

Data Mining & Machine Learning

CS37300
Purdue University

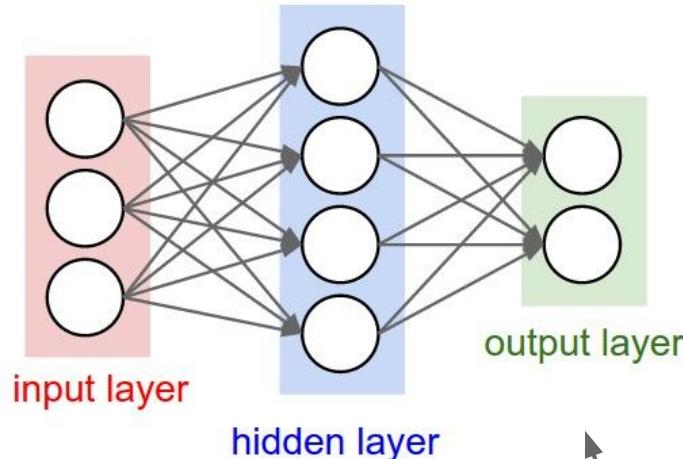
October 25, 2017

Deep Learning Architectures

Overview

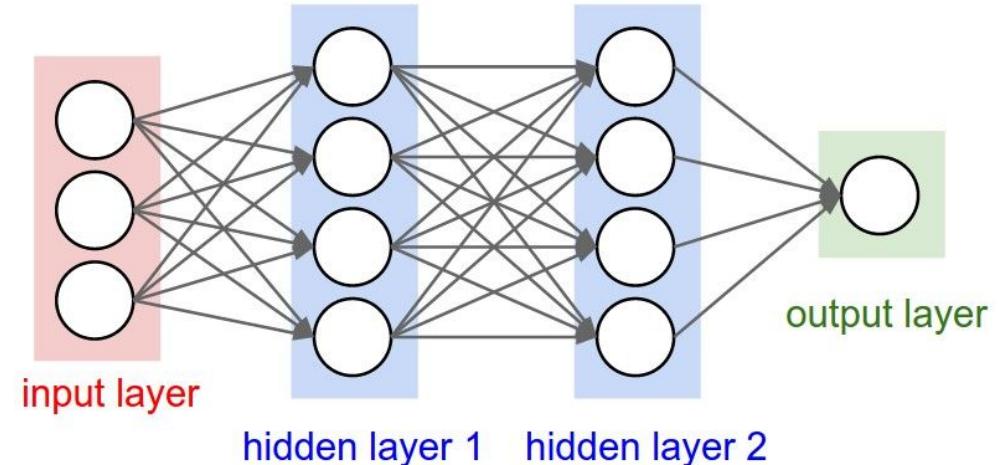
- Deep Learning Architectures
 - Feedforward neural networks
 - Convolutional neural networks
 - Filters
 - Filter Banks
 - Max Pooling

Feedforward Neural Networks



“2-layer Neural Net”, or
“1-hidden-layer Neural Net”

“Fully-connected” layers



“3-layer Neural Net”, or
“2-hidden-layer Neural Net”

Ack: Fei-Fei Li & Andrej Karpathy & Justin Johnson

- Layers do not need to be fully connected
- Size of layer (number of units) is another parameter

How Feedforward Networks Work

<https://www.youtube.com/watch?v=aircAruvnKk>

Convolutional Neural Networks (Motivation)

- Feedforward networks as input as a vector
- From image to vector... hard to account for spatial correlations in the vector representation (which pixels are next to each other?)

