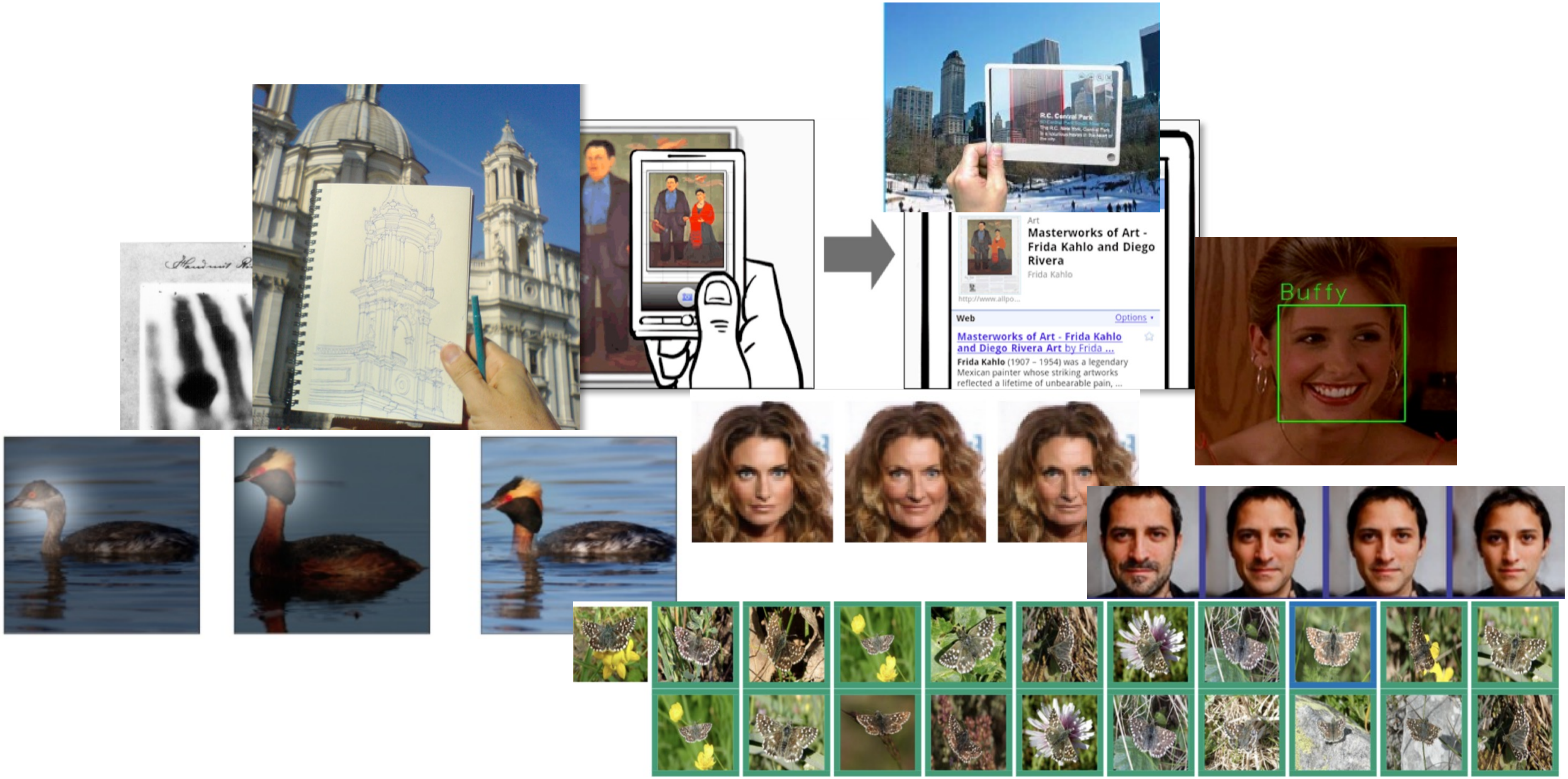


COURS RDFIA deep Image

Matthieu Cord

Sorbonne University

Course Outline – Week timeline

1. Computer Vision basics: Visual (local) feature detection and description, Bag of Word Image representation
2. Supervised learning: Introduction to Neural Networks (NNs)
3. Machine Learning basics: Risk, Classification, Datasets, benchmarks and evaluation, Linear classification (SVM)

Classification – Visual Recognition

4. Convolutional Nets for visual classification
5. **Large deep convnets** and Vision Transformers
6. Beyond ImageNet: FCNs and Segmentation
7. Transfer Learning and domain adaptation
8. Generative models with (conditional) GANs
9. Vision-Language models
10. Control
11. Explainable AI and applications

12/14. Bayesian deep learning

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?

How to improve AlexNet architecture?

+++Deep?

+++Convolutional?

+++Fully connected?

All?

⇒A lot of empirical studies

⇒Tuning various design parameters

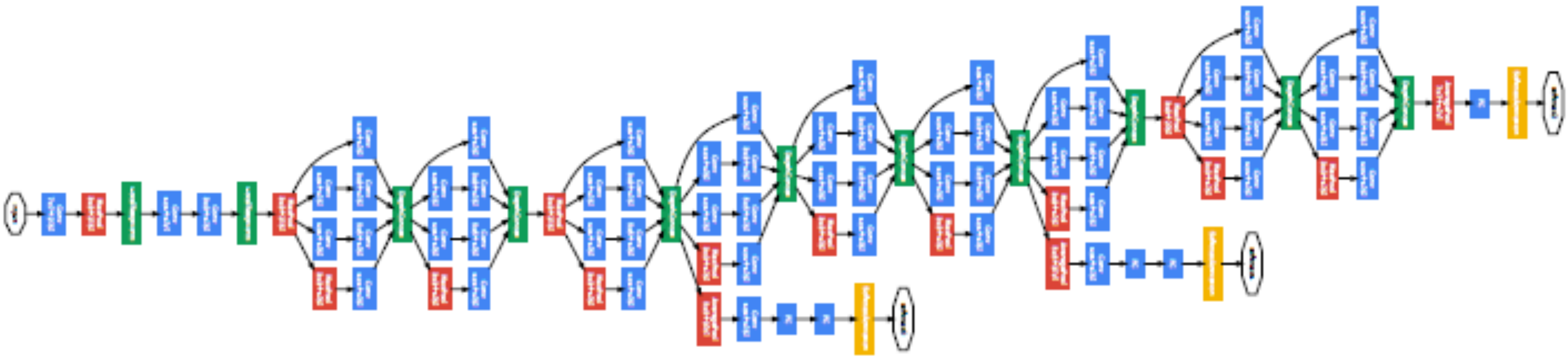
⇒what really works?

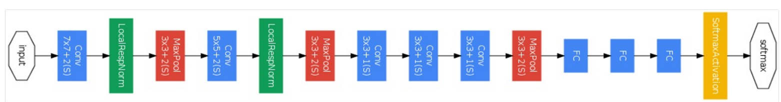
⇒Winners: **GoogLeNet**, VGG, ResNet

GoogLeNet (2014)

