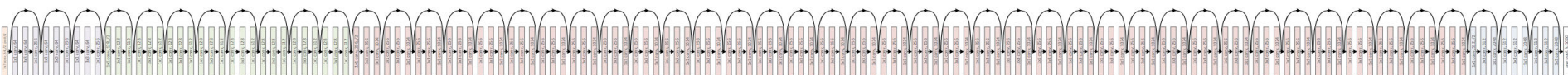


# Deep Residual Learning for Image Recognition

“CVPR 2016 Best Paper Award”

Presenter : Jingyun Ning



# Introduction

## Deep Residual Networks (ResNets)

- A simple and clean framework of training “very” deep nets
- State-of-the-art performance for
  - Image classification
  - Object detection
  - Semantic segmentation
  - and more...

# ResNets @ 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

# Result

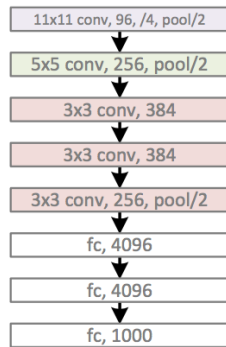
- Performances increase absolutely

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

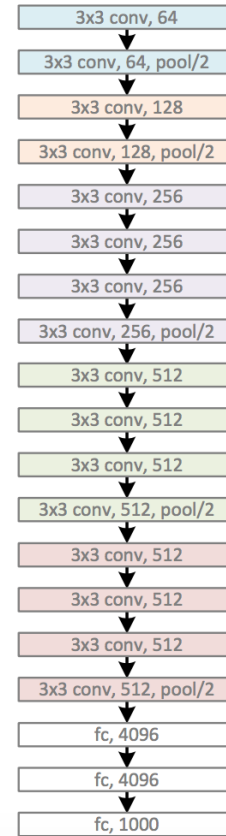
- Based on ResNet-101
- Existing techniques can use residual networks or features from it

# Revolution of Depth

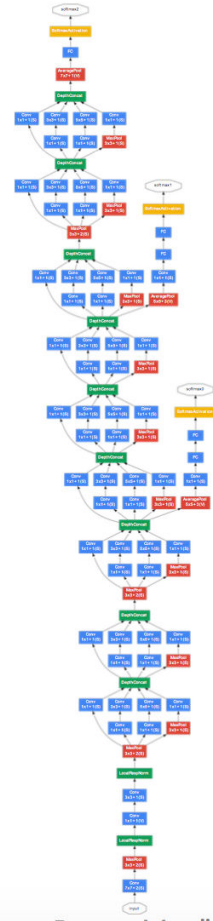
## AlexNet, 8 layers (ILSVRC 2012)



## VGG, 19 layers (ILSVRC 2014)



GoogleNet, 22 layers  
(ILSVRC 2014)



# Revolution of Depth

AlexNet, 8 layers  
(ILSVRC 2012)



VGG, 19 layers  
(ILSVRC 2014)



