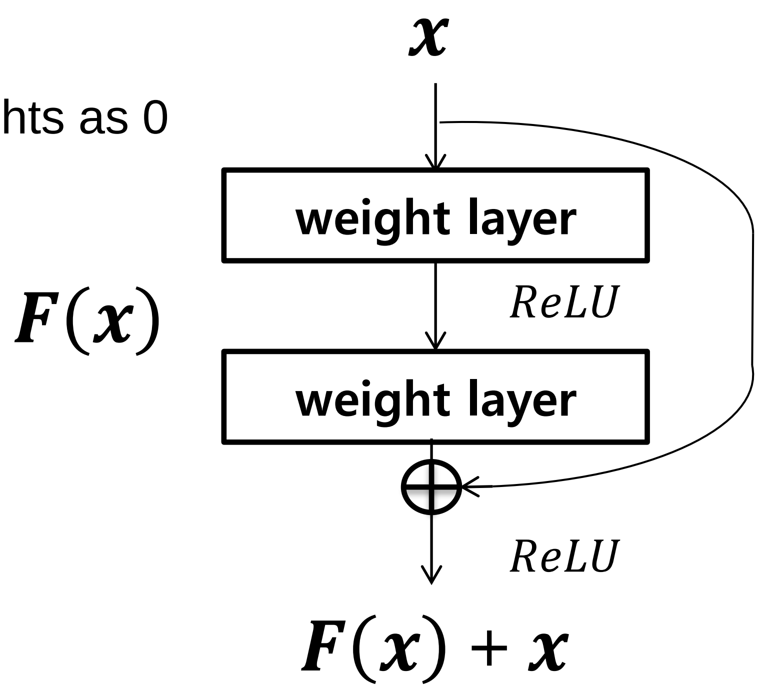
Highway Networks vs ResNet

- Low parameter (identity shortcut – parameter free)
- Not demonstrated accuracy gains with extremely increased depth (highway)



Residual Learning

- If identity were optimal, easy to set weights as 0
- If optimal mapping is closer to identify, easier to find small functions



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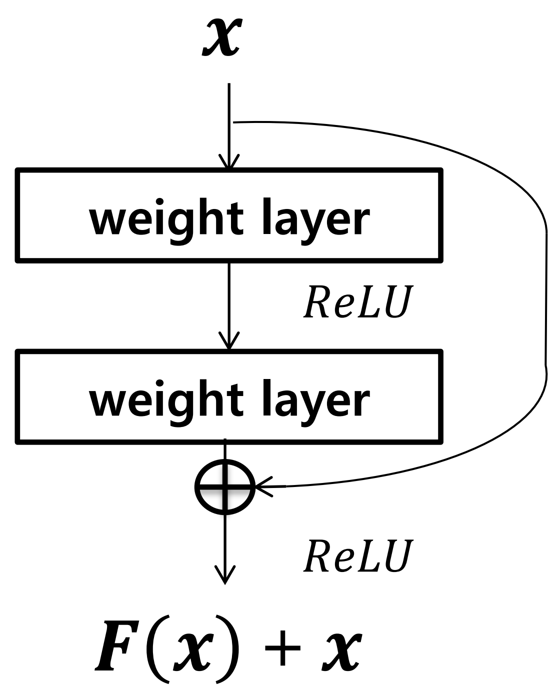