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

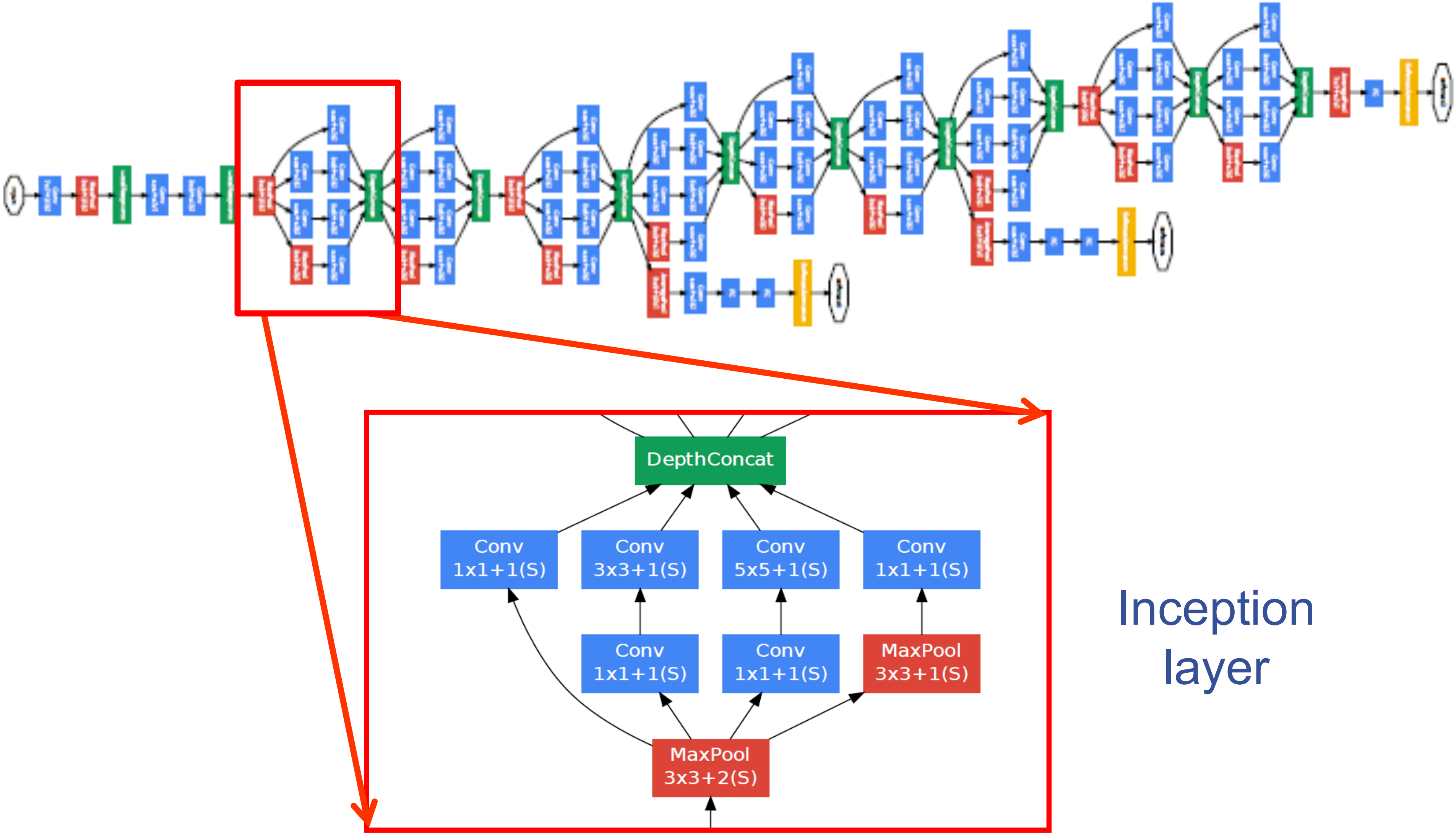
- Network–in-network–in-network
- Removed fully connected layers → small # of parameters (5M weights)





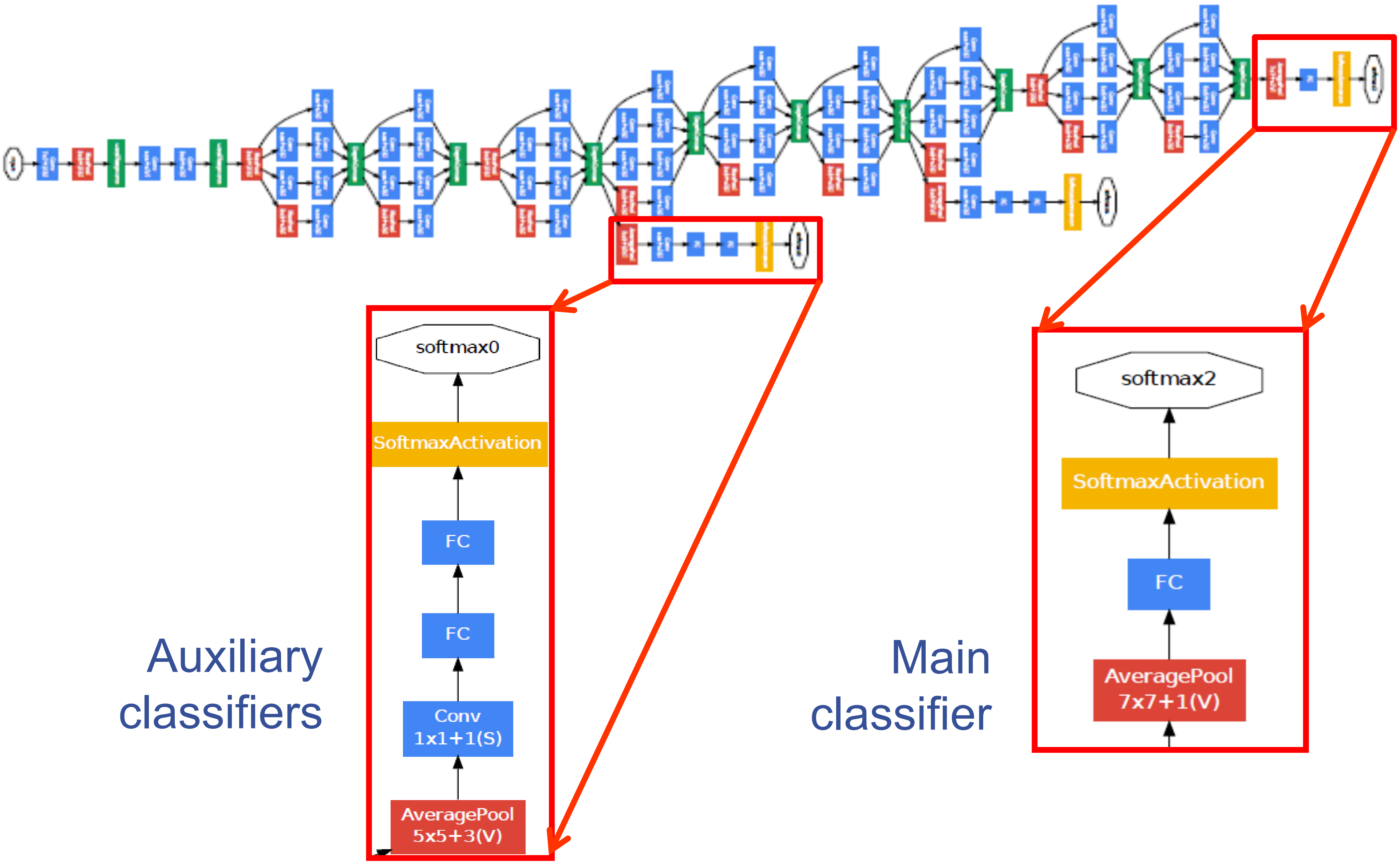
Convolution
Pooling
Softmax
Other

GoogLeNet (2014)



Inception layer

GoogLeNet (2014)



Recap AlexNet: What's next?

How to improve AlexNet architecture?

+++Deep?

+++Convolutional?

+++Fully connected?

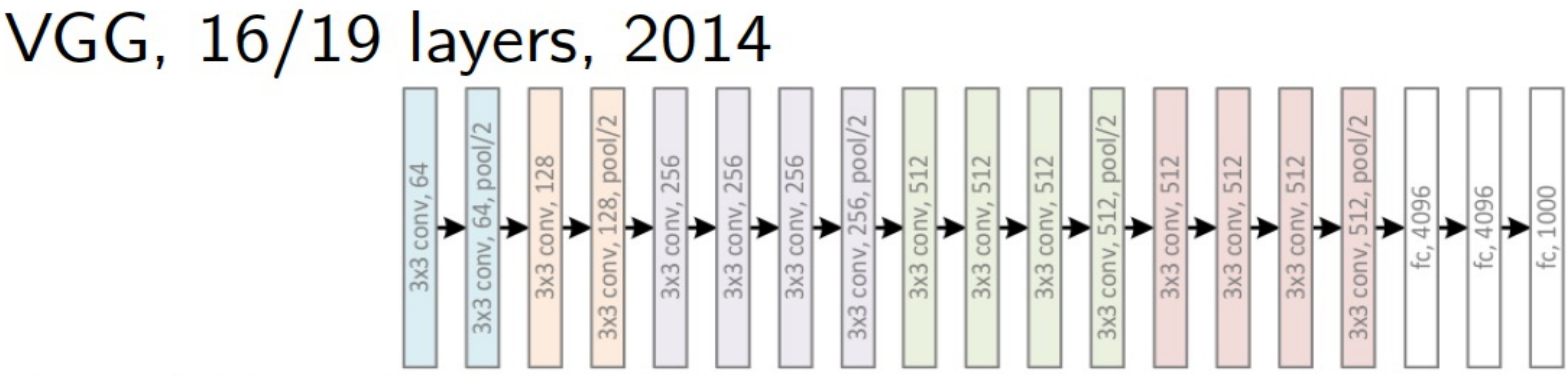
All?

