Deep Residual Networks

Deep Learning Gets Way Deeper

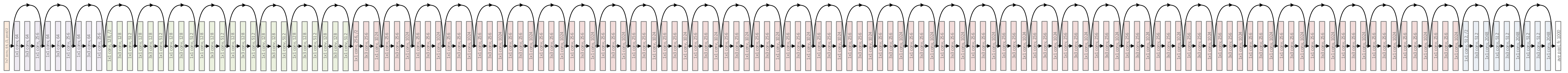
8:30-10:30am, June 19

ICML 2016 tutorial

Kaiming He

Facebook AI Research*

*as of July 2016. Formerly affiliated with Microsoft Research Asia



Overview

- Introduction
- Background
  - From shallow to deep
- Deep Residual Networks
  - From 10 layers to 100 layers
  - From 100 layers to 1000 layers
- Applications
- Q & A

Introduction

Introduction

Deep Residual Networks (ResNets)

- "Deep Residual Learning for Image Recognition". CVPR 2016 (next week)

- A simple and clean framework of training "very" deep nets

- State-of-the-art performance for
  - Image classification
  - Object detection
  - Semantic segmentation
  - and more…

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". CVPR 2016.

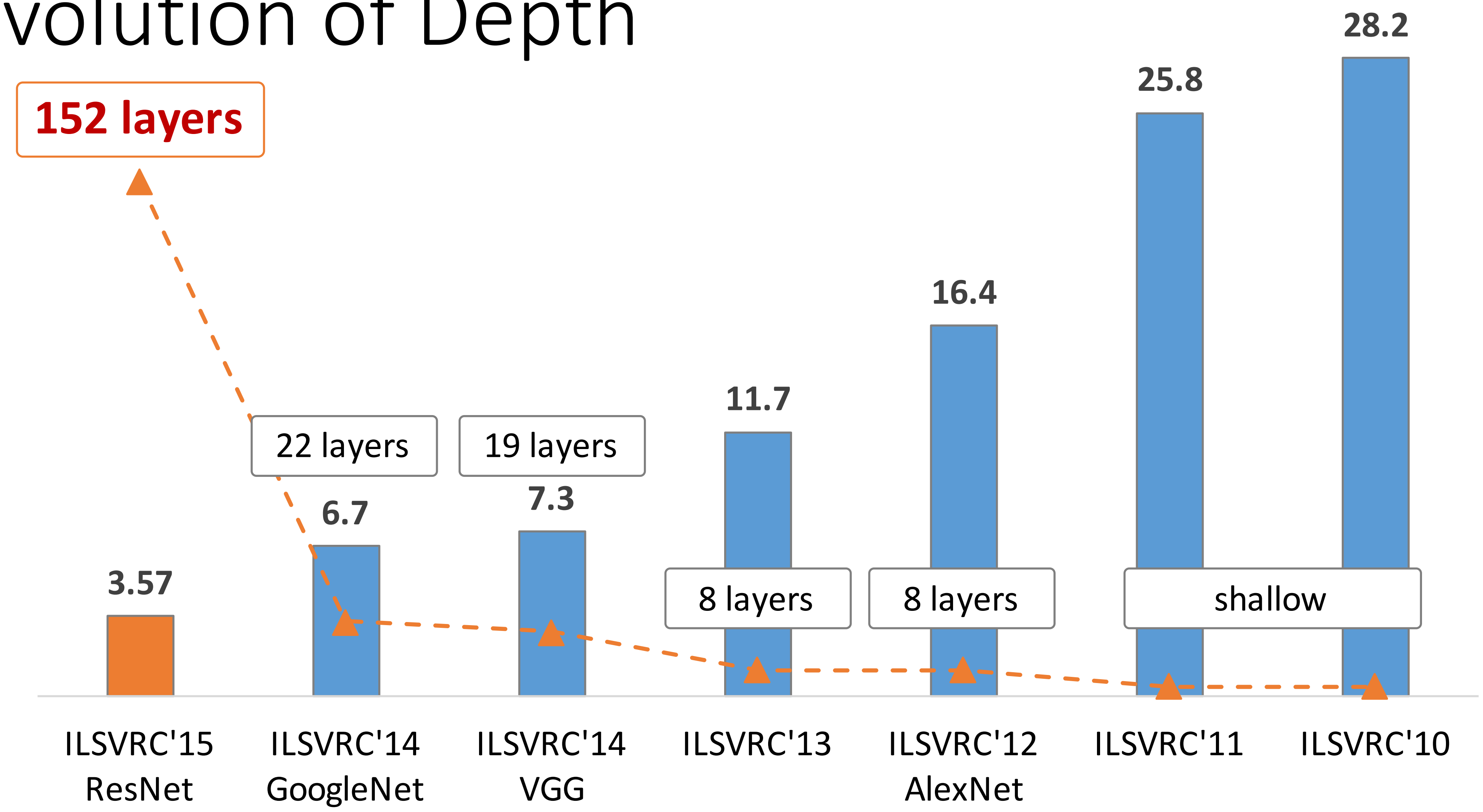
ResNets @ ILSVRC & COCO 2015 Competitions

- **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

*improvements are relative numbers

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". CVPR 2016.

Revolution of Depth

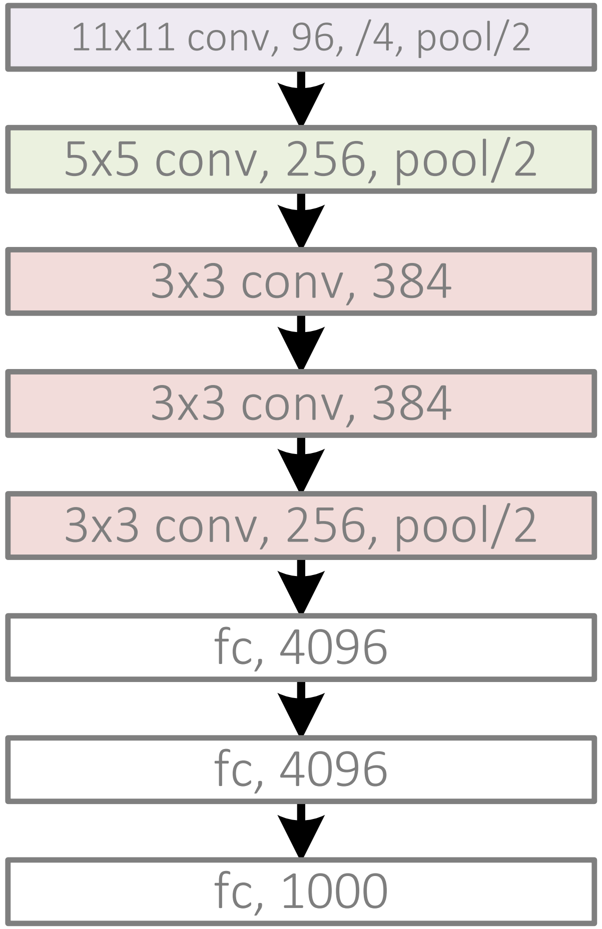


ImageNet Classification top-5 error (%)

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". CVPR 2016.

Revolution of Depth

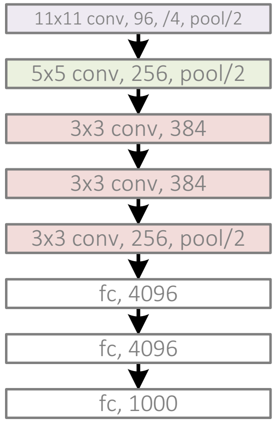
AlexNet, 8 layers
(ILSVRC 2012)



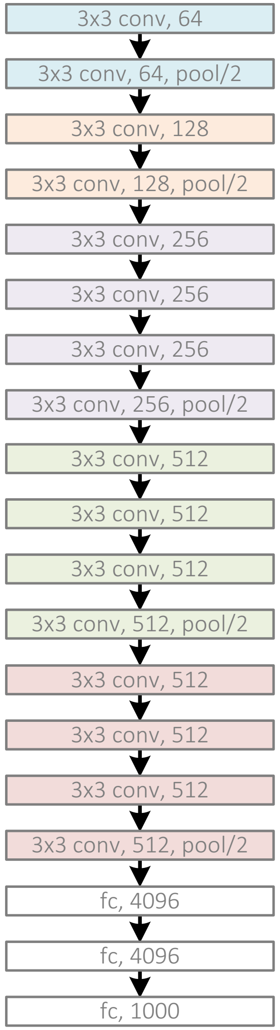
Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. CVPR 2016.

Revolution of Depth

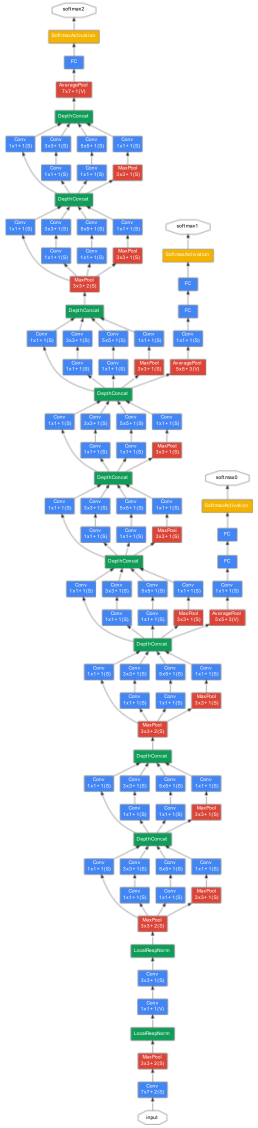
AlexNet, 8 layers
(ILSVRC 2012)



VGG, 19 layers
(ILSVRC 2014)



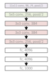
GoogleNet, 22 layers
(ILSVRC 2014)



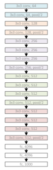
Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. CVPR 2016.

Revolution of Depth

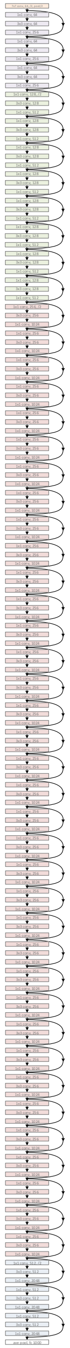
AlexNet, 8 layers
(ILSVRC 2012)



VGG, 19 layers
(ILSVRC 2014)



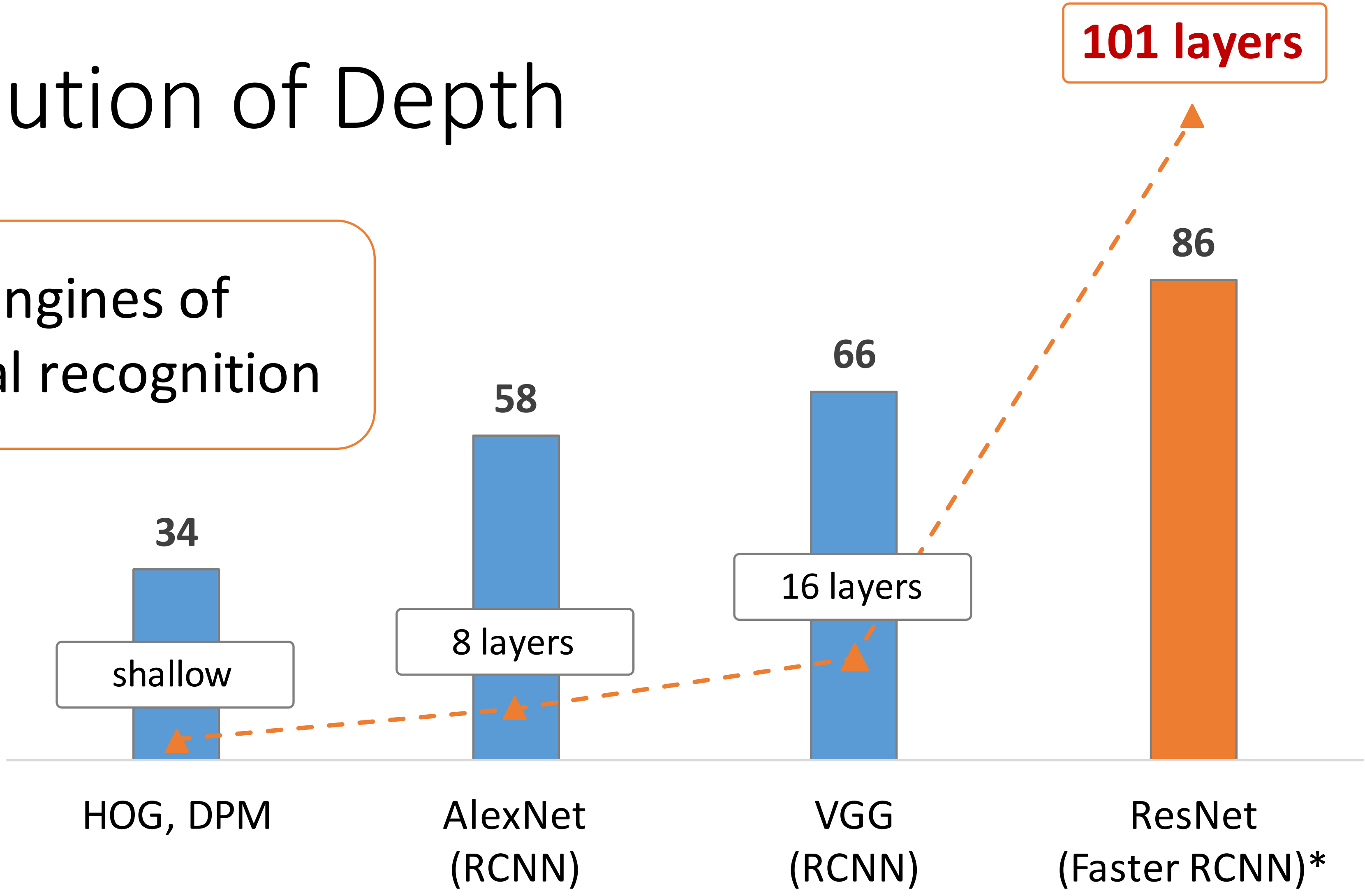
ResNet, 152 layers
(ILSVRC 2015)



Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. CVPR 2016.

Revolution of Depth

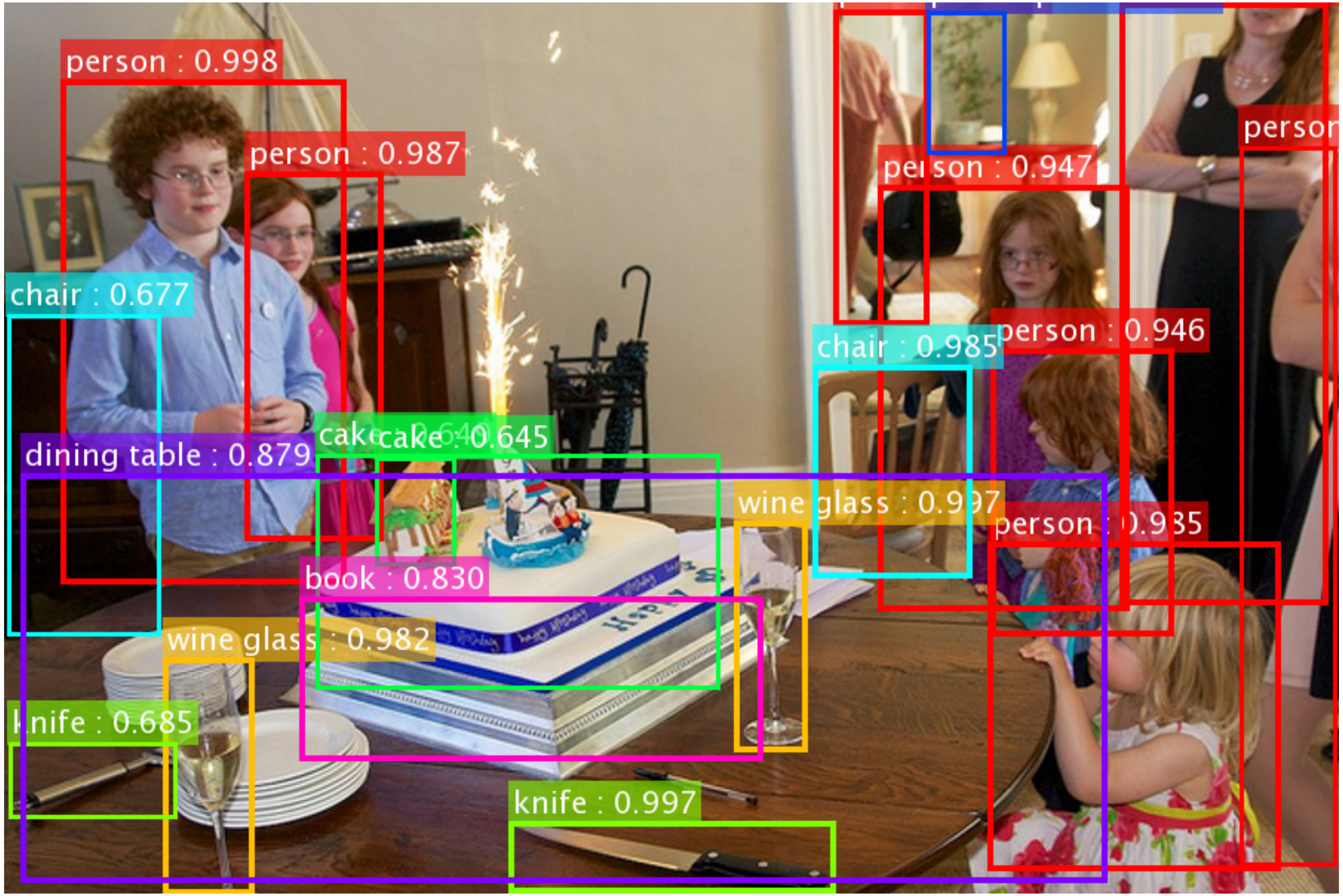
Engines of
visual recognition



PASCAL VOC 2007 **Object Detection** mAP (%)

*w/ other improvements & more data

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". CVPR 2016.



ResNet's object detection result on COCO

*the original image is from the COCO dataset

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". CVPR 2016.

Very simple, easy to follow

- Many third-party implementations (list in https://github.com/KaimingHe/deep-residual-networks)
    - Facebook AI Research's Torch ResNet:
    - Torch, CIFAR-10, with ResNet-20 to ResNet-110, training code, and curves: code
    - Lasagne, CIFAR-10, with ResNet-32 and ResNet-56 and training code: code
    - Neon, CIFAR-10, with pre-trained ResNet-32 to ResNet-110 models, training code, and curves: code
    - Torch, MNIST, 100 layers: blog, code
    - A winning entry in Kaggle's right whale recognition challenge: blog, code
    - Neon, Place2 (mini), 40 layers: blog, code
    - …
- Easily reproduced results (e.g. Torch ResNet: https://github.com/facebook/fb.resnet.torch)
- A series of extensions and follow-ups
    - > 200 citations in 6 months after posted on arXiv (Dec. 2015)

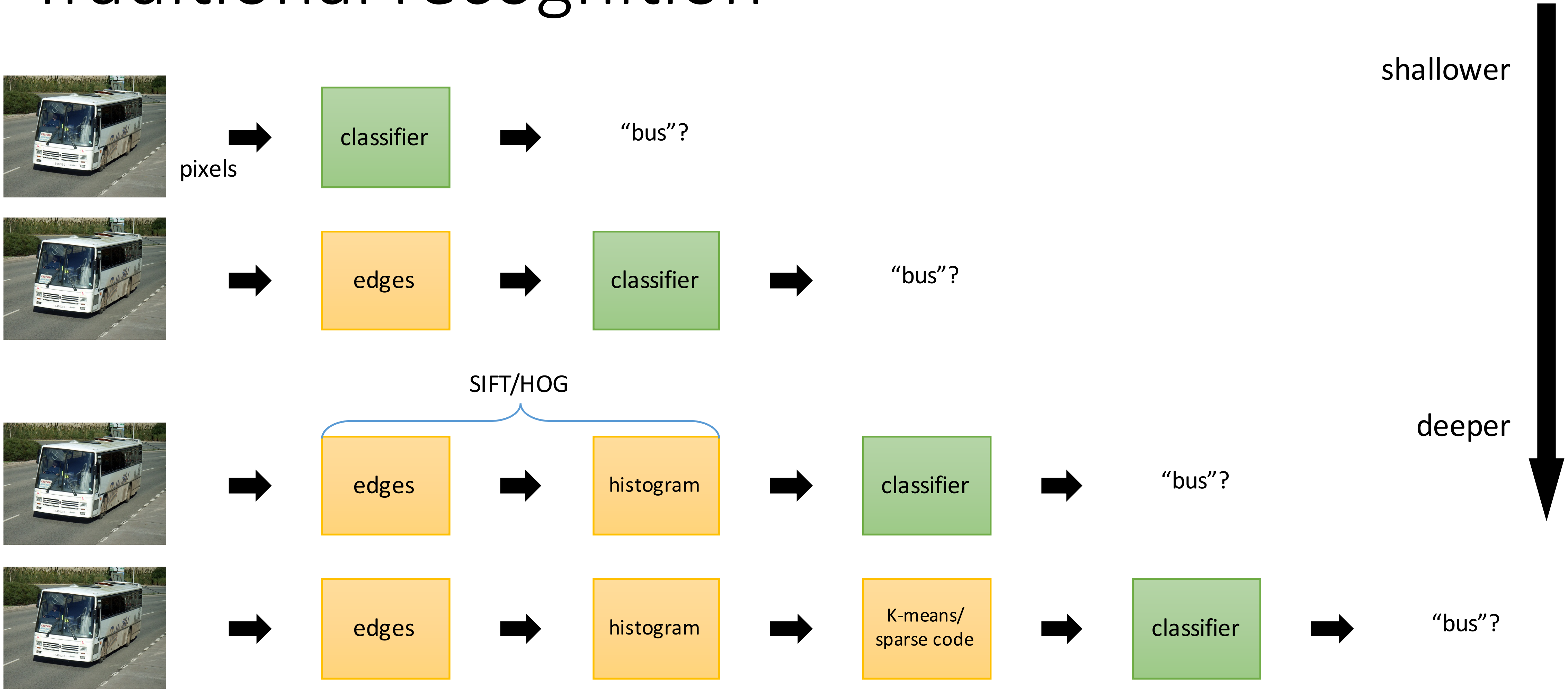
Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". CVPR 2016.

Background

From shallow to deep

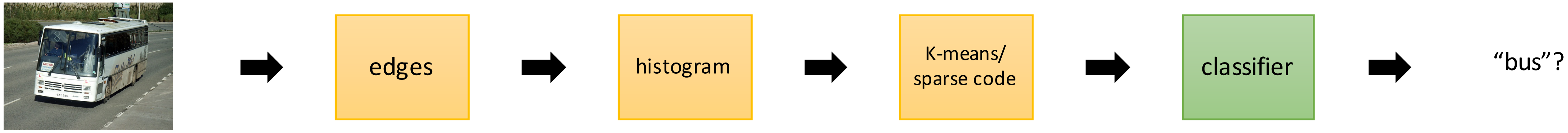
Traditional recognition

But what’s next?

