Machine Learning – Lecture 16

Convolutional Neural Networks III

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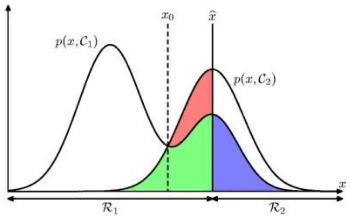
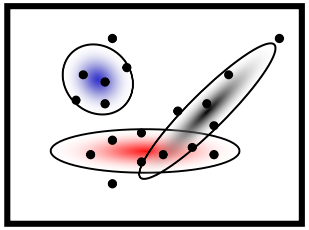
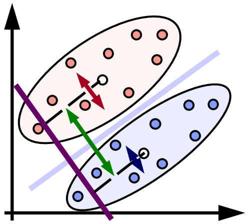
Course Outline

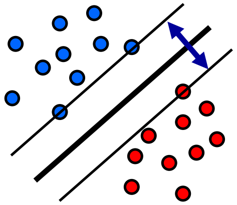
- Fundamentals
  - Bayes Decision Theory
  - Probability Density Estimation

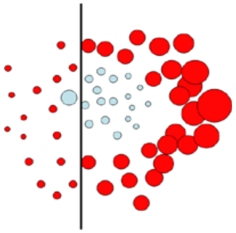


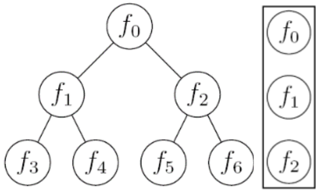


- Classification Approaches
  - Linear Discriminants
  - Support Vector Machines
  - Ensemble Methods & Boosting
  - Random Forests

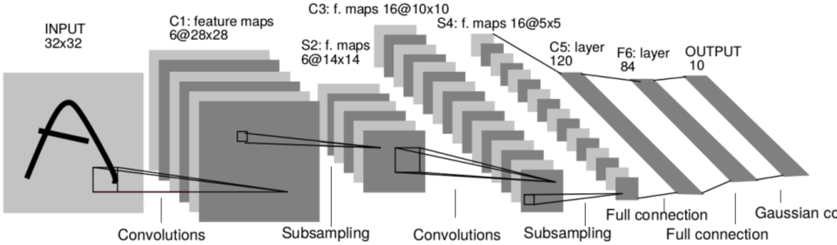








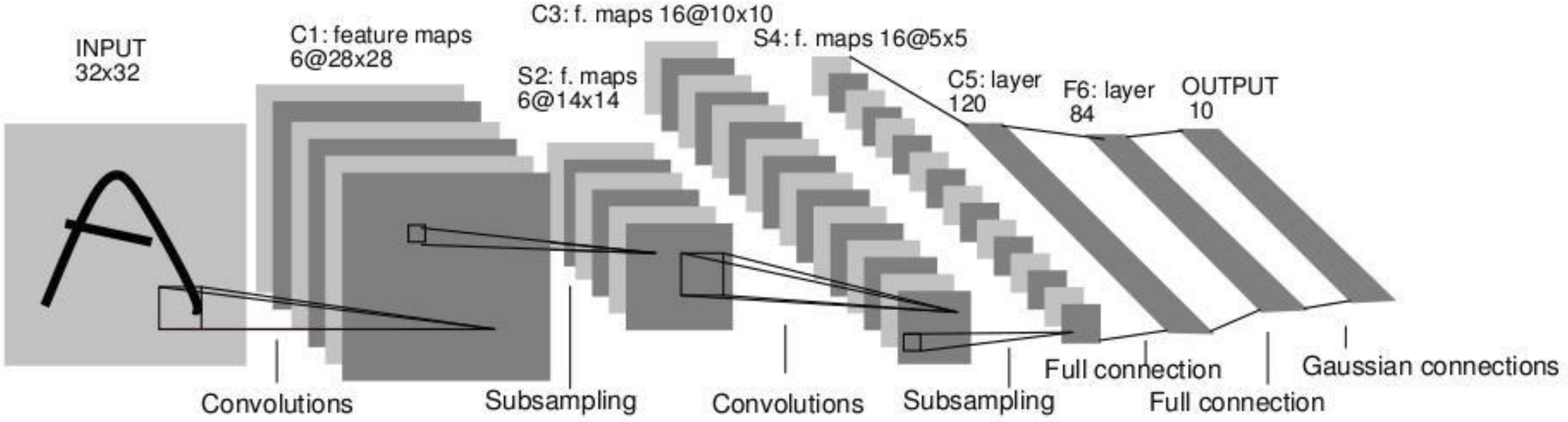
- Deep Learning
  - Foundations
  - Convolutional Neural Networks
  - Recurrent Neural Networks



Topics of This Lecture

- Recap: CNN Architectures
- Residual Networks
  - Detailed analysis
  - ResNets as ensembles of shallow networks
- Visualizing CNNs
  - Visualizing CNN features
  - Visualizing responses
  - Visualizing learned structures
- Applications of CNNs
  - Object detection
  - Semantic segmentation
  - Face identification

Recap: Convolutional Neural Networks

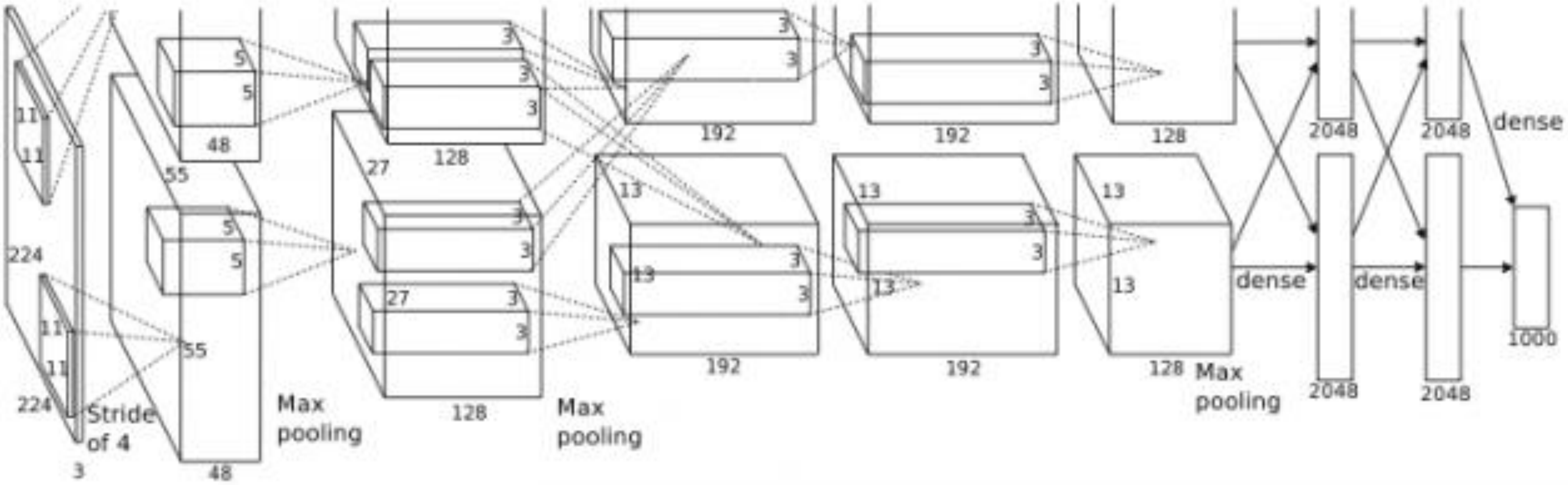


- Neural network with specialized connectivity structure
  - Stack multiple stages of feature extractors
  - Higher stages compute more global, more invariant features
  - Classification layer at the end

Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, Gradient-based learning applied to document recognition, Proceedings of the IEEE 86(11): 2278–2324, 1998.

Slide credit: Svetlana Lazebnik

Recap: AlexNet (2012)



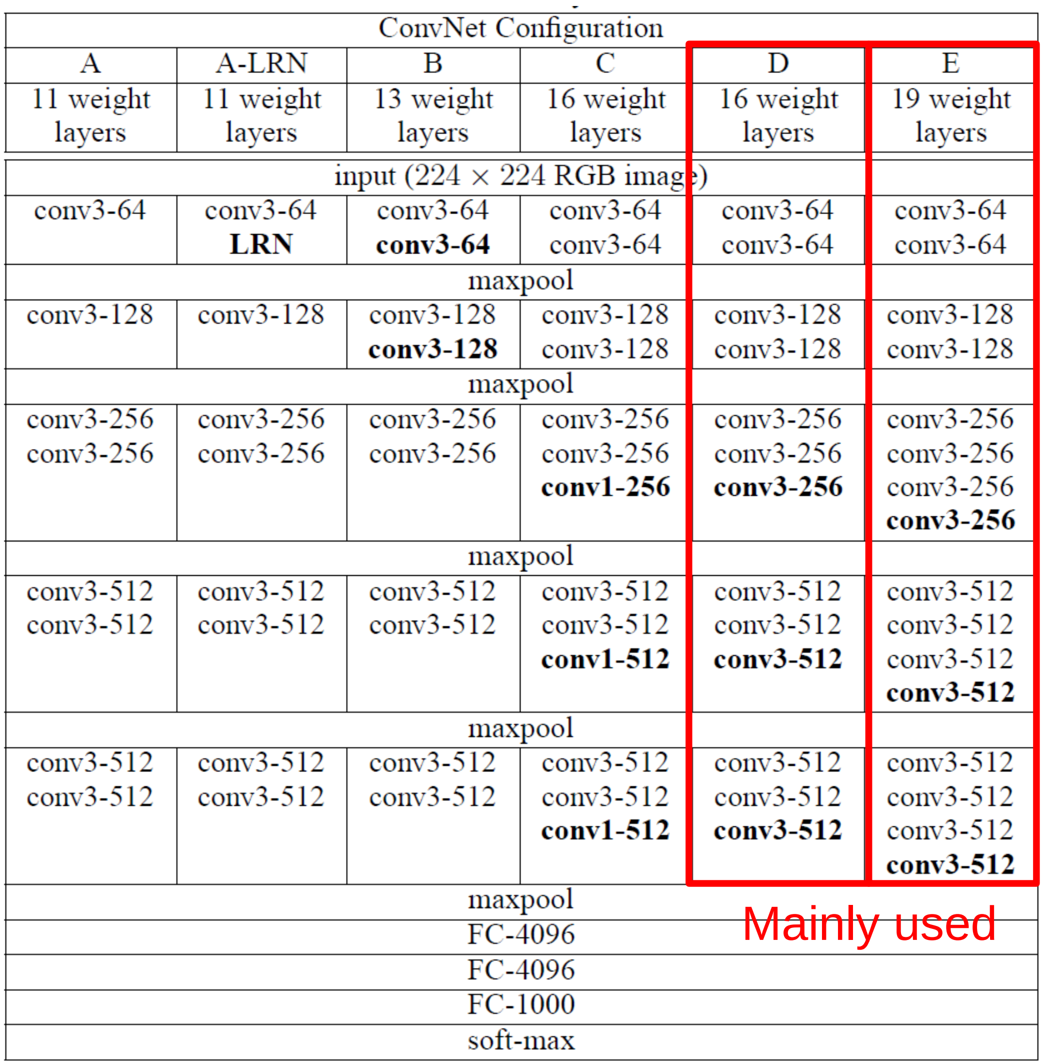
- Similar framework as LeNet, but
  - Bigger model (7 hidden layers, 650k units, 60M parameters)
  - More data (10^6 images instead of 10^3)
  - GPU implementation
  - Better regularization and up-to-date tricks for training (Dropout)

A. Krizhevsky, I. Sutskever, and G. Hinton, ImageNet Classification with Deep Convolutional Neural Networks, NIPS 2012.

Image source: A. Krizhevsky, I. Sutskever and G.E. Hinton, NIPS 2012

Recap: VGGNet (2014/15)

- Main ideas
  - Deeper network
  - Stacked convolutional layers with smaller filters (+ nonlinearity)
  - Detailed evaluation of all components
- Results
  - Improved ILSVRC top-5 error rate to 6.7%.



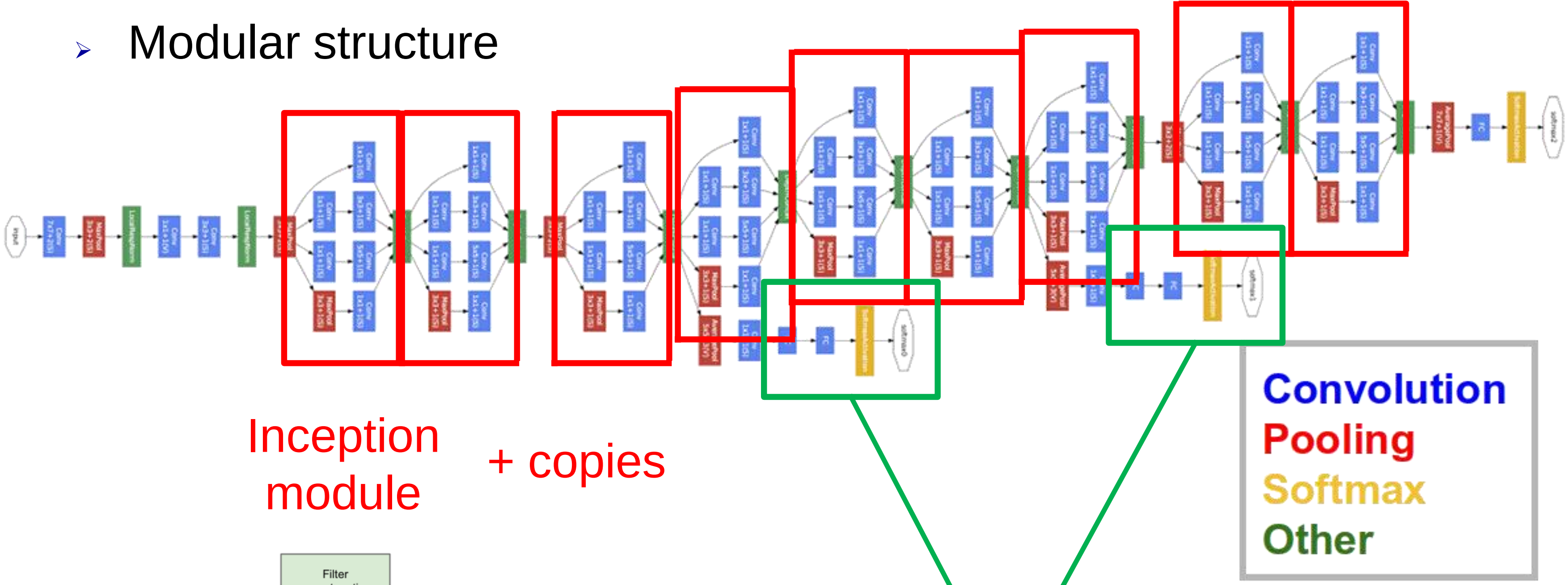
ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	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					

Mainly used

Image source: Simonyan & Zisserman

Recap: GoogLeNet (2014)

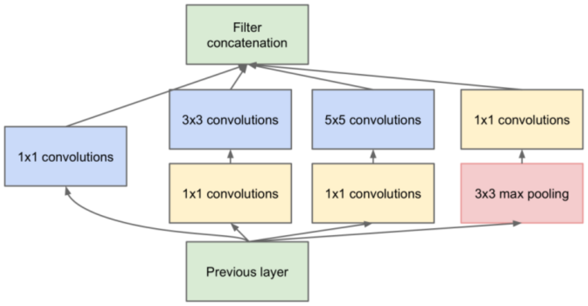
- Ideas:
  - Learn features at multiple scales
  - Modular structure



Inception module

+ copies

Auxiliary classification outputs for training the lower layers (deprecated)



(b) Inception module with dimension reductions

Image source: Szegedy et al.

Discussion

- GoogLeNet
  - 12× fewer parameters than AlexNet

  ⇒ ~5M parameters
  - *Where does the main reduction come from?*

  ⇒ From throwing away the fully connected (FC) layers.
- Effect
  - After last pooling layer, volume is of size [7×7×1024]
  - Normally you would place the first 4096-D FC layer here (Many million params).
  - Instead: use Average pooling in each depth slice:

  ⇒ Reduces the output to [1×1×1024].

  ⇒ Performance actually improves by 0.6% compared to when using FC layers (less overfitting?)

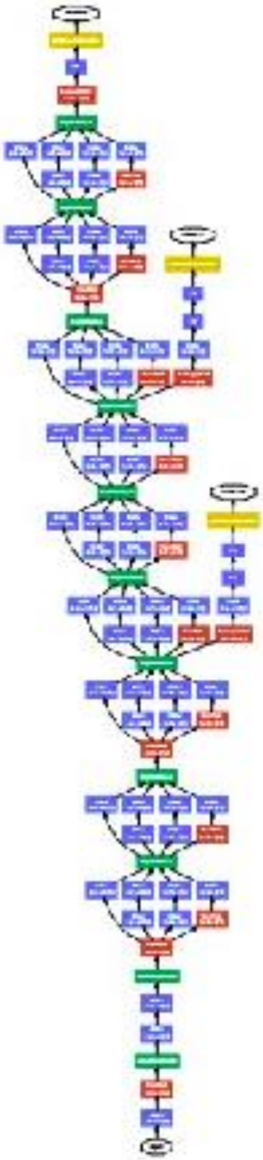


Image source: Szegedy et al.

