Advanced Machine Learning
Lecture 16

Convolutional Neural Networks II

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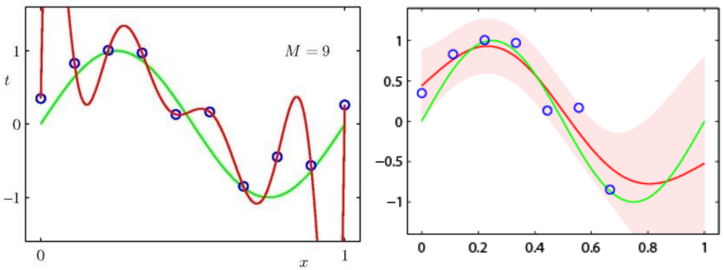
Announcements

- **Lecture evaluation**
  - Please fill out the evaluation forms.

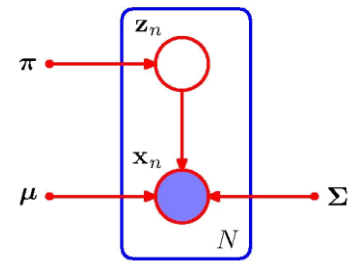
This Lecture: *Advanced Machine Learning*

- Regression Approaches
  - Linear Regression
  - Regularization (Ridge, Lasso)
  - Gaussian Processes

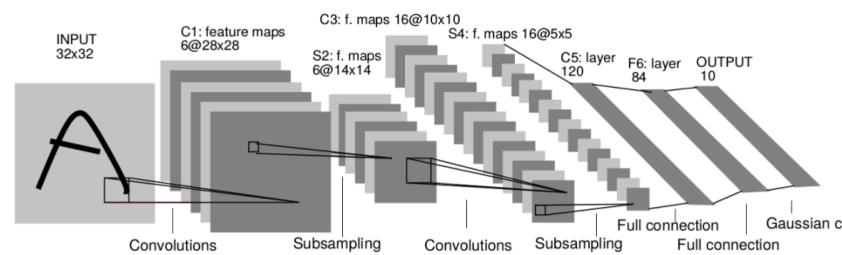
$$f : \mathcal{X} \rightarrow \mathbb{R}$$



- Learning with Latent Variables
  - Prob. Distributions & Approx. Inference
  - Mixture Models
  - EM and Generalizations



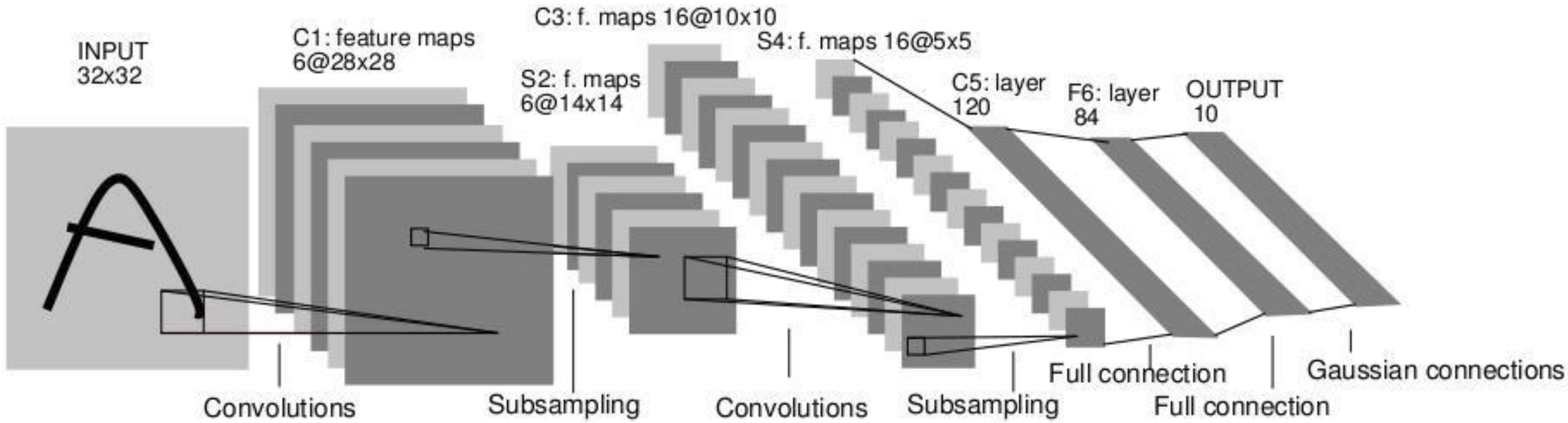
- Deep Learning
  - Linear Discriminants
  - Neural Networks
  - Backpropagation & Optimization
  - CNNs, RNNs, RBMs, etc.



Topics of This Lecture

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

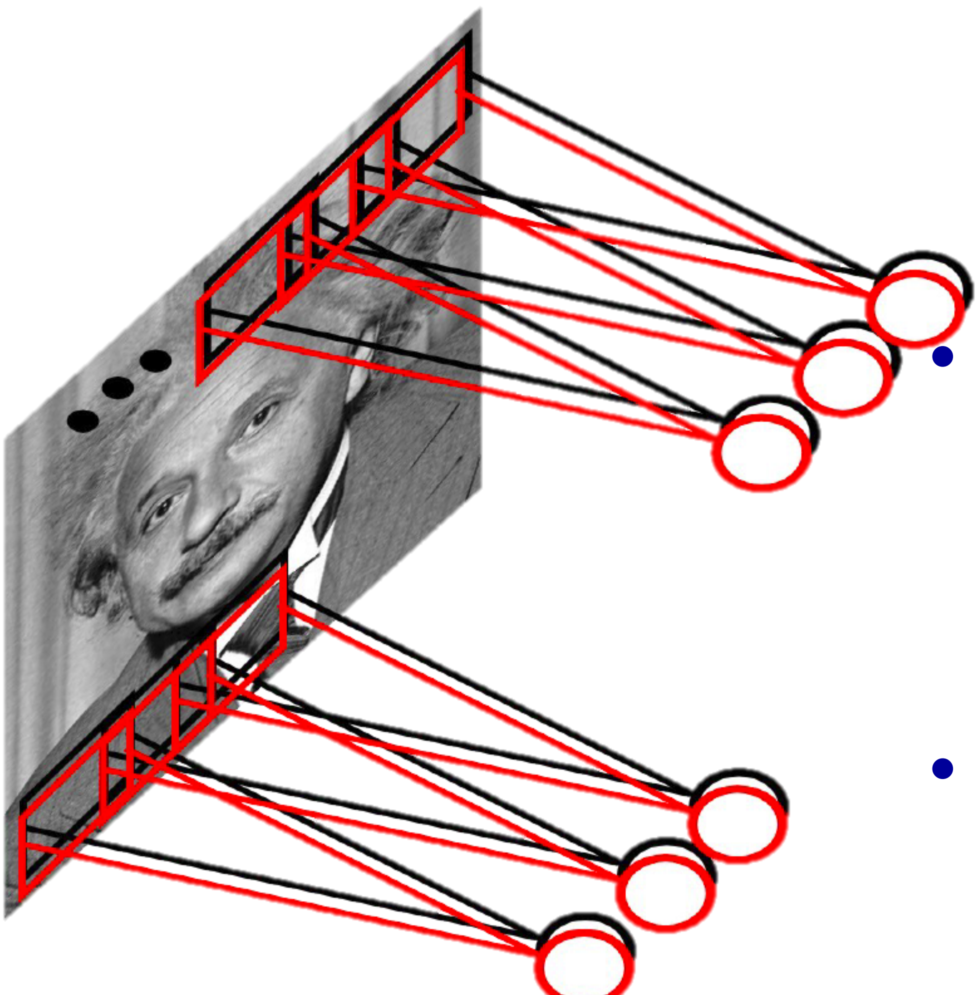
Recap: Convolutional Neural Networks



- 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

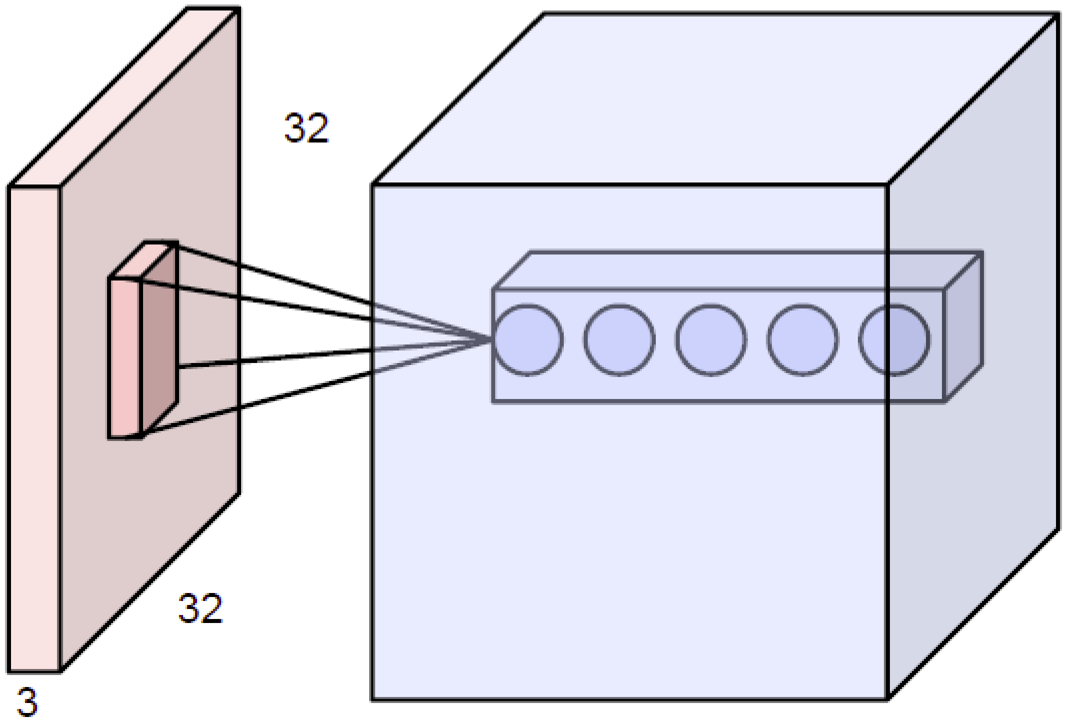


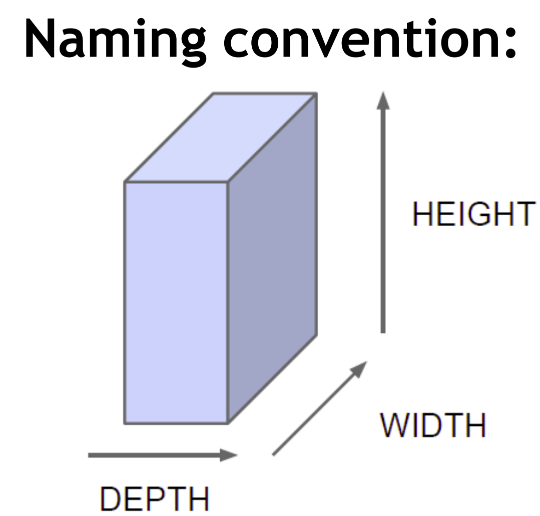
- Convolutional net
  - Share the same parameters across different locations
  - Convolutions with learned kernels
- Learn *multiple* filters
  - E.g. 1000×1000 image
    100 filters
    10×10 filter size

