Machine Learning – Lecture 14

Convolutional Neural Networks II

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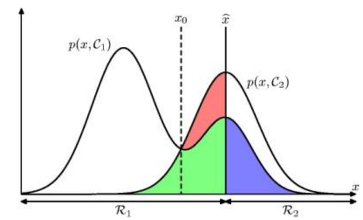
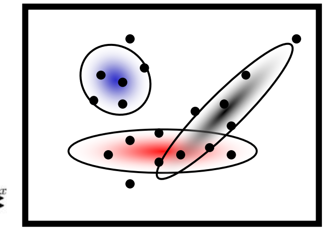
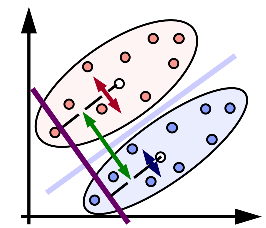
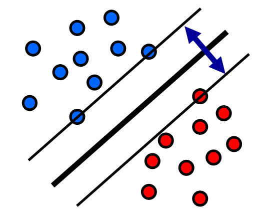
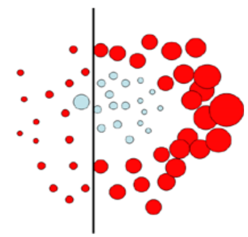
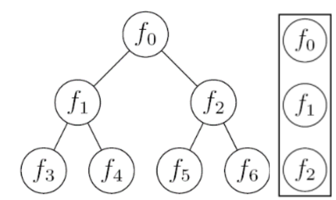
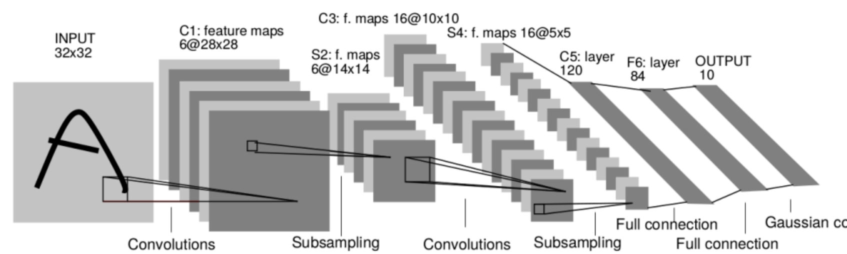
Course Outline

- 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

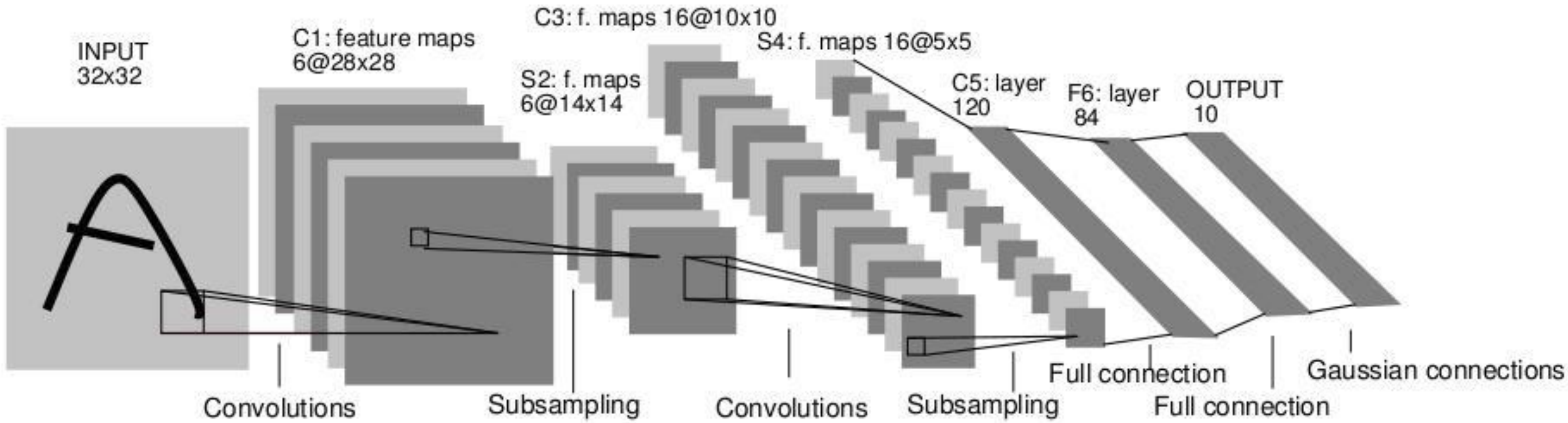









Topics of This Lecture

- Recap: CNNs
- CNN Architectures
  - LeNet
  - AlexNet
  - VGGNet
  - GoogLeNet
  - ResNets
- Visualizing CNNs
  - Visualizing CNN features
  - Visualizing responses
  - Visualizing learned structures
- Applications

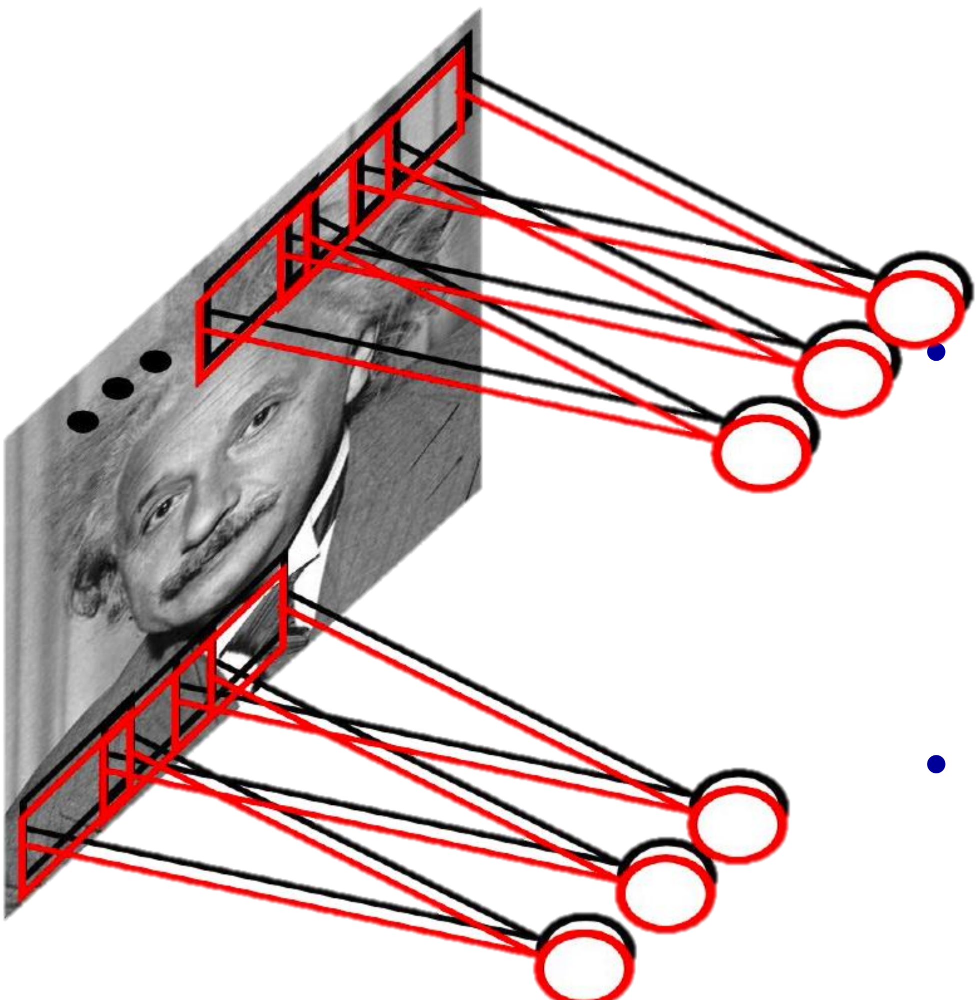
Recap: Convolutional Neural Networks



- 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.

Recap: Intuition of CNNs

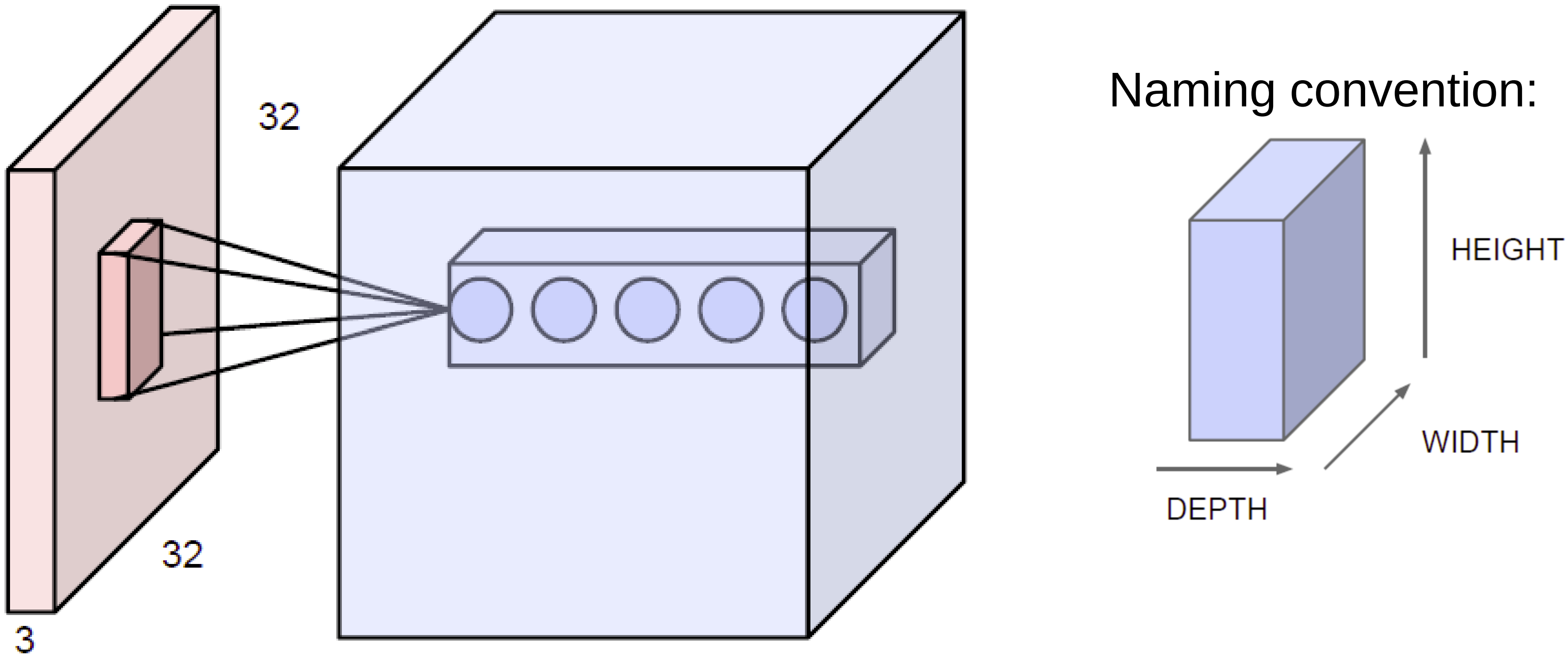


- Convolutional net
  - Share the same parameters across different locations
  - Convolutions with learned kernels
- Learn *multiple* filters
  - E.g. 1000×1000 image
    100 filters
    10×10 filter size

  ⇒ only 10k parameters
- Result: Response map
  - size: 1000×1000×100
  - Only memory, not params!

Image source: Yann LeCun

Recap: Convolution Layers

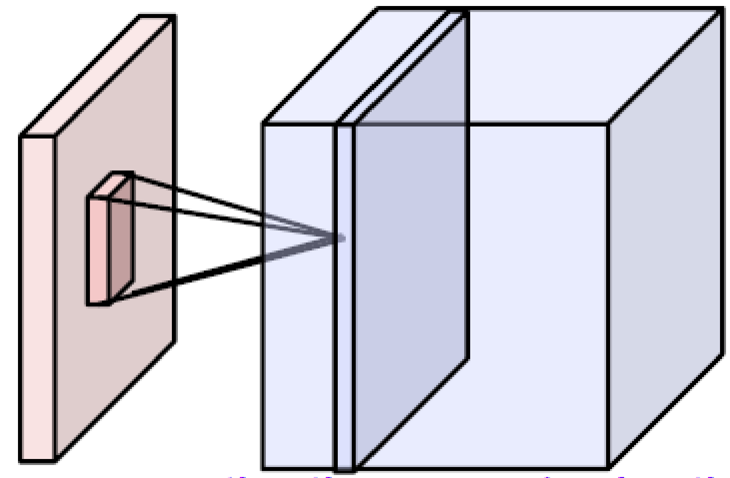


- All Neural Net activations arranged in 3 dimensions
  - Multiple neurons all looking at the same input region, stacked in depth
  - Form a single [$1\times1\times$depth] depth column in output volume.

Recap: Activation Maps

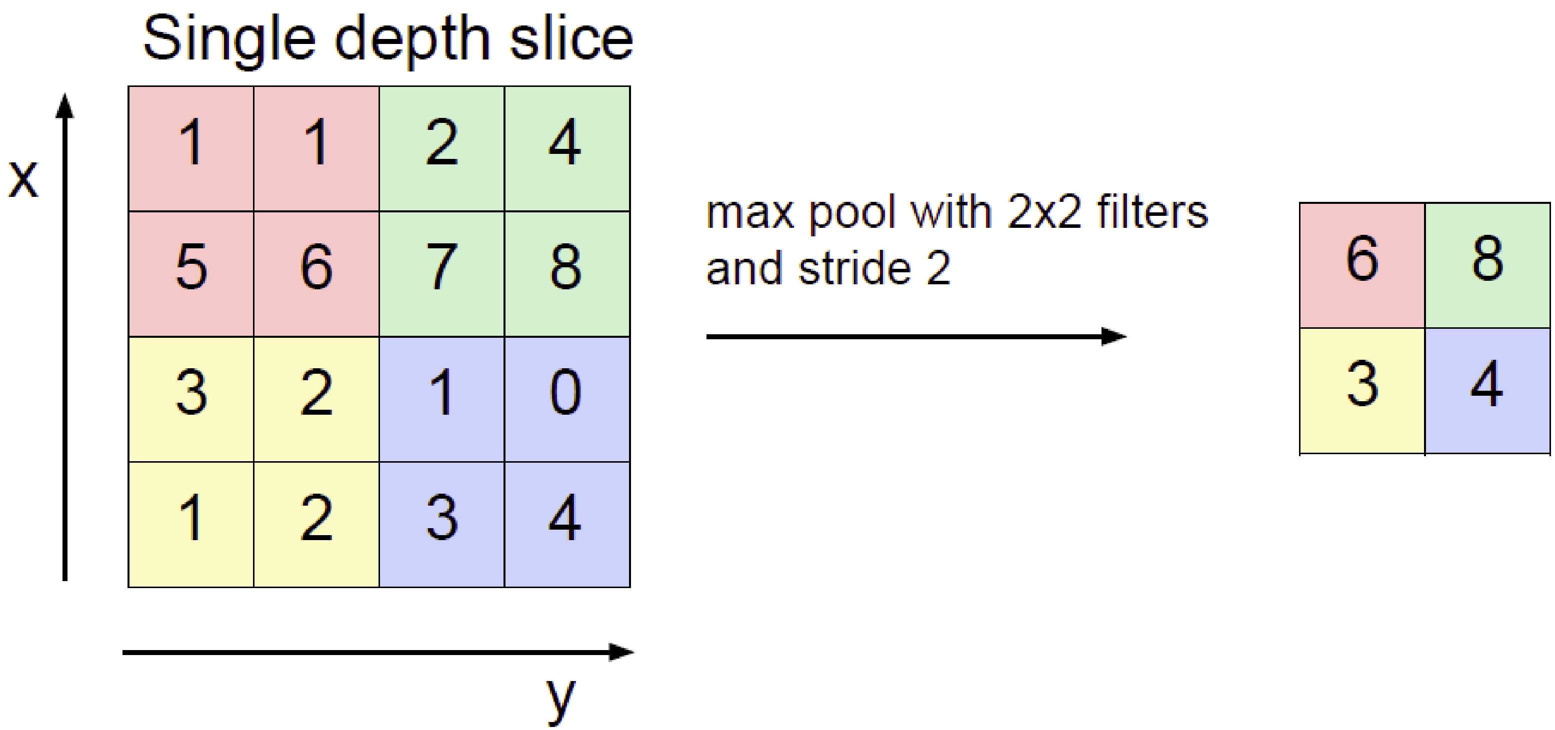
5×5 filters

Activation maps



Each activation map is a depth slice through the output volume.

Recap: Pooling Layers



- Effect:
  - Make the representation smaller without losing too much information
  - Achieve robustness to translations
  - Pooling happens independently across each slice, preserving the number of slices

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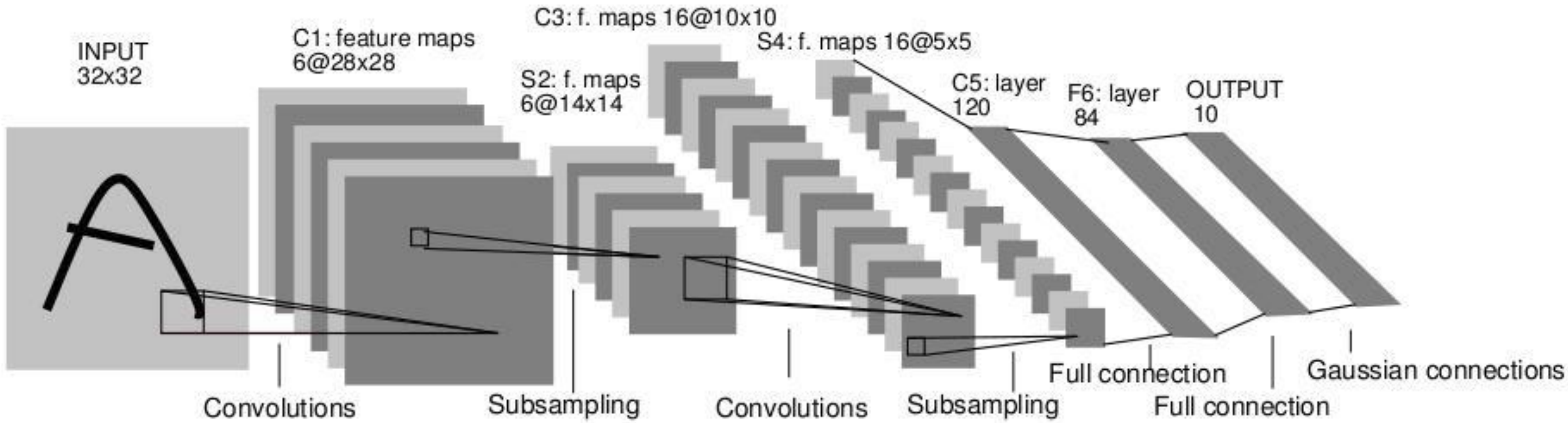
CNN Architectures: LeNet (1998)



- Early convolutional architecture
  - 2 Convolutional layers, 2 pooling layers
  - Fully-connected NN layers for classification
  - Successfully used for handwritten digit recognition (MNIST)

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.