$$y = F(x, W_i) + W_s x$$

Residual block

Residual Learning

- If identity were optimal, easy to set weights as 0
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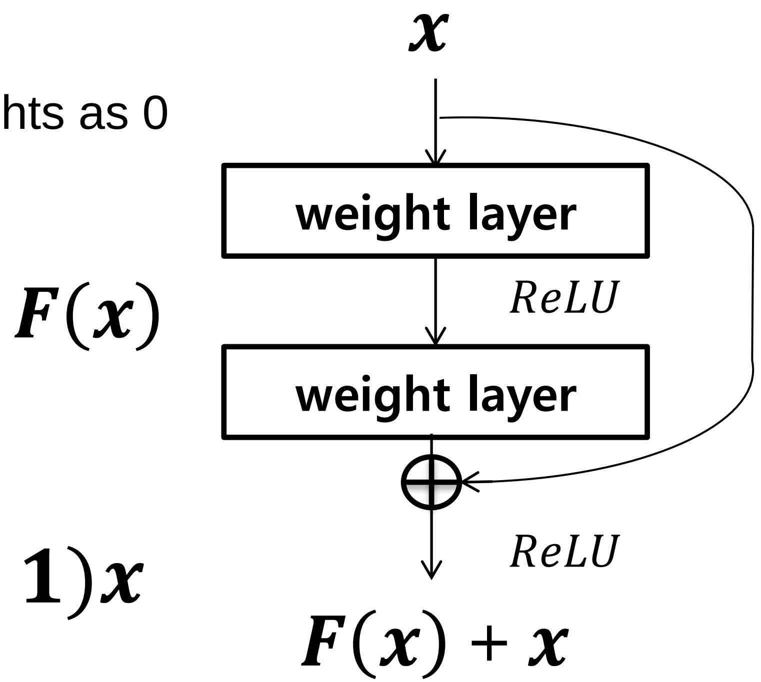
$$\boldsymbol{y} = \boldsymbol{W_1 x} + \boldsymbol{x} = (\boldsymbol{W_1} + \boldsymbol{1})\boldsymbol{x}$$



Residual block

Deep Residual Learning

Network Architectures

- **Keep it simple**
- **Basic design (VGG-style)**
  - All 3×3 conv (almost)
  - Spatial size / 2 => # filters × 2
  - Simple design; just deep!

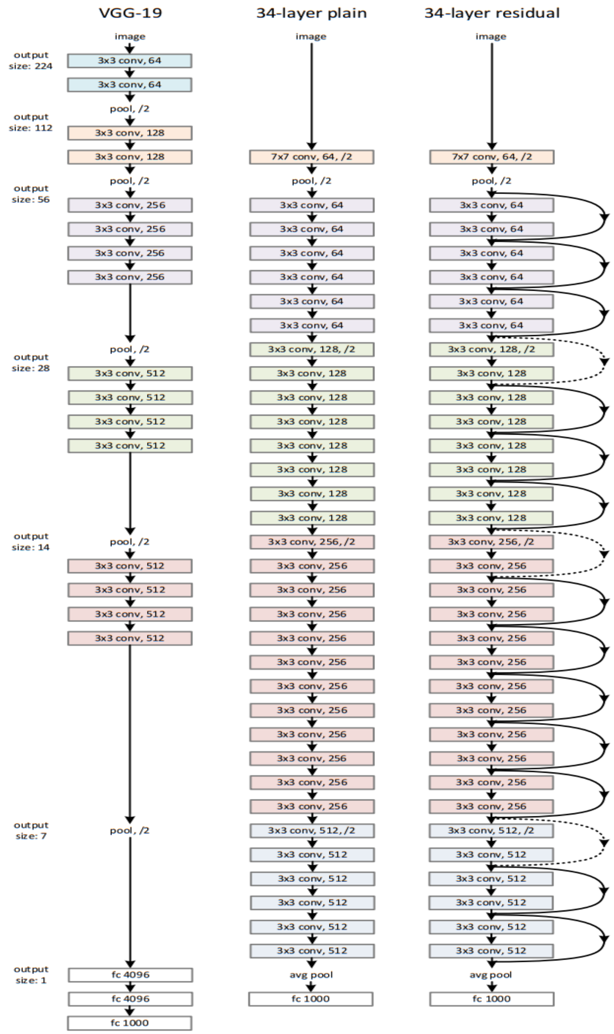
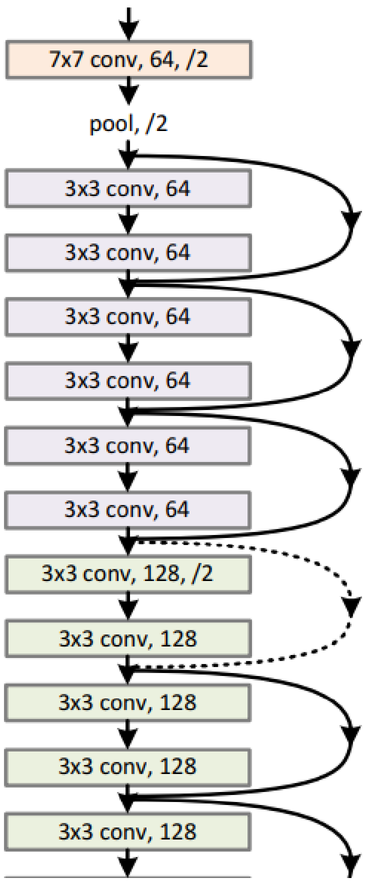