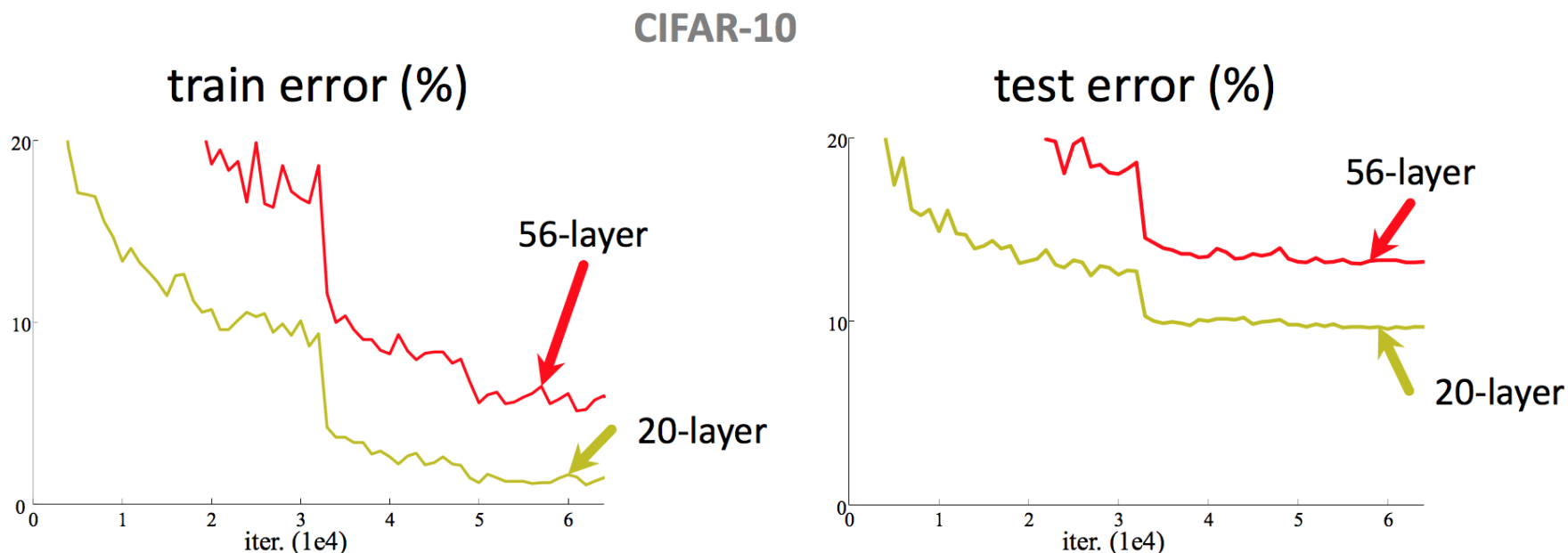
ResNet, **152 layers**  
(ILSVRC 2015)



Is learning better networks as simple as s

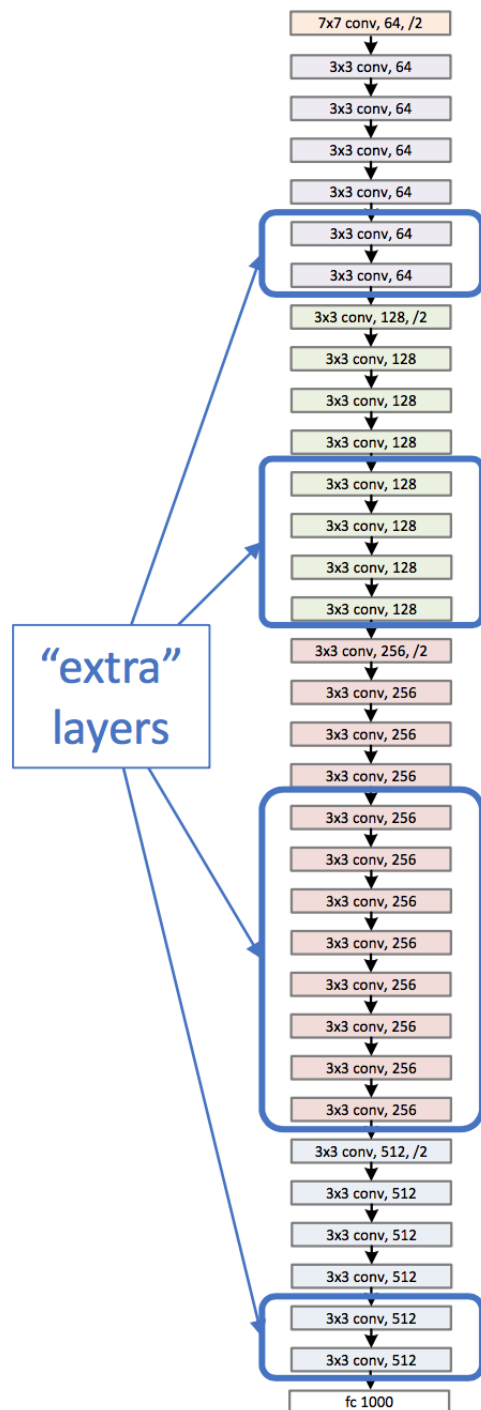
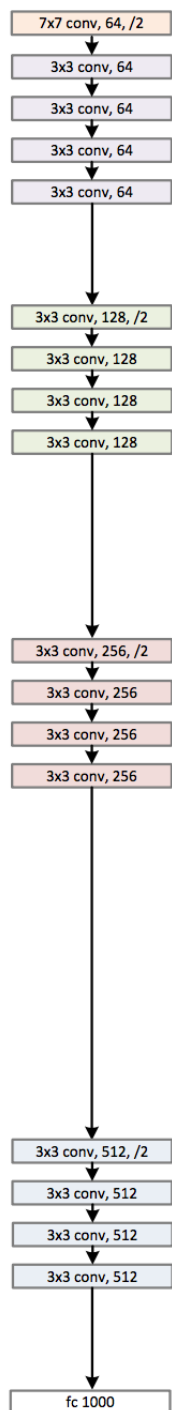
No!