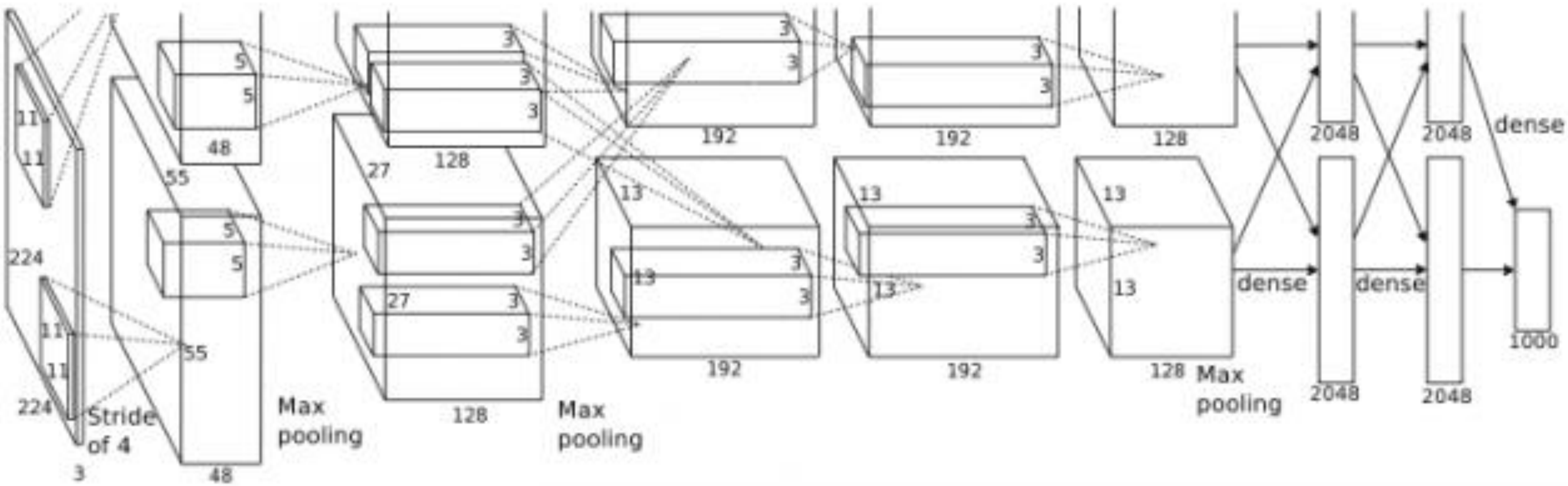
ImageNet Challenge 2012

- ImageNet
  - ~14M labeled internet images
  - 20k classes
  - Human labels via Amazon Mechanical Turk

[Deng et al., CVPR’09]

- Challenge (ILSVRC)
  - 1.2 million training images
  - 1000 classes
  - Goal: Predict ground-truth class within top-5 responses
  - Currently one of the top benchmarks in Computer Vision

CNN Architectures: AlexNet (2012)

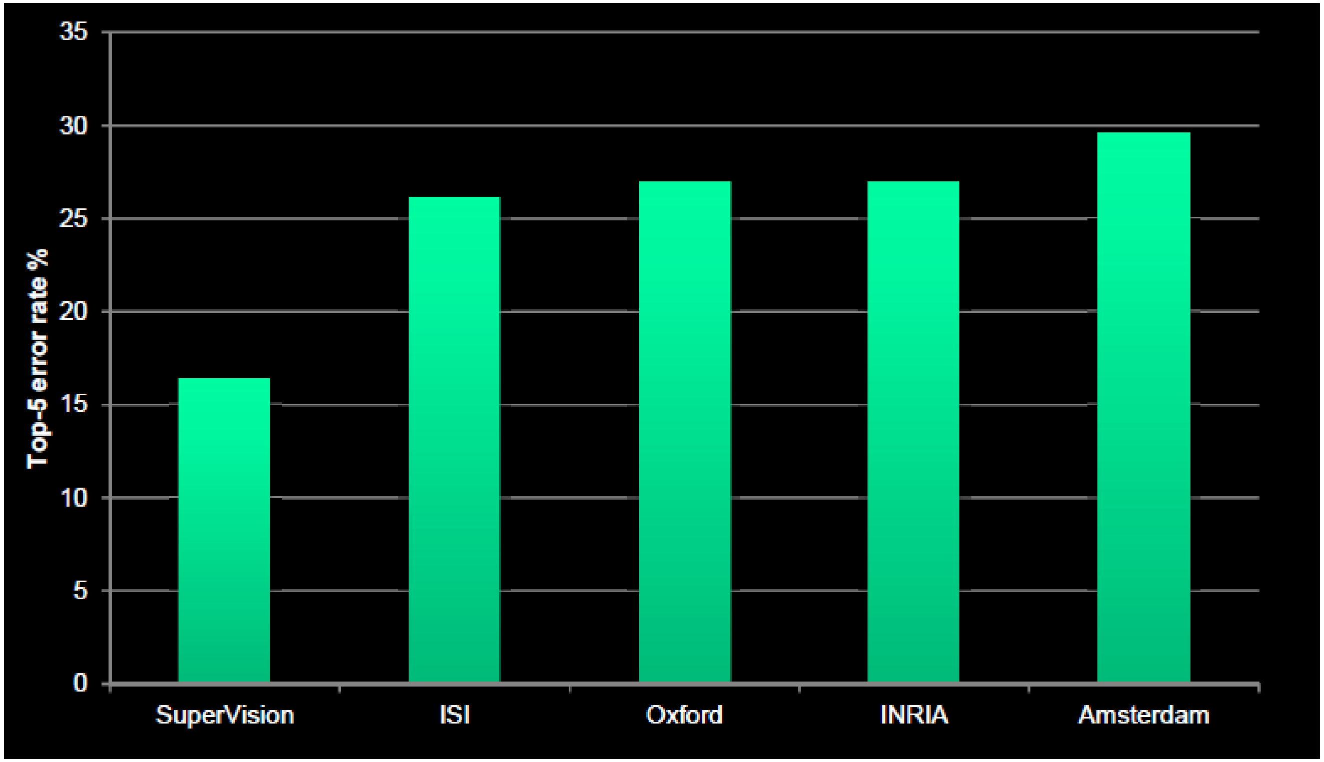


- Similar framework as LeNet, but
  - Bigger model (7 hidden layers, 650k units, 60M parameters)
  - More data (10^6 images instead of 10^3)
  - GPU implementation
  - Better regularization and up-to-date tricks for training (Dropout)

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

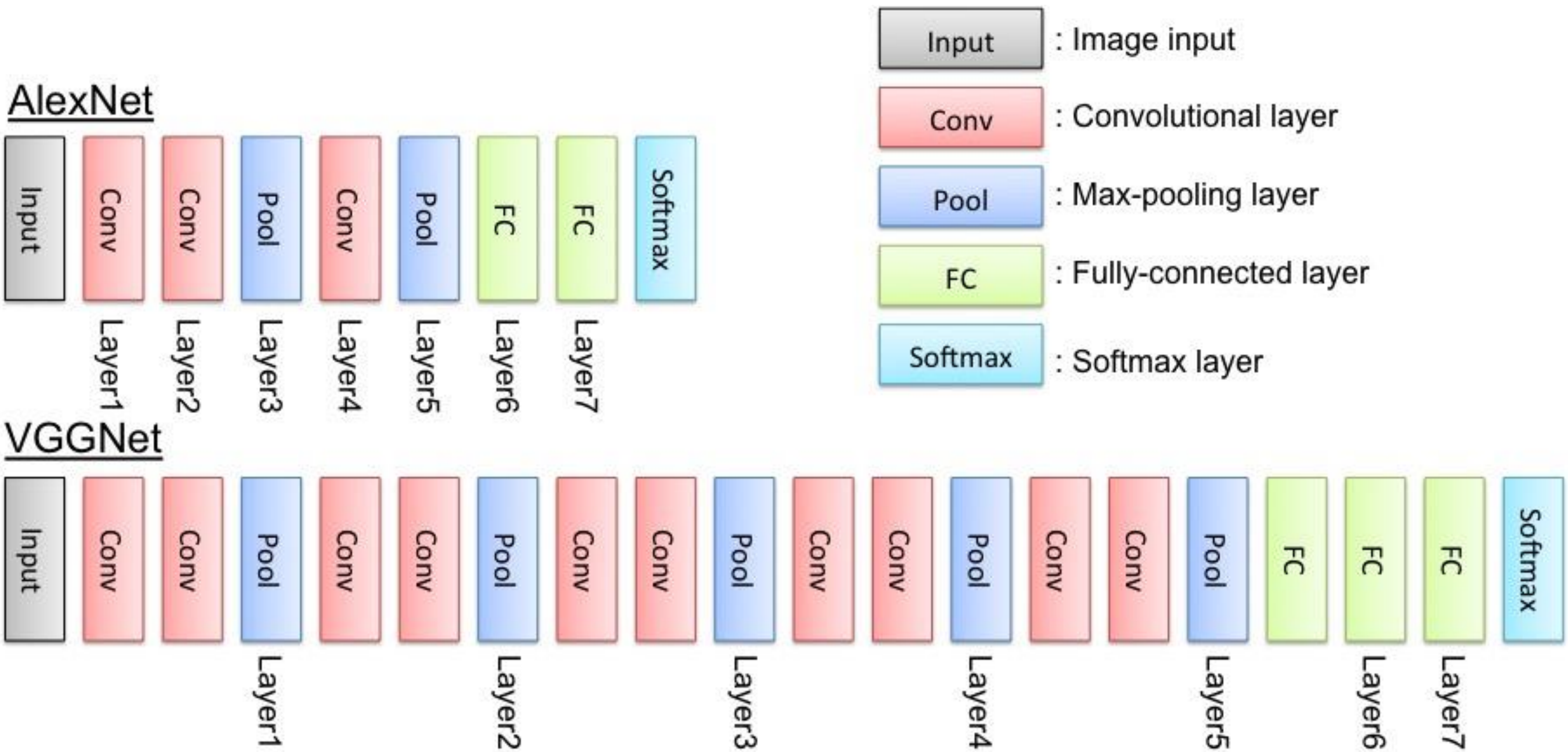
Image source: A. Krizhevsky, I. Sutskever and G.E. Hinton, NIPS 2012

ILSVRC 2012 Results



- AlexNet almost halved the error rate
  - 16.4% error (top-5) vs. 26.2% for the next best approach
  - ⇒ A revolution in Computer Vision
  - Acquired by Google in Jan ‘13, deployed in Google+ in May ‘13

CNN Architectures: VGGNet (2014/15)



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

Image source: Hirokatsu Kataoka

CNN Architectures: 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

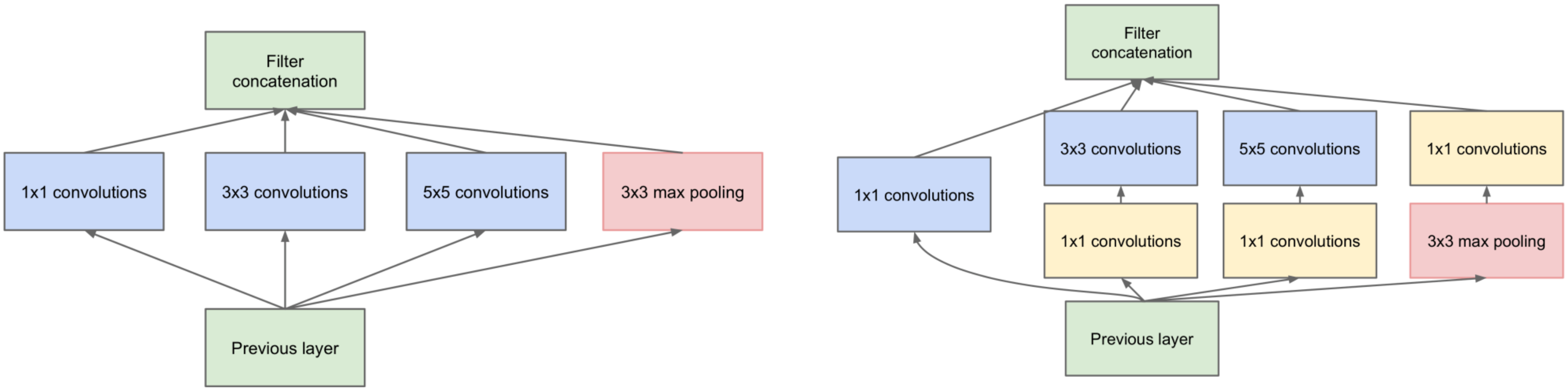
Image source: Simonyan & Zisserman

Comparison: AlexNet vs. VGGNet

- Receptive fields in the first layer
  - AlexNet: 11×11, stride 4
  - Zeiler & Fergus: 7×7, stride 2
  - VGGNet: 3×3, stride 1

- Why that?
  - If you stack a 3×3 on top of another 3×3 layer, you effectively get a 5×5 receptive field.
  - With three 3×3 layers, the receptive field is already 7×7.
  - But much fewer parameters: $3\cdot3^2 = 27$ instead of $7^2 = 49$.
  - In addition, non-linearities in-between 3×3 layers for additional discriminativity.

CNN Architectures: GoogLeNet (2014/2015)



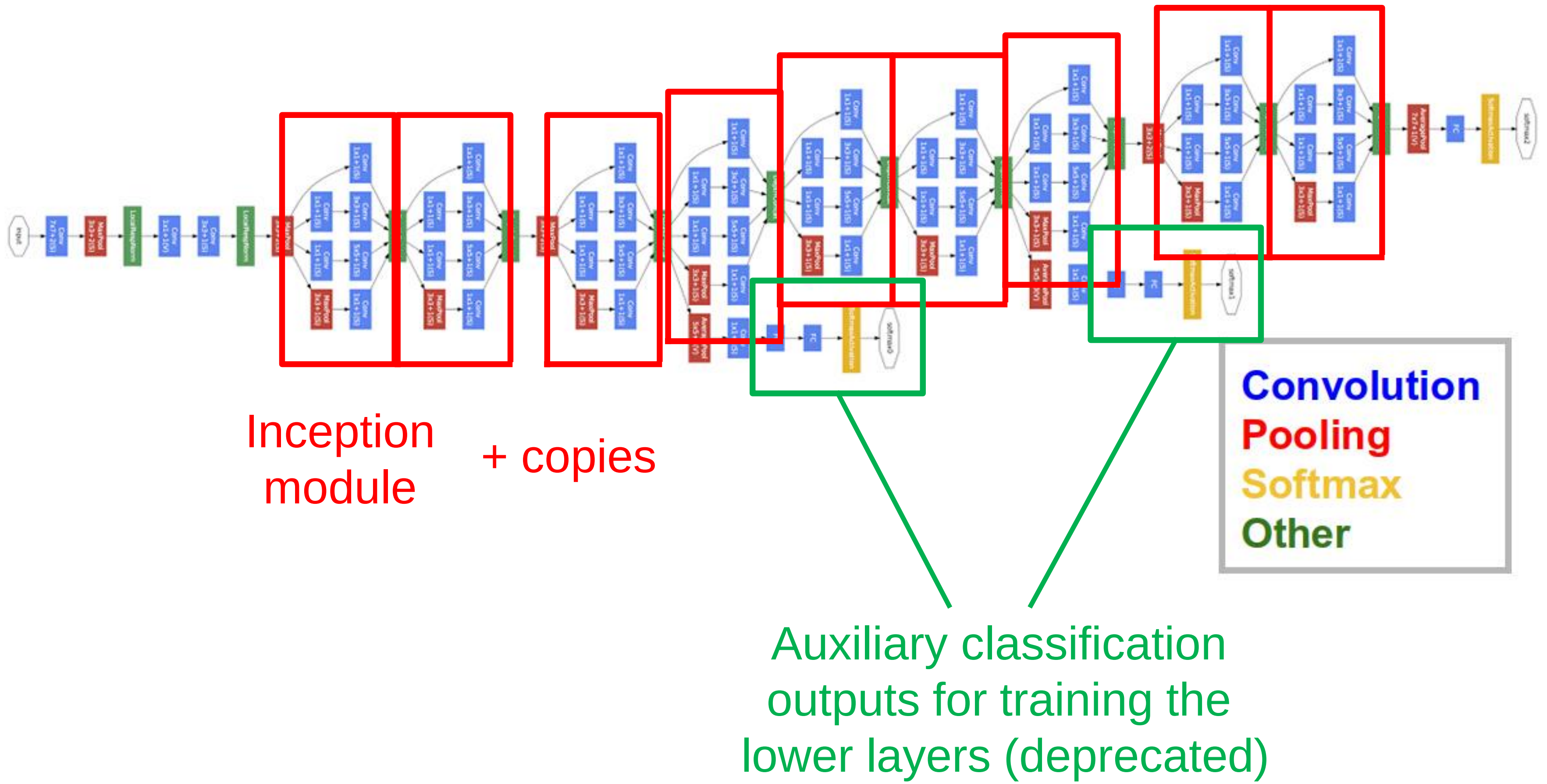
(a) Inception module, naïve version

(b) Inception module with dimension reductions

- Main ideas
  - "Inception" module as modular component
  - Learns filters at several scales within each module

C. Szegedy, W. Liu, Y. Jia, et al, Going Deeper with Convolutions, arXiv:1409.4842, 2014, CVPR'15, 2015.

GoogLeNet Visualization



Results on ILSVRC

Method	top-1 val. error (%)	top-5 val. error (%)	top-5 test error (%)
VGG (2 nets, multi-crop & dense eval.)	**23.7**	**6.8**	**6.8**
VGG (1 net, multi-crop & dense eval.)	24.4	7.1	7.0
VGG (ILSVRC submission, 7 nets, dense eval.)	24.7	7.5	7.3
GoogLeNet (Szegedy et al., 2014) (1 net)	-	7.9	
GoogLeNet (Szegedy et al., 2014) (7 nets)	-	**6.7**	
MSRA (He et al., 2014) (11 nets)	-	-	8.1
MSRA (He et al., 2014) (1 net)	27.9	9.1	9.1
Clarifai (Russakovsky et al., 2014) (multiple nets)	-	-	11.7
Clarifai (Russakovsky et al., 2014) (1 net)	-	-	12.5
Zeiler & Fergus (Zeiler & Fergus, 2013) (6 nets)	36.0	14.7	14.8
Zeiler & Fergus (Zeiler & Fergus, 2013) (1 net)	37.5	16.0	16.1
OverFeat (Sermanet et al., 2014) (7 nets)	34.0	13.2	13.6
OverFeat (Sermanet et al., 2014) (1 net)	35.7	14.2	-
Krizhevsky et al. (Krizhevsky et al., 2012) (5 nets)	38.1	16.4	16.4
Krizhevsky et al. (Krizhevsky et al., 2012) (1 net)	40.7	18.2	-