Slide credit: Andrej Karpathy

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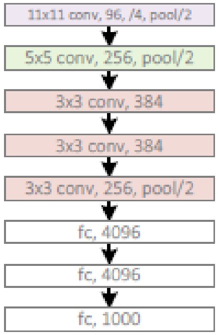
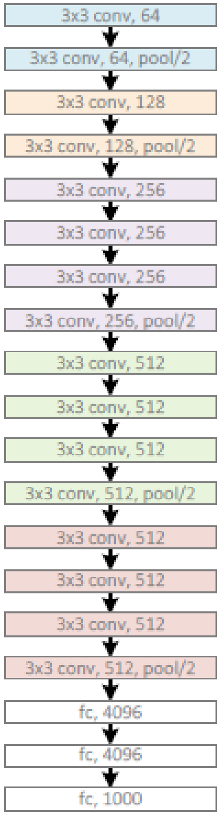
Recap: Residual Networks

AlexNet, 8 layers
(ILSVRC 2012)



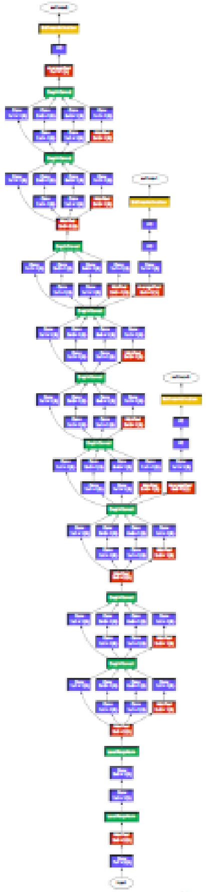
11x11 conv, 96, /4, pool/2
5x5 conv, 256, pool/2
3x3 conv, 384
3x3 conv, 384
3x3 conv, 256, pool/2
fc, 4096
fc, 4096
fc, 1000

VGG, 19 layers
(ILSVRC 2014)



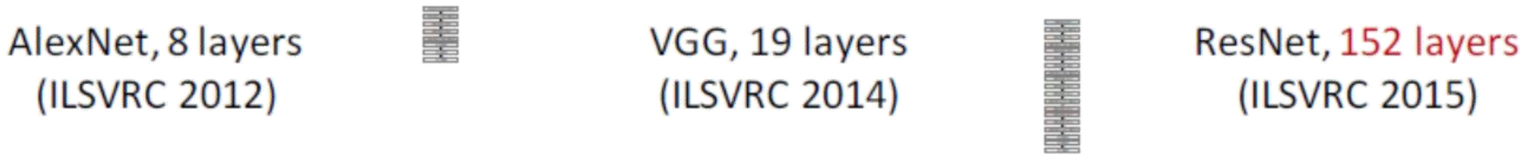
3x3 conv, 64
3x3 conv, 64, pool/2
3x3 conv, 128
3x3 conv, 128, pool/2
3x3 conv, 256
3x3 conv, 256
3x3 conv, 256
3x3 conv, 256, pool/2
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512, pool/2
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512, pool/2
fc, 4096
fc, 4096
fc, 1000

GoogleNet, 22 layers
(ILSVRC 2014)

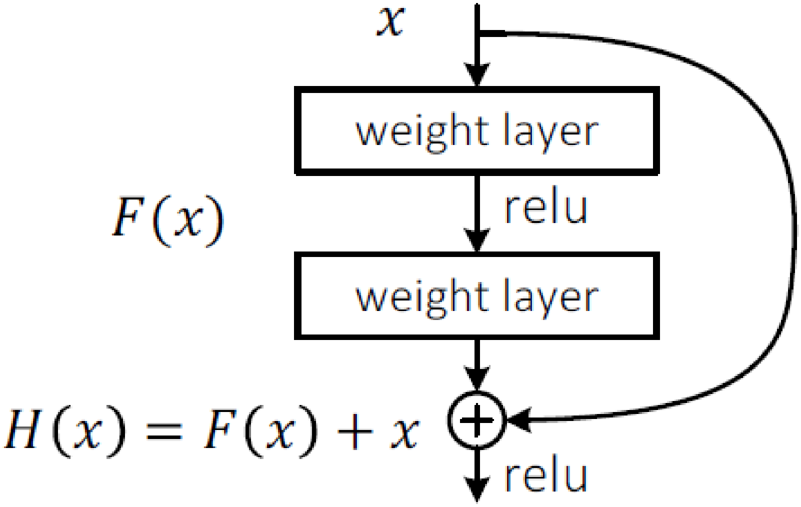


Slide credit: Kaiming He

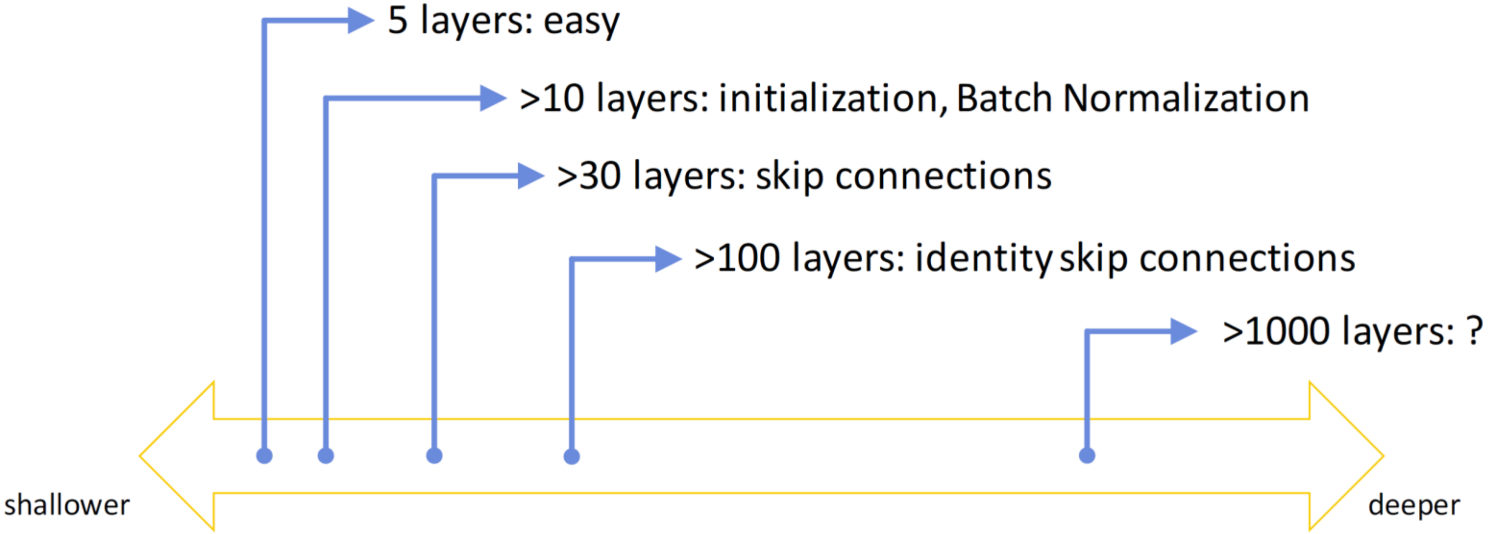
Recap: Residual Networks



- Core component
  - Skip connections bypassing each layer
  - Better propagation of gradients to the deeper layers



Spectrum of Depth



5 layers: easy

>10 layers: initialization, Batch Normalization

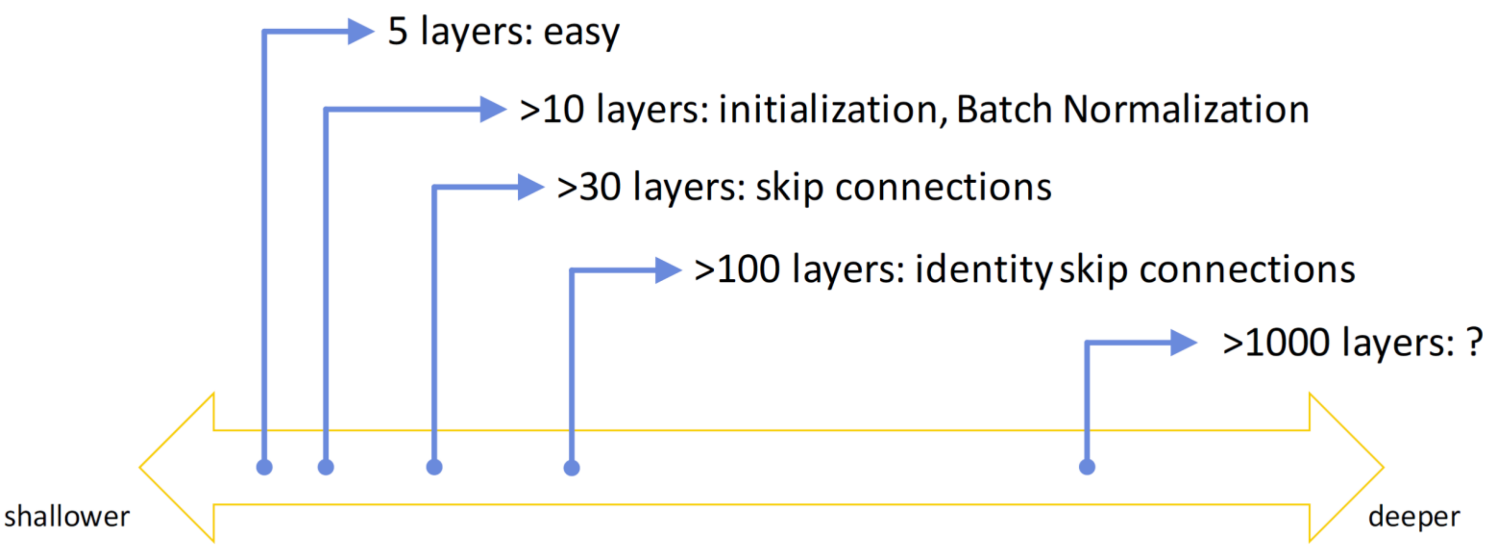
>30 layers: skip connections

>100 layers: identity skip connections

>1000 layers: ?

Slide credit: Kaiming He

Spectrum of Depth

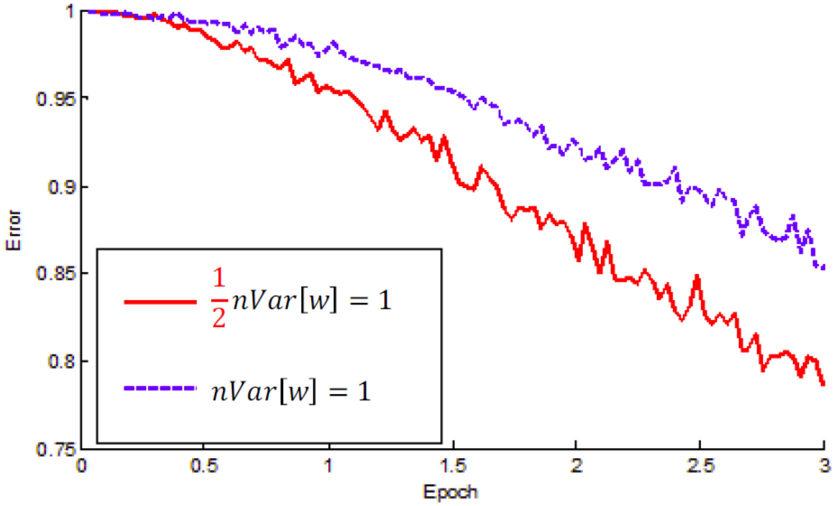

5 layers: easy
>10 layers: initialization, Batch Normalization
>30 layers: skip connections
>100 layers: identity skip connections
>1000 layers: ?
shallower
deeper

- Deeper models are more powerful
  - But training them is harder.
  - Main problem: getting the gradients back to the early layers
  - The deeper the network, the more effort is required for this.

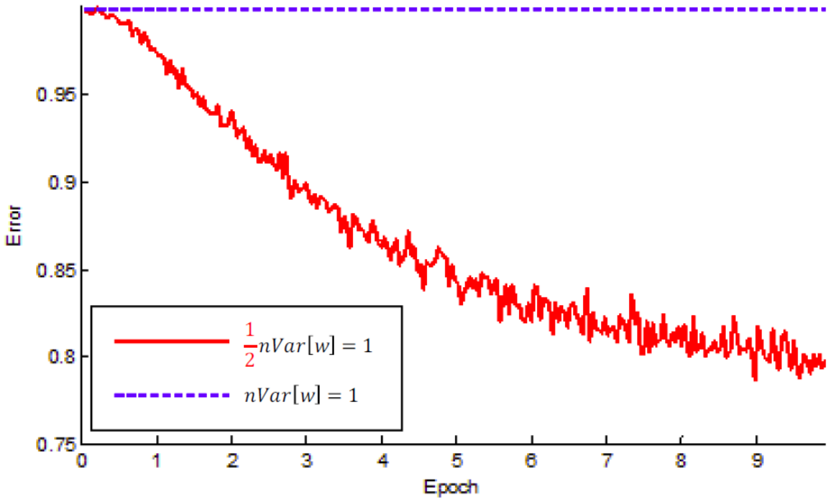
Slide adapted from Kaiming He

Initialization

22-layer ReLU net:
good init converges faster



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

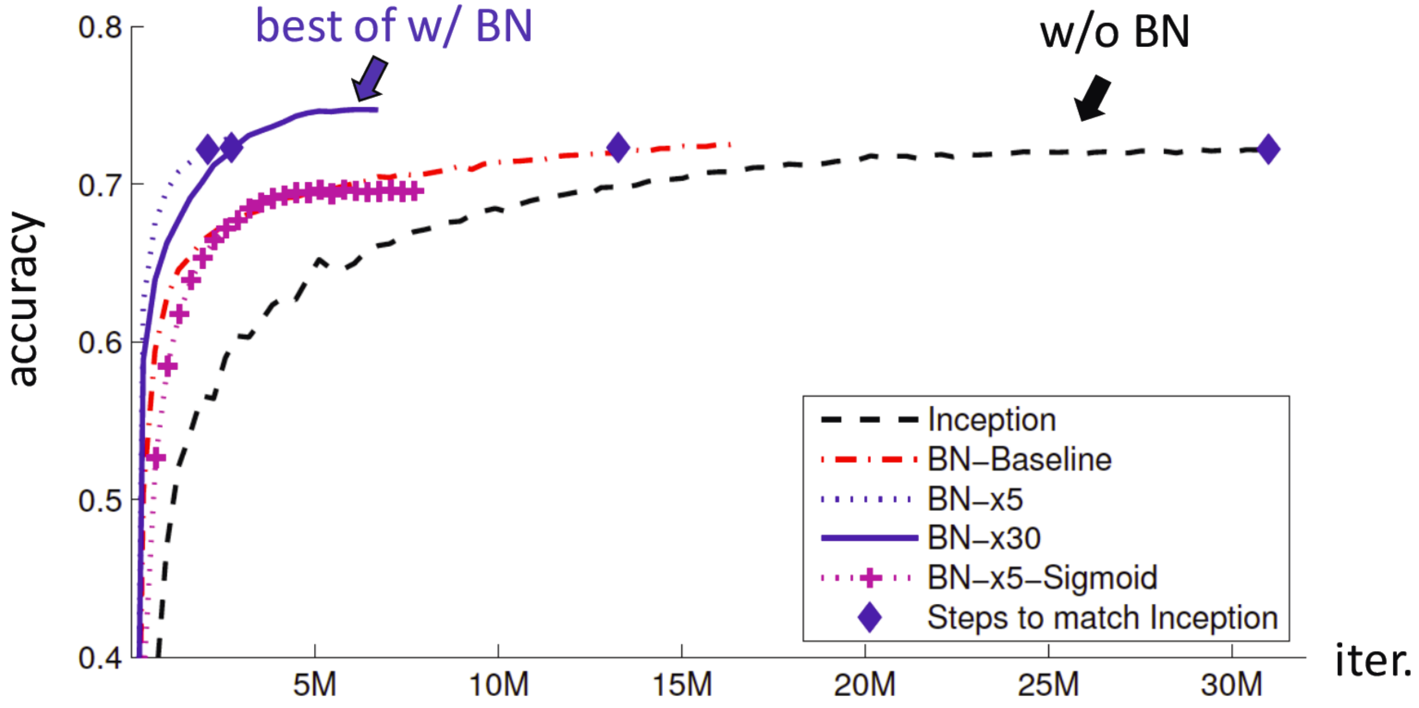


- Importance of proper initialization (Recall Lecture 15)
  - Glorot initialization for tanh nonlinearities
  - He initialization for ReLU nonlinearities

  ⇒ For deep networks, this really makes a difference!

Slide credit: Kaiming He

Batch Normalization



- Effect of batch normalization
  - Greatly improved speed of convergence
  - Often better accuracy achievable

Image source: Ioffe & Szegedy

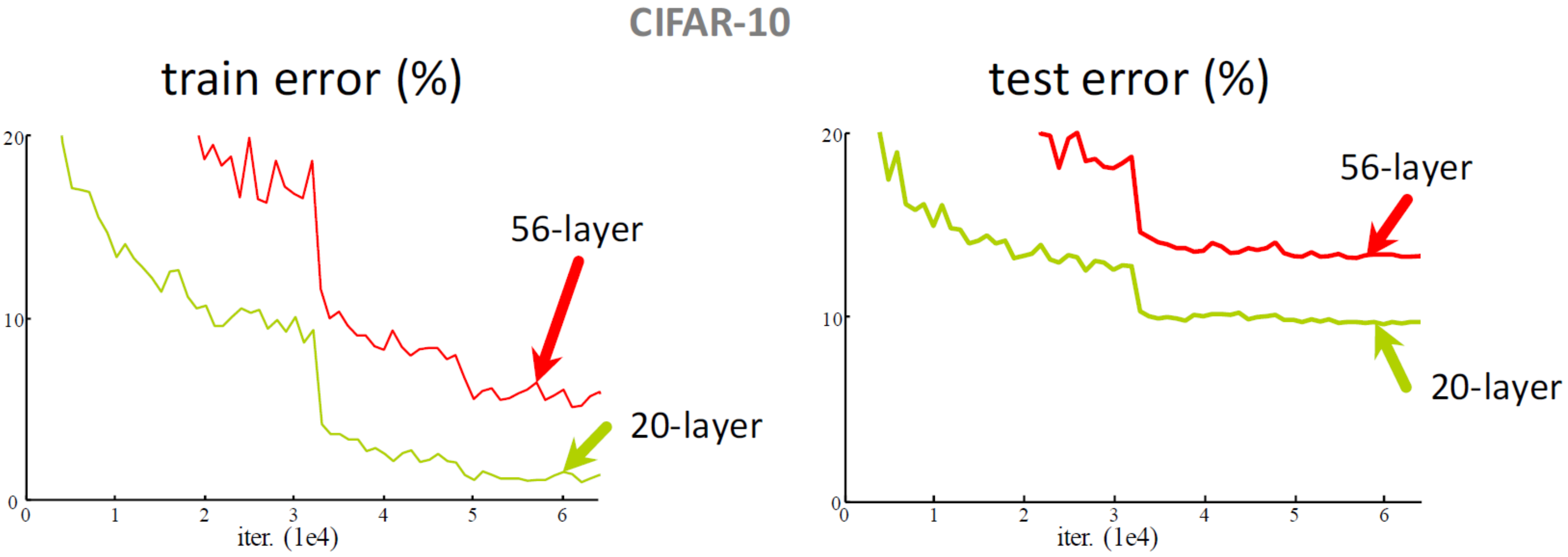
Going Deeper

- Checklist
  - Initialization ok
  - Batch normalization ok

  - Are we now set?
    - Is learning better networks now as simple as stacking more layers?

Slide credit: Kaiming He

Simply Stacking Layers?

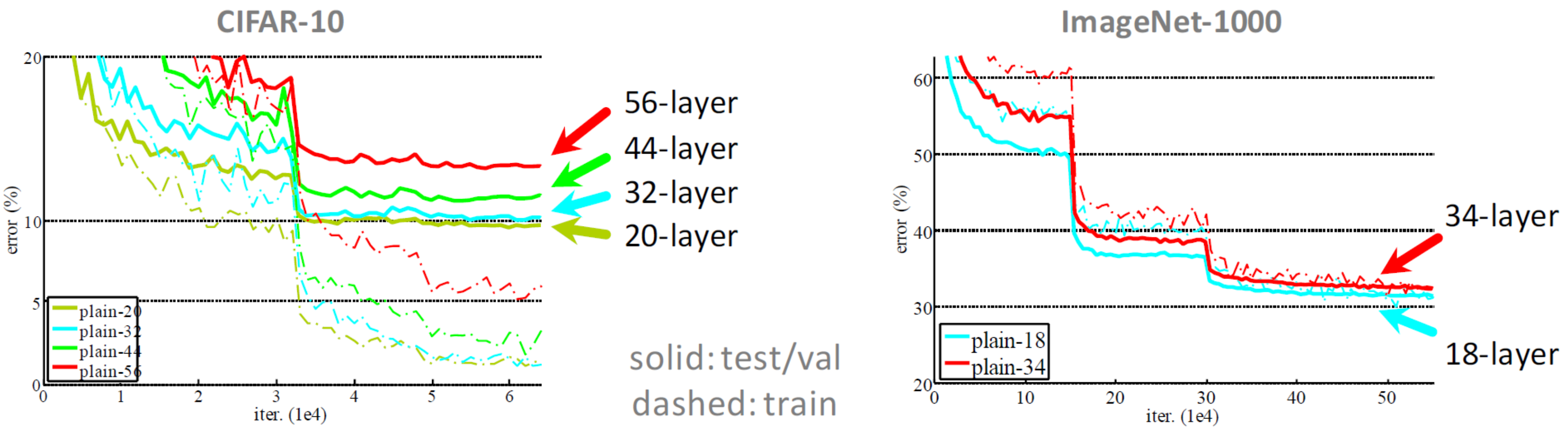


- Experiment going deeper
  - Plain nets: stacking 3×3 convolution layers

⇒ 56-layer net has higher training error than 20-layer net

Slide credit: Kaiming He

Simply Stacking Layers?