Figure 3. Example network architectures for ImageNet. **Left**: the VGG-19 model [41] (19.6 billion FLOPs) as a reference. **Middle**: a plain network with 34 parameter layers (3.6 billion FLOPs). **Right**: a residual network with 34 parameter layers (3.6 billion FLOPs). The dotted shortcuts increase dimensions. **Table 1** shows more details and other variants.

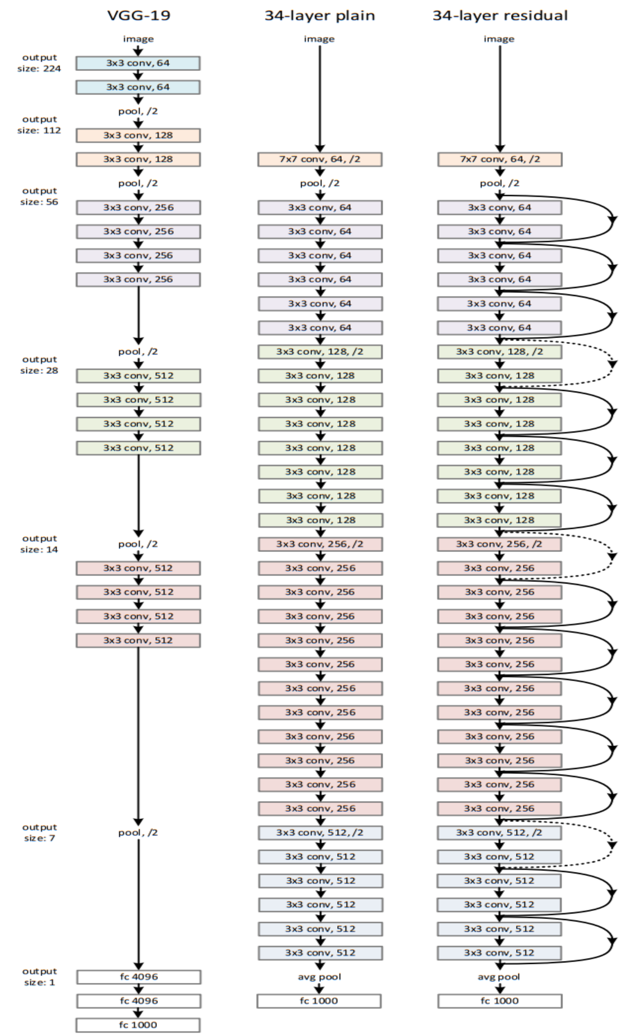
Deep Residual Learning

Network Architectures



Just added

Additional techniques
- **Zero padding → identity mapping**
- **Projection Shortcut**



