Deep Residual Learning

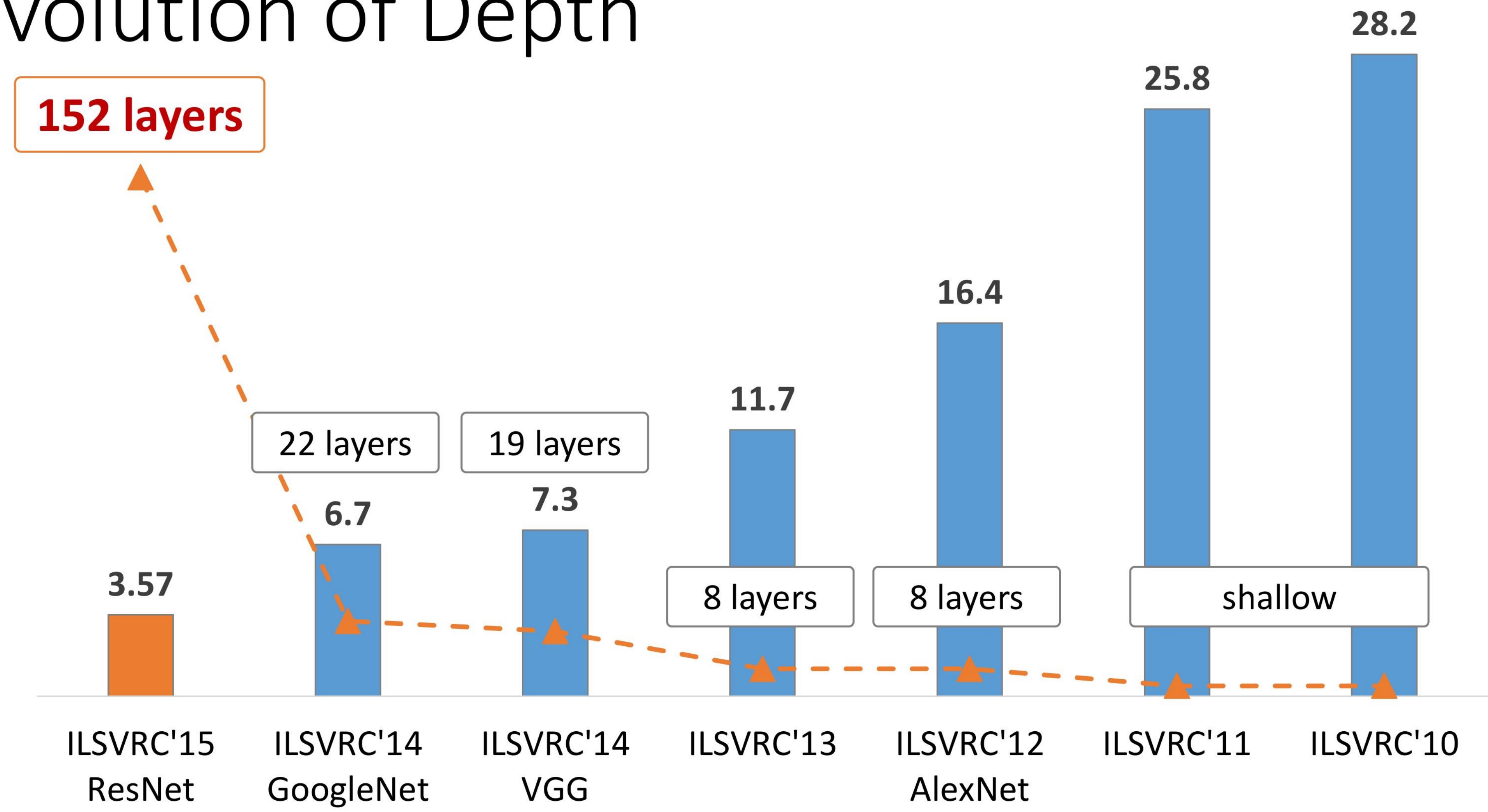
MSRA @ ILSVRC & COCO 2015 competitions

Kaiming He

with Xiangyu Zhang, Shaoqing Ren, Jifeng Dai, & Jian Sun

Microsoft Research Asia (MSRA)

Revolution of Depth

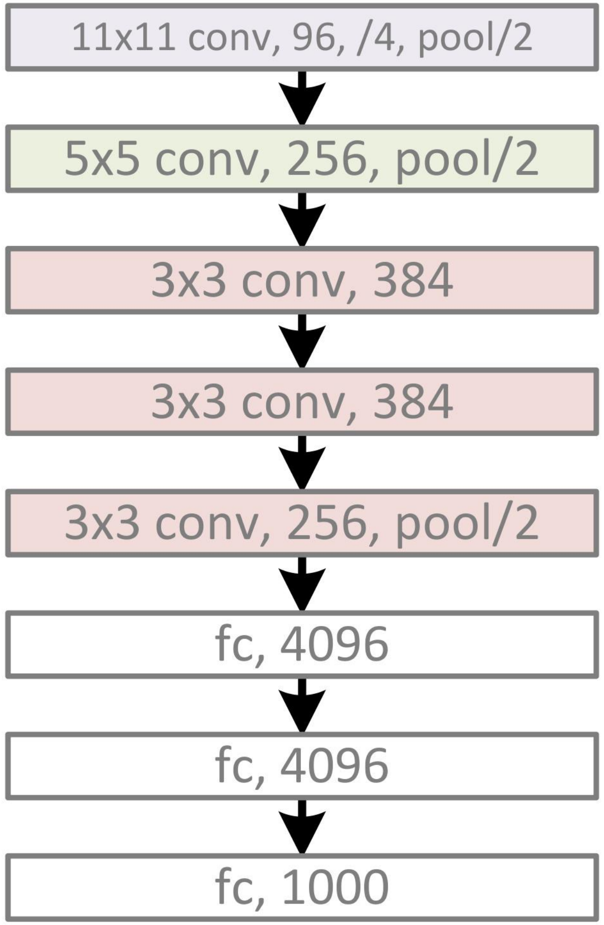


ImageNet Classification top-5 error (%)

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. arXiv 2015.