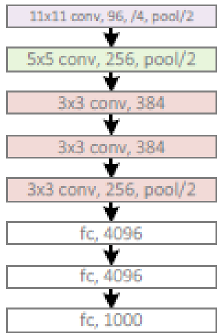
- VGGNet and GoogLeNet perform at similar level
  - Comparison: human performance ~5% [Karpathy]

http://karpathy.github.io/2014/09/02/what-i-learned-from-competing-against-a-convnet-on-imagenet/

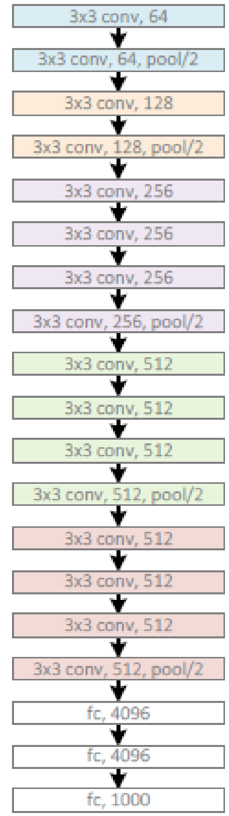
Image source: Simonyan & Zisserman

Newer Developments: Residual Networks

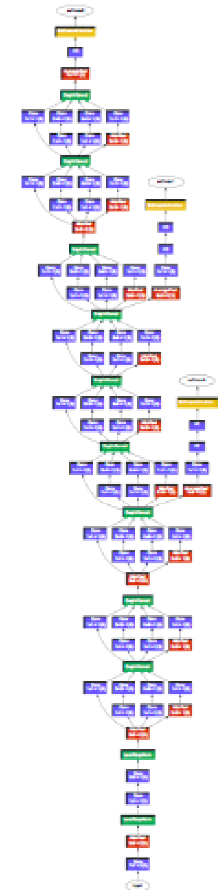
AlexNet, 8 layers
(ILSVRC 2012)



VGG, 19 layers
(ILSVRC 2014)



GoogleNet, 22 layers
(ILSVRC 2014)



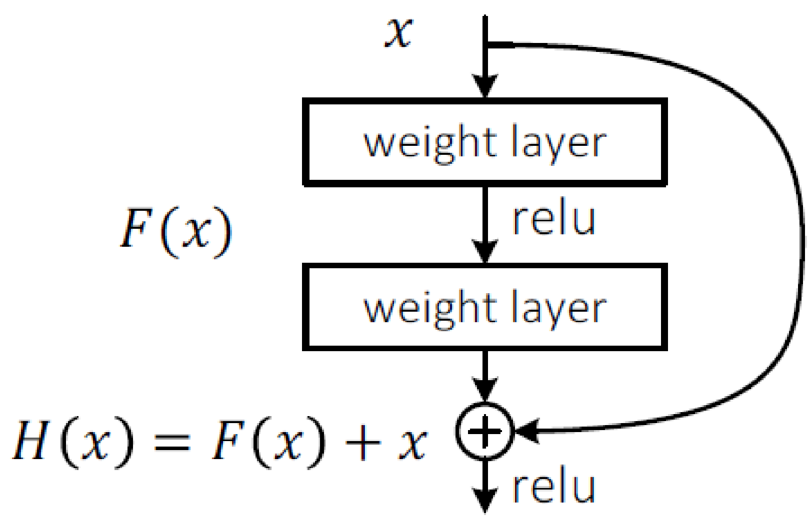
Newer Developments: Residual Networks

AlexNet, 8 layers
(ILSVRC 2012)

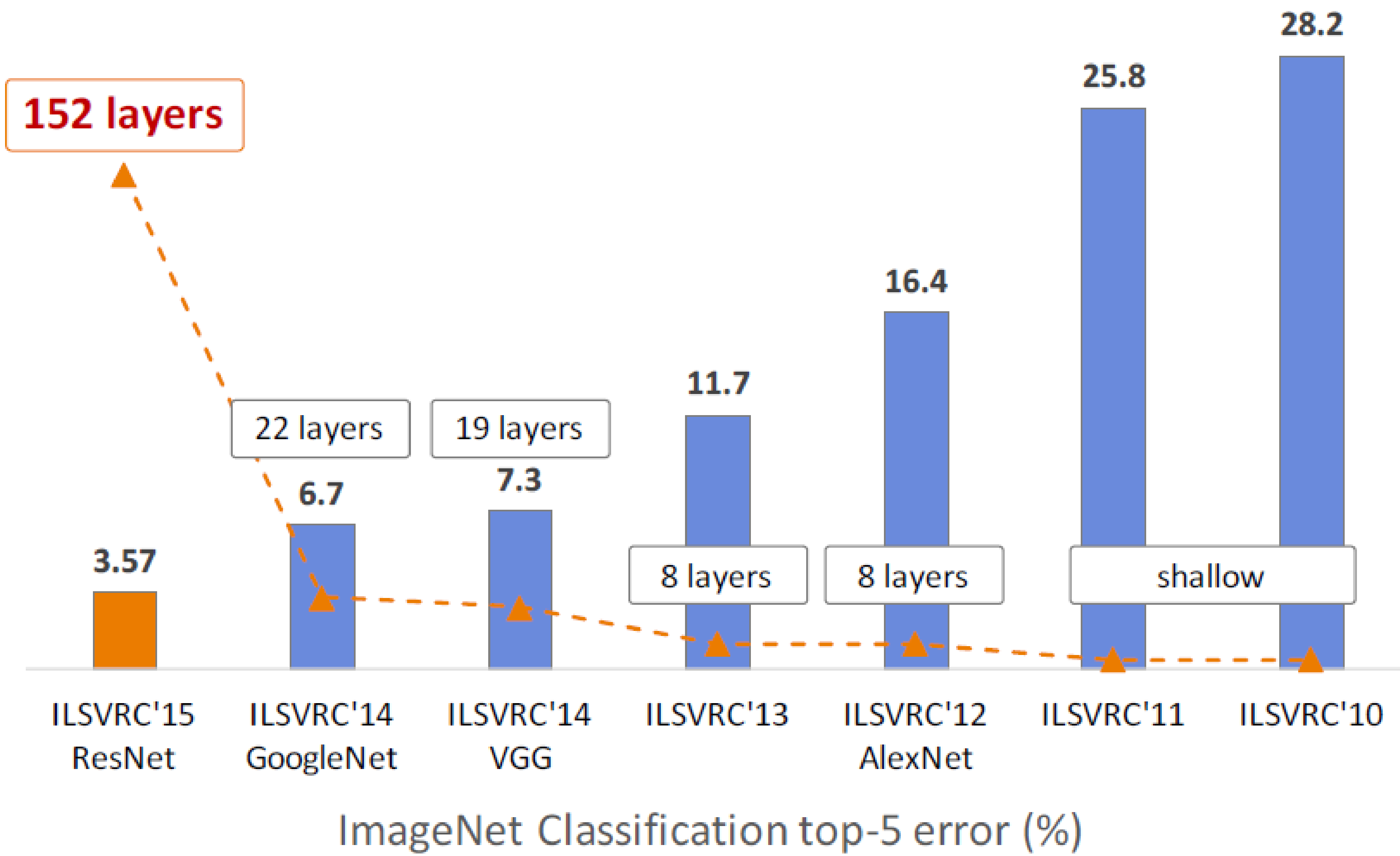
VGG, 19 layers
(ILSVRC 2014)

ResNet, 152 layers
(ILSVRC 2015)

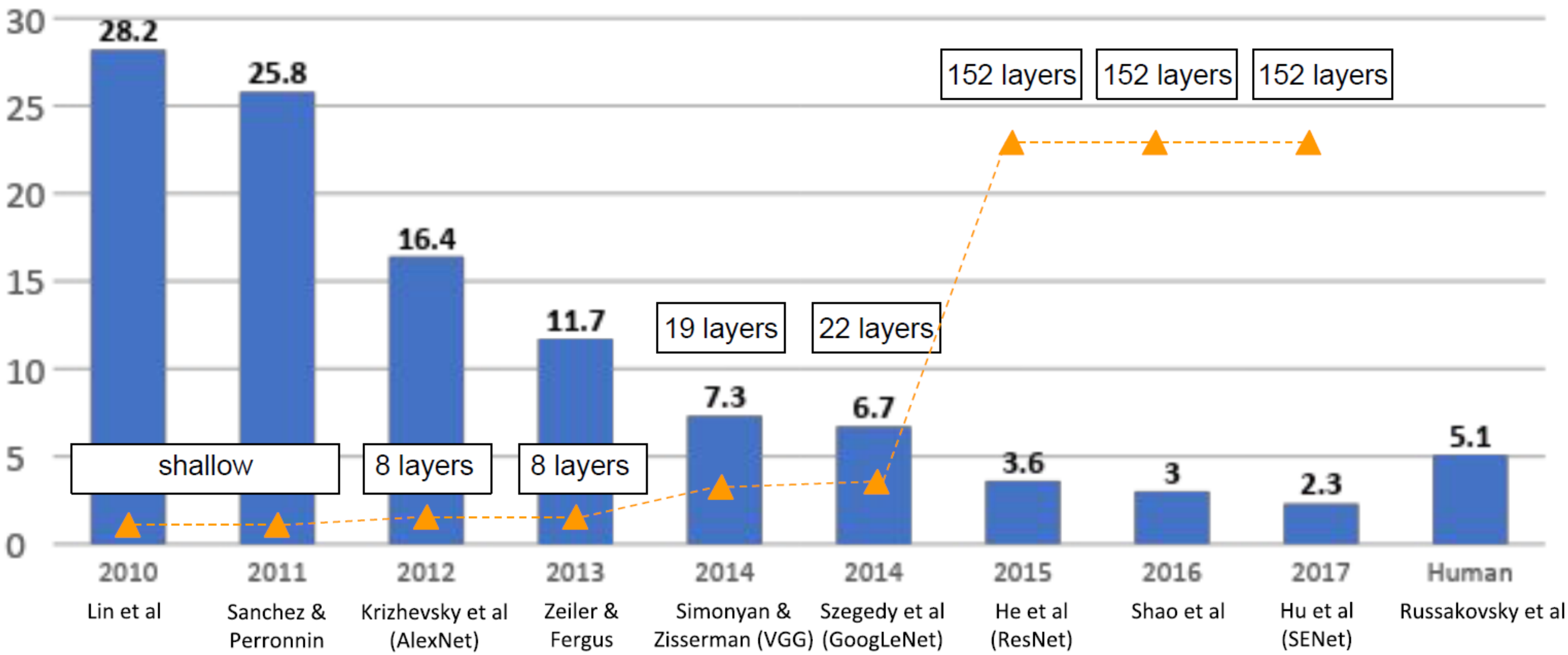
- Core component
  - Skip connections bypassing each layer
  - Better propagation of gradients to the deeper layers
  - We'll analyze this mechanism in more detail later…



ImageNet Performance

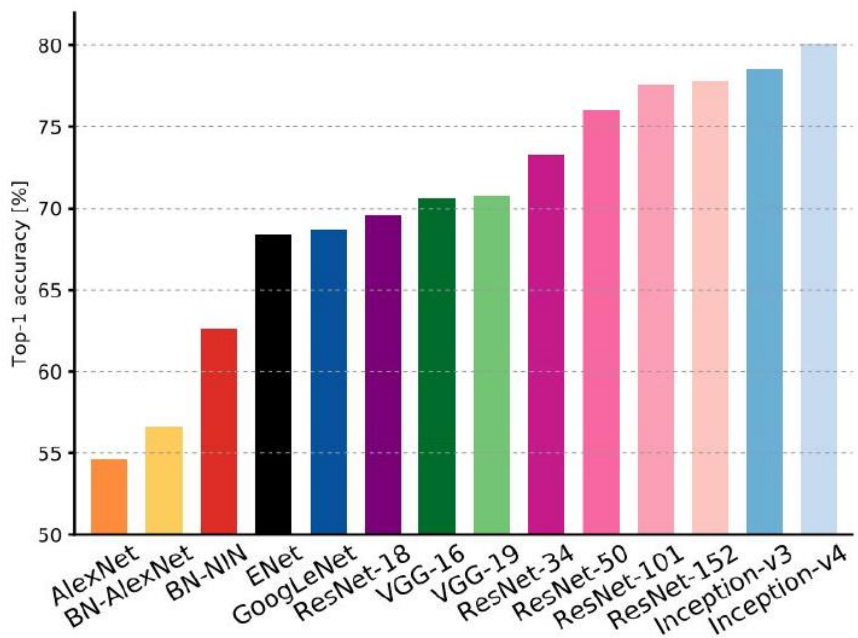


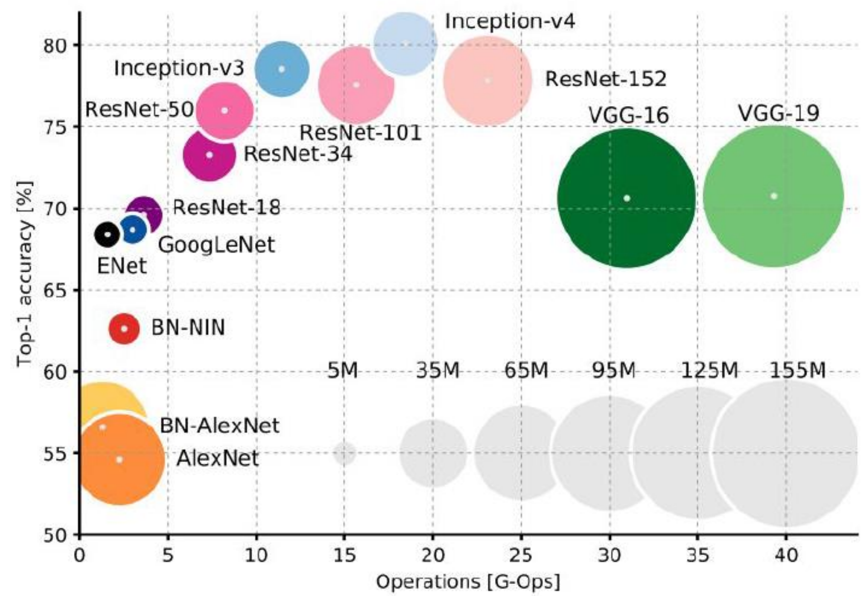
ILSRVC Winners



Slide credit: FeiFei Li

Comparing Complexity





A. Canziano, A. Paszke, E. Culurcello, An Analysis of Deep Neural Network Models for Practical Applications, arXiv 2017.

Figure credit: Alfredo Canziano, Adam Paszke, Eugenio Culurcello

Understanding the ILSVRC Challenge

- Imagine the scope of the problem!
  - 1000 categories
  - 1.2M training images
  - 50k validation images

- This means...
  - Speaking out the list of category names at 1 word/s...
    ...takes 15mins.
  - Watching a slideshow of the validation images at 2s/image...
    ...takes a full day (24h+).
  - Watching a slideshow of the training images at 2s/image...
    ...takes a full month.

rier, Airedale, airliner, airship, albatross, alligator lizard, alp, altar, ambulance, American alligator, American black bear, American chameleon, American coot, American egret, American lobster, American Staffordshire terrier, amphibian, analog clock, anemone fish, Angora, ant, apiary, Appenzeller, apron, Arabian camel, Arctic fox, armadillo, artichoke, ashcan, assault rifle, Australian terrier, axolotl, baboon, backpack, badger, bagel, bakery, balance beam, bald eagle, balloon, ballplayer, ballpoint, banana, Band Aid, banded gecko, banjo, bannister, barbell, barber chair, barbershop, barn, barn spider, barometer, barracouta, barrel, barrow, baseball, basenji, basketball, basset, bassinet, bassoon, bath towel, bathing cap, bathtub, beach wagon, beacon, beagle, beaker, bearskin, beaver, Bedlington terrier, bee, bee eater, beer bottle, beer glass, bell cote, bell pepper, Bernese mountain dog, bib, bicycle-built-for-two, bighorn, bikini, binder, binoculars, birdhouse, bison, bittern, black and gold garden spider, black grouse, black stork, black swan, black widow, black-and-tan coonhound, black-footed ferret, Blenheim spaniel, bloodhound, bluetick, boa constrictor, boathouse, bobsled, bolete, bolo tie, bonnet, book jacket, bookcase, bookshop, Border collie, Border terrier, borzoi, Boston bull, bottlecap, Bouvier des Flandres, bow, bow tie, box turtle, boxer, Brabancon griffon, brain coral, brambling, brass, brassiere, breakwater, breastplate, briard, Brittany spaniel, broccoli, broom, brown bear, bubble, bucket, buckeye, buckle, bulbul, bull mastiff, bullet train, bulletproof vest, bullfrog, burrito, bustard, butcher shop, butternut squash, cab, cabbage butterfly, cairn, caldron, can opener, candle, cannon, canoe, capuchin, car mirror, car wheel, carbonara, Cardigan, cardigan, cardoon, carousel, carpenter's kit, carton, cash machine, cassette, cassette player, castle, catamaran, cauliflower, CD player, cello, cellular telephone, centipede, chain, chain mail, chain saw, chainlink fence, chambered nautilus, cheeseburger, cheetah, Chesapeake Bay retriever, chest, chickadee, chiffonier, Chihuahua, chime, chimpanzee, china cabinet, chiton, chocolate sauce, chow, Christmas stocking, church, cicada, cinema, cleaver, cliff, cliff dwelling, cloak, clog, clumber, cock, cocker spaniel, cockroach, cocktail shaker, coffee mug, coffeepot, coho, coil, collie, colobus, combination lock, comic book, common iguana, common newt, computer keyboard, conch, confectionery, consomme, container ship, convertible, coral fungus, coral reef, corkscrew, corn, cornet, coucal, cougar, cowboy boot, cowboy hat, coyote, cradle, crane, crane, crash helmet, crate, crayfish, crib, cricket, Crock Pot, croquet ball, crossword puzzle, crutch, cucumber, cuirass, cup, curly-coated retriever, custard apple, daisy, dalmatian, dam, damselfly, Dandie Dinmont, desk, desktop computer, dhole, dial telephone, diamondback, diaper, digital clock, digital watch, dingo, dining table, dishrag, dishwasher, disk brake, Doberman, dock, dogsled, dome, doormat, dough, dowitcher, dragonfly, drake, drilling platform, drum, drumstick, dugong, dumbbell, dung beetle, Dungeness crab, Dutch oven, ear, earthstar, echidna, eel, eft, eggnog, Egyptian cat, electric fan, electric guitar, electric locomotive, electric ray, English foxhound, English setter, English springer, entertainment center, EntleBucher, envelope, Eskimo dog, espresso, espresso maker, European fire salamander, European gallinule, face powder, feather boa, fiddler crab, fig, file, fire engine, fire screen, fireboat, flagpole, flamingo, flat-coated retriever, flatworm, flute, fly, folding chair, football helmet, forklift, fountain, fountain pen, four-poster, fox squirrel, freight car, French bulldog, French horn, French loaf, frilled lizard, frying pan, fur coat, gar, garbage truck, garden spider, garter snake, gas pump, gasmask, gazelle, German shepherd, German short-haired pointer, geyser, giant panda, giant schnauzer, gibbon, Gila monster, go-kart, goblet, golden retriever, goldfinch, goldfish, golf ball, golfcart, gondola, gong, goose, Gordon setter, gorilla, gown, grand piano, Granny Smith, grasshopper, Great Dane, great grey owl, Great Pyrenees, great white shark,

More Finegrained Classes

Image source: O. Russakovsky et al.