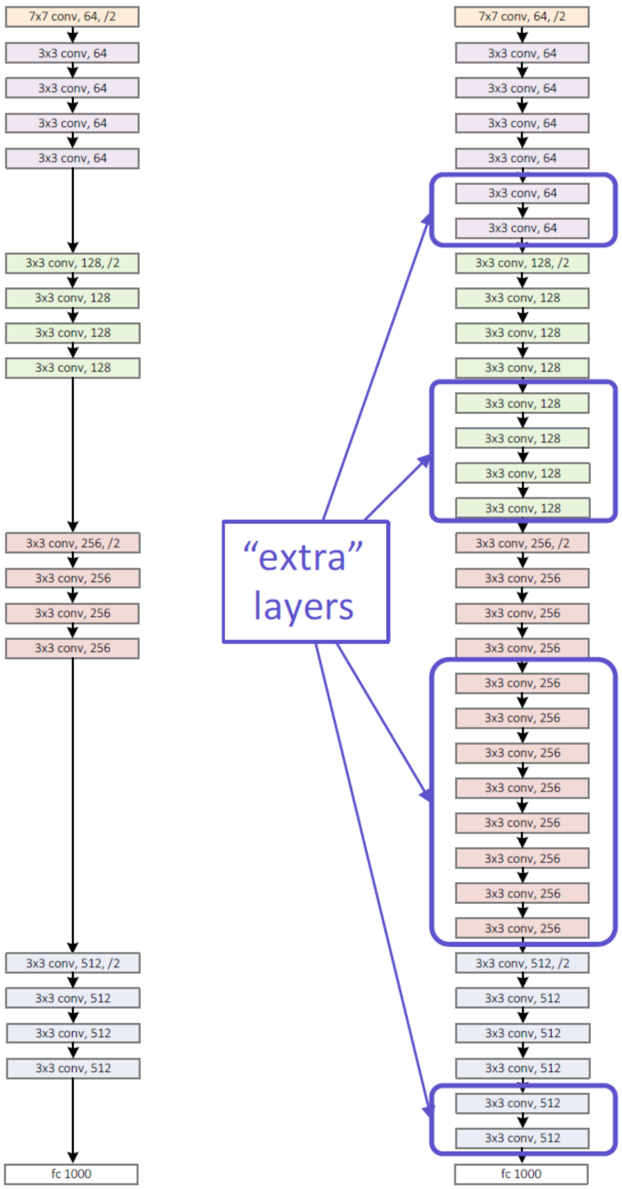
solid: test/val
dashed: train

- General observation
  - Overly deep networks have higher training error
  - A general phenomenon, observed in many training sets

Slide credit: Kaiming He

Why Is That???

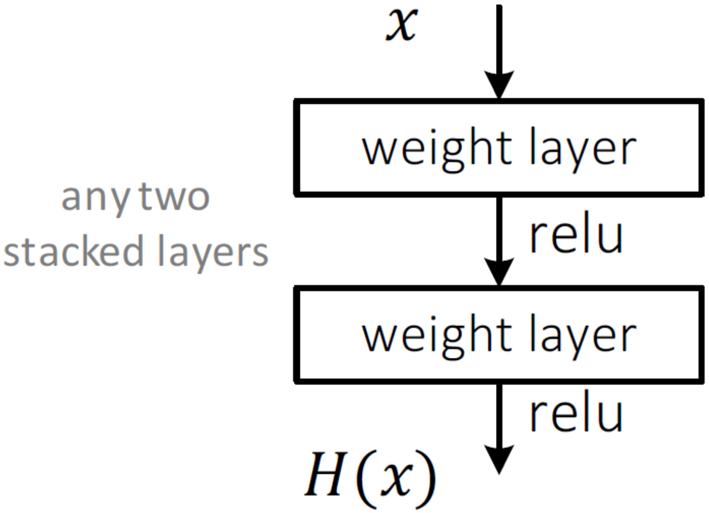
- A deeper model should not have higher training error!
  - Richer solution space should allow it to find better solutions
- Solution by construction
  - Copy the original layers from a learned shallower model
  - Set the extra layers as identity
  - Such a network should achieve at least the same low training error.
- Reason: Optimization difficulties
  - Solvers cannot find the solution when going deeper…



Slide credit: Kaiming He

Deep Residual Learning

- Plain net

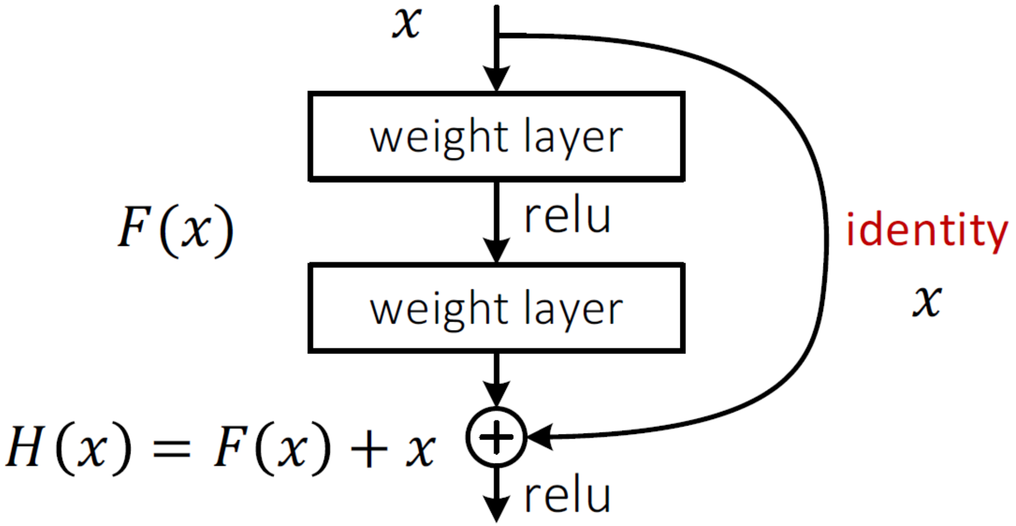


  - $H(x)$ is any desired mapping
  - Hope the 2 weight layers fit $H(x)$

Slide credit: Kaiming He

Deep Residual Learning

- Residual net

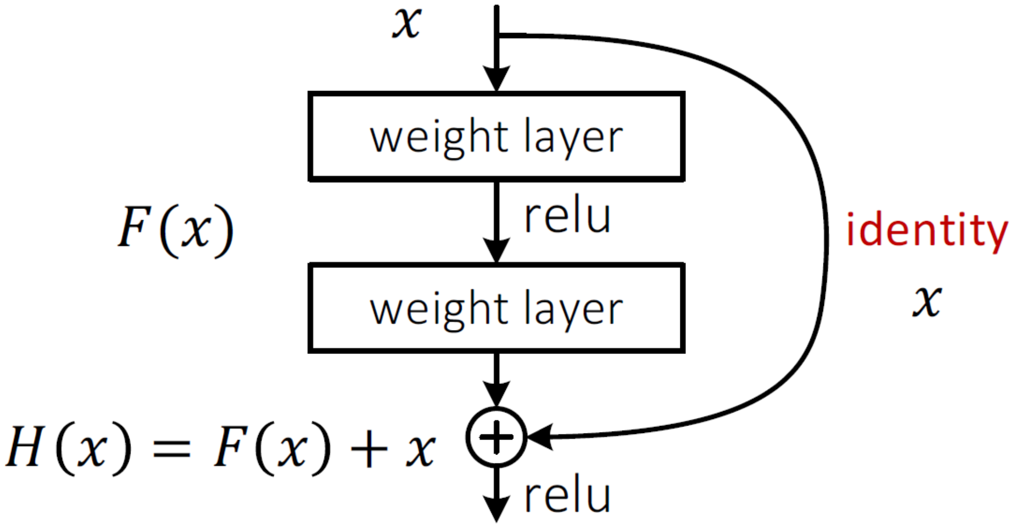


- $H(x)$ is any desired mapping
- ~~Hope the 2 weight layers fit $H(x)$~~
- Hope the 2 weight layers fit $F(x)$
  Let $H(x) = F(x) + x$

Slide credit: Kaiming He

Deep Residual Learning

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



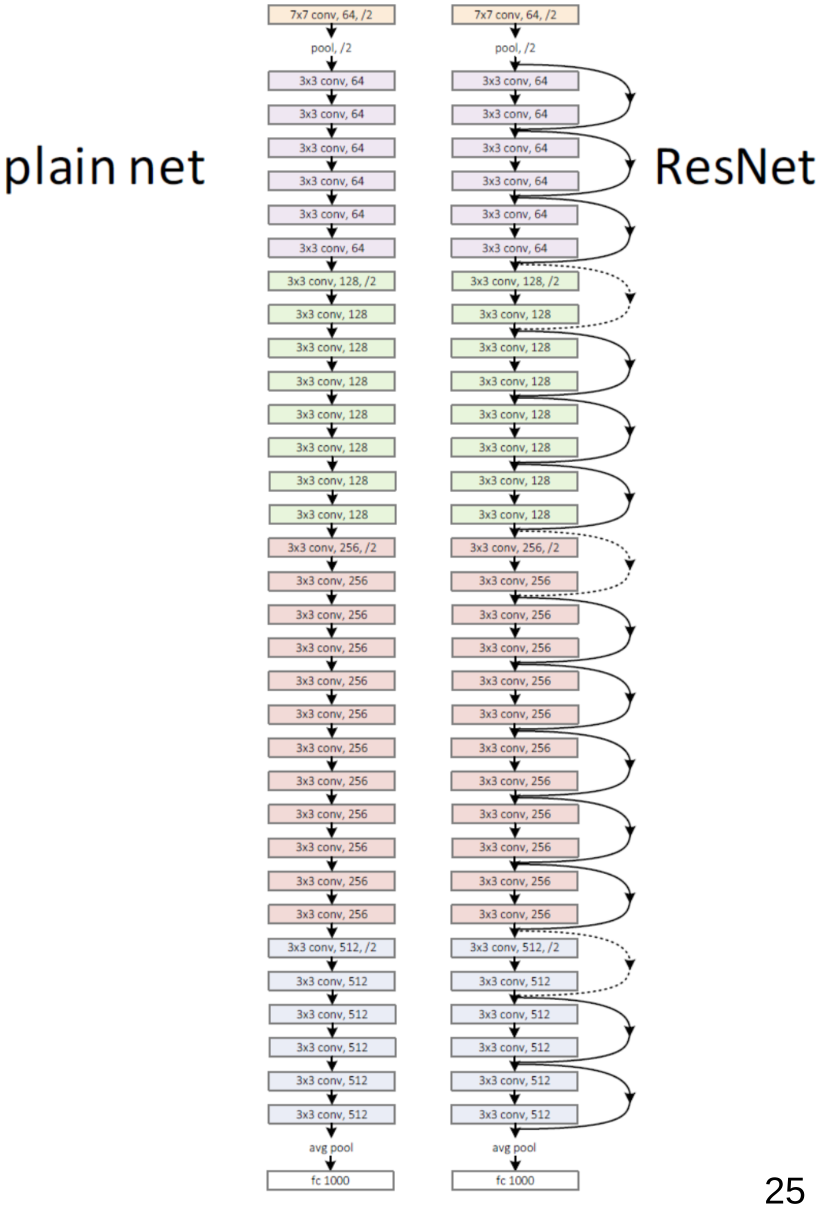
  - If identity were optimal, it is easy to set weights as 0
  - If optimal mapping is closer to identity, it is easier to find small fluctuations
  - Further advantage: direct path for the gradient to flow to the previous stages

Slide credit: Kaiming He

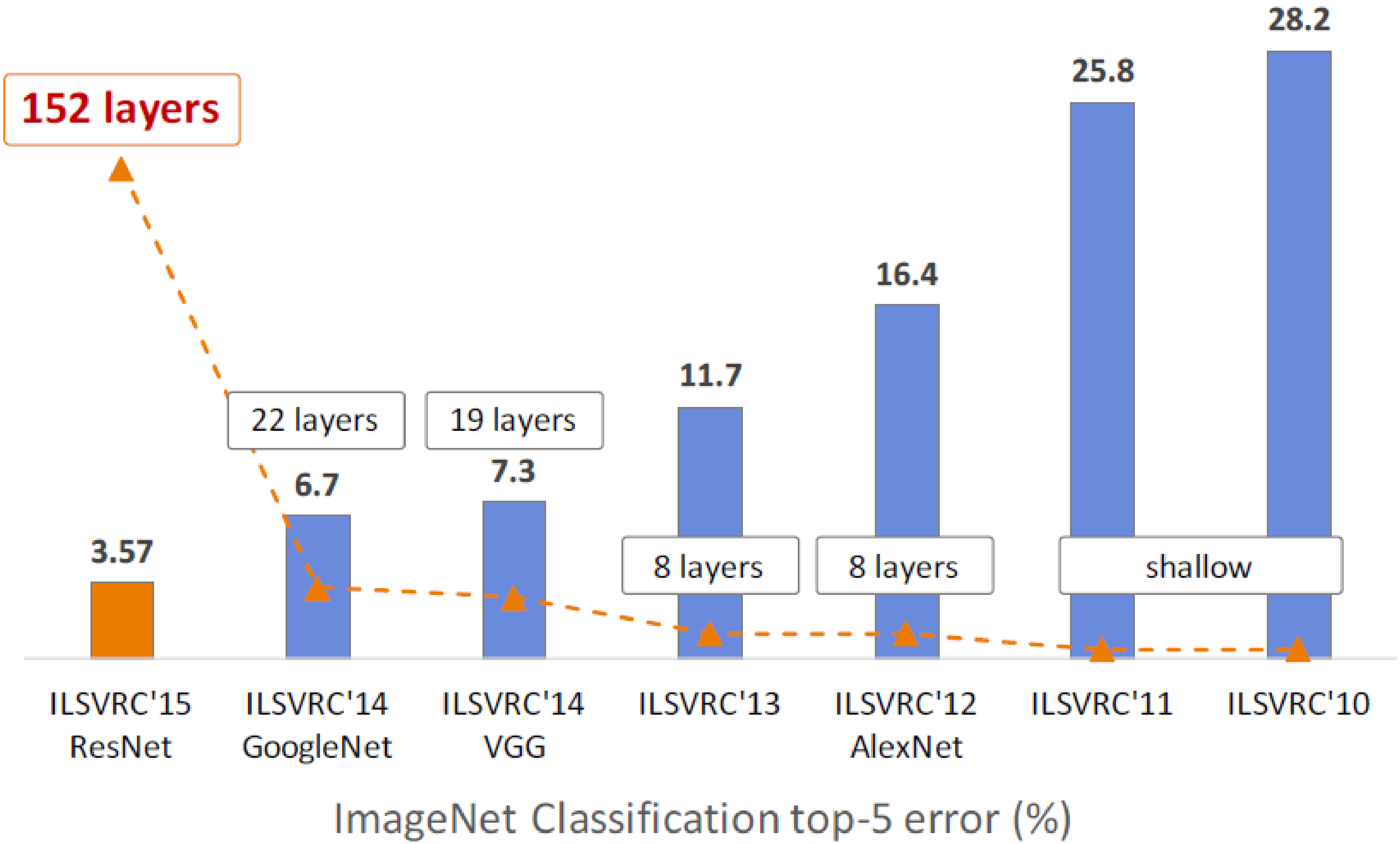
Network Design

- Simple, VGG-style design
  - (Almost) all 3×3 convolutions
  - Spatial size /2 ⇒ #filters · 2
    (same complexity per layer)
  - Batch normalization

  ⇒ Simple design, just deep.

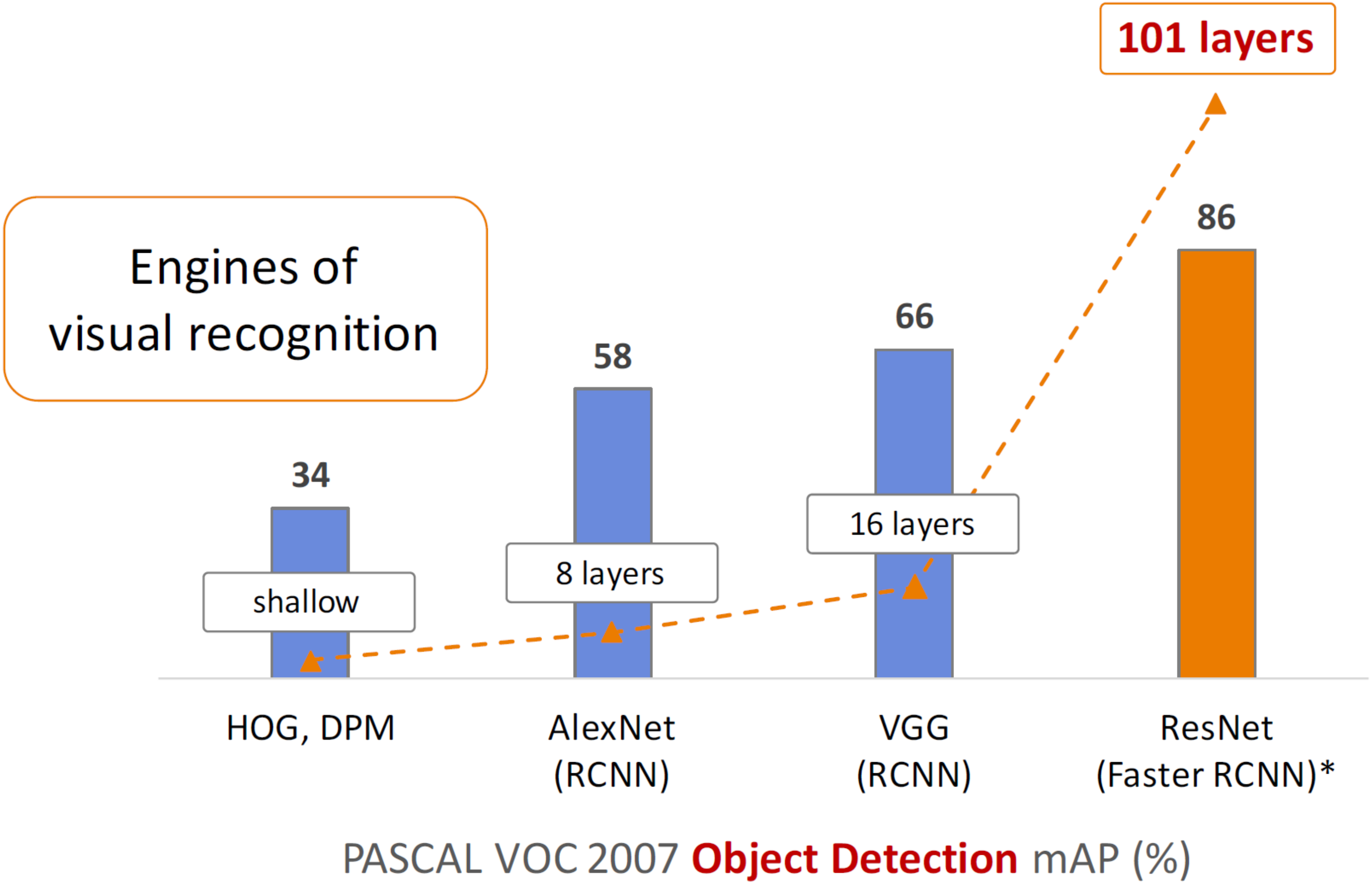


ImageNet Performance



Slide credit: Kaiming He

PASCAL VOC Object Detection Performance



Slide credit: Kaiming He

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What Is The Secret Behind ResNets?