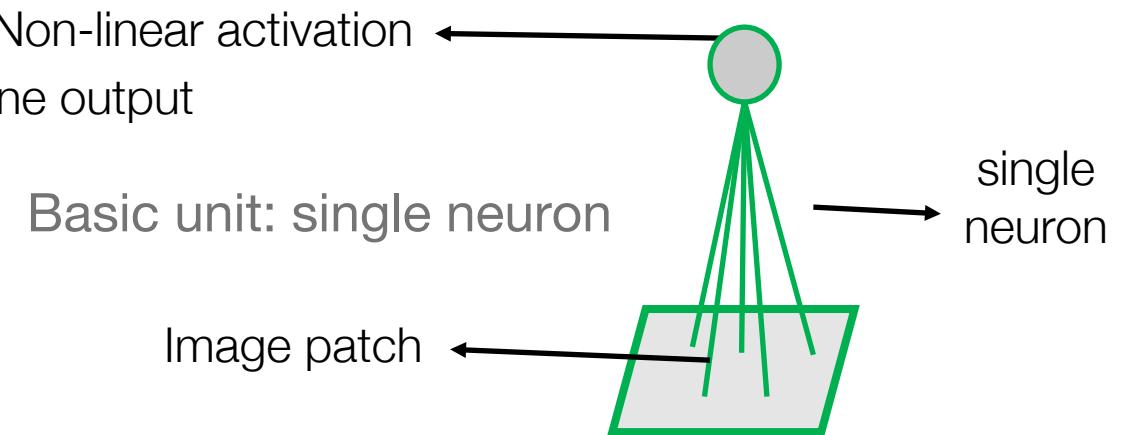


- Even harder to account for location and **colors**



Convolutional Neural Network (CNN)