Revolution of Depth

AlexNet, 8 layers
(ILSVRC 2012)



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Revolution of Depth

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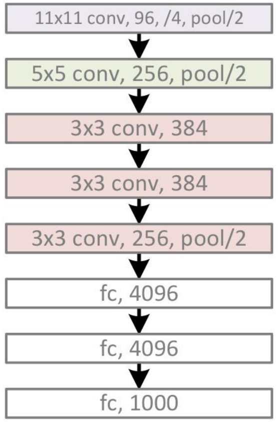
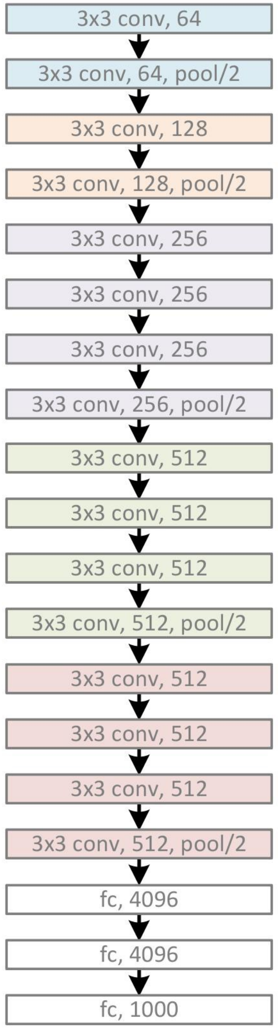
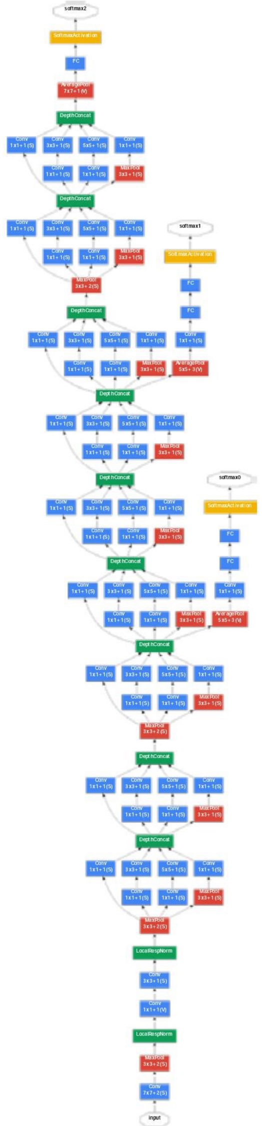


VGG, 19 layers
(ILSVRC 2014)



GoogleNet, 22 layers
(ILSVRC 2014)



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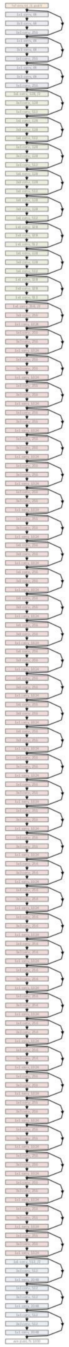
Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". arXiv 2015.

Revolution of Depth

AlexNet, 8 layers
(ILSVRC 2012)

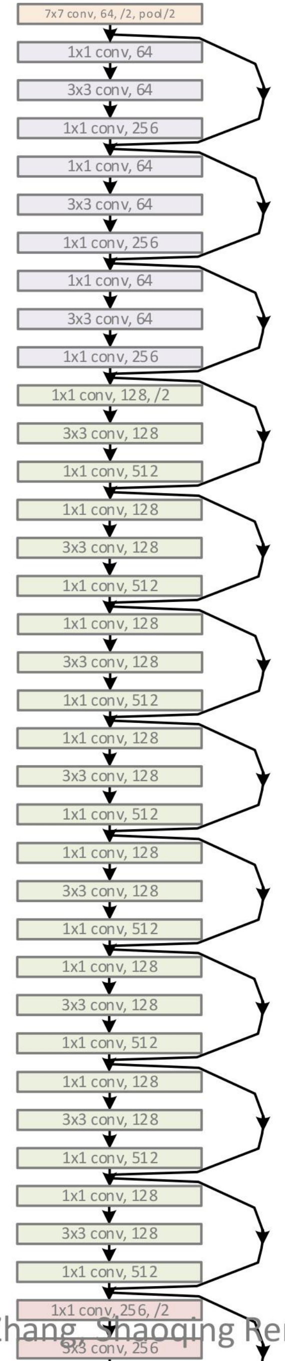
VGG, 19 layers
(ILSVRC 2014)

ResNet, 152 layers
(ILSVRC 2015)



Revolution of Depth

ResNet, 152 layers

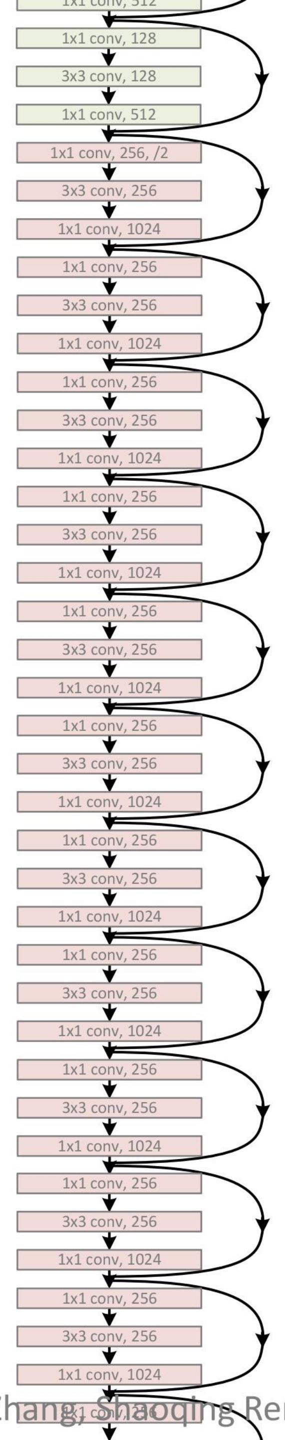


(there was an animation here)

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. arXiv 2015.