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

Image source: Yann LeCun

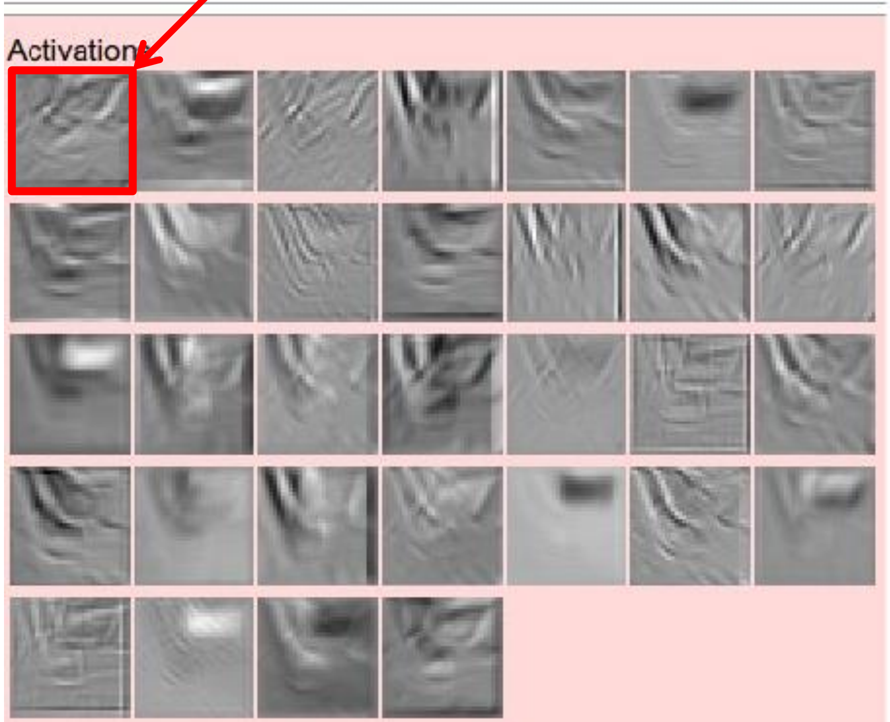
Recap: Convolution Layers



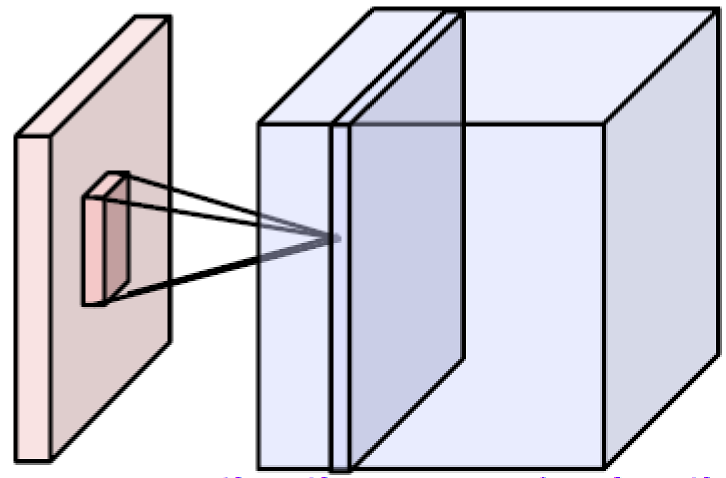


- All Neural Net activations arranged in 3 dimensions
  - Multiple neurons all looking at the same input region, stacked in depth
  - Form a single [1×1×depth] depth column in output volume.

Recap: Activation Maps

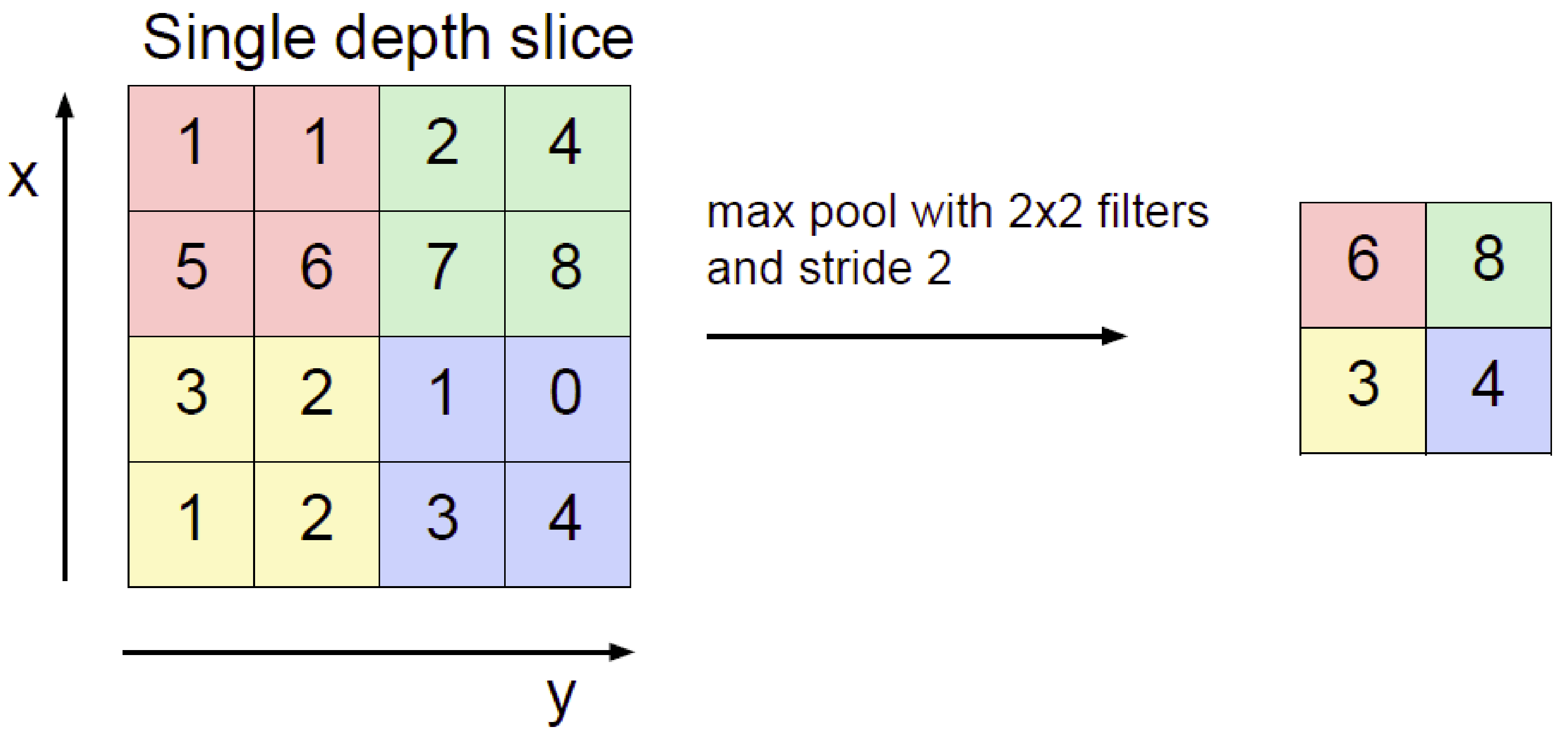


Activation maps



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**

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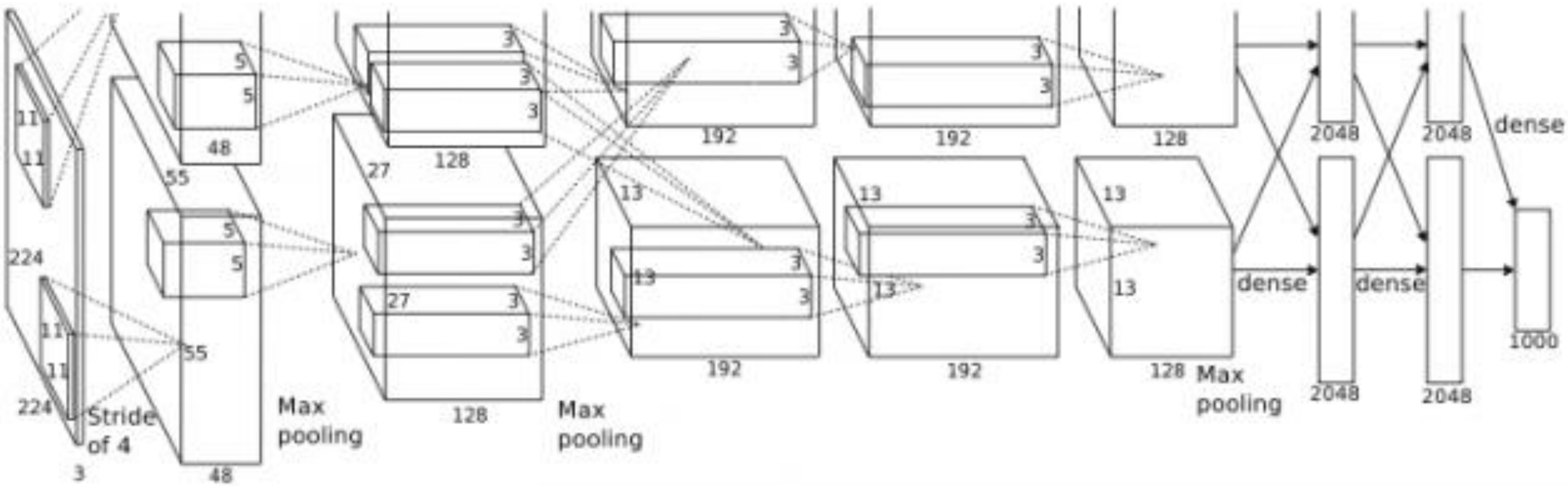
Recap: ImageNet Challenge 2012

- 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)

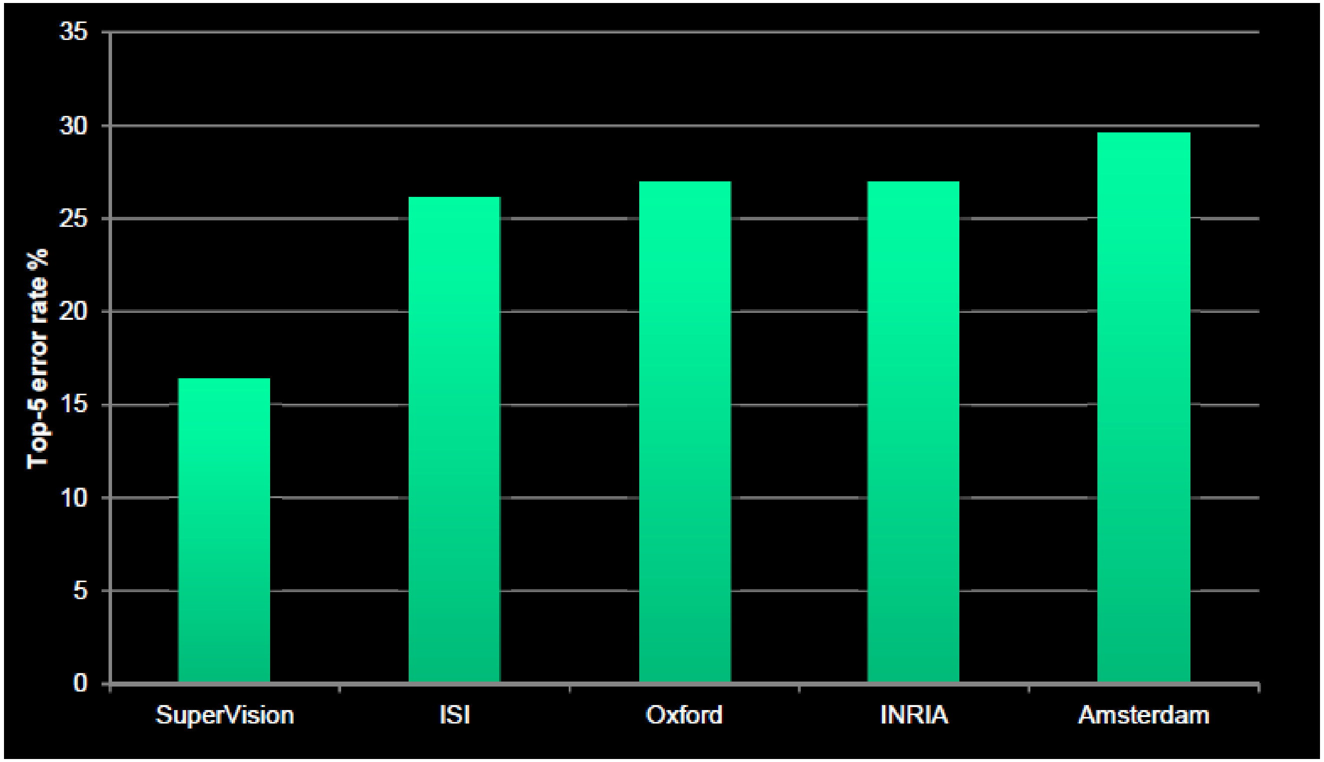


- **Similar framework as LeNet, but**
  - **Bigger model (7 hidden layers, 650k units, 60M parameters)**
  - **More data (10^6 images instead of 10^3)**
  - **GPU implementation**
  - **Better regularization and up-to-date tricks for training (Dropout)**

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 (2015)