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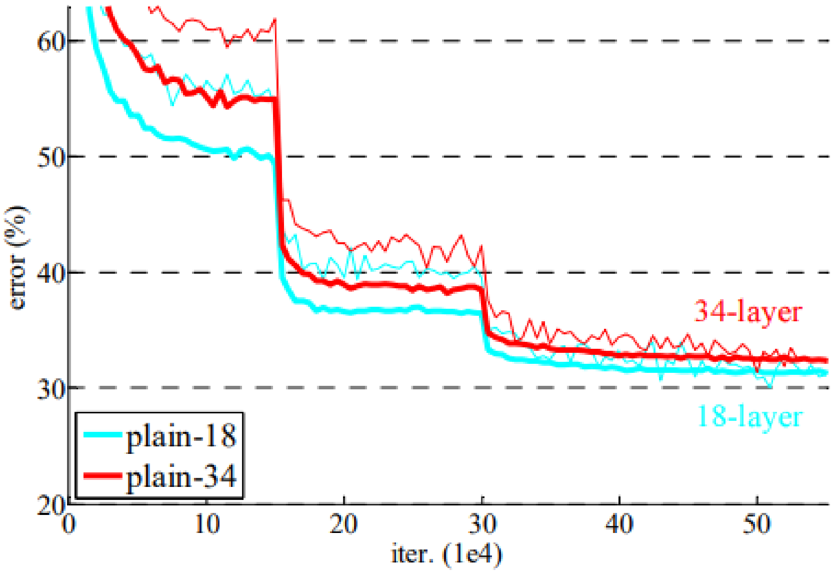
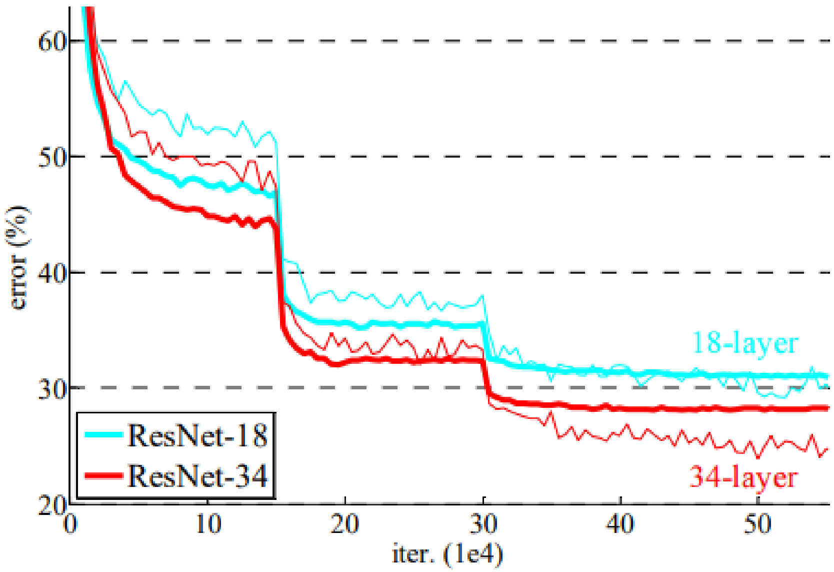
Experiments

ImageNet experiments



Plain networks of 18 and 34 layers.