- Empirically, they perform very well, but why is that?

- He's original explanation [He, 2016]
  - ResNets allow gradients to pass through the skip connections in unchanged form.
  - This makes it possible to effectively train deeper networks.

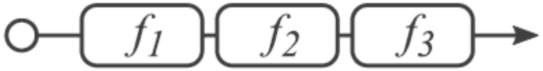
  ⇒ Secret of success: depth is good

- More recent explanation [Veit, 2016]
  - ResNets actually do not use deep network paths.
  - Instead, they effectively implement an ensemble of shallow network paths.

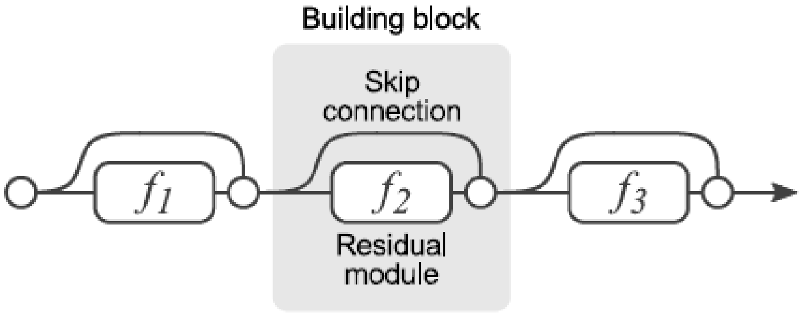
  ⇒ Secret of success: ensembles are good

A, Veit, M. Wilber, S. Belongie, Residual Networks Behave Like Ensembles of Relatively Shallow Networks, NIPS 2016

Idea of the Analysis

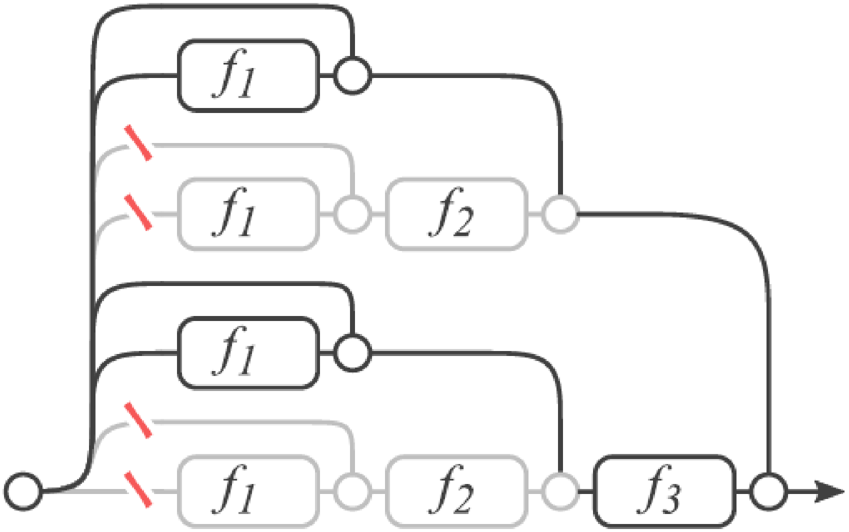


Ordinary feedforward network



Residual network

Effect of deleting layer f_2

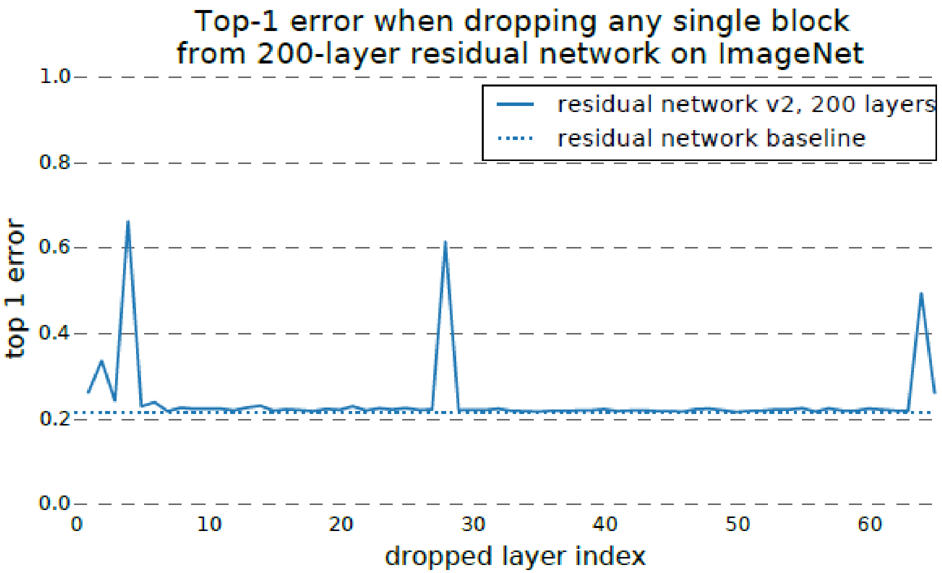


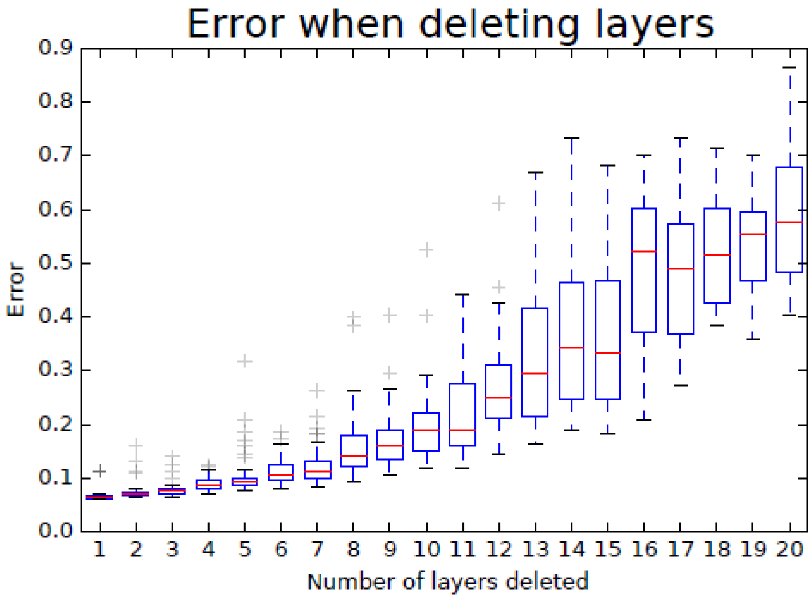
Unraveled view

- Unraveling ResNets
  - ResNets can be viewed as a collection of shorter paths through different subsets of the layers.
  - Deleting a layer corresponds to removing only some of those paths

Image source: Veit et al., 2016

Effect of Deleting Layers at Test Time



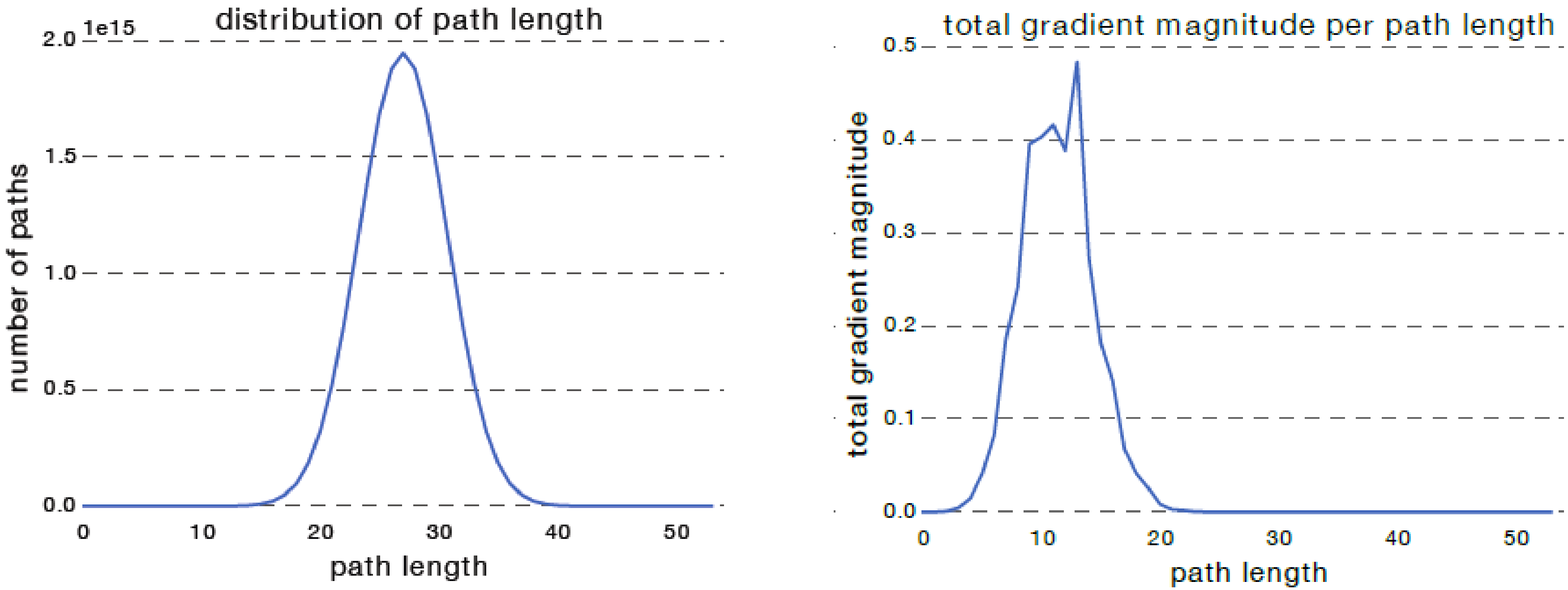


- Experiments on ImageNet classification
  - When deleting a layer in VGG-Net, it breaks down completely.
  - In ResNets, deleting a single layer has almost no effect (except for the pooling layers)
  - Deleting an increasing number of layers increases the error smoothly

  ⇒ *Paths in a ResNet do not strongly depend on each other.*

Image source: Veit et al., 2016

Which Paths Are Important?



- How much does each of the paths contribute?
  - Distribution of path lengths follows a Binomial distribution
  - Sample individual paths and measure their gradient magnitude

  ⇒ Effectively, only shallow paths with 5-17 modules are used!

  ⇒ This corresponds to only 0.45% of the available paths here.

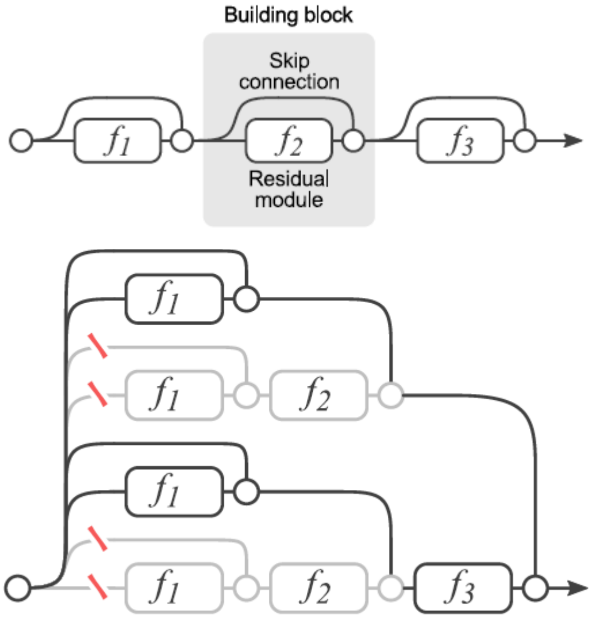
Image source: Veit et al., 2016

Summary

- The effective paths in ResNets are relatively shallow
    - Effectively only 5-17 active modules

- This explains the resilience to deletion
    - Deleting any single layer only affects a subset of paths (and the shorter ones less than the longer ones).

- New interpretation of ResNets
    - ResNets work by creating an ensemble of relatively shallow paths
    - Making ResNets deeper increases the size of this ensemble
    - Excluding longer paths from training does not negatively affect the results.



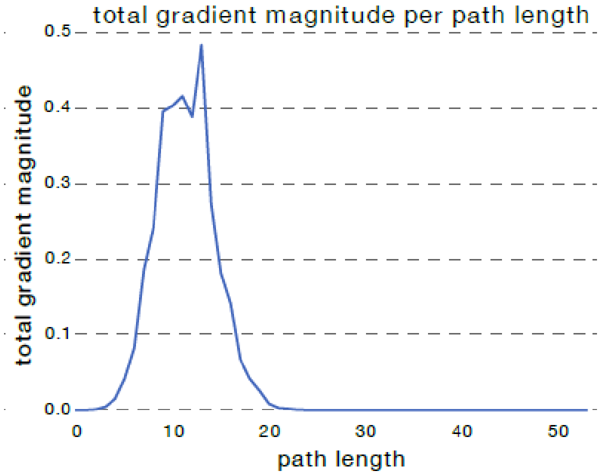


Image source: Veit et al., 2016

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Visualizing CNNs

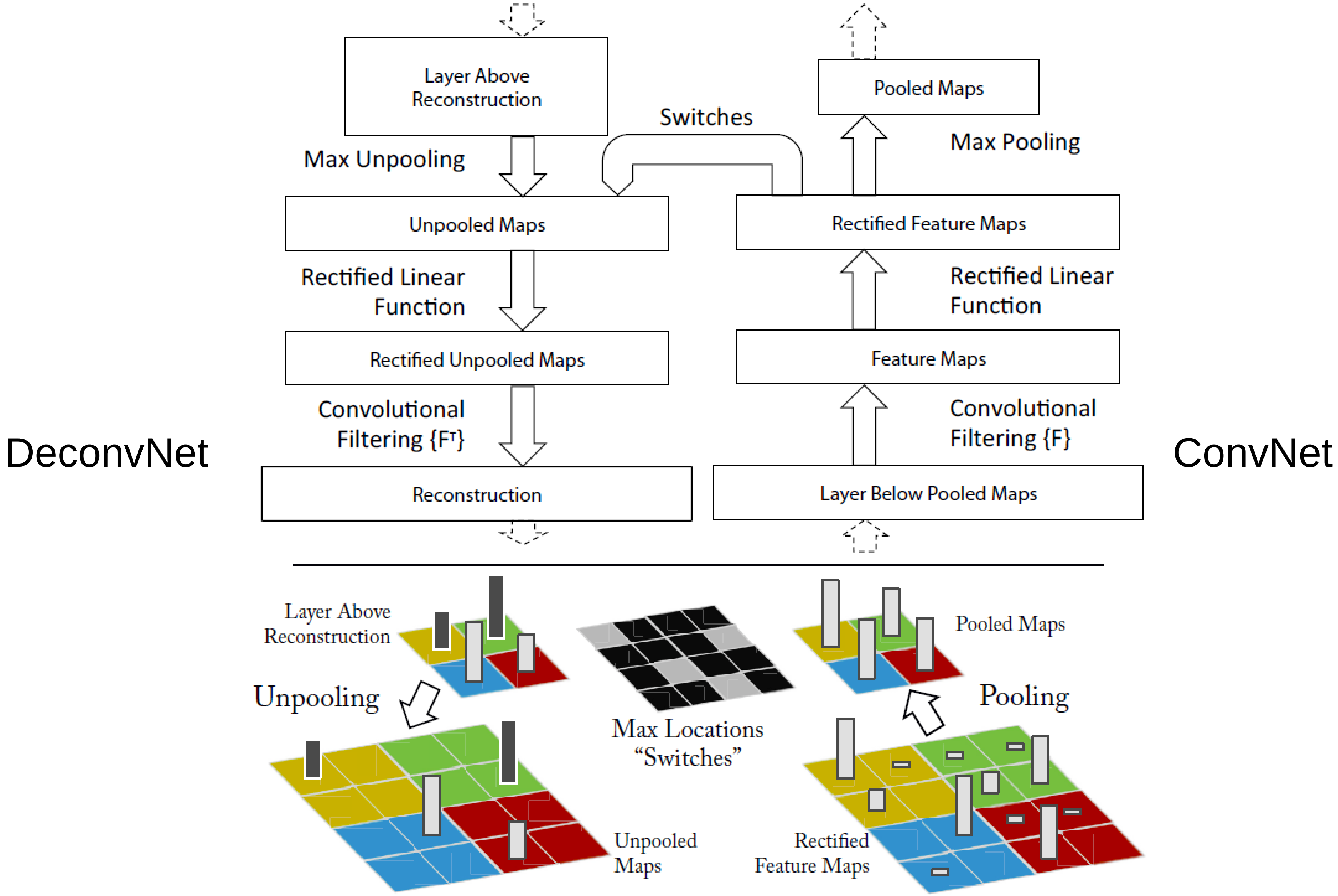
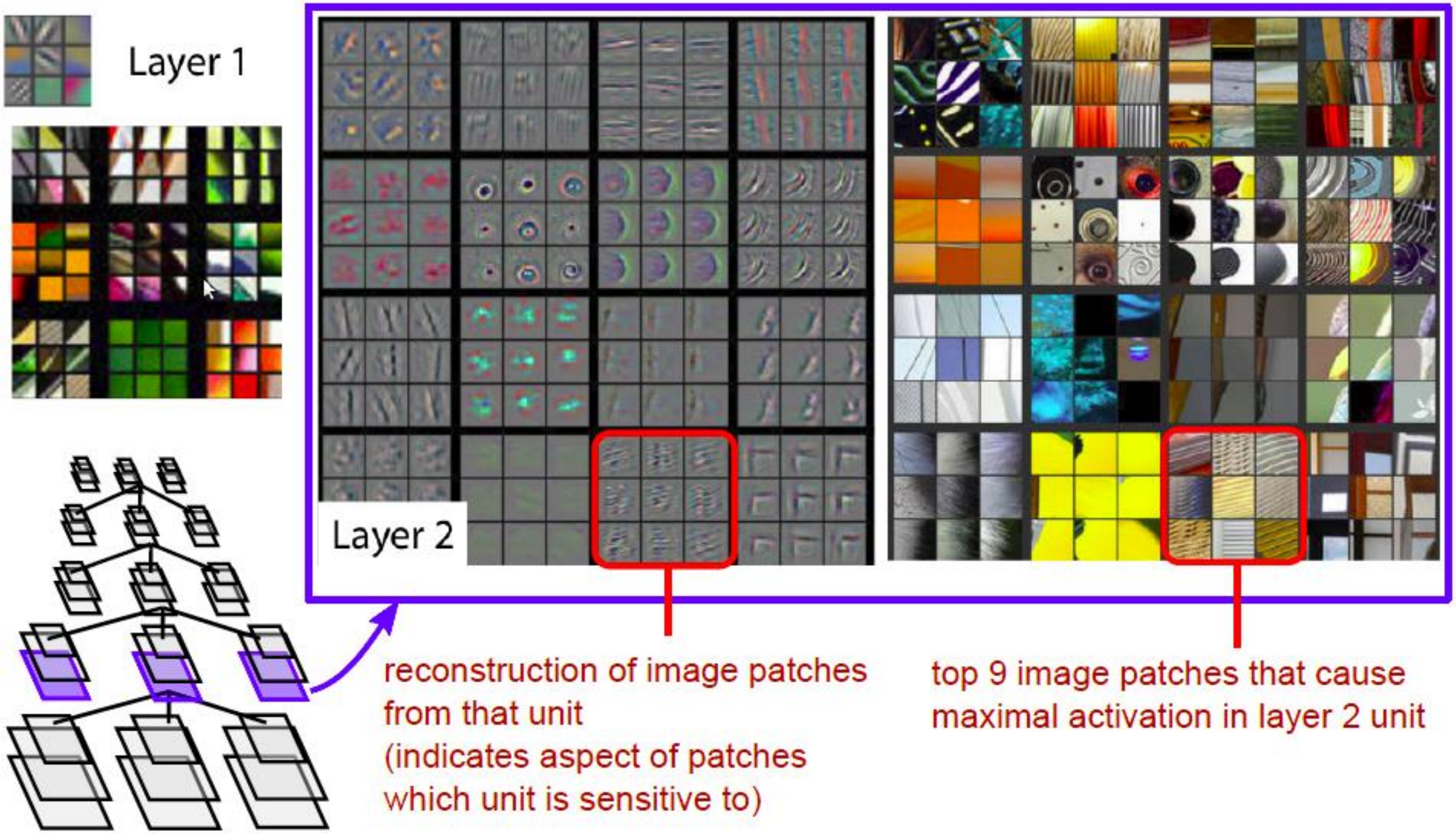