# Simply stacking layers?



- Plain nets: stacking 3x3 Convlayers...
- 56-layer net has **higher training error** and test error than 20-layer net





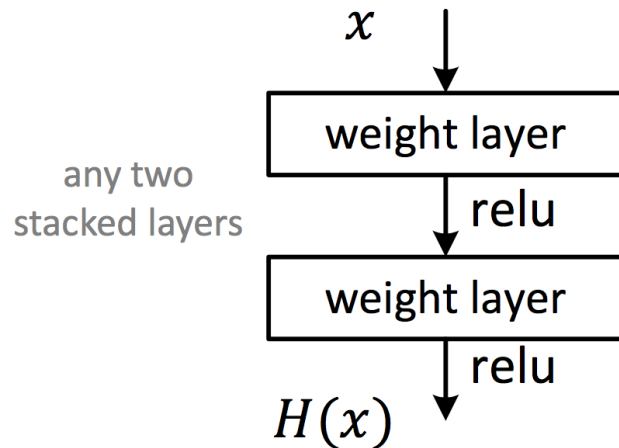
Left : a shallower model (18 layers)  
 Right : a deeper counterpart (34 layers)

- A deeper model should not have **higher training error**
- A solution by construction:
  - original layers: copied from a learned shallower model
  - extra layers: set as **identity**
  - at least the same training error
- **Optimization difficulties**: solvers cannot find the solution when going deeper...