⇒A lot of empirical studies

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

⇒Winners: GoogLeNet, **VGG**, ResNet

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					

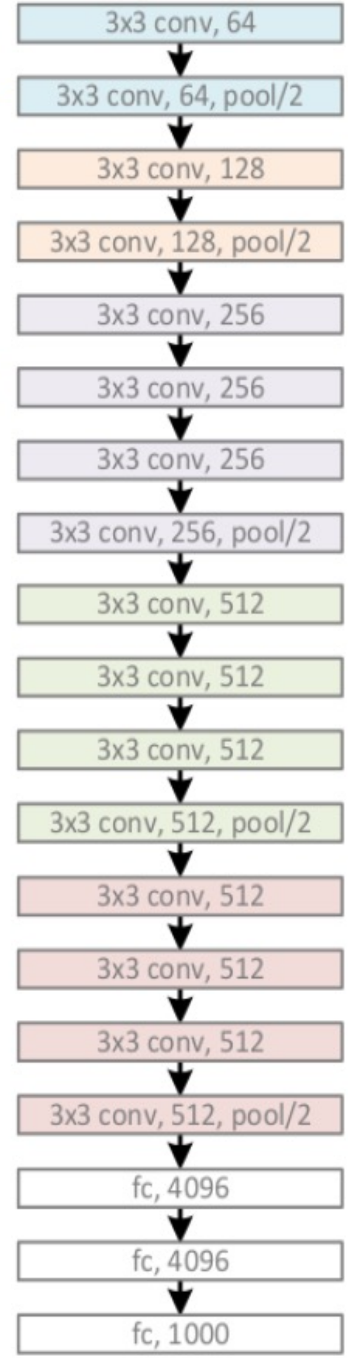


TABLE CREDIT:VERY DEEP CONVOLUTIONAL NETWORKS FOR LARGE-SCALE IMAGE RECOGNITION, ICLR2015

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?

+++Deep?

+++Convolutional?

+++Fully connected?

All?

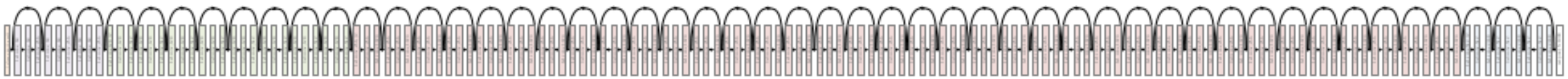
⇒A lot of empirical studies

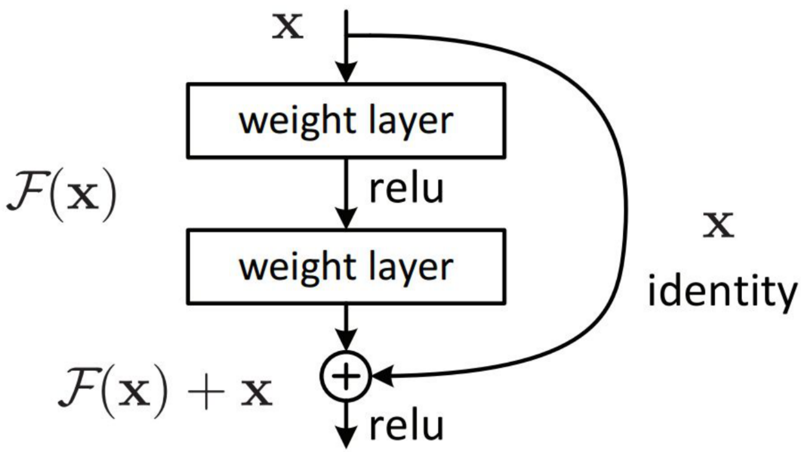
- ⇒Tuning various design parameters
- ⇒what really works?

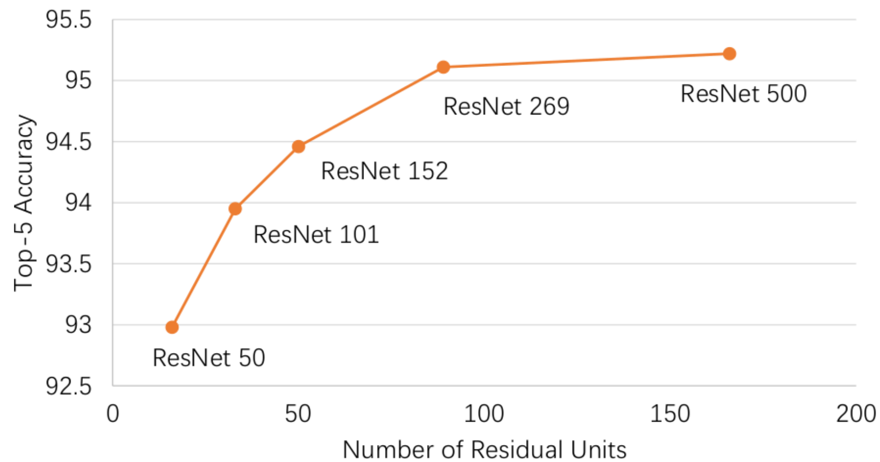
⇒Winners: GoogLeNet, VGG, **ResNet**

Deep ConvNets for image classification

- **ResNet** 152 layers, 60M parameters

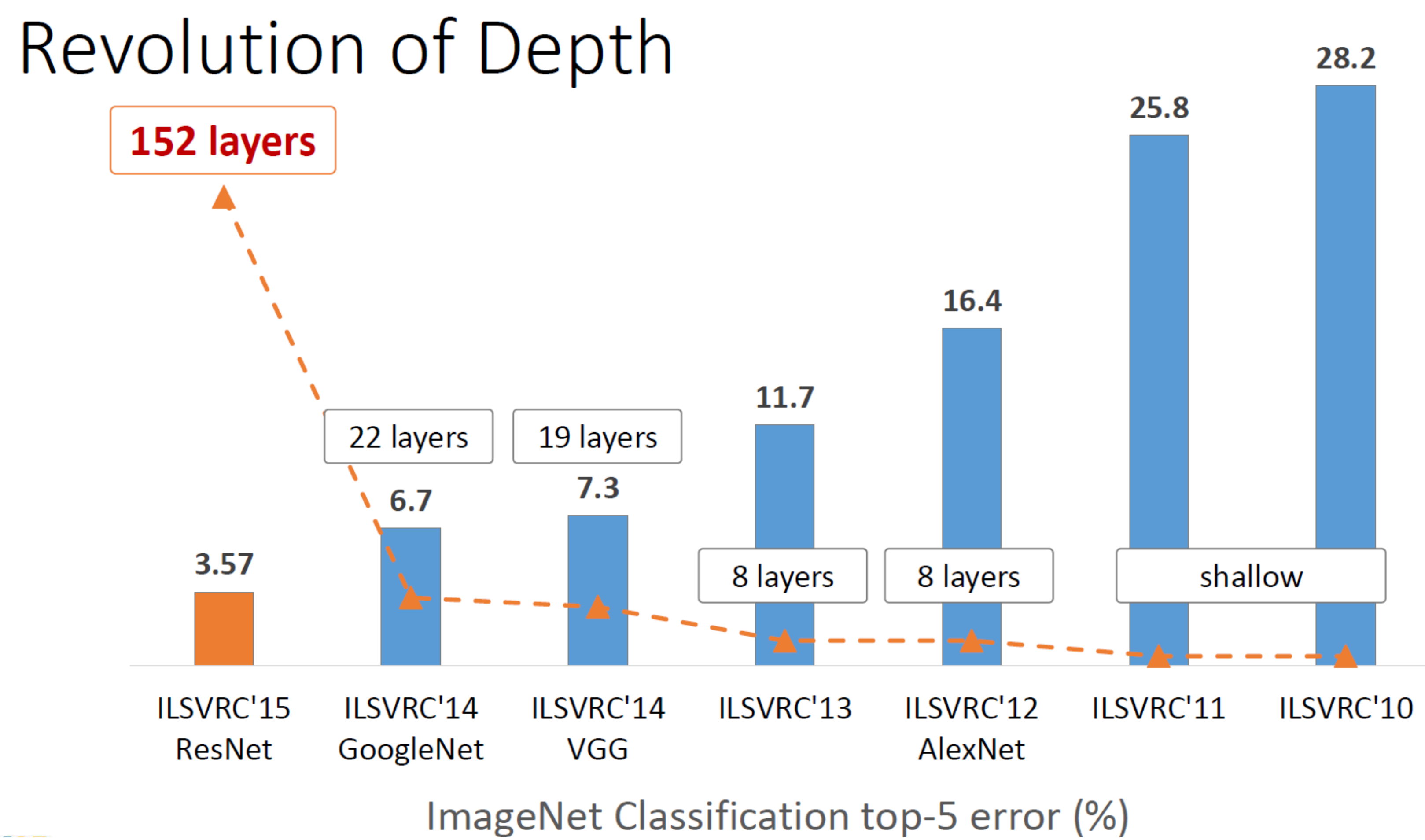






Kaiming He, Xiangyu Zhang, Shaoqing Ren and Jian Sun
Deep Residual Learning for Image Recognition.
In *CVPR*, 2016.