Image source: M. Zeiler, R. Fergus

Visualizing CNNs


Layer 1
Layer 2
reconstruction of image patches from that unit (indicates aspect of patches which unit is sensitive to)
top 9 image patches that cause maximal activation in layer 2 unit

M. Zeiler, R. Fergus, Visualizing and Understanding Convolutional Neural Networks, ECCV 2014.

Slide credit: Richard Turner

Image source: M. Zeiler, R. Fergus

Visualizing CNNs

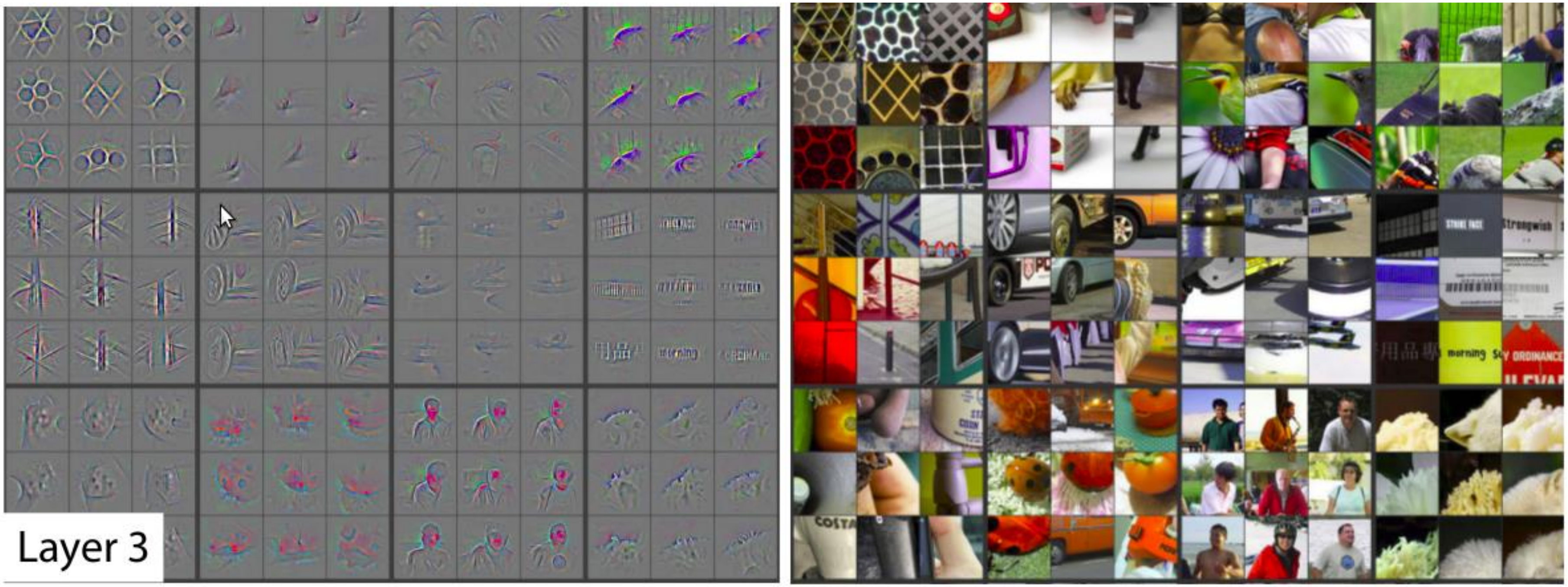


Image source: M. Zeiler, R. Fergus

Visualizing CNNs

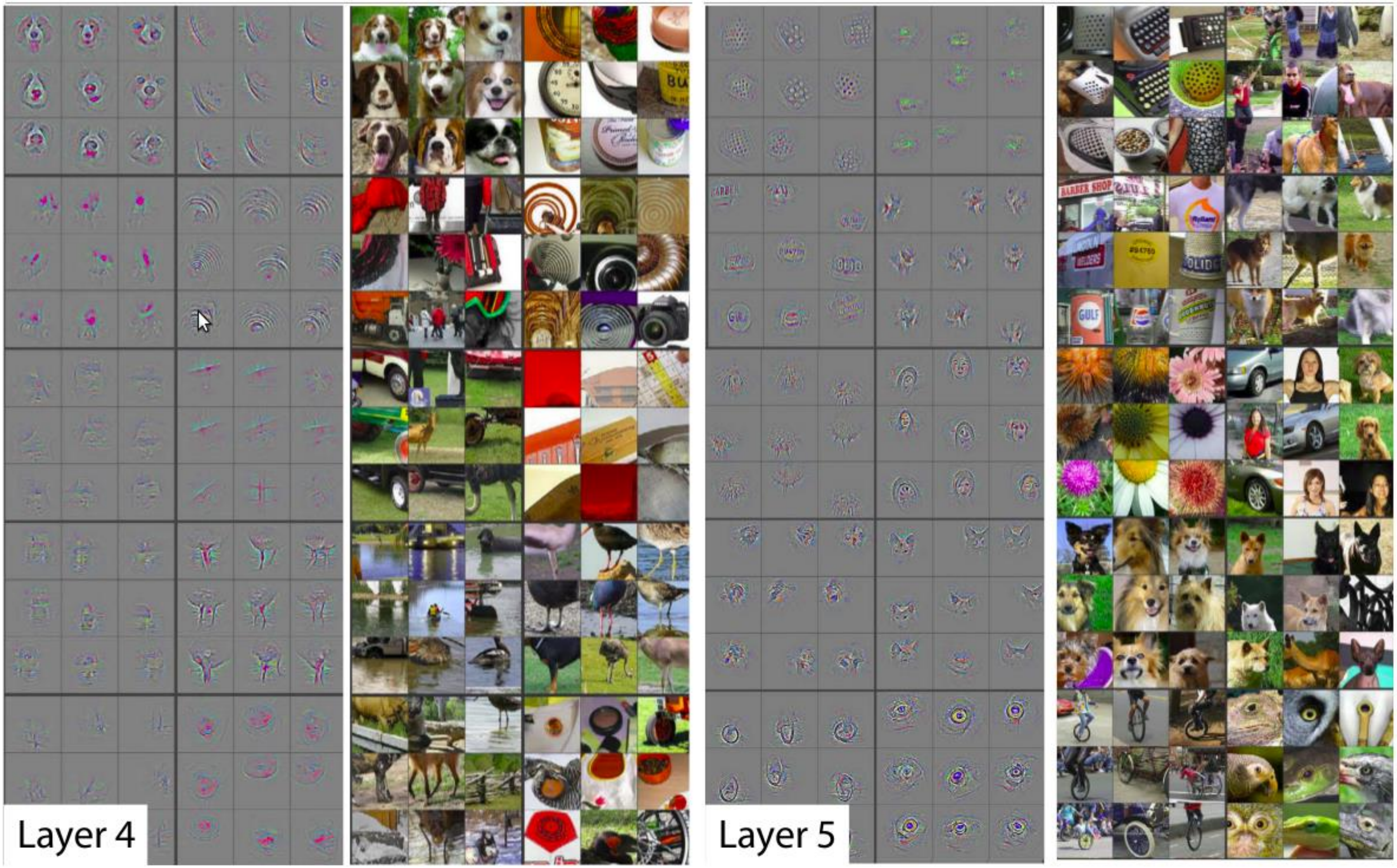
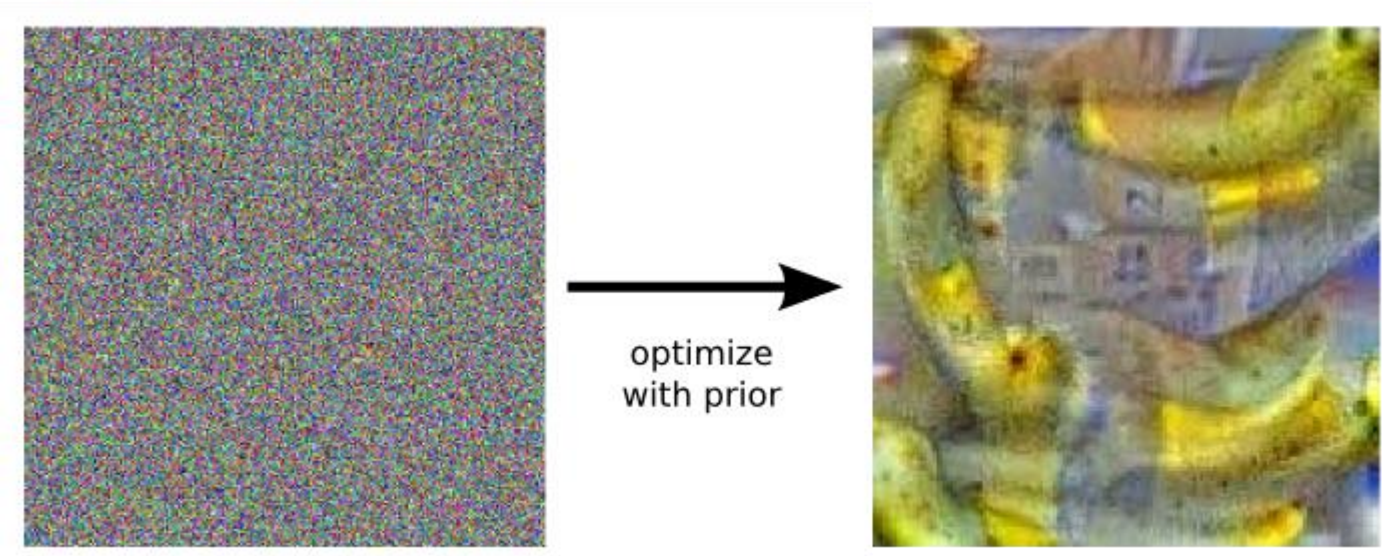


Image source: M. Zeiler, R. Fergus

Inceptionism: Dreaming ConvNets



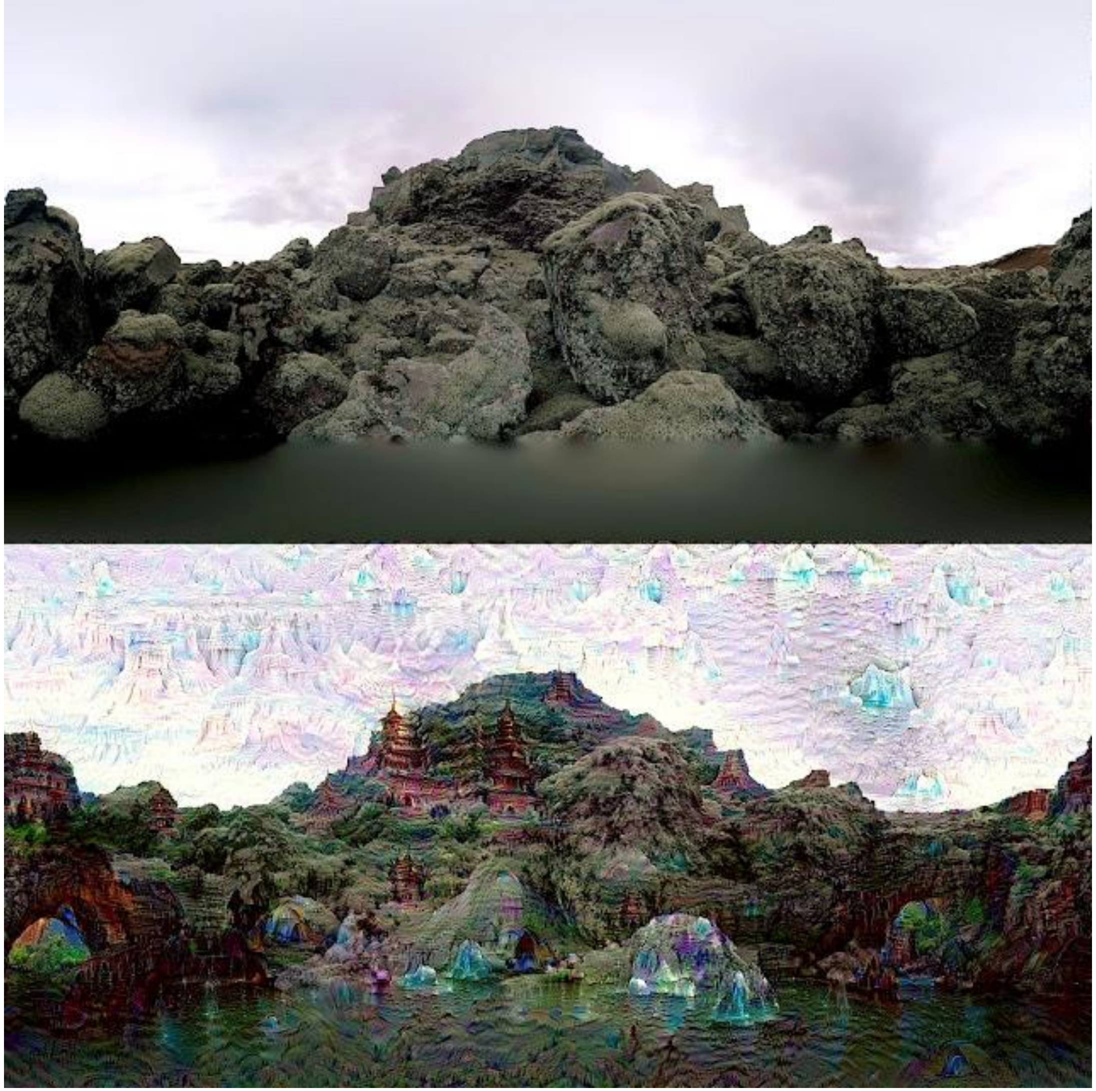
- Idea
  - Start with a random noise image.
  - Enhance the input image such as to enforce a particular response (e.g., banana).
  - Combine with prior constraint that image should have similar statistics as natural images.

  ⇒ Network hallucinates characteristics of the learned class.

http://googleresearch.blogspot.de/2015/06/inceptionism-going-deeper-into-neural.html

Inceptionism: Dreaming ConvNets

- Results



http://googleresearch.blogspot.de/2015/07/deepdream-code-example-for-visualizing.html

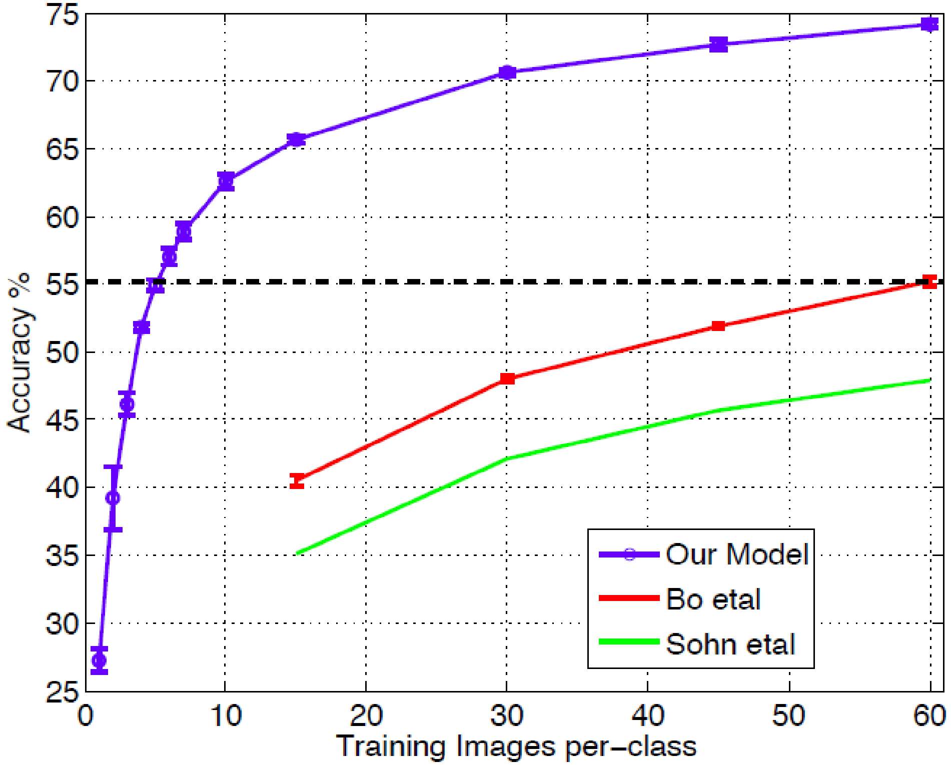
Inceptionism: Dreaming ConvNets

https://www.youtube.com/watch?v=IREsx-xWQ0g

Topics of This Lecture

- Recap: CNN Architectures
- Residual Networks
  - Detailed analysis
  - ResNets as ensembles of shallow networks
- Visualizing CNNs
  - Visualizing CNN features
  - Visualizing responses
  - Visualizing learned structures
- Applications of CNNs
  - Object detection
  - Semantic segmentation
  - Face identification

The Learned Features are Generic



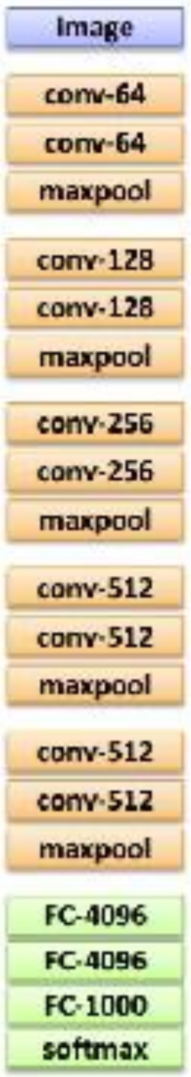
state of the art level (pre-CNN)

- Experiment: feature transfer
  - Train AlexNet-like network on ImageNet
  - Chop off last layer and train classification layer on CalTech256

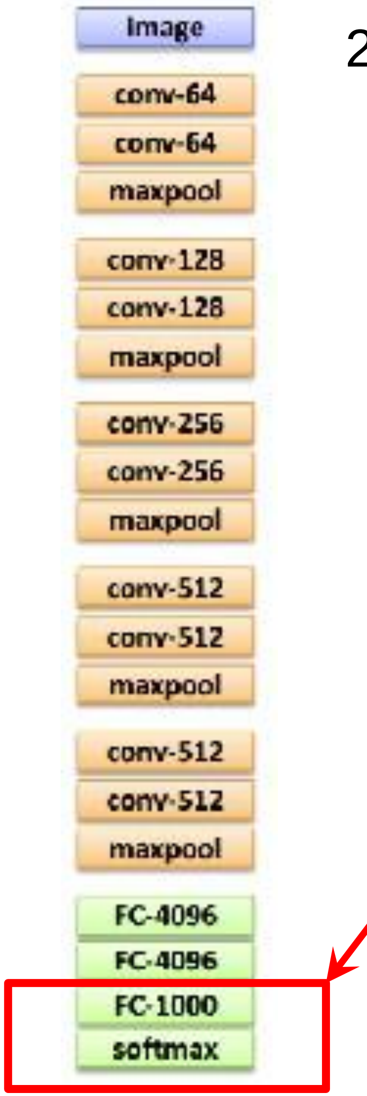
⇒ State of the art accuracy already with only 6 training images!