Transforms large image patch into one output



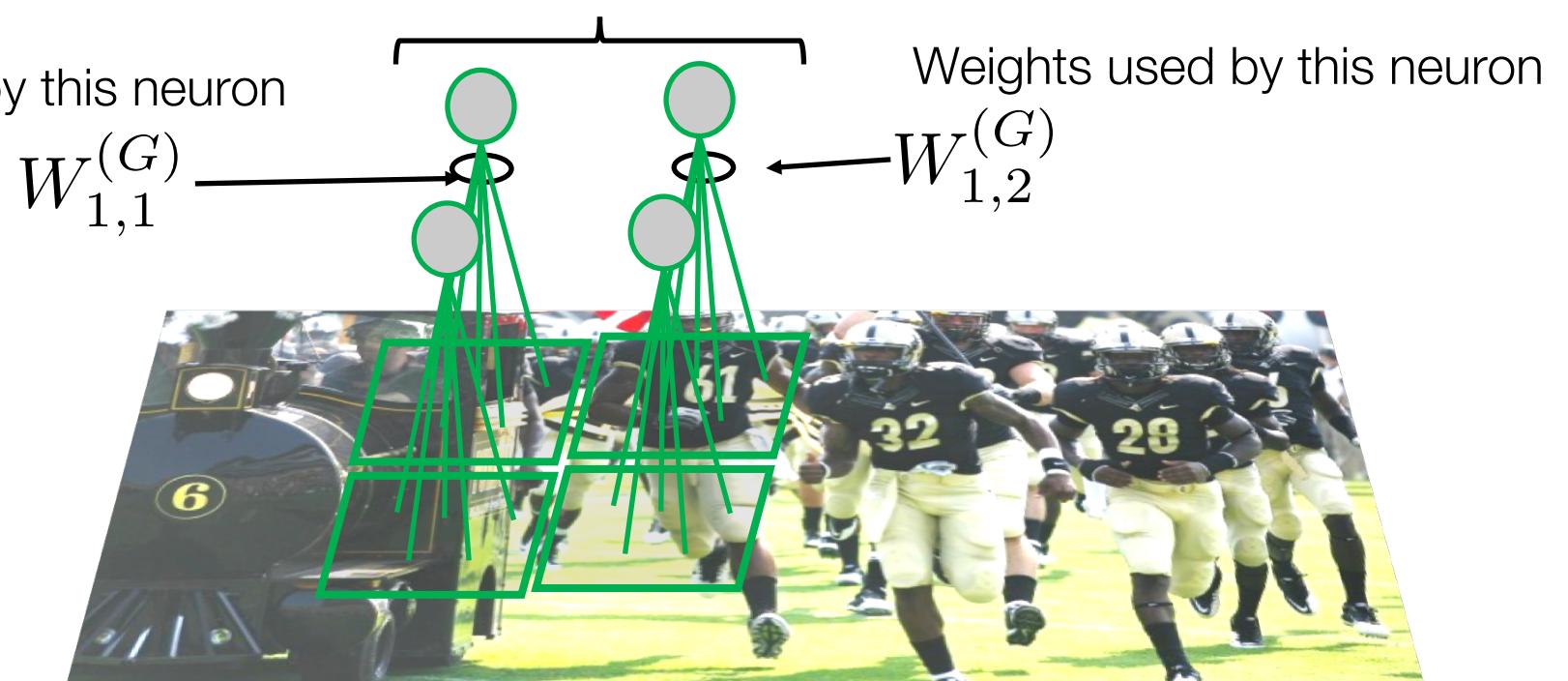
filter G

Weights used by this neuron

$W_{1,1}^{(G)}$

