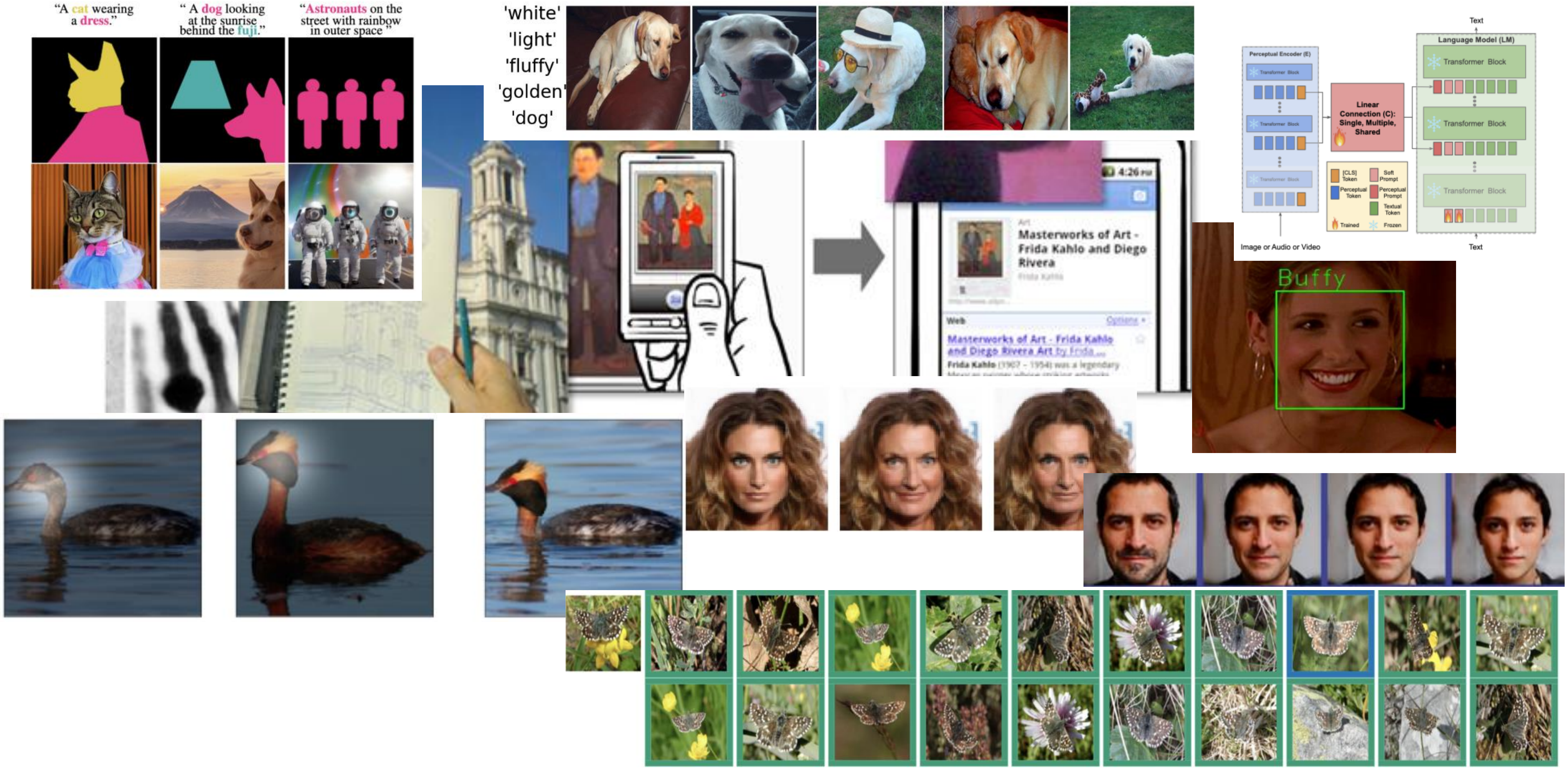

COURS RDFIA deep Image

https://cord.isir.upmc.fr/teaching-rdfia/

Very Large ConvNets

Recap AlexNet: What’s next?

How to improve AlexNet architecture?

+++Deep?

+++Convolutional?

+++Fully connected?

All?

⇒A lot of empirical studies

- ⇒Tuning various design parameters
- ⇒what really works?

⇒Winners: GoogLeNet, VGG, ResNet

Recap AlexNet: What’s next?

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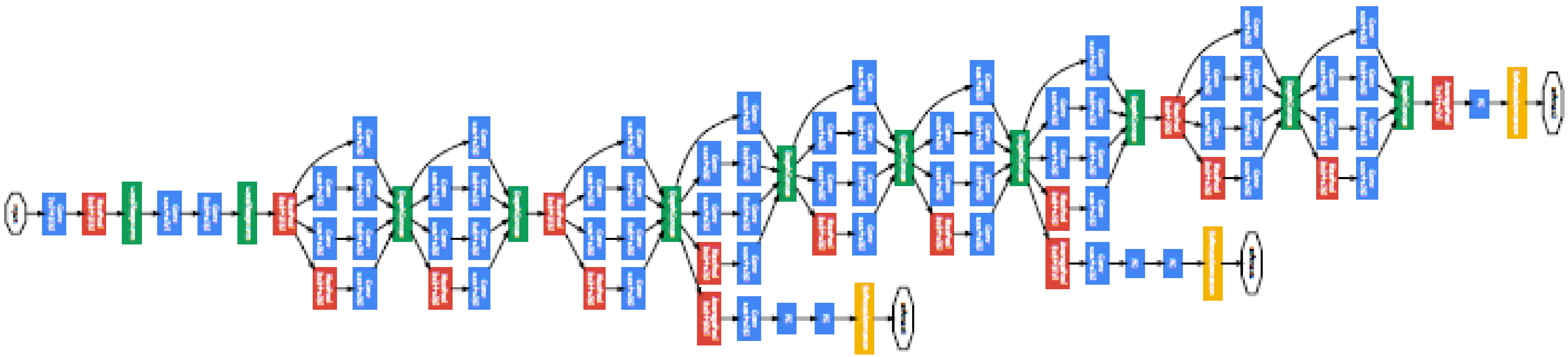
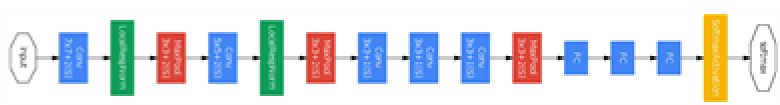
GoogLeNet (2014)

Winner of ILSVRC -2014. Very deep network with 22 layers:

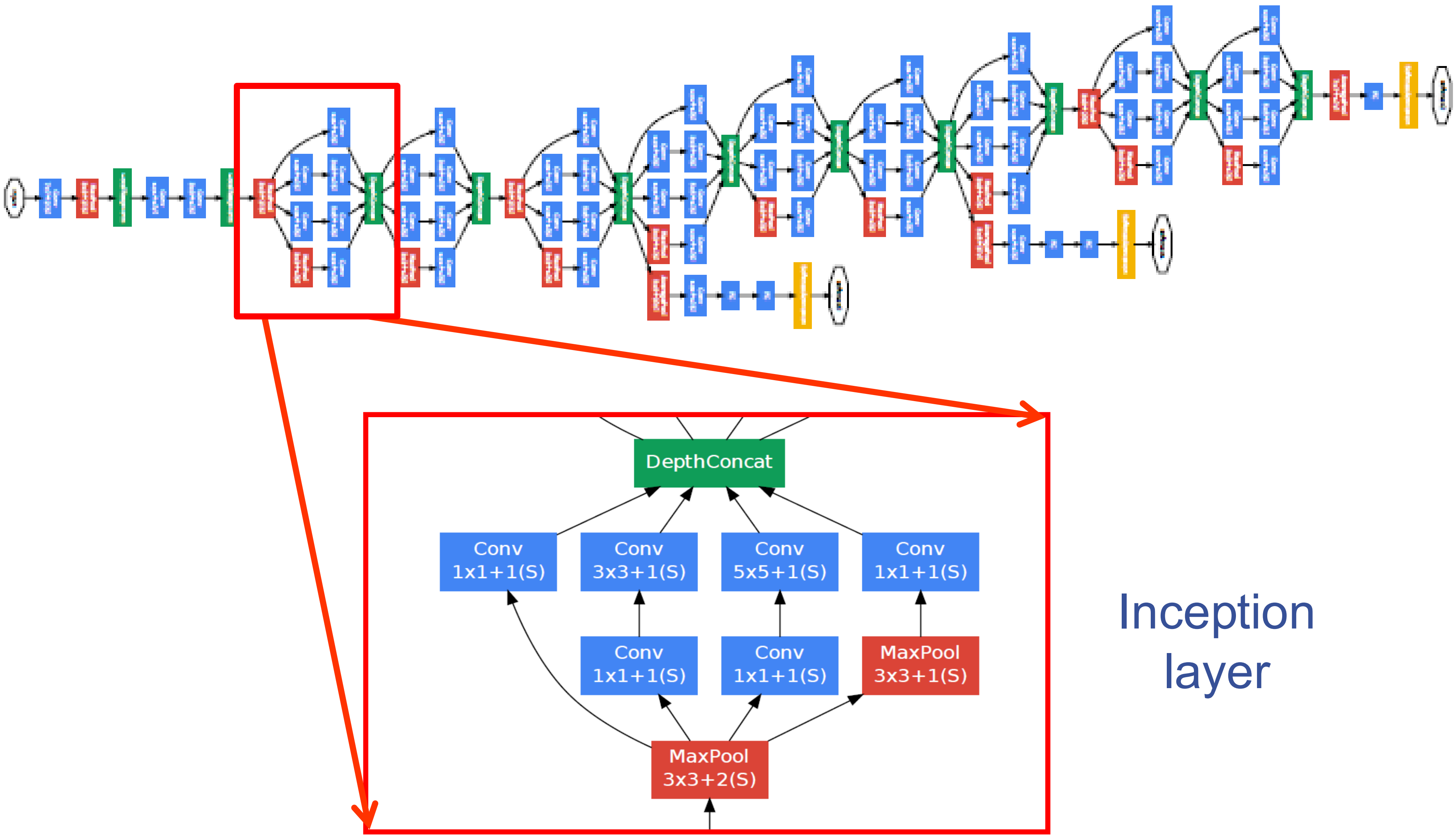
- Network–in-network–in-network
- Removed fully connected layers → small # of parameters (5M weights)