Image source: M. Zeiler, R. Fergus

Transfer Learning with CNNs



1. Train on ImageNet

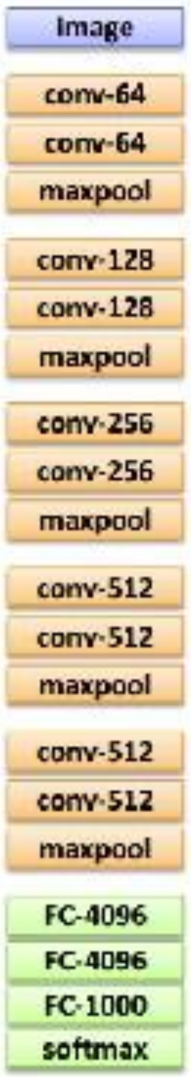


2. If small dataset: fix all weights (treat CNN as fixed feature extractor), retrain only the classifier

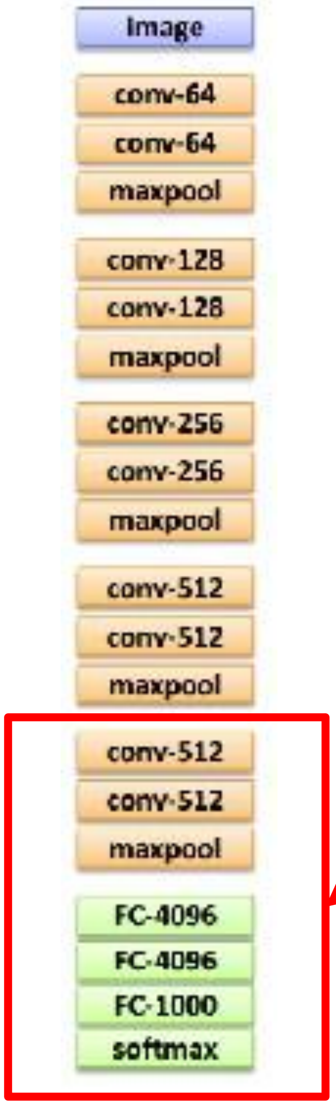
I.e., swap the Softmax layer at the end

Slide credit: Andrej Karpathy

Transfer Learning with CNNs



1. Train on ImageNet

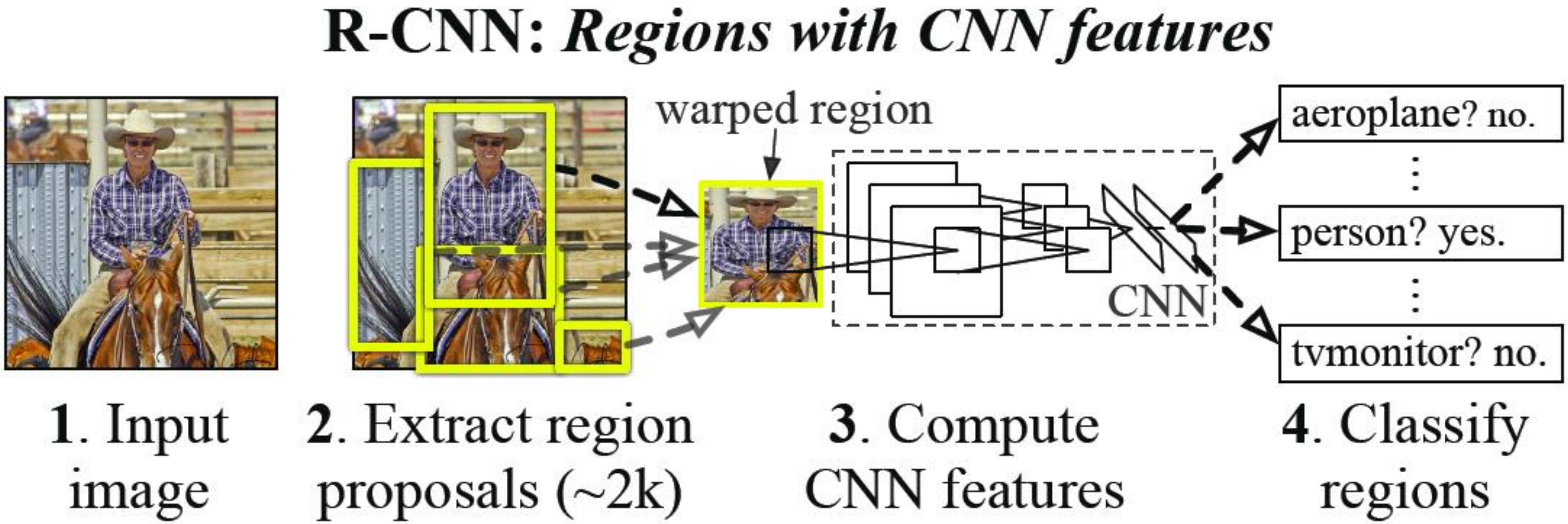


3. If you have medium sized dataset, “finetune” instead: use the old weights as initialization, train the full network or only some of the higher layers.

Retrain bigger portion of the network

Slide credit: Andrej Karpathy

Other Tasks: Detection



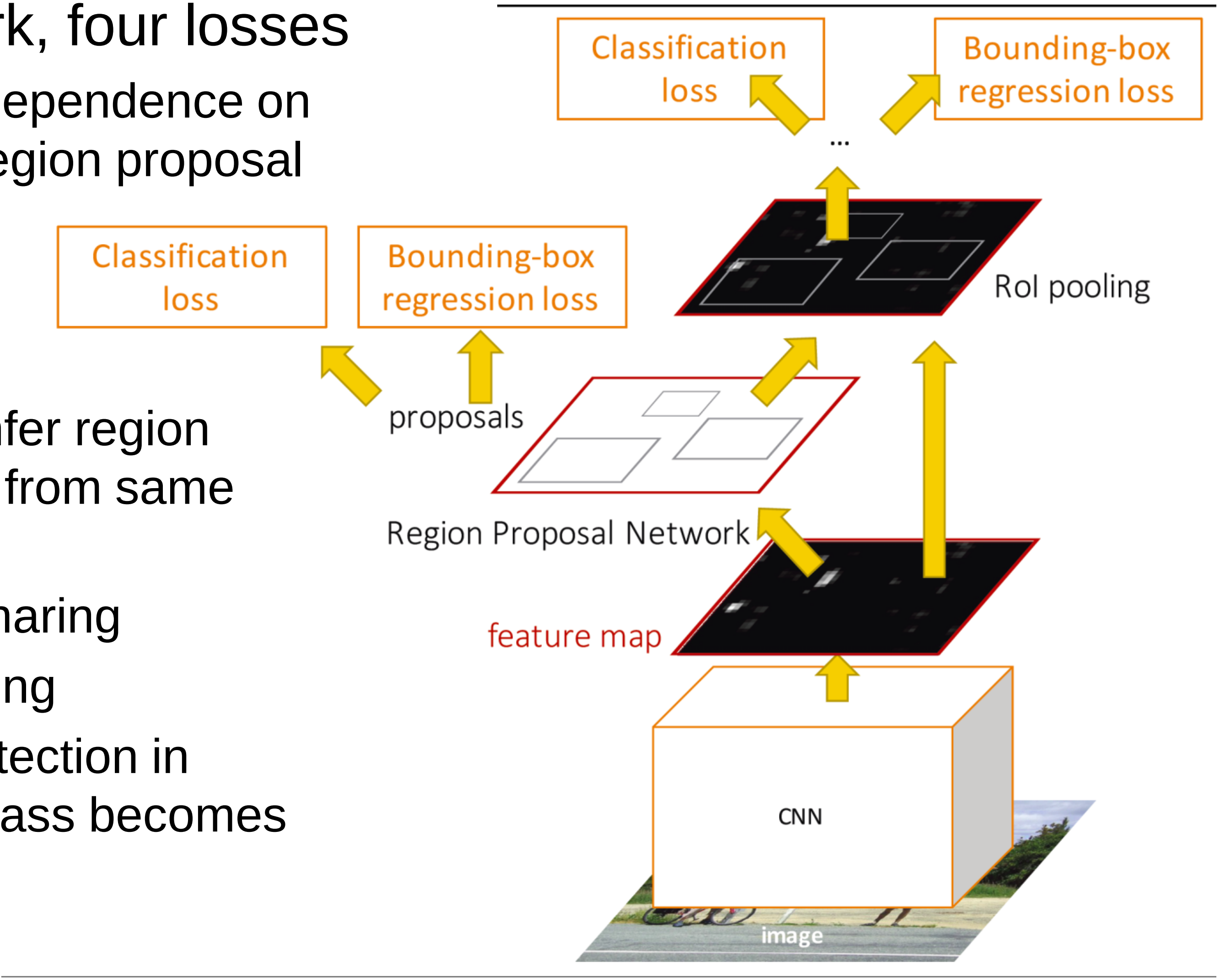
- Results on PASCAL VOC Detection benchmark
  - Pre-CNN state of the art: 35.1% mAP [Uijlings et al., 2013]
    33.4% mAP DPM
  - R-CNN: 53.7% mAP

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

More Recent Version: Faster R-CNN

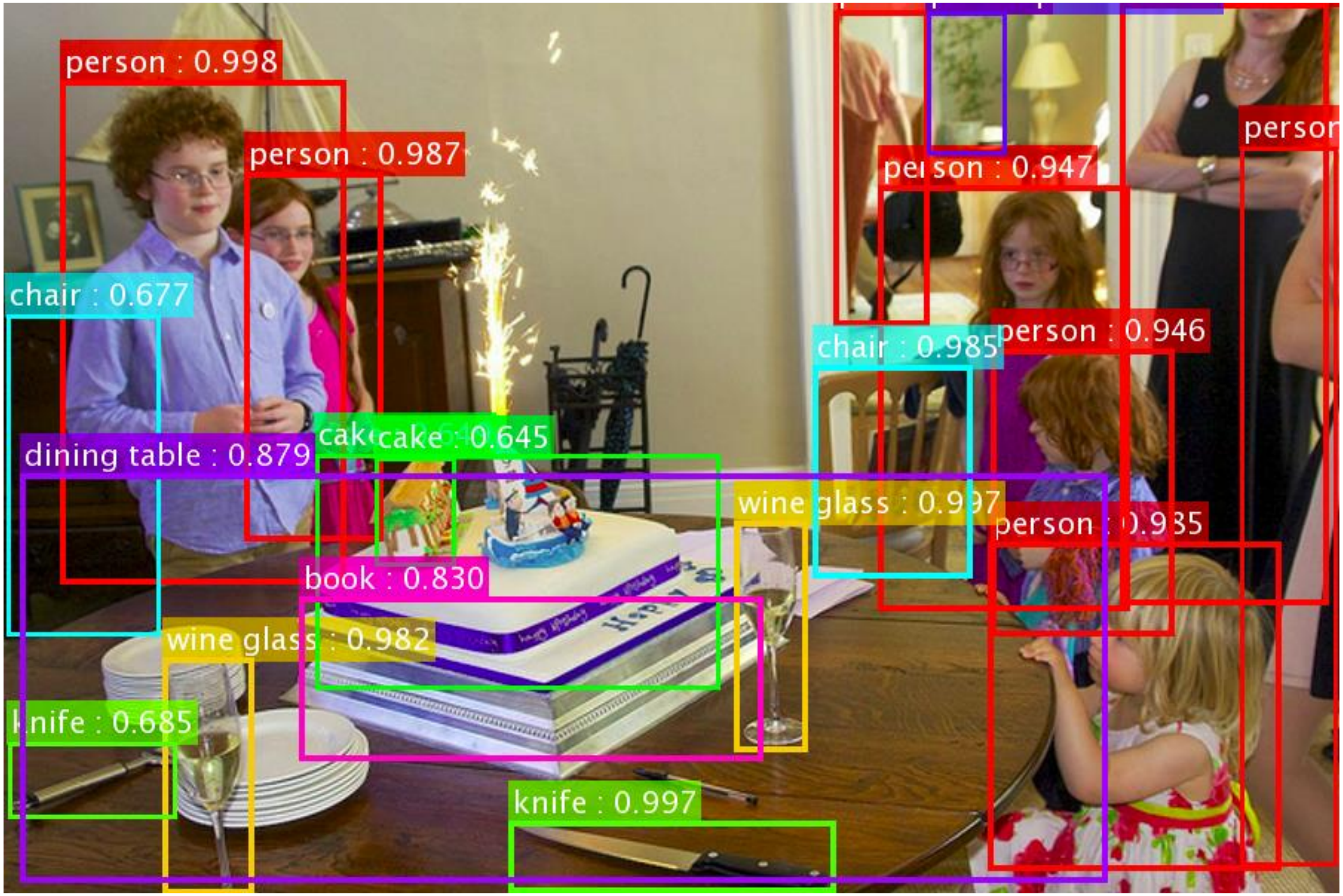
- One network, four losses
  - Remove dependence on external region proposal algorithm.
  - Instead, infer region proposals from same CNN.
  - Feature sharing
  - Joint training

⇒ Object detection in a single pass becomes possible.



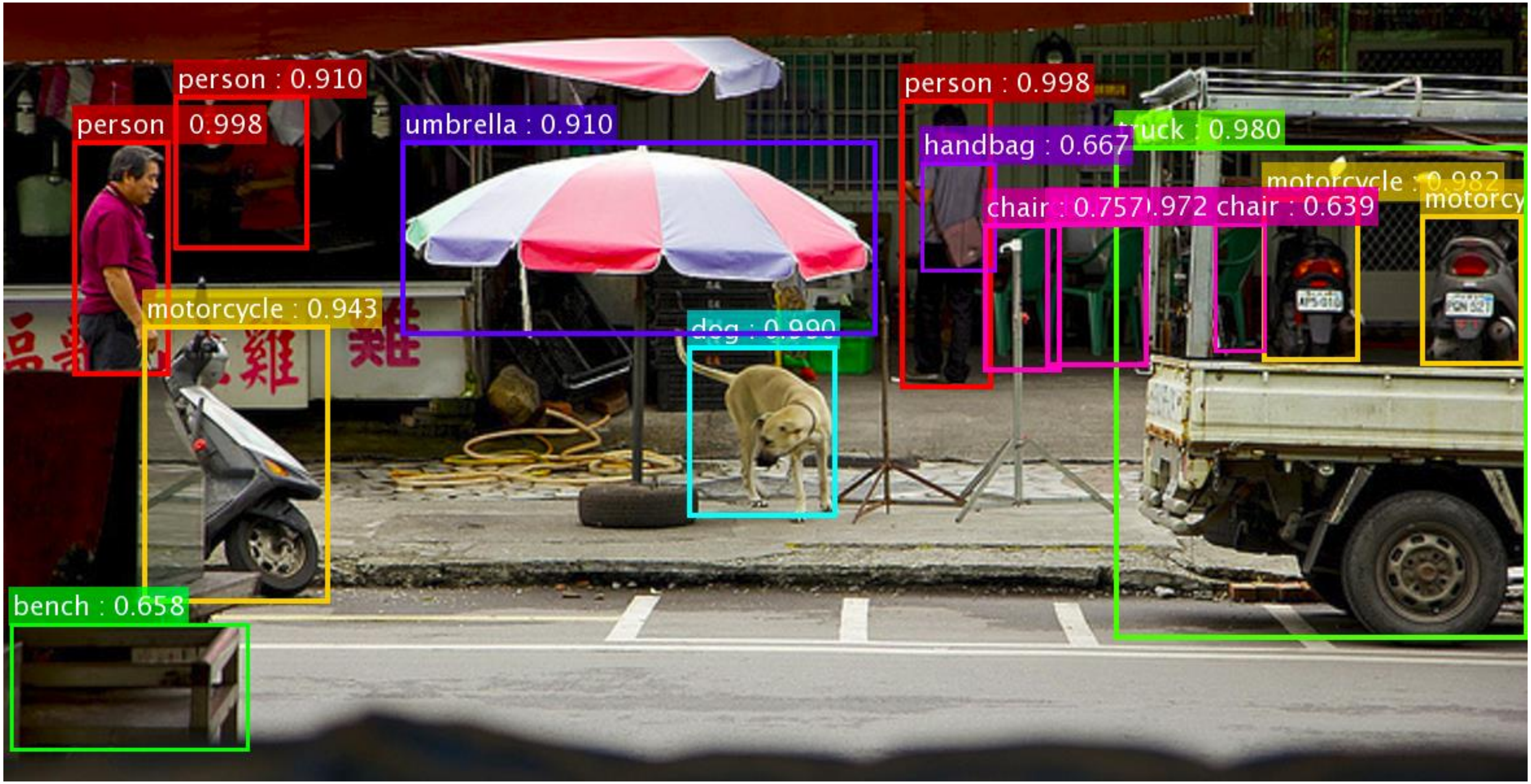
Slide credit: Ross Girshick

Faster R-CNN (based on ResNets)