Quirks and Limitations of the Data Set

- Generated from WordNet ontology
  - Some animal categories are overrepresented
  - E.g., 120 subcategories of dog breeds

$\Rightarrow$ 6.7% top-5 error looks all the more impressive

Image source: A. Karpathy

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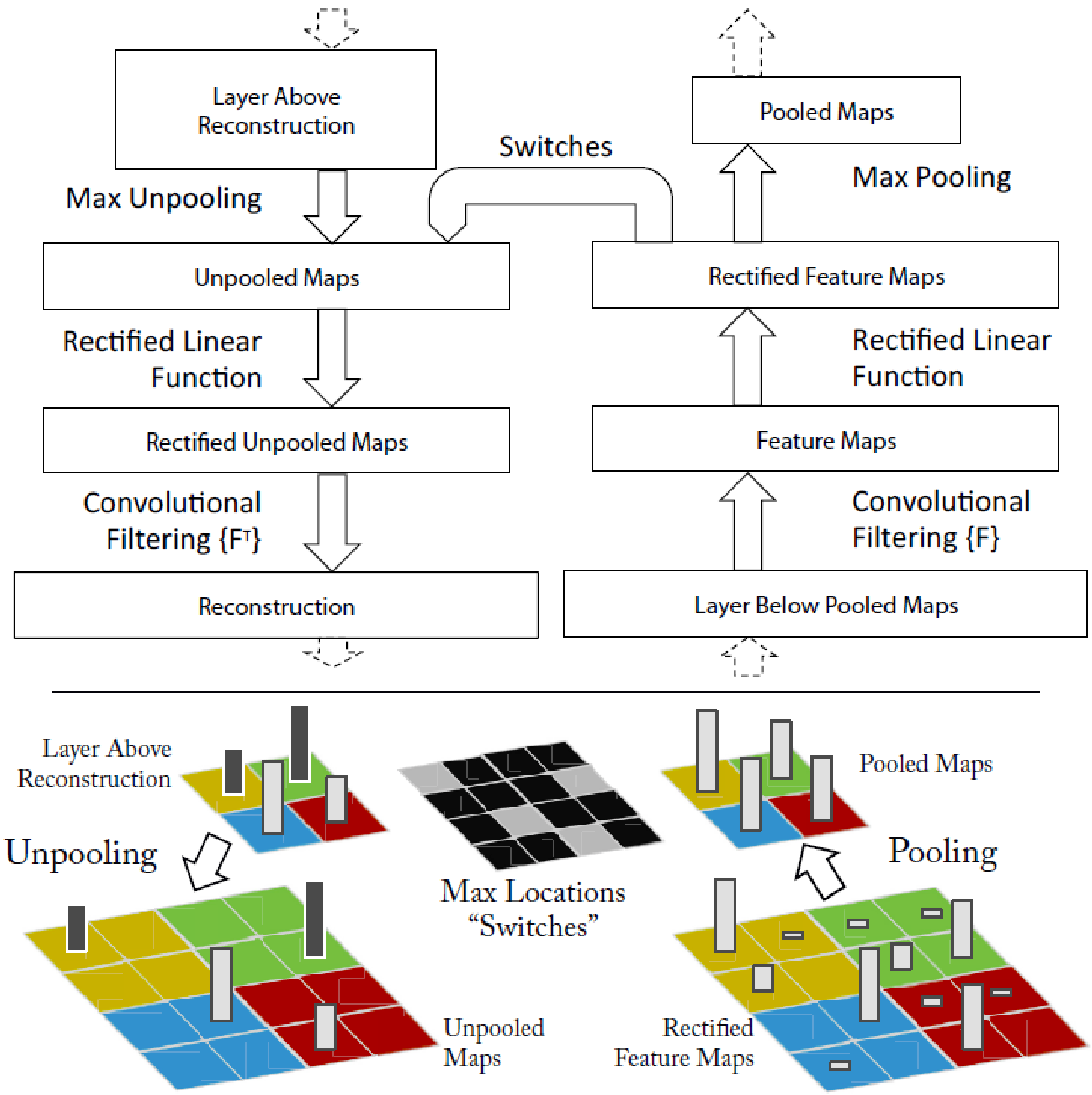
Visualizing CNNs

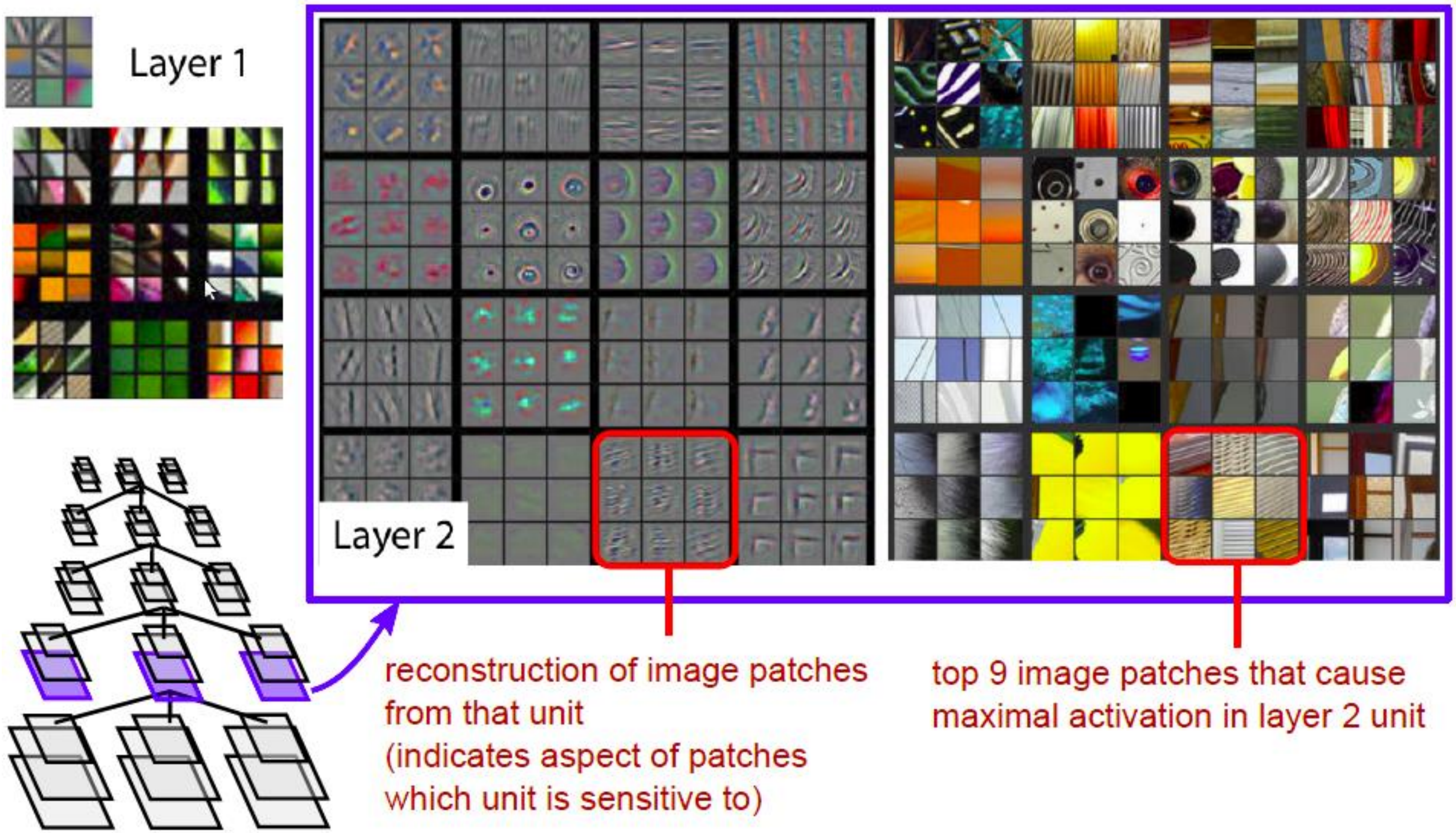
DeconvNet



ConvNet

Image source: M. Zeiler, R. Fergus

Visualizing CNNs



M. Zeiler, R. Fergus, [Visualizing and Understanding Convolutional Neural Networks](), ECCV 2014.

Image source: M. Zeiler, R. Fergus

Visualizing CNNs

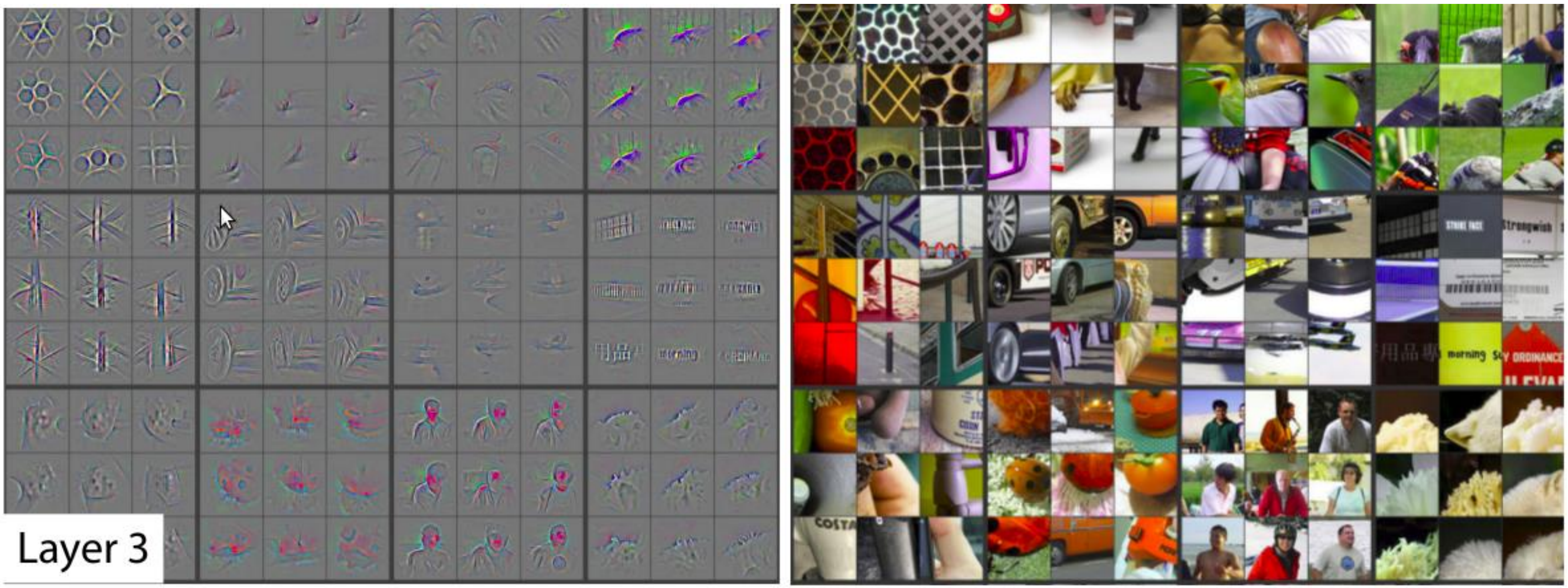


Image source: M. Zeiler, R. Fergus

Visualizing CNNs

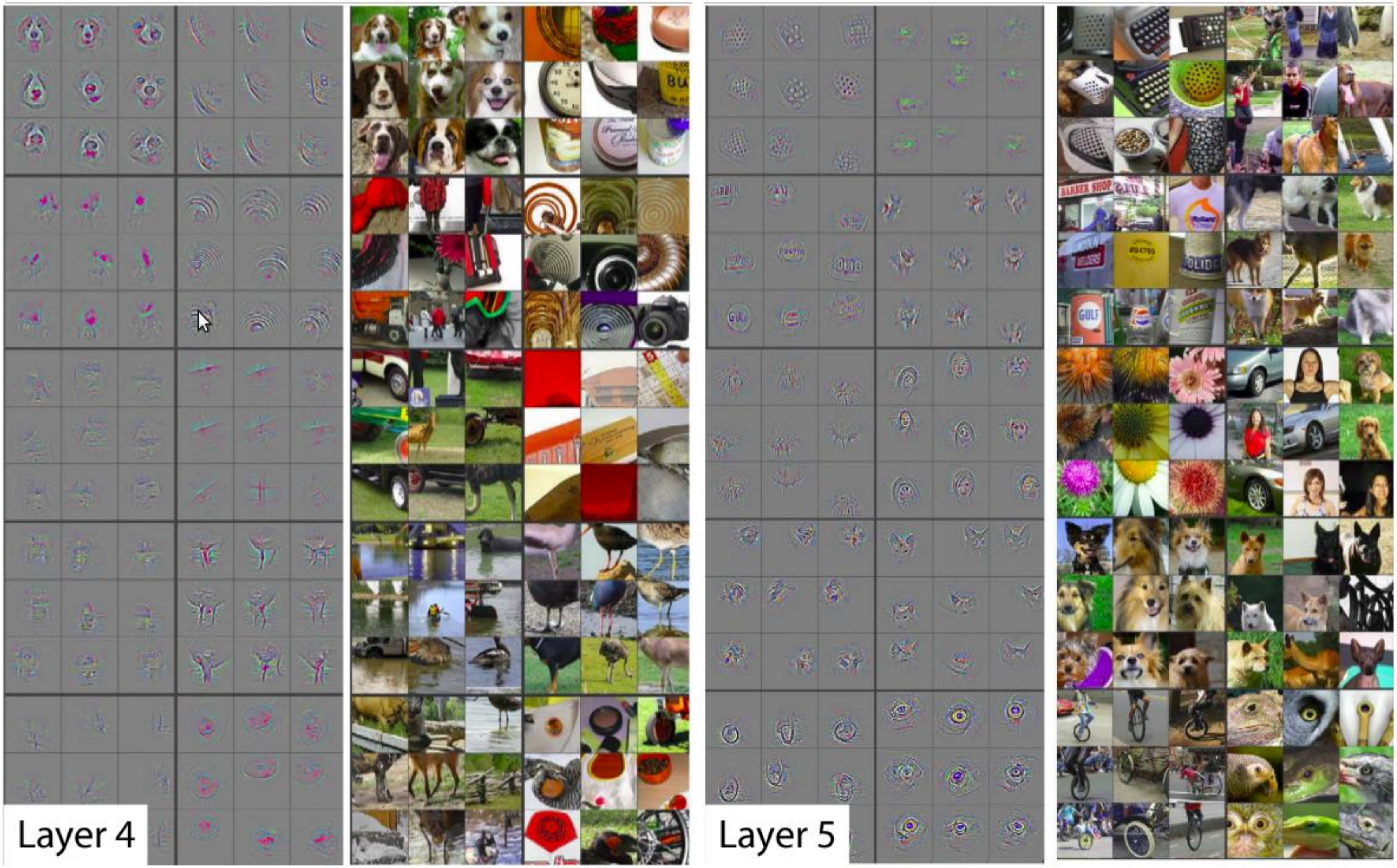


Image source: M. Zeiler, R. Fergus

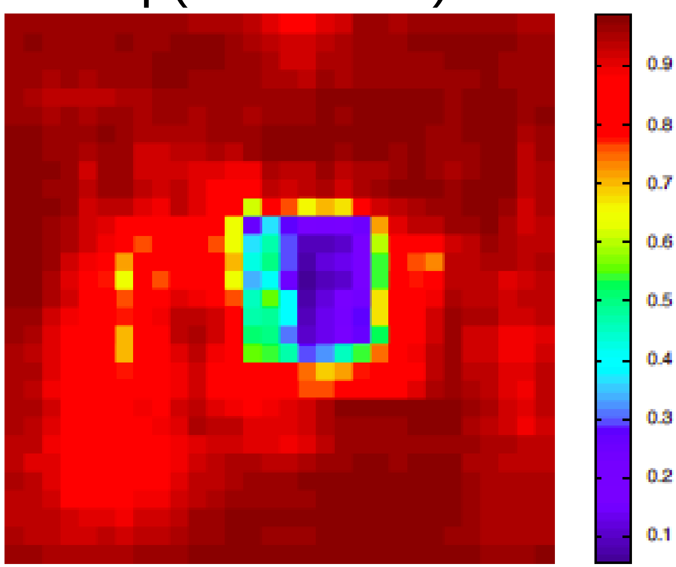
What Does the Network React To?

- Occlusion Experiment
  - Mask part of the image with an occluding square.
  - Monitor the output

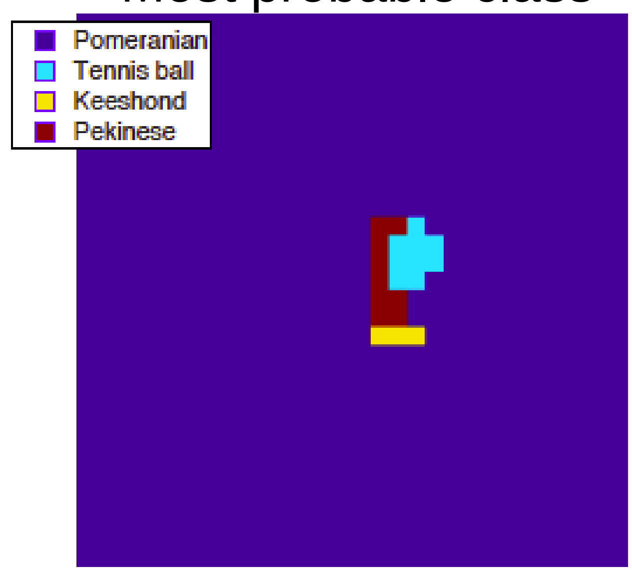
What Does the Network React To?

Input image

p(True class)



Most probable class



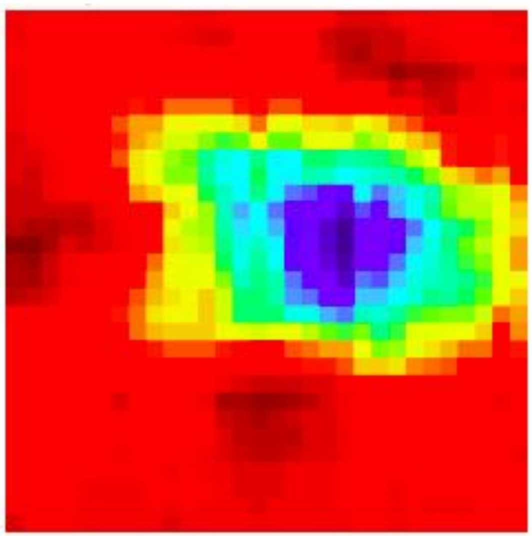
Slide credit: Svetlana Lazebnik, Rob Fergus

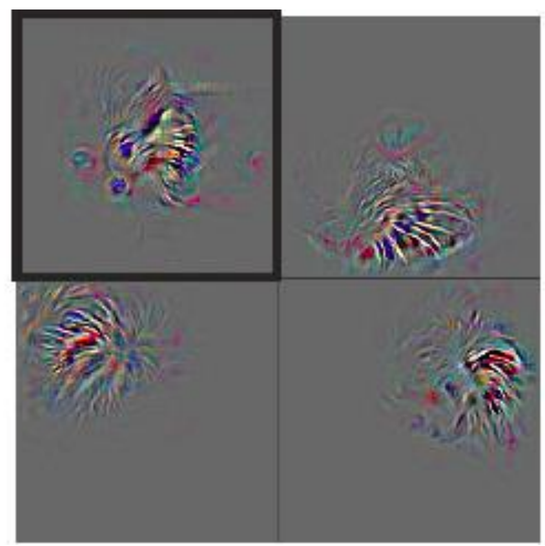
Image source: M. Zeiler, R. Fergus

What Does the Network React To?