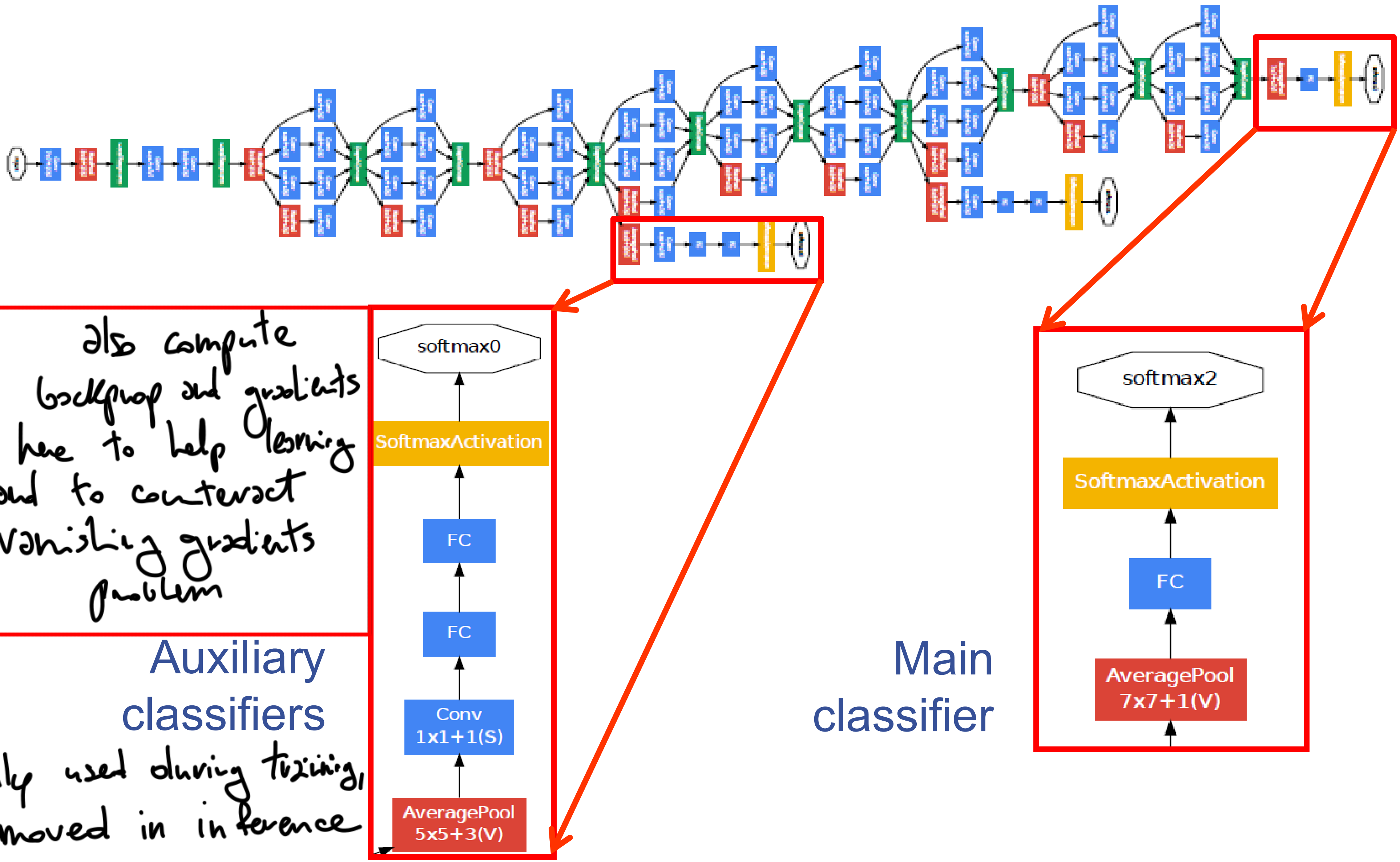


Convolution
Pooling
Softmax
Other

GoogLeNet (2014)



GoogLeNet (2014)



also compute backprop and gradients here to help learning and to counteract vanishing gradients problem

only used during training, removed in inference

Recap AlexNet: What’s next?

How to improve AlexNet architecture?

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+++Convolutional?

+++Fully connected?

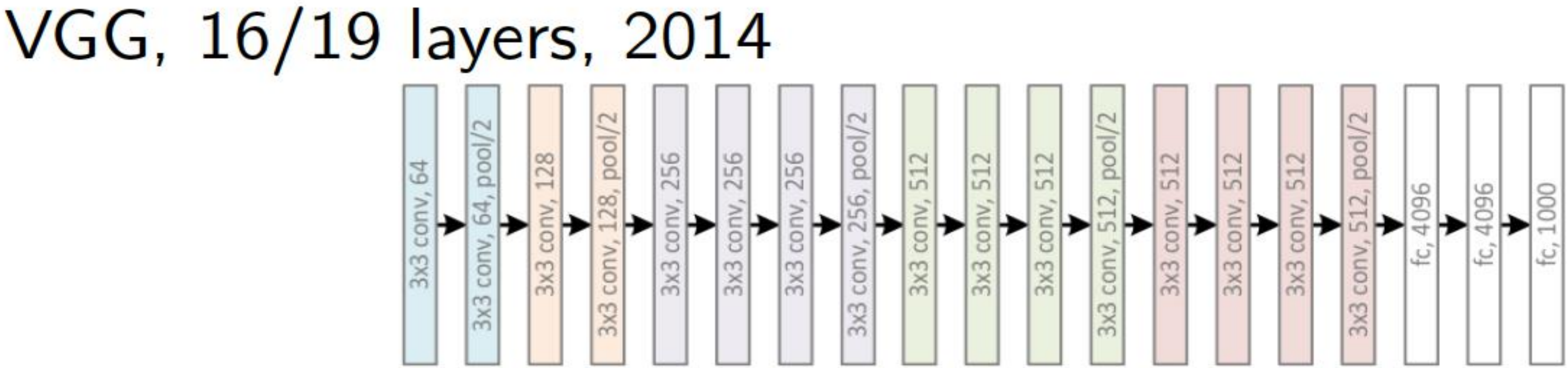
All?

$\Rightarrow$A lot of empirical studies

- $\Rightarrow$Tuning various design parameters
- $\Rightarrow$what really works?

$\Rightarrow$Winners: GoogLeNet, **VGG**, ResNet

VGG Net: Archi post-2012 revolution



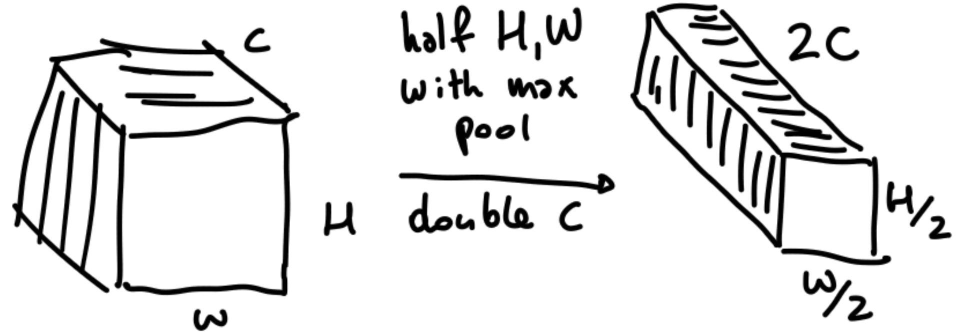
K. Simonyan, A. Zisserman, Very Deep Convolutional Networks for Large-Scale Image Recognition, ICLR 2015

VGG Net

Basic Idea: Investigate the **effect of depth** in large scale image recognition

- **Fix other parameters** of architecture, and steadily increase depth

Fixed configuration:



- Convolutional Layers: from 8 to 16
- Fully Connected Layers: 3
- Stride: 1
- ReLu: Follow all hidden layers
- Max-Pooling: 2x2 window
- Padding: s/t spatial resolution is preserved
- #Convolutional filters: Starting from 64, double after each max-pooling layer until 512
- Filter sizes: 3x3 and 1x1