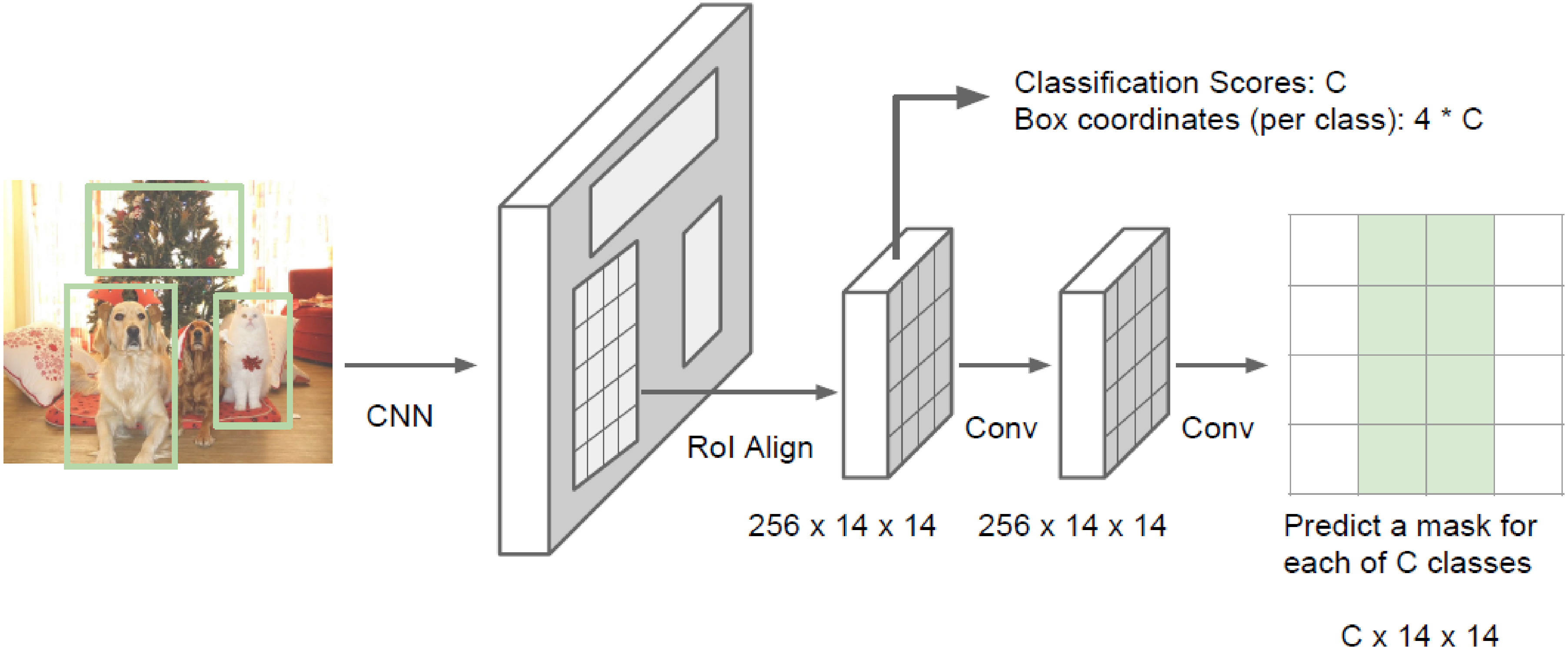
K. He, X. Zhang, S. Ren, J. Sun, Deep Residual Learning for Image Recognition, CVPR 2016.

Faster R-CNN (based on ResNets)



K. He, X. Zhang, S. Ren, J. Sun, Deep Residual Learning for Image Recognition, CVPR 2016.

Most Recent Version: Mask R-CNN

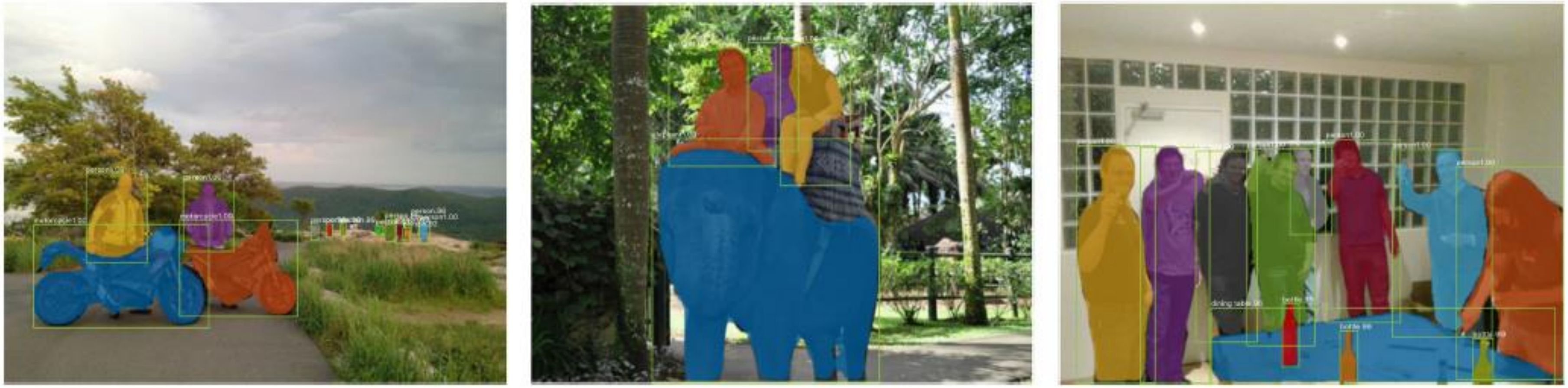


K. He, G. Gkioxari, P. Dollar, R. Girshick, Mask R-CNN, arXiv 1703.06870.

Slide credit: FeiFei Li

Mask R-CNN Results

- Detection + Instance segmentation



- Detection + Pose estimation

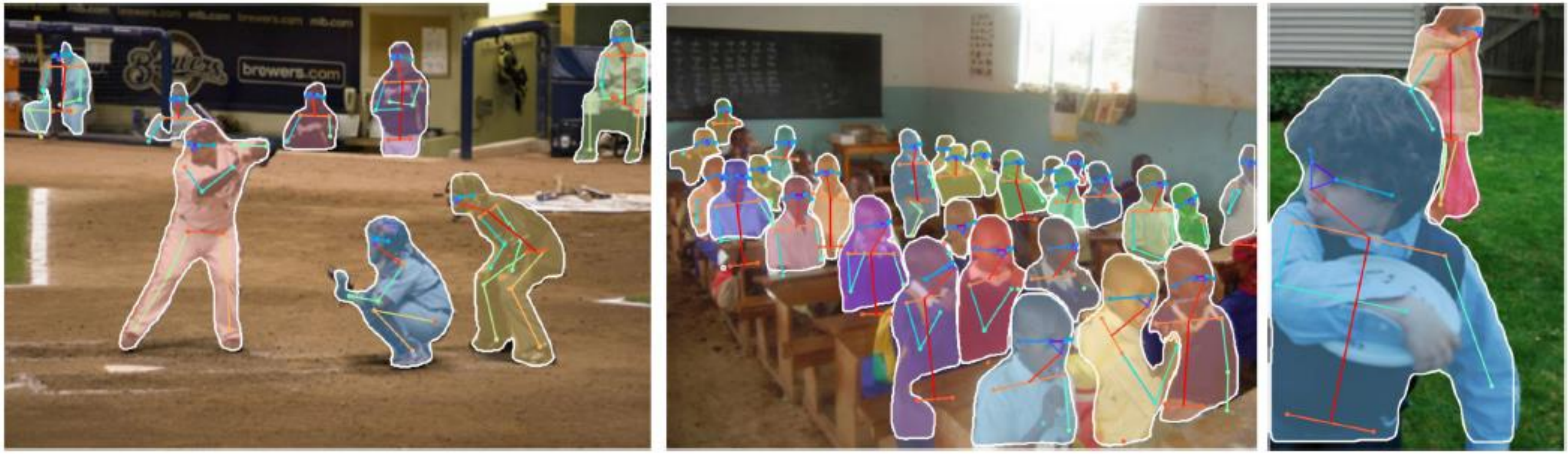
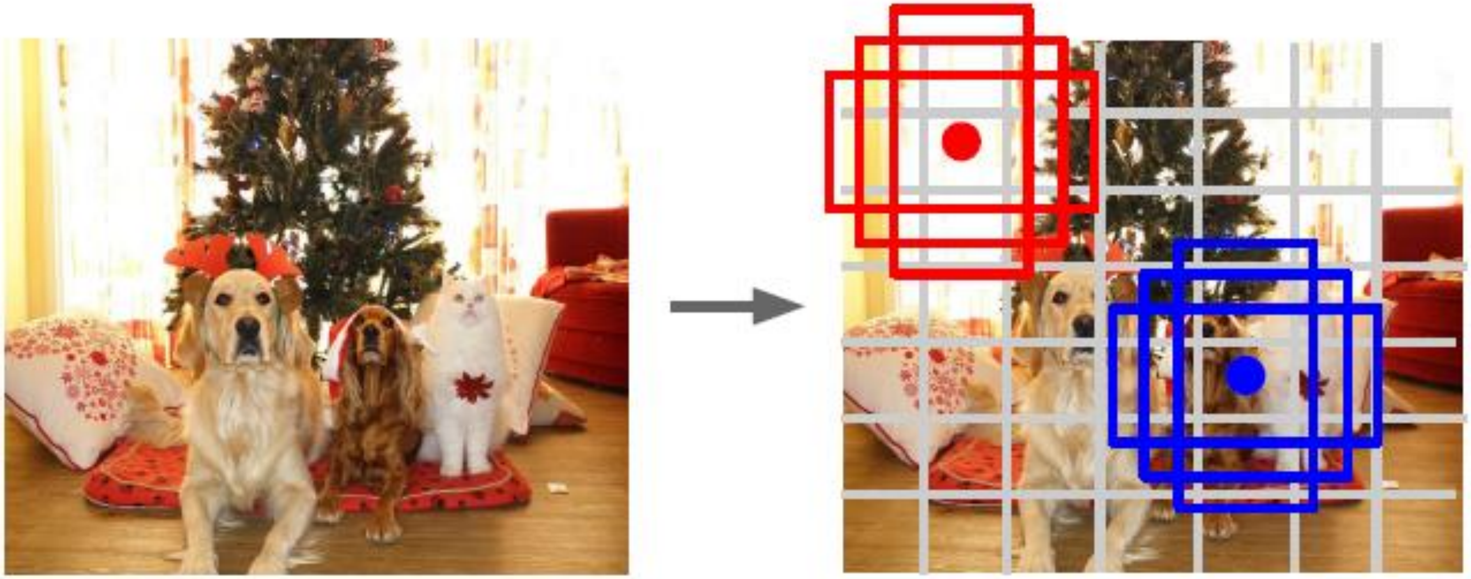


Figure credit: K. He, G. Gkioxari, P. Dollar, R. Girshick

YOLO / SSD



Input image
3 x H x W

Divide image into grid
7 x 7

- Idea: Directly go from image to detection scores
- Within each grid cell
  - Start from a set of anchor boxes
  - Regress from each of the B anchor boxes to a final box
  - Predict scores for each of C classes (including background)