Deep ConvNets for image classification



ResNet
The deeper, the better

\+ Deeper network covers more complex problems

- Receptive field size ↑
- Non-linearity ↑

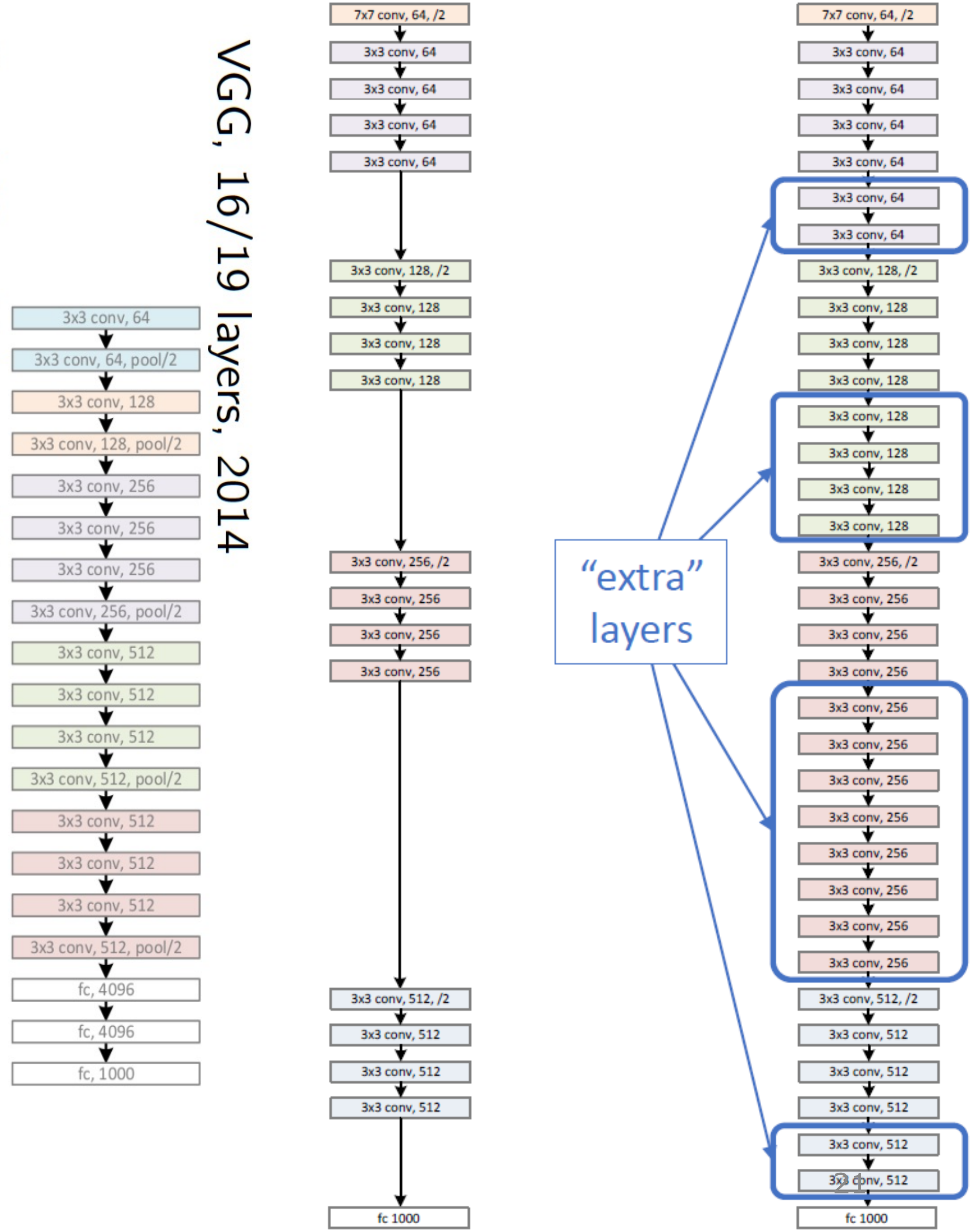
\- Training deeper network more difficult because of vanishing/exploding gradients problem

@ Kaiming He ILSVRC & COCO 2015

Deeper VGG:

Naïve solution

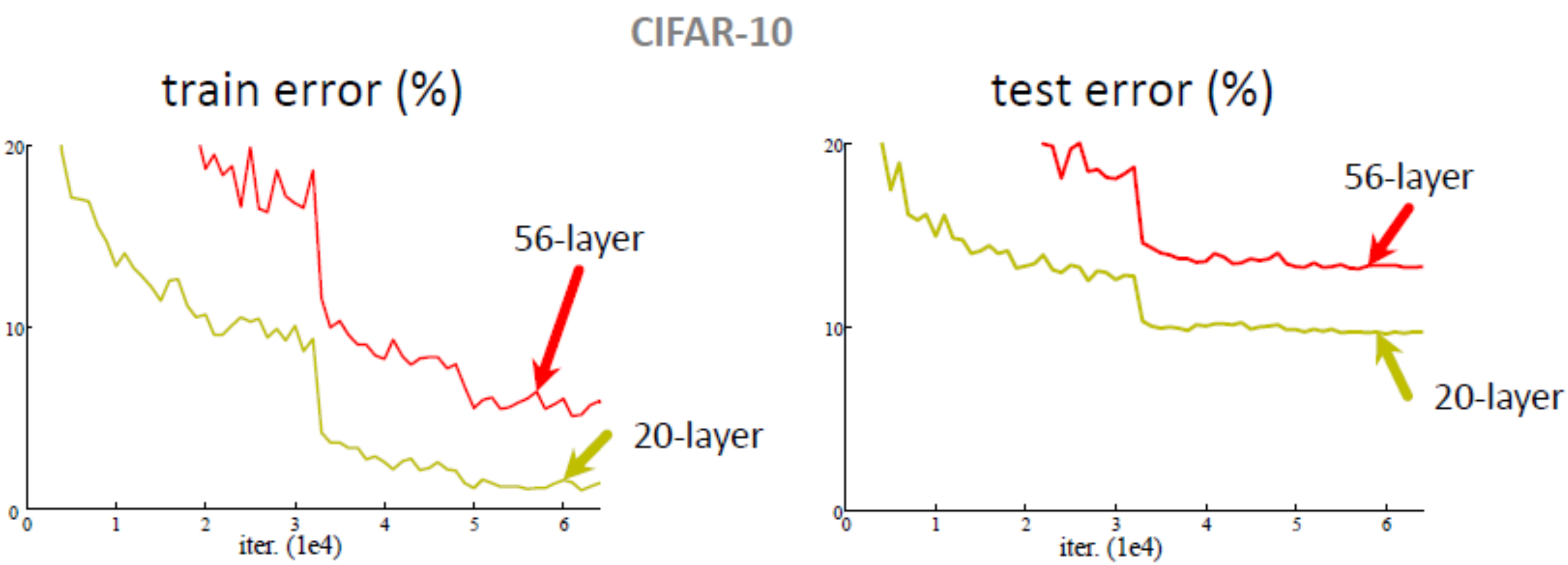
If extra layers identity mapping, training error not increase