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

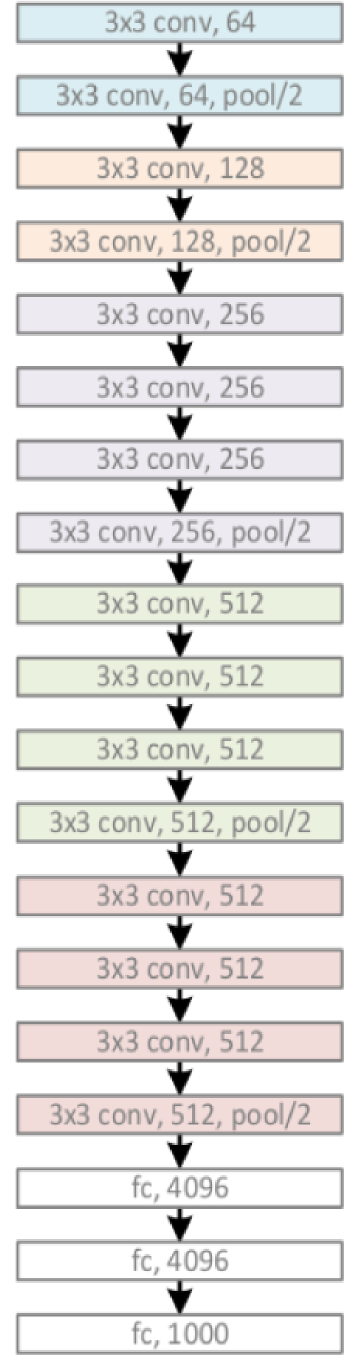


TABLE CREDIT:VERY DEEP CONVOLUTIONAL NETWORKS FOR LARGE-SCALE IMAGE RECOGNITION, ICLR2015

VGG Net

Results:

- First place in localization (25.3% error), second in classification (7.3% error) in ILSVRC 2014 using ensemble of 7 networks
- Outperforms Szegedy et.al (GoogLeNet) in terms of single network classification accuracy (7.1% vs 7.9%)

Observations with VGG testing:

- Deepnets with small filters outperform shallow networks with large filters
  - Shallow version of B: 2 layers of 3x3 replaced with single 5x5 performs worse
- Classification error decreases with increases ConvNet depth
- Important to capture more spatial context (config D vs C)
- Error rate saturated at 19 layers
- Scale jittering at training helps capturing multiscale statistics and leads to better performance

Recap AlexNet: What's next?

How to improve AlexNet architecture?

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All?

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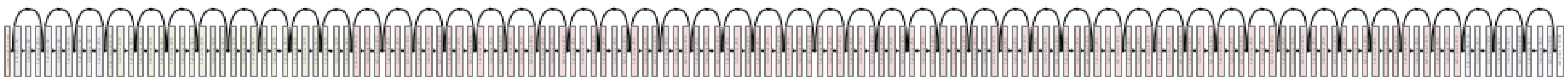
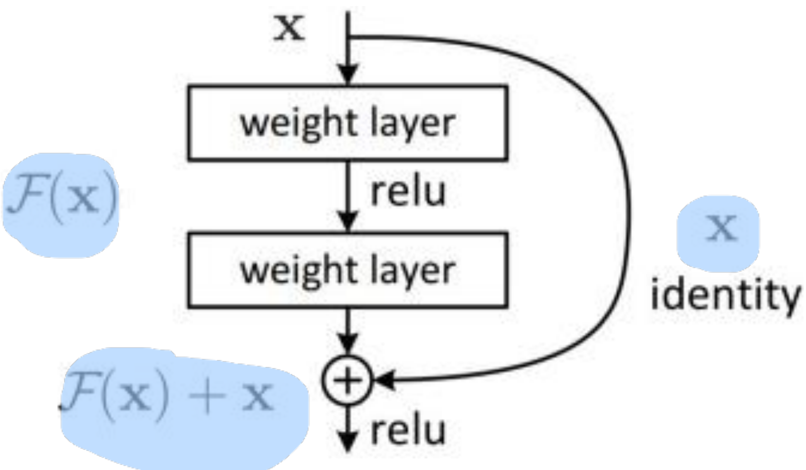
- ⇒what really works?

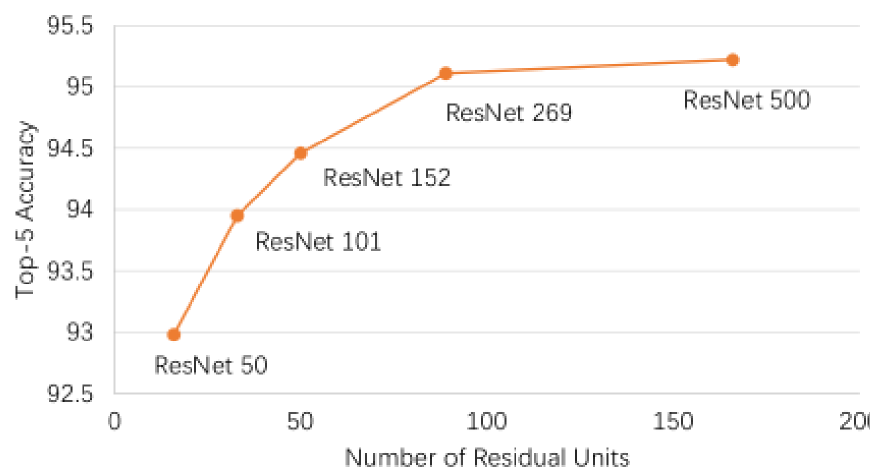
⇒Winners: GoogLeNet, VGG, **ResNet**

Deep ConvNets for image classification

- ResNet 152 layers, 60M parameters

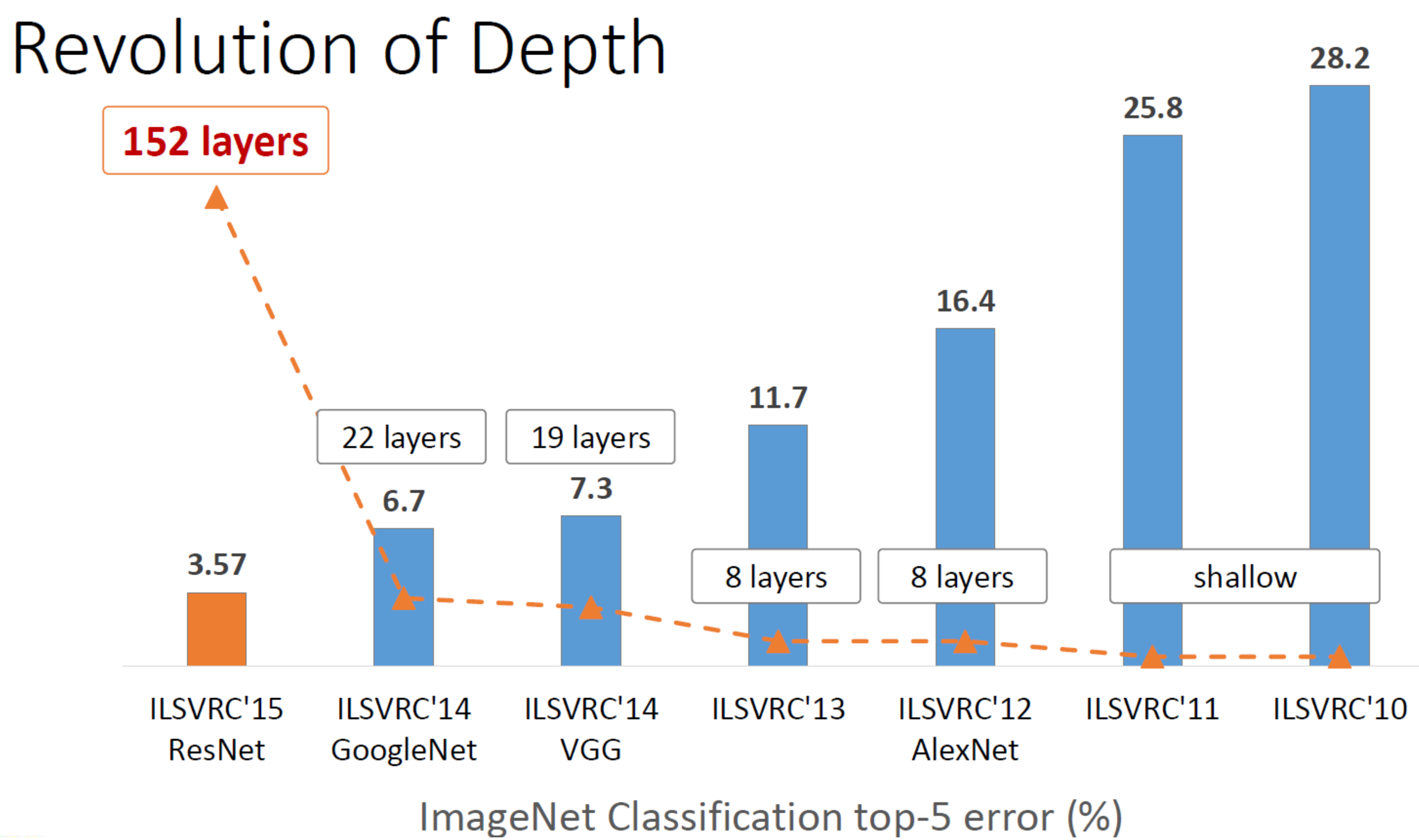


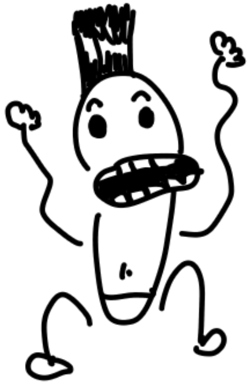




Kaiming He, Xiangyu Zhang, Shaoqing Ren and Jian Sun
Deep Residual Learning for Image Recognition.
In *CVPR*, 2016.