Revolution of Depth

ResNet, 152 layers



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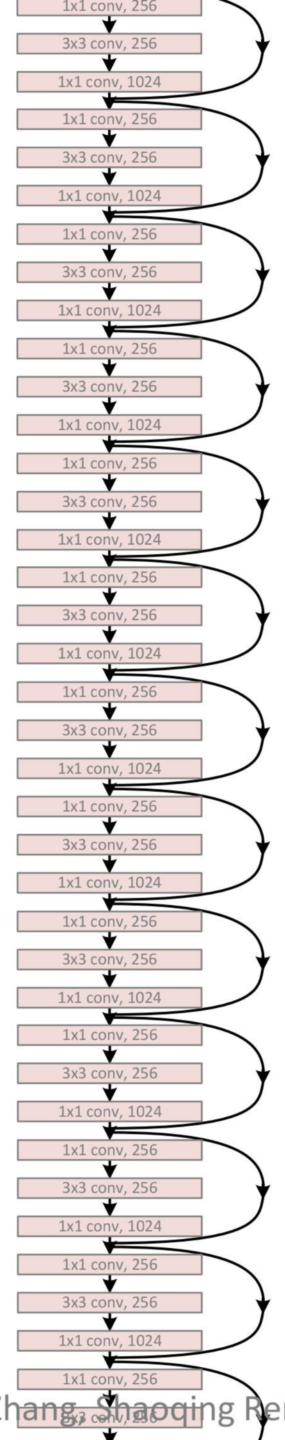
Revolution of Depth

ResNet, 152 layers



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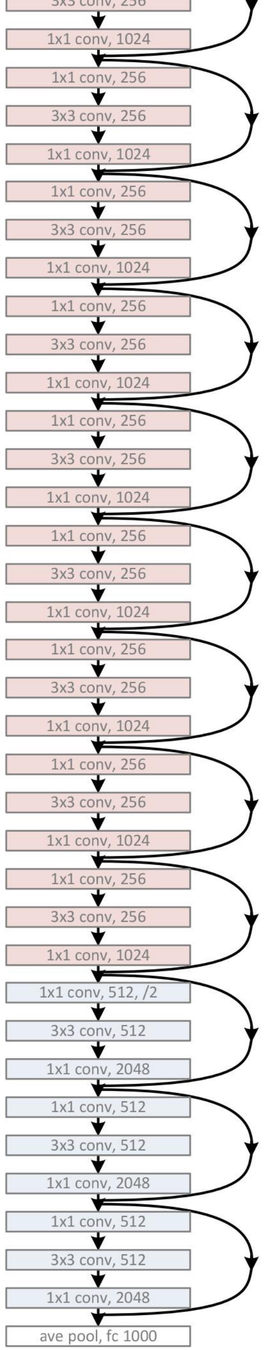
Revolution of Depth

ResNet, 152 layers



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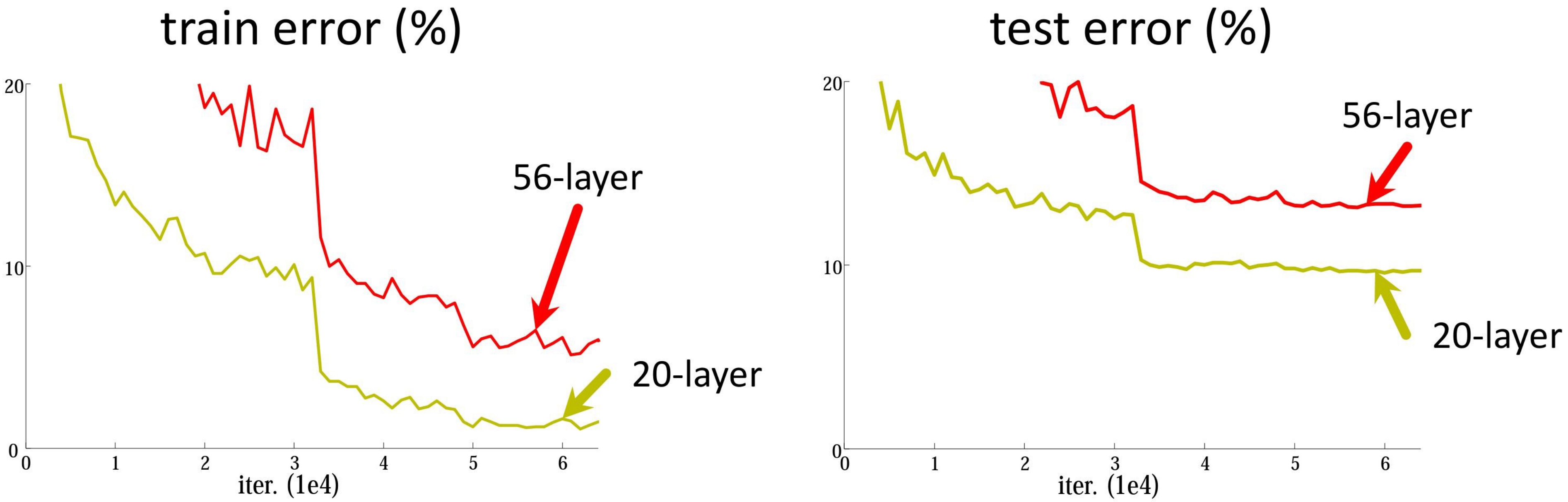
Is learning better networks as simple as stacking more layers?