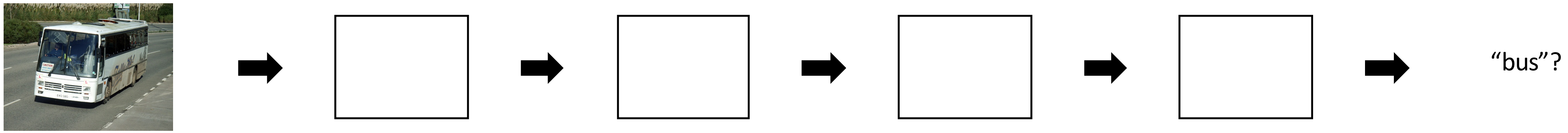


Deep Learning

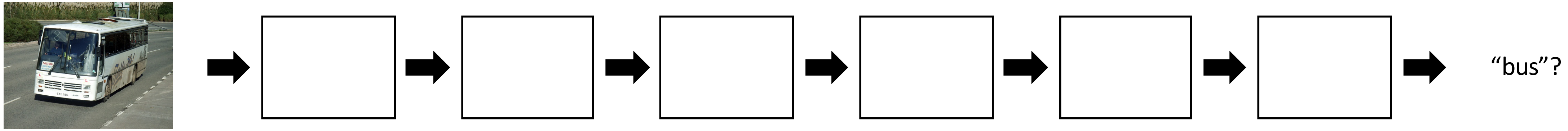
Specialized components, domain knowledge required



Generic components (“layers”), less domain knowledge

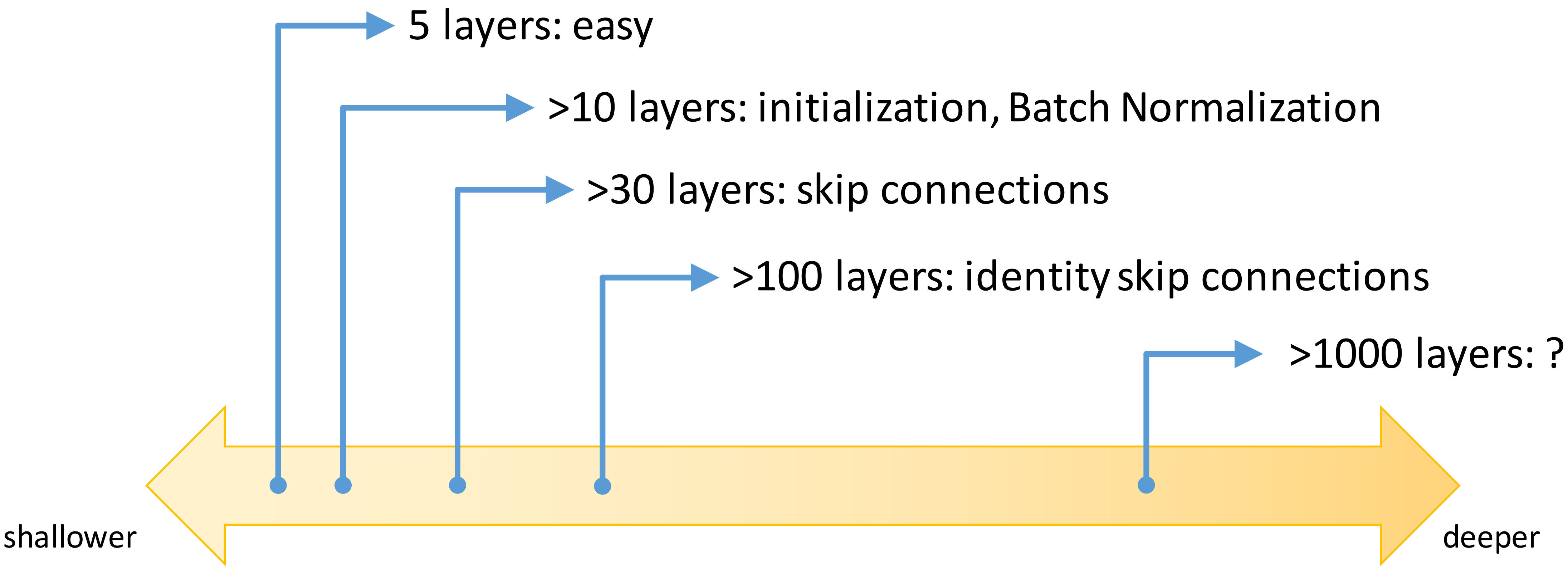


Repeat elementary layers => Going deeper



- End-to-end learning
- Richer solution space

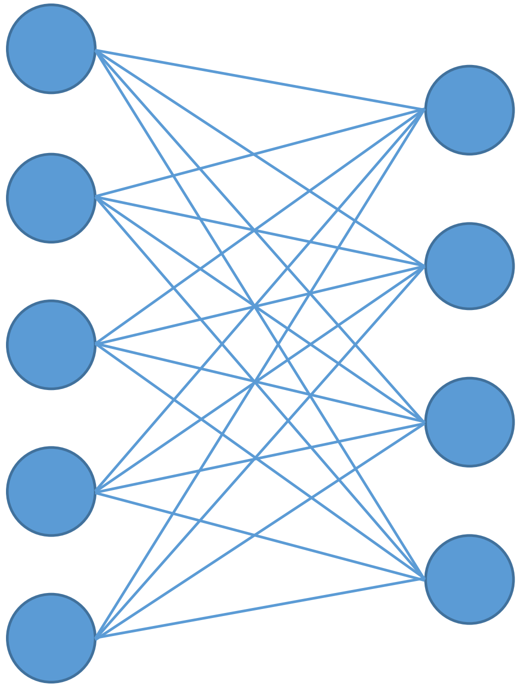
Spectrum of Depth



Initialization

weight
W

input
X



output
$Y = WX$

n^{in} n^{out}

If:

- Linear activation
- x, y, w: independent

Then:

1-layer:

$$Var[y] = (n^{in}Var[w])Var[x]$$

Multi-layer:

$$Var[y] = (\prod_d n_d^{in}Var[w_d])Var[x]$$

LeCun et al 1998 “Efficient Backprop”
Glorot & Bengio 2010 “Understanding the difficulty of training deep feedforward neural networks”

Initialization

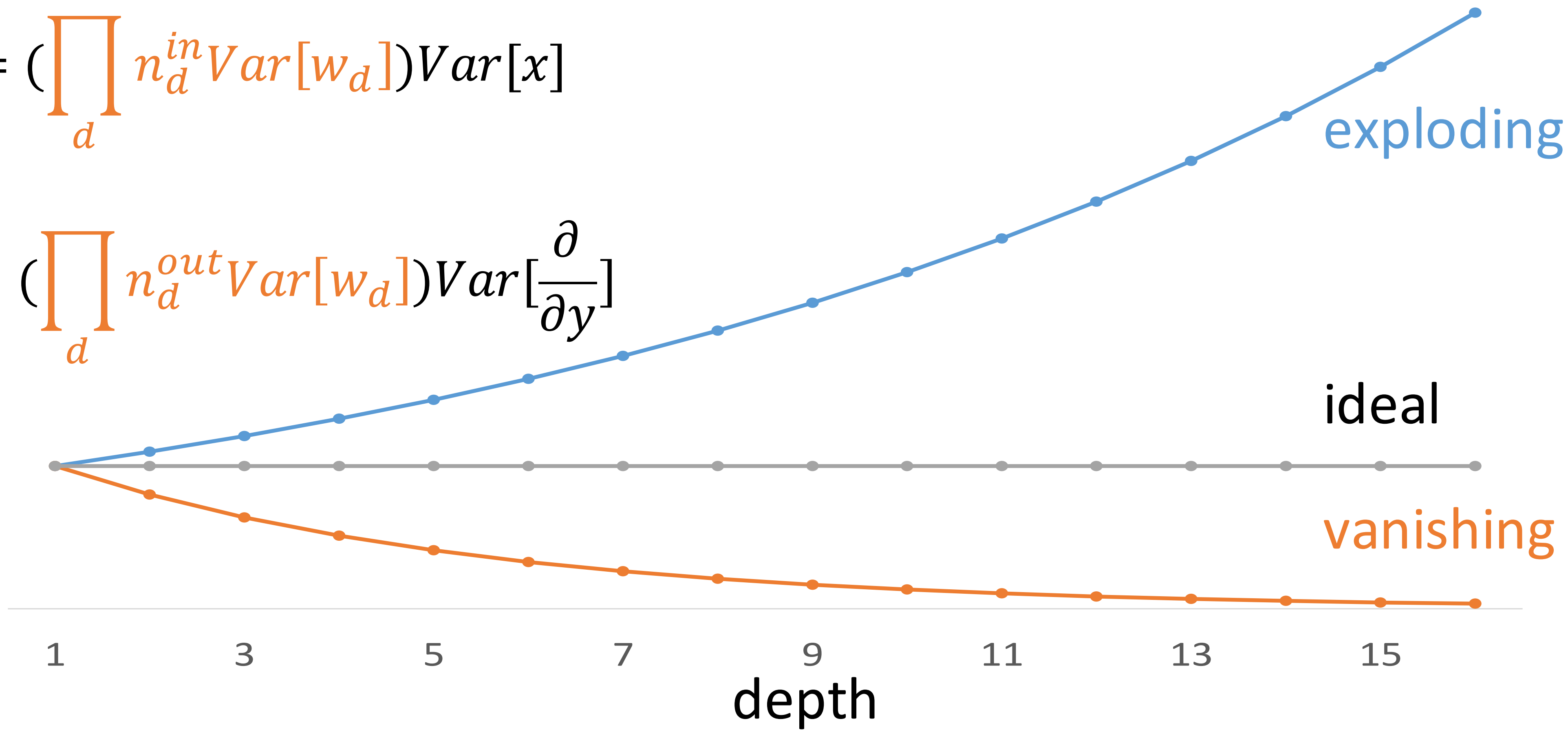
Both forward (response) and backward (gradient) signal can vanish/explode

Forward:

$$Var[y] = \left(\prod_d n_d^{in} Var[w_d]\right) Var[x]$$

Backward:

$$Var\left[\frac{\partial}{\partial x}\right] = \left(\prod_d n_d^{out} Var[w_d]\right) Var\left[\frac{\partial}{\partial y}\right]$$



LeCun et al 1998 “Efficient Backprop”

Glorot & Bengio 2010 “Understanding the difficulty of training deep feedforward neural networks”

Initialization

- Initialization under **linear** assumption

$$\prod_d n_d^{in} Var[w_d] = const_{\text{fw}} \text{ (healthy forward)}$$

and

$$\prod_d n_d^{out} Var[w_d] = const_{\text{bw}} \text{(healthy backward)}$$

$$\Rightarrow \boxed{\begin{array}{c} n_d^{in} Var[w_d] = 1 \\ \text{or*} \\ n_d^{out} Var[w_d] = 1 \end{array}}$$

*: $n_d^{out} = n_{d+1}^{in}$, so $\frac{const_{\text{bw}}}{const_{\text{fw}}} = \frac{n_{\text{last}}^{out}}{n_{\text{first}}^{in}} < \infty$.

It is sufficient to use either form.

"*Xavier*" init in Caffe

LeCun et al 1998 "Efficient Backprop"

Glorot & Bengio 2010 "Understanding the difficulty of training deep feedforward neural networks"

Initialization

- Initialization under **ReLU** activation

$$\prod_d \frac{1}{2} n_d^{in} Var[w_d] = const_{\mathrm{fw}} \text{ (healthy forward)}$$

and

$$\prod_d \frac{1}{2} n_d^{out} Var[w_d] = const_{\mathrm{bw}} \text{(healthy backward)}$$

➡ $$\boxed{\begin{array}{c} \frac{1}{2} n_d^{in} Var[w_d] = 1 \\ \text{or} \\ \frac{1}{2} n_d^{out} Var[w_d] = 1 \end{array}}$$

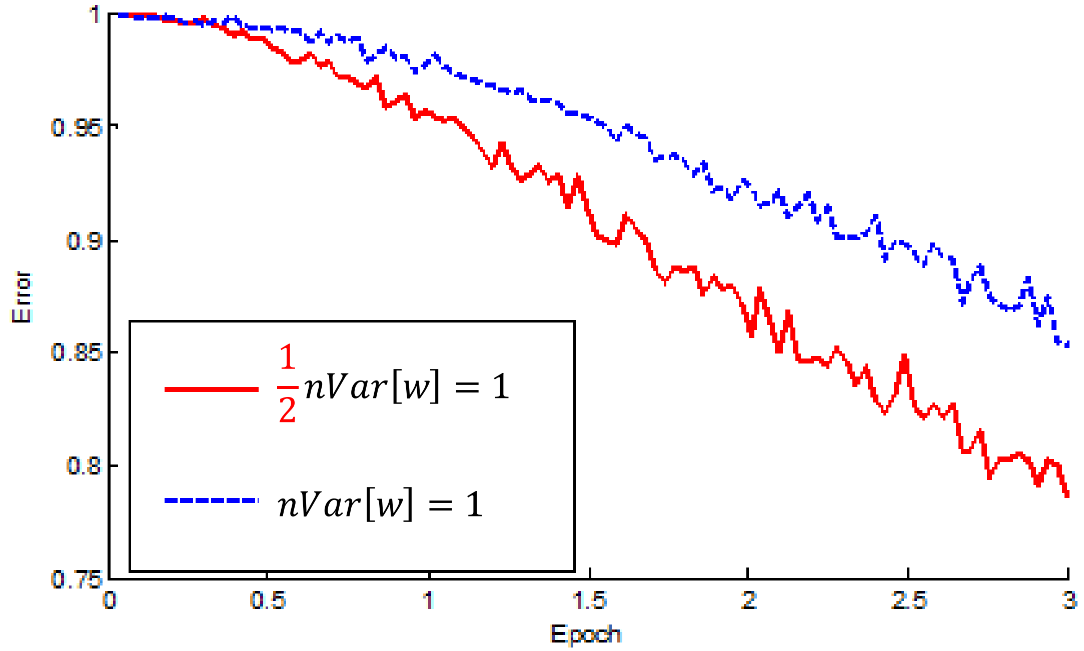
"*MSRA*" init in Caffe

With D layers, a factor of 2 per layer has exponential impact of 2^D

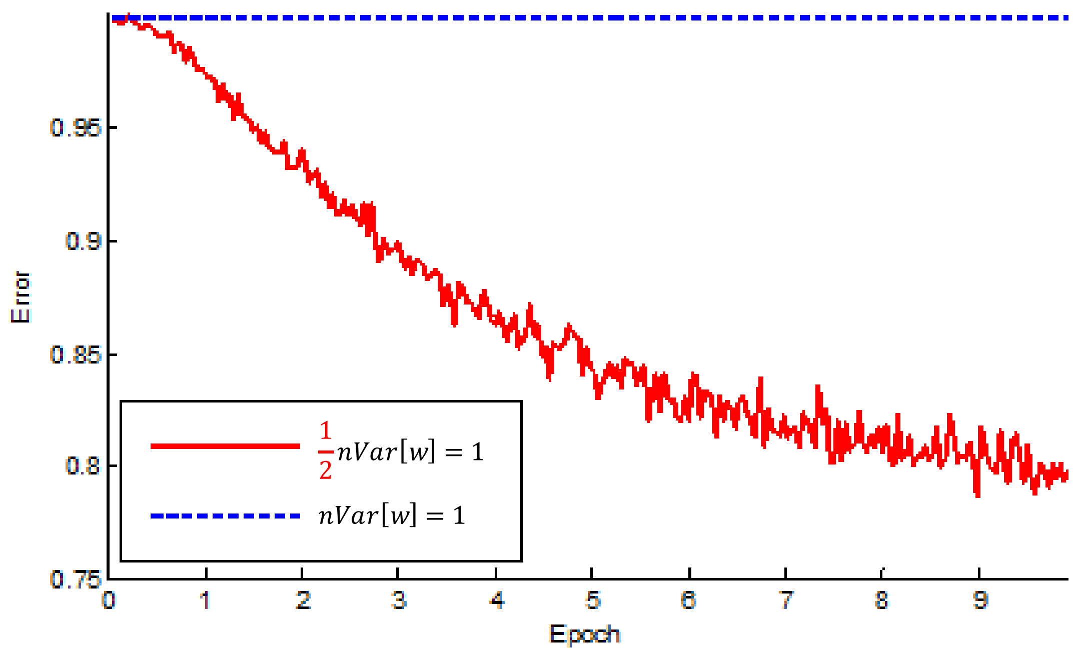
Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Delving Deep into Rectifiers: Surpassing Human-Level Performance on ImageNet Classification". ICCV 2015.

Initialization

22-layer ReLU net:
good init converges faster



30-layer ReLU net:
good init is able to converge



*Figures show the beginning of training

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Delving Deep into Rectifiers: Surpassing Human-Level Performance on ImageNet Classification”. ICCV 2015.

Batch Normalization (BN)

- Normalizing input (LeCun et al 1998 “Efficient Backprop”)
- BN: normalizing each layer, for each mini-batch
- Greatly accelerate training
- Less sensitive to initialization
- Improve regularization

S. Ioffe & C. Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. ICML 2015

Batch Normalization (BN)

$$\rightarrow \boxed{\text{layer}} \rightarrow x \rightarrow \quad \hat{x} = \frac{x - \mu}{\sigma} \quad \rightarrow \quad y = \gamma \hat{x} + \beta$$

- μ: mean of x in mini-batch
- σ: std of x in mini-batch
- γ: scale
- β: shift

- μ, σ: functions of x, analogous to responses
- γ, β: parameters to be learned, analogous to weights

S. Ioffe & C. Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. ICML 2015

Batch Normalization (BN)

$$\rightarrow \boxed{\text{layer}} \rightarrow x \rightarrow \quad \hat{x} = \frac{x - \mu}{\sigma} \quad \rightarrow \quad y = \gamma \hat{x} + \beta$$

2 modes of BN:

- Train mode:
  - μ, σ are functions of x; backprop gradients
- Test mode:
  - μ, σ are pre-computed* on training set

Caution: make sure your BN is in a correct mode

*: by running average, or post-processing after training

S. Ioffe & C. Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. ICML 2015

Batch Normalization (BN)

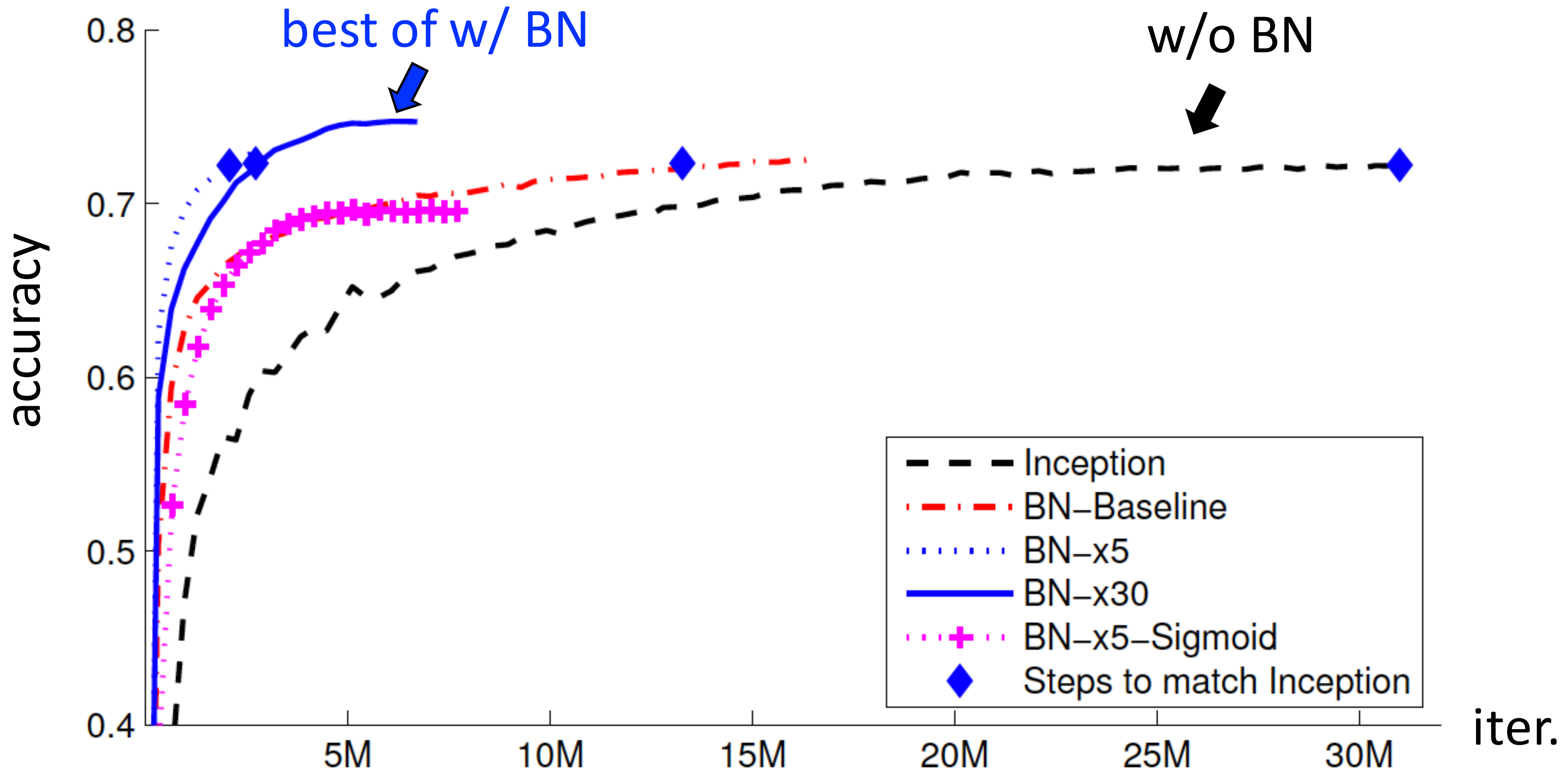


Figure taken from [S. Ioffe & C. Szegedy]

S. Ioffe & C. Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. ICML 2015

Deep Residual Networks

From 10 layers to 100 layers

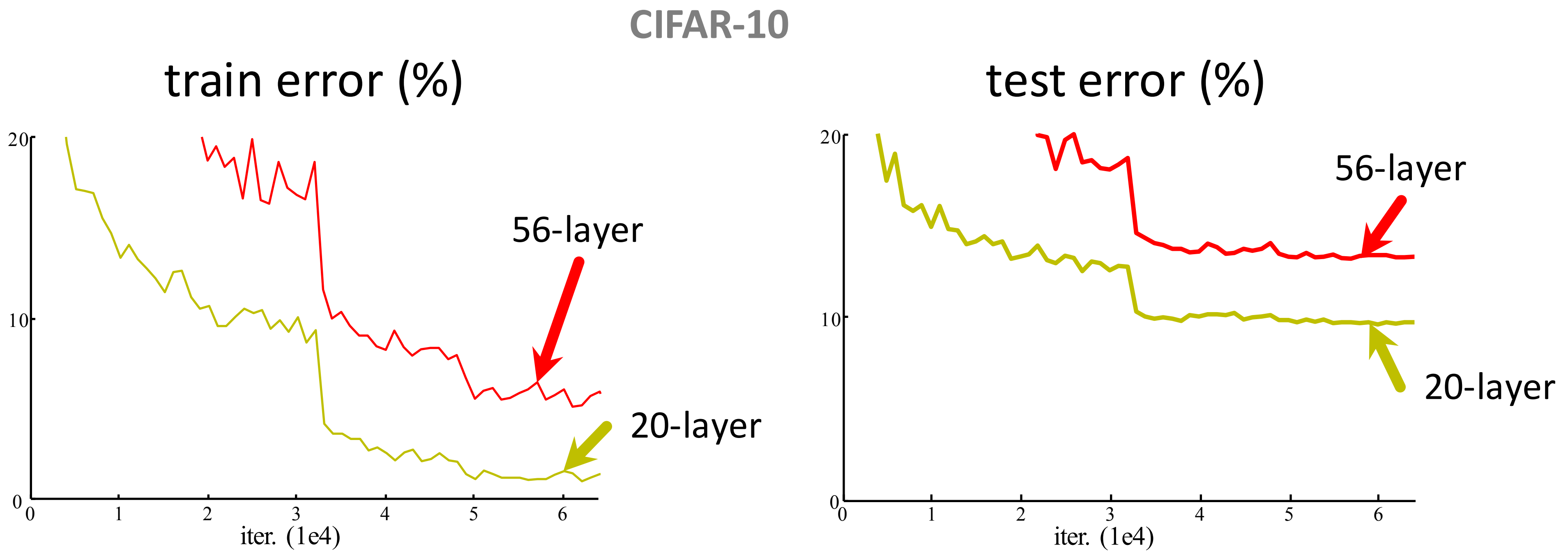
Going Deeper

- Initialization algorithms ✓
- Batch Normalization ✓

- **Is learning better networks as simple as stacking more layers?**

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". CVPR 2016.

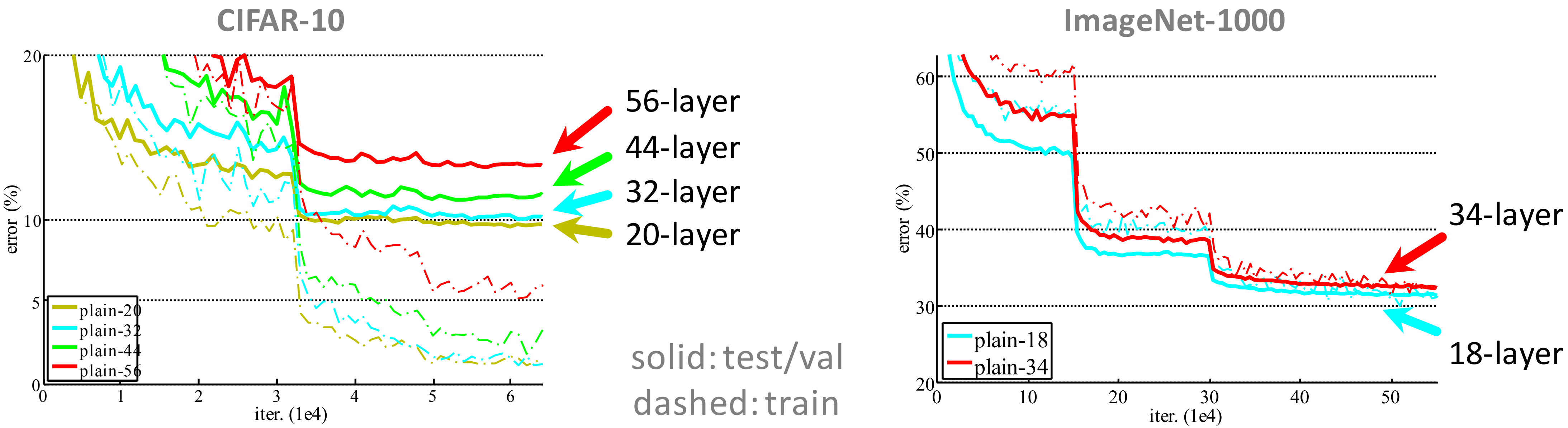
Simply stacking layers?



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

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. CVPR 2016.

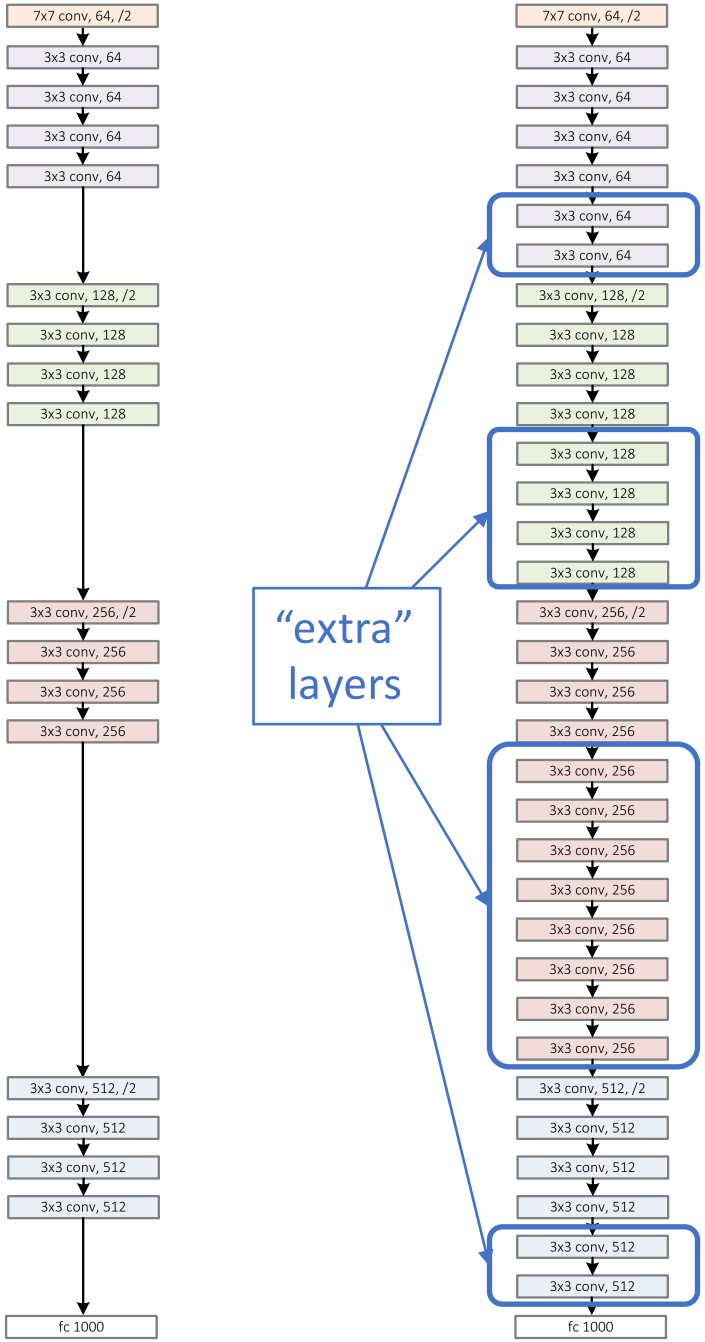
Simply stacking layers?



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

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. CVPR 2016.

a shallower model
(18 layers)



a deeper counterpart
(34 layers)

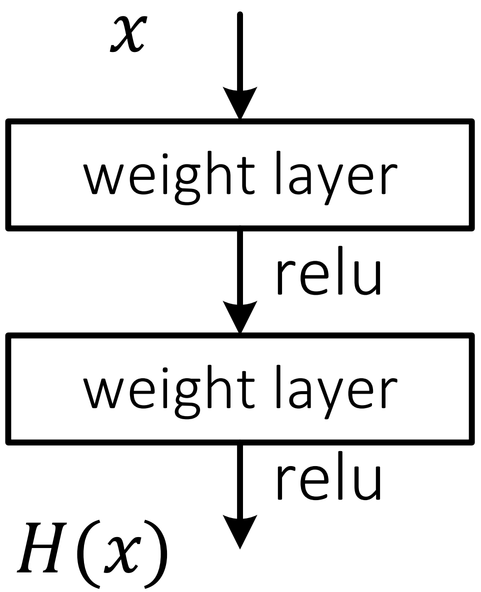
- Richer solution space
- A deeper model should not have **higher training error**
- A solution *by construction*:
  - original layers: copied from a learned shallower model
  - extra layers: set as identity
  - at least the same training error
- Optimization difficulties: solvers cannot find the solution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

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. CVPR 2016.

Deep Residual Learning

- Plaint net

any two
stacked layers



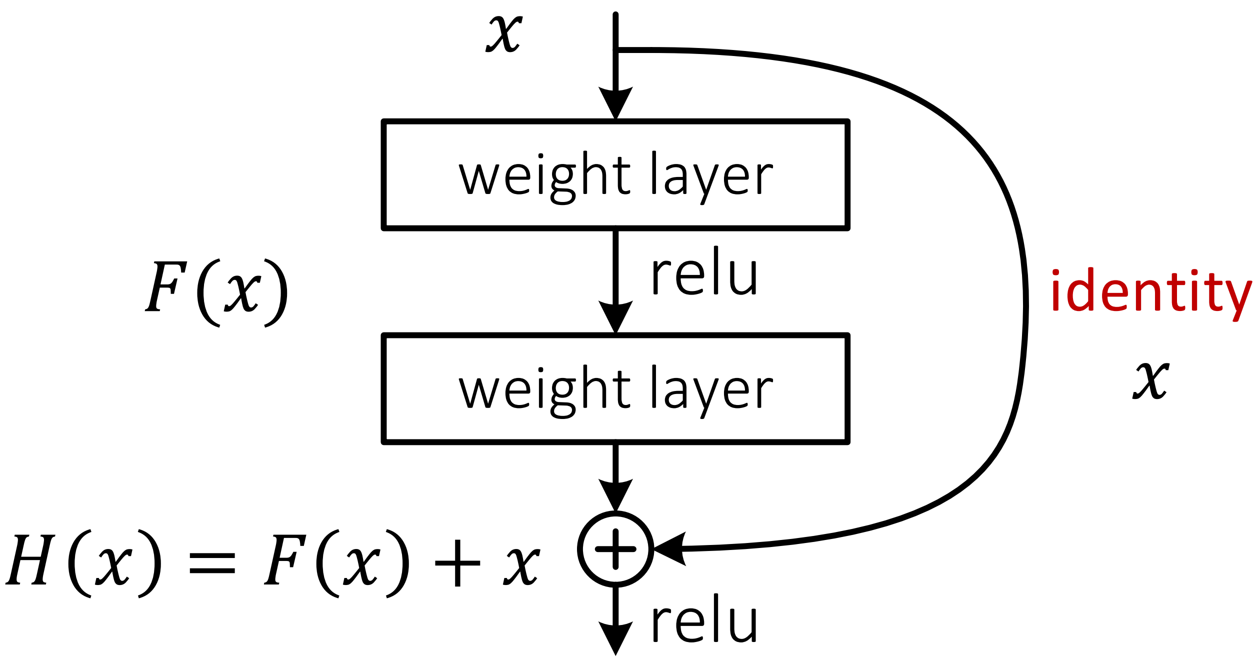
$H(x)$ is any desired mapping,

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

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". CVPR 2016.

Deep Residual Learning

- Residual net



$H(x)$ is any desired mapping,

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

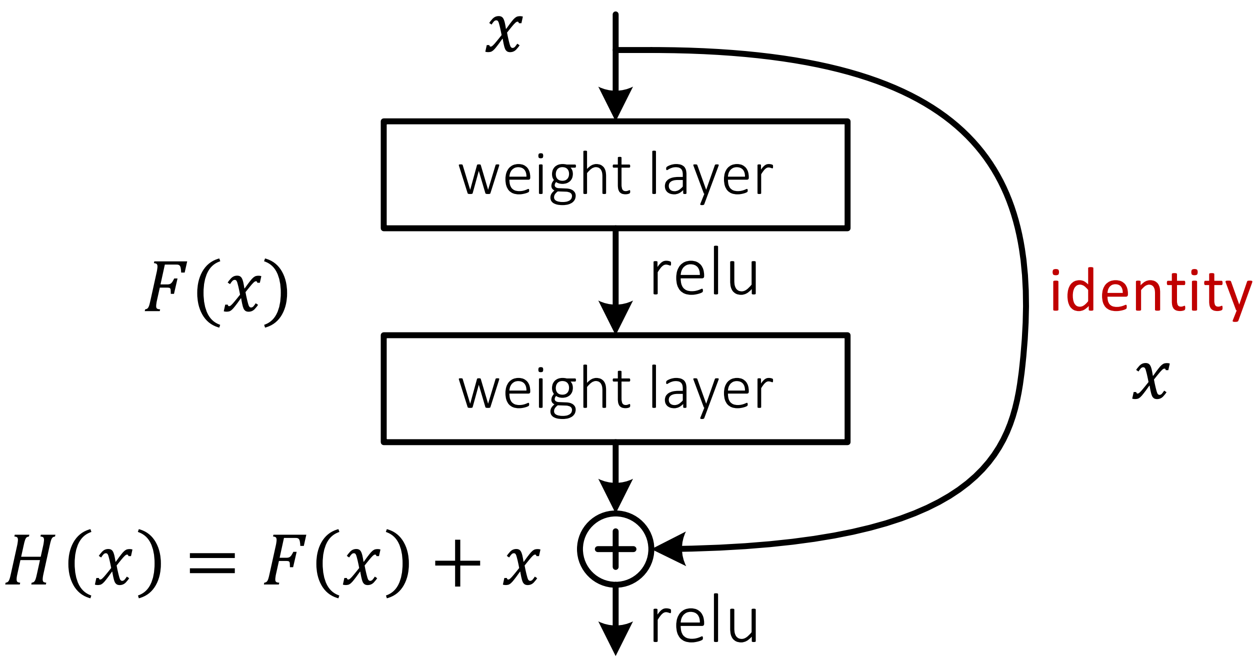
hope the 2 weight layers fit $F(x)$

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

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". CVPR 2016.

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

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. CVPR 2016.

Related Works – Residual Representations

- VLAD & Fisher Vector [Jegou et al 2010], [Perronnin et al 2007]
  - Encoding residual vectors; powerful shallower representations.
- Product Quantization (IVF-ADC) [Jegou et al 2011]
  - Quantizing residual vectors; efficient nearest-neighbor search.
- MultiGrid & Hierarchical Precondition [Briggs, et al 2000], [Szeliski 1990, 2006]
  - Solving residual sub-problems; efficient PDE solvers.

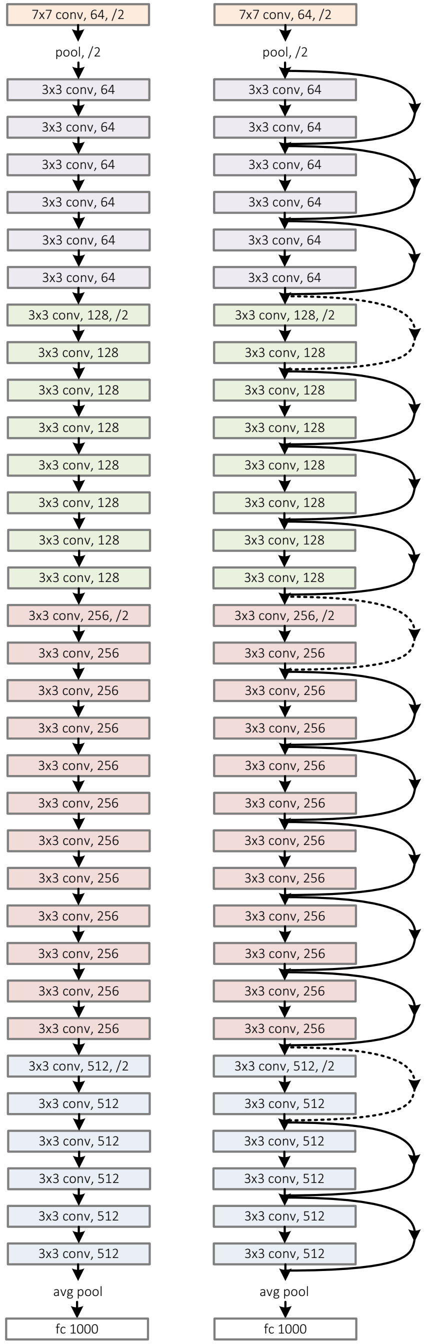
Network “Design”

- Keep it simple

- Our basic design (VGG-style)
  - all 3x3 conv (almost)
  - spatial size /2 => # filters x2 (~same complexity per layer)
  - Simple design; just deep!

- Other remarks:
  - no hidden fc
  - no dropout

plain net



ResNet

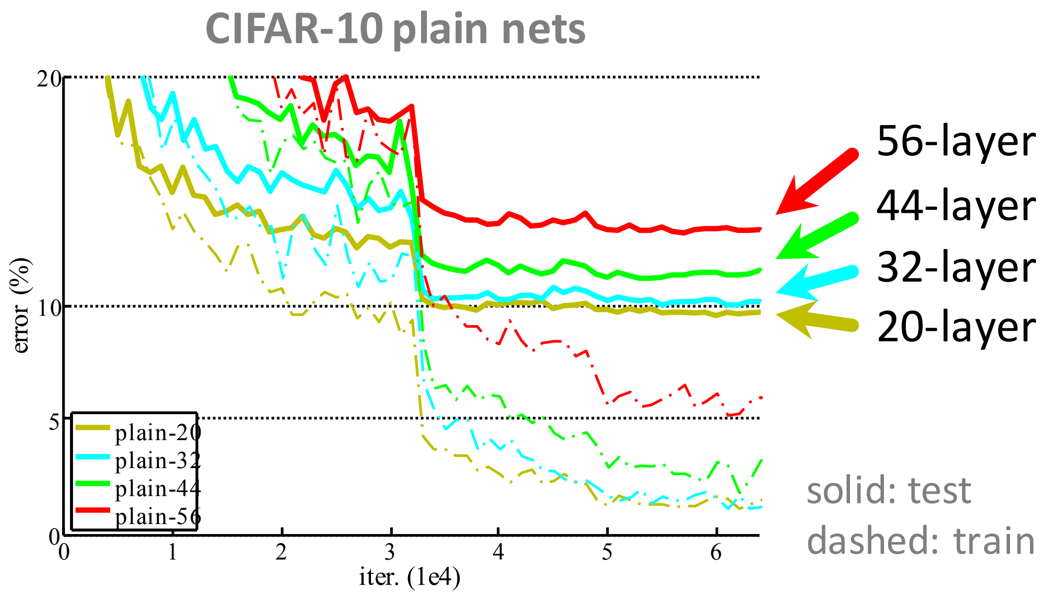
Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. CVPR 2016.

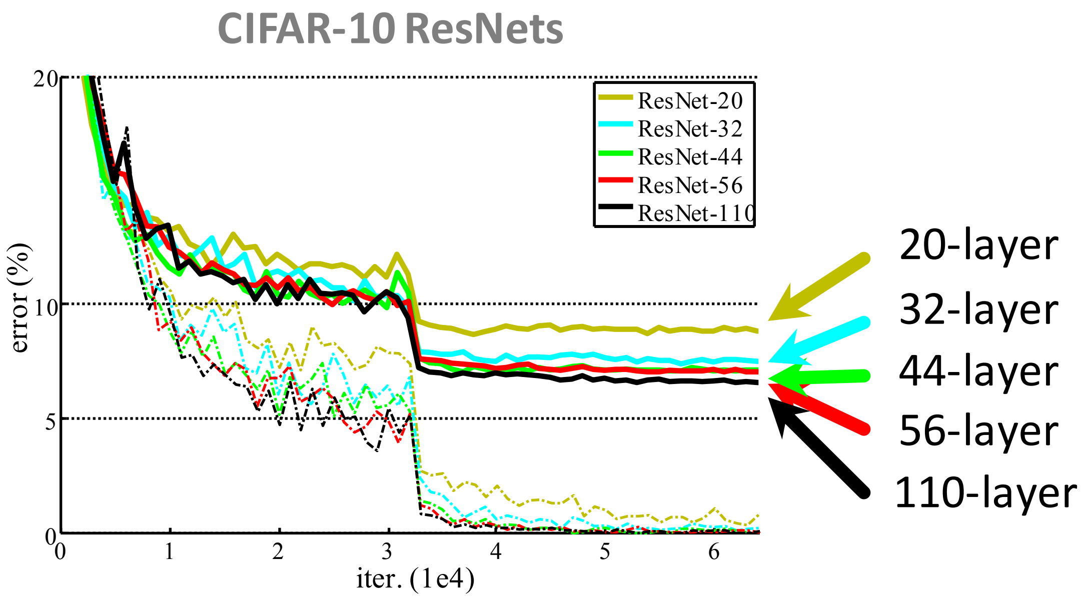
Training

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

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. CVPR 2016.

CIFAR-10 experiments

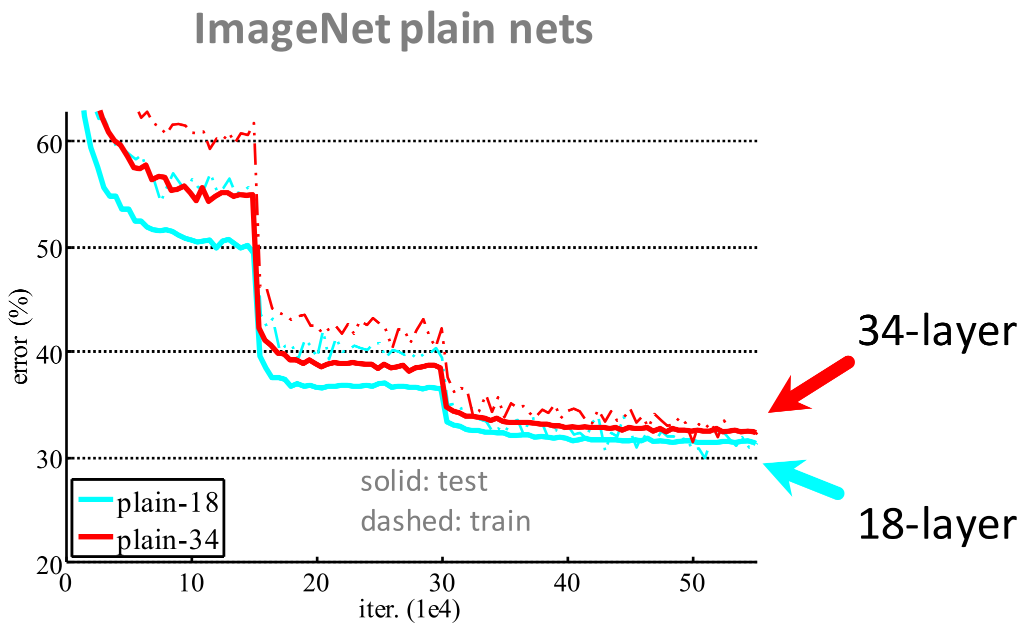


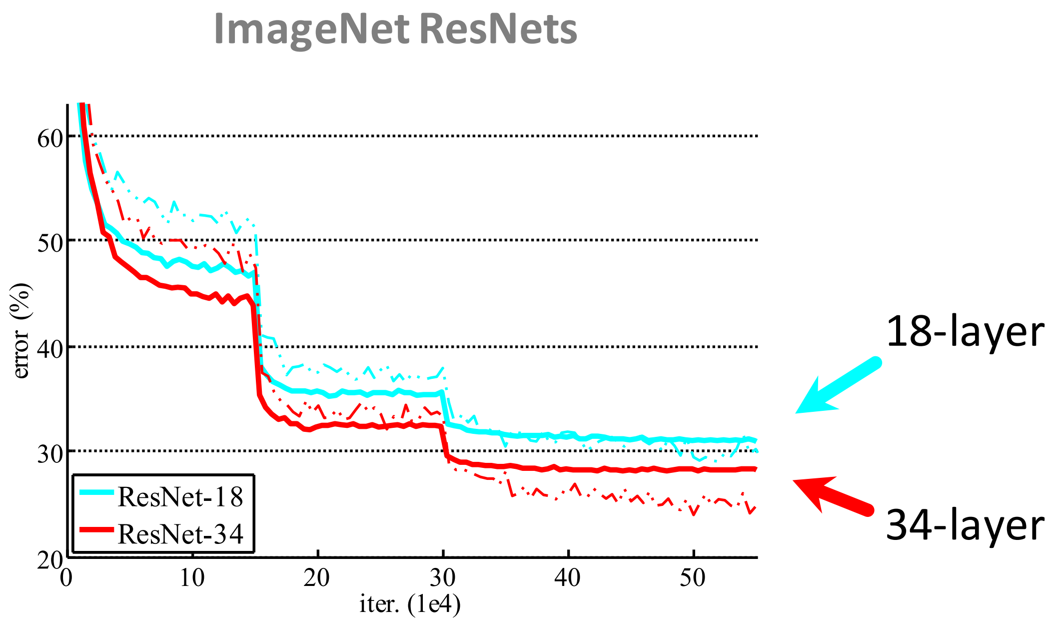


- Deep ResNets can be trained without difficulties
- Deeper ResNets have **lower training error**, and also lower test error

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". CVPR 2016.

ImageNet experiments



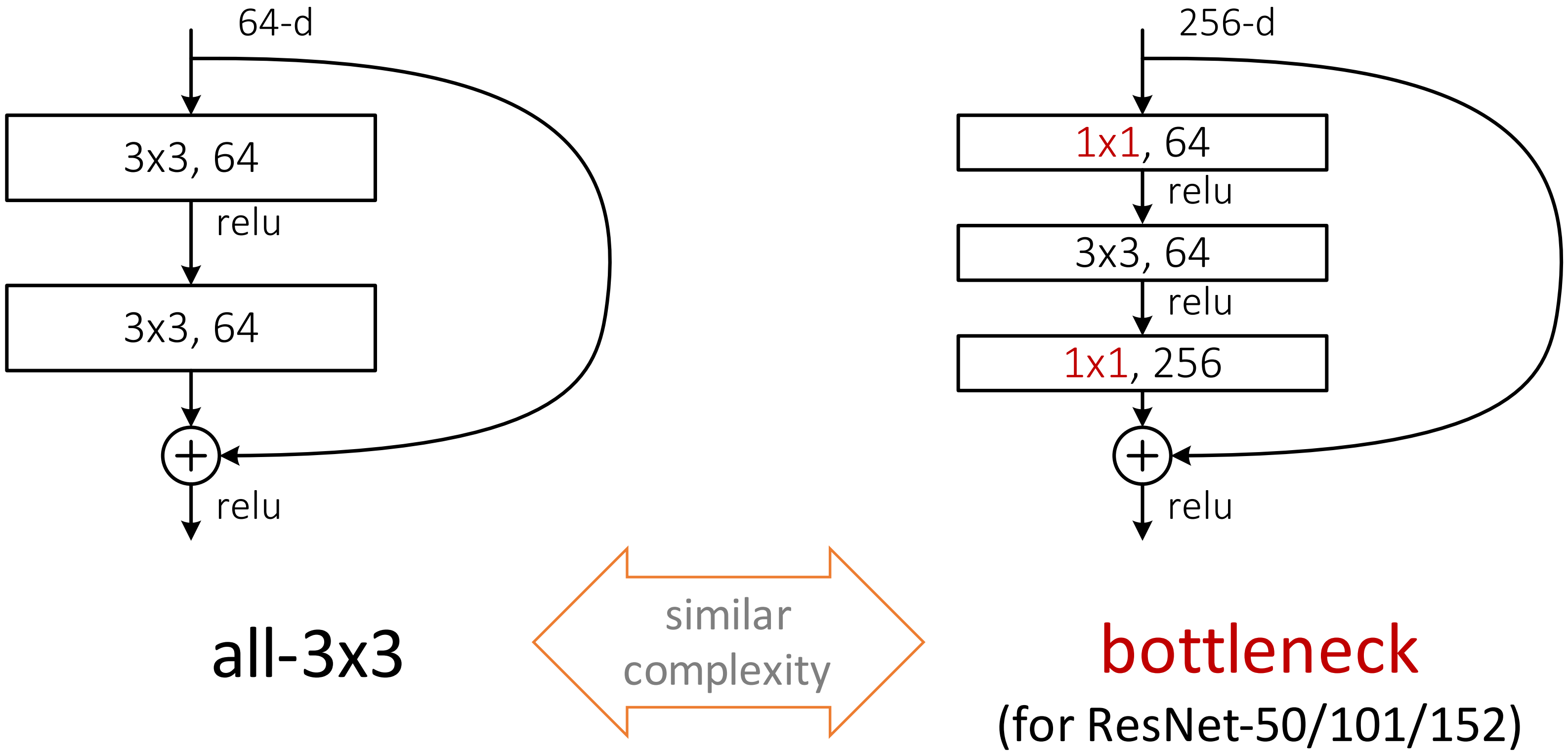


- Deep ResNets can be trained without difficulties
- Deeper ResNets have **lower training error**, and also lower test error

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. CVPR 2016.

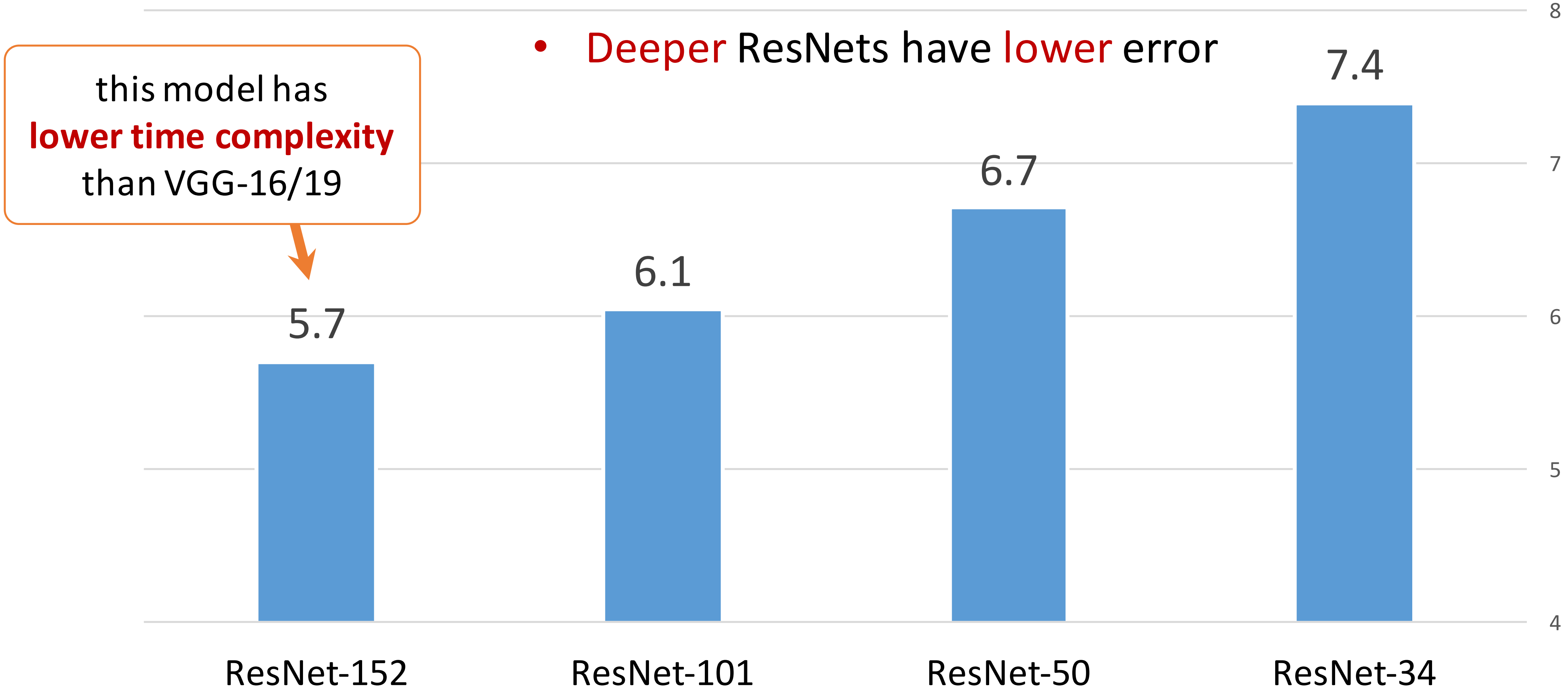
ImageNet experiments

- A practical design of going deeper



Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". CVPR 2016.

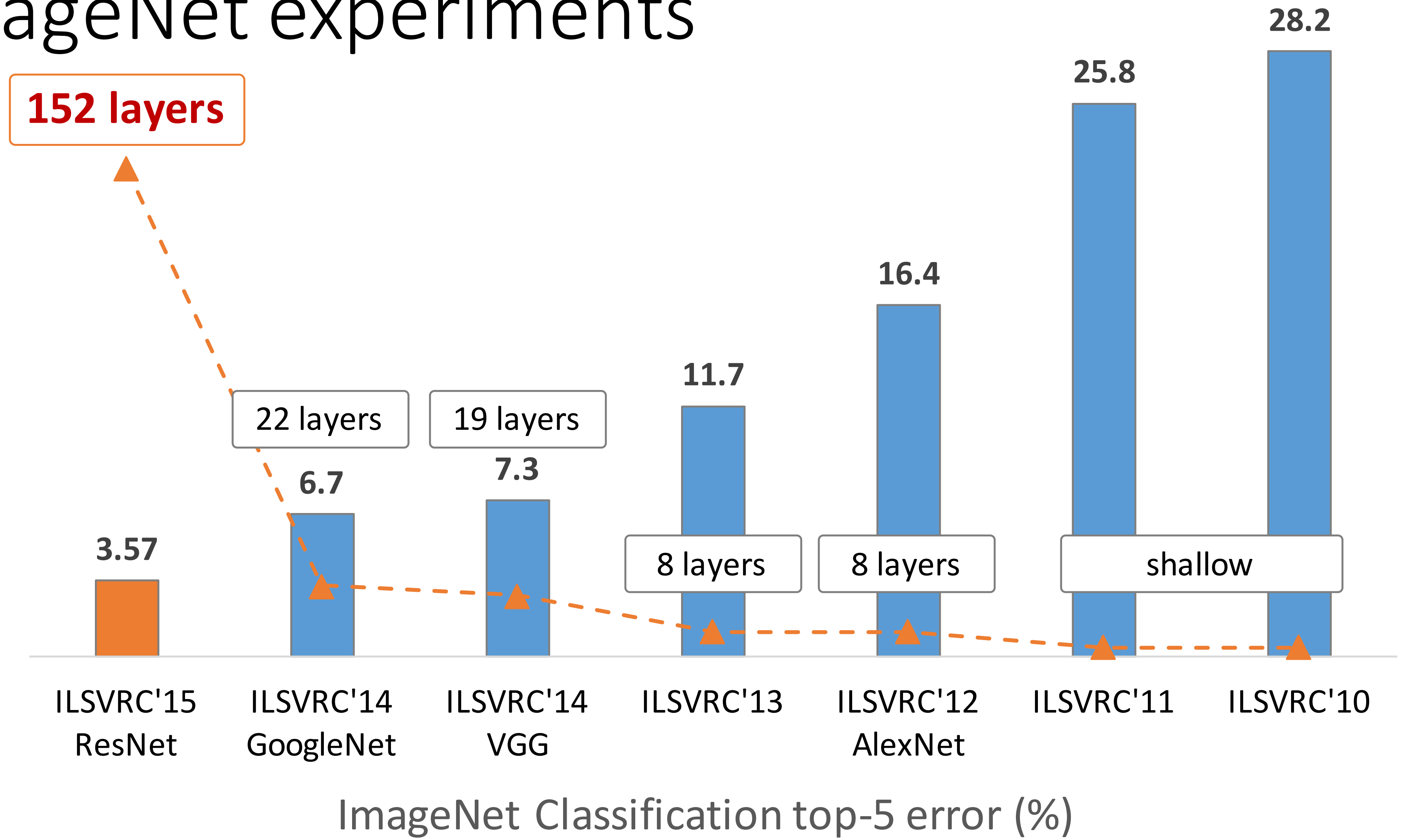
ImageNet experiments



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

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. CVPR 2016.

ImageNet experiments



Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. CVPR 2016.

Discussions

Representation, Optimization, Generalization

Issues on learning deep models

- **Representation** ability
  - Ability of model to fit training data, if optimum could be found
  - If model A's solution space is a superset of B's, A should be better.
- **Optimization** ability
  - Feasibility of finding an optimum
  - Not all models are equally easy to optimize
- **Generalization** ability
  - Once training data is fit, how good is the test performance

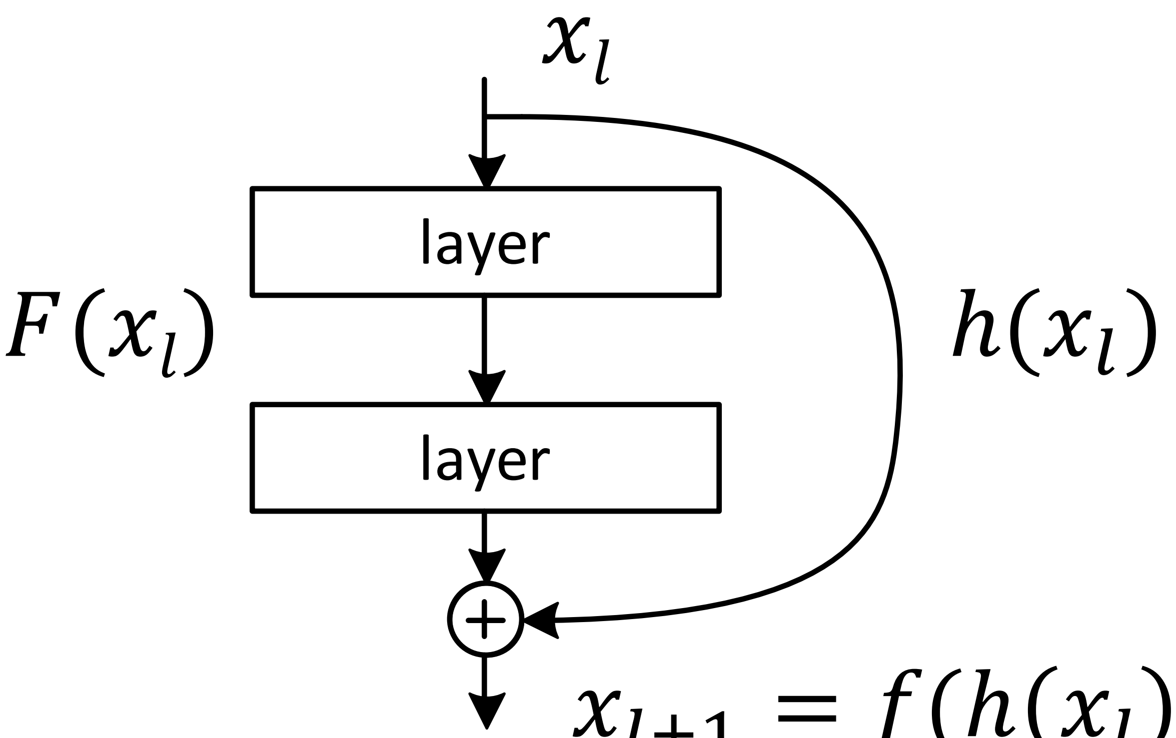
How do ResNets address these issues?

- **Representation** ability
  - No explicit advantage on representation (only re-parameterization), but
  - Allow models to go deeper
- **Optimization** ability
  - Enable very smooth forward/backward prop
  - Greatly ease optimizing deeper models
- **Generalization** ability
  - Not explicitly address generalization, but
  - Deeper+thinner is good generalization

On the Importance of Identity Mapping

From 100 layers to 1000 layers

On identity mappings for **optimization**

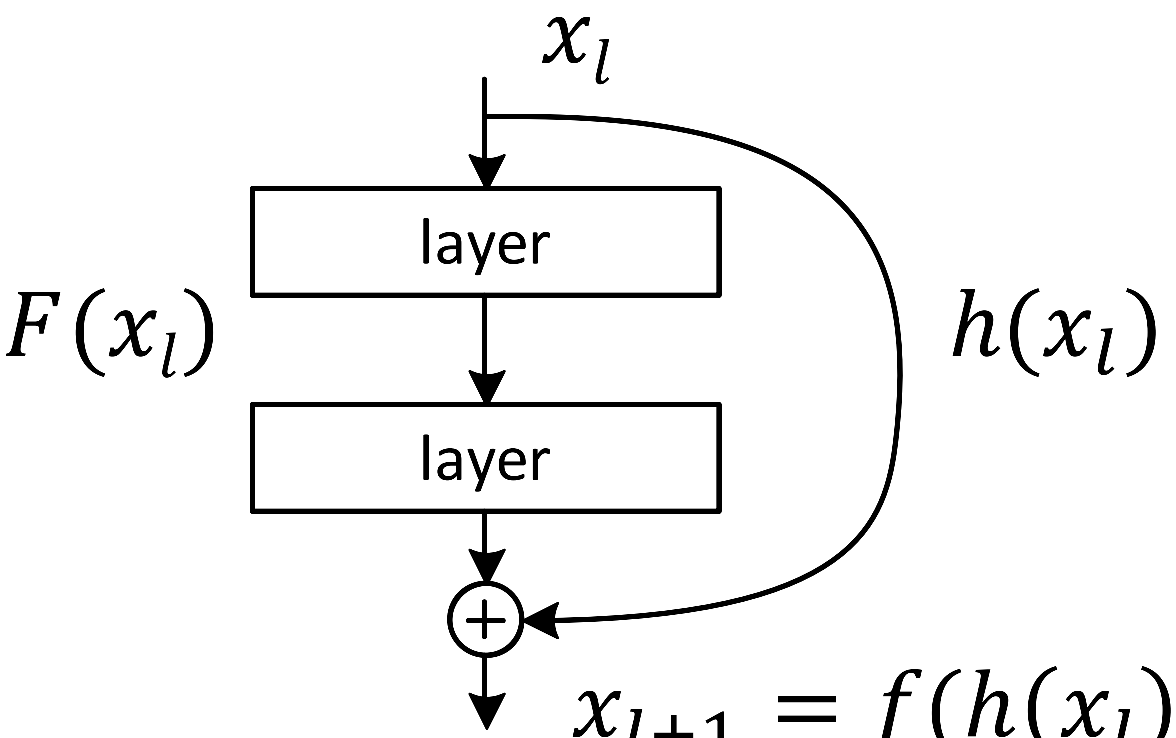


$$x_{l+1} = f(h(x_l) + F(x_l))$$

- shortcut mapping: h = identity
- after-add mapping: f = ReLU

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Identity Mappings in Deep Residual Networks". arXiv 2016.

On identity mappings for **optimization**

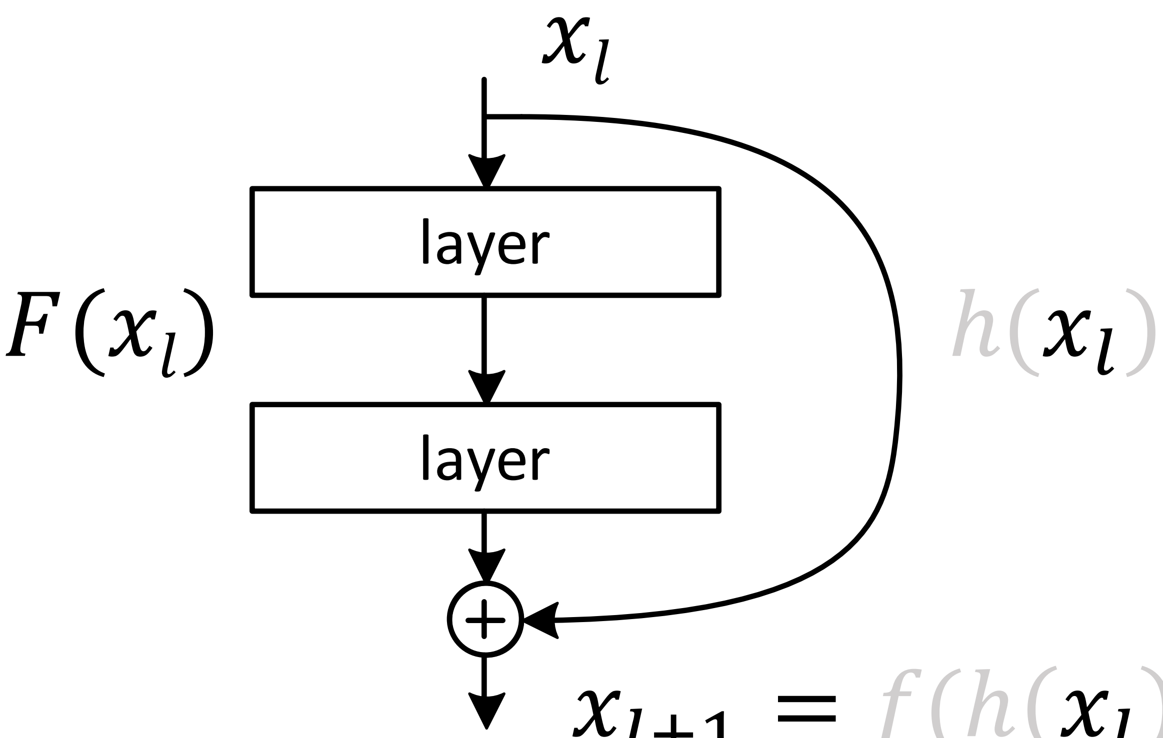


$$x_{l+1} = f(h(x_l) + F(x_l))$$

- shortcut mapping: h = identity
- ~~after-add mapping: f = ReLU~~
- What if f = identity?

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Identity Mappings in Deep Residual Networks". arXiv 2016.

On identity mappings for **optimization**



$$x_{l+1} = f(h(x_l) + F(x_l))$$

- shortcut mapping: h = identity
- ~~after-add mapping: f = ReLU~~
- What if f = identity?

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Identity Mappings in Deep Residual Networks". arXiv 2016.

Very smooth forward propagation

$$x_{l+1} = x_l + F(x_l)$$

$$x_{l+2} = x_{l+1} + F(x_{l+1})$$

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Identity Mappings in Deep Residual Networks". arXiv 2016.

Very smooth forward propagation

$$x_{l+1} = x_l + F(x_l)$$

$$x_{l+2} = x_{l+1} + F(x_{l+1})$$

$$x_{l+2} = x_l + F(x_l) + F(x_{l+1})$$

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Identity Mappings in Deep Residual Networks”. arXiv 2016.

Very smooth forward propagation

$$x_{l+1} = x_l + F(x_l)$$

$$x_{l+2} = x_{l+1} + F(x_{l+1})$$

$$x_{l+2} = x_l + F(x_l) + F(x_{l+1})$$

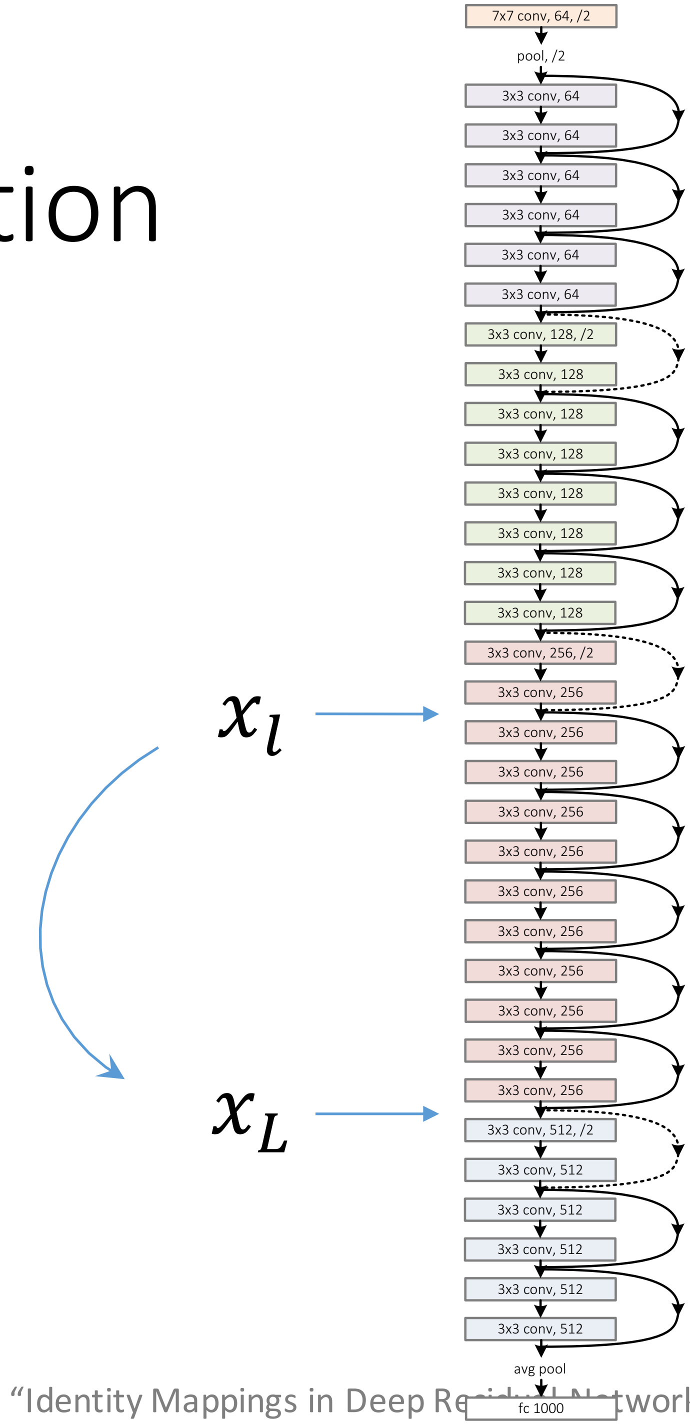
$$x_L = x_l + \sum_{i=l}^{L-1} F(x_i)$$

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Identity Mappings in Deep Residual Networks”. arXiv 2016.

Very smooth forward propagation

$$x_L = x_l + \sum_{i=l}^{L-1} F(x_i)$$

- Any x_l is directly forward-prop to any x_L, plus residual.
- Any x_L is an additive outcome.
  - in contrast to multiplicative: $x_L = \prod_{i=l}^{L-1} W_i x_l$



Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Identity Mappings in Deep Residual Networks”. arXiv 2016.

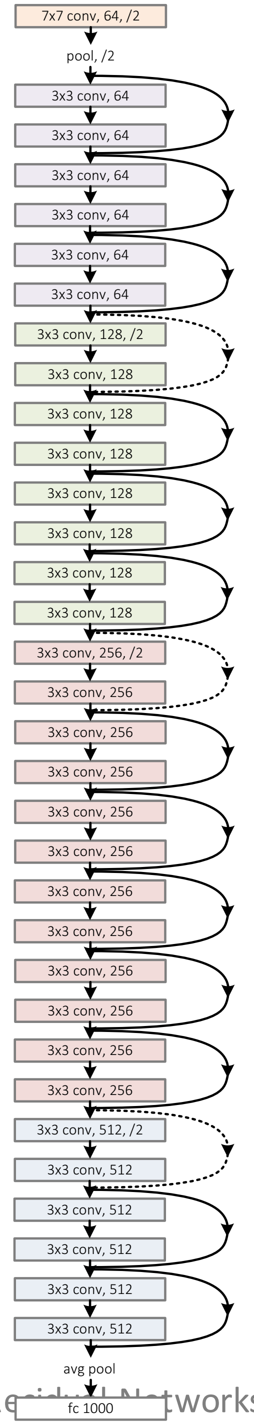
Very smooth backward propagation

$$x_L = x_l + \sum_{i=l}^{L-1} F(x_i)$$

$$\frac{\partial E}{\partial x_l} = \frac{\partial E}{\partial x_L}\frac{\partial x_L}{\partial x_l} = \frac{\partial E}{\partial x_L}\left(1 + \frac{\partial}{\partial x_l}\sum_{i=1}^{L-1} F(x_i)\right)$$

$$\frac{\partial E}{\partial x_l}$$

$$\frac{\partial E}{\partial x_L}$$

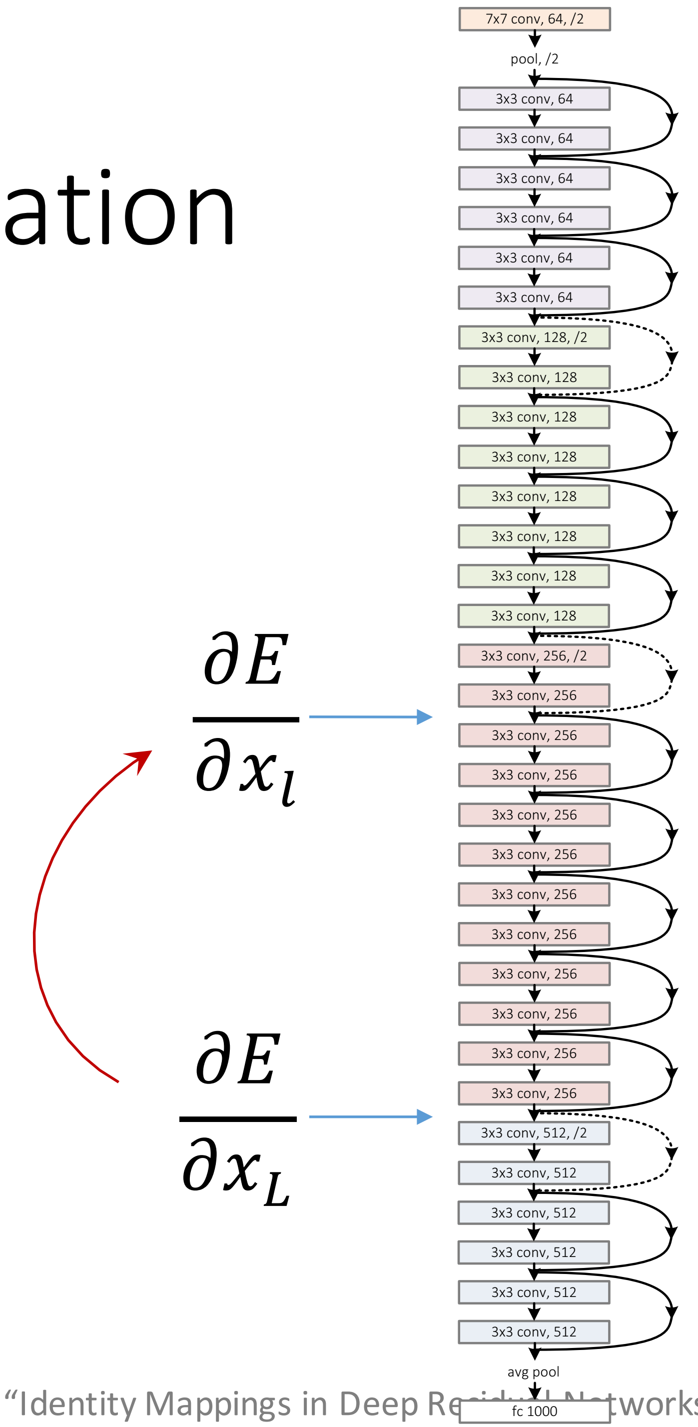


Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Identity Mappings in Deep Residual Networks". arXiv 2016.

Very smooth backward propagation

$$\frac{\partial E}{\partial x_l} = \frac{\partial E}{\partial x_L}\left(1 + \frac{\partial}{\partial x_l}\sum_{i=1}^{L-1} F(x_i)\right)$$

- Any $\frac{\partial E}{\partial x_L}$ is directly back-prop to any $\frac{\partial E}{\partial x_l}$, plus residual.
- Any $\frac{\partial E}{\partial x_l}$ is additive; unlikely to vanish
  - in contrast to multiplicative: $\frac{\partial E}{\partial x_l} = \prod_{i=l}^{L-1} W_i \frac{\partial E}{\partial x_L}$



Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Identity Mappings in Deep Residual Networks”. arXiv 2016.

Residual for every layer

forward: $$x_L = x_l + \sum_{i=l}^{L-1} F(x_i)$$

Enabled by:

- shortcut mapping: h = identity
- after-add mapping: f = identity

backward: $$\frac{\partial E}{\partial x_l} = \frac{\partial E}{\partial x_L}\left(1 + \frac{\partial}{\partial x_l}\sum_{i=1}^{L-1} F(x_i)\right)$$

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Identity Mappings in Deep Residual Networks". arXiv 2016.

Experiments

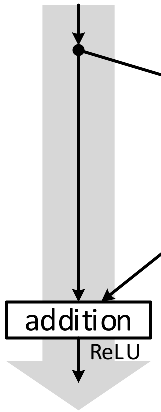
- Set 1: what if shortcut mapping $h \neq$ identity
- Set 2: what if after-add mapping f is identity
- Experiments on ResNets with more than 100 layers
  - deeper models suffer more from optimization difficulty

Experiment Set 1:
what if shortcut mapping $h \neq$ identity?

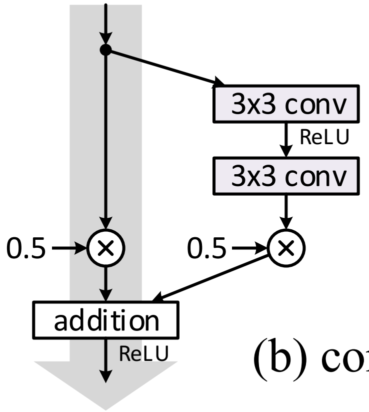
* ResNet-110 on CIFAR-10

$h(x) = x$

error: 6.6%



(a) original



(b) constant scaling

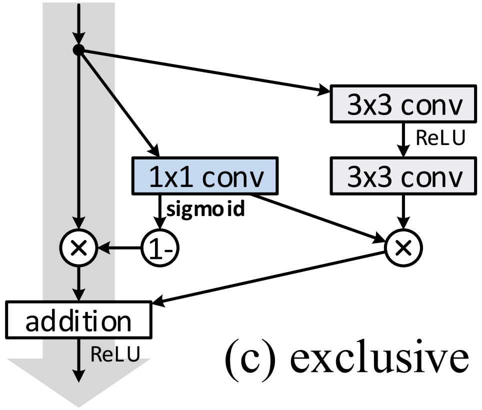
$h(x) = 0.5x$

error: 12.4%

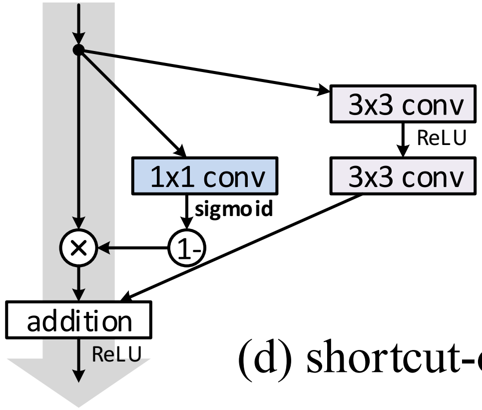
$h(x) = \text{gate} \cdot x$

error: 8.7%

*similar to “Highway Network”



(c) exclusive gating



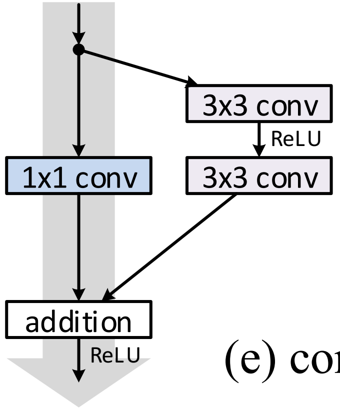
(d) shortcut-only gating

$h(x) = \text{gate} \cdot x$

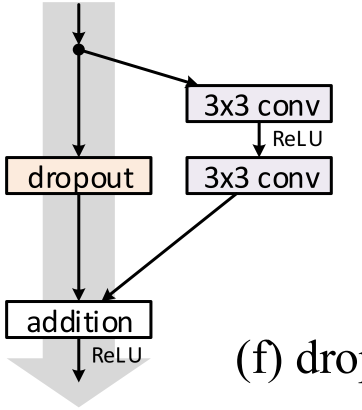
error: 12.9%

$h(x) = \text{conv}(x)$

error: 12.2%



(e) conv shortcut



(f) dropout shortcut

$h(x) = \text{dropout}(x)$

error: > 20%

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Identity Mappings in Deep Residual Networks”. arXiv 2016.

* ResNet-110 on CIFAR-10

$h(x) = x$
error: 6.6%

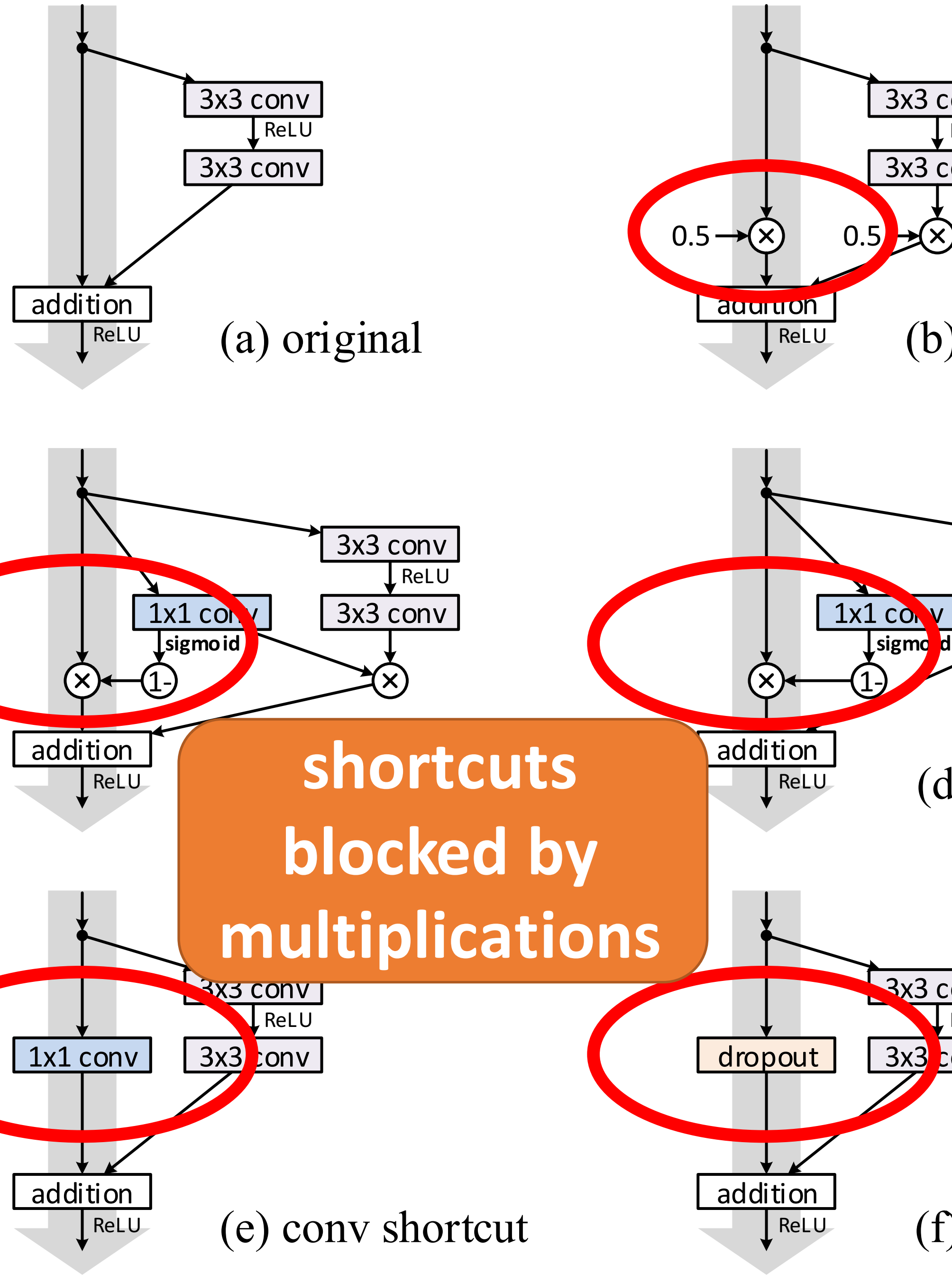
$h(x) = 0.5x$
error: 12.4%

$h(x) = \text{gate} \cdot x$
error: 8.7%

$h(x) = \text{gate} \cdot x$
error: 12.9%

$h(x) = \text{conv}(x)$
error: 12.2%

$h(x) = \text{dropout}(x)$
error: > 20%



(a) original
(b) constant scaling
(d) shortcut-only gating
(e) conv shortcut
(f) dropout shortcut

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Identity Mappings in Deep Residual Networks”. arXiv 2016.

If h is multiplicative, e.g. $h(x) = \lambda x$

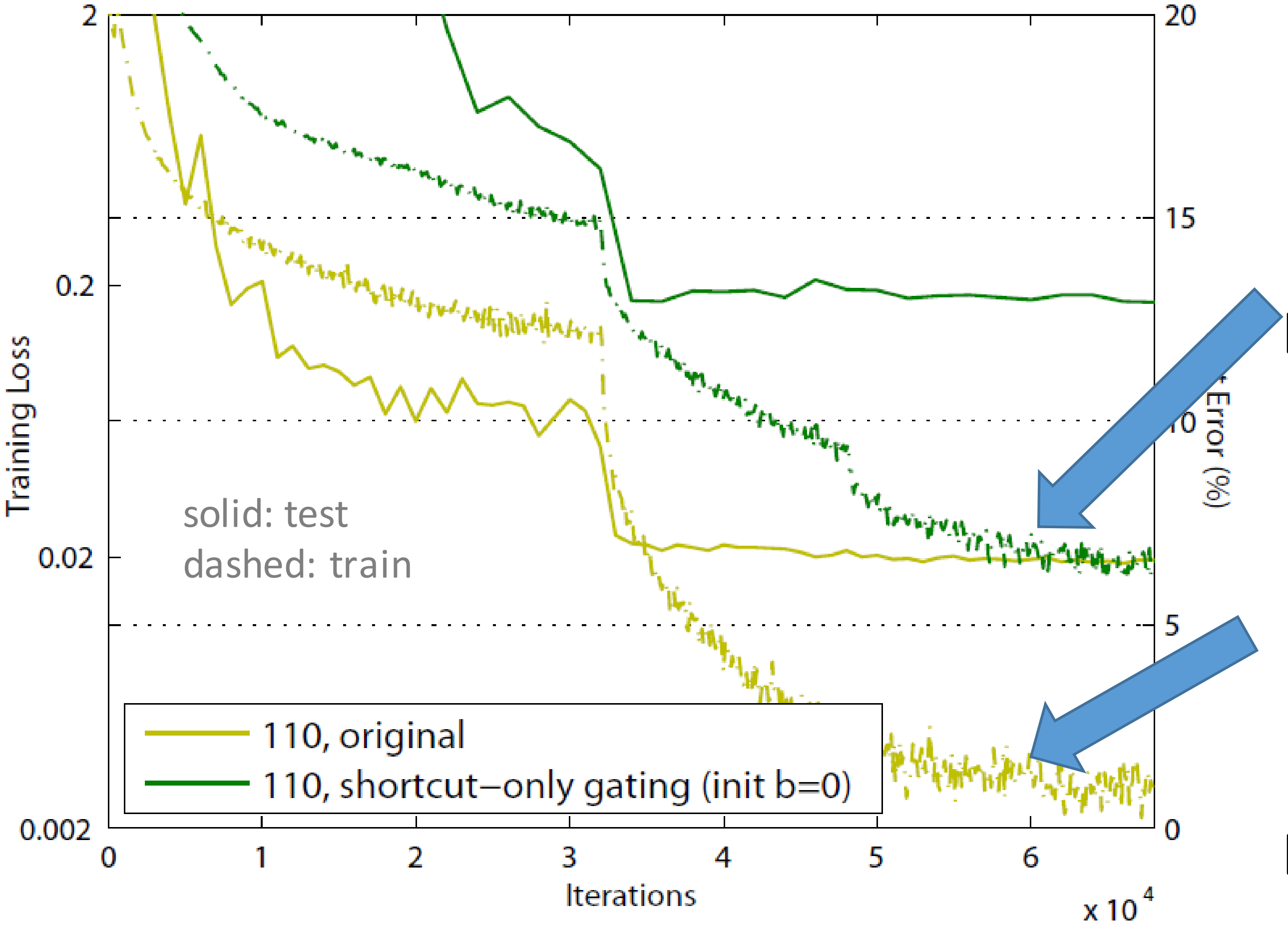
forward: $$x_L = \lambda^{L-l} x_l + \sum_{i=l}^{L-1} \hat{F}(x_i)$$

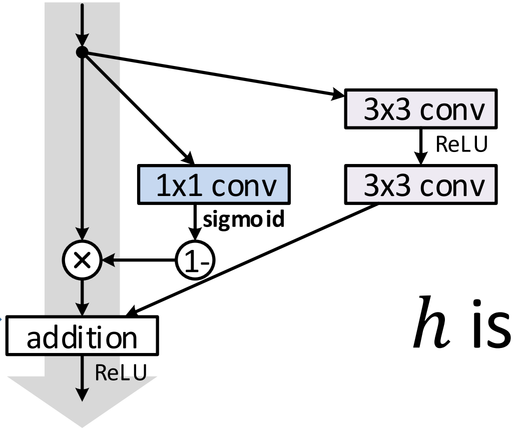
- if h is multiplicative, shortcuts are blocked
- direct propagation is decayed

backward: $$\frac{\partial E}{\partial x_l} = \frac{\partial E}{\partial x_L}\left(\lambda^{L-l} + \frac{\partial}{\partial x_l}\sum_{i=1}^{L-1} \hat{F}(x_i)\right)$$

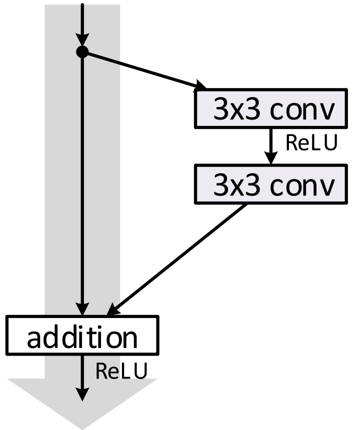
*assuming f = identity

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Identity Mappings in Deep Residual Networks”. arXiv 2016.





h is gating

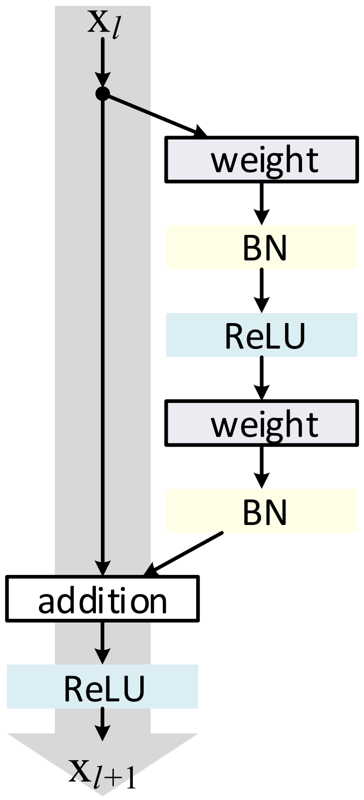


h is identity

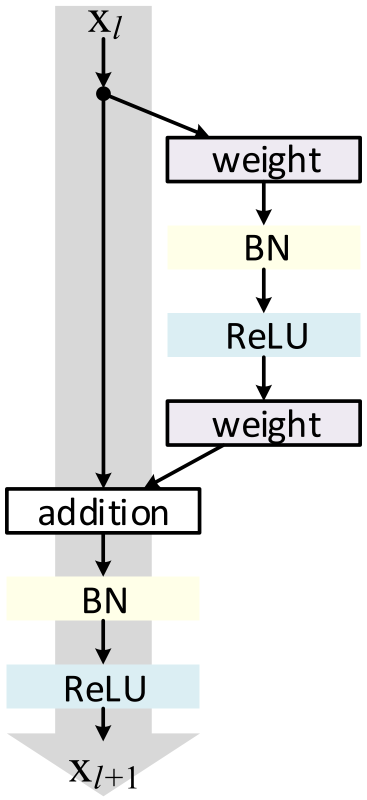
- gating should have better representation ability (identity is a special case), but
- optimization difficulty dominates results

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Identity Mappings in Deep Residual Networks”. arXiv 2016.

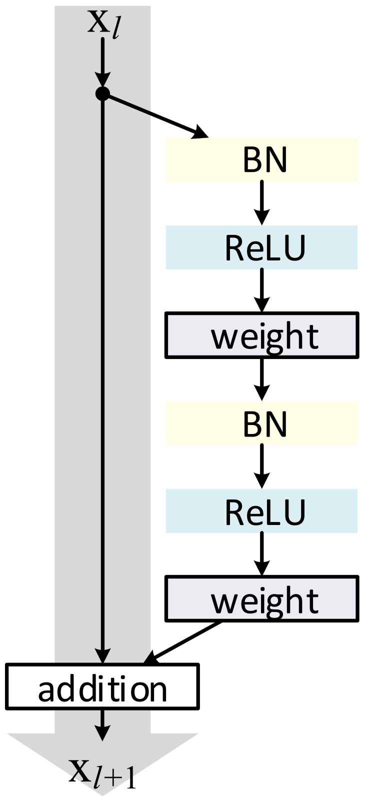
Experiment Set 2:
what if after-add mapping f is identity



f is ReLU
(original ResNet)

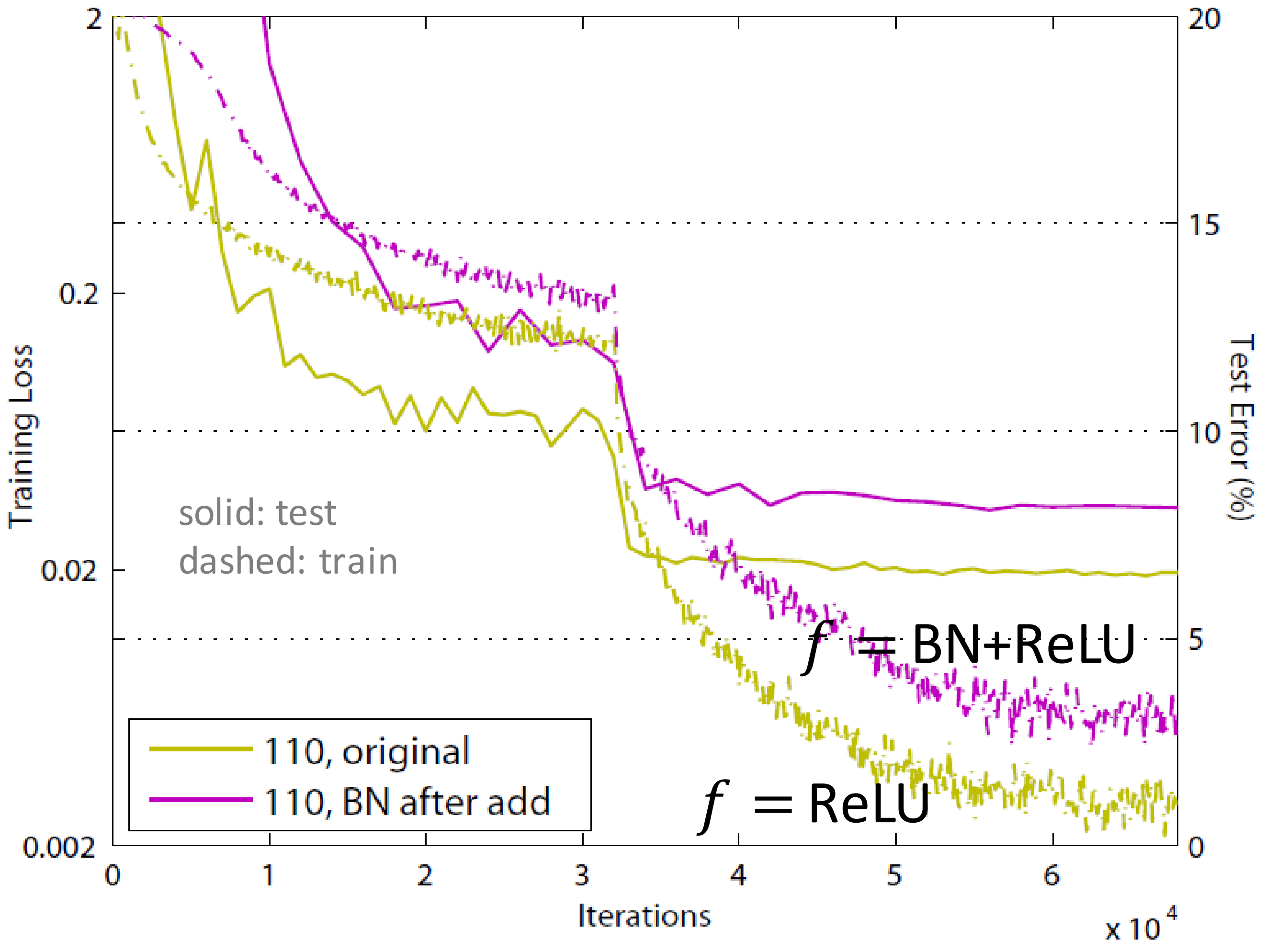


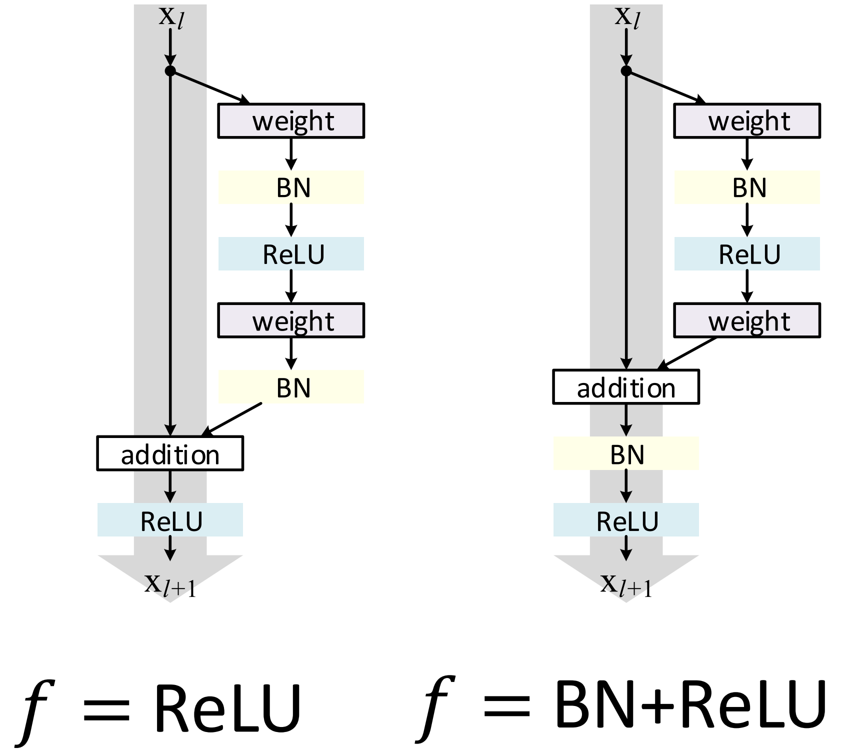
f is BN+ReLU



f is identity
(**pre-activation** ResNet)

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Identity Mappings in Deep Residual Networks". arXiv 2016.

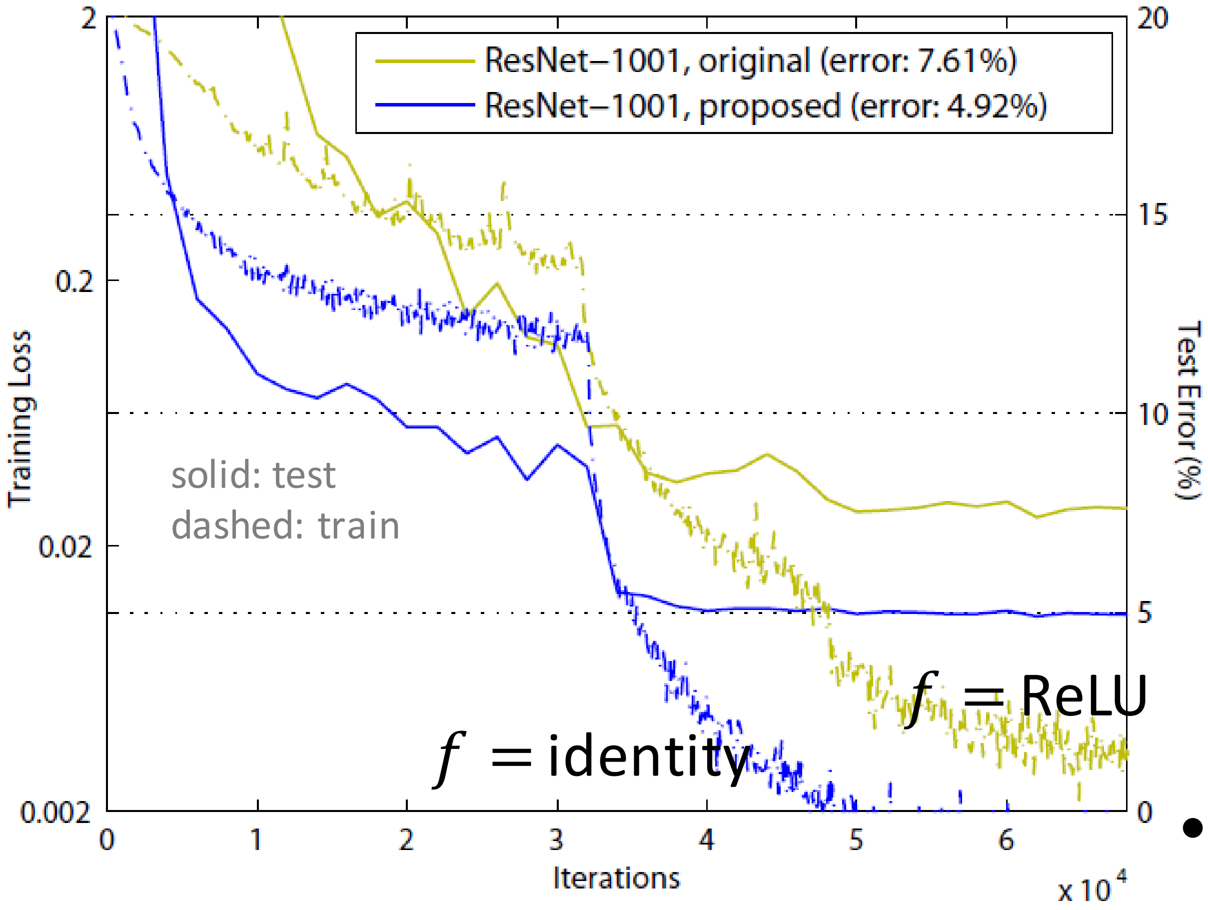


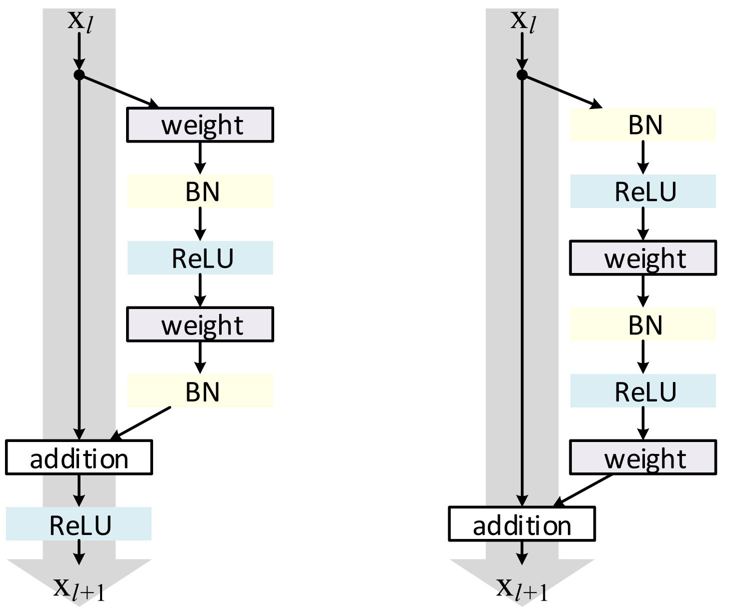


- BN could block prop
- Keep the shortest pass as smooth as possible

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Identity Mappings in Deep Residual Networks". arXiv 2016.

1001-layer ResNets on CIFAR-10





f = ReLU f = identity

- ReLU could block prop when there are 1000 layers
- pre-activation design eases optimization (and improves generalization; see paper)

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Identity Mappings in Deep Residual Networks". arXiv 2016.

Comparisons on CIFAR-10/100

CIFAR-10

method	error (%)
NIN	8.81
DSN	8.22
FitNet	8.39
Highway	7.72
ResNet-110 (1.7M)	6.61
ResNet-1202 (19.4M)	7.93
ResNet-164, pre-activation (1.7M)	5.46
ResNet-1001, pre-activation (10.2M)	**4.92** (4.89±0.14)

CIFAR-100

method	error (%)
NIN	35.68
DSN	34.57
FitNet	35.04
Highway	32.39
ResNet-164 (1.7M)	25.16
ResNet-1001 (10.2M)	27.82
ResNet-164, pre-activation (1.7M)	24.33
ResNet-1001, pre-activation (10.2M)	**22.71** (22.68±0.22)

*all based on moderate augmentation

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Identity Mappings in Deep Residual Networks”. arXiv 2016.

ImageNet Experiments

ImageNet single-crop (320x320) val error

method	data augmentation	top-1 error (%)	top-5 error (%)
ResNet-152, original	scale	21.3	5.5
ResNet-152, pre-activation	scale	21.1	5.5
ResNet-200, original	scale	21.8	6.0
ResNet-200, pre-activation	scale	**20.7**	**5.3**
ResNet-200, pre-activation	scale + aspect ratio	**20.1***	**4.8***

*independently reproduced by:

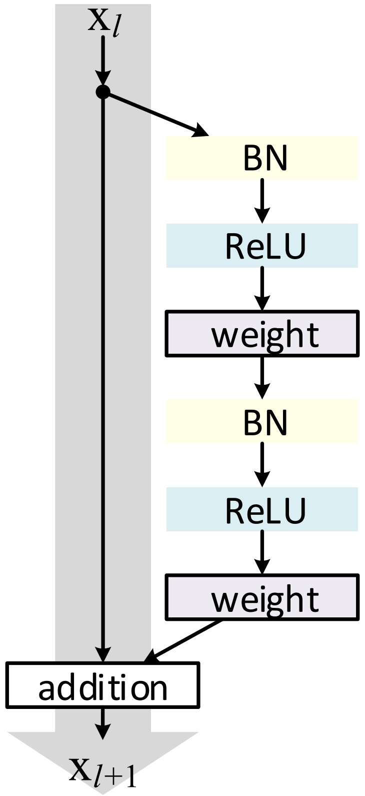
https://github.com/facebook/fb.resnet.torch/tree/master/pretrained#notes

training code and models available.

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Identity Mappings in Deep Residual Networks". arXiv 2016.

Summary of observations

- Keep the shortest path as smooth as possible
  - by making h and f identity
  - forward/backward signals directly flow through this path
- Features of any layers are additive outcomes
- 1000-layer ResNets can be easily trained and have better accuracy



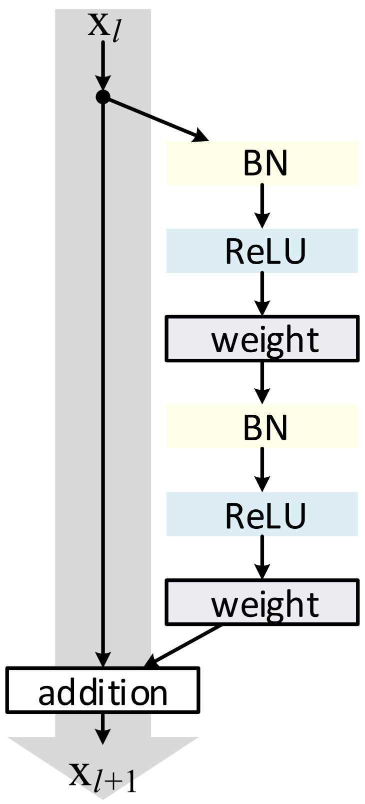
Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Identity Mappings in Deep Residual Networks”. arXiv 2016.

Future Works

- **Representation**
  - skipping 1 layer vs. multiple layers?
  - Flat vs. Bottleneck?
  - Inception-ResNet [Szegedy et al 2016]
  - ResNet in ResNet [Targ et al 2016]
  - Width vs. Depth [Zagoruyko & Komodakis 2016]

- **Generalization**
  - DropOut, MaxOut, DropConnect, …
  - Drop Layer (Stochastic Depth) [Huang et al 2016]

- **Optimization**
  - Without residual/shortcut?



Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Identity Mappings in Deep Residual Networks". arXiv 2016.

Applications

“Features matter”

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

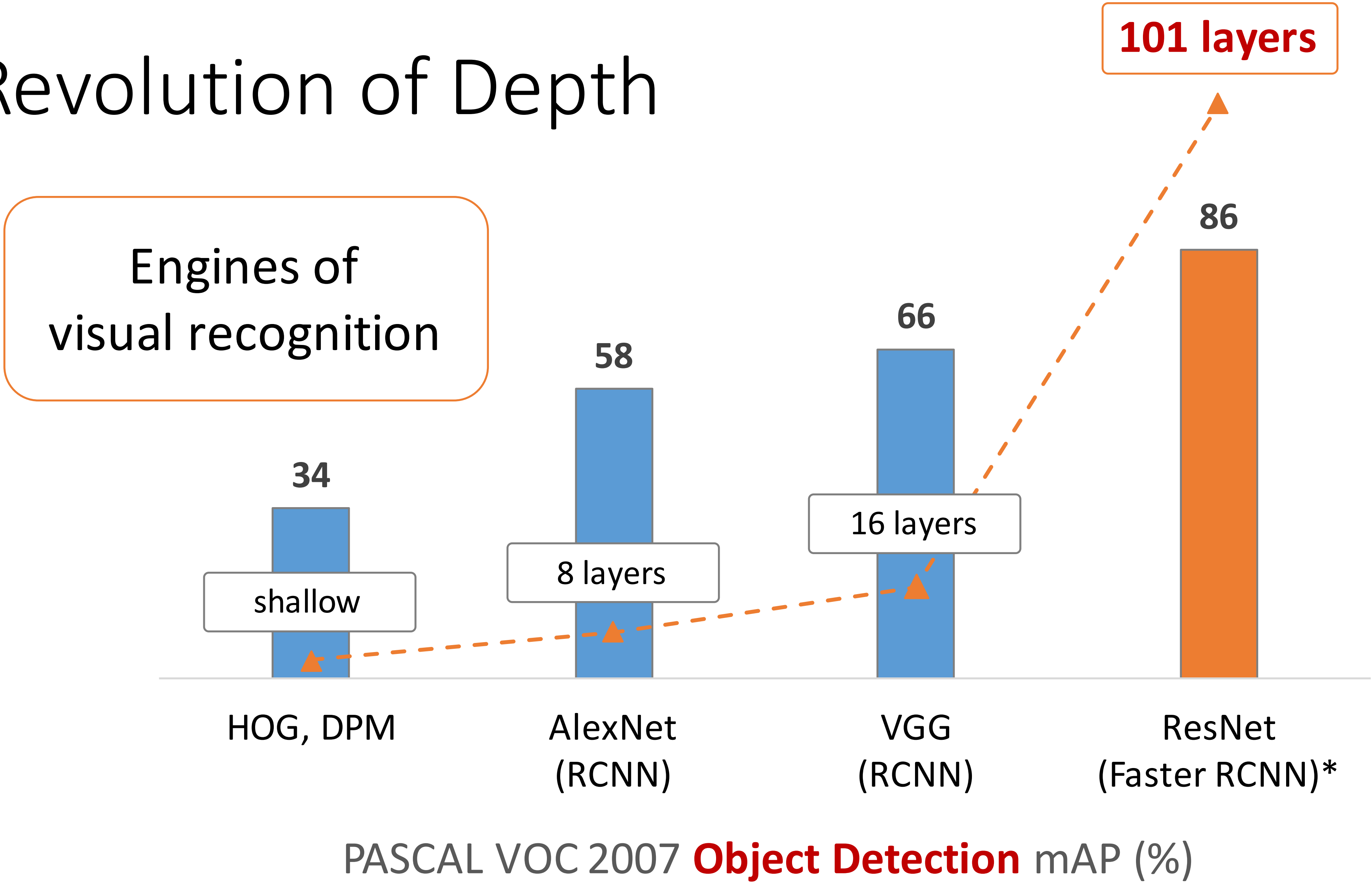
task	2nd-place winner	ResNets	margin (relative)
ImageNet Localization (top-5 error)	12.0	9.0	**27%**
ImageNet Detection (mAP@.5)	53.6	62.1	**16%**
COCO Detection (mAP@.5:.95)	33.5	37.3	**11%**
COCO Segmentation (mAP@.5:.95)	25.1	28.2	**12%**

absolute 8.5% better!

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

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". CVPR 2016.

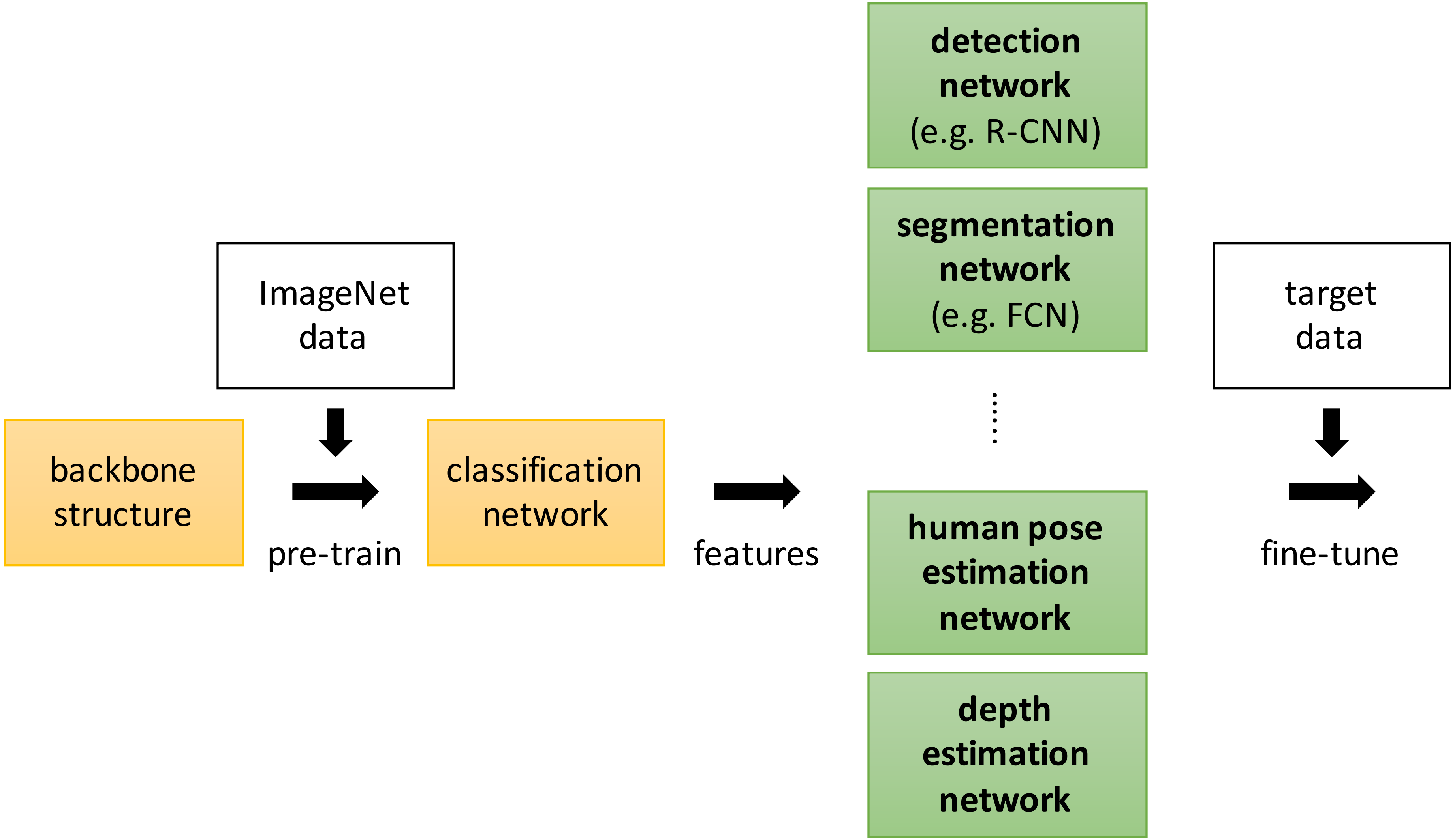
Revolution of Depth



*w/ other improvements & more data

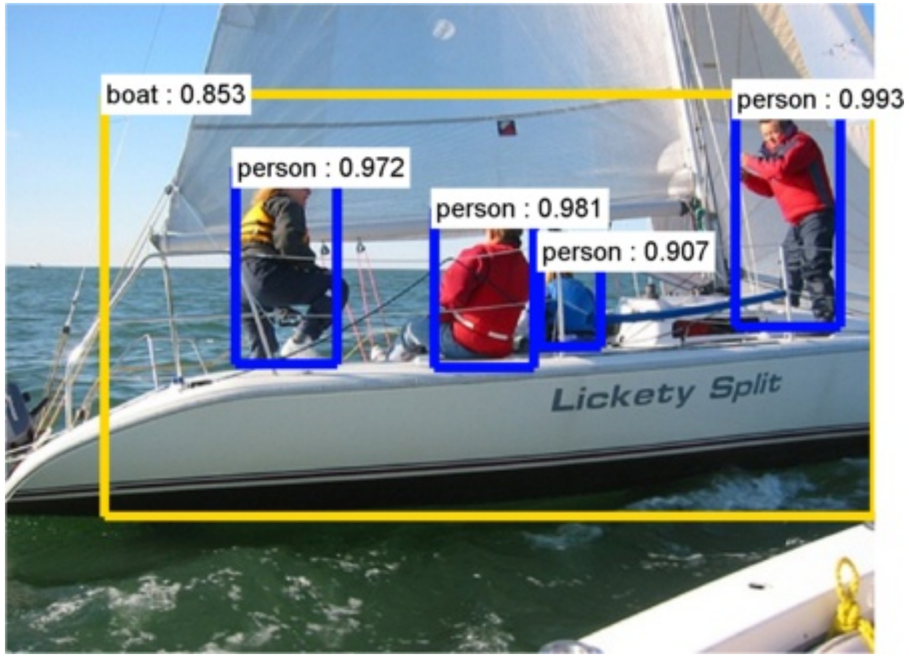
Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". CVPR 2016.

Deep Learning for Computer Vision



Example: Object Detection

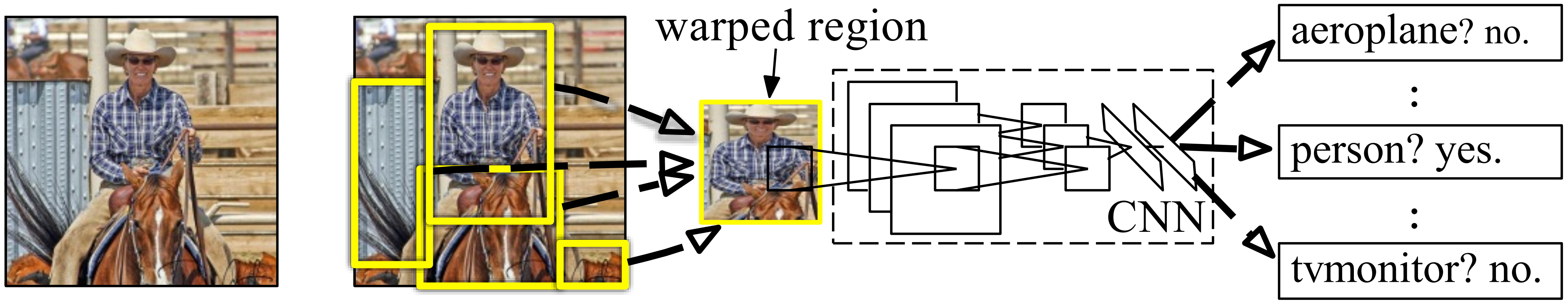
Image Classification
(what?)



Object Detection
(what + where?)

Object Detection: R-CNN

figure credit: R. Girshick et al.



input image

region proposals
~2,000

1 CNN for each region

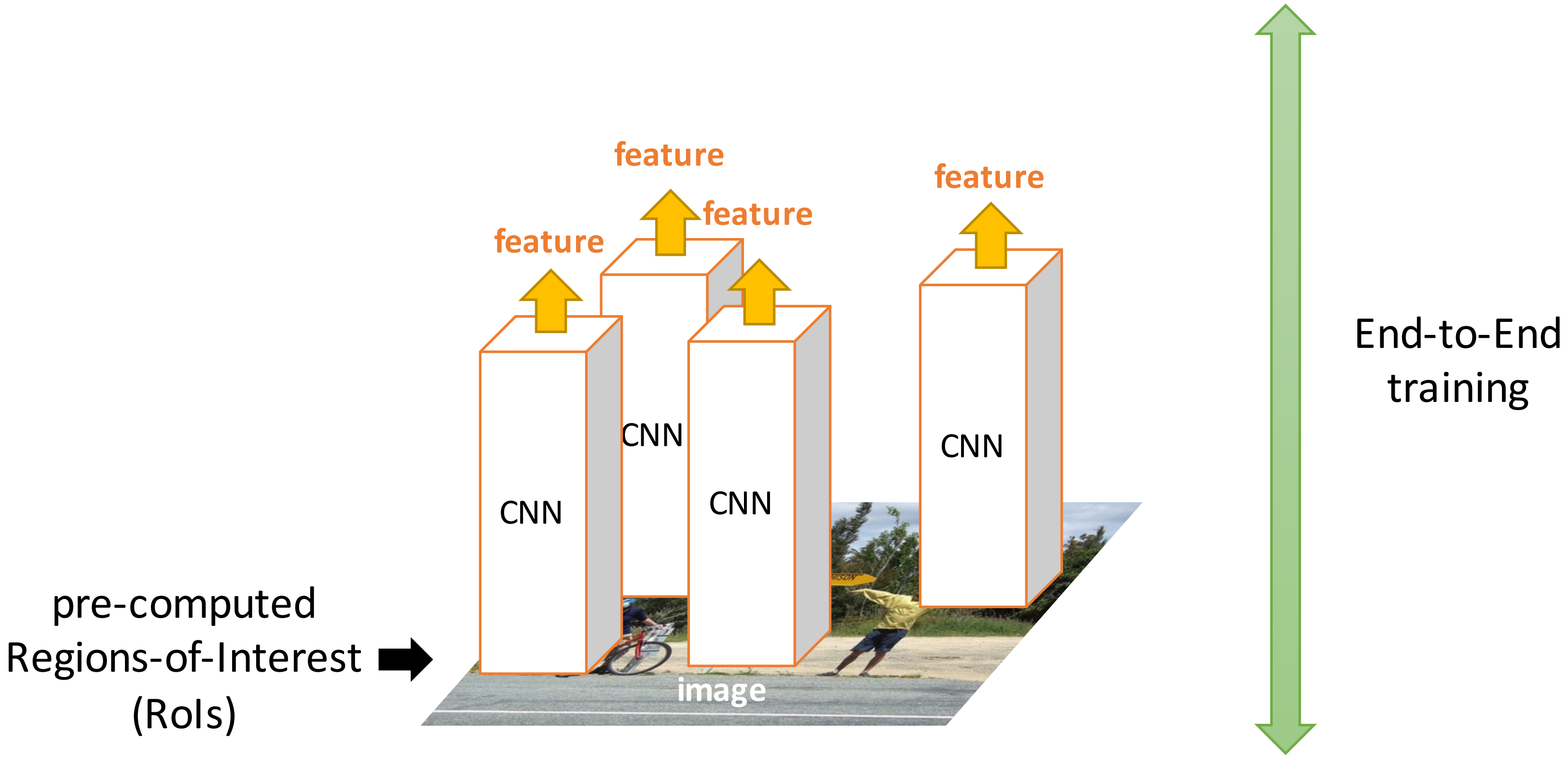
classify regions

Region-based **CNN** pipeline

Girshick, Donahue, Darrell, Malik. Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation. CVPR 2014

Object Detection: R-CNN

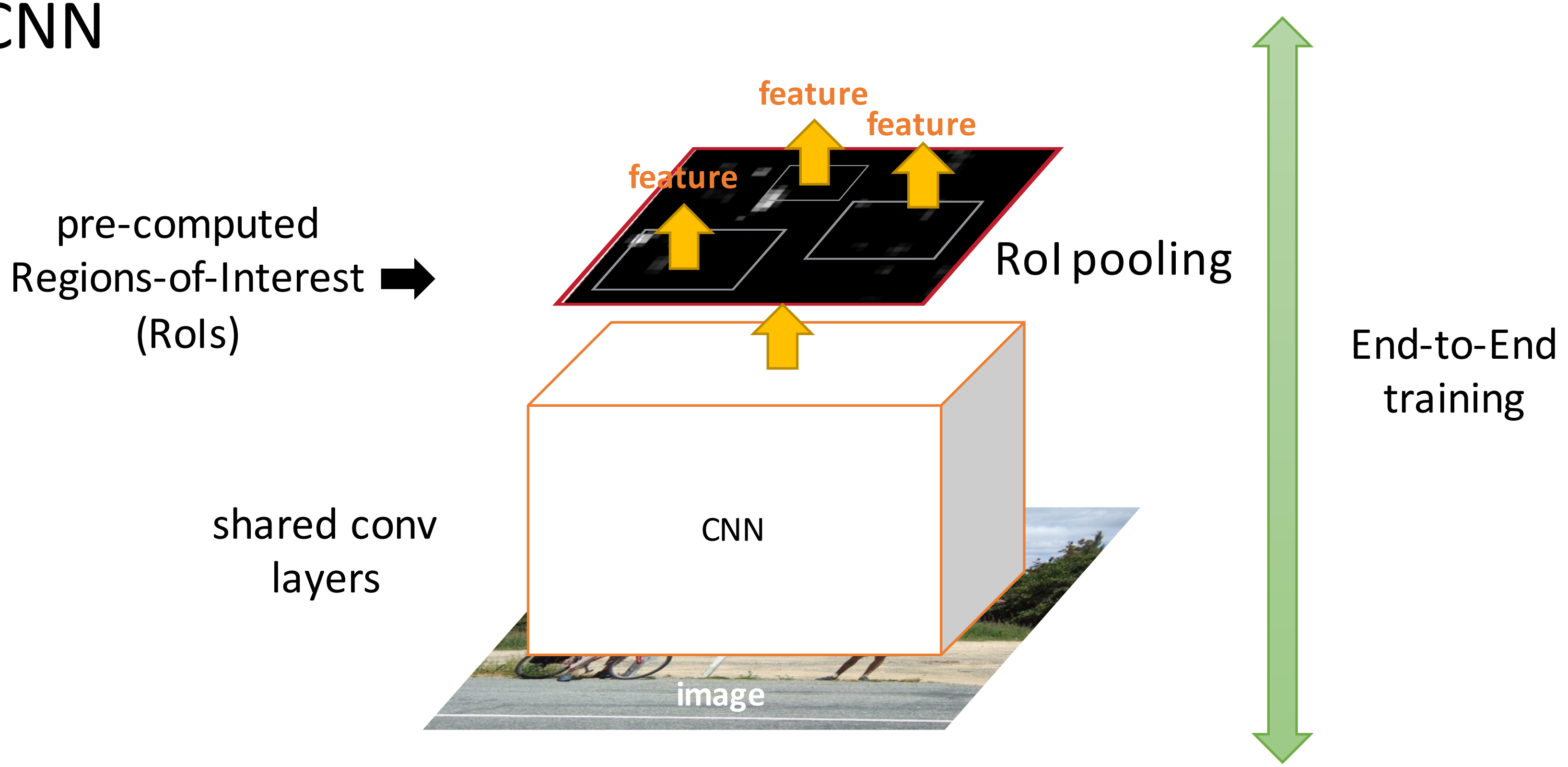
- R-CNN



Girshick, Donahue, Darrell, Malik. Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation. CVPR 2014

Object Detection: Fast R-CNN

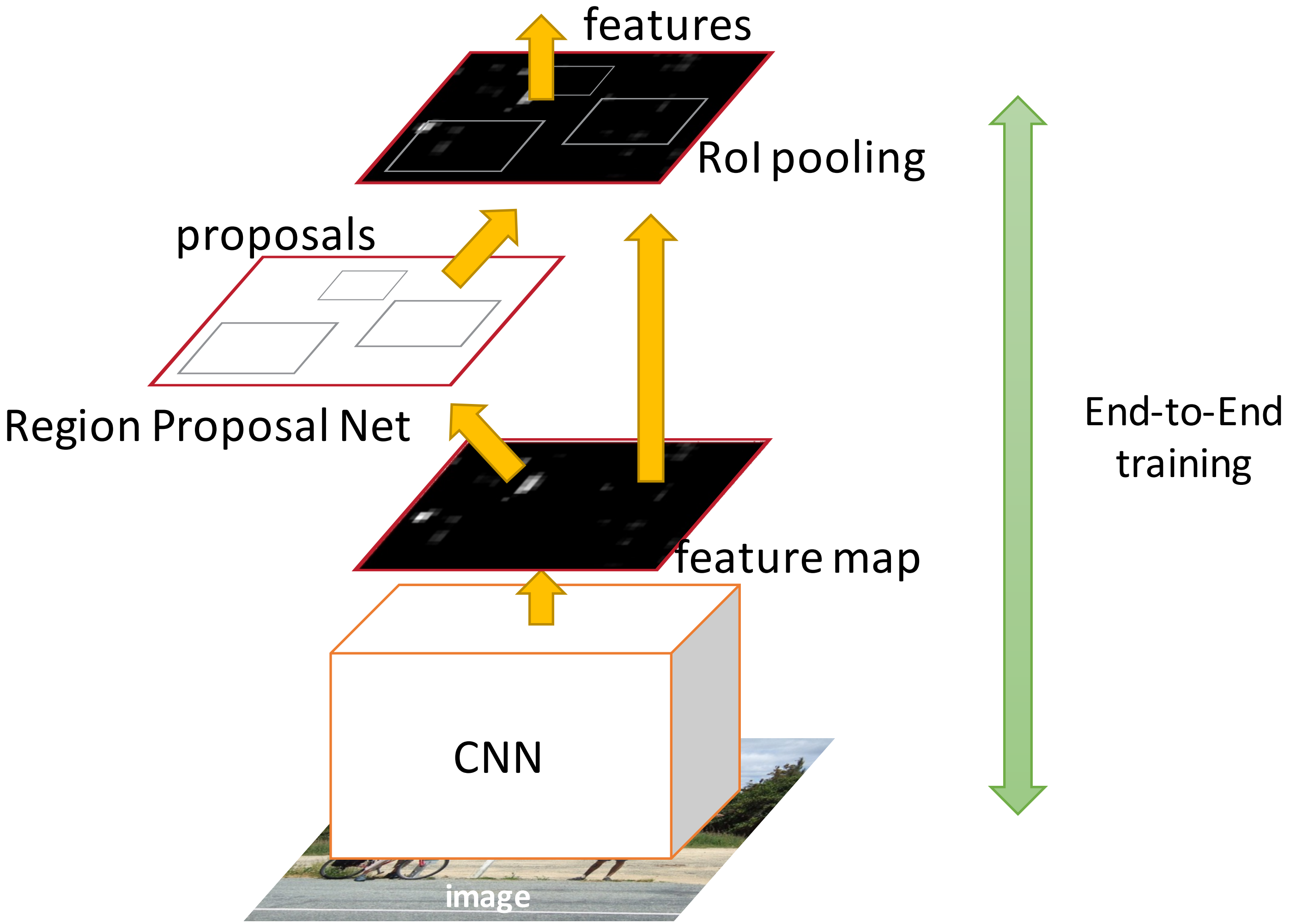
- Fast R-CNN



Girshick. Fast R-CNN. ICCV 2015

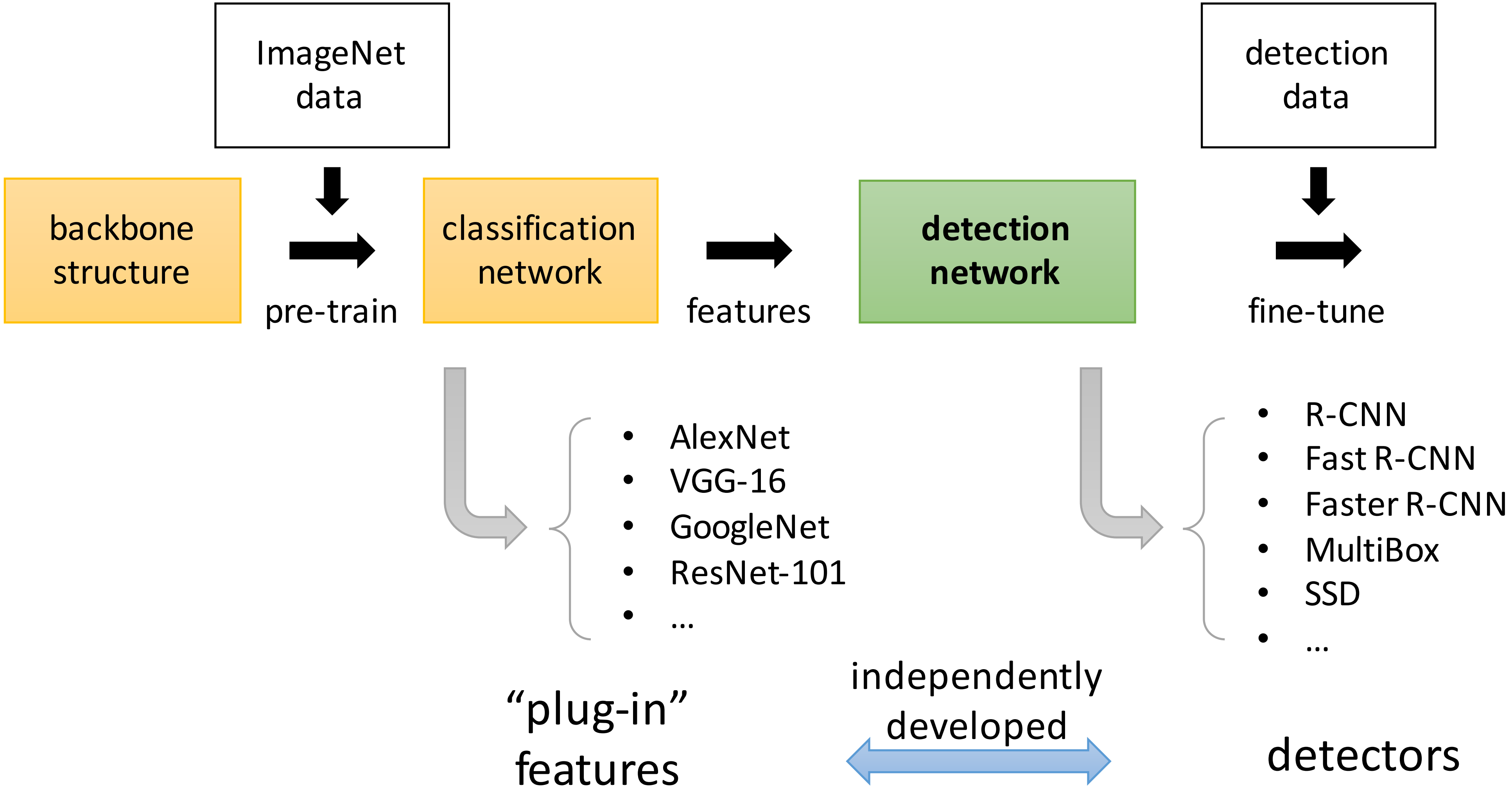
Object Detection: Faster R-CNN

- Faster R-CNN
  - Solely based on CNN
  - No external modules
  - Each step is end-to-end



Shaoqing Ren, Kaiming He, Ross Girshick, & Jian Sun. "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks". NIPS 2015.

Object Detection



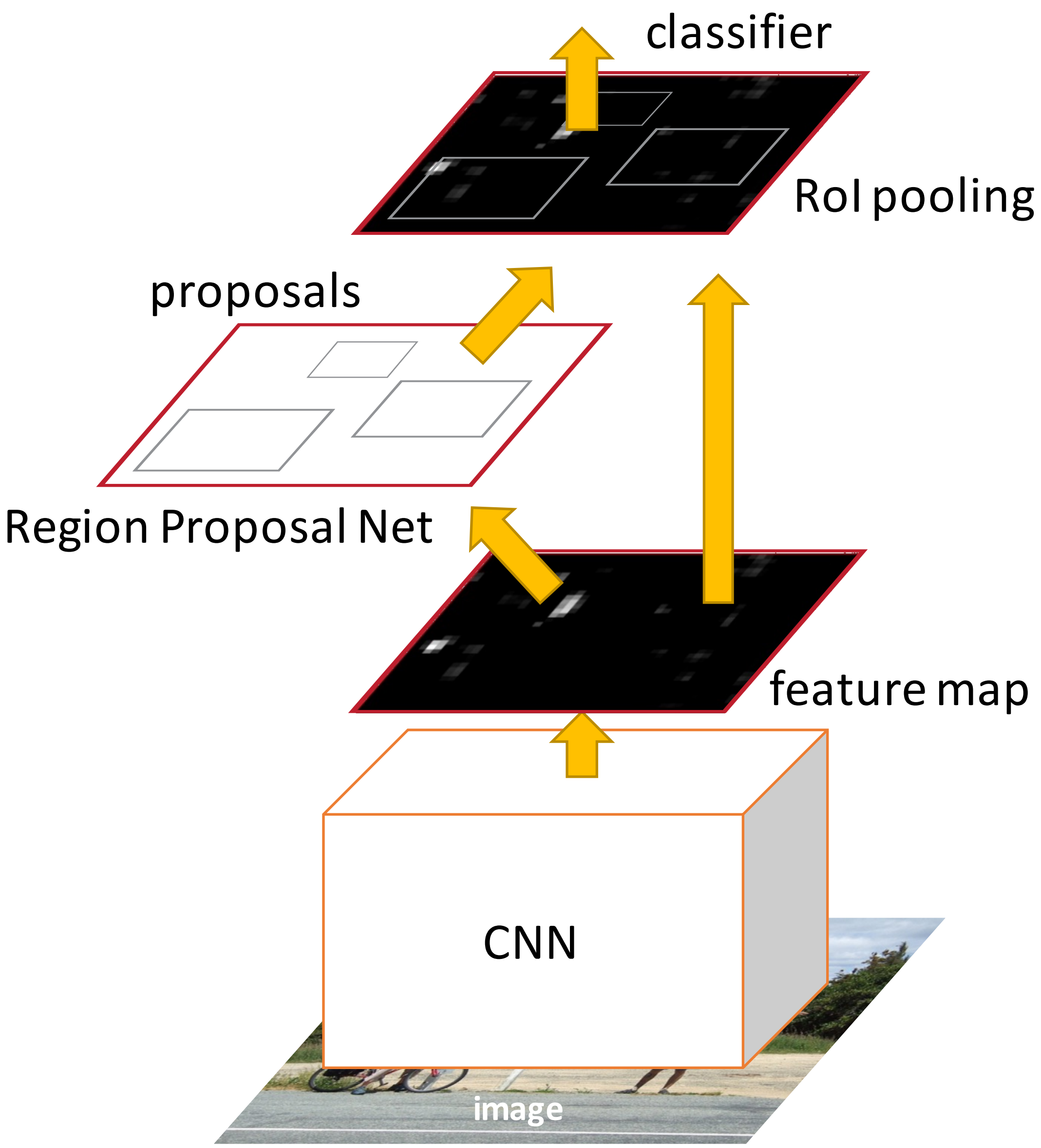
Object Detection

- Simply “Faster R-CNN + ResNet”

Faster R-CNN baseline	mAP@.5	mAP@.5:.95
VGG-16	41.5	21.5
ResNet-101	**48.4**	**27.2**

COCO detection results

ResNet-101 has 28% relative gain vs VGG-16



Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. CVPR 2016.
Shaoqing Ren, Kaiming He, Ross Girshick, & Jian Sun. “Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks”. NIPS 2015.

Object Detection

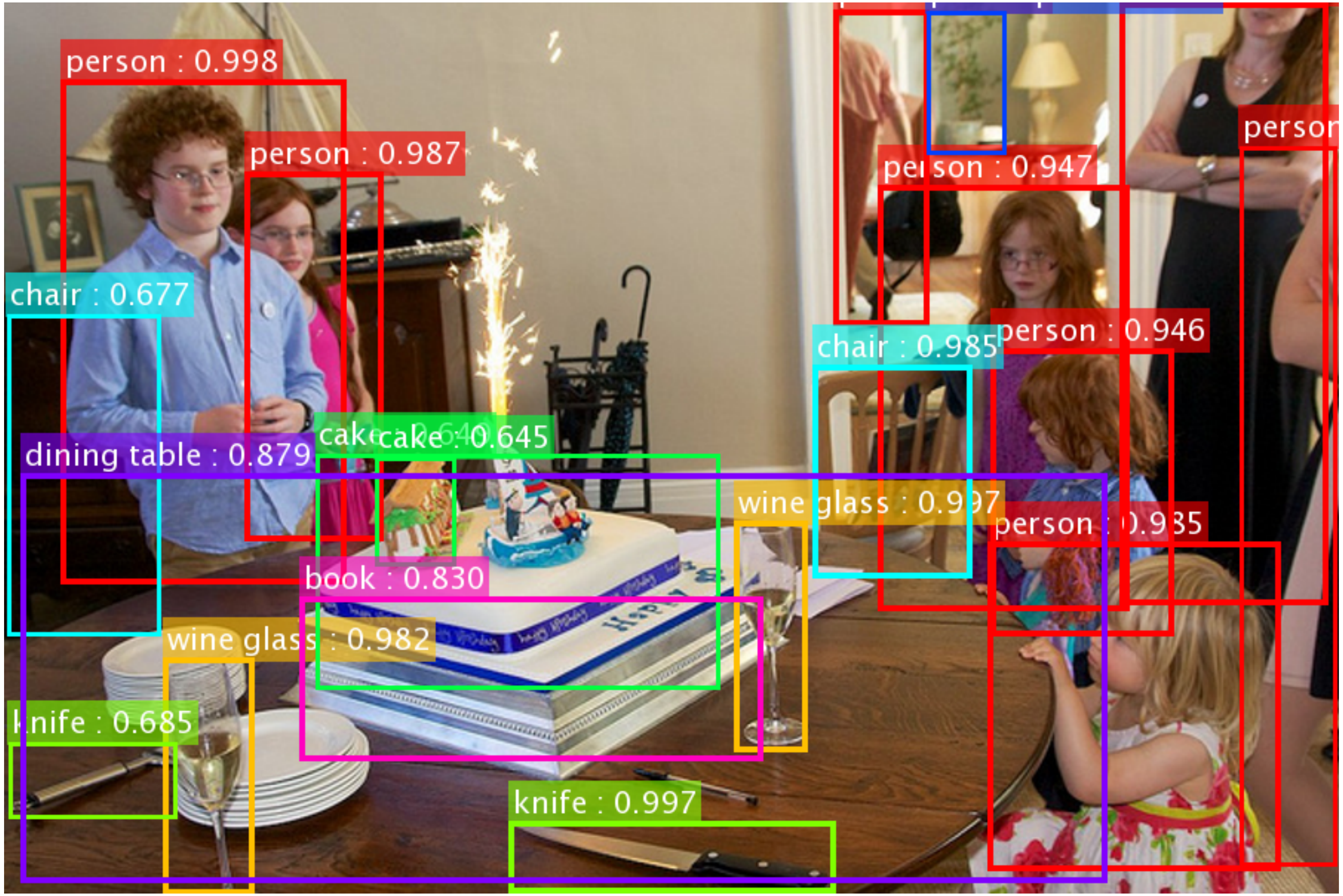
- RPN learns proposals by extremely deep nets
  - We use only 300 proposals (no hand-designed proposals)

- Add components:
  - Iterative localization
  - Context modeling
  - Multi-scale testing

- All are based on CNN features; all are end-to-end

- All benefit more from deeper features – cumulative gains!

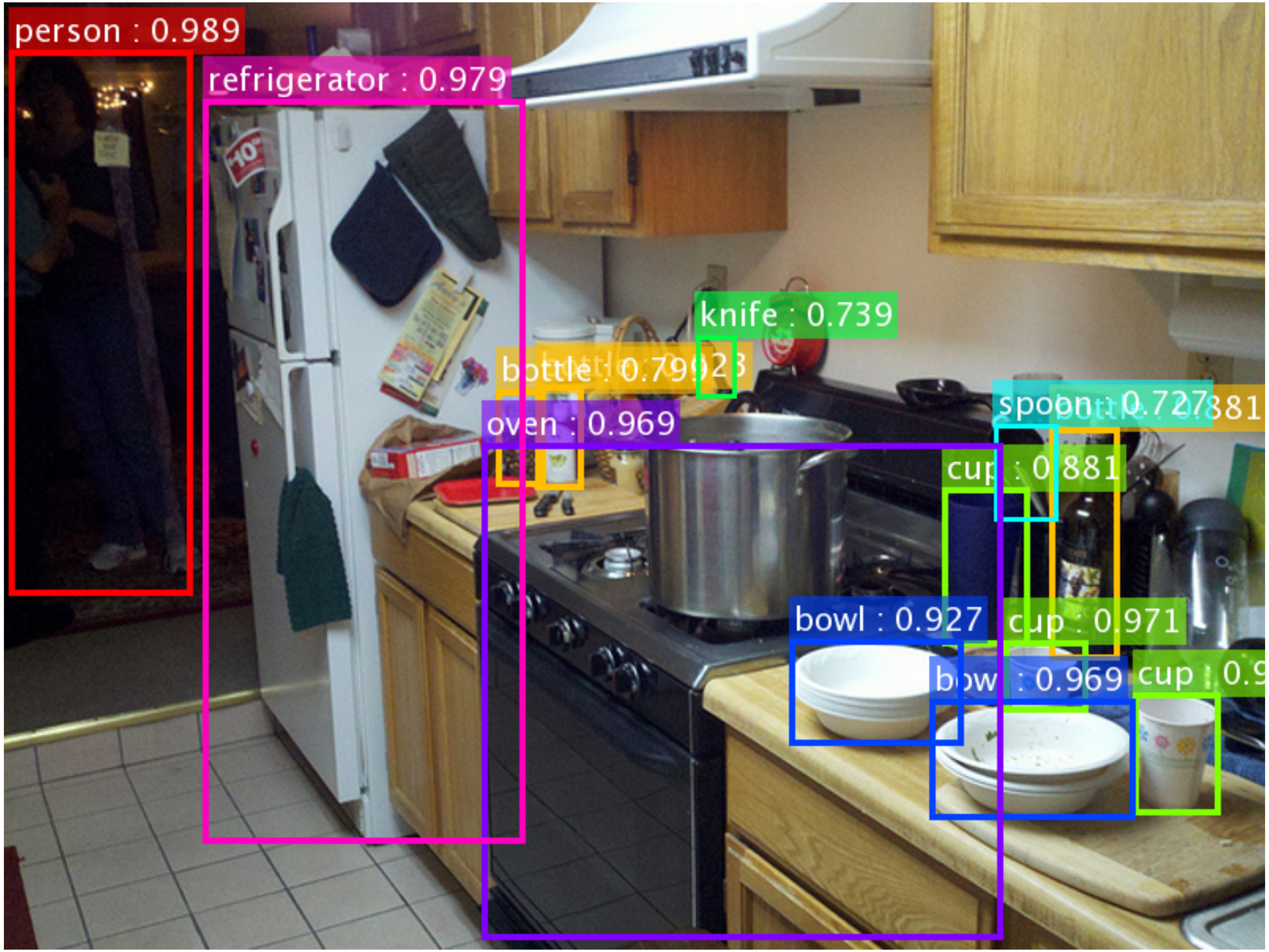
Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". CVPR 2016.
Shaoqing Ren, Kaiming He, Ross Girshick, & Jian Sun. "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks". NIPS 2015.



ResNet’s object detection result on COCO

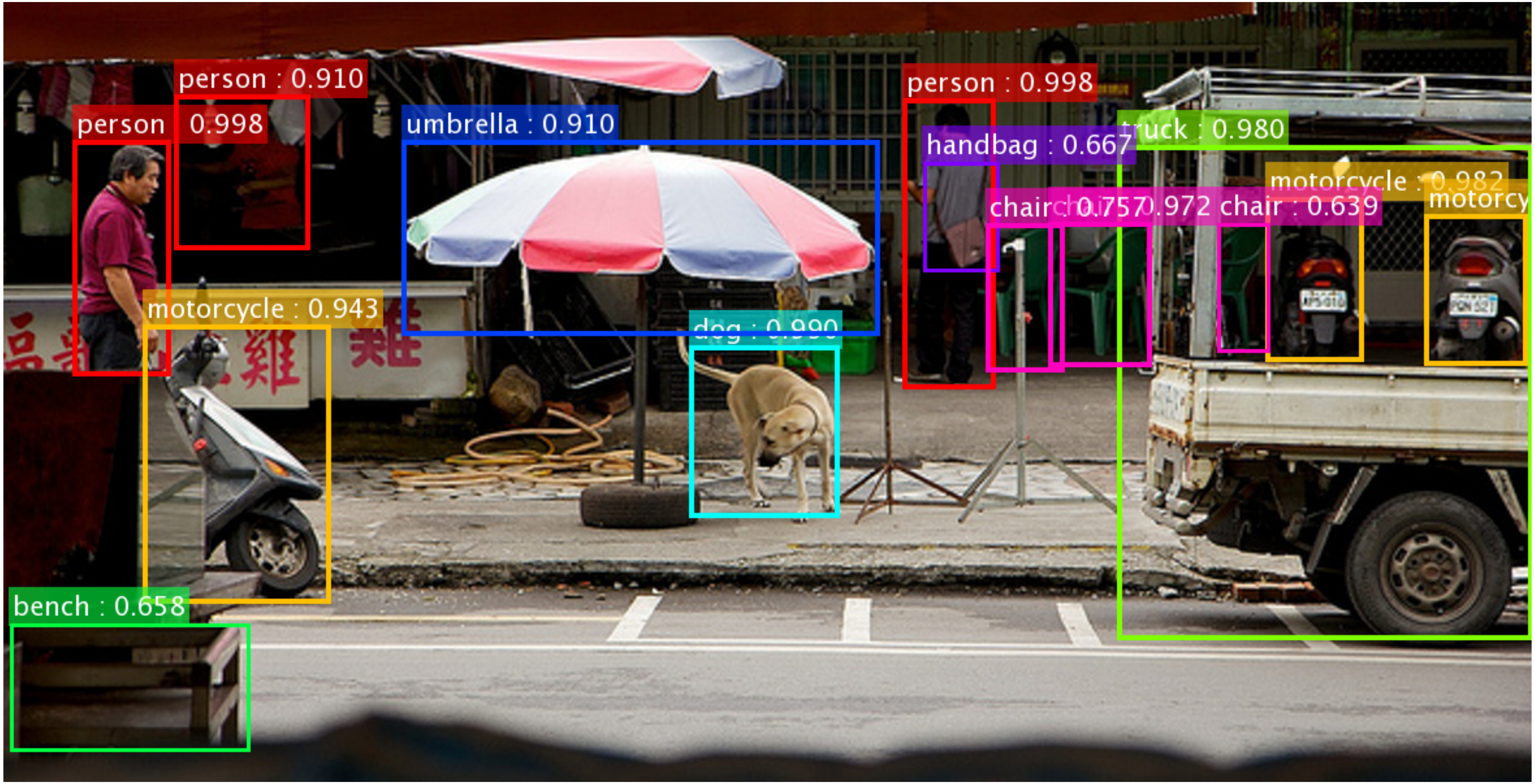
*the original image is from the COCO dataset

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. arXiv 2015.
Shaoqing Ren, Kaiming He, Ross Girshick, & Jian Sun. “Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks”. NIPS 2015.



*the original image is from the COCO dataset

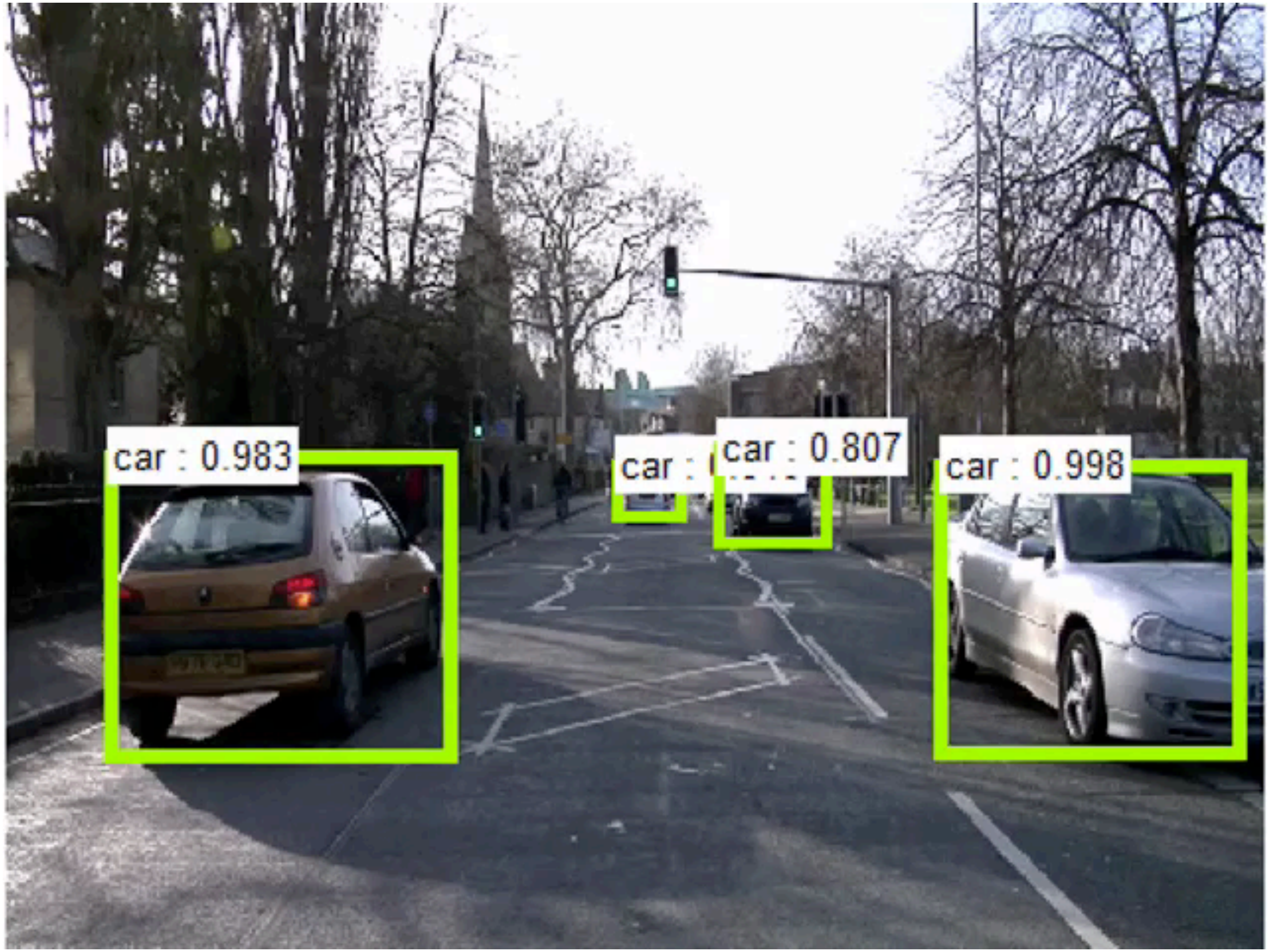
Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". arXiv 2015.
Shaoqing Ren, Kaiming He, Ross Girshick, & Jian Sun. "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks". NIPS 2015.



*the original image is from the COCO dataset

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

Shaoqing Ren, Kaiming He, Ross Girshick, & Jian Sun. "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks". NIPS 2015.



this video is available online: https://youtu.be/WZmSMkK9VuA

Results on real video. Models trained on MS COCO (80 categories).
(frame-by-frame; no temporal processing)

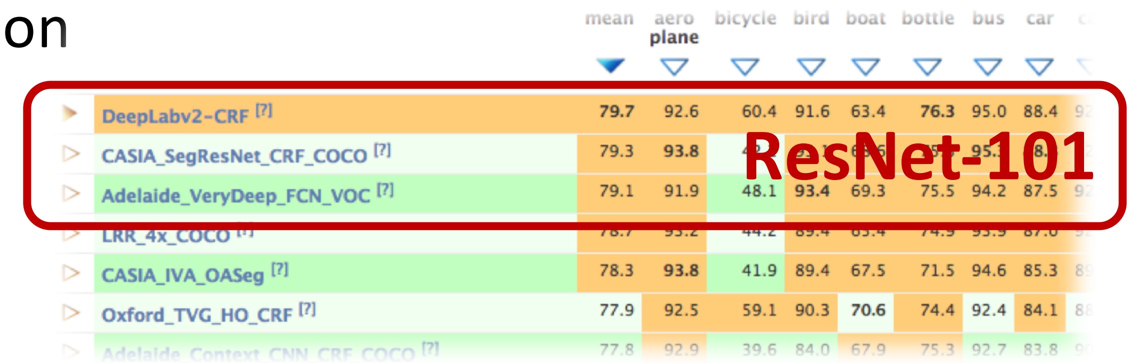
Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". arXiv 2015.
Shaoqing Ren, Kaiming He, Ross Girshick, & Jian Sun. "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks". NIPS 2015.

More Visual Recognition Tasks

ResNet-based methods lead on these benchmarks (incomplete list):

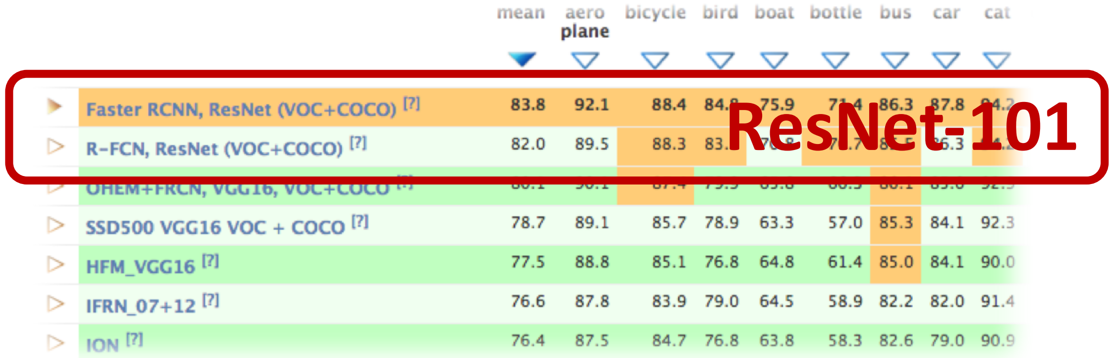
- ImageNet classification, detection, localization
- MS COCO detection, segmentation
- PASCAL VOC detection, segmentation

- Human pose estimation [Newell et al 2016]
- Depth estimation [Laina et al 2016]
- Segment proposal [Pinheiro et al 2016]
- …



	mean	aero plane	bicycle	bird	boat	bottle	bus	car
DeepLabv2-CRF [?]	79.7	92.6	60.4	91.6	63.4	76.3	95.0	88.4
CASIA_SegResNet_CRF_COCO [?]	79.3	93.8	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Adelaide_VeryDeep_FCN_VOC [?]	79.1	91.9	48.1	93.4	69.3	75.5	94.2	87.5
LRR_4x_COCO [?]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
CASIA_IVA_OASeg [?]	78.3	93.8	41.9	89.4	67.5	71.5	94.6	85.3
Oxford_TVG_HO_CRF [?]	77.9	92.5	59.1	90.3	70.6	74.4	92.4	84.1
Adelaide_Context_CNN_CRF_COCO [?]	77.8	92.9	39.6	84.0	67.9	75.3	92.7	83.8

PASCAL **segmentation** leaderboard



	mean	aero plane	bicycle	bird	boat	bottle	bus	car	cat
Faster RCNN, ResNet (VOC+COCO) [?]	83.8	92.1	88.4	[illegible]	75.9	71.4	86.3	87.8	94.2
R-FCN, ResNet (VOC+COCO) [?]	82.0	89.5	88.3	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
OHEM+FRCN, VGG16, VOC+COCO [?]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
SSD500 VGG16 VOC + COCO [?]	78.7	89.1	85.7	78.9	63.3	57.0	85.3	84.1	92.3
HFM_VGG16 [?]	77.5	88.8	85.1	76.8	64.8	61.4	85.0	84.1	90.0
IFRN_07+12 [?]	76.6	87.8	83.9	79.0	64.5	58.9	82.2	82.0	91.4
ION [?]	76.4	87.5	84.7	76.8	63.8	58.3	82.6	79.0	90.9

PASCAL **detection** leaderboard

Potential Applications

ResNets have shown outstanding or promising results on:

- Visual Recognition
- Image Generation
  (Pixel RNN, Neural Art, etc.)
- Natural Language Processing
  (Very deep CNN)
- Speech Recognition
  (preliminary results)
- Advertising, user prediction
  (preliminary results)

Conclusions of the Tutorial

- 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!

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. CVPR 2016.
Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Identity Mappings in Deep Residual Networks”. arXiv 2016.

Resources

- Models and Code
  - Our ImageNet models in Caffe: https://github.com/KaimingHe/deep-residual-networks

- Many available implementation
  (list in https://github.com/KaimingHe/deep-residual-networks)
  - Facebook AI Research's Torch ResNet:
    https://github.com/facebook/fb.resnet.torch
  - Torch, CIFAR-10, with ResNet-20 to ResNet-110, training code, and curves: code
  - Lasagne, CIFAR-10, with ResNet-32 and ResNet-56 and training code: code
  - Neon, CIFAR-10, with pre-trained ResNet-32 to ResNet-110 models, training code, and curves: code
  - Torch, MNIST, 100 layers: blog, code
  - A winning entry in Kaggle's right whale recognition challenge: blog, code
  - Neon, Place2 (mini), 40 layers: blog, code
  - ....

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". CVPR 2016.
Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Identity Mappings in Deep Residual Networks". arXiv 2016.