Deep ConvNets for image classification





ResNet
The deeper, the better

\+ Deeper network covers more complex problems

- Receptive field size ↑
- Non-linearity ↑

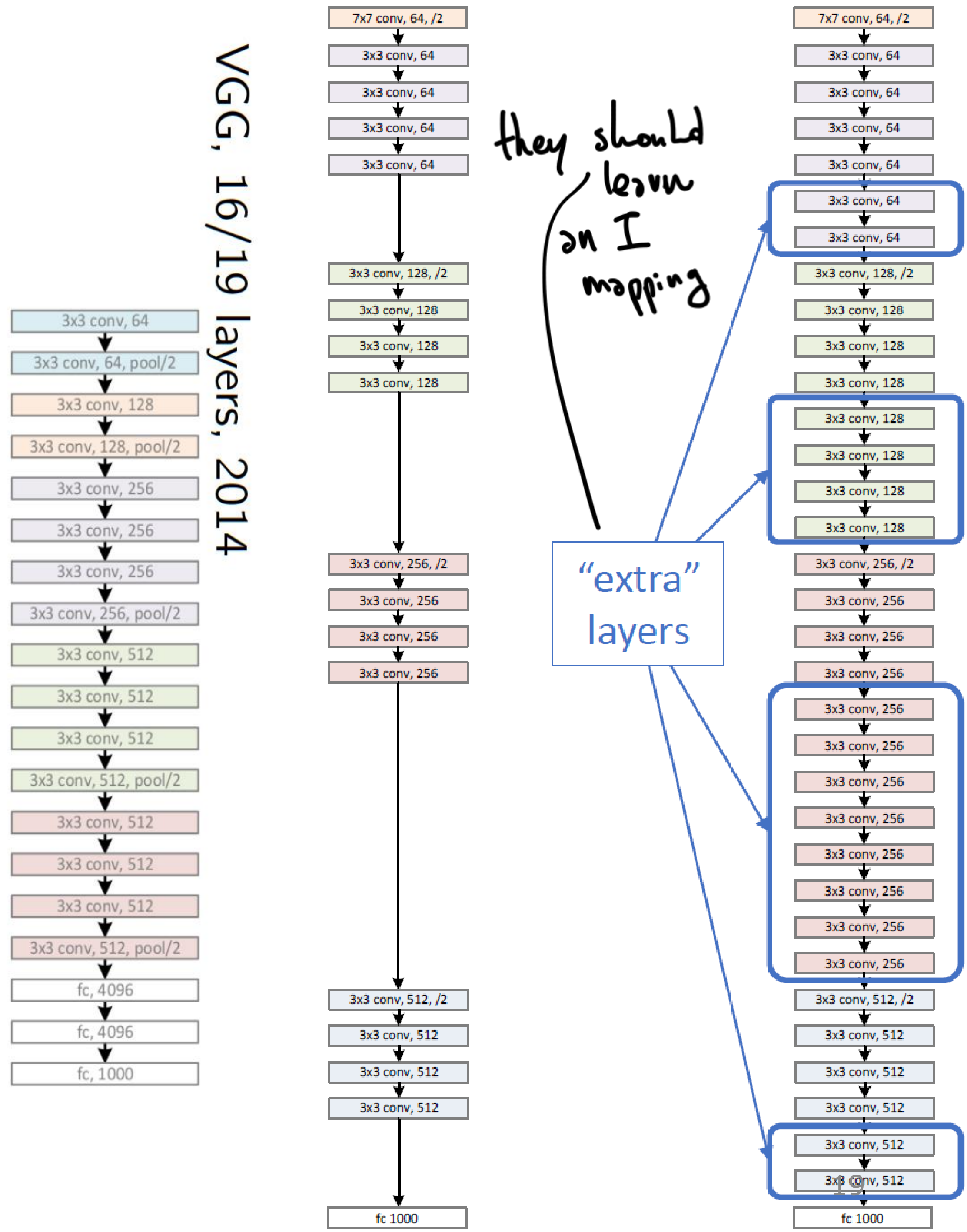
\- Training deeper network more difficult because of vanishing/exploding gradients problem

@ Kaiming He ILSVRC & COCO 2015

Deeper VGG:

Naïve solution

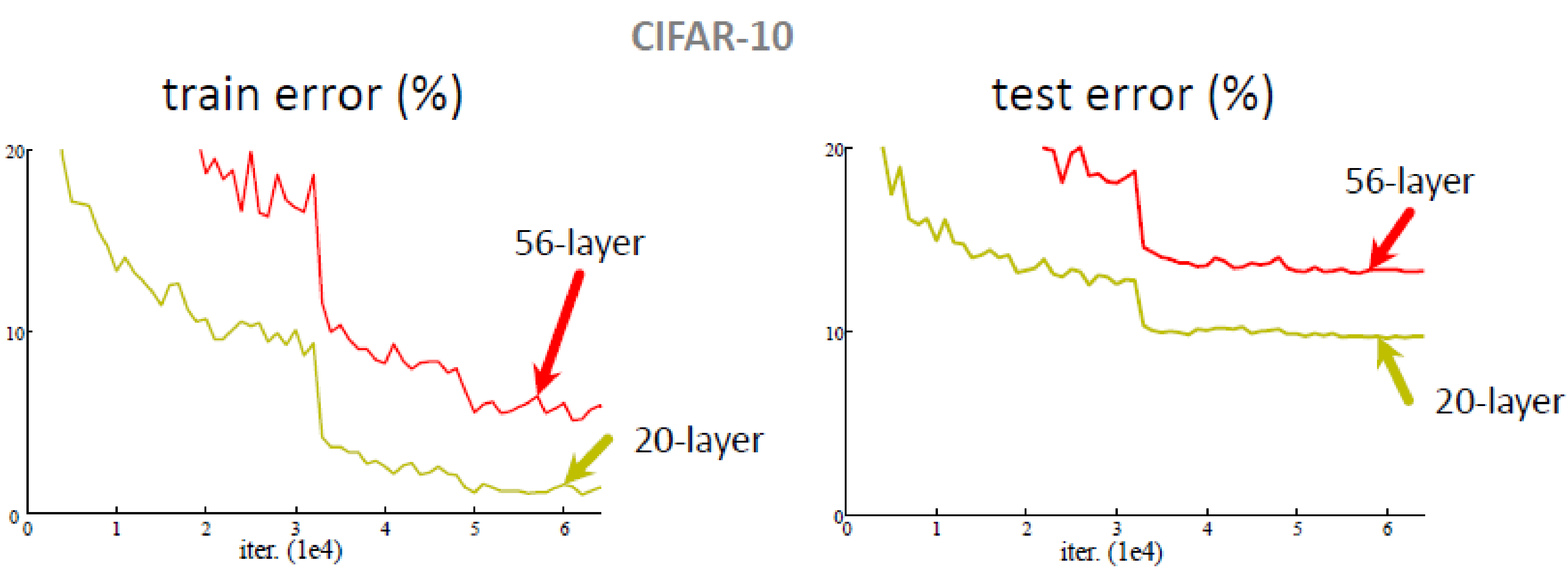
If extra layers identity mapping, training error not increase

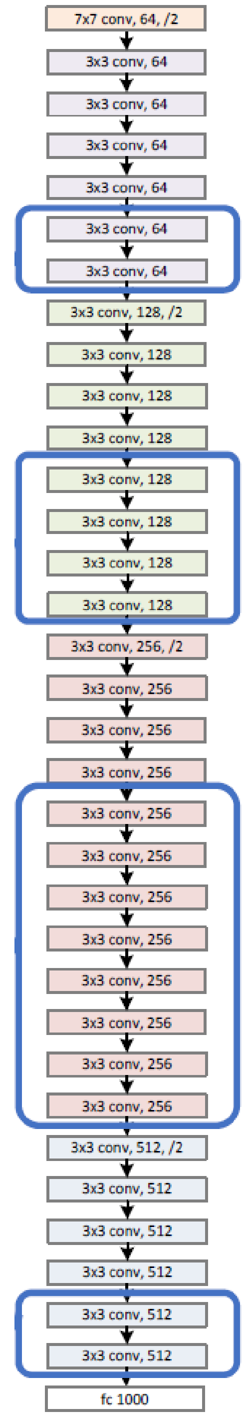


Deeper VGG: 56 Plain Network

Plain nets: stacking 3x3 conv layers

- 56-layer net has higher training error and test error than 20-layers net



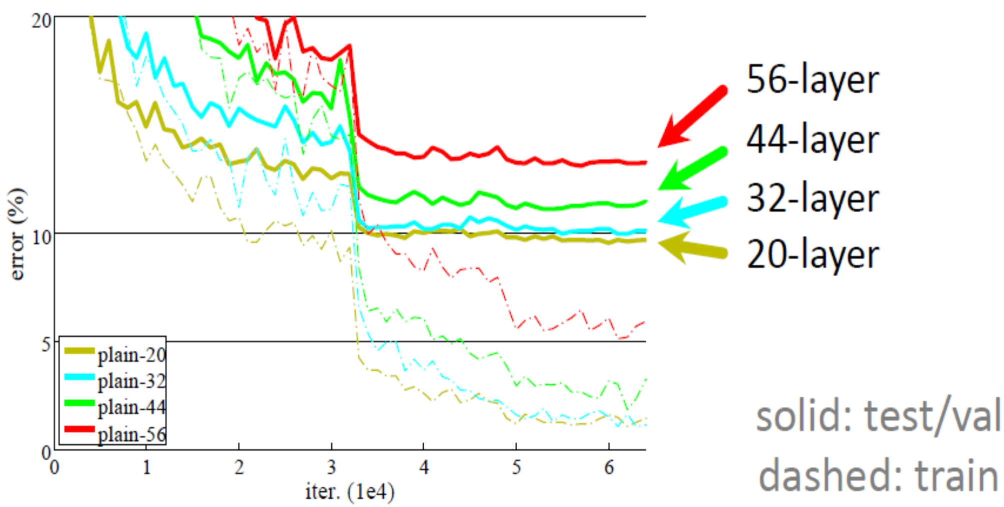


Deeper VGG:

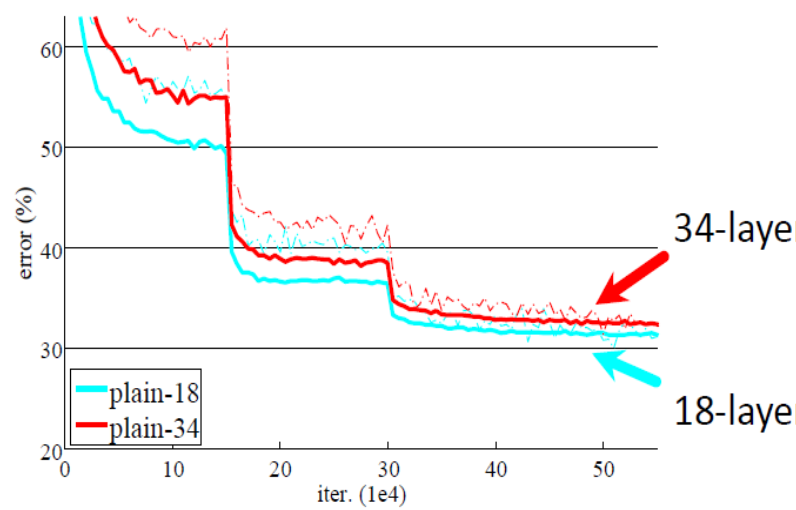
“Overly deep” plain nets have higher training error

A general phenomenon, observed in many datasets

CIFAR-10



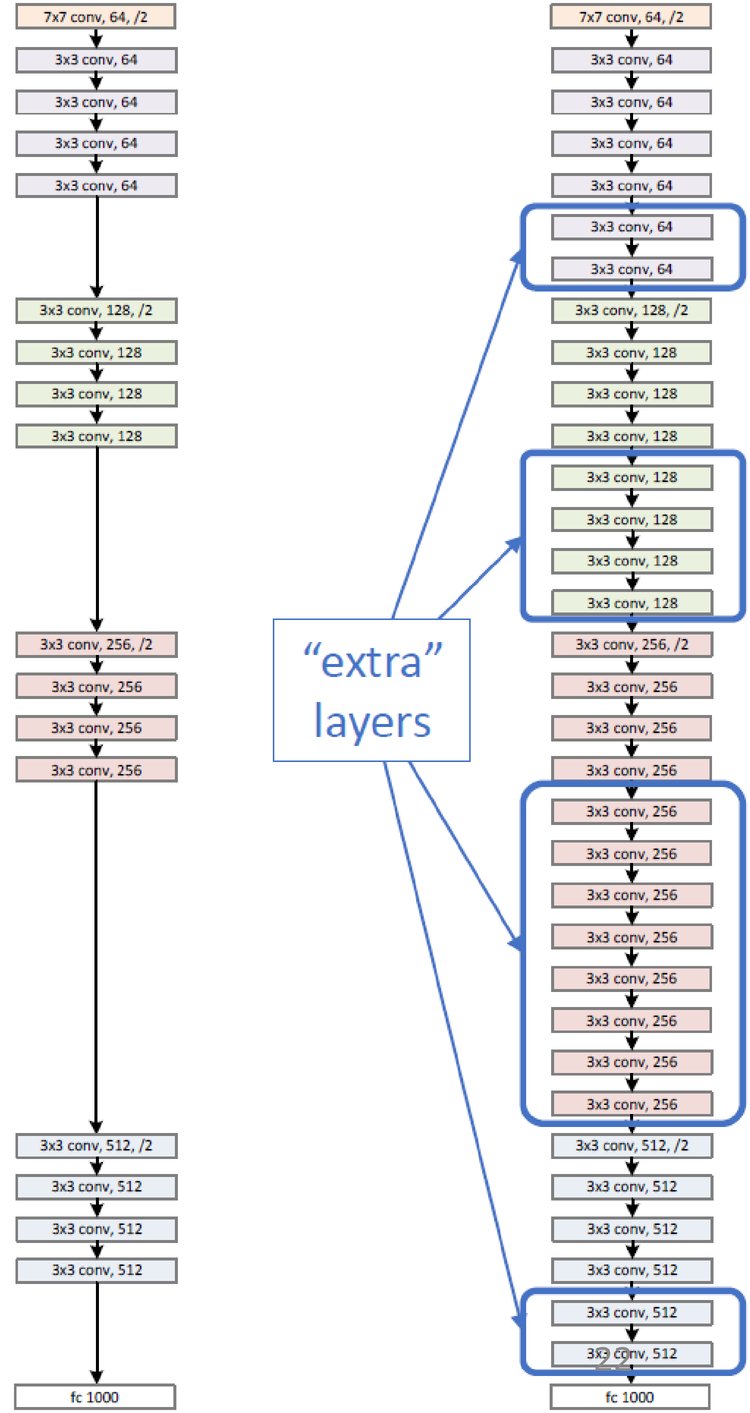
ImageNet-1000



Deeper VGG:

Deeper networks maintain the tendency of results

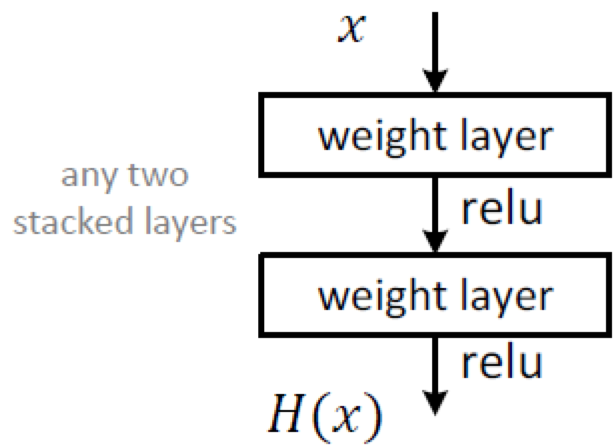
- Features in same level will be almost same
- An amount of changes is fixed
- Adding layers make smaller differences
- Optimal mappings closer to an identity



Residual Network

Plain block:

Difficult to make identity mapping because of multiple non-linear layers



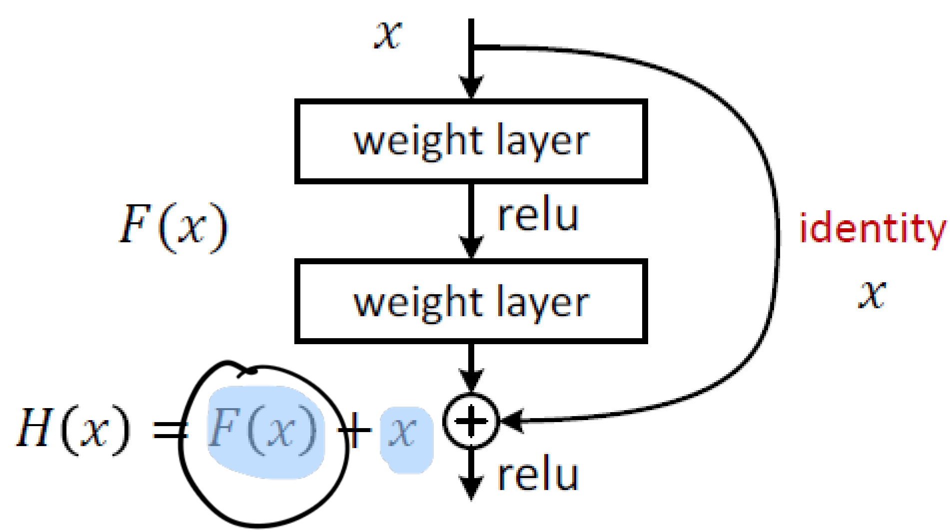
Residual Network

Residual block:

If identity were optimal, easy to set weights as 0

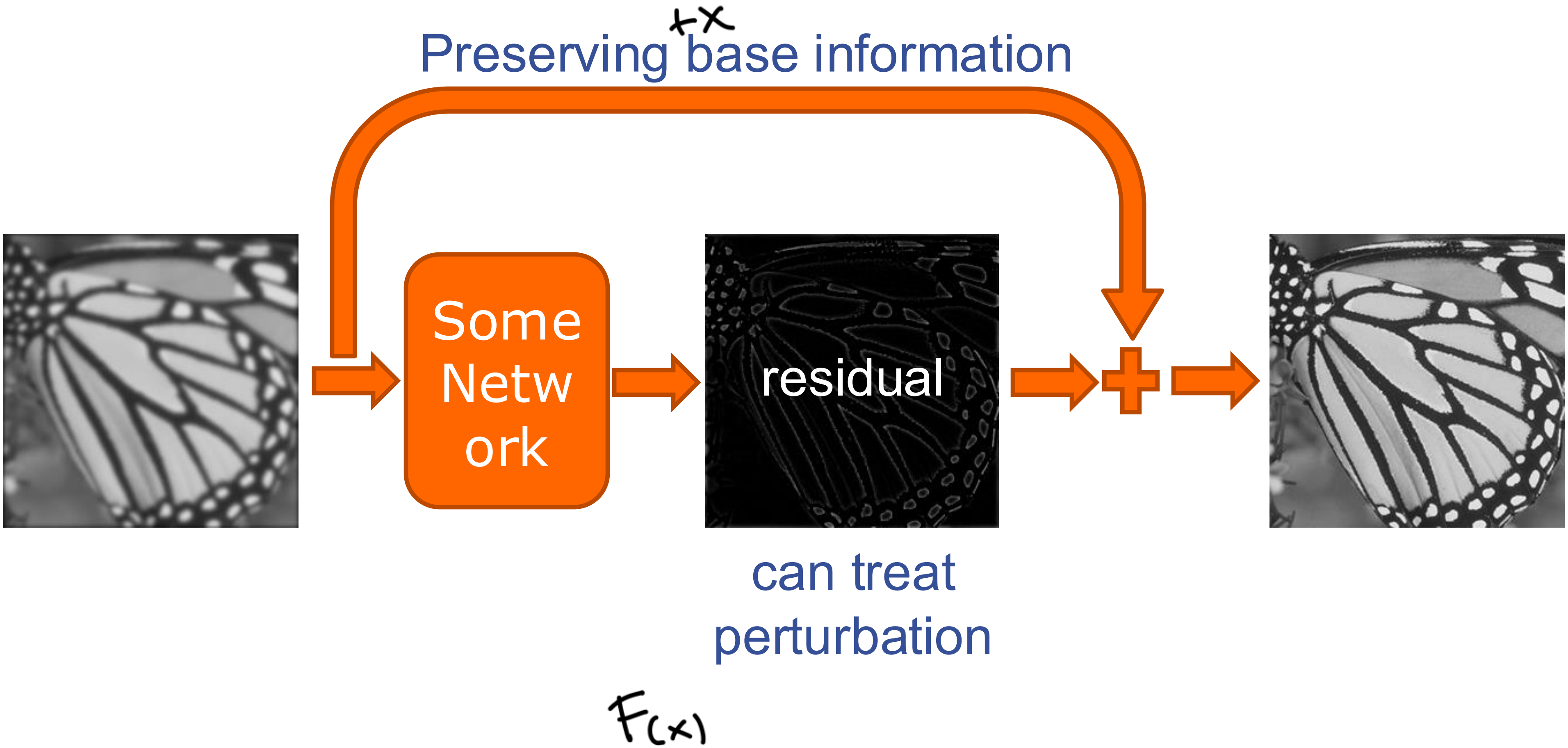
If optimal mapping is closer to identity, easier to find small fluctuations

-> Appropriate for treating perturbation as keeping a base information



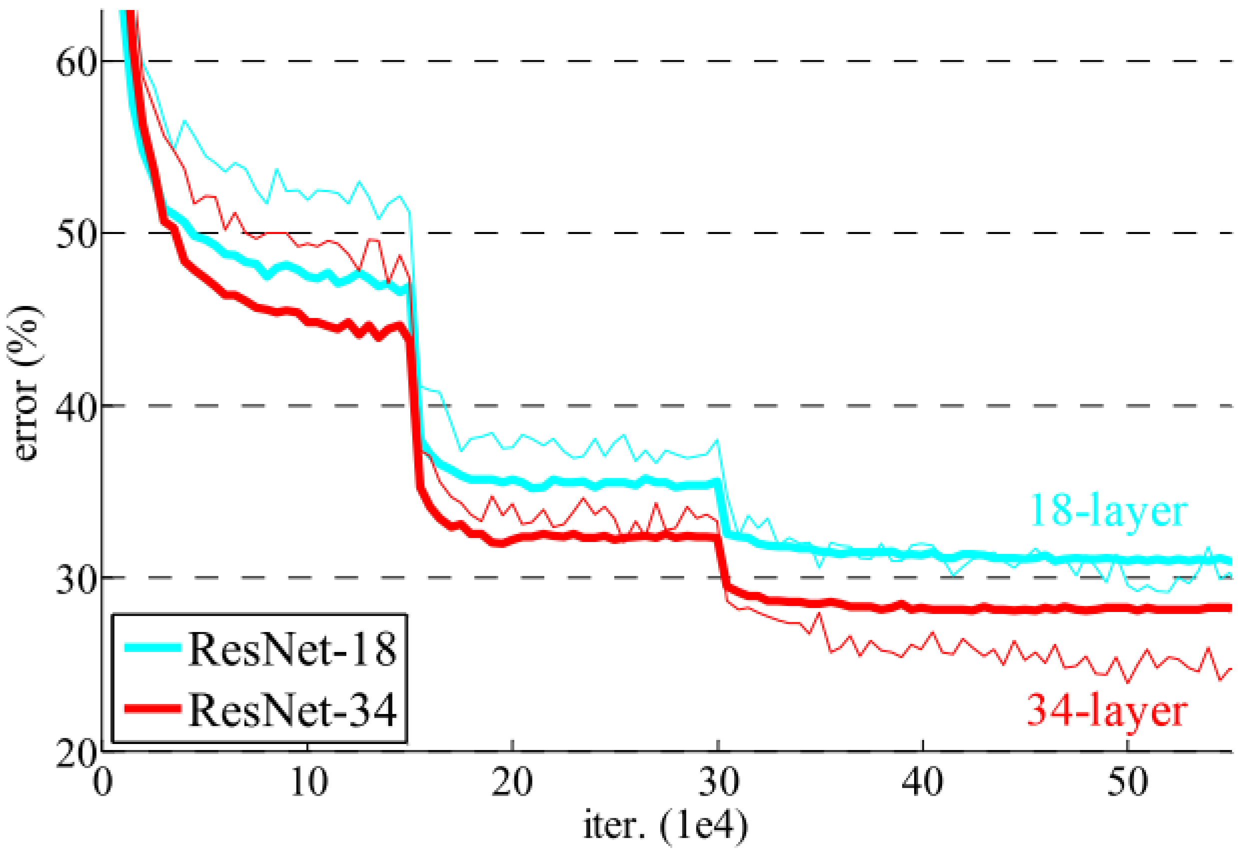
Residual Network

- Difference between an original image and a changed image



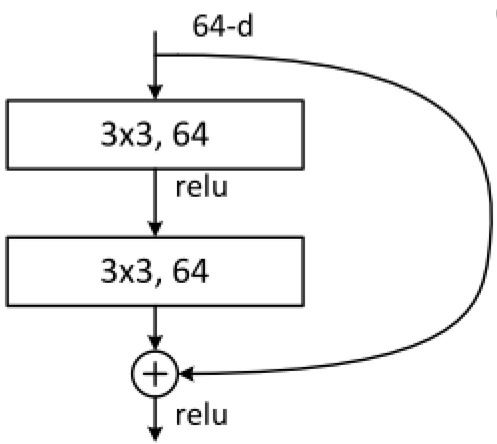
Residual Network

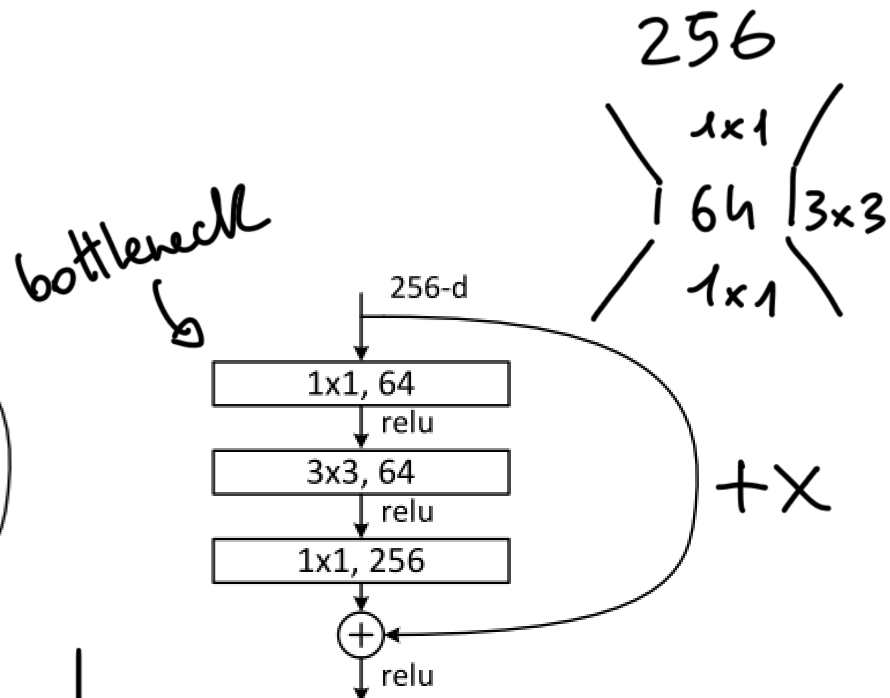
Deeper ResNets have lower training error



Residual Network

- Residual block
  - Very simple
  - Parameter-free





A naïve residual block | “bottleneck” residual block

(for ResNet-50/101/152)