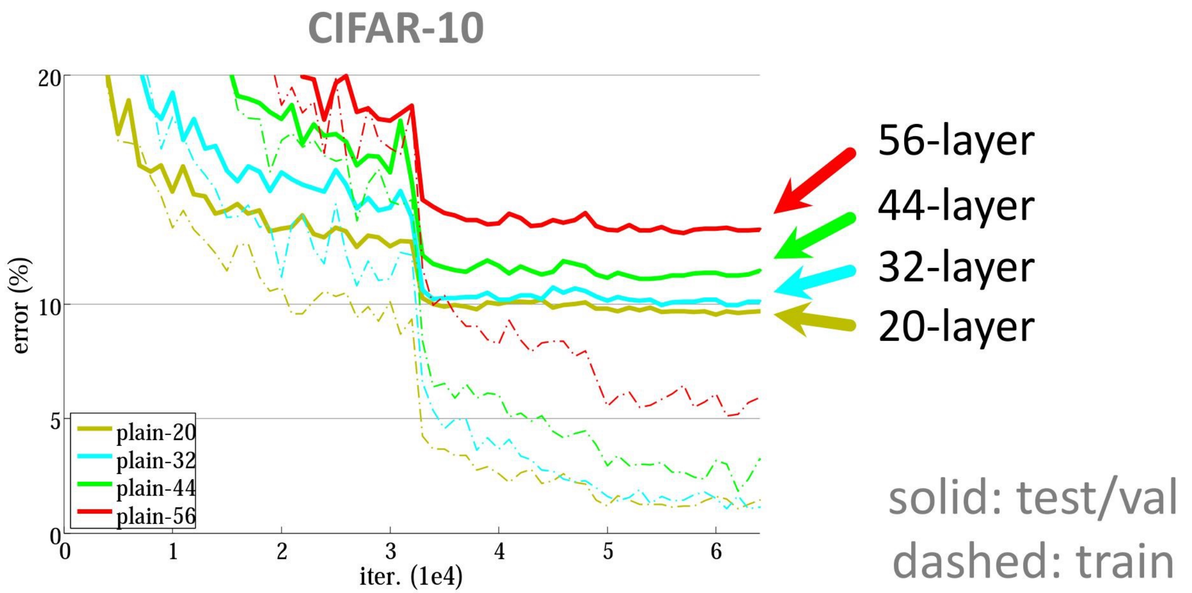
Simply stacking layers?

CIFAR-10



- *Plain* nets: stacking 3x3 conv layers…
- 56-layer net has **higher training error** and test error than 20-layer net

Simply stacking layers?

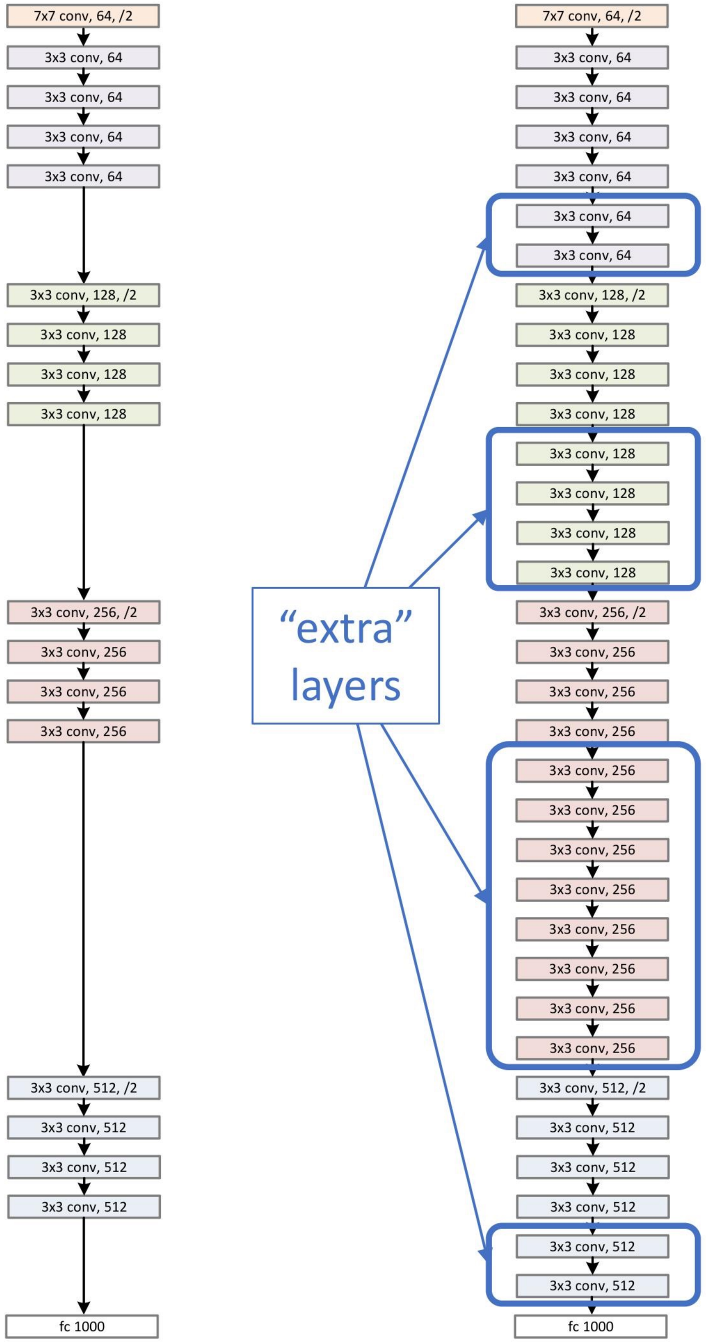


Vanishing/exploding gradient?

- “Overly deep” plain nets have **higher training error**
- A general phenomenon, observed in many datasets

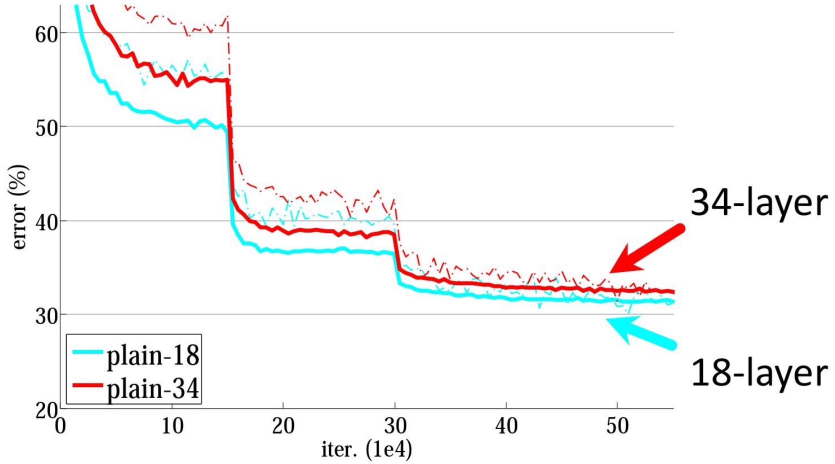
a shallower model (18 layers)

a deeper counterpart (34 layers)