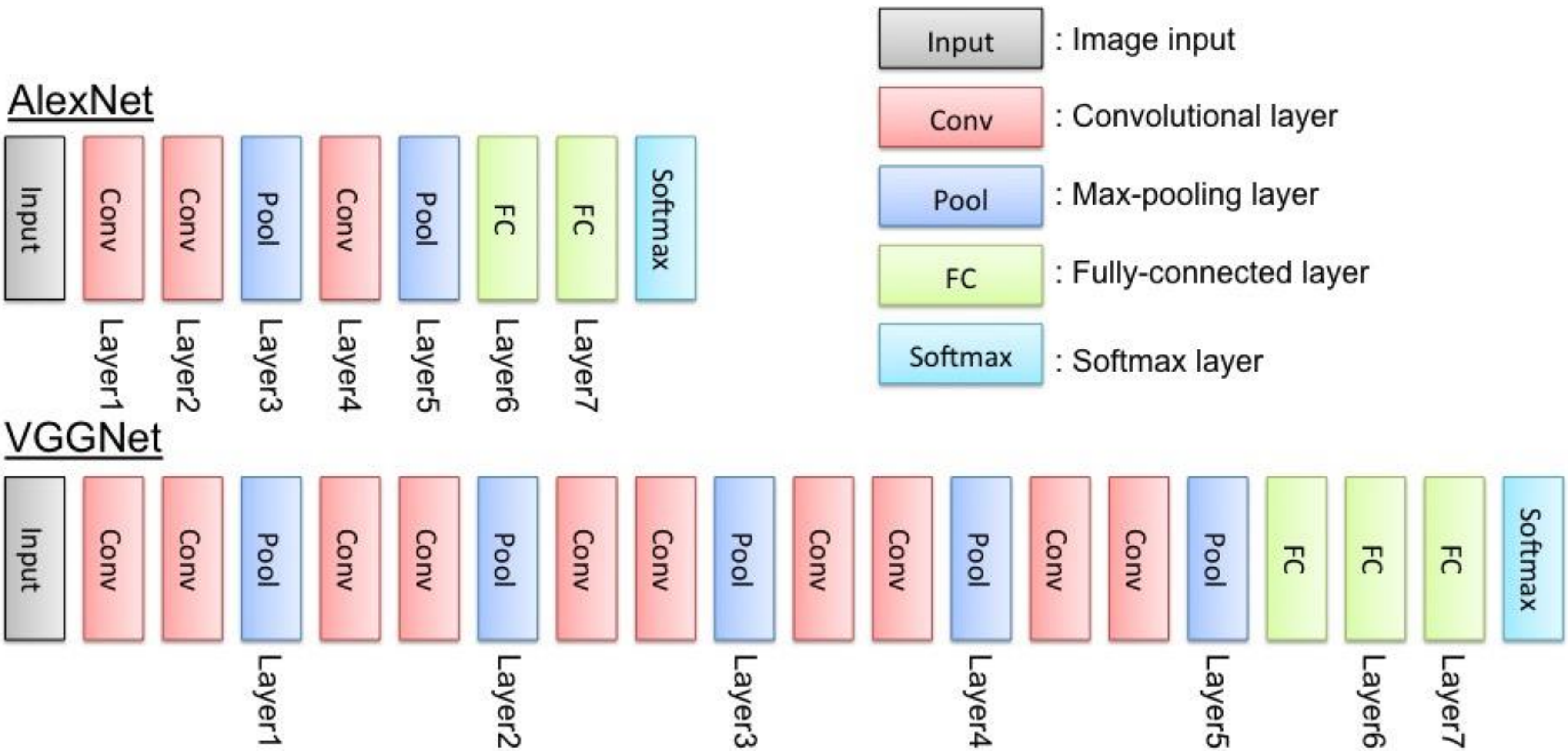
- **Main ideas**
  - Deeper network
  - Stacked convolutional layers with smaller filters (+ nonlinearity)
  - Detailed evaluation of all components

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



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

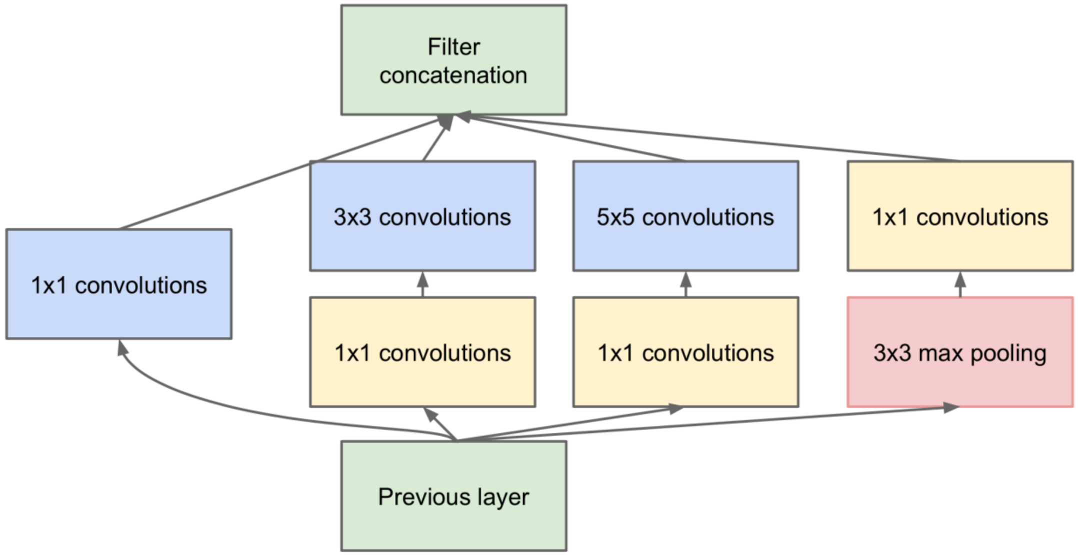
Image source: Hirokatsu Kataoka

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 three 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: $3\cdot 3^2 = 27$ instead of $7^2 = 49$.
  - In addition, non-linearities in-between 3×3 layers for additional discriminativity.

CNN Architectures: GoogLeNet (2014)



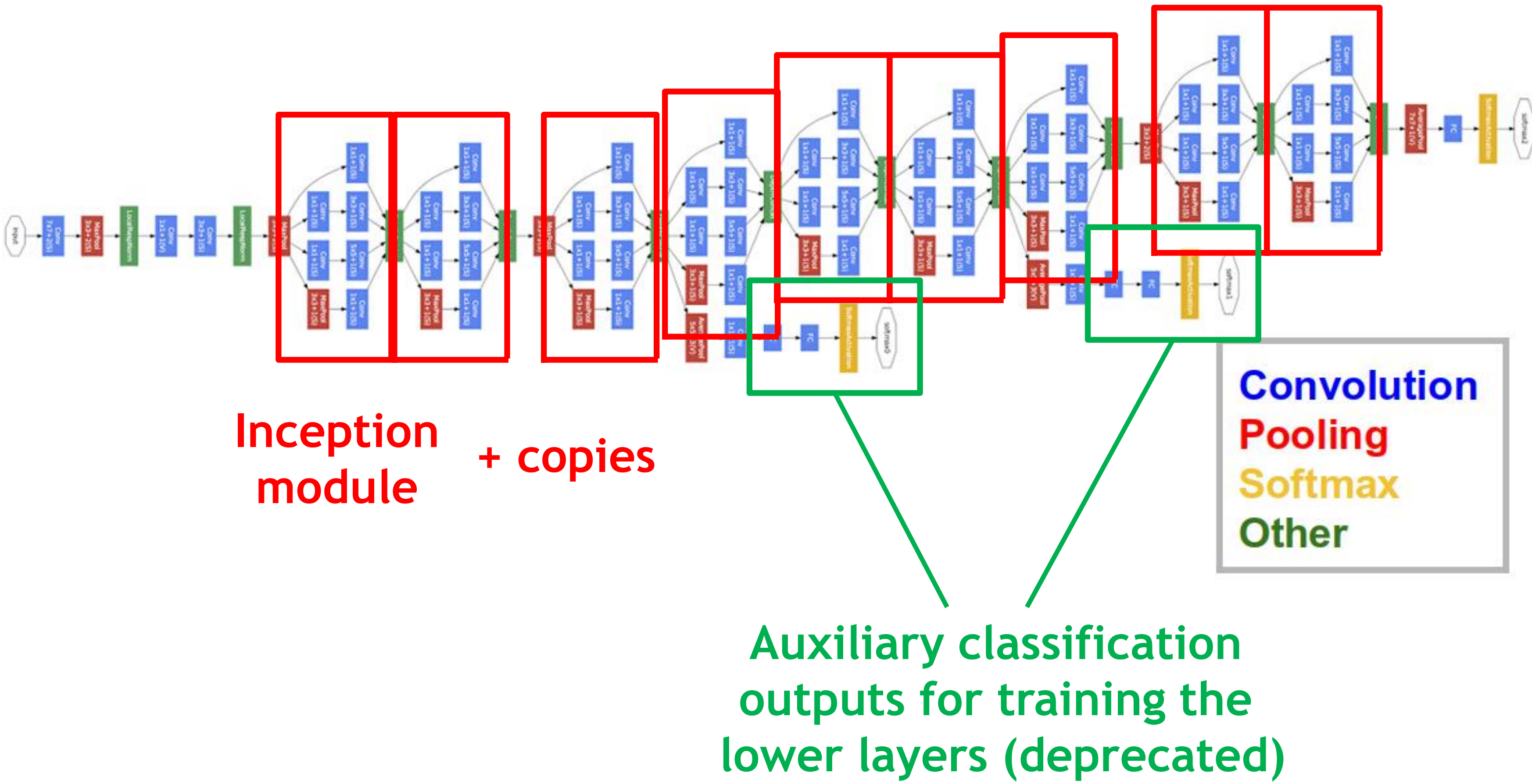
Inception module with dimension reductions

- **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.

Image source: Szegedy et al.

GoogLeNet Visualization



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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

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, chain-

machine, Shetland sheepdog, shield, Shih-Tzu, shoe shop, shoji, shopping basket, shopping cart, shovel, shower cap, shower curtain, siamang, Siamese cat, Siberian husky, sidewinder, silky terrier, ski, ski mask, skunk, sleeping bag, slide rule, sliding door, slot, sloth bear, slug, snail, snorkel, snow leopard, snowmobile, snowplow, soap dispenser, soccer ball, sock, soft-coated wheaten terrier, solar dish, sombrero, sorrel, soup bowl, space bar, space heater, space shuttle, spaghetti squash, spatula, speedboat, spider monkey, spider web, spindle, spiny lobster, spoonbill, sports car, spotlight, spotted salamander, squirrel monkey, Staffordshire bullterrier, stage, standard poodle, standard schnauzer, starfish, steam locomotive, steel arch bridge, steel drum, stethoscope, stingray, stinkhorn, stole, stone wall, stopwatch, stove, strainer, strawberry, street sign, streetcar, stretcher, studio couch, stupa, sturgeon, submarine, suit, sulphur butterfly, sulphur-crested cockatoo, sundial, sunglass, sunglasses, sunscreen, suspension bridge, Sussex spaniel, swab, sweatshirt, swimming trunks, swing, switch, syringe, tabby, table lamp, tailed frog, tank, tape player, tarantula, teapot, teddy, television, tench, tennis ball, terrapin, thatch, theater curtain, thimble, three-toed sloth, thresher, throne, thunder snake, Tibetan mastiff, Tibetan terrier, tick, tiger, tiger beetle, tiger cat, tiger shark, tile roof, timber wolf, titi, toaster, tobacco shop, toilet seat, toilet tissue, torch, totem pole, toucan, tow truck, toy poodle, toy terrier, toyshop, tractor, traffic light, trailer truck, tray, tree frog, trench coat, triceratops, tricycle, trifle, trilobite, trimaran, tripod, triumphal arch, trolleybus, trombone, tub, turnstile, tusker, typewriter keyboard, umbrella, unicycle, upright, vacuum, valley, vase, vault, velvet, vending machine, vestment, viaduct, vine snake, violin, vizsla, volcano, volleyball, vulture, waffle iron, Walker hound, walking stick, wall clock, wallaby, wallet, wardrobe, warplane, warthog, washbasin, washer, water bottle, water buffalo, water jug, water ouzel, water snake, water tower, weasel, web site, weevil, Weimaraner, Welsh springer spaniel, West Highland white terrier, whippet, whiptail, whiskey jug,

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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