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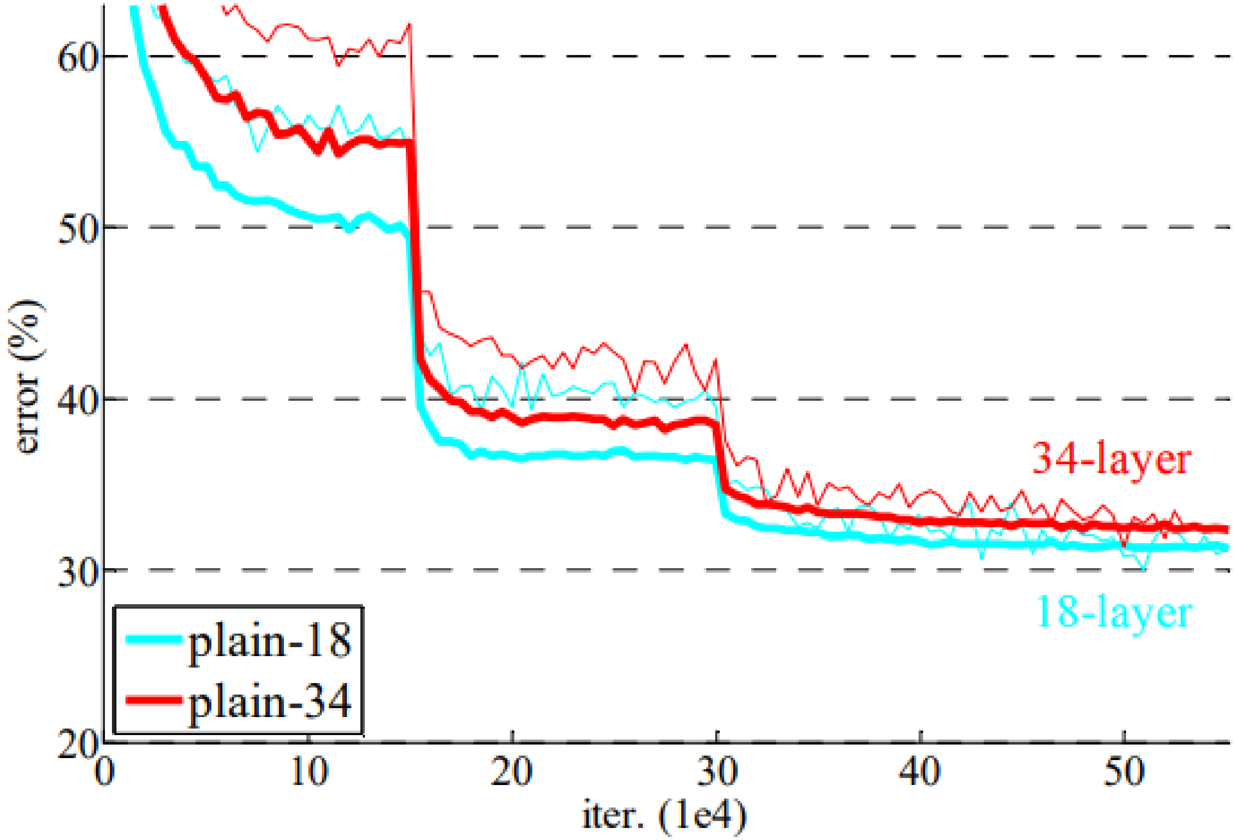