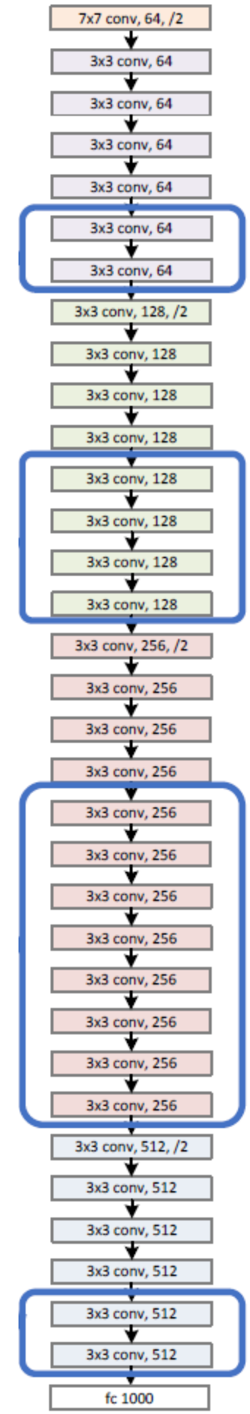


Deeper VGG: 56 Plain Network

Plain nets: stacking 3x3 conv layers

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

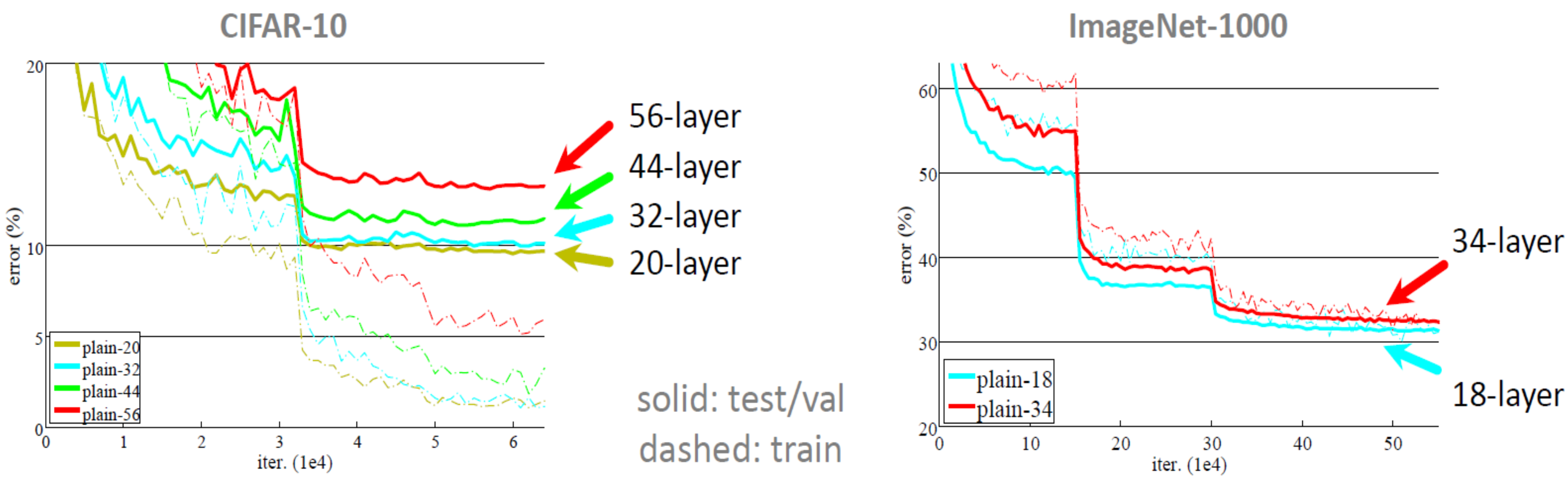




Deeper VGG:

"Overly deep" plain nets have higher training error

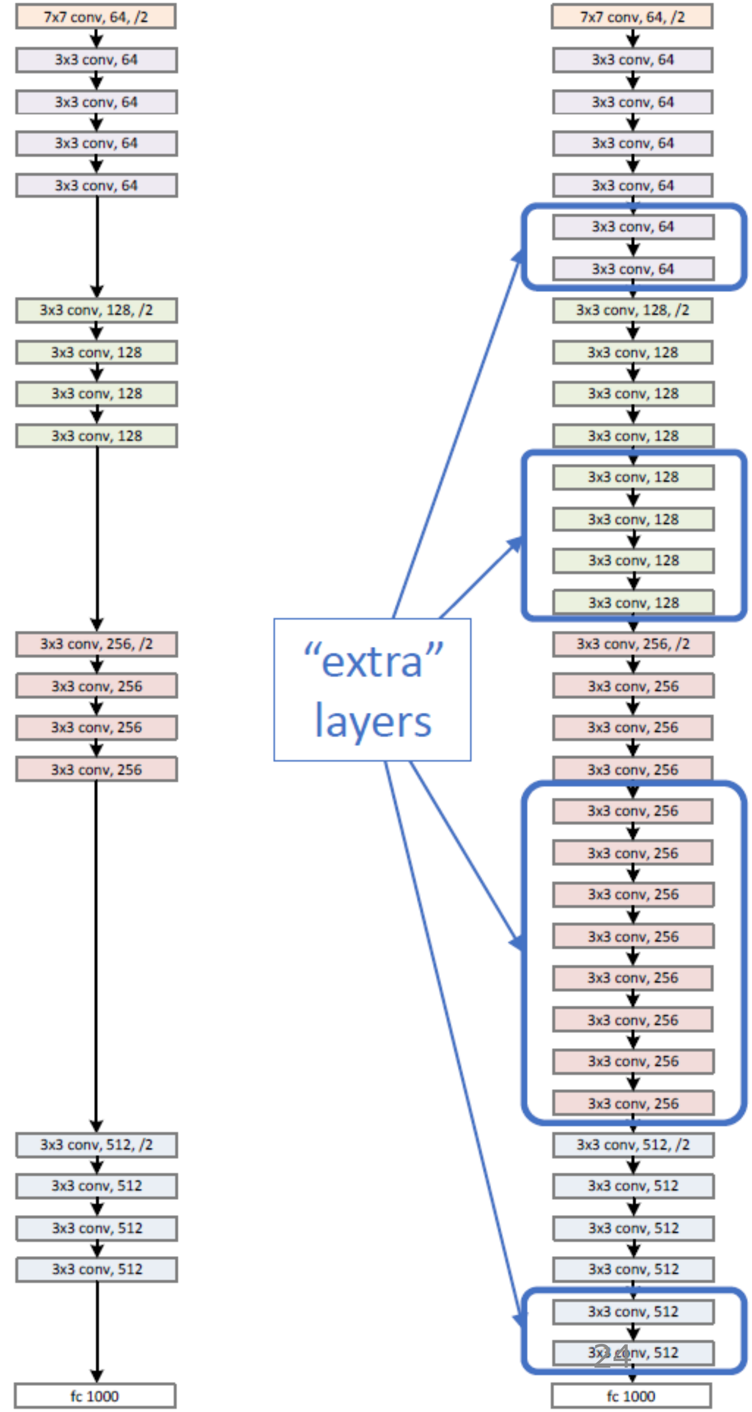
A general phenomenon, observed in many datasets



Deeper VGG:

Deeper networks maintain the tendency of results

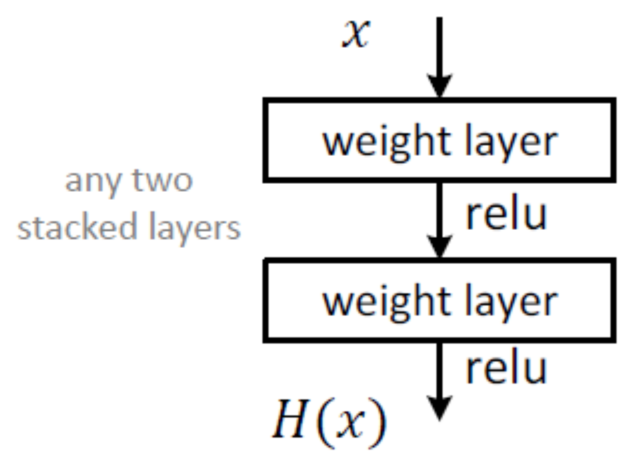
- Features in same level will be almost same
- An amount of changes is fixed
- Adding layers make smaller differences
- Optimal mappings closer to an identity