⇒ 6.7% top-5 error looks all the more impressive

Image source: A. Karpathy

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Visualizing CNNs

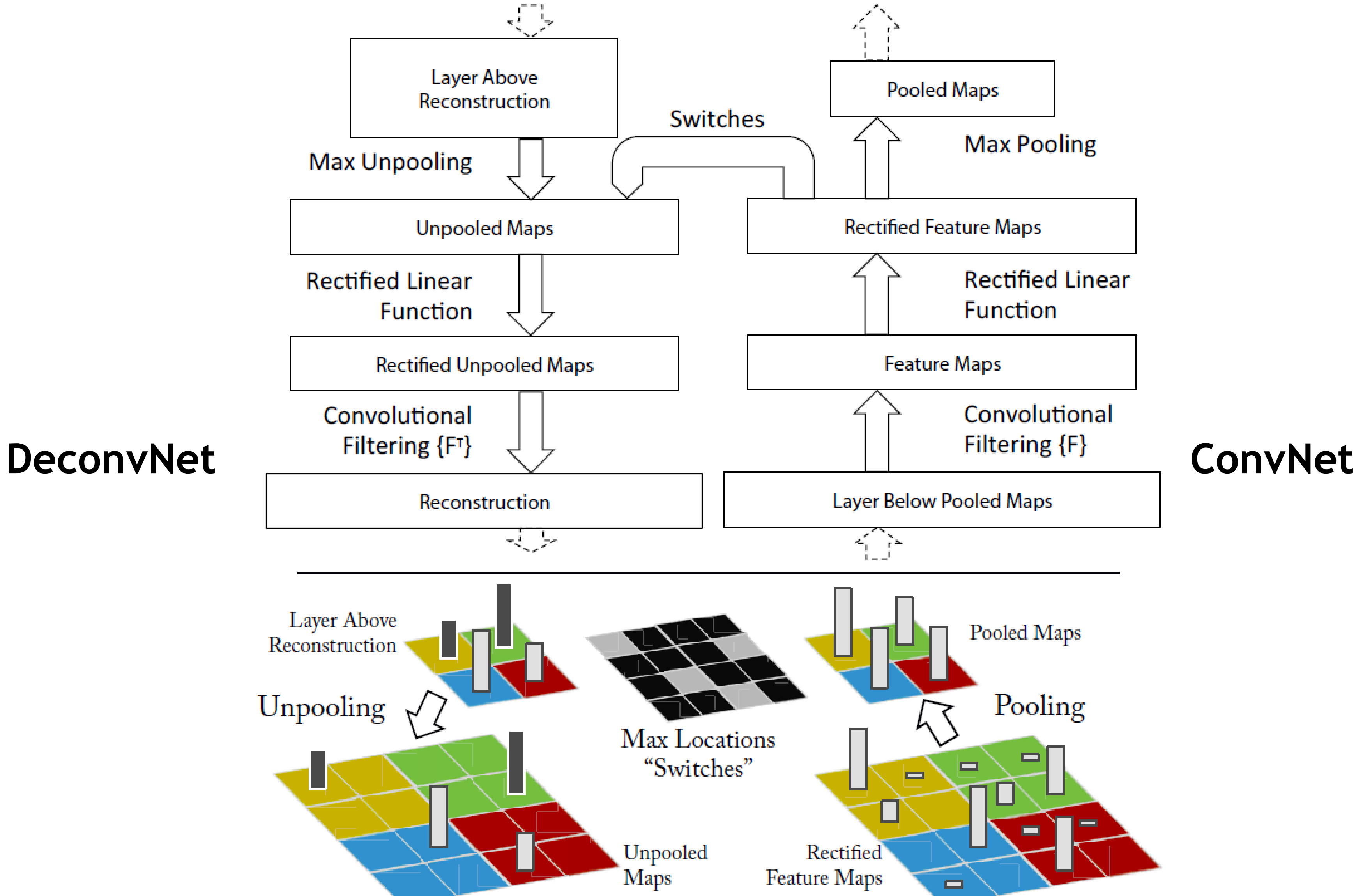
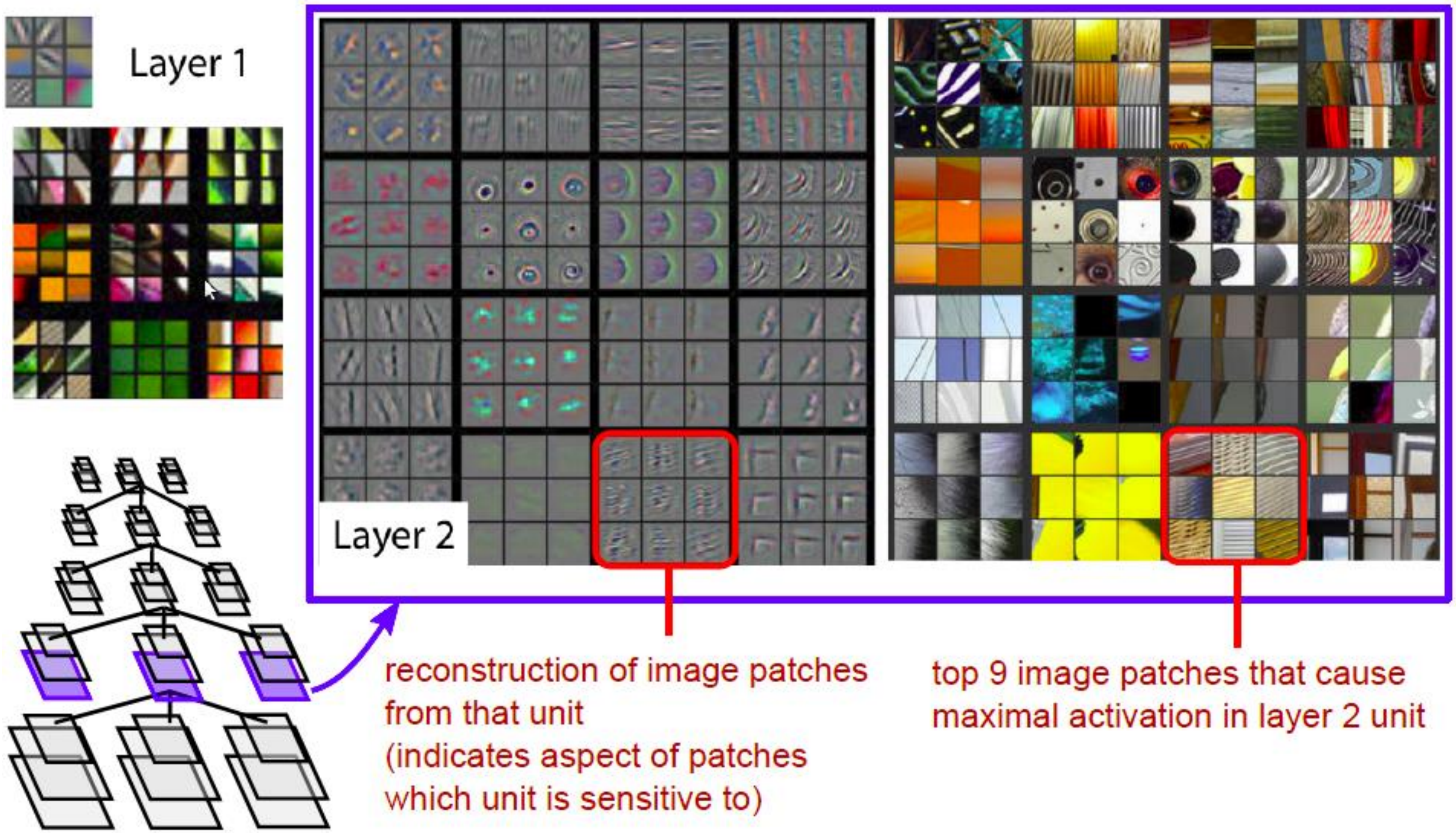