# Deep Residual Learning

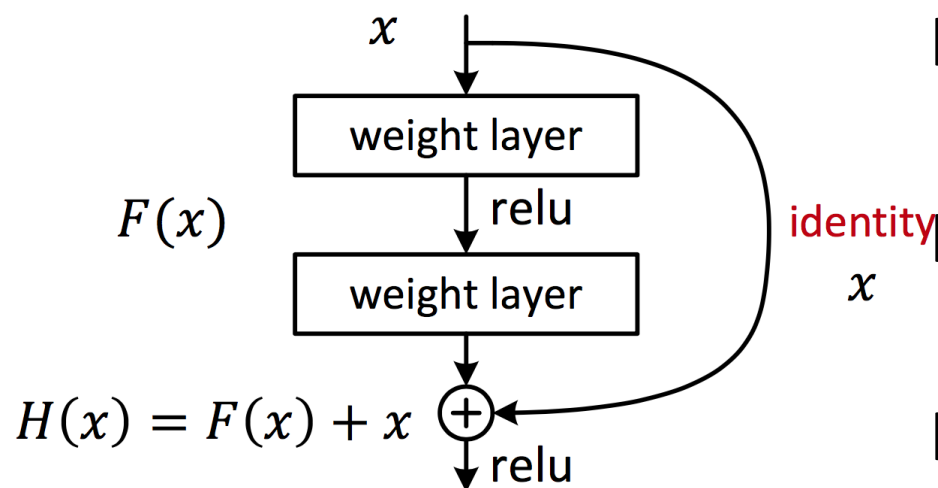
- Plain net

$H(x)$  is any **desired mapping**, hope the 2 weight layers fit  $H(x)$



# Deep Residual Learning

- **Residual** net



$H(x)$  is any desired mapping,

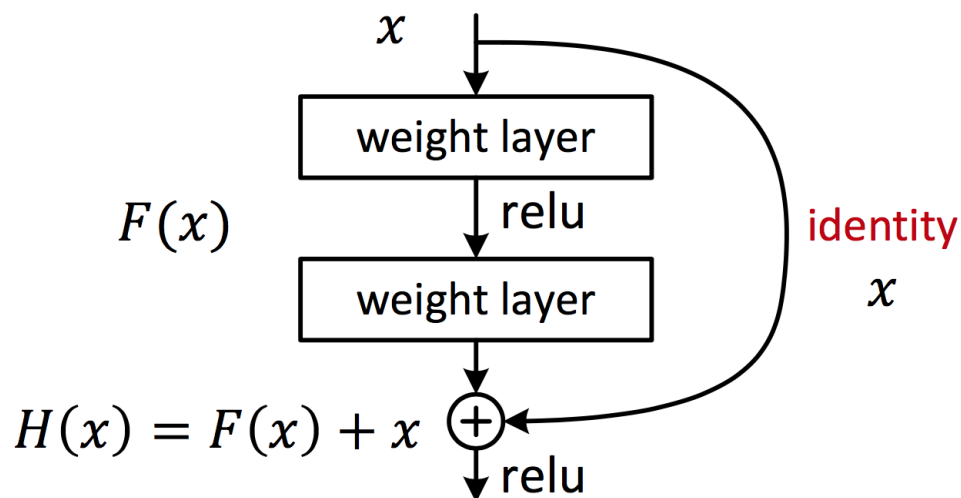
hope the 2 weight layers fit  $H(x)$

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

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

# Deep Residual Learning

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



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

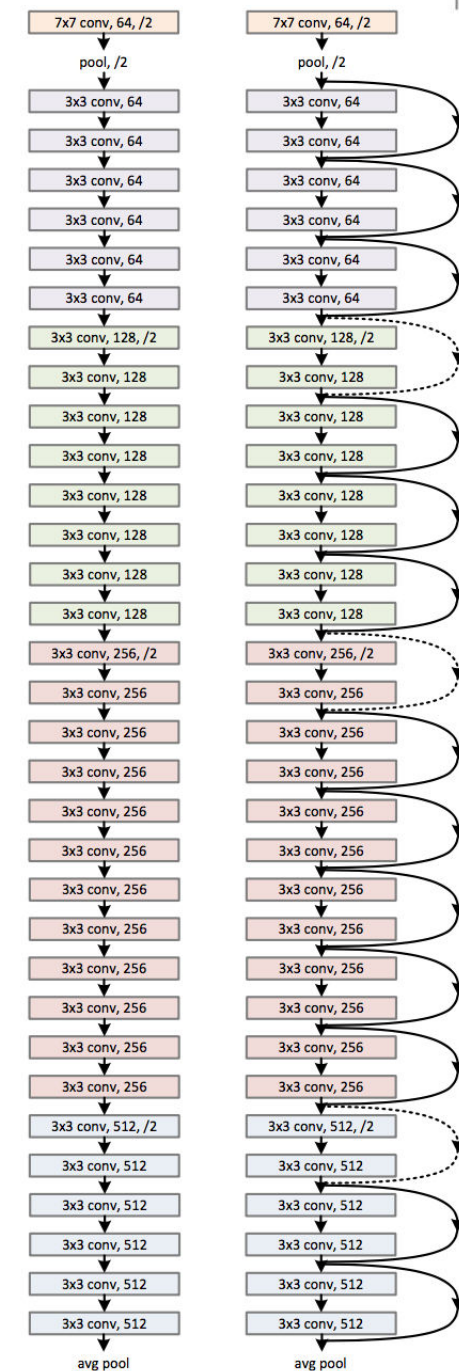
# Network “Design”