- A deeper model should not have **higher training error**

ImageNet-1000



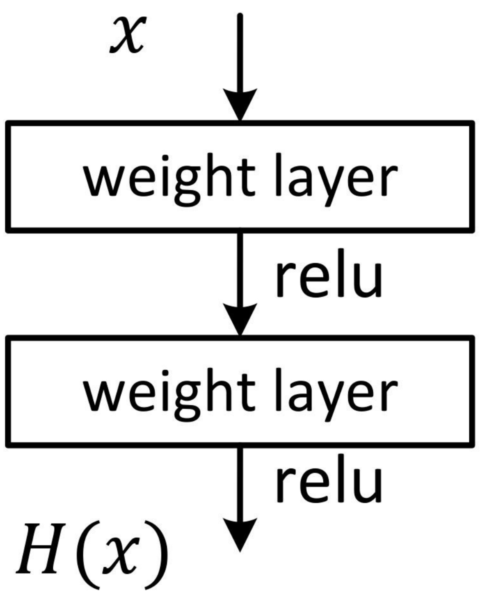
- Optimization difficulties: solvers cannot find the solution when going deeper…

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. arXiv 2015.

Deep Residual Learning

- Plaint net

any two
stacked layers

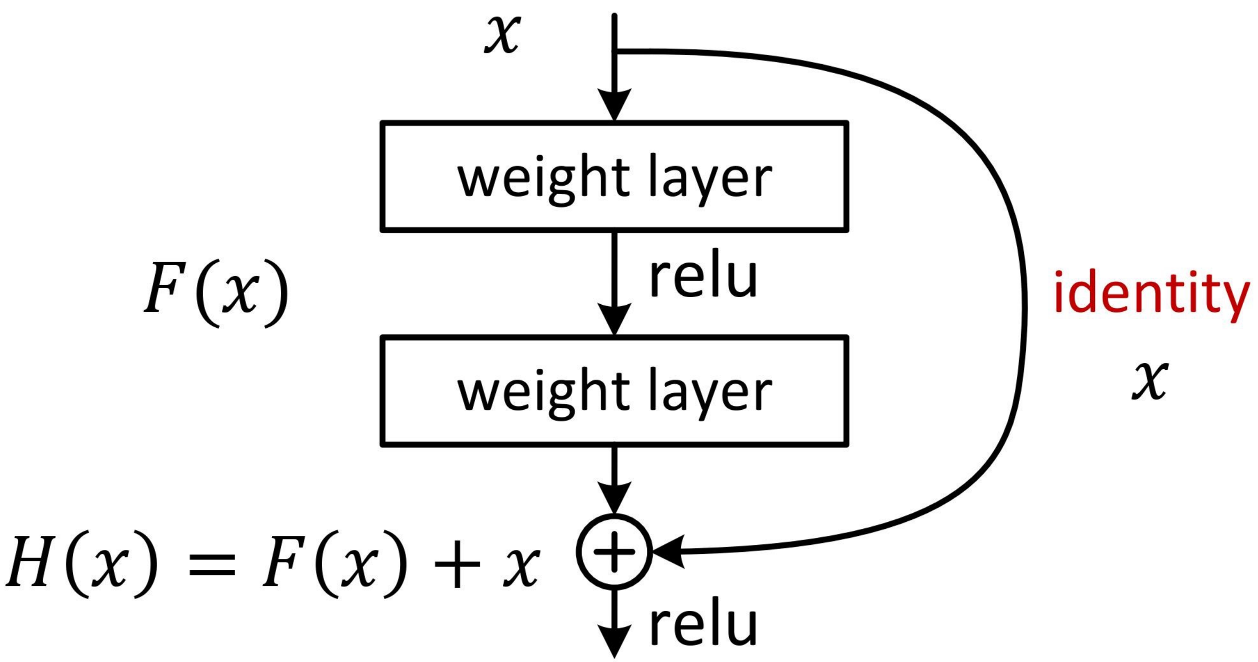


$H(x)$ is any desired mapping,

hope the 2 weight layers fit $H(x)$

Deep Residual Learning

- Residual net



$H(x)$ is any desired mapping,

~~hope the 2 weight layers fit $H(x)$~~

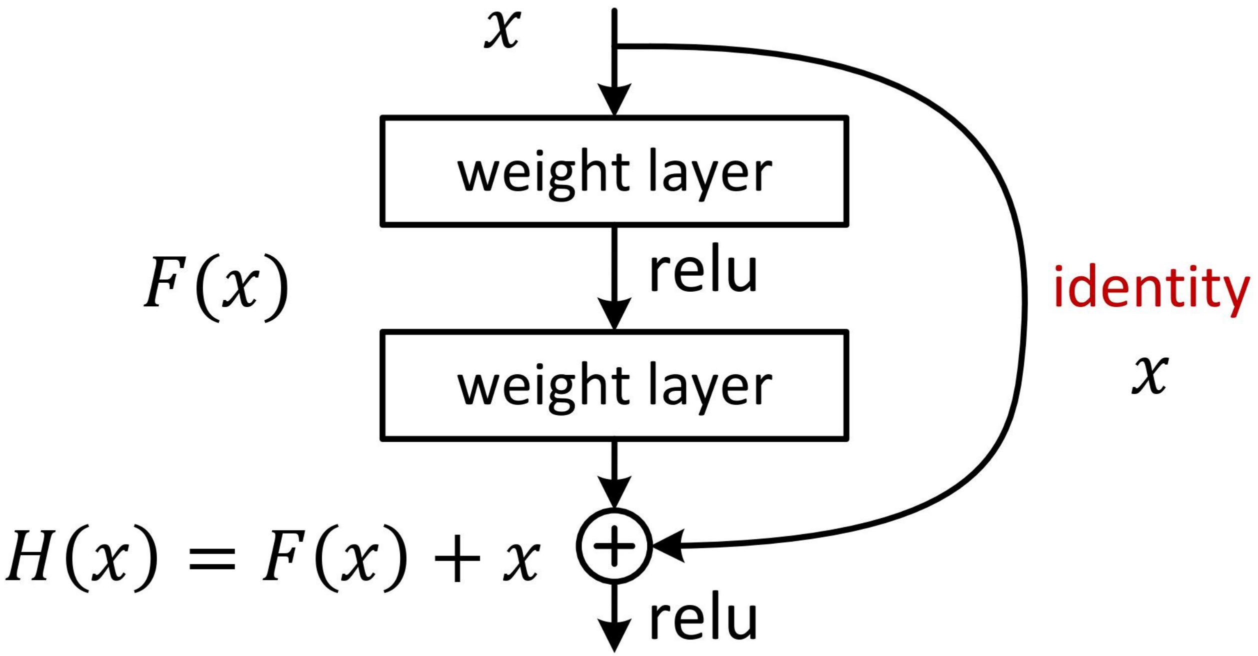
hope the 2 weight layers fit $F(x)$

let $H(x) = F(x) + x$

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". arXiv 2015.