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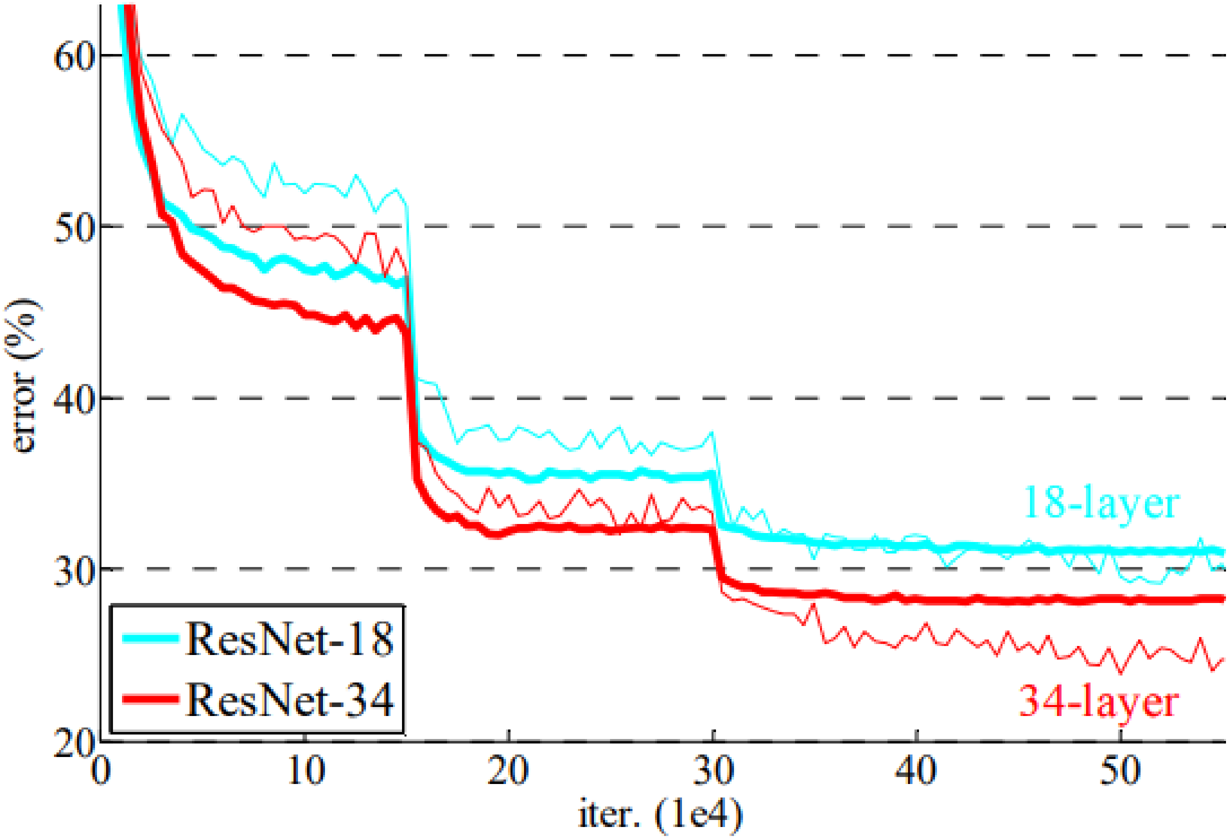
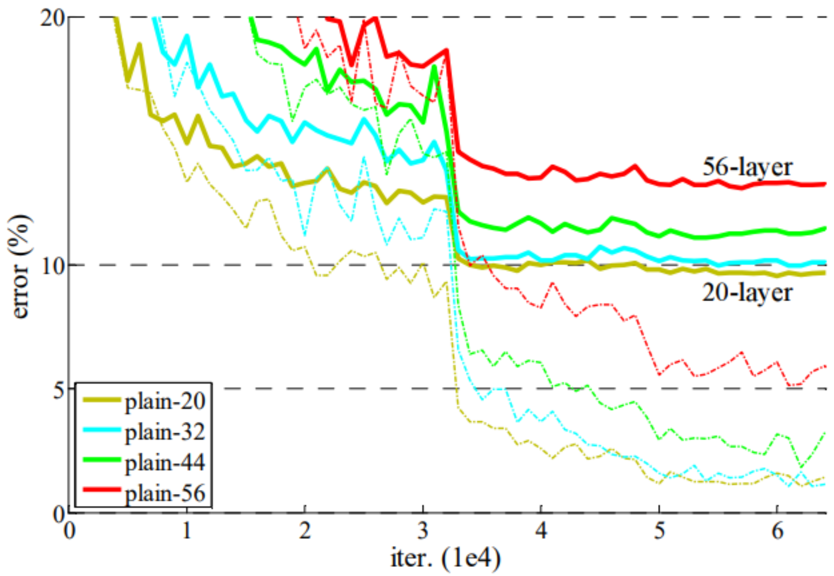
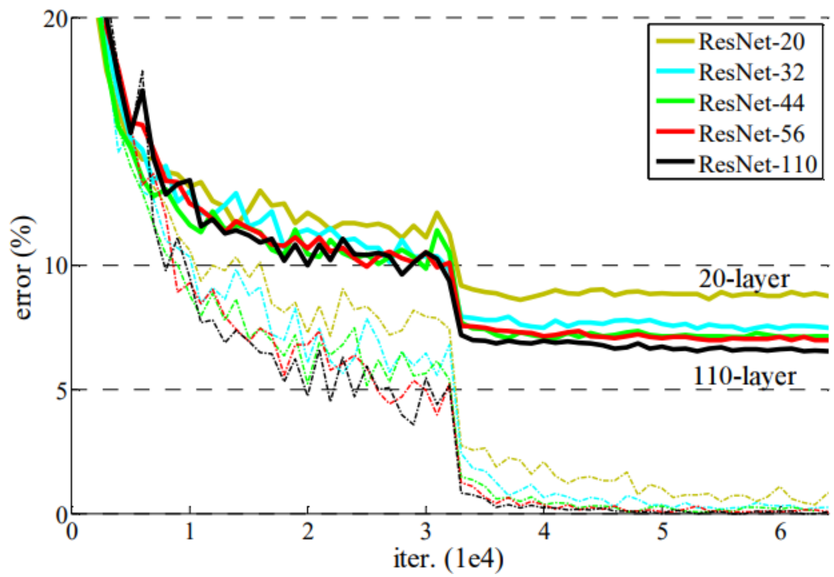