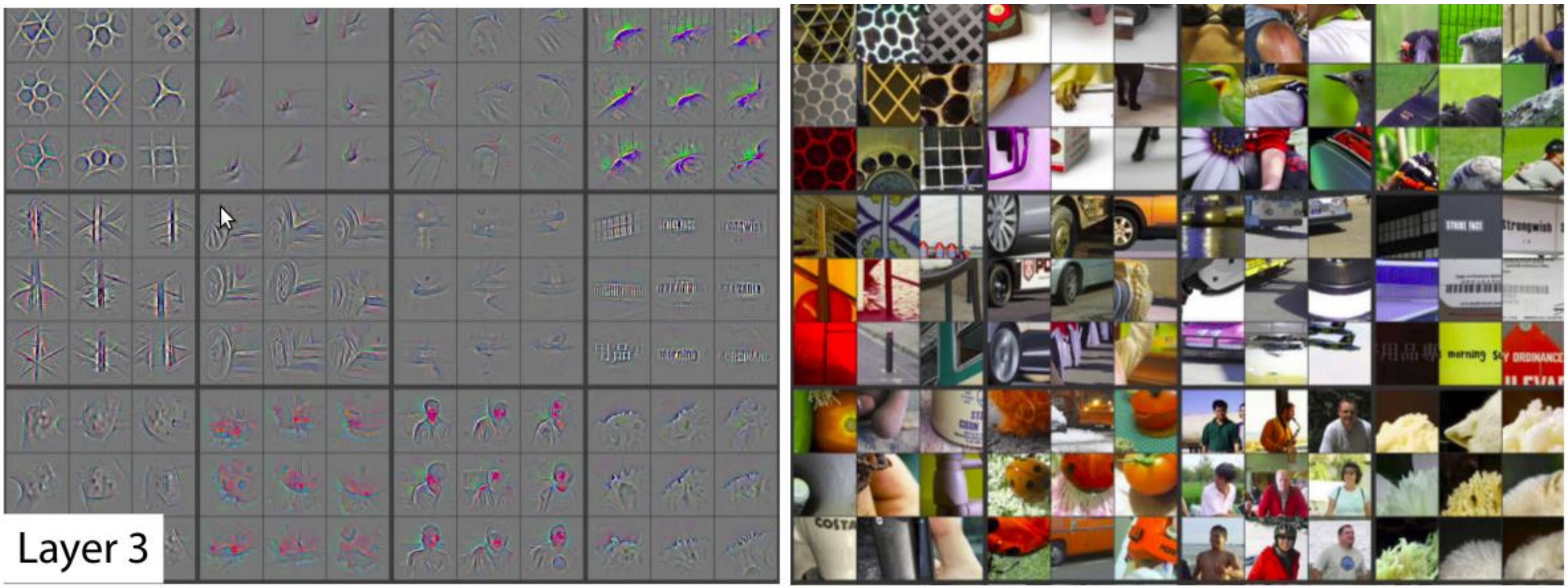
Image source: M. Zeiler, R. Fergus

Visualizing CNNs



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

Visualizing CNNs



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Visualizing CNNs

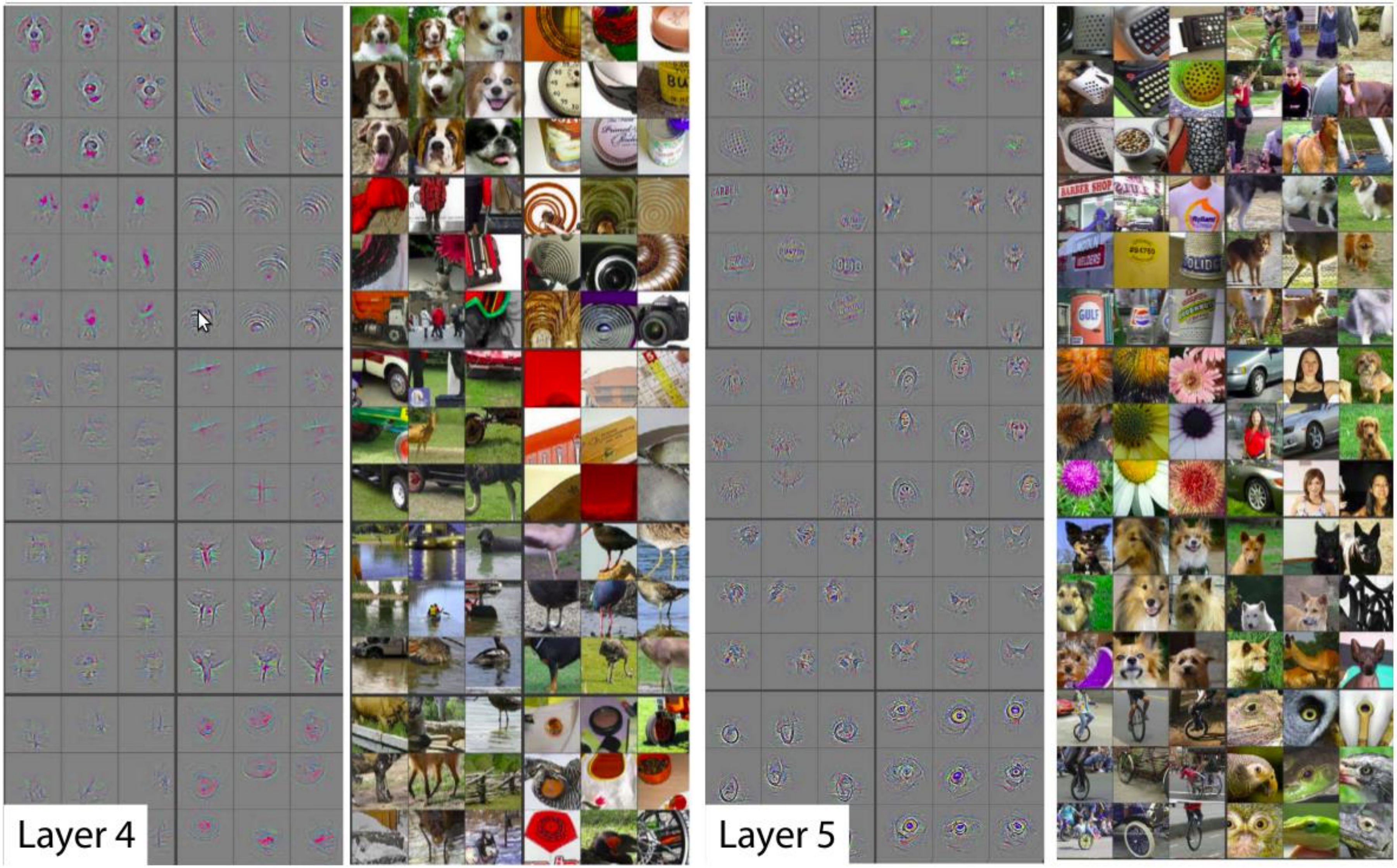


Image source: M. Zeiler, R. Fergus

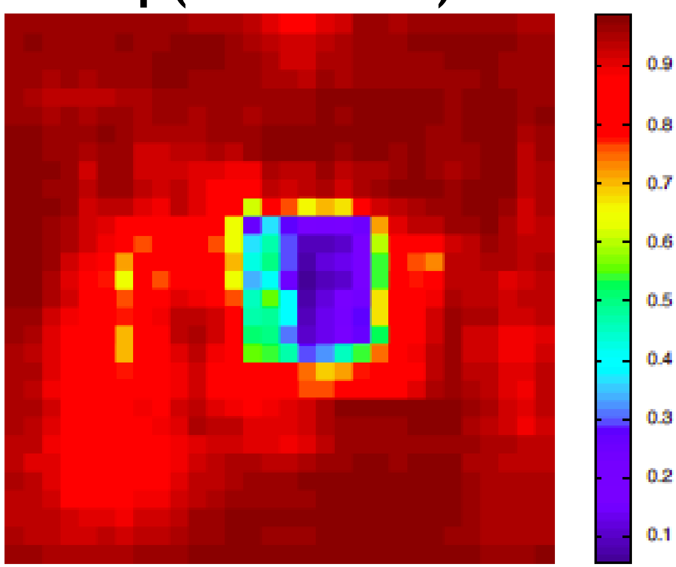
What Does the Network React To?

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

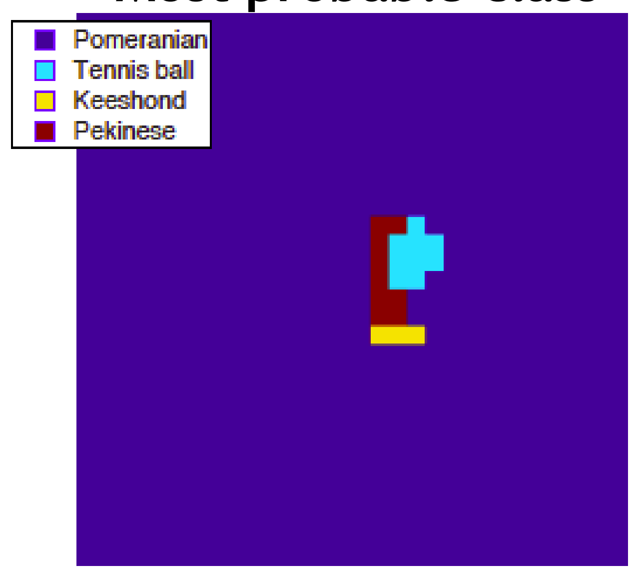
What Does the Network React To?

Input image

p(True class)



Most probable class



Slide credit: Svetlana Lazebnik, Rob Fergus

Image source: M. Zeiler, R. Fergus

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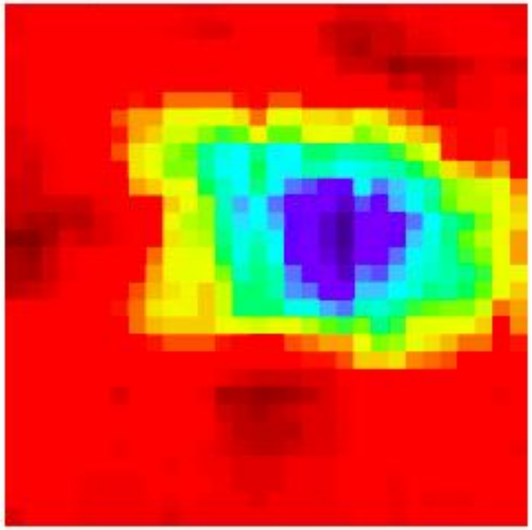
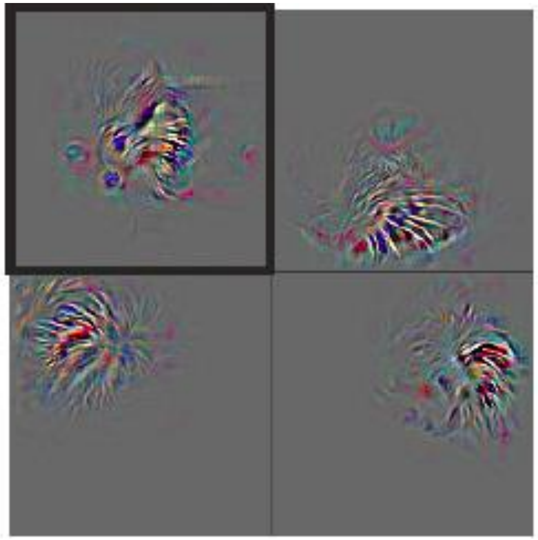
What Does the Network React To?

Input image

Total activation in most active 5th layer feature map





Other activations from the same feature map.

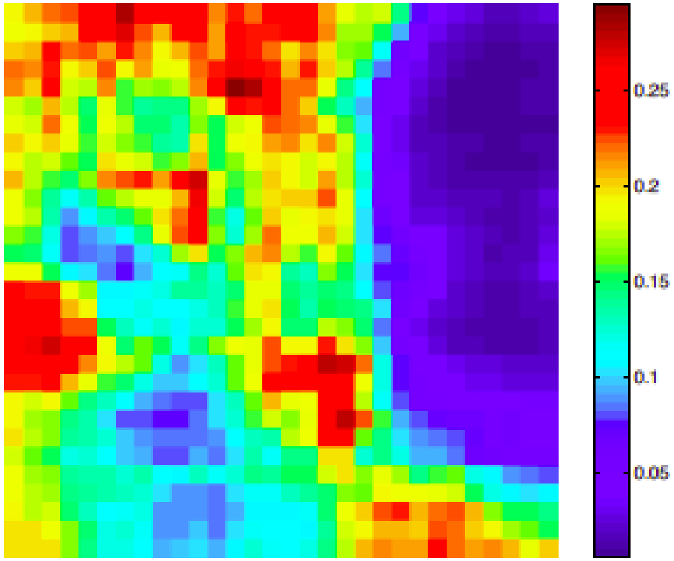
Slide credit: Svetlana Lazebnik, Rob Fergus

Image source: M. Zeiler, R. Fergus

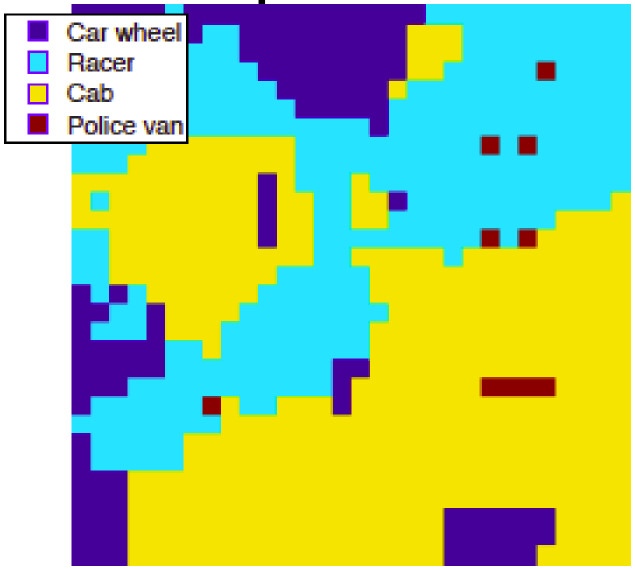
What Does the Network React To?

Input image

p(True class)



Most probable class



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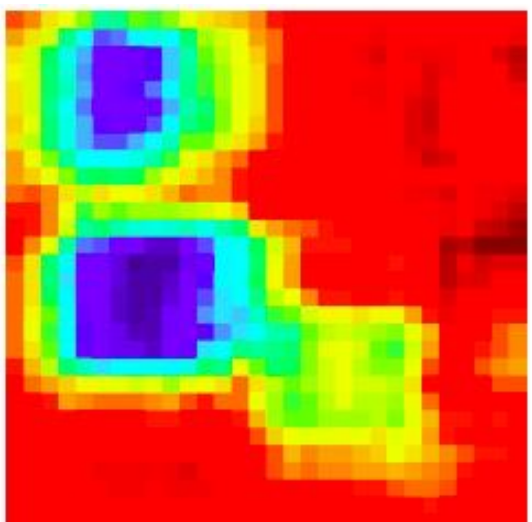

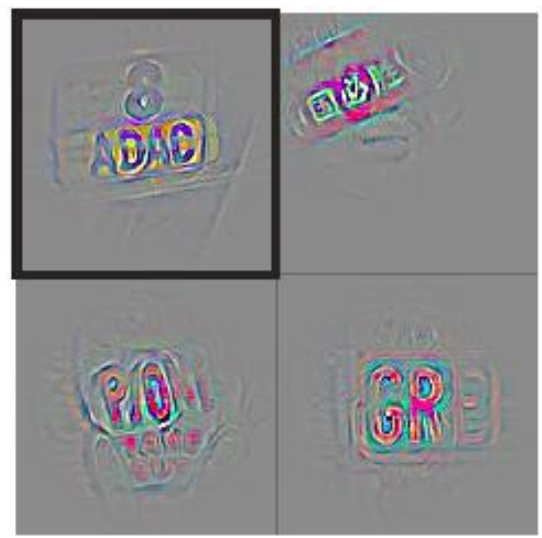

Other activations from the same feature map.