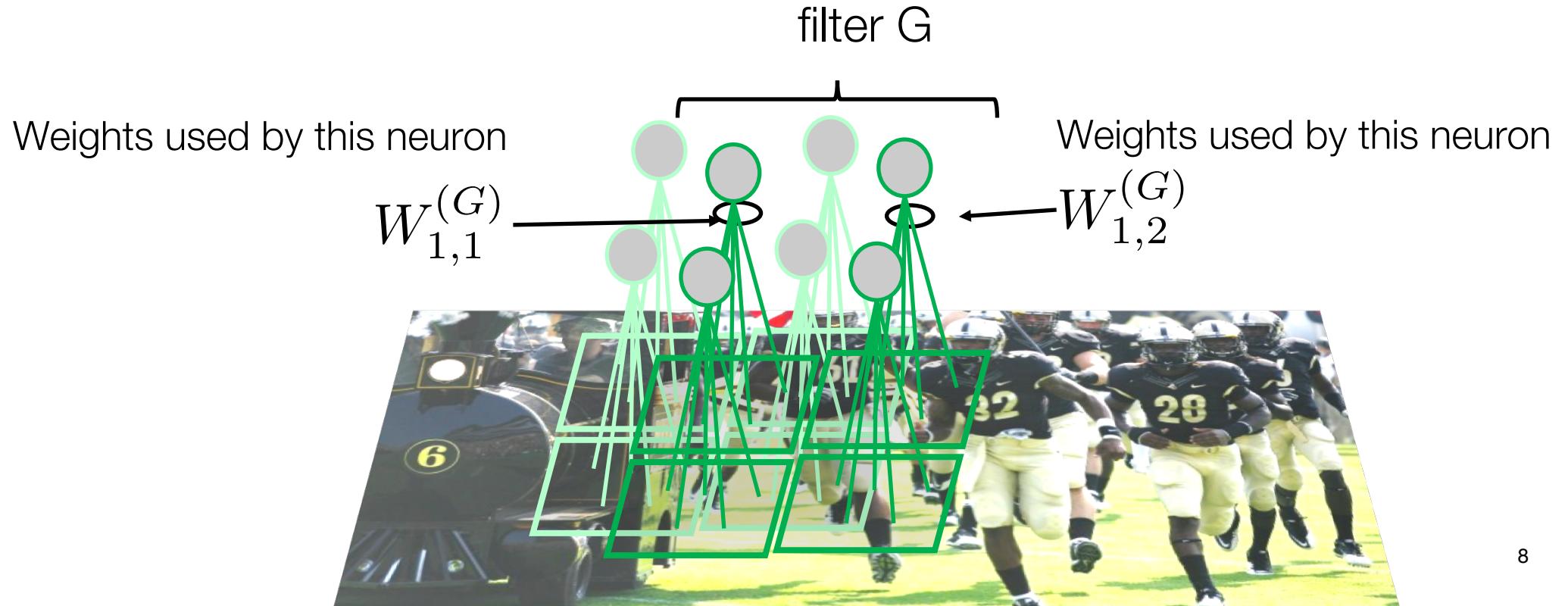
Weights used by this neuron

$W_{1,2}^{(G)}$



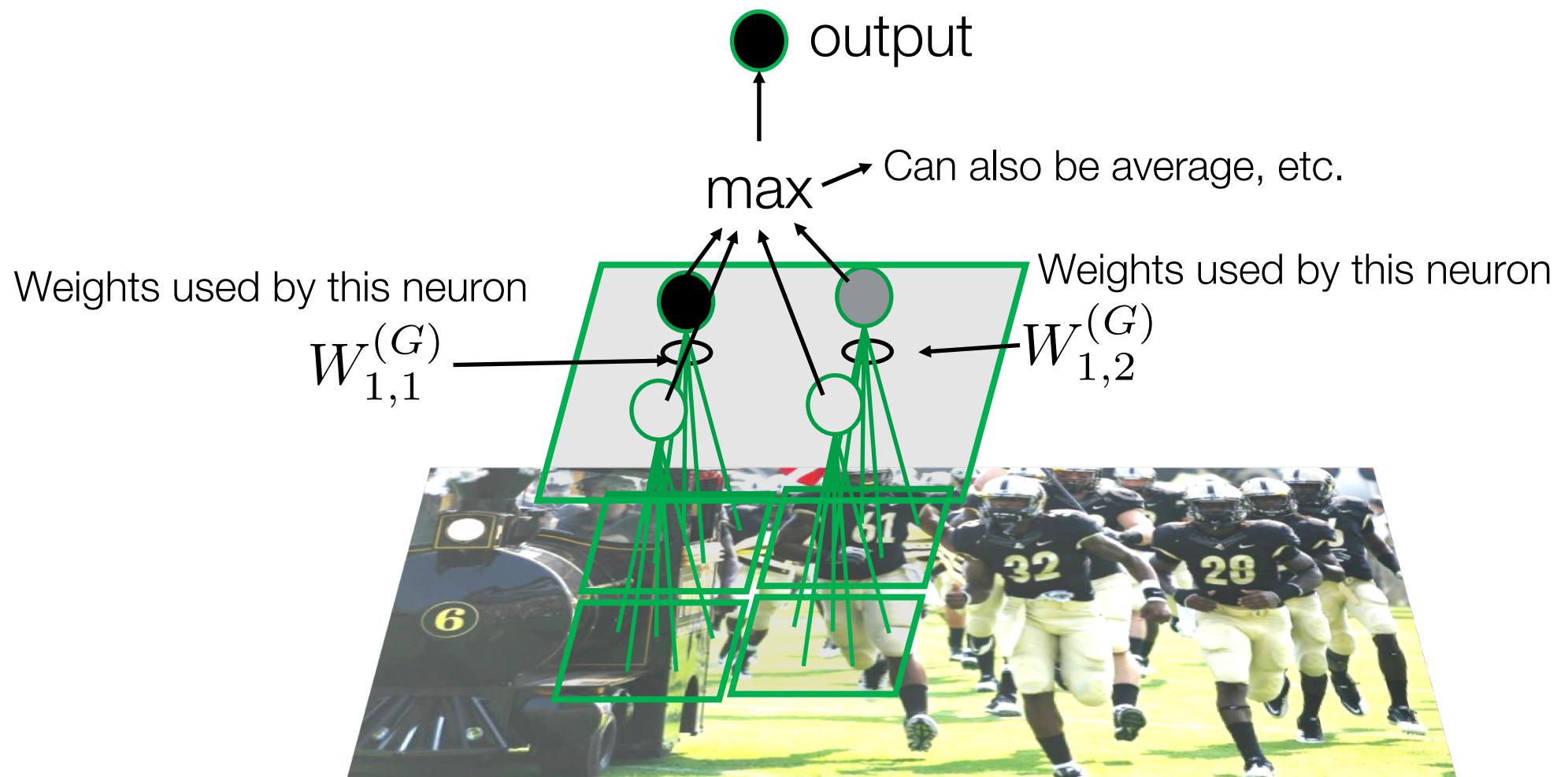
Convolutional Neural Network (CNN)