Deep Residual Learning

- $F(x)$ is a residual mapping w.r.t. identity

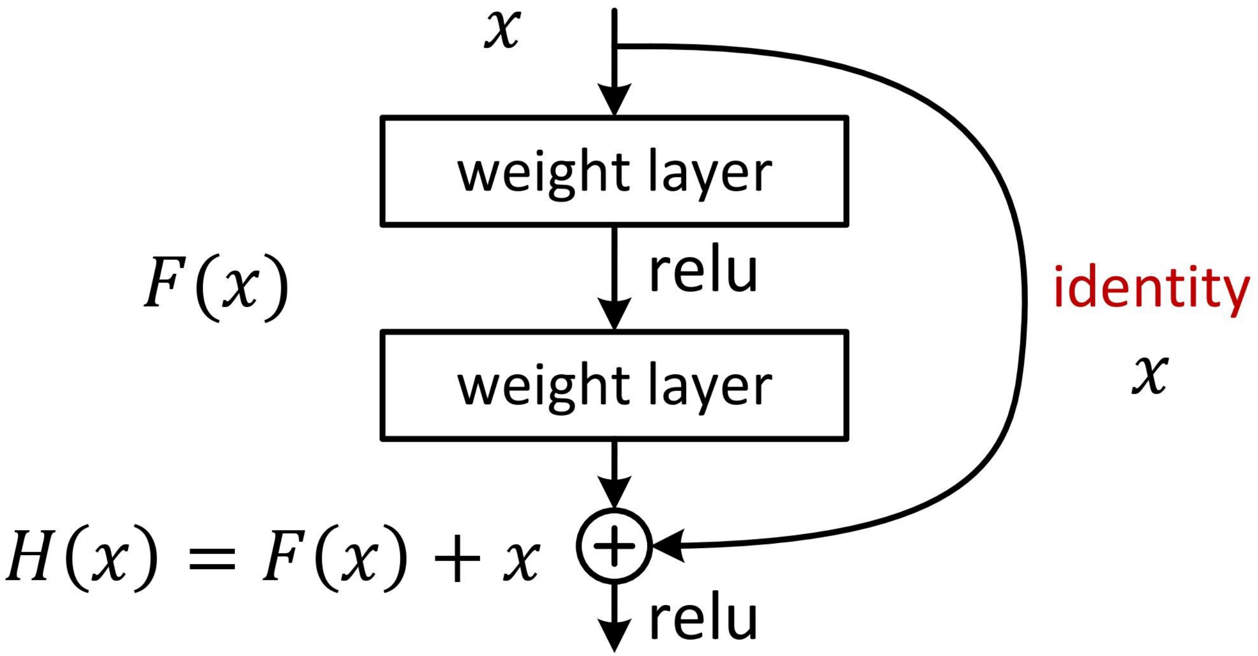


- It's an element wise addition, between the feature maps and channel by channel
- Resnet of 1 layer do not improve, minimum 2

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". arXiv 2015.

Deep Residual Learning

- $F(x)$ is a residual mapping w.r.t. identity



- If the dimension of x and F is different:

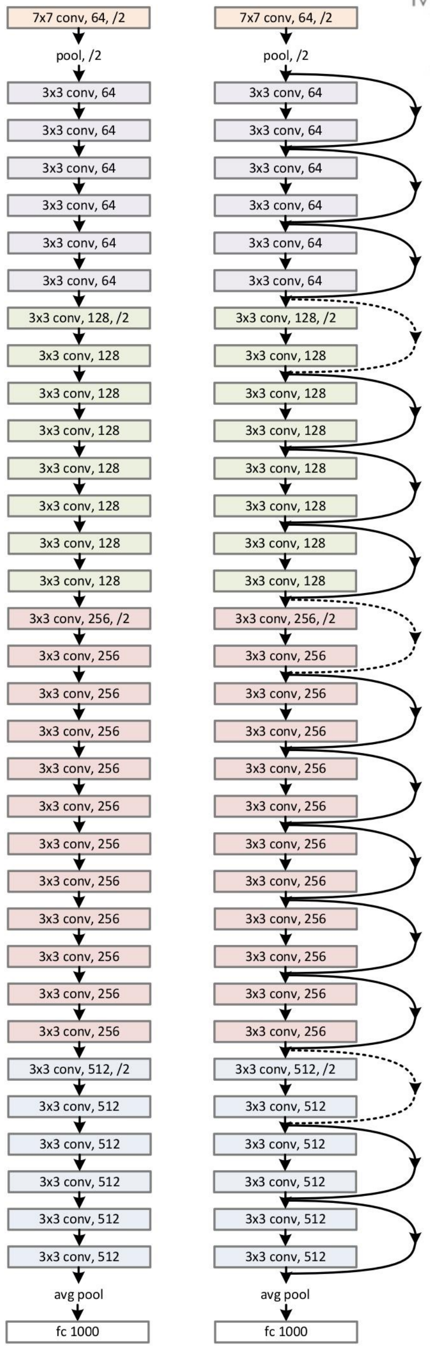
$$H(x) = \mathcal{F}(\mathbf{x}, \{W_i\}) + W_s\mathbf{x}$$

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. arXiv 2015.