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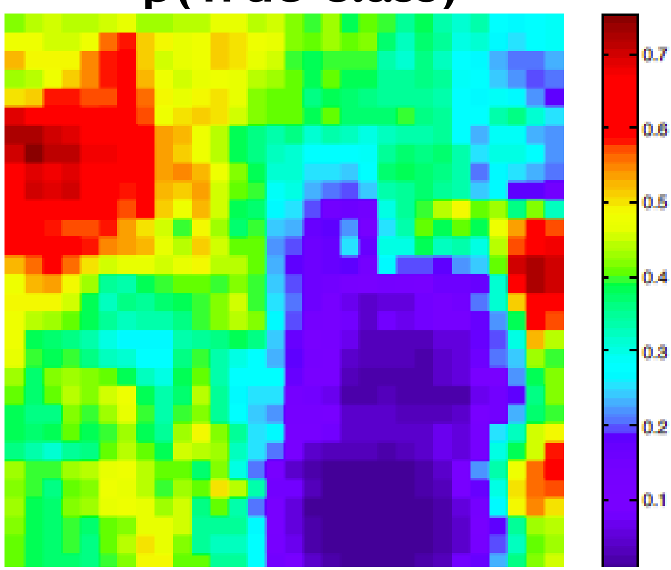
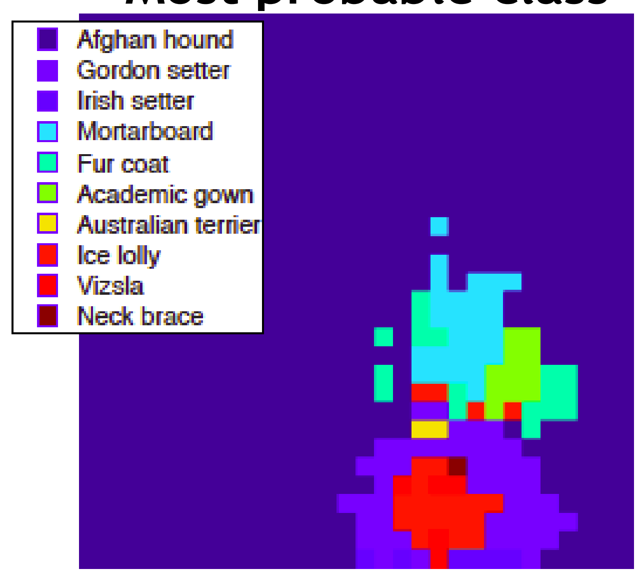
Input image

p(True class)



Most probable class



Slide credit: Svetlana Lazebnik, Rob Fergus

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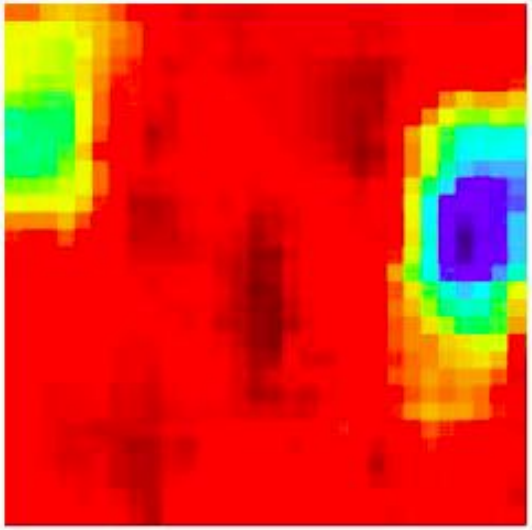
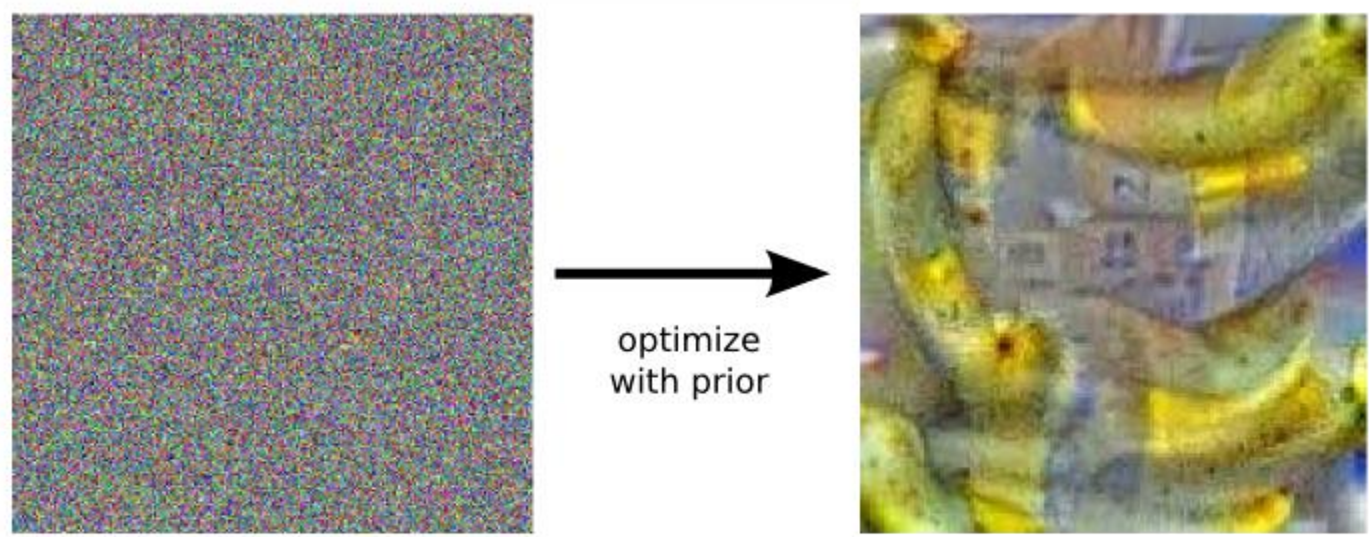


Other activations from the same feature map.

Slide credit: Svetlana Lazebnik, Rob Fergus

Image source: M. Zeiler, R. Fergus

Inceptionism: Dreaming ConvNets



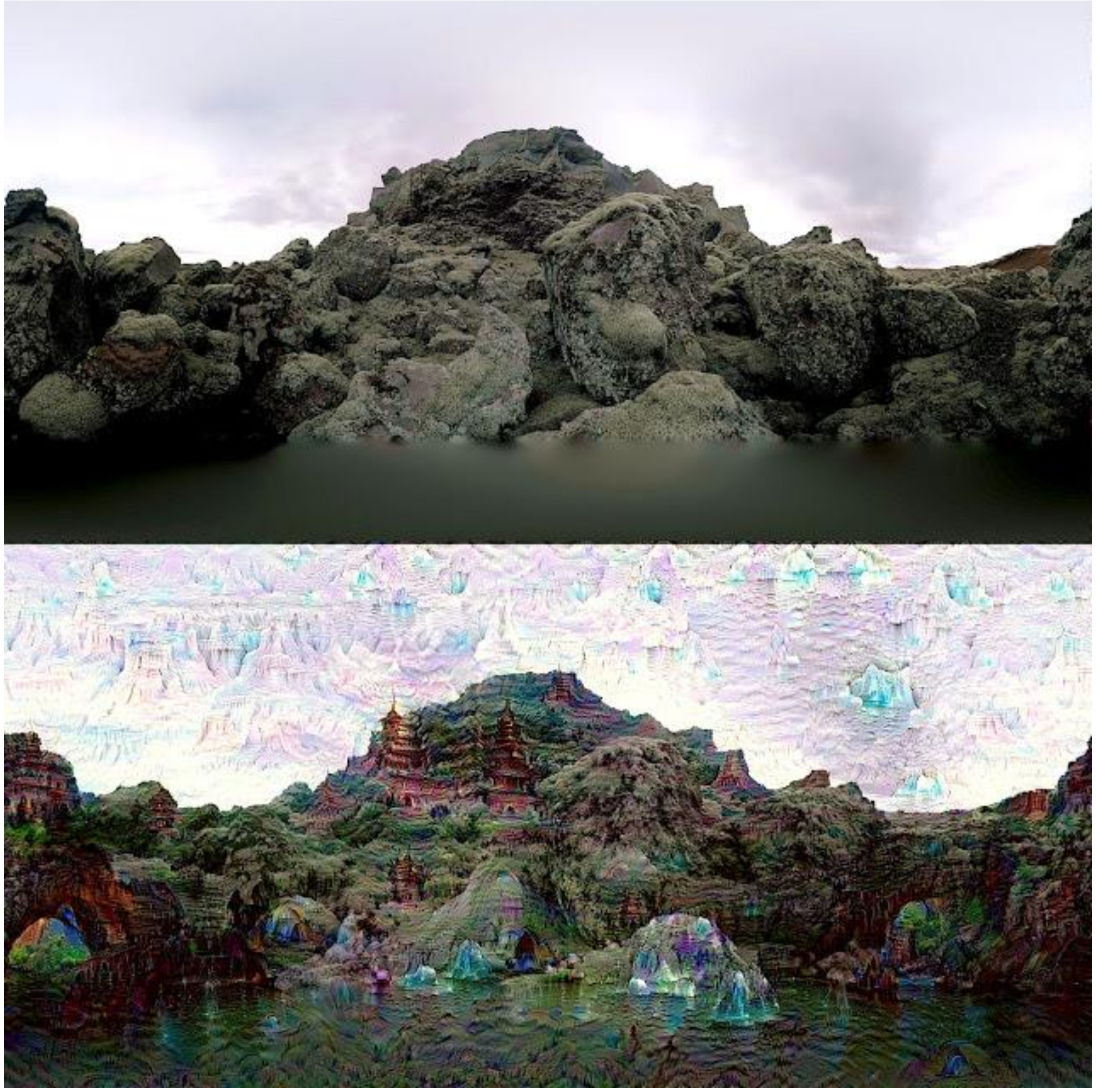
- **Idea**
  - Start with a random noise image.
  - Enhance the input image such as to enforce a particular response (e.g., banana).
  - Combine with prior constraint that image should have similar statistics as natural images.

  ⇒ Network hallucinates characteristics of the learned class.