- Keep it simple
- The 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

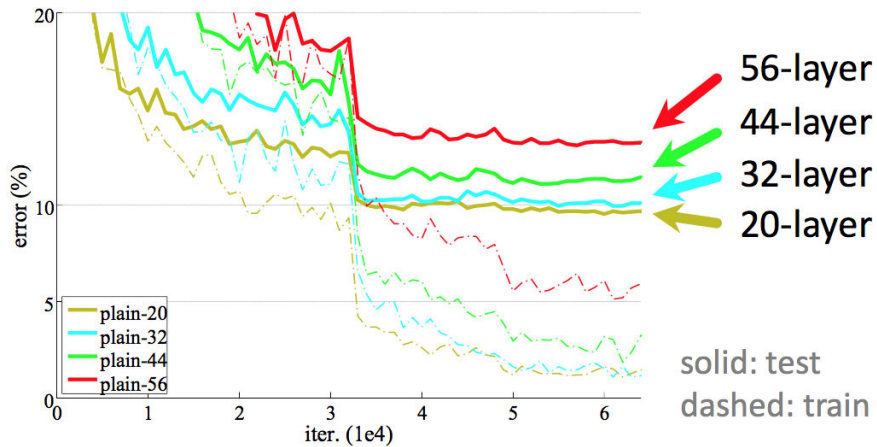
plain net



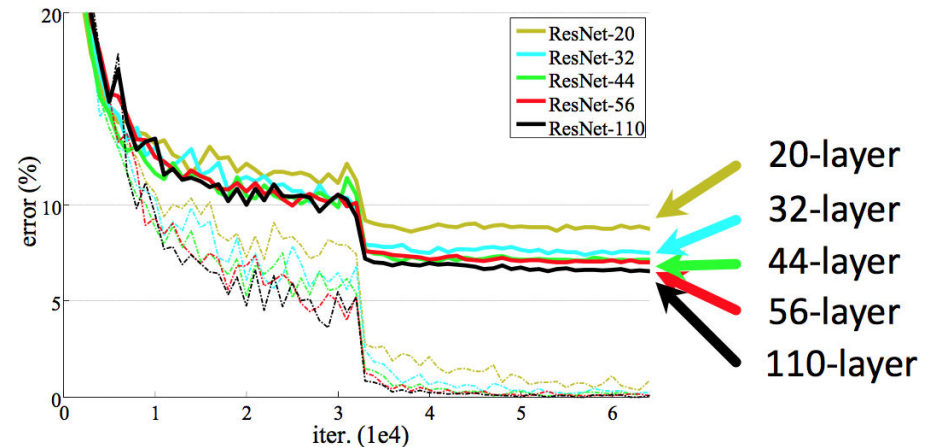
ResNet

# CIFAR-10 experiments

CIFAR-10 plain nets



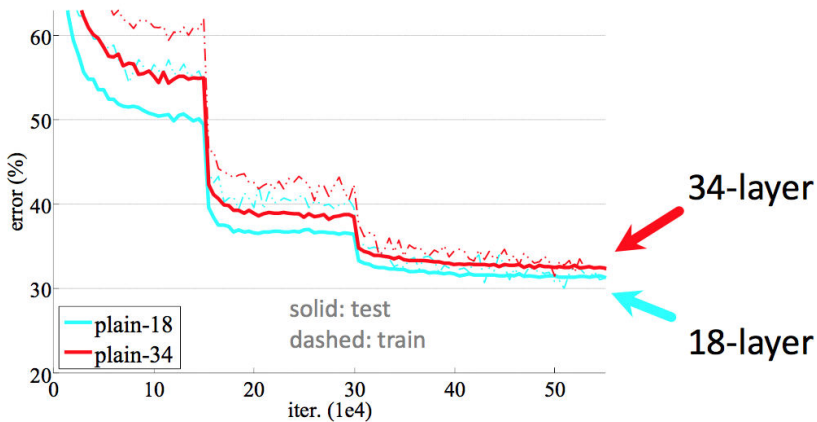
CIFAR-10 ResNets



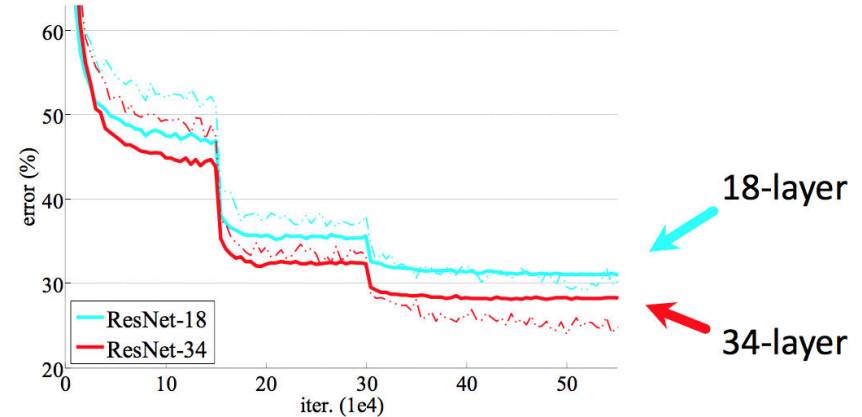
- Deep ResNets can be trained without difficulties