Input image

Total activation in most active 5th layer feature map





Other activations from the same feature map.

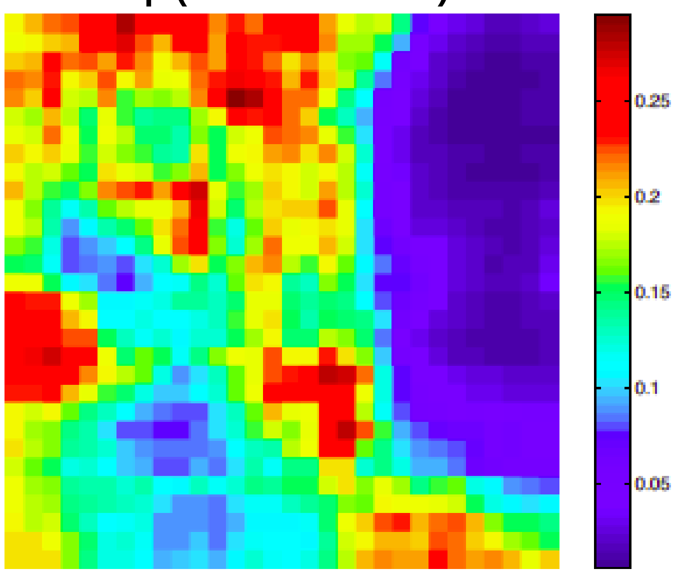
Slide credit: Svetlana Lazebnik, Rob Fergus

Image source: M. Zeiler, R. Fergus

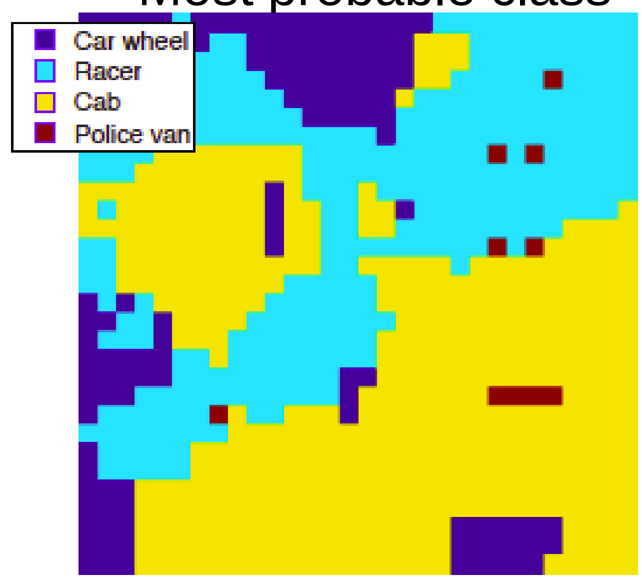
What Does the Network React To?

Input image

p(True class)



Most probable class



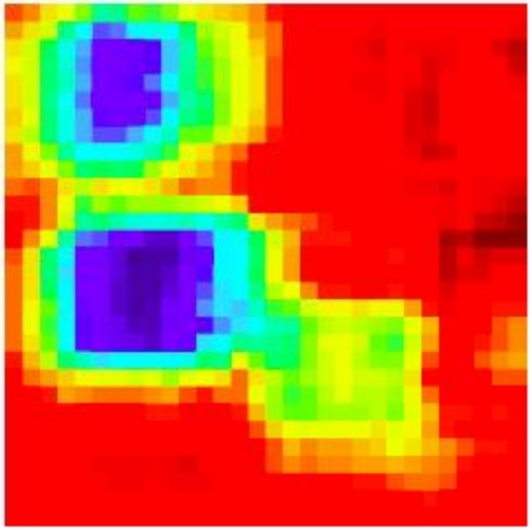
Slide credit: Svetlana Lazebnik, Rob Fergus

Image source: M. Zeiler, R. Fergus

What Does the Network React To?

Input image

Total activation in most active 5th layer feature map



Other activations from the same feature map.

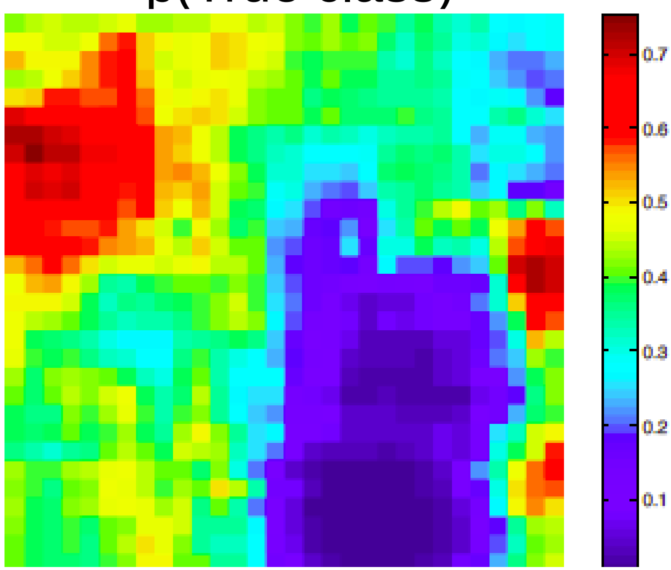
Slide credit: Svetlana Lazebnik, Rob Fergus

Image source: M. Zeiler, R. Fergus

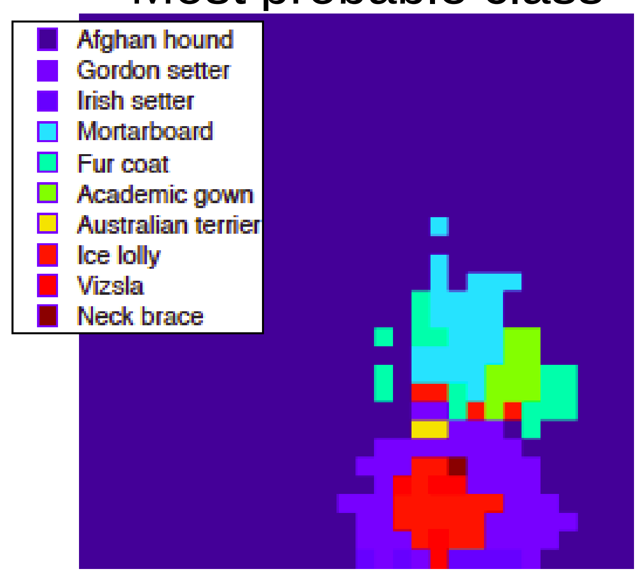
What Does the Network React To?

Input image

p(True class)



Most probable class



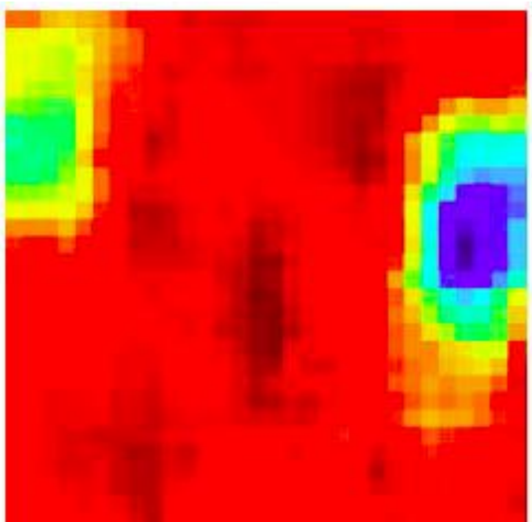
Slide credit: Svetlana Lazebnik, Rob Fergus

Image source: M. Zeiler, R. Fergus

What Does the Network React To?

Input image

Total activation in most active 5th layer feature map

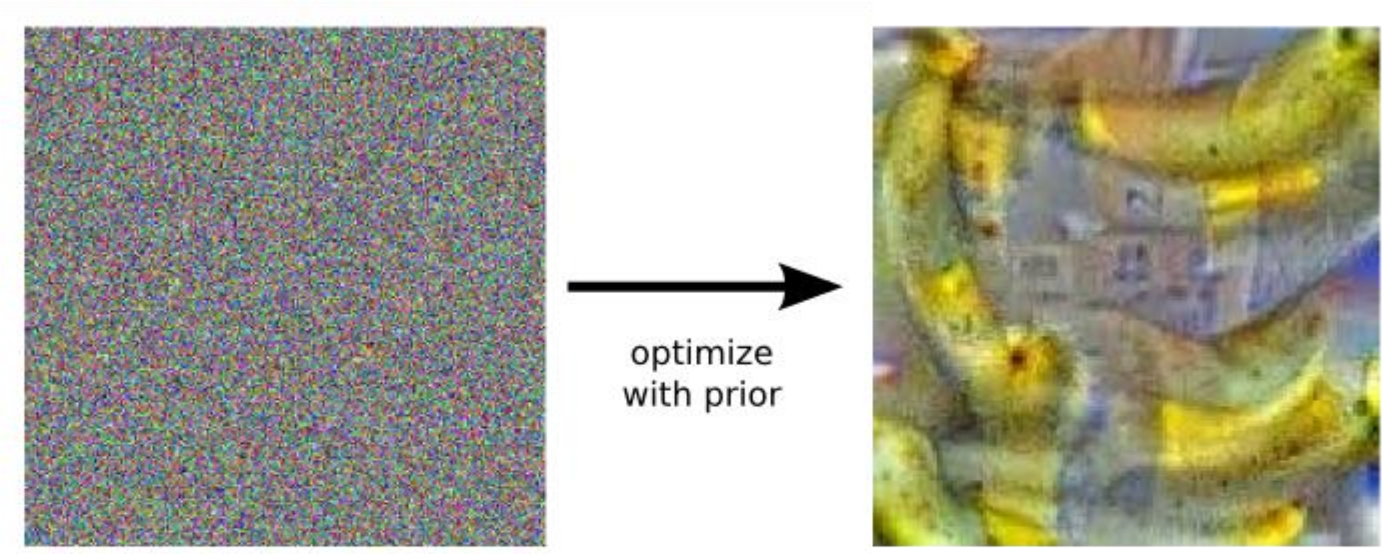


Other activations from the same feature map.

Slide credit: Svetlana Lazebnik, Rob Fergus

Image source: M. Zeiler, R. Fergus

Inceptionism: Dreaming ConvNets



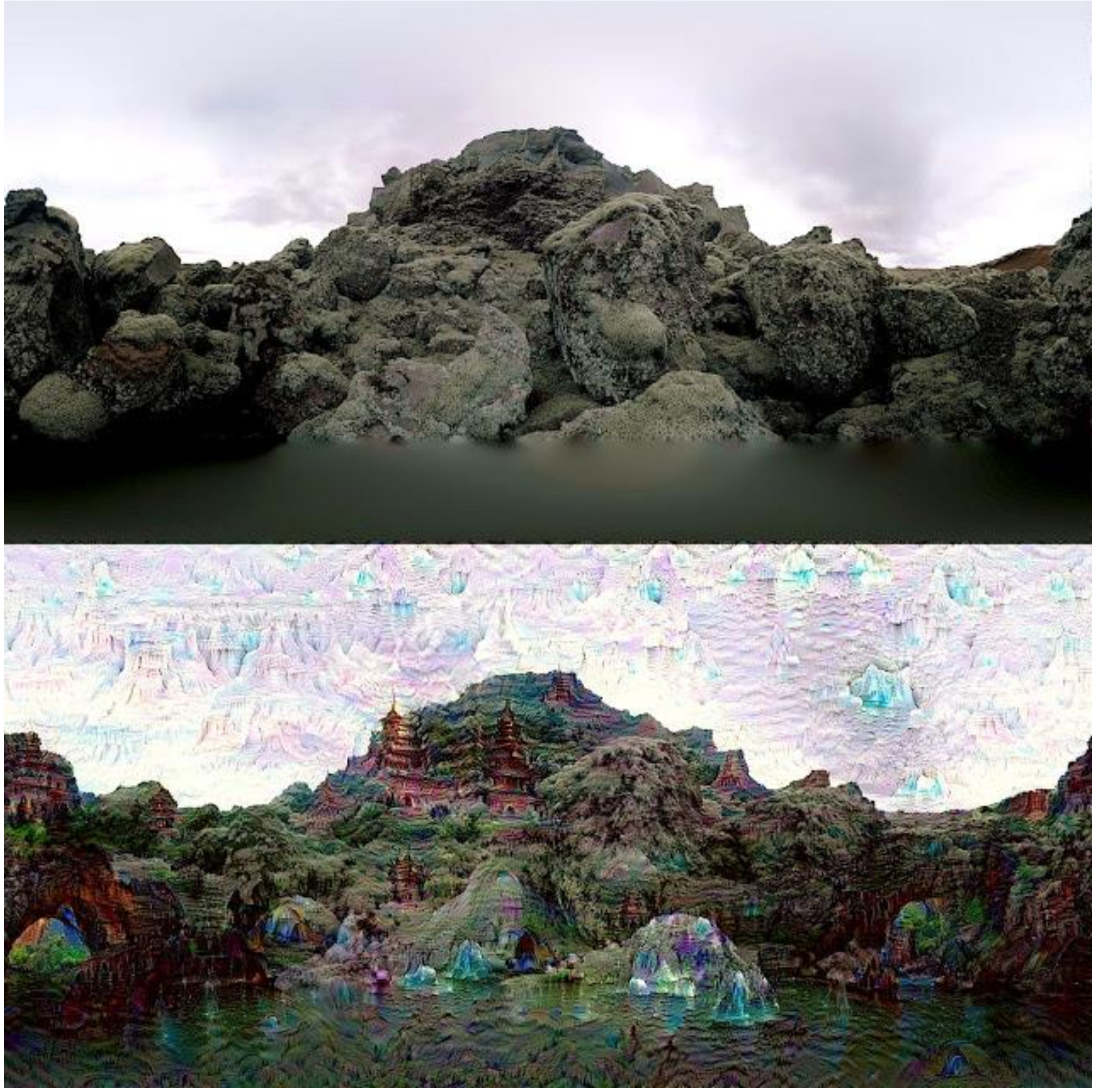
- Idea
  - Start with a random noise image.
  - Enhance the input image such as to enforce a particular response (e.g., banana).
  - Combine with prior constraint that image should have similar statistics as natural images.

  $\Rightarrow$ Network hallucinates characteristics of the learned class.

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

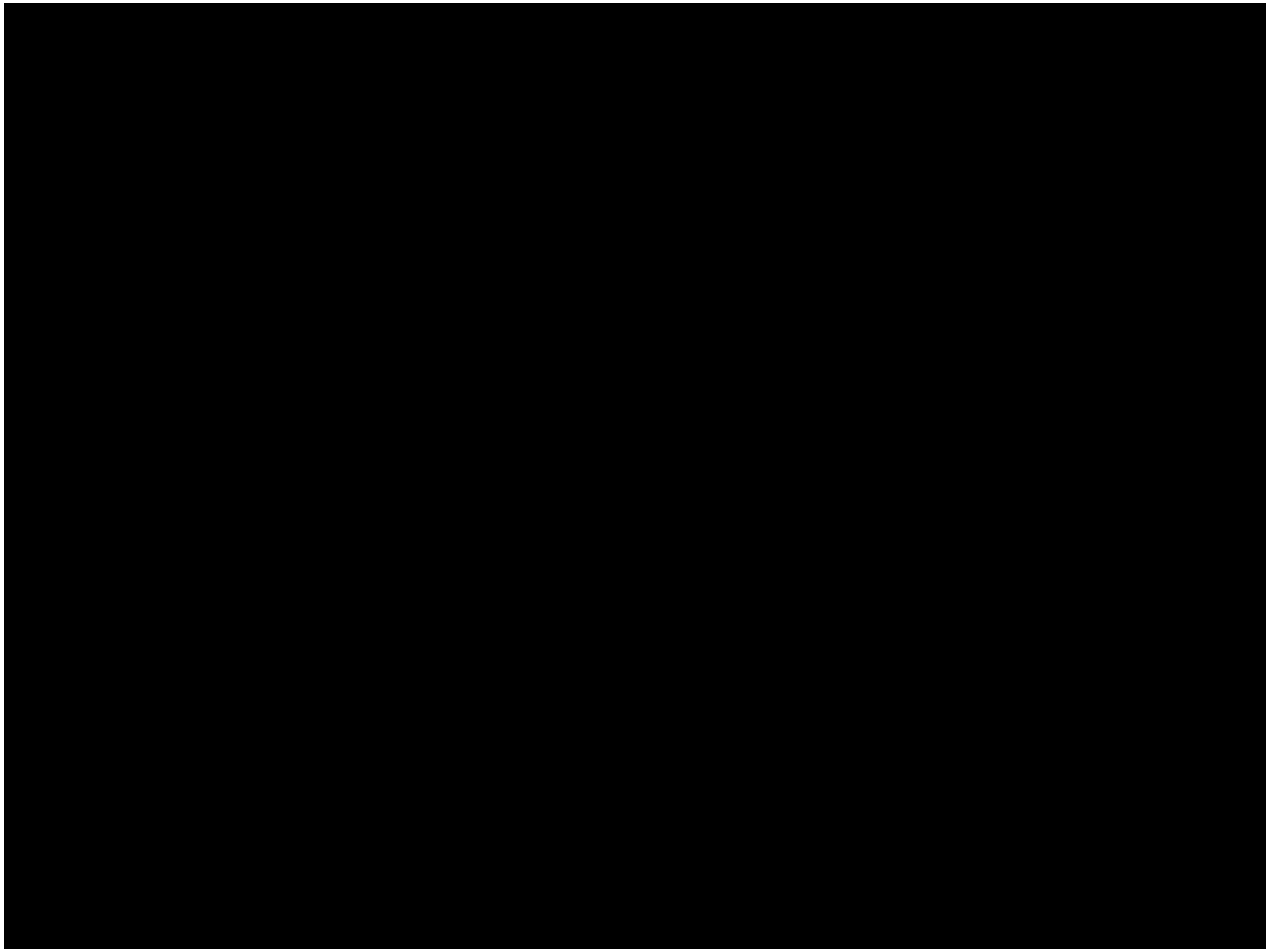
Inceptionism: Dreaming ConvNets

- Results



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

Inceptionism: Dreaming ConvNets

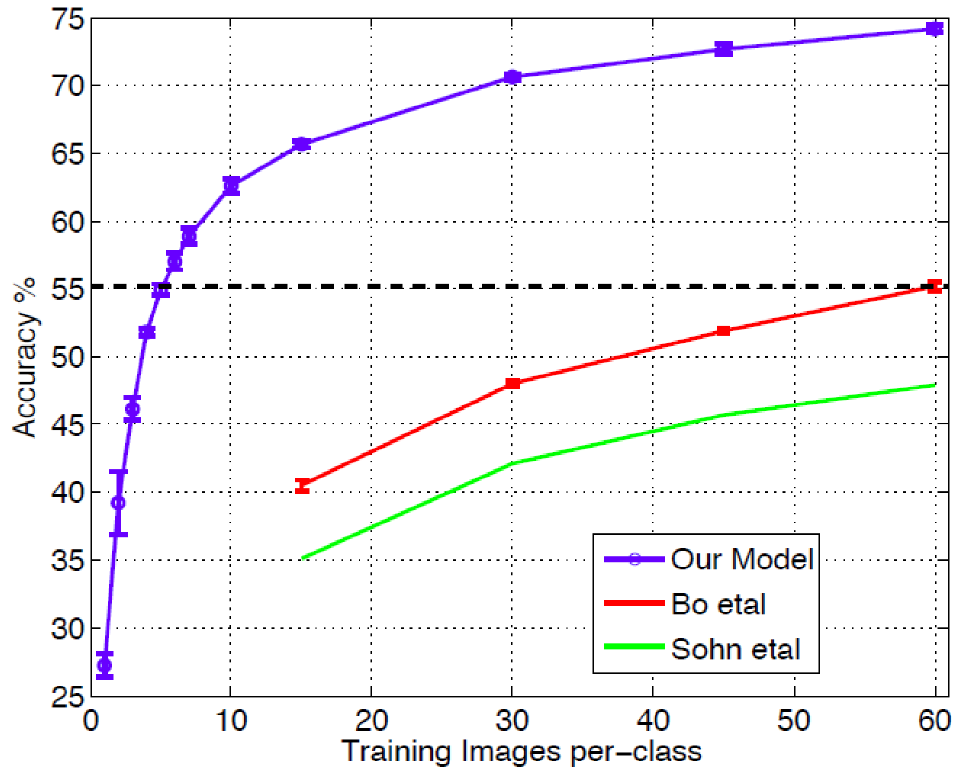


https://www.youtube.com/watch?v=IREsx-xWQ0g

Topics of This Lecture

- Recap: CNNs
- CNN Architectures
  - LeNet
  - AlexNet
  - VGGNet
  - GoogLeNet
  - ResNets
- Visualizing CNNs
  - Visualizing CNN features
  - Visualizing responses
  - Visualizing learned structures
- Applications