ResNets of 18 and 34 layers.

Experiments

CIFAR-10 experiments





- Deep ResNets can be trained without difficulties
- Deeper ResNets have lower training error, and also lower test error

Experiments

Does the performance continue to increase if you continue to increase the layers of the model?

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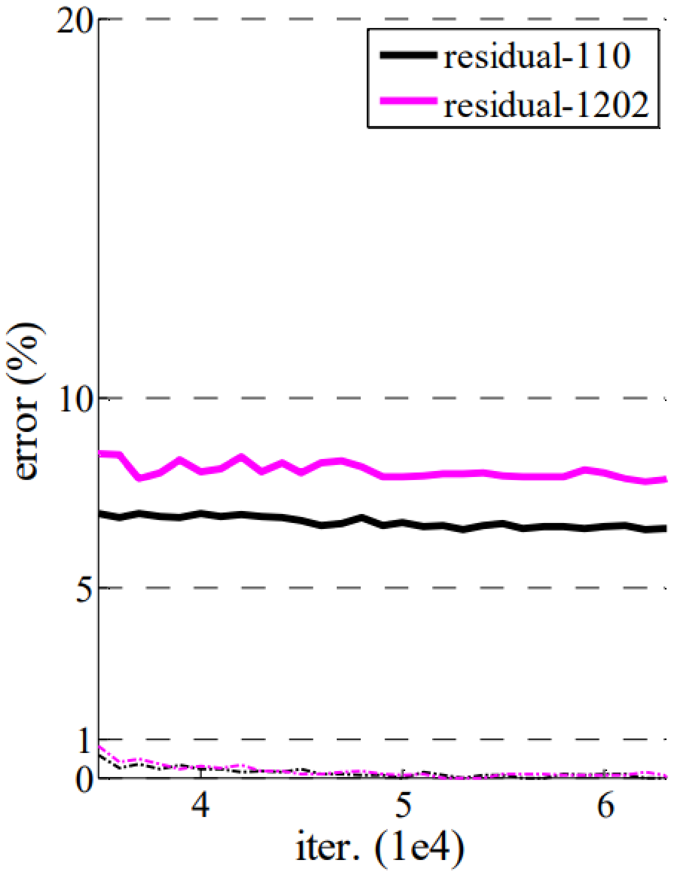

No → Because of **overfitting.**

But it could be studied by adding regularization**.**

Conclusions

- **Deep Residual Networks:**
  - **Easy to train**
  - **Simply gain accuracy from depth**
  - **Well transferable**