Residual Network

Plain block

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



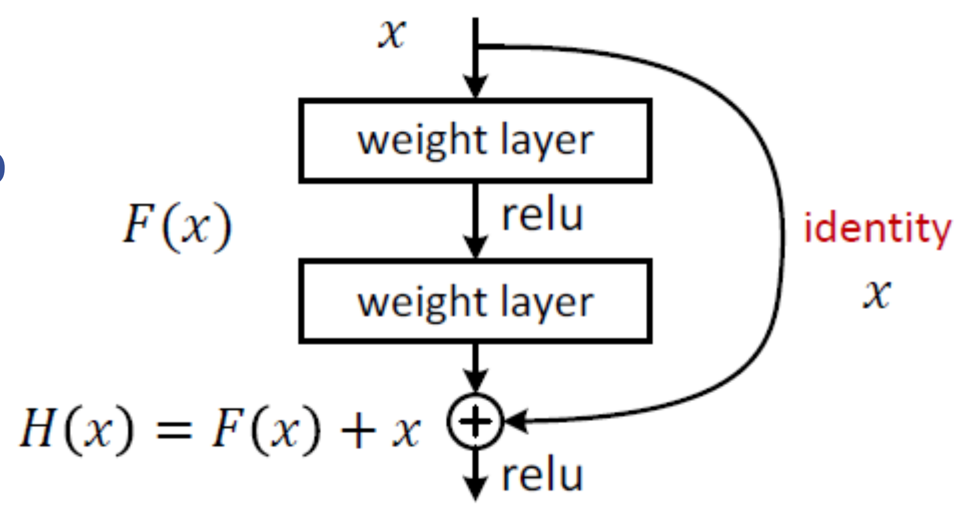
Residual Network

Residual block

If identity were optimal, easy to set weights as 0

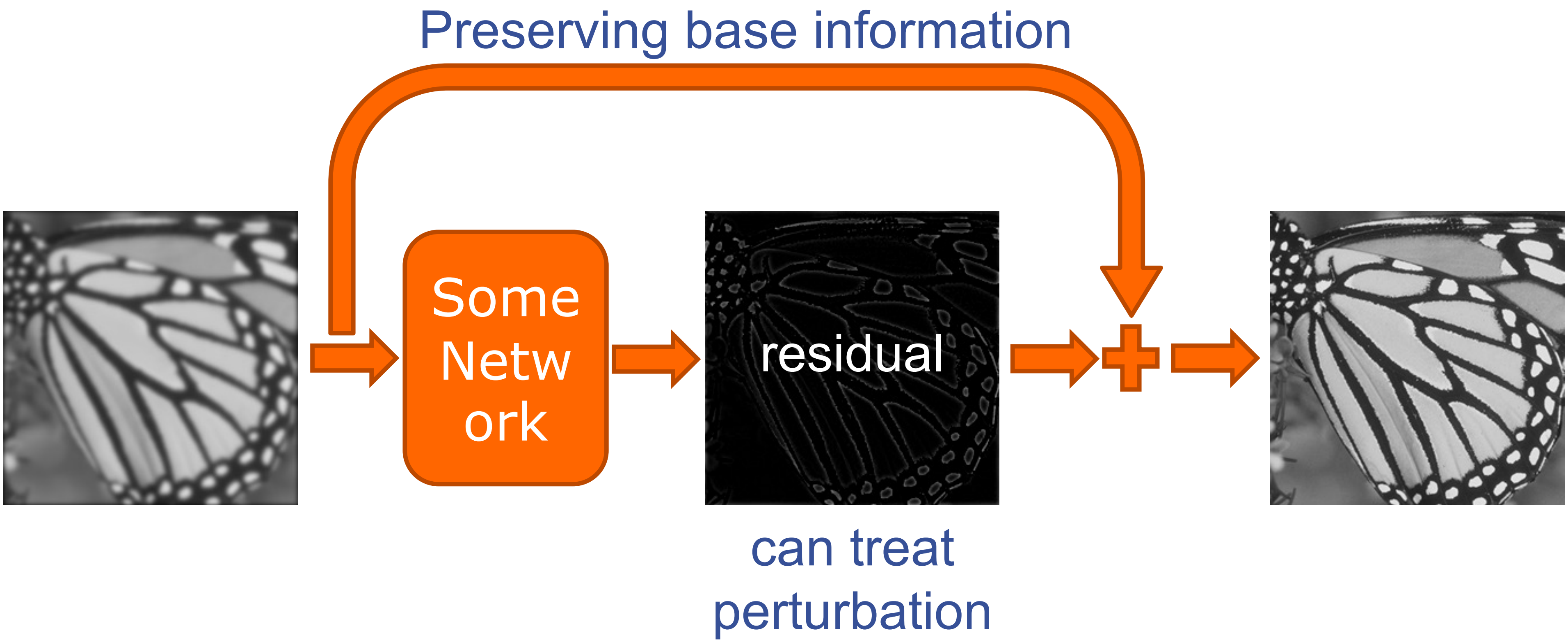
If optimal mapping is closer to identity, easier to find small fluctuations

-> Appropriate for treating perturbation as keeping a base information



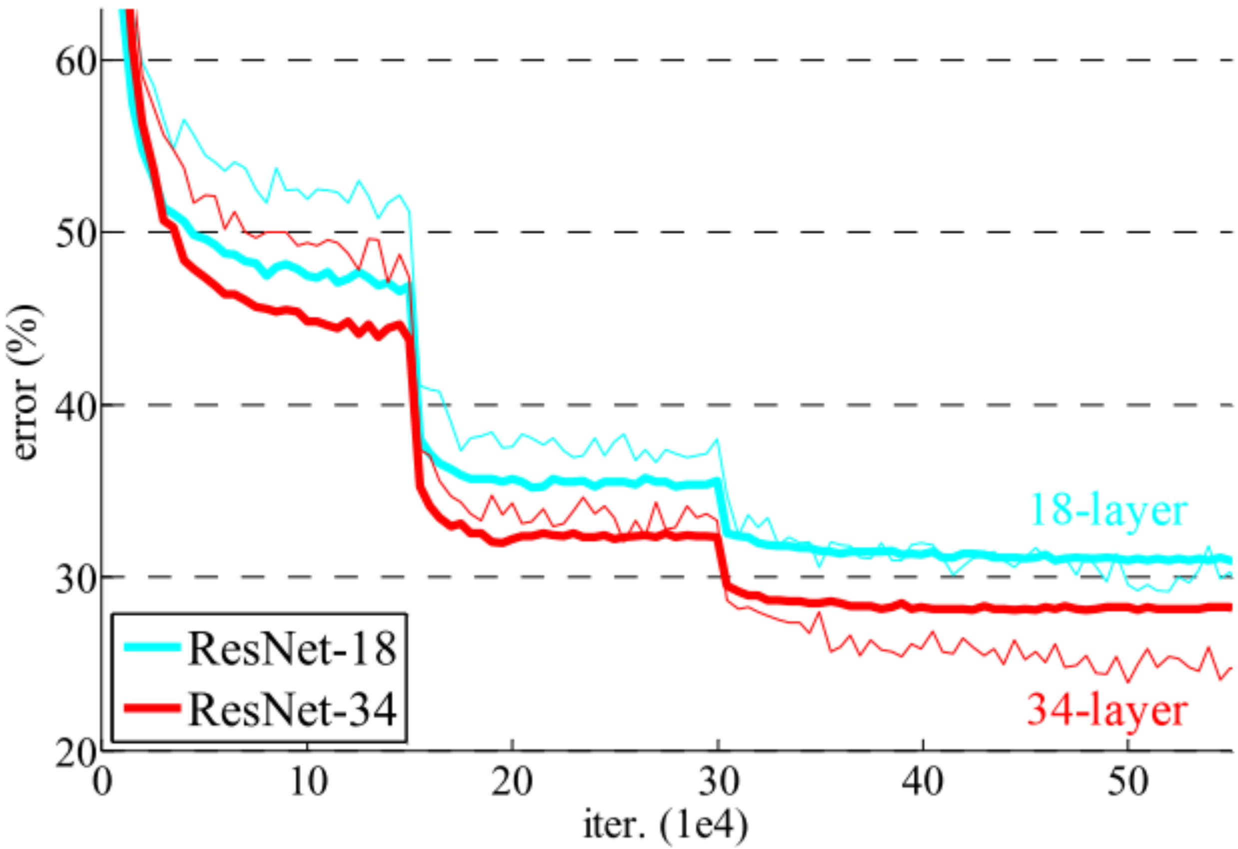
Residual Network

- Difference between an original image and a changed image



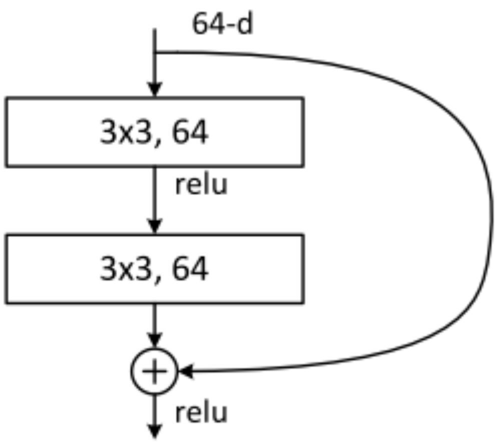
Residual Network

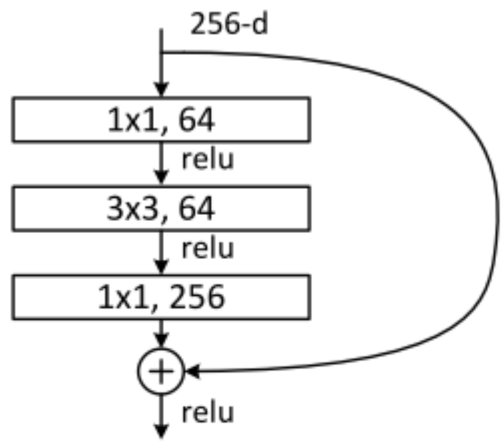
Deeper ResNets have lower training error