The Learned Features are Generic



state of the art level (pre-CNN)

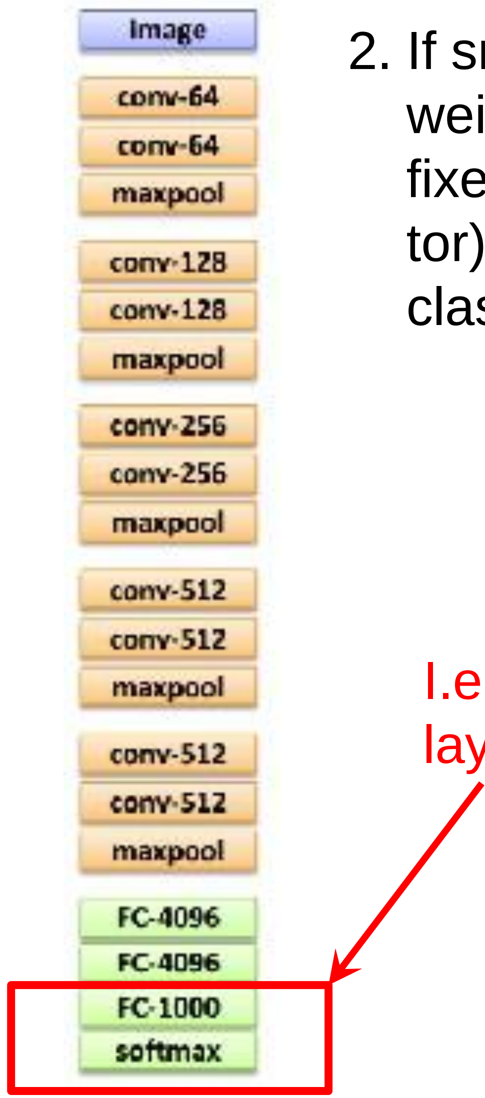
- Experiment: feature transfer
  - Train network on ImageNet
  - Chop off last layer and train classification layer on CalTech256

  ⇒ 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 extrac-tor), retrain only the classifier

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

Transfer Learning with CNNs

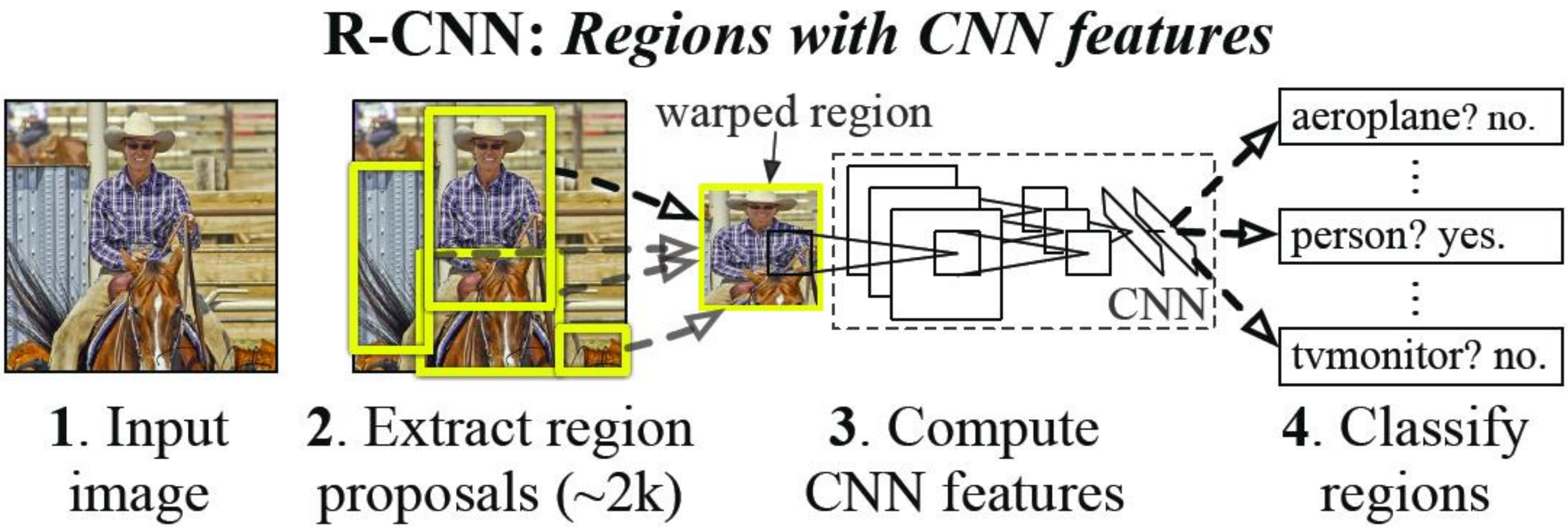
1. Train on ImageNet

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

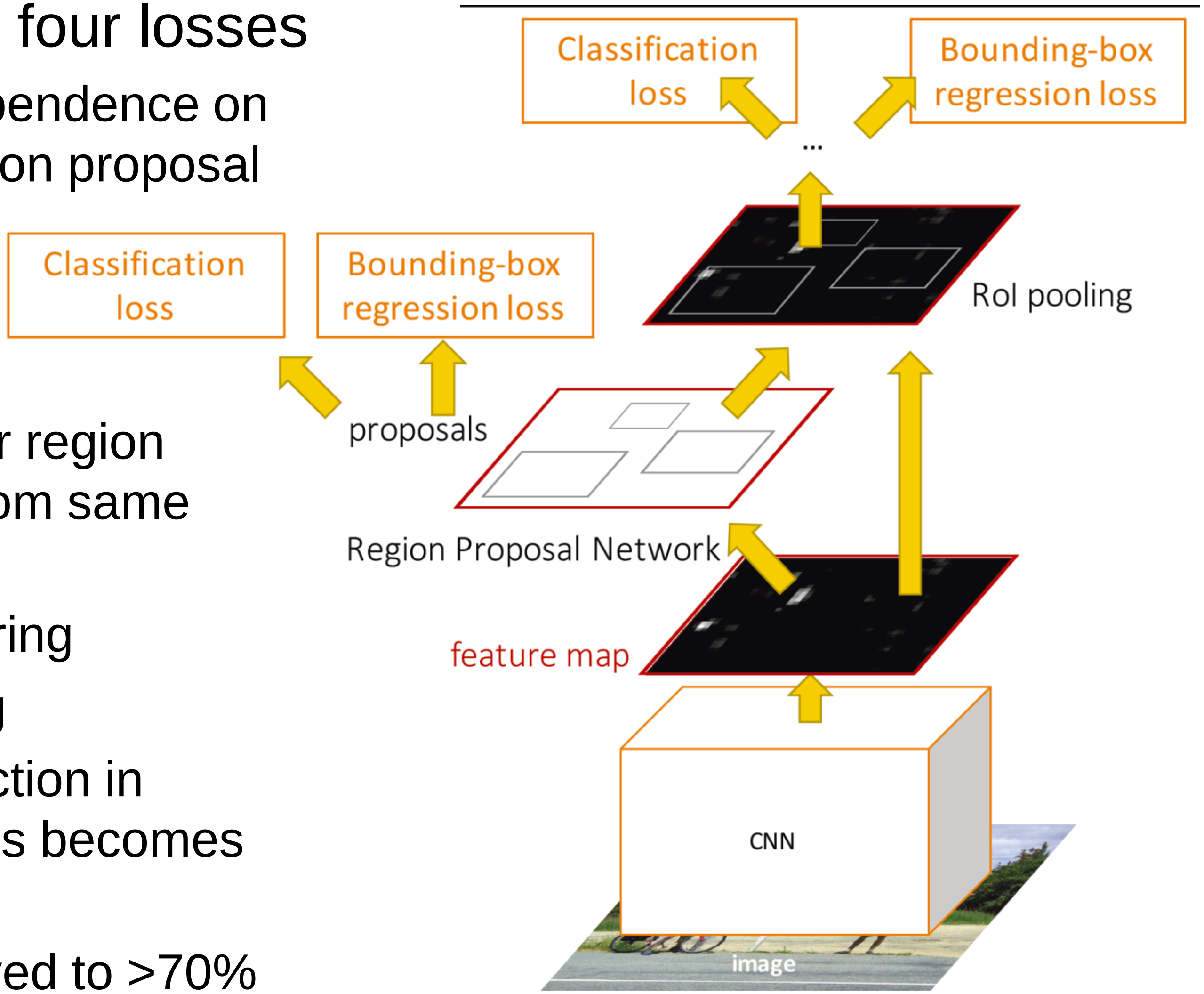


- Results on PASCAL VOC Detection benchmark
  - Pre-CNN state of the art: 35.1% mAP [Uijlings et al., 2013]
    33.4% mAP DPM
  - R-CNN: 53.7% mAP

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

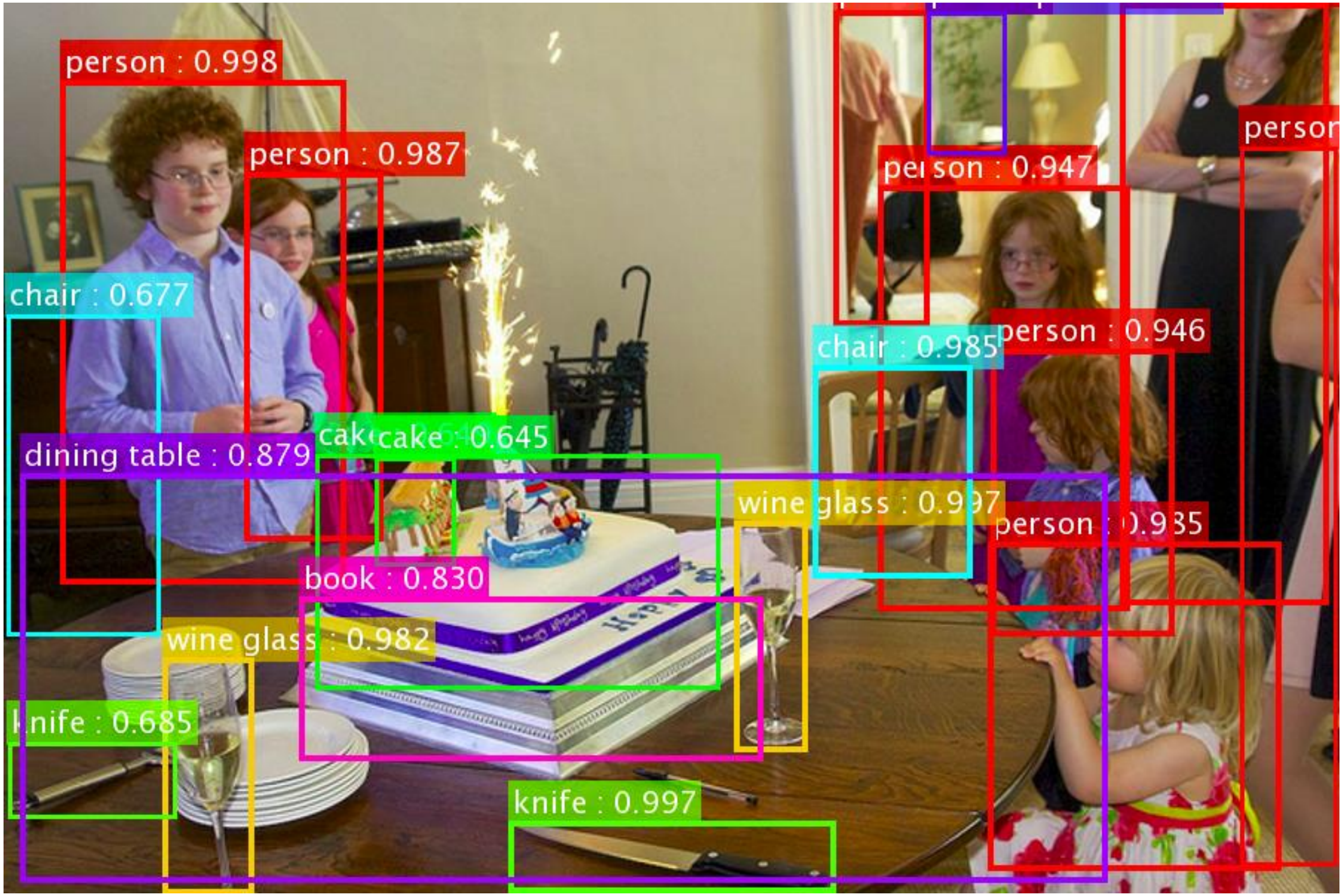
Most Recent Version: Faster R-CNN

- 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.
  - ⇒ mAP improved to >70%



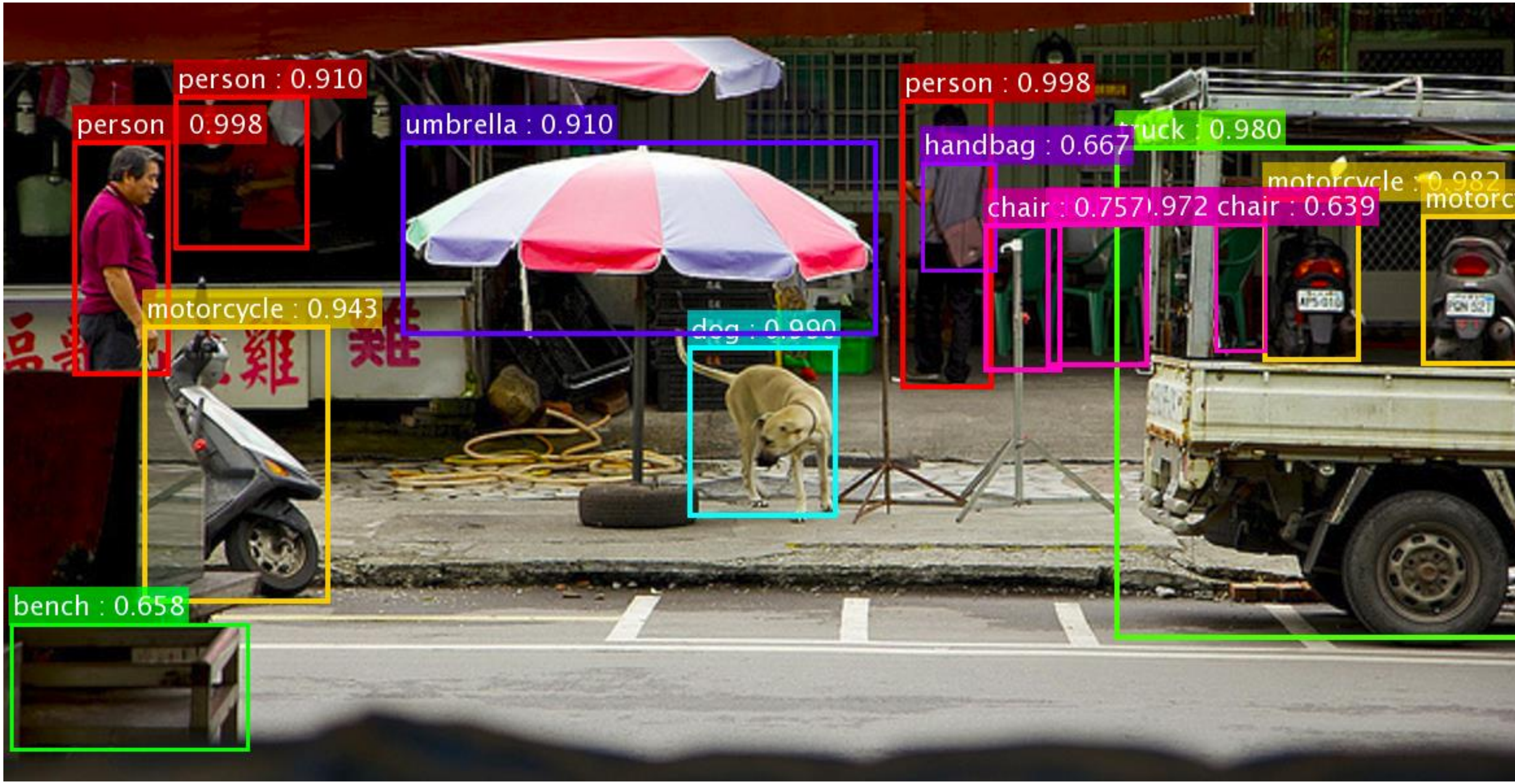
Slide credit: Ross Girshick

Faster R-CNN (based on ResNets)