- Deeper ResNets have **lower training error**, and also lower test error

# ImageNet experiments

ImageNet plain nets



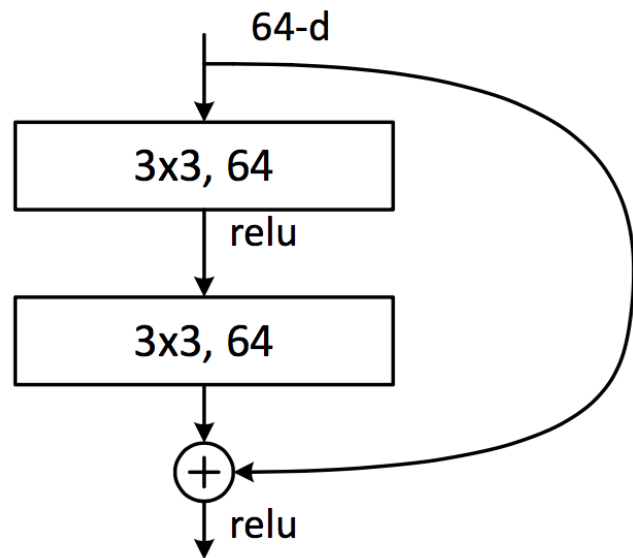
ImageNet ResNets



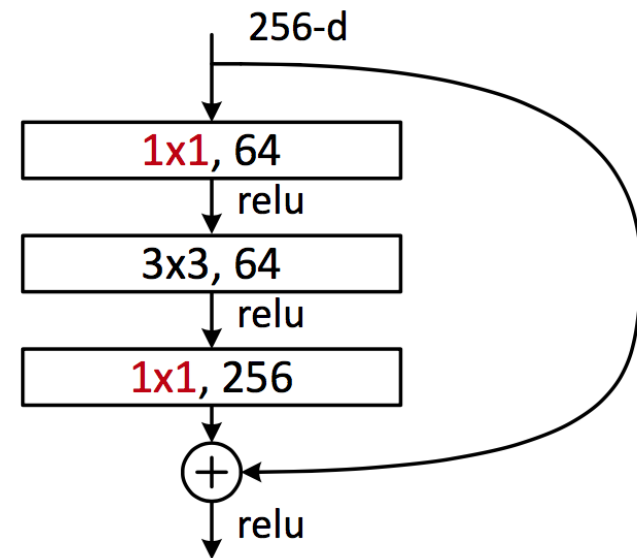
- Deep ResNets can be trained without difficulties
- Deeper ResNets have **lower training error**, and also lower test error