Cover the rest of the image by sliding the filter



Pooling

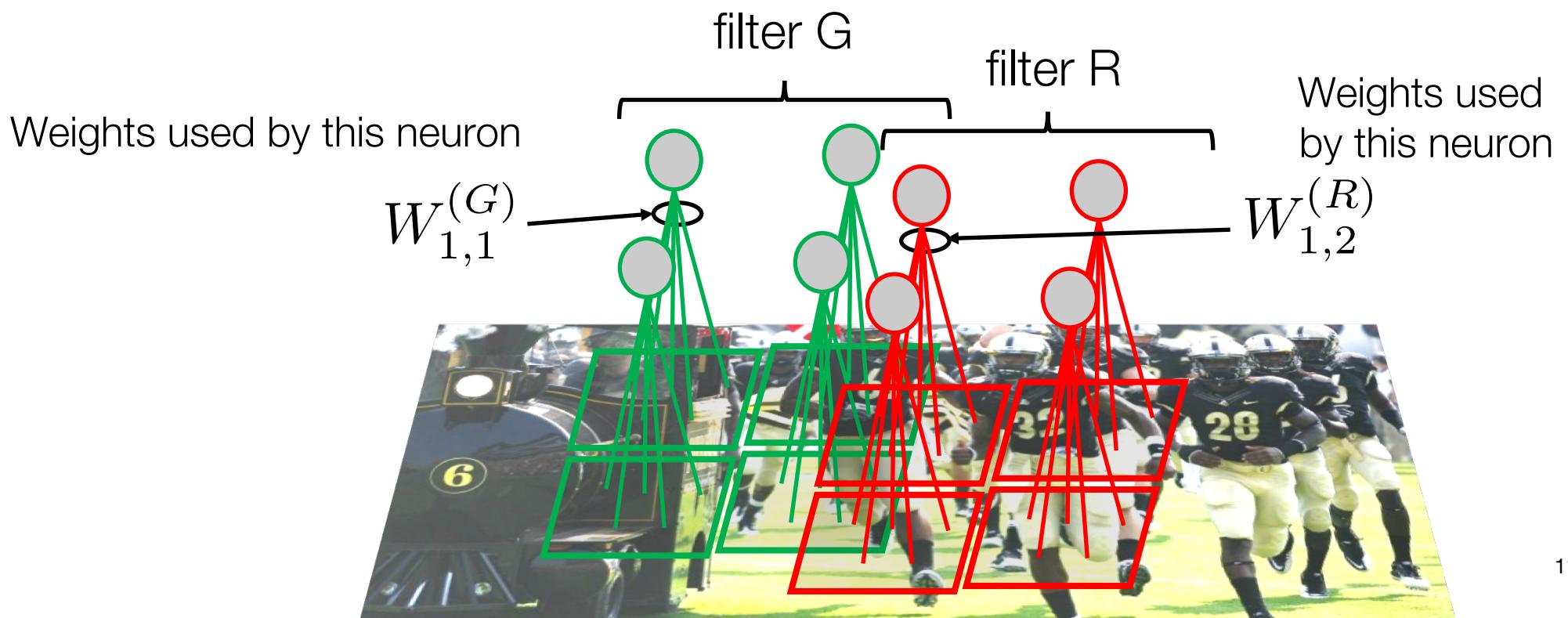
- Max pooling is a way to get a single output out of a filter



How to represent the image with different colors?