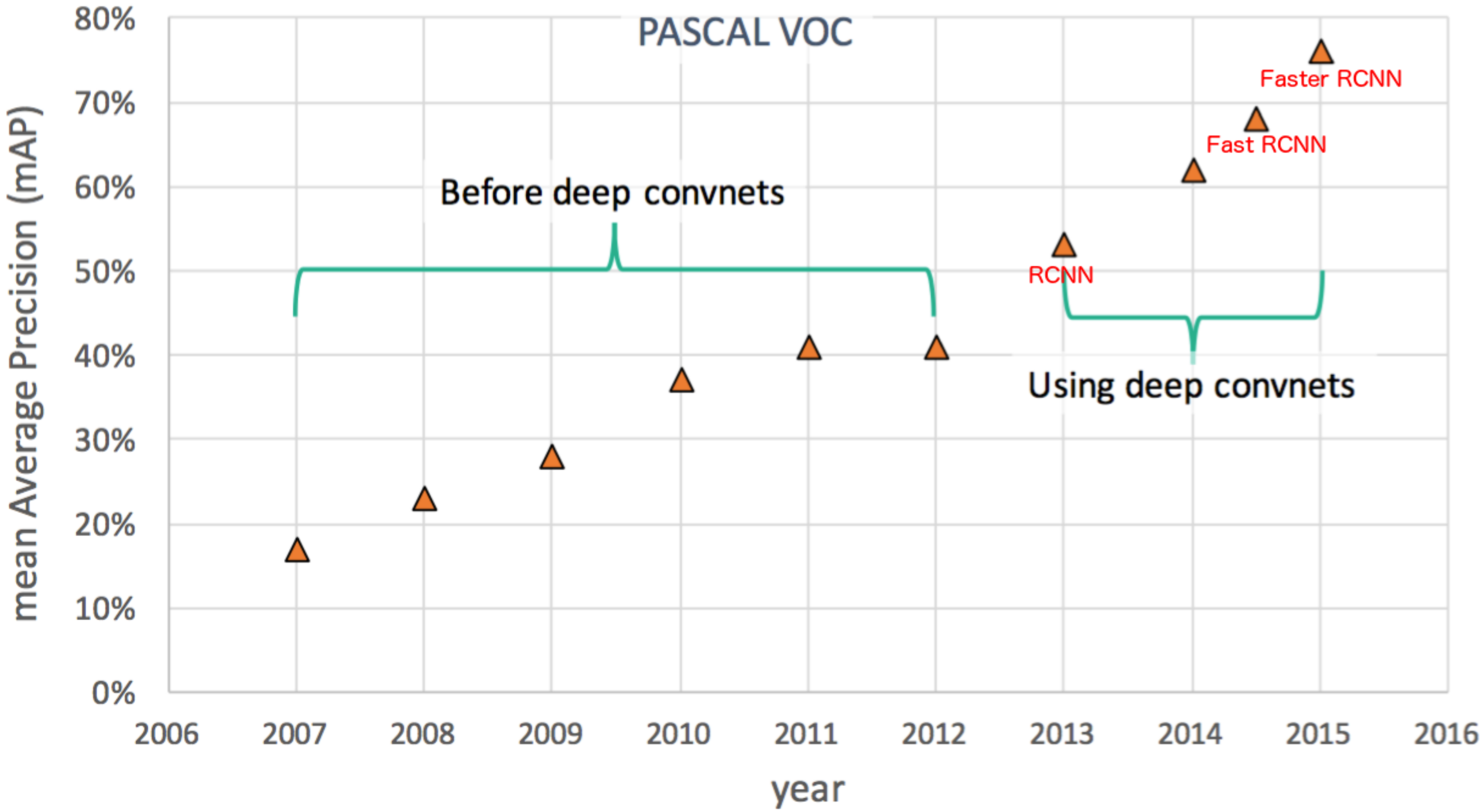
K. He, X. Zhang, S. Ren, J. Sun, [Deep Residual Learning for Image Recognition](), CVPR 2016.

Faster R-CNN (based on ResNets)

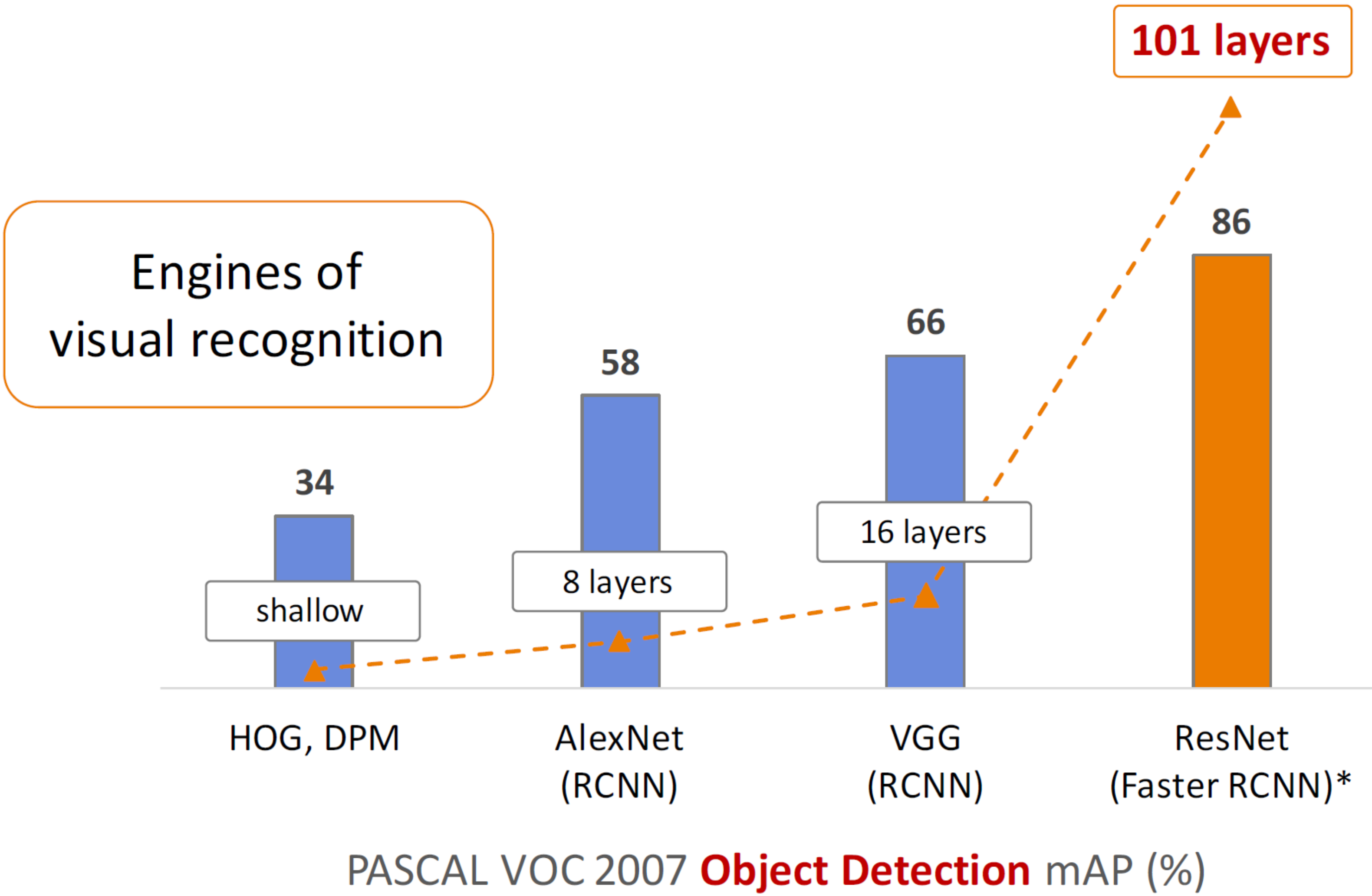


K. He, X. Zhang, S. Ren, J. Sun, [Deep Residual Learning for Image Recognition](), CVPR 2016.

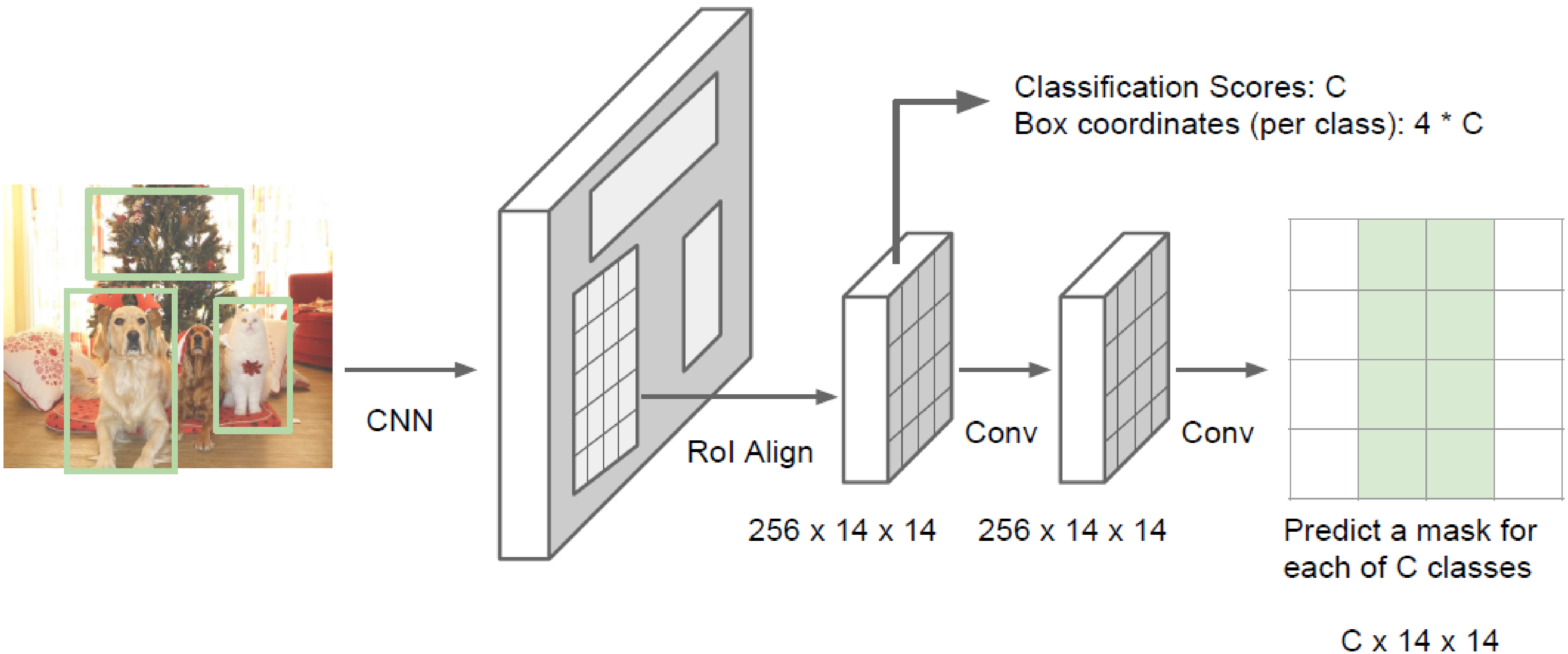
Object Detection Performance



PASCAL VOC Object Detection Performance



Most Recent Version: Mask R-CNN

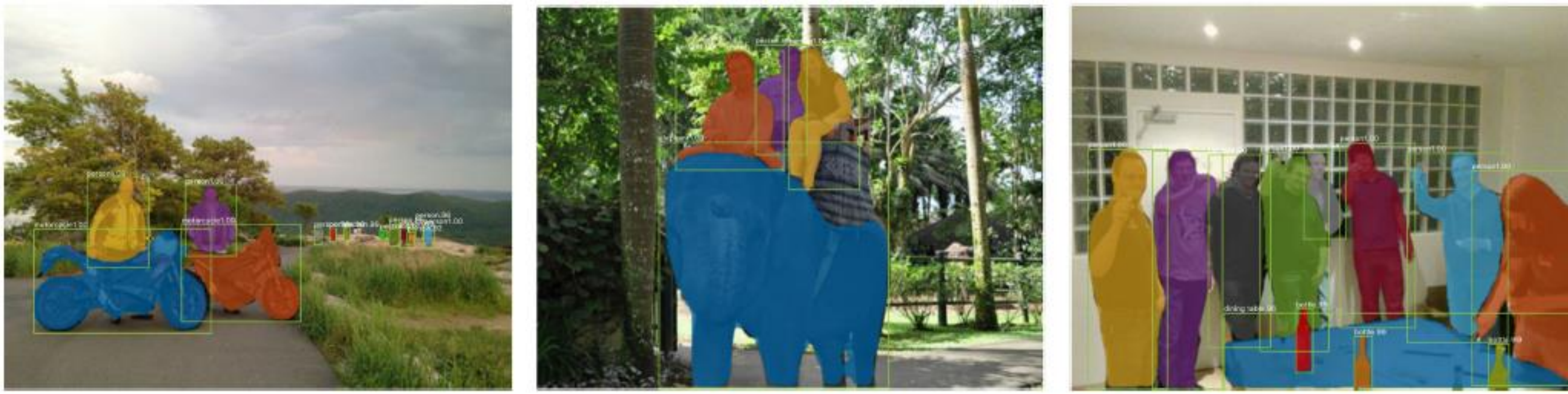


K. He, G. Gkioxari, P. Dollar, R. Girshick, Mask R-CNN, arXiv 1703.06870.

Slide credit: FeiFei Li

Mask R-CNN Results

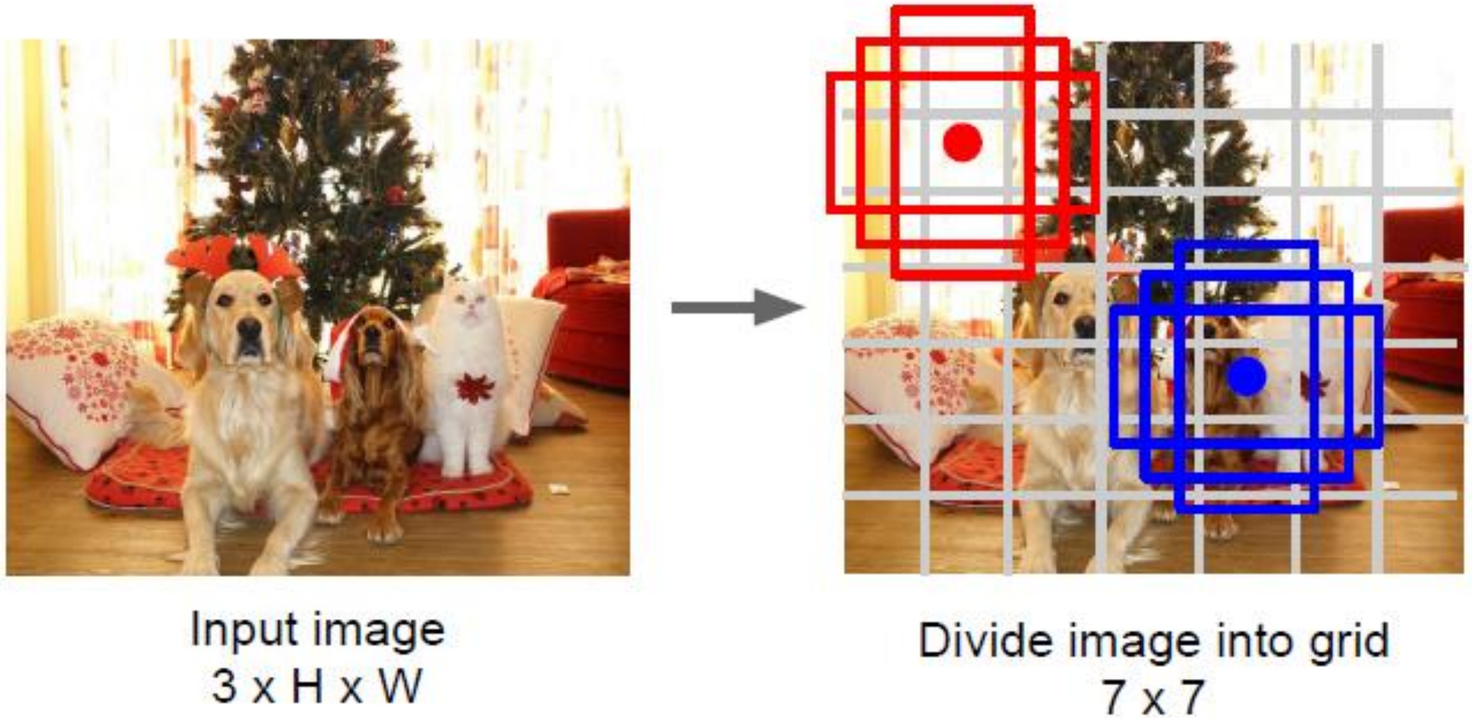
- Detection + Instance segmentation



- Detection + Pose estimation

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

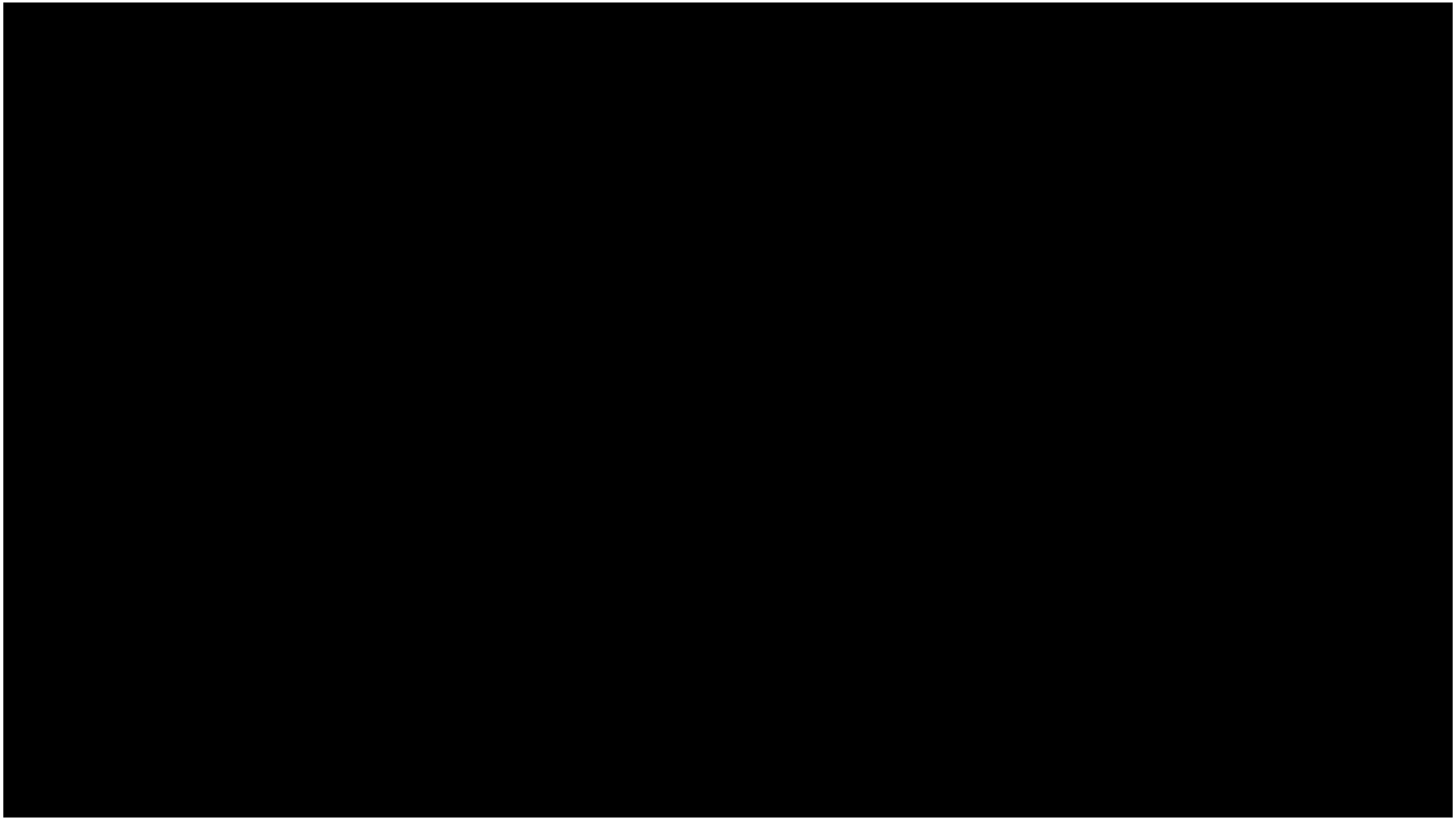
YOLO / SSD



- 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)