Residual Network

- Shortcuts connections
  - Identity shortcuts

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

  - Projection shortcuts

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

Network Design

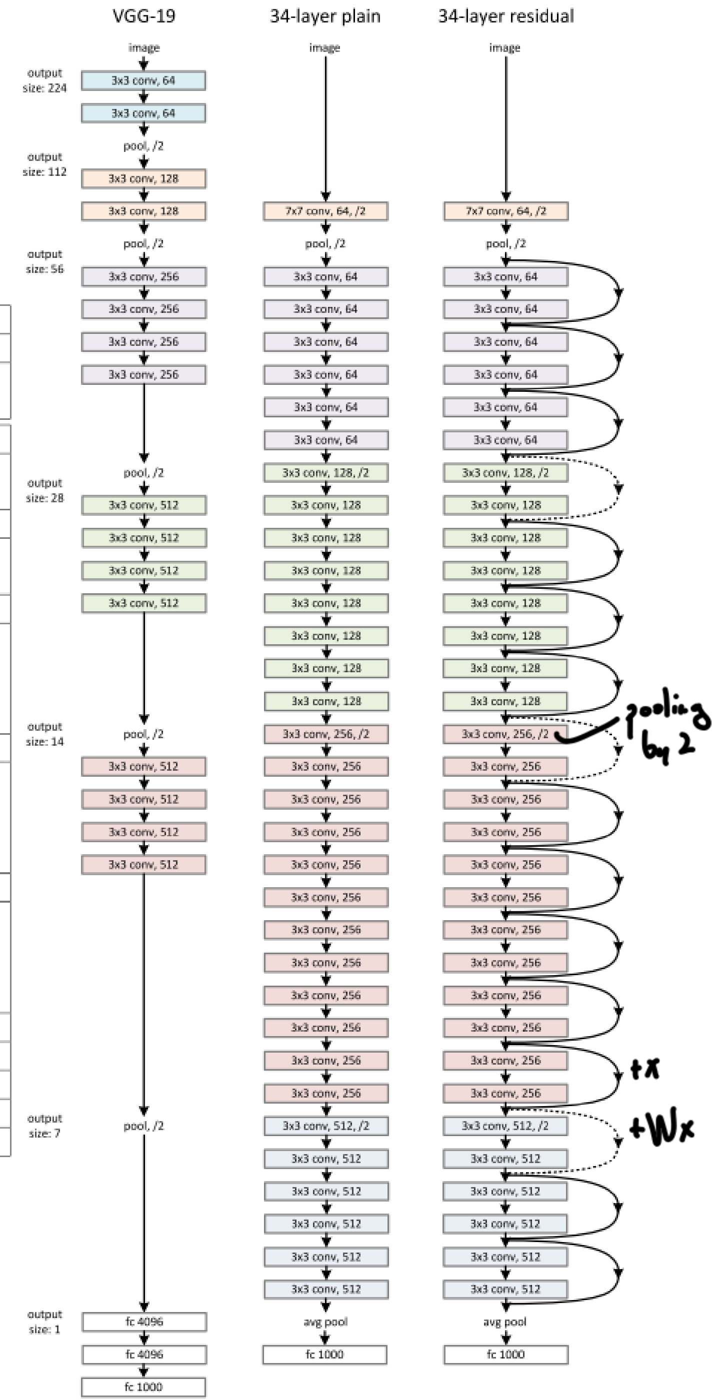
Basic design (VGG-style)

- All 3x3 conv (almost)
- Spatial size/2 => #filters x2
- Batch normalization
- Simple design, just deep

Other remarks

- No max pooling (almost)
- No hidden fc
- No dropout

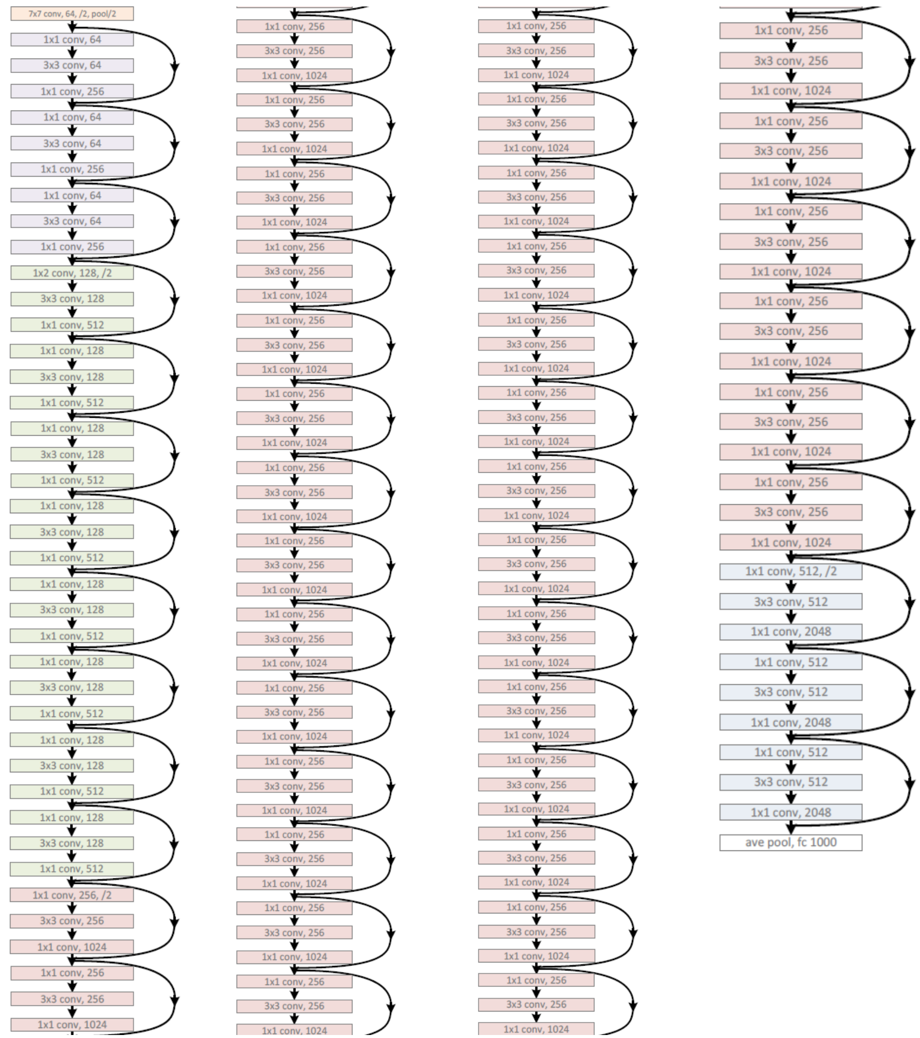
ConvNet Configuration			
B	C	D	E
13 weight layers	16 weight layers	16 weight layers	19 weight layers
ut (224 × 224 RGB image)			
conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool			
conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool			
conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool			
conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool			
conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool			
FC-4096			
FC-4096			
FC-1000			
soft-max			



in backprop the gradient goes back in 2 directions

→ reduced vanishing ∇ problem

Network Design



ResNet-152

Use bottlenecks

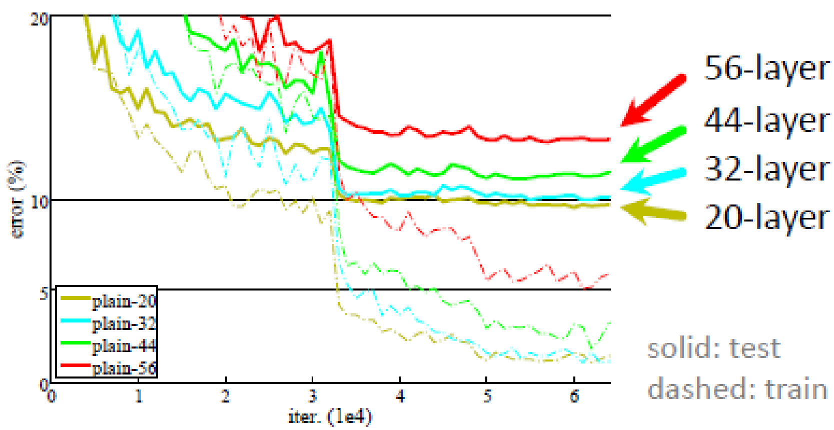
ResNet-152 (11.3 billion FLOPs) lower complexity than VGG-16/19 nets (15.3/19.6 billion FLOPs)