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

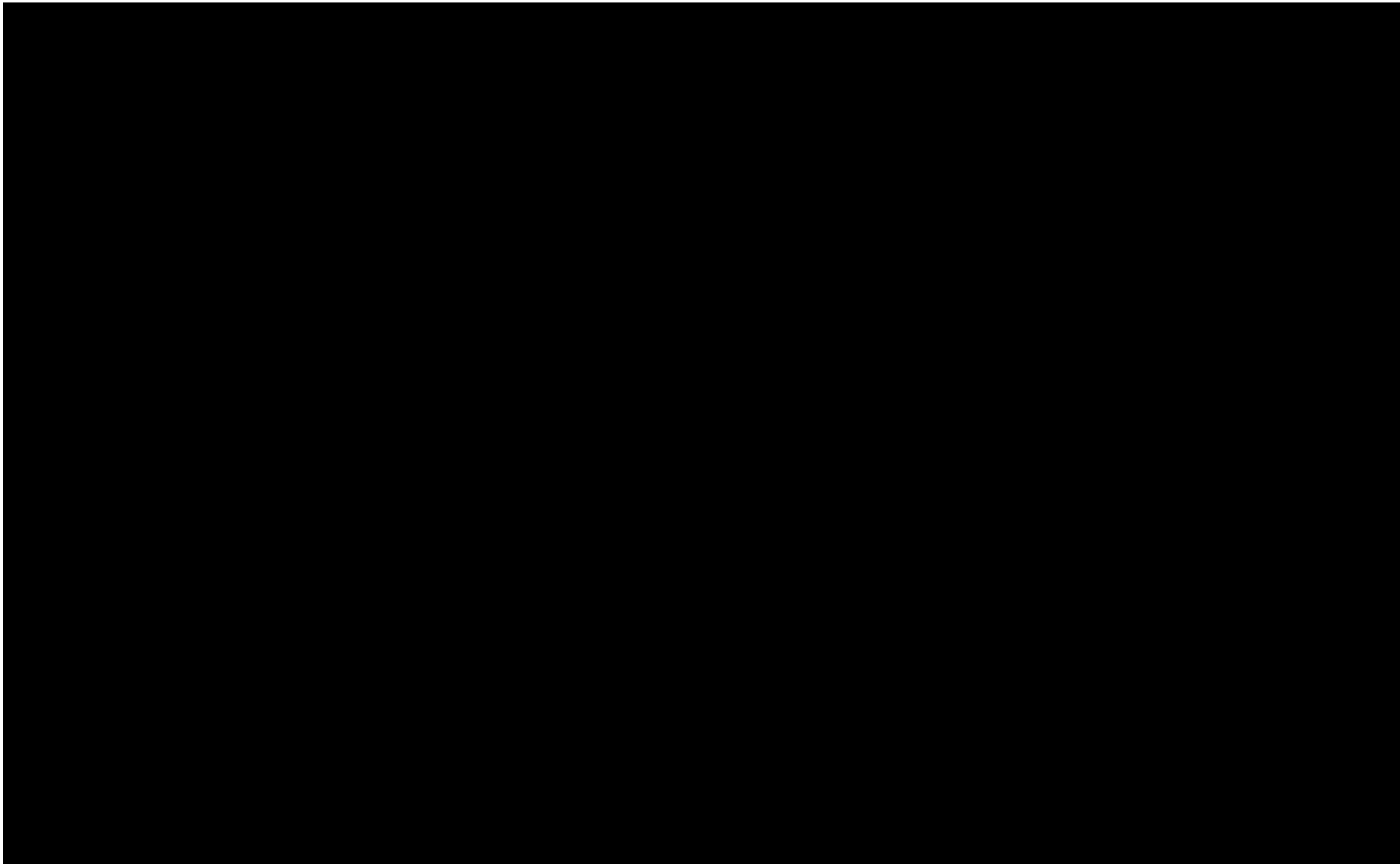
Inceptionism: Dreaming ConvNets

- **Results**



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

Inceptionism: Dreaming ConvNets

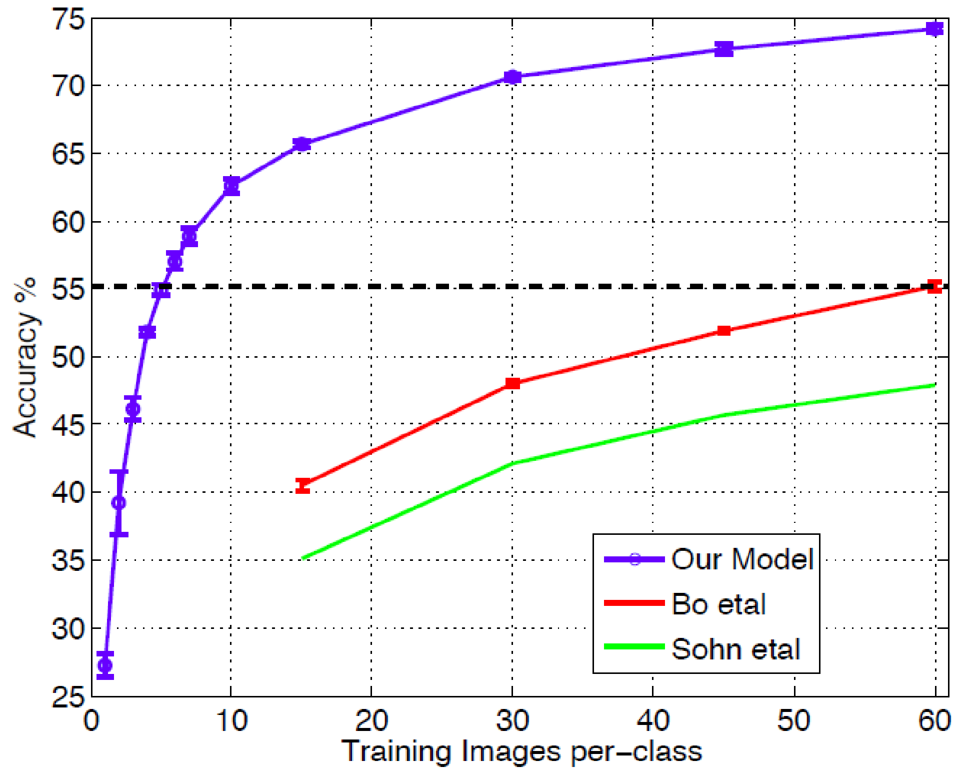


https://www.youtube.com/watch?v=IREsx-xWQ0g

Topics of This Lecture

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

The Learned Features are Generic

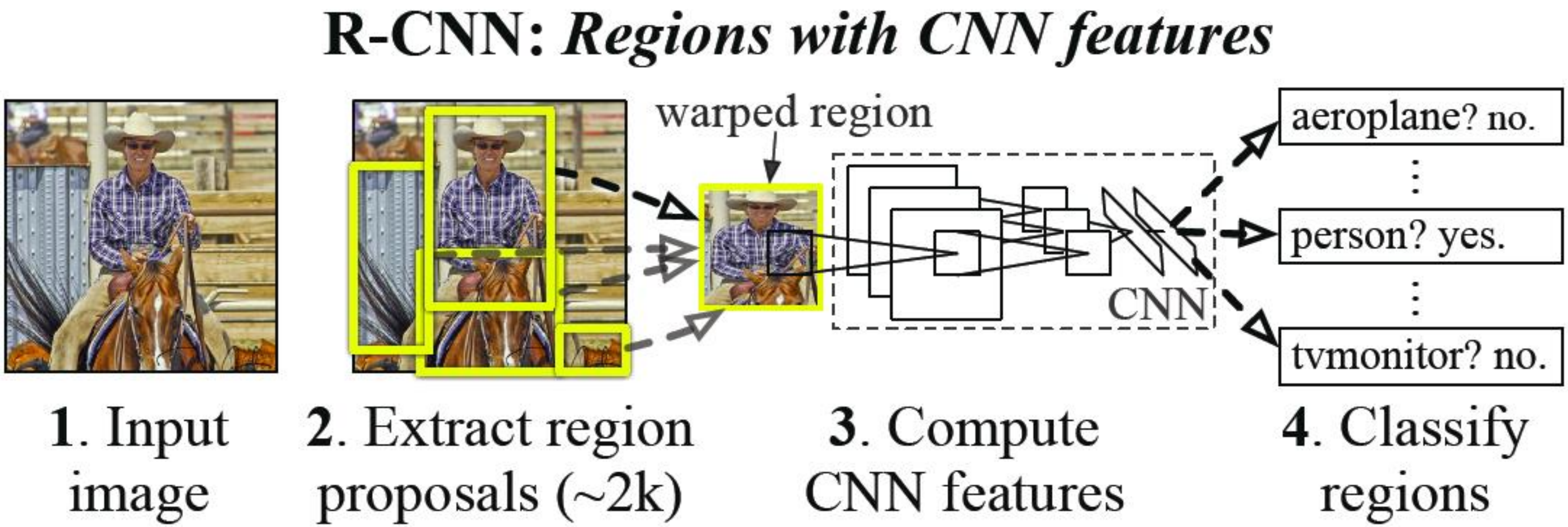


state of the art level (pre-CNN)

- 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

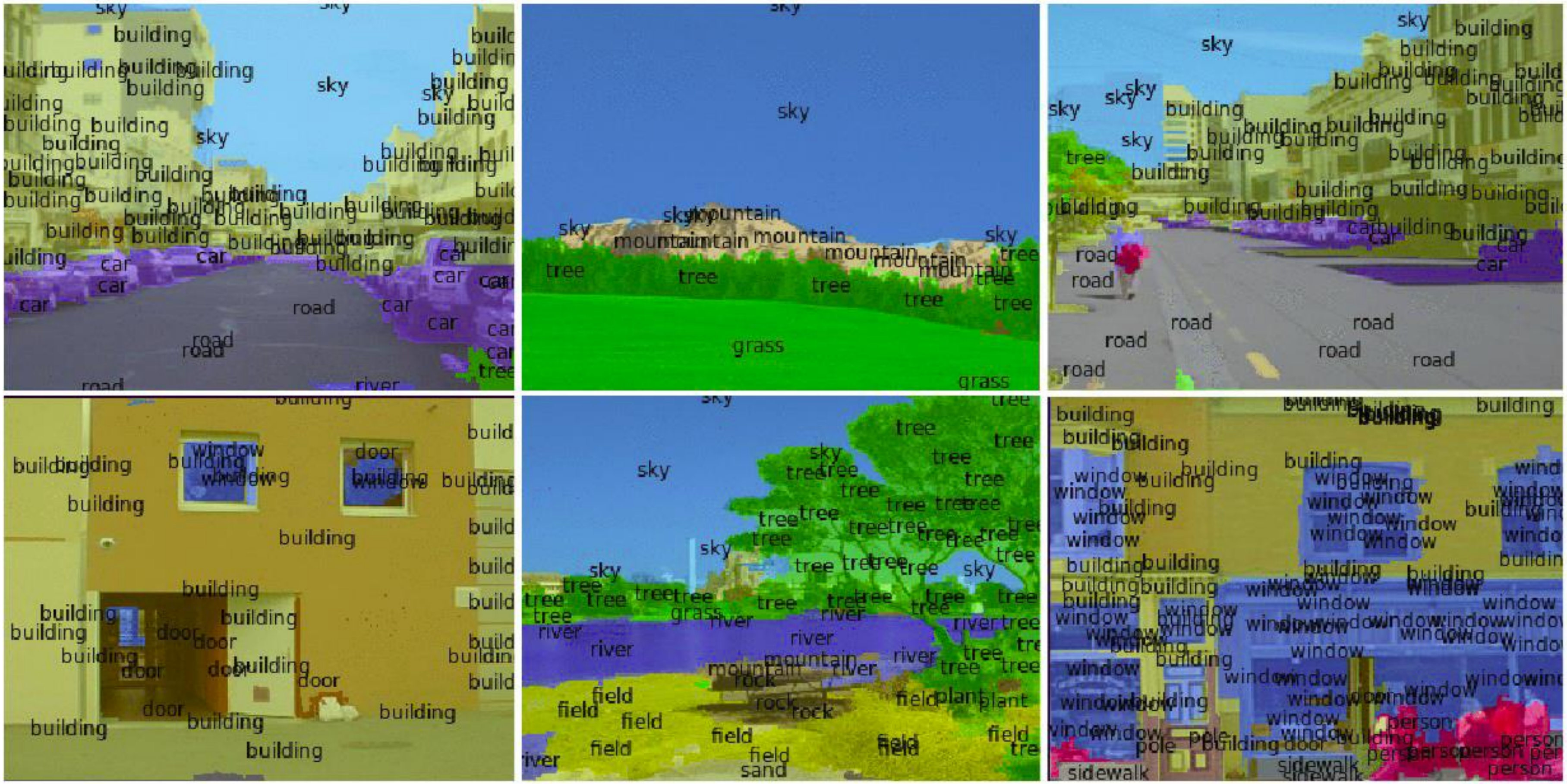
Other Tasks: Detection



- **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

Other Tasks: Semantic Segmentation

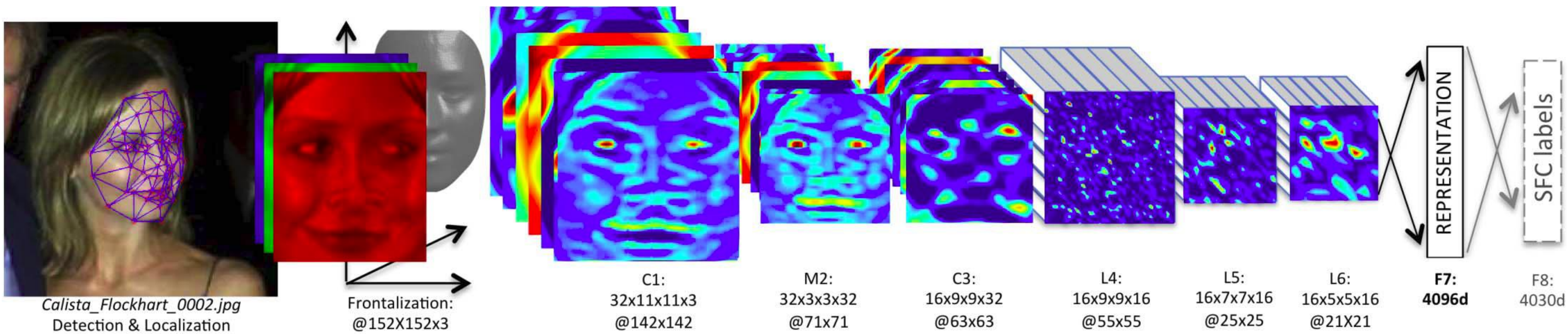


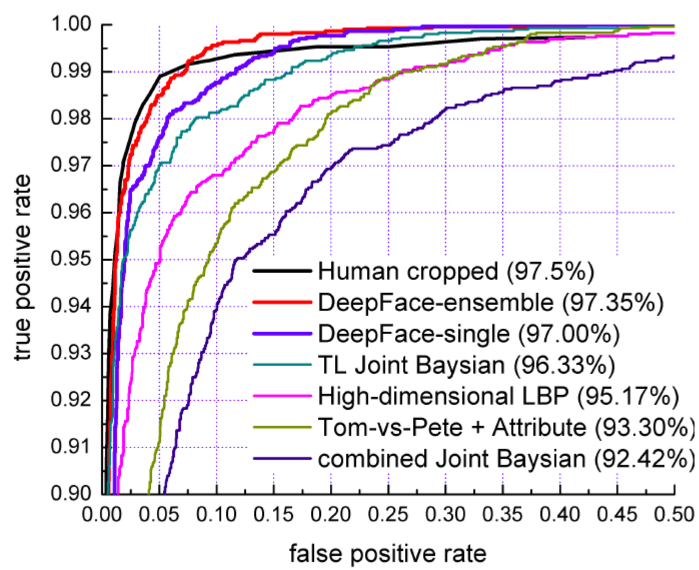
[Farabet et al. ICML 2012, PAMI 2013]

Other Tasks: Semantic Segmentation

[Farabet et al. ICML 2012, PAMI 2013]