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

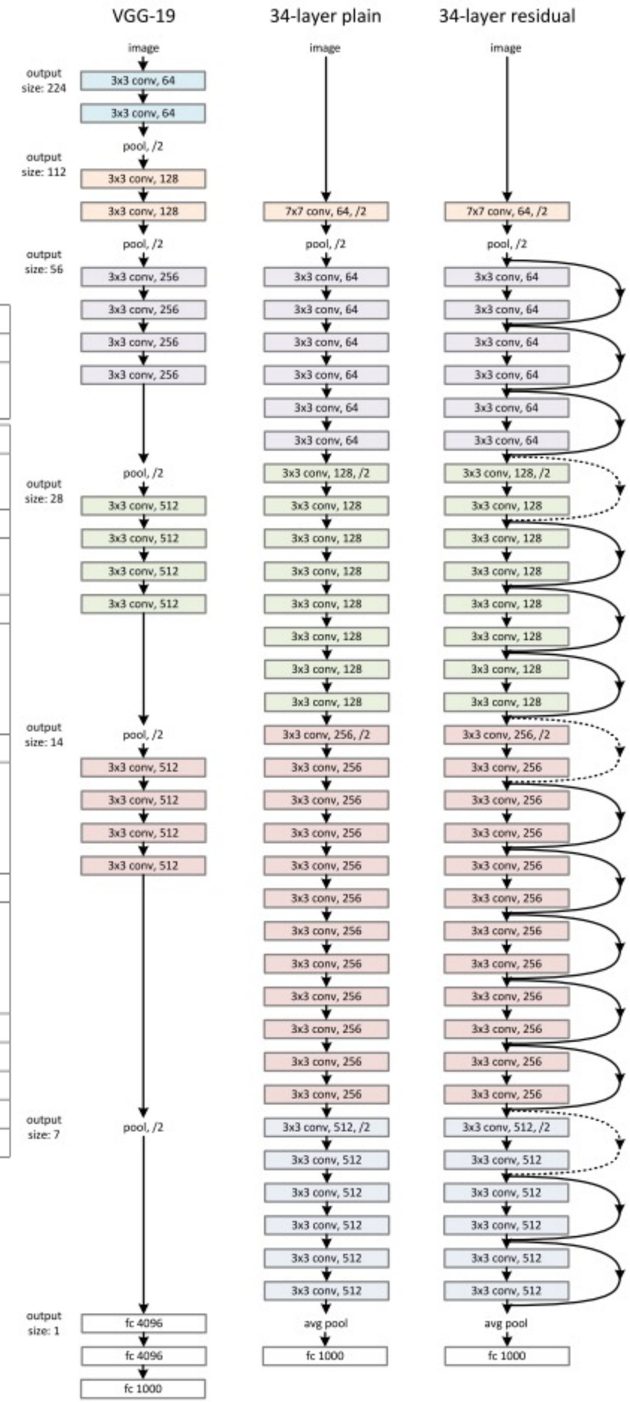
Basic design (VGG-style)