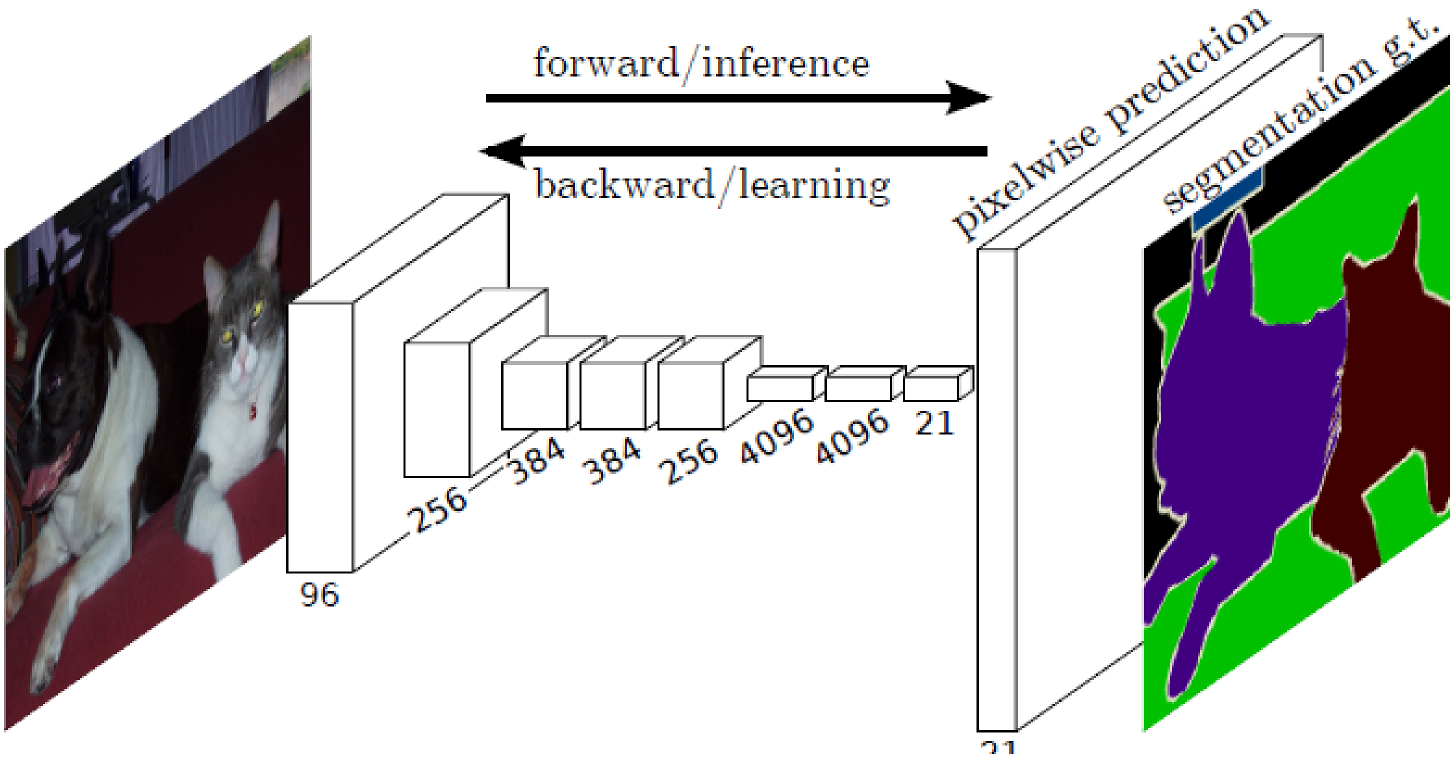
Slide credit: FeiFei Li

YOLO-v3 Results



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

Semantic Image Segmentation

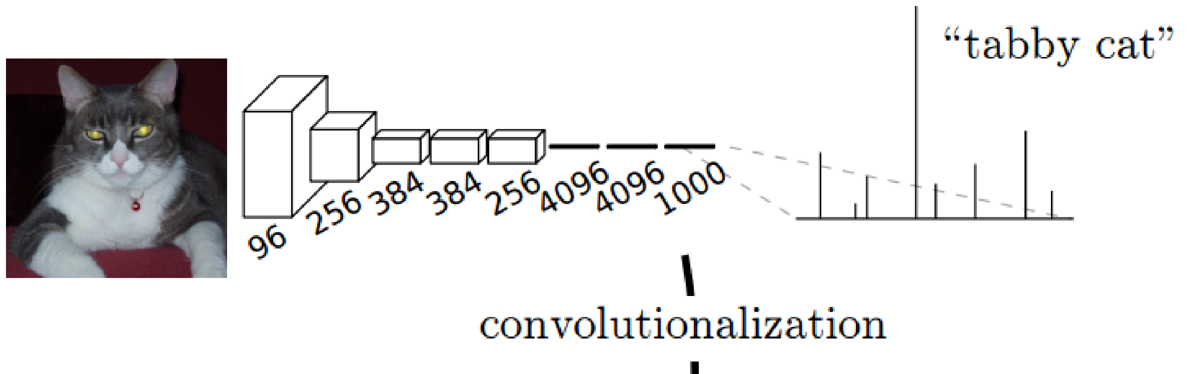


- Perform pixel-wise prediction task
  - Usually done using Fully Convolutional Networks (FCNs)
    - All operations formulated as convolutions
    - Advantage: can process arbitrarily sized images

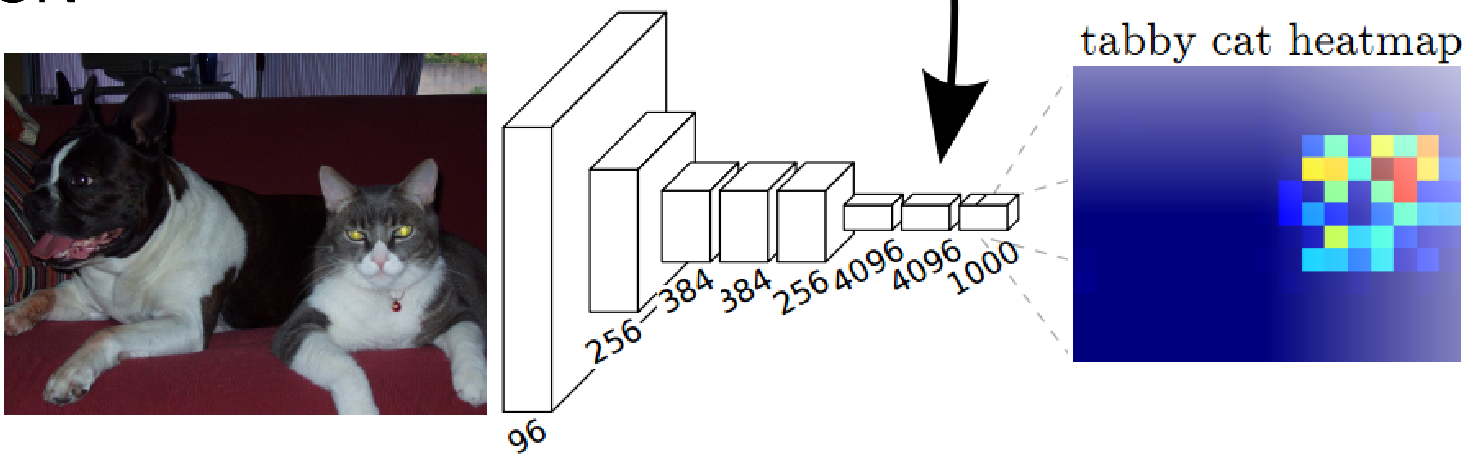
Image source: Long, Shelhamer, Darrell

CNNs vs. FCNs

- CNN



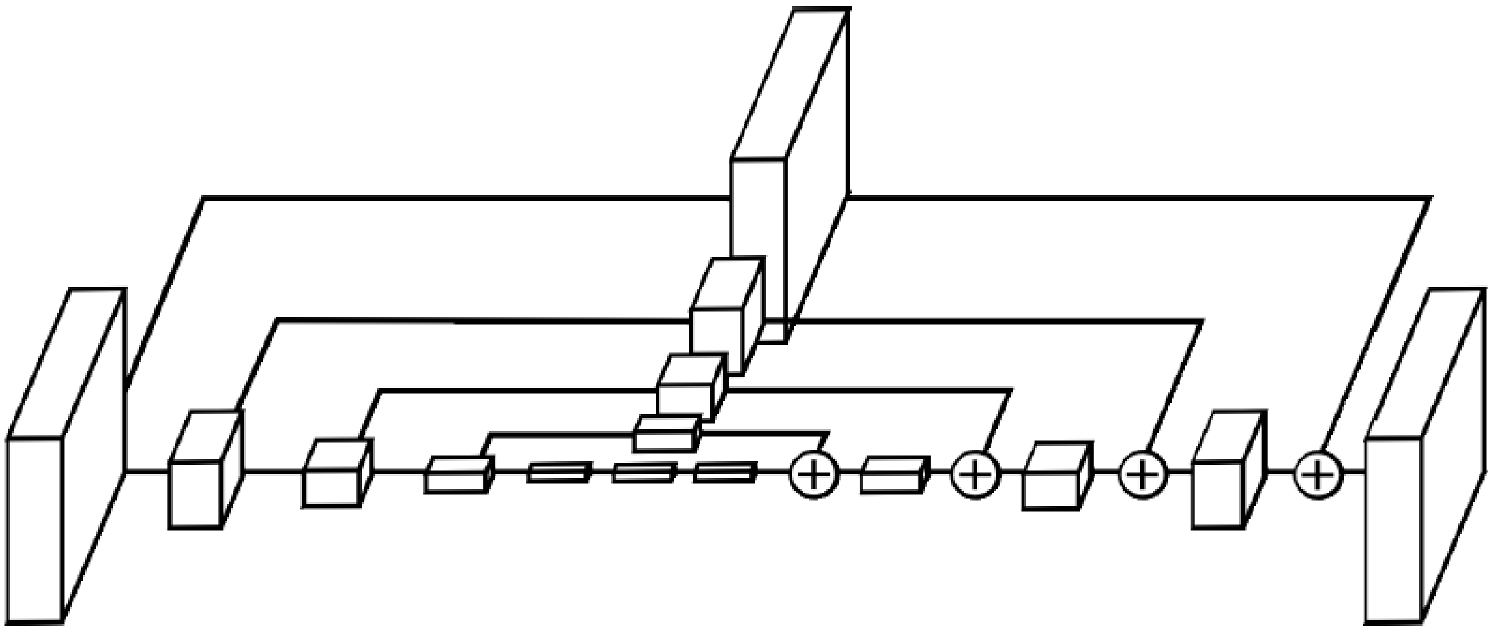
- FCN



- 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

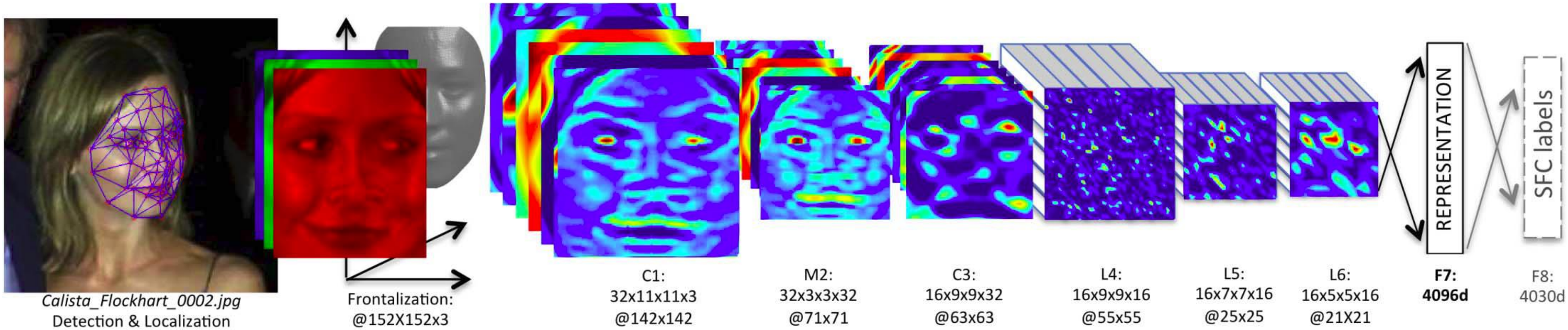
Image source: Newell et al.

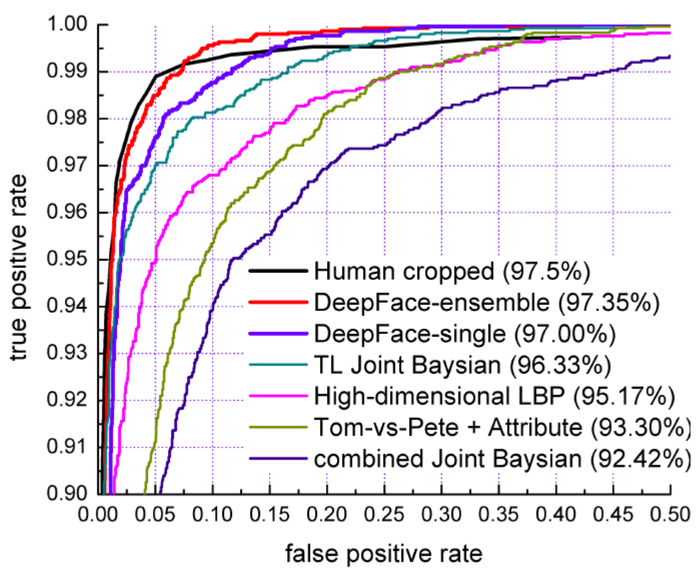
Semantic Segmentation

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

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

Other Tasks: Face Verification



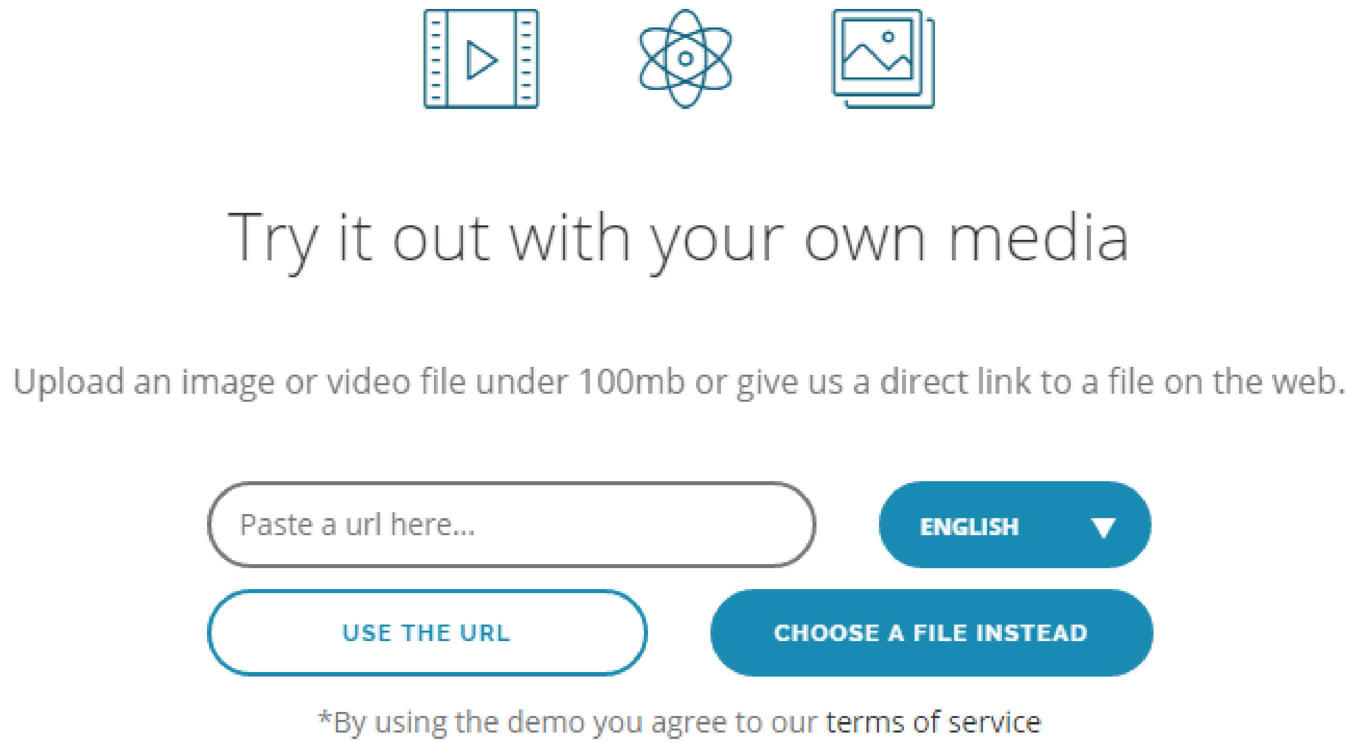


Y. Taigman, M. Yang, M. Ranzato, L. Wolf, DeepFace: Closing the Gap to Human-Level Performance in Face Verification, CVPR 2014

Slide credit: Svetlana Lazebnik

Commercial Recognition Services

- E.g., clarifai



- Be careful when taking test images from Google Search
  - Chances are they may have been seen in the training set...

Image source: clarifai.com

References and Further Reading

- LeNet
  - 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.
- AlexNet
  - A. Krizhevsky, I. Sutskever, and G. Hinton, ImageNet Classification with Deep Convolutional Neural Networks, NIPS 2012.
- VGGNet
  - K. Simonyan, A. Zisserman, Very Deep Convolutional Networks for Large-Scale Image Recognition, ICLR 2015
- GoogLeNet
  - C. Szegedy, W. Liu, Y. Jia, et al, Going Deeper with Convolutions, arXiv:1409.4842, 2014.

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.
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References: Computer Vision Tasks

- 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.