Other Tasks: Face Verification



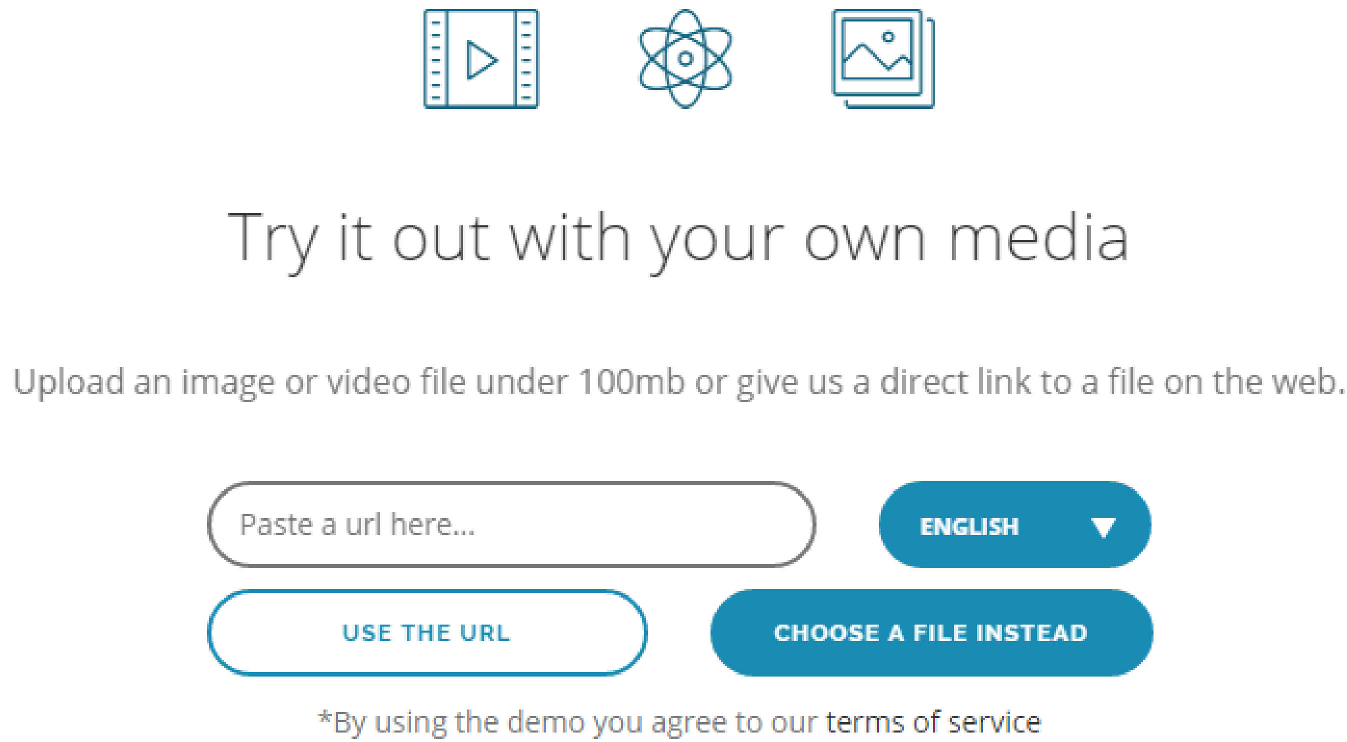


Y. Taigman, M. Yang, M. Ranzato, L. Wolf, [DeepFace: Closing the Gap to Human-Level Performance in Face Verification](), CVPR 2014

Slide credit: Svetlana Lazebnik

Commercial Recognition Services

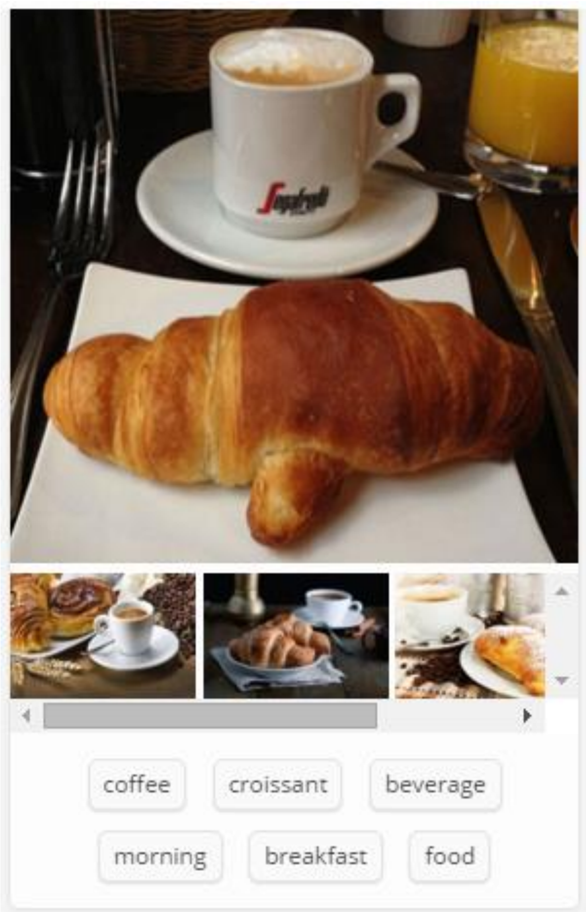
- E.g., clarifai

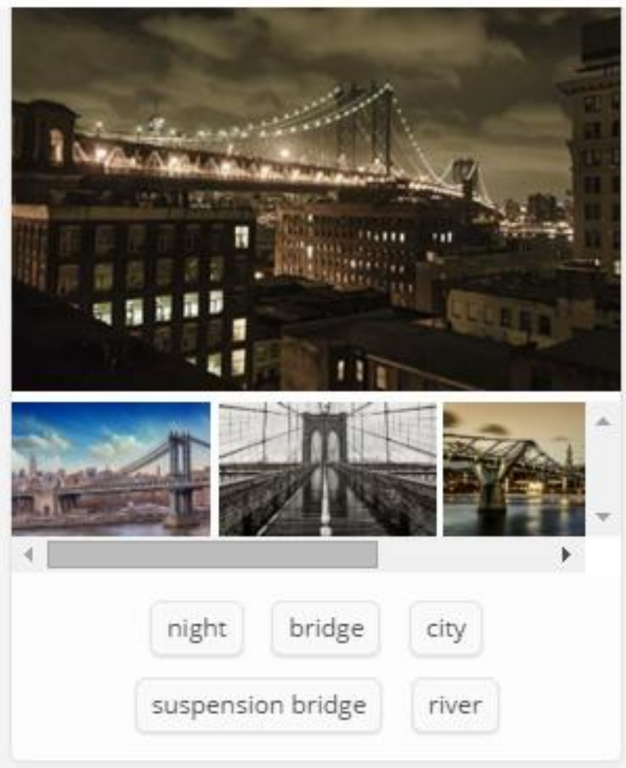


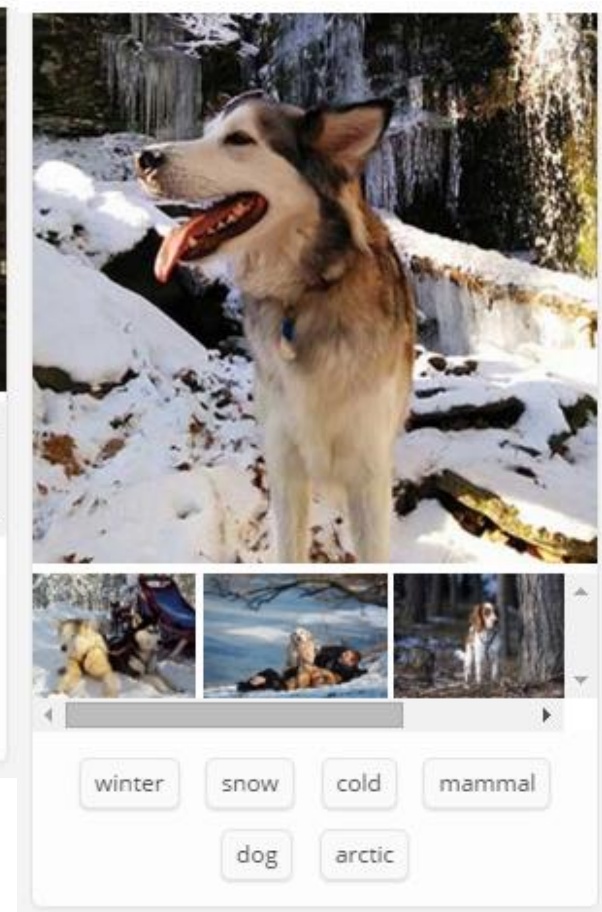
- **Be careful when taking test images from Google Search**
  - **Chances are they may have been seen in the training set...**

Image source: clarifai.com

Commercial Recognition Services







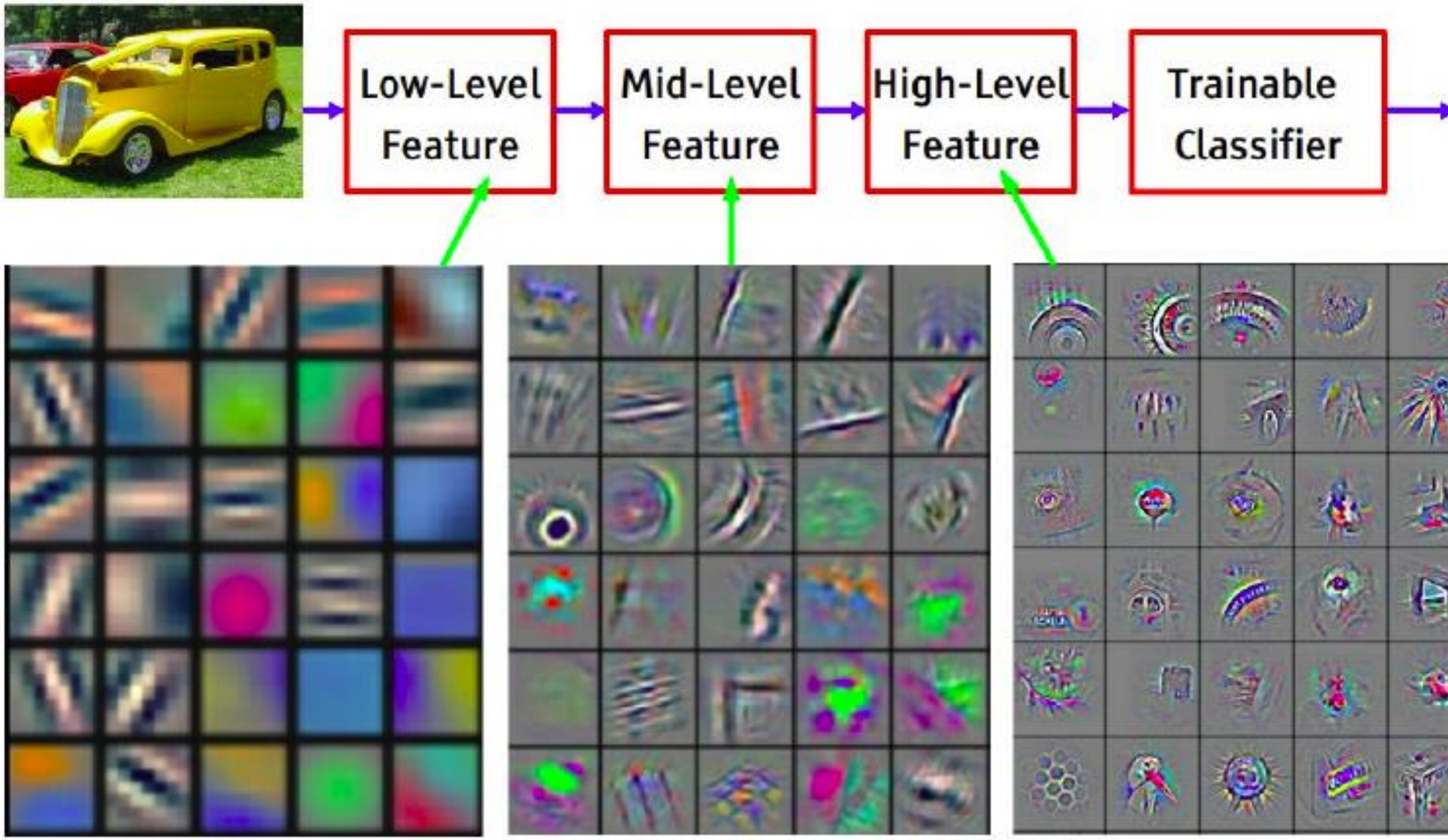
clarifai

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.

Effect of Multiple Convolution Layers



Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]