Network “Design”

- Keep it simple
- Our basic design (VGG-style)
    - all 3x3 conv (almost)
    - spatial size /2 => # filters x2
    - Simple design; just deep!
- Other remarks:
    - no max pooling (almost)
    - no hidden fc
    - no dropout

plain net



ResNet

Training

- All plain/residual nets are trained from scratch
- All plain/residual nets use Batch Normalization
- Standard augmentation

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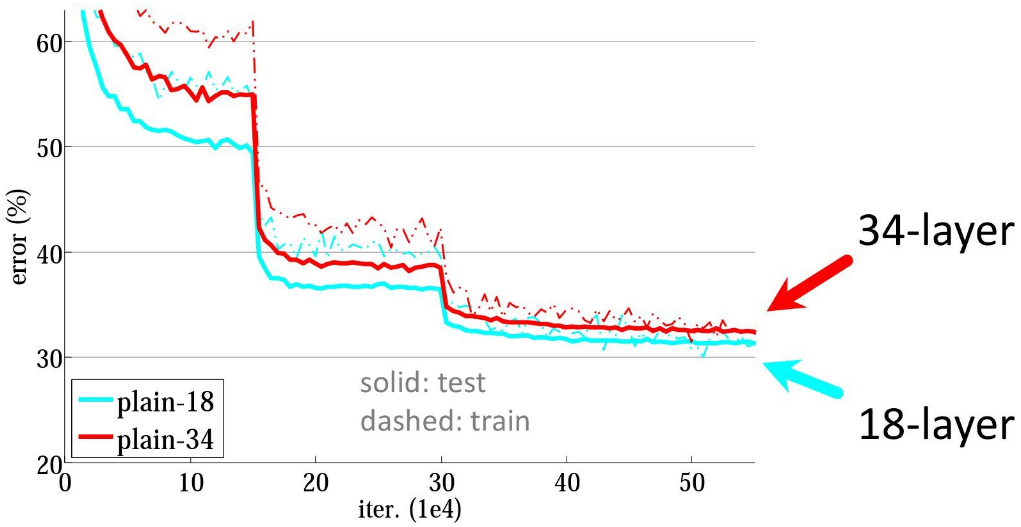
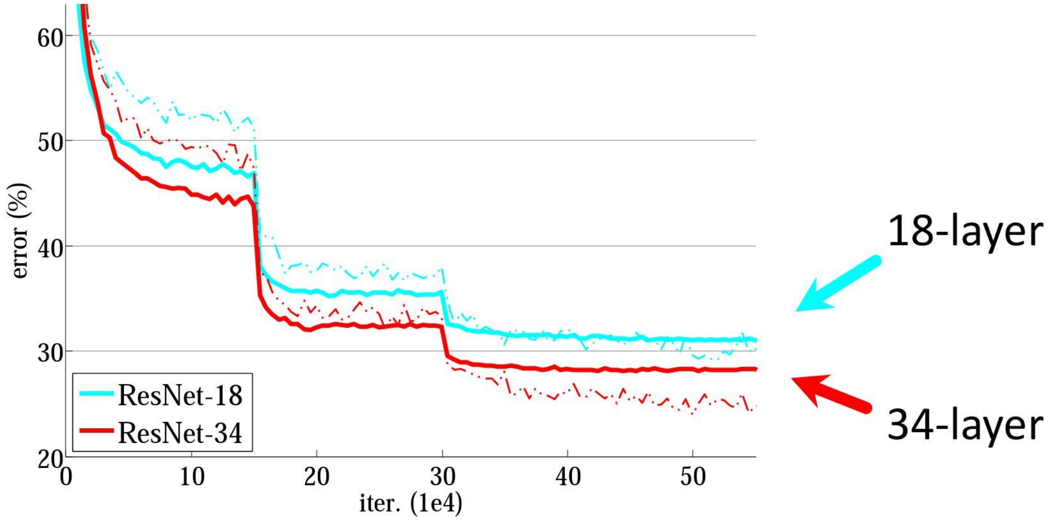
ImageNet experiments

ImageNet plain nets



ImageNet ResNets



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

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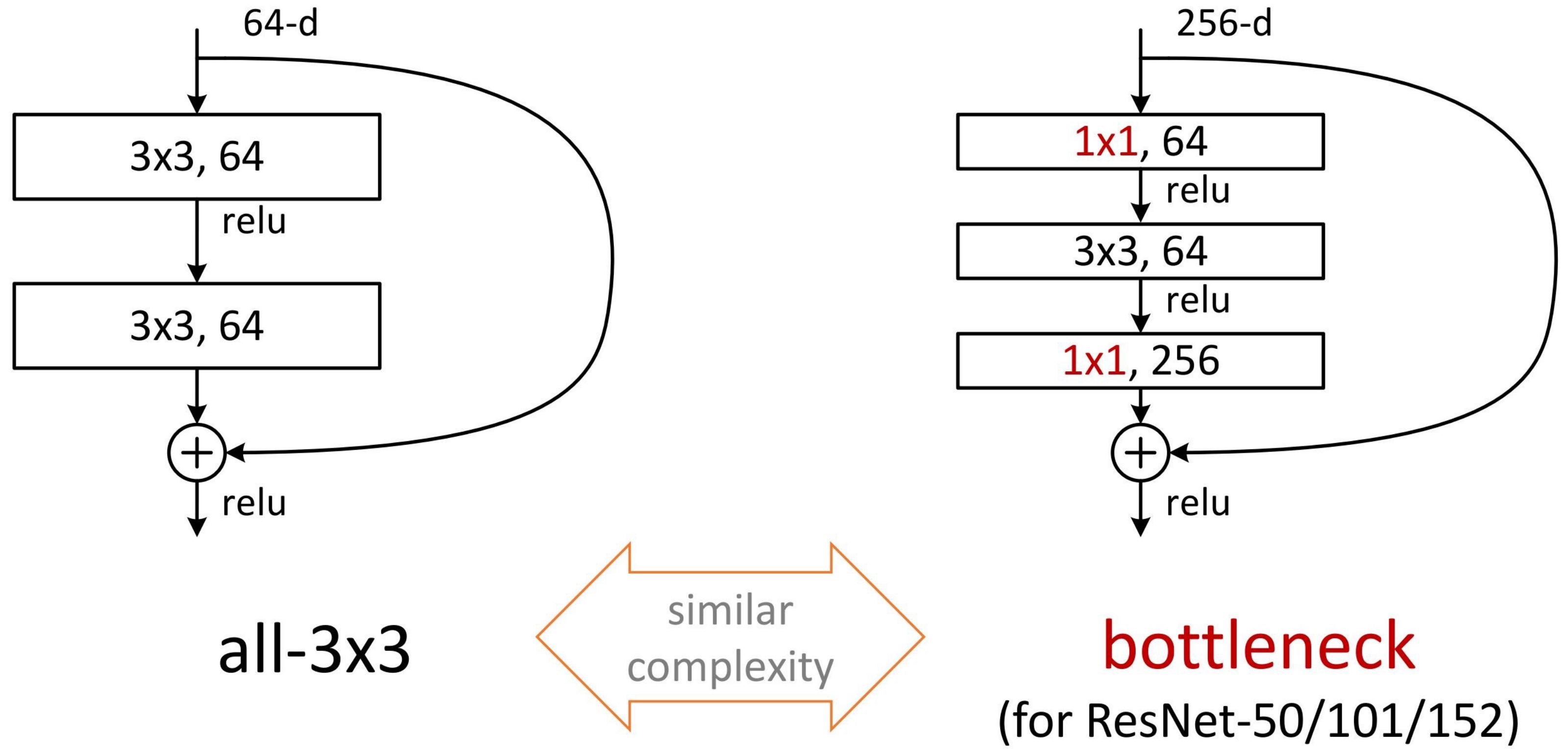
ImageNet experiments