# ImageNet experiments

- A practical design of going deeper



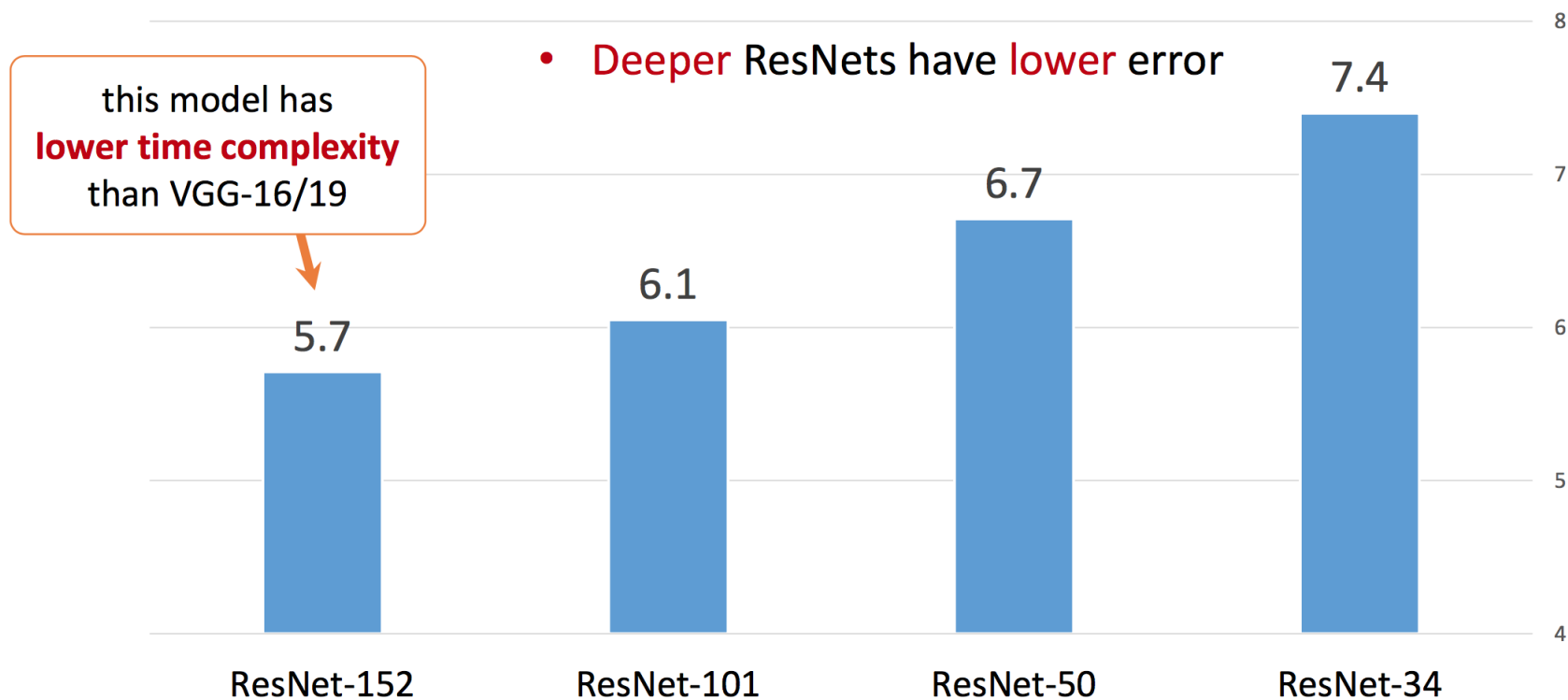
all-3x3



**bottleneck**  
(for ResNet-50/101/152)

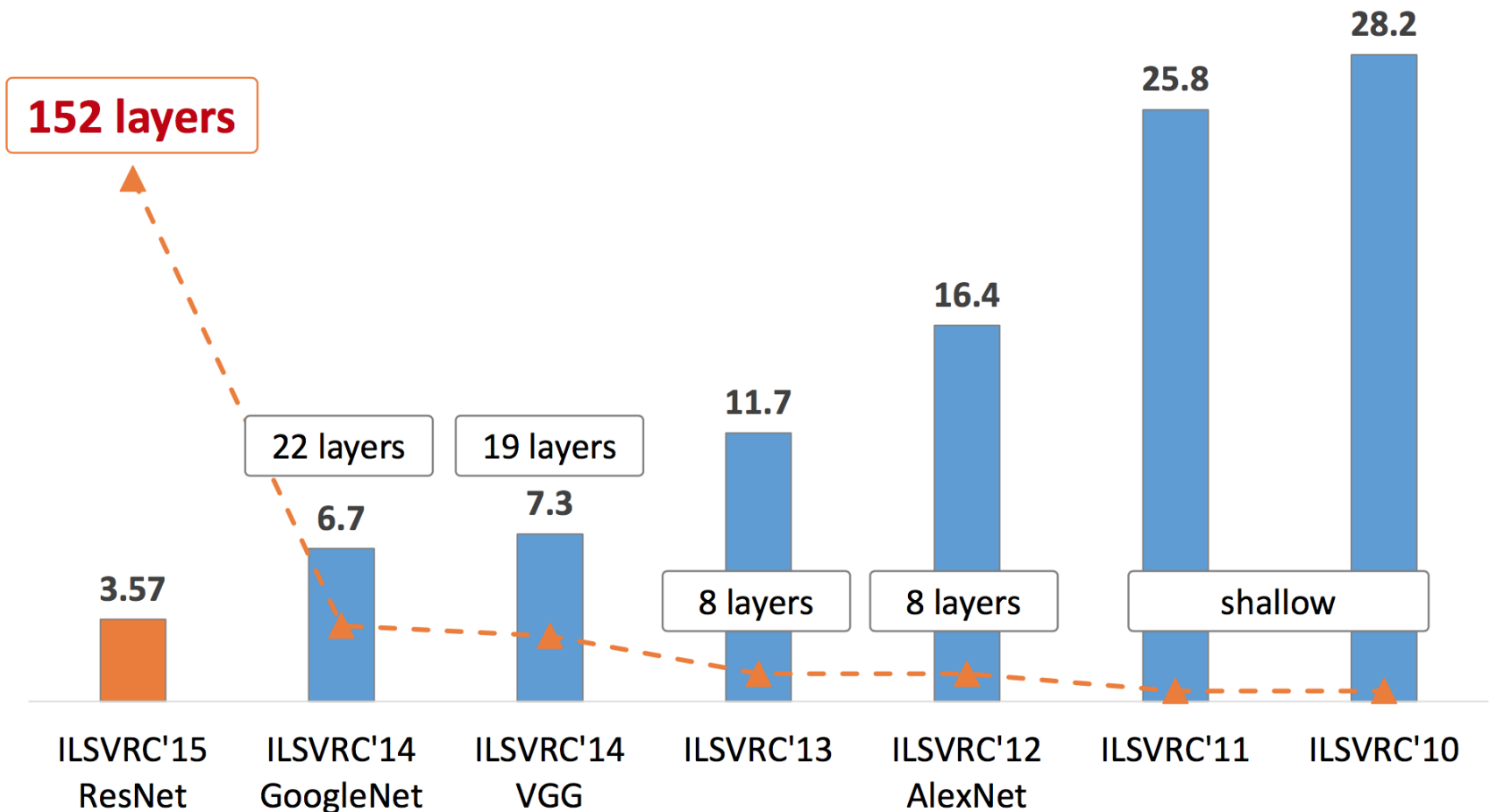


# ImageNet experiments



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

# ImageNet experiments



ImageNet Classification top-5 error (%)

# Exploring over 1000 layers

- Test 1202 layers
  - Training is finished
  - Training error is similar
  - Testing error is high because of over fitting

method			error (%)
Maxout [10]			9.38
NIN [25]			8.81
DSN [24]			8.22
	# layers	# params	
FitNet [35]	19	2.5M	8.39
Highway [42, 43]	19	2.3M	7.54 (7.72±0.16)
Highway [42, 43]	32	1.25M	8.80
ResNet	20	0.27M	8.75
ResNet	32	0.46M	7.51
ResNet	44	0.66M	7.17
ResNet	56	0.85M	6.97
ResNet	110	1.7M	<b>6.43</b> (6.61±0.16)
ResNet	1202	19.4M	7.93

# Conclusion

- Deep Residual Learning:
  - Ultra deep networks can be easy to train
- Ultra deep networks can gain accuracy from depth
- Ultra deep representations are well transferrable
- Now 200 layers on ImageNet and 1000 layers on CIFAR!

# Reference

- Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. arXiv 2015.
- Slides of Deep Residual Learning @ ILSVRC & COCO 2015 competitions

Thank You!