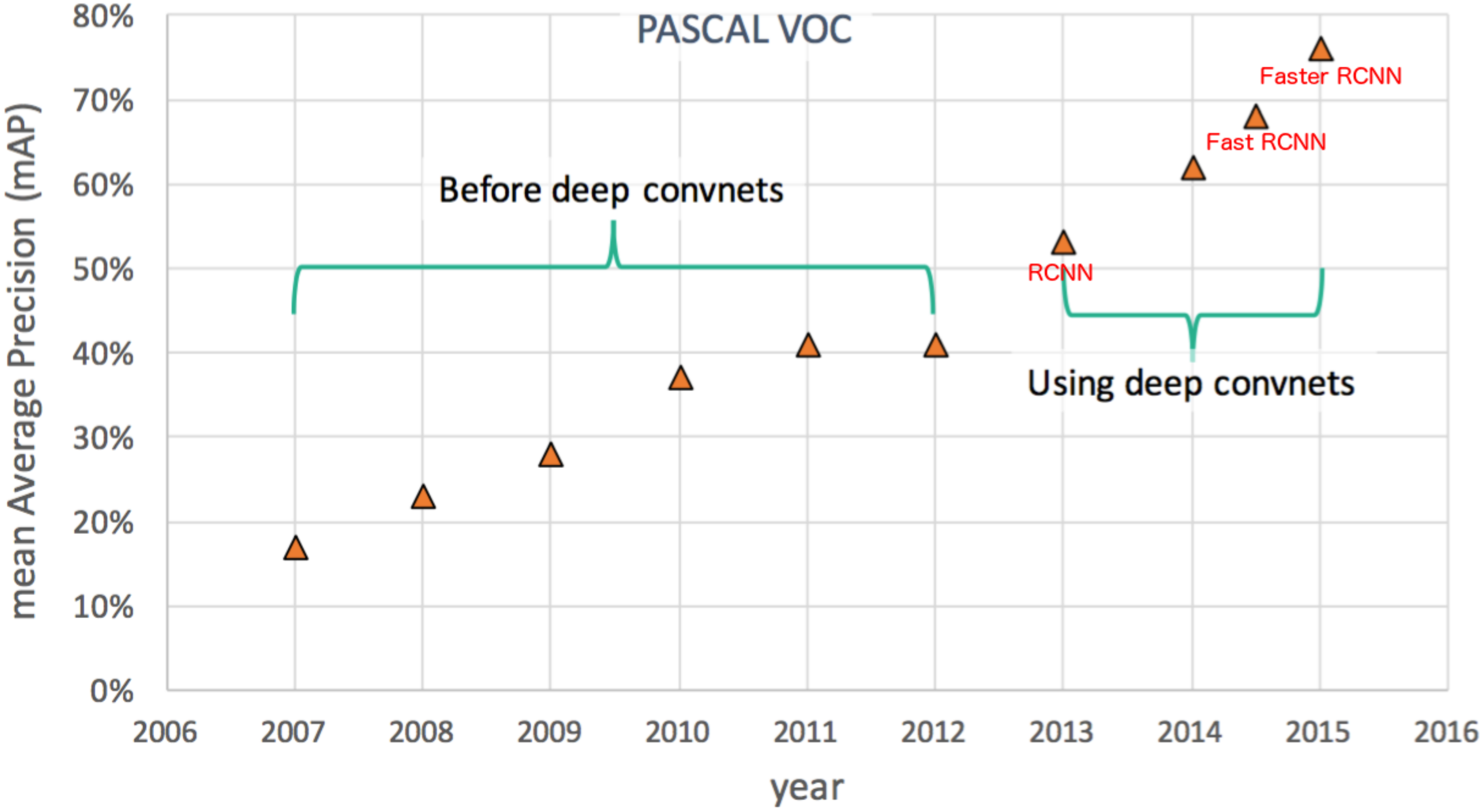
Slide credit: FeiFei Li

YOLO

J. Redmon, S. Divvala, R. Girshick, A. Farhadi, You Only Look Once: Unified, Real-Time Object Detection, CVPR 2016.

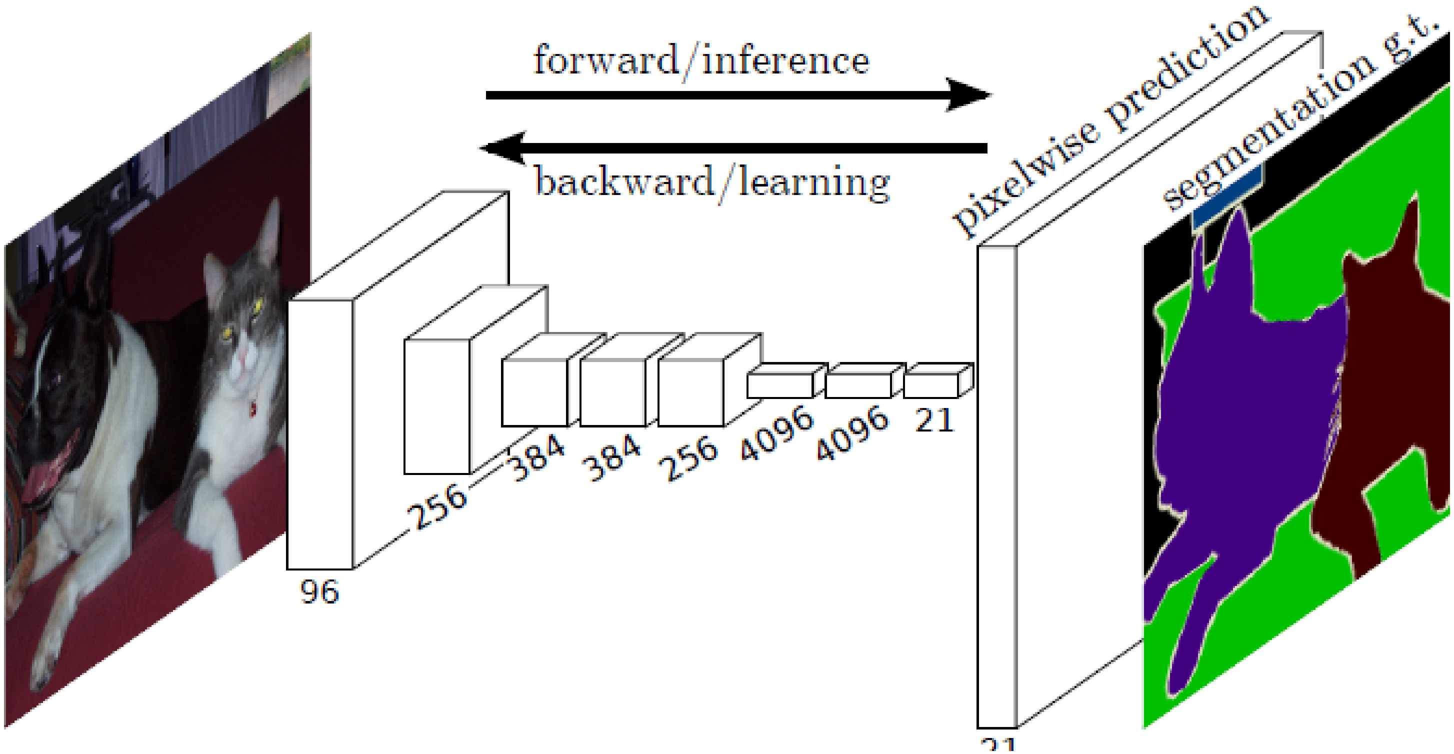
Machine Learning Winter ‘19

Object Detection Performance



Slide credit: Ross Girshick

Semantic Image Segmentation

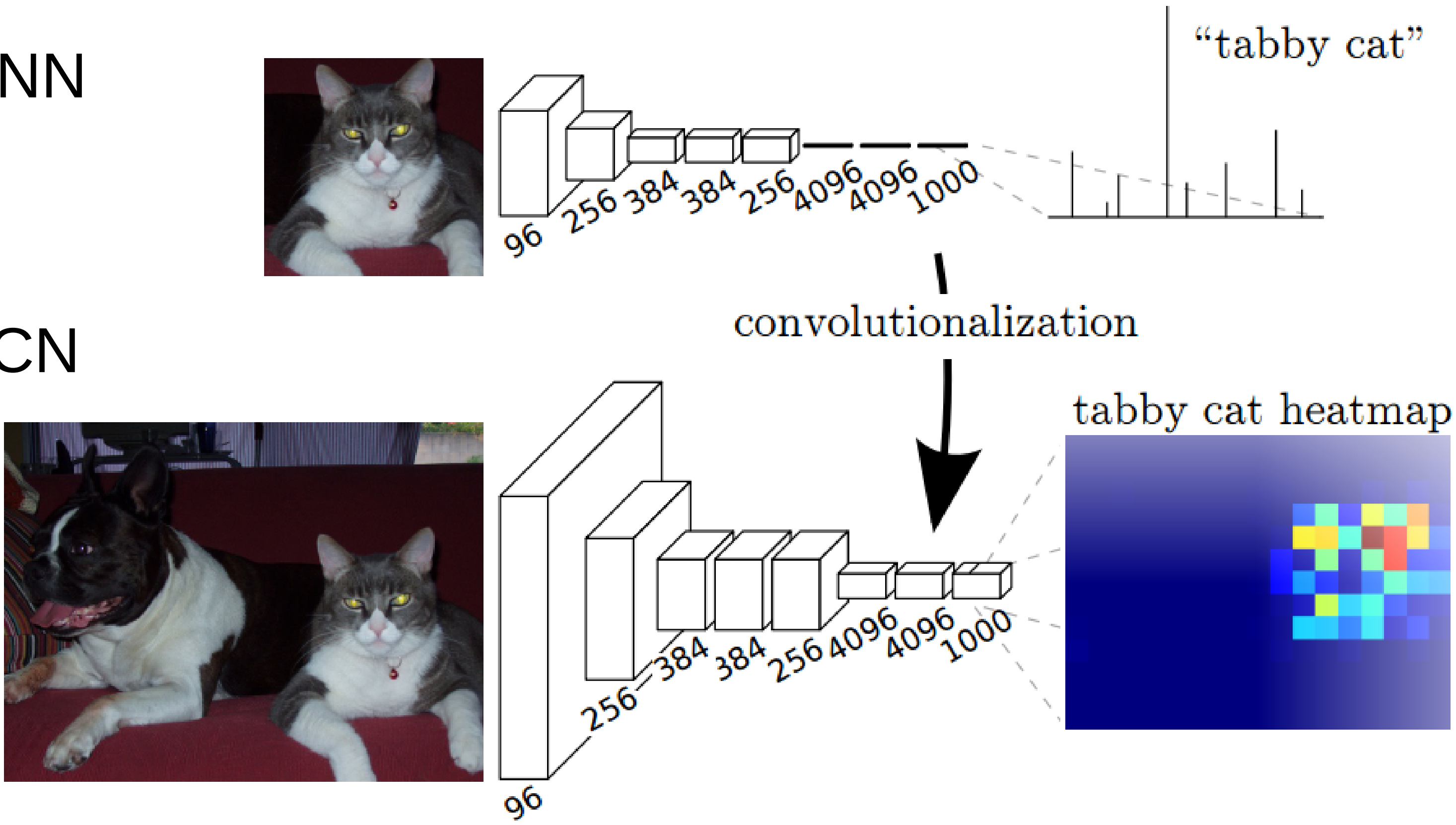


- Perform pixel-wise prediction task
  - Usually done using Fully Convolutional Networks (FCNs)
    - All operations formulated as convolutions
    - Advantage: can process arbitrarily sized images

Image source: Long, Shelhamer, Darrell

CNNs vs. FCNs

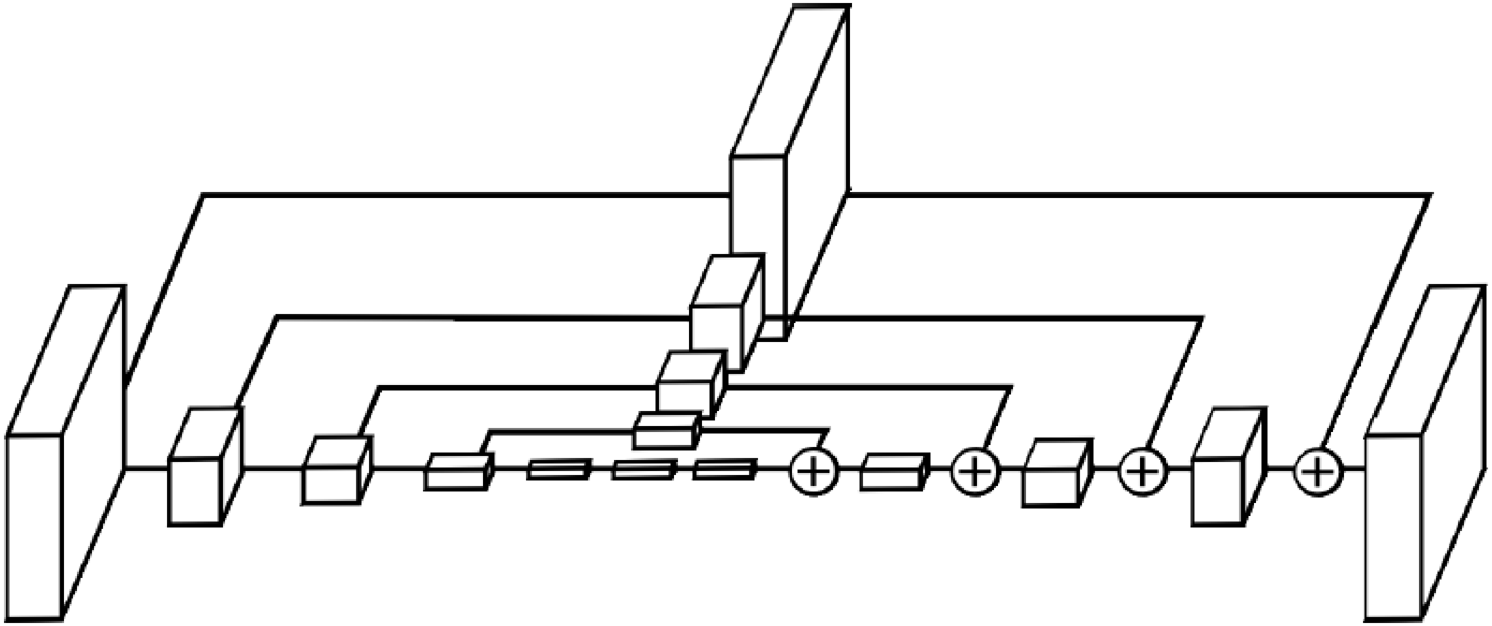
- CNN
- FCN



- Intuition
  - Think of FCNs as performing a sliding-window classification, producing a heatmap of output scores for each class

Image source: Long, Shelhamer, Darrell

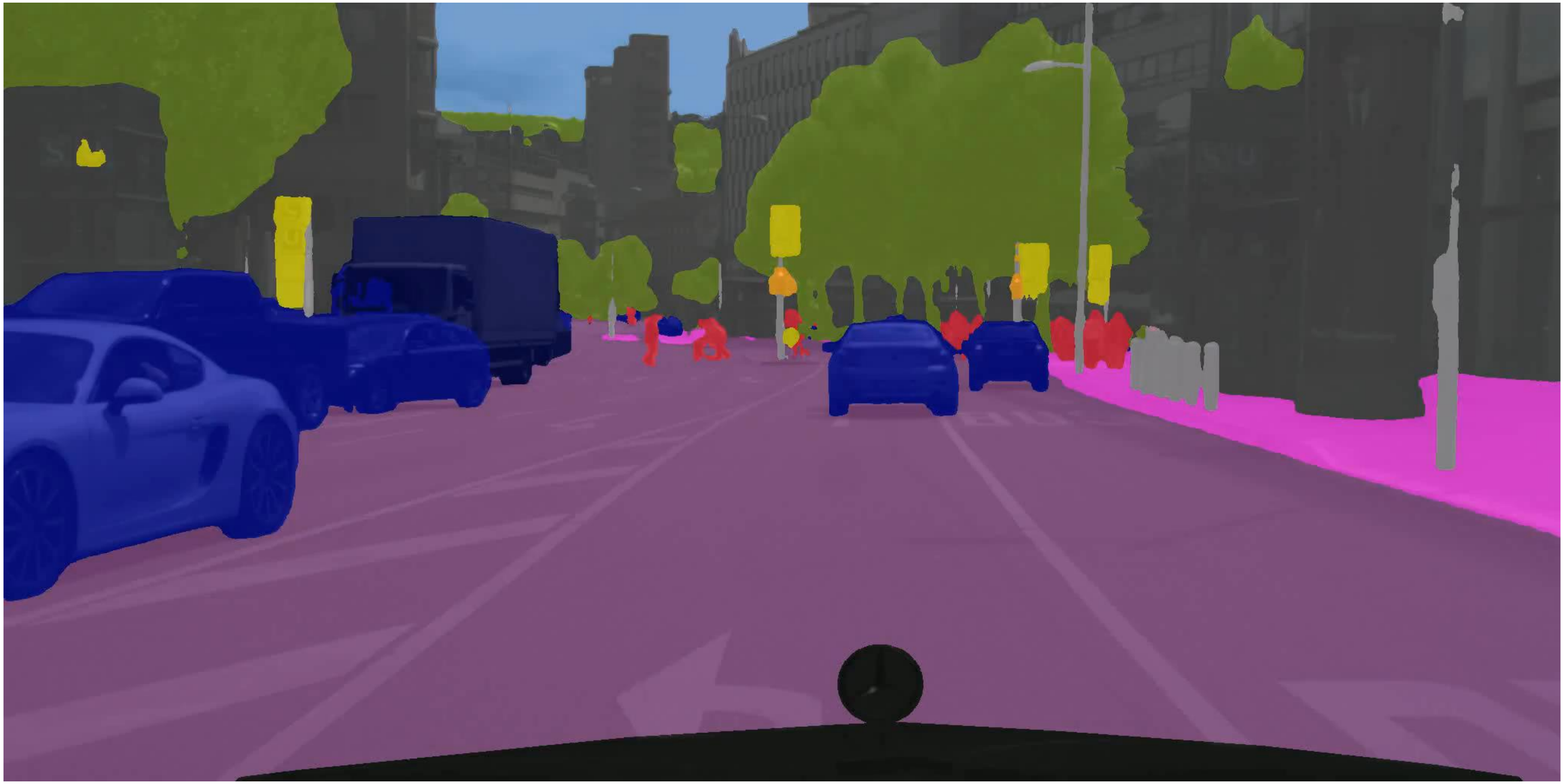
Semantic Image Segmentation



- Encoder-Decoder Architecture
  - Problem: FCN output has low resolution
  - Solution: perform upsampling to get back to desired resolution
  - Use skip connections to preserve higher-resolution information

Image source: Newell et al.

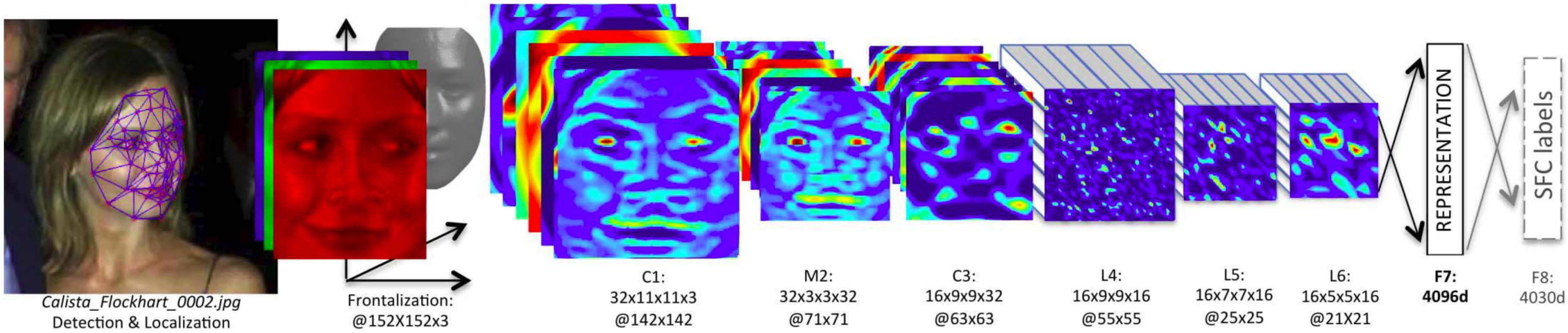
Semantic Segmentation

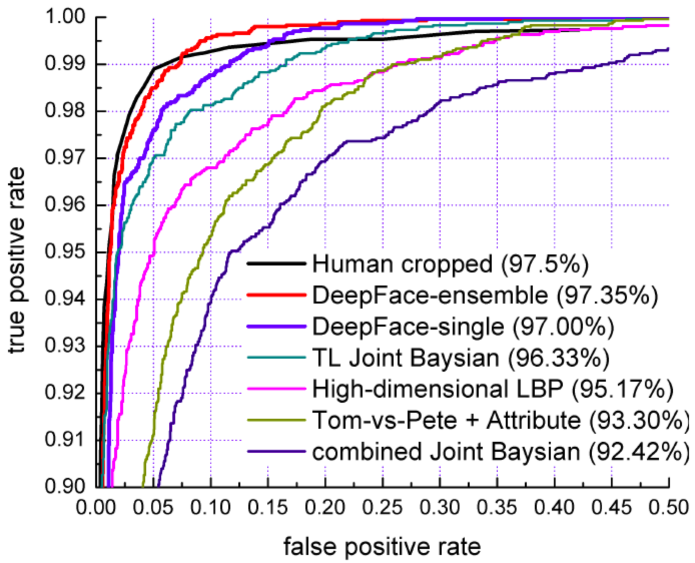


- Current state-of-the-art
  - Based on an extension of ResNets

[Pohlen, Hermans, Mathias, Leibe, CVPR 2017]

Other Tasks: Face Identification





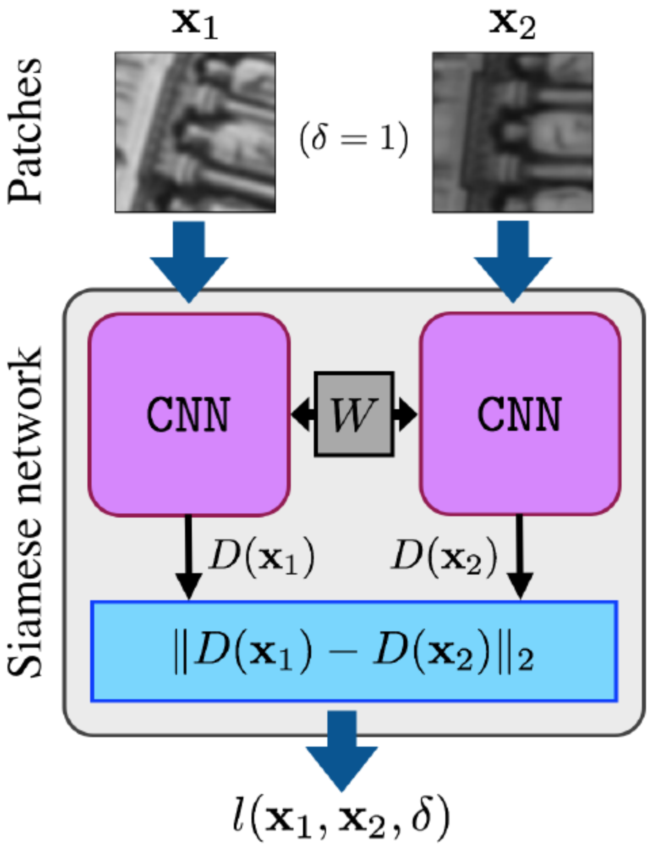
Y. Taigman, M. Yang, M. Ranzato, L. Wolf, DeepFace: Closing the Gap to Human-Level Performance in Face Verification, CVPR 2014

Slide credit: Svetlana Lazebnik

Learning Similarity Functions

- Siamese Network
  - Present the two stimuli to two identical copies of a network (with shared parameters)
  - Train them to output similar values if the inputs are (semantically) similar.

- Used for many matching tasks
  - Face identification
  - Stereo estimation
  - Optical flow
  - …



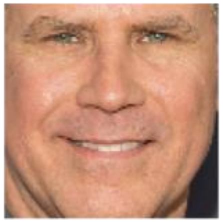
Extension: Triplet Loss Networks

- Learning a discriminative embedding
  - Present the network with triplets of examples

Negative

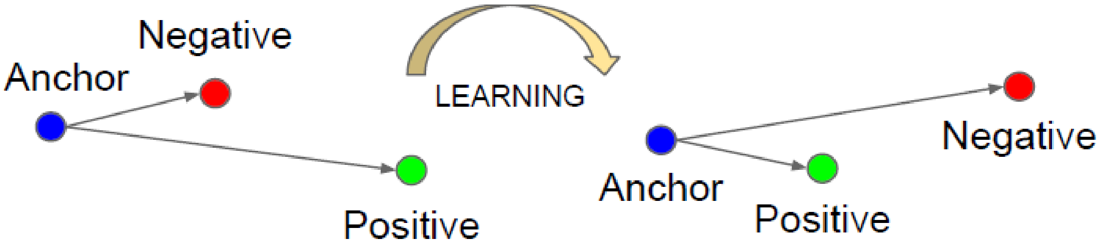
Anchor

Positive



  - Apply triplet loss to learn an embedding $f(\cdot)$ that groups the positive example closer to the anchor than the negative one.

$$\|f(x_i^a) - f(x_i^p)\|_2^2 < \|f(x_i^a) - f(x_i^n)\|_2^2$$



⇒ Used with great success in Google's FaceNet face identification

References and Further Reading

- ResNets
  - K. He, X. Zhang, S. Ren, J. Sun, Deep Residual Learning for Image Recognition, CVPR 2016.
  - A, Veit, M. Wilber, S. Belongie, Residual Networks Behave Like Ensembles of Relatively Shallow Networks, NIPS 2016.

References: Computer Vision Tasks

- Object Detection
  - R. Girshick, J. Donahue, T. Darrell, J. Malik, Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation, CVPR 2014.
  - S. Ren, K. He, R. Girshick, J. Sun, Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks, NIPS 2015.
  - J. Redmon, S. Divvala, R. Girshick, A. Farhadi, You Only Look Once: Unified Real-Time Object Detection, CVPR 2016.
  - W. Liu, D. Anguelov, D. Erhan, C. Szegedy, S. Reed, C-Y. Fu, A.C. Berg, SSD: Single Shot Multi Box Detector, ECCV 2016.

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- Semantic Segmentation
  - J. Long, E. Shelhamer, T. Darrell, Fully Convolutional Networks for Semantic Segmentation, CVPR 2015.
  - H. Zhao, J. Shi, X. Qi, X. Wang, J. Jia, Pyramid Scene Parsing Network, arXiv 1612.01105, 2016.