- A practical design of going deeper



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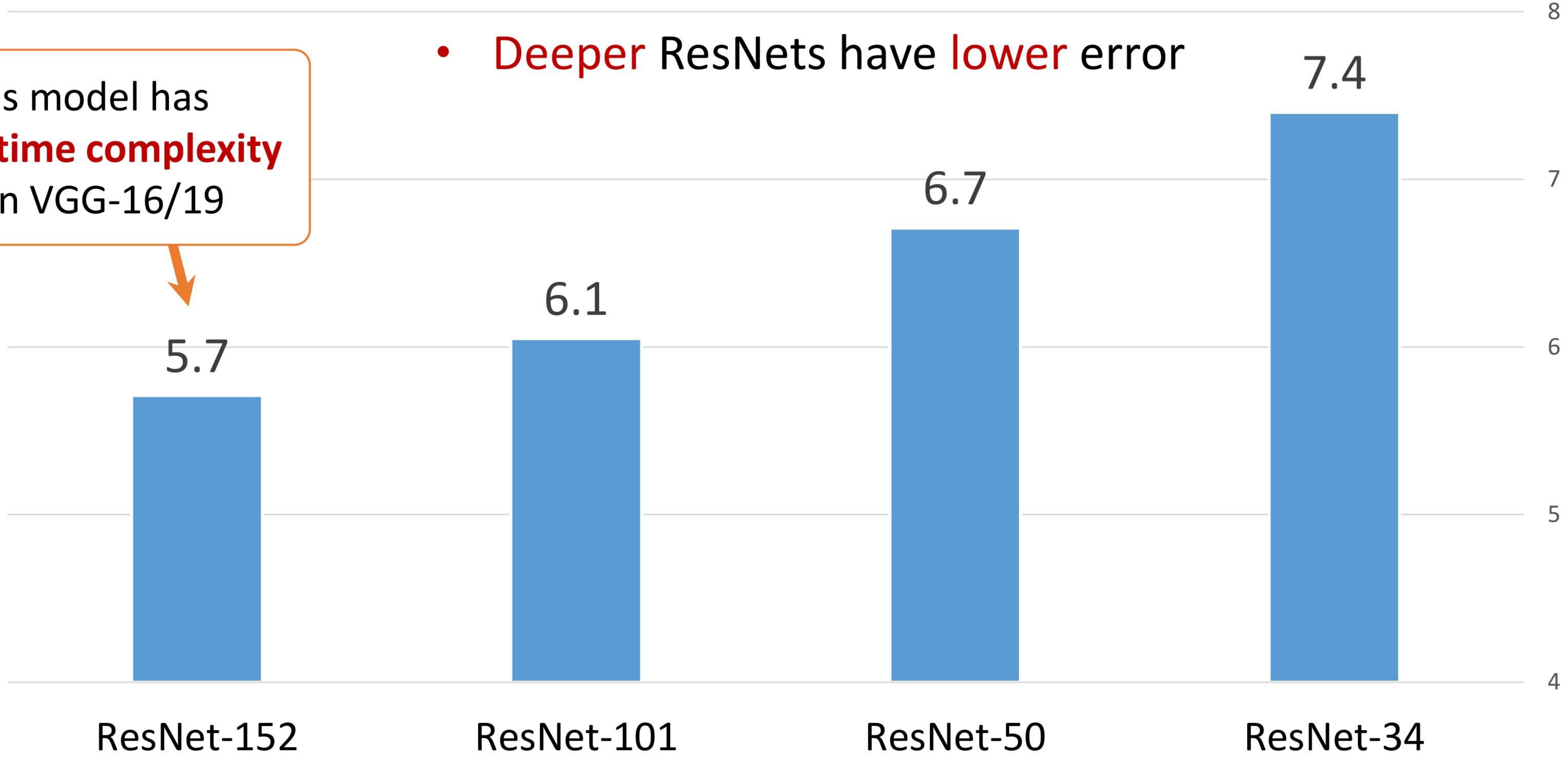
layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$
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

The 152-layers ResNet still has lower complexity than VGG-16/19 (15.3/19.6 billion FLOPs) !!!

ImageNet experiments

- Deeper ResNets have lower error

this model has
lower time complexity
than VGG-16/19



10-crop testing, top-5 val error (%)

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"Features matter." (quote [Girshick et al. 2014], the R-CNN paper)

task	2nd-place winner	MSRA	margin (relative)
ImageNet Localization (top-5 error)	12.0	9.0	**27%**
ImageNet Detection (mAP@.5)	53.6	62.1	**16%**
COCO Detection (mAP@.5:.95)	33.5	37.3	**11%**
COCO Segmentation (mAP@.5:.95)	25.1	28.2	**12%**

absolute 8.5% better!

- Our results are all based on ResNet-101
- Our features are well transferrable

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