- 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			



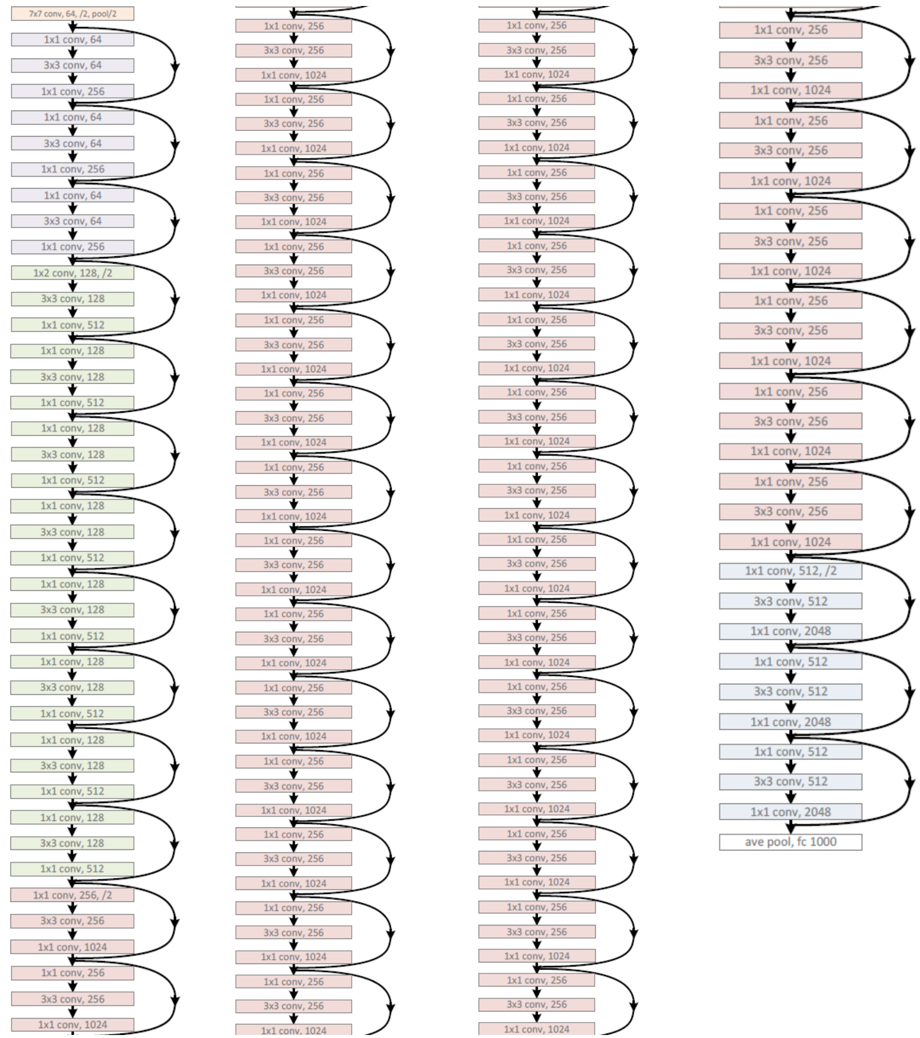
Network Design

ResNet-152

Use bottlenecks

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

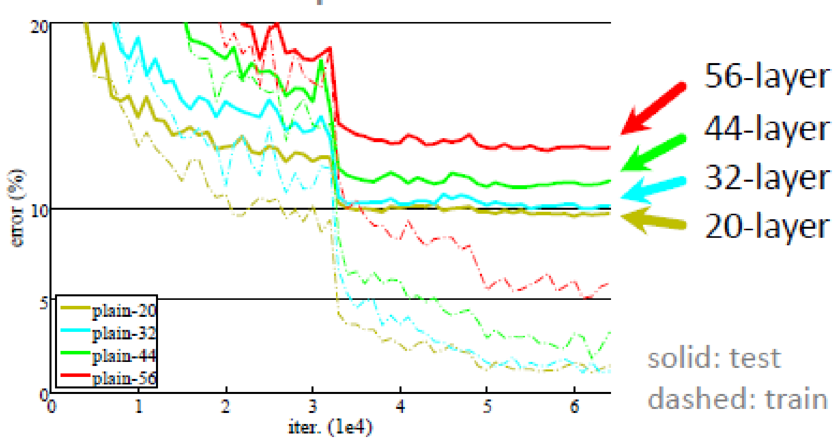
About 64M parameters



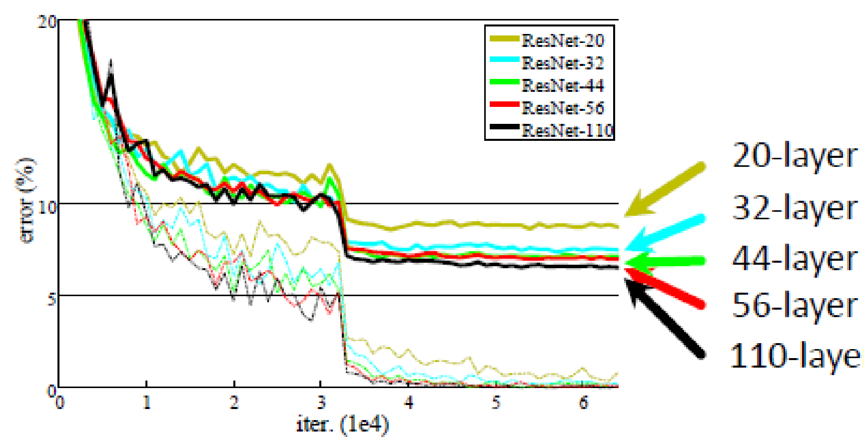
Results

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

CIFAR-10 plain nets



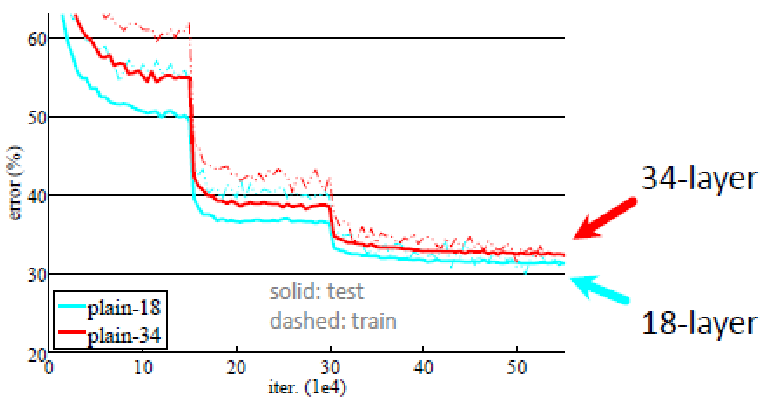
CIFAR-10 ResNets



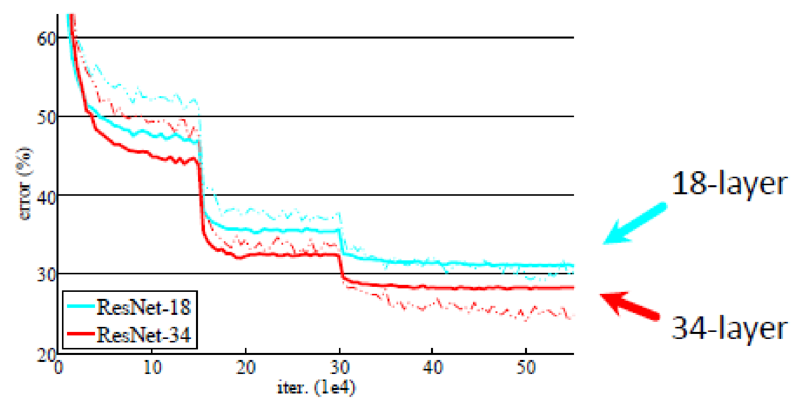
Results

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

ImageNet plain nets



ImageNet ResNets

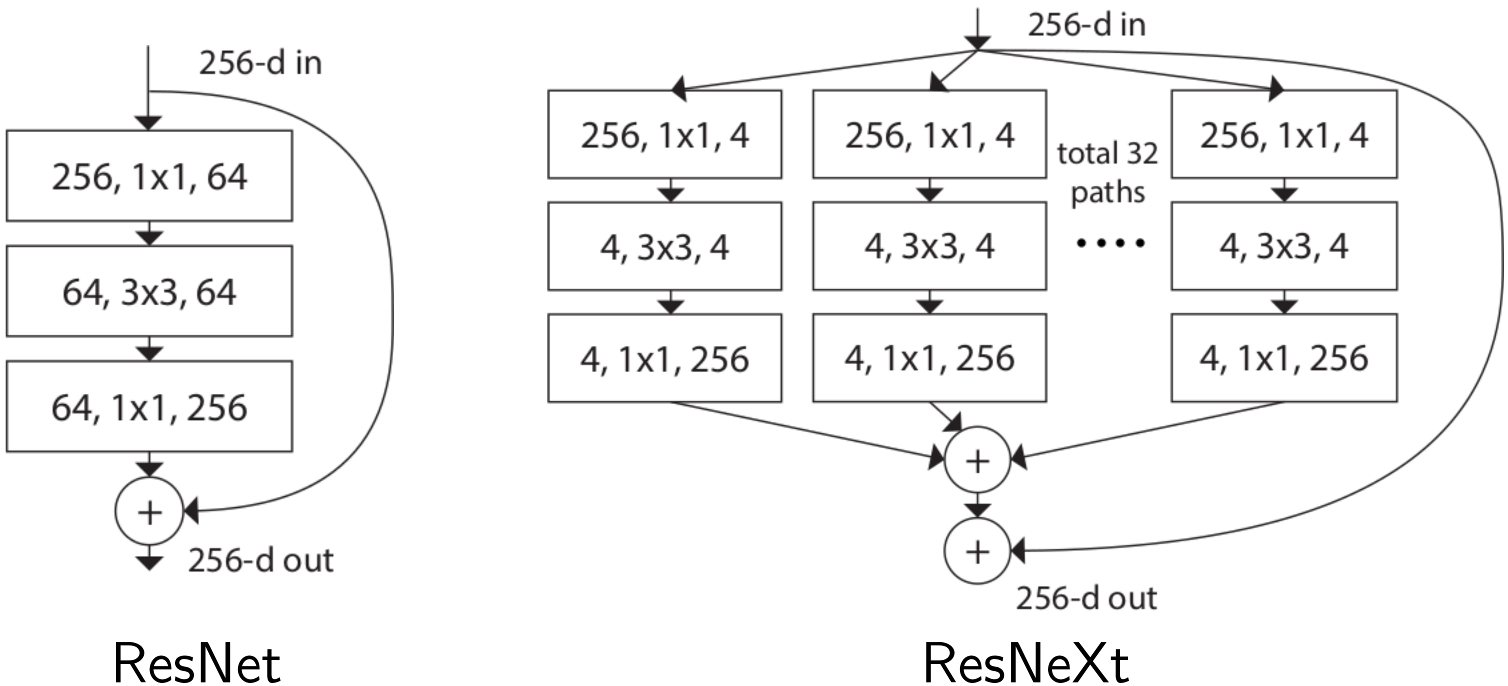


Results

- 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

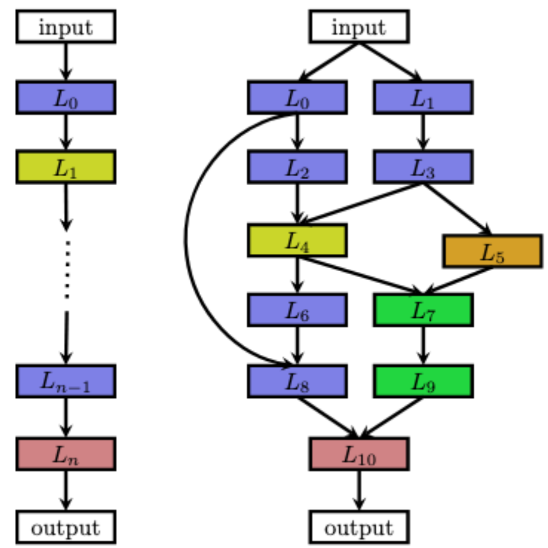
- **ResNeXt**
  - Multi-branch architecture

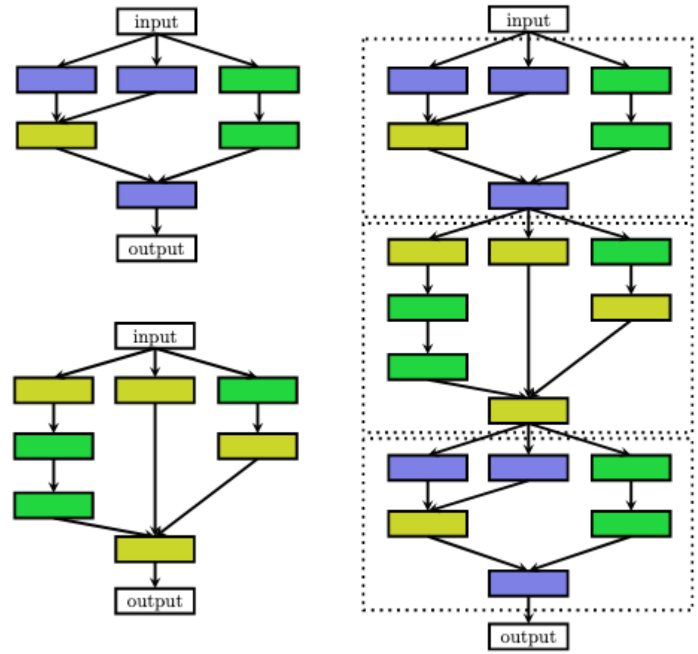


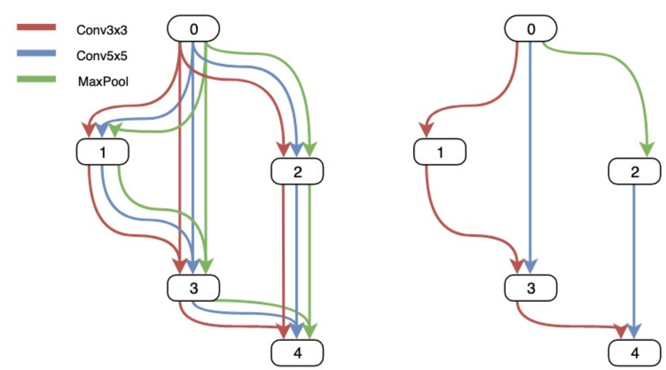
Saining Xie, Ross Girshick, Piotr Dollàr, Zhuowen Tu and Kaiming He
Aggregated Residual Transformations for Deep Neural Networks.
In *CVPR*, 2017.

Exploring type of deep modules in Neural Nets

NAS Neural Architecture Search







Conclusion

- ResNet: currently the best ConvNet archi for large scale image classification
- Not yet consensus about the design of the Net, Neural Architecture Search
- Fully Convolutional Net (FCN) very interesting option

- *Next:*
  - *ResNet 50: details of training*
  - *New type of architecture: Vision transformers*