About 64M parameters

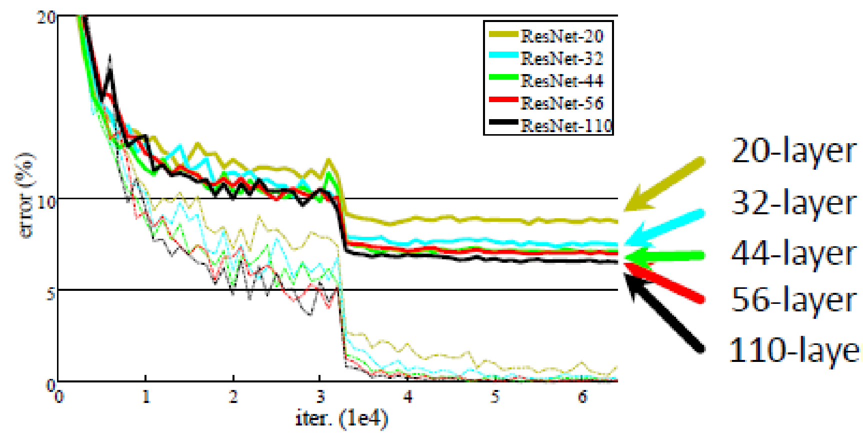
Results

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

CIFAR-10 plain nets

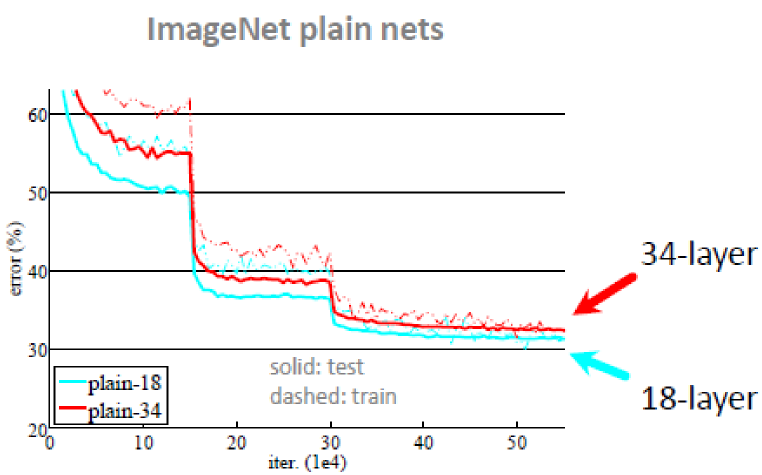


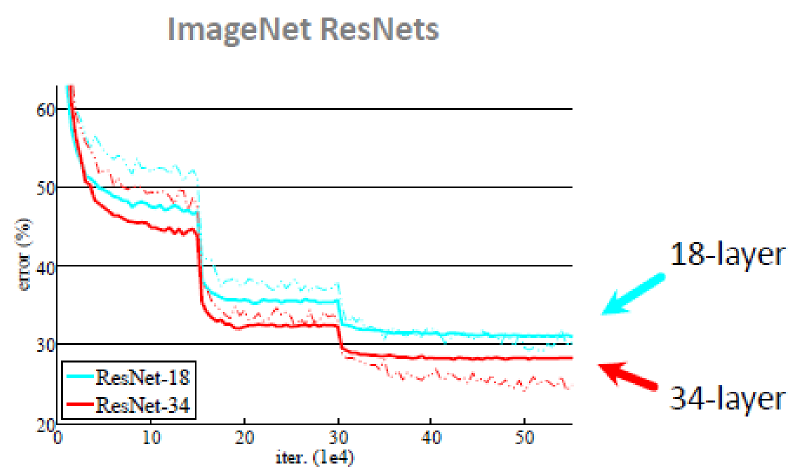
CIFAR-10 ResNets



Results

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





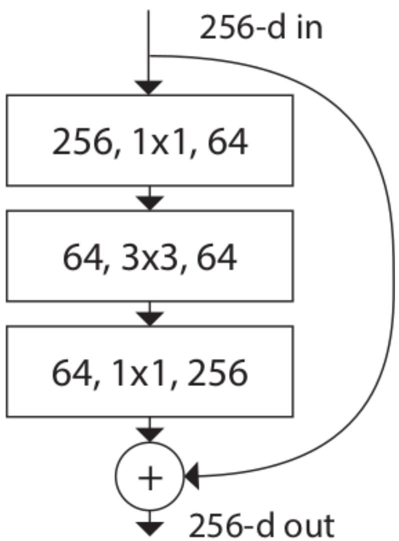
Results

- 1st places in all five main tracks in “ILSVRC & COCO 2015 Competitions”
    - ImageNet Classification
    - ImageNet Detection
    - ImageNet Localization
    - COCO Detection
    - COCO Segmentation

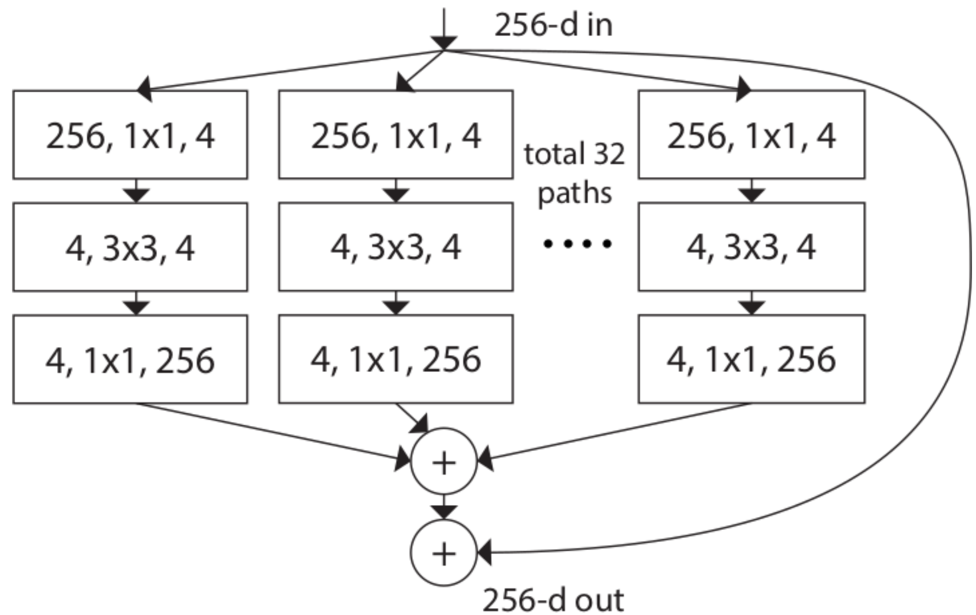
Deep ConvNets for image classification

- ResNeXt
  - Multi-branch architecture

GoogleNet
+
ResNet



ResNet

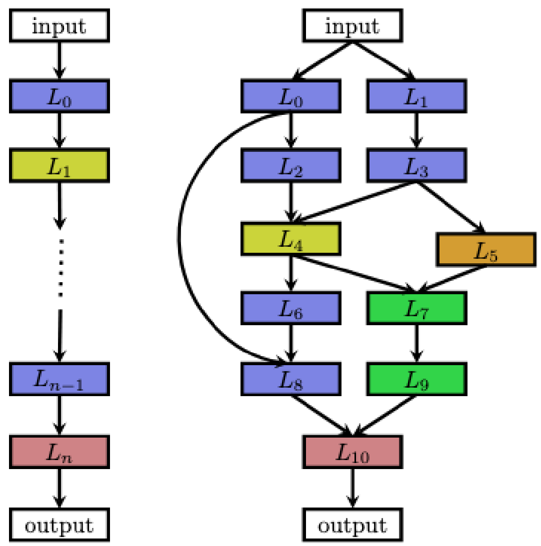


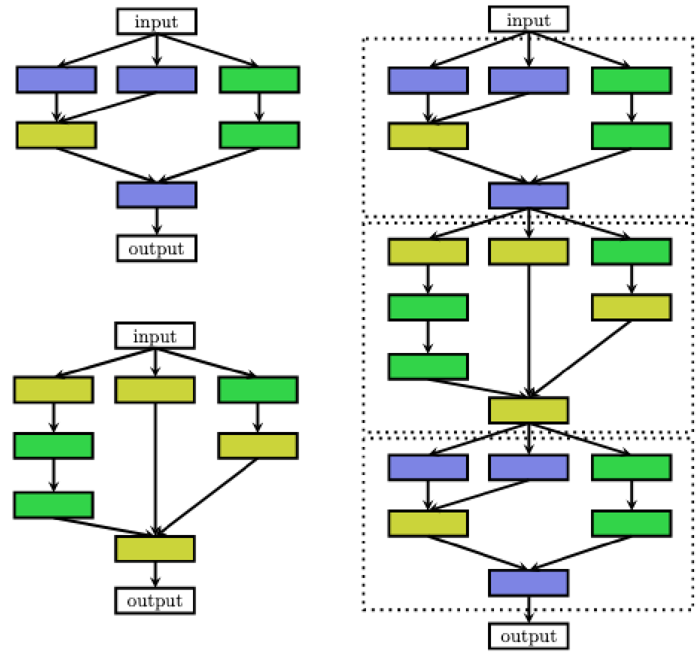
ResNeXt

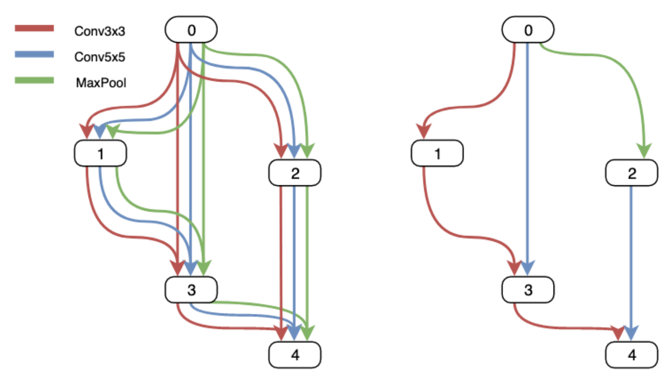
Saining Xie, Ross Girshick, Piotr Dollàr, Zhuowen Tu and Kaiming He
Aggregated Residual Transformations for Deep Neural Networks.
In *CVPR*, 2017.

Exploring type of deep modules in Neural Nets

NAS Neural Architecture Search







Conclusion

- ResNet: currently the best ConvNet framework for large scale image classification
- Fully Convolutional Net (FCN) very interesting option
- Limitation: at each layer, convolution only considers local interaction/attention (limited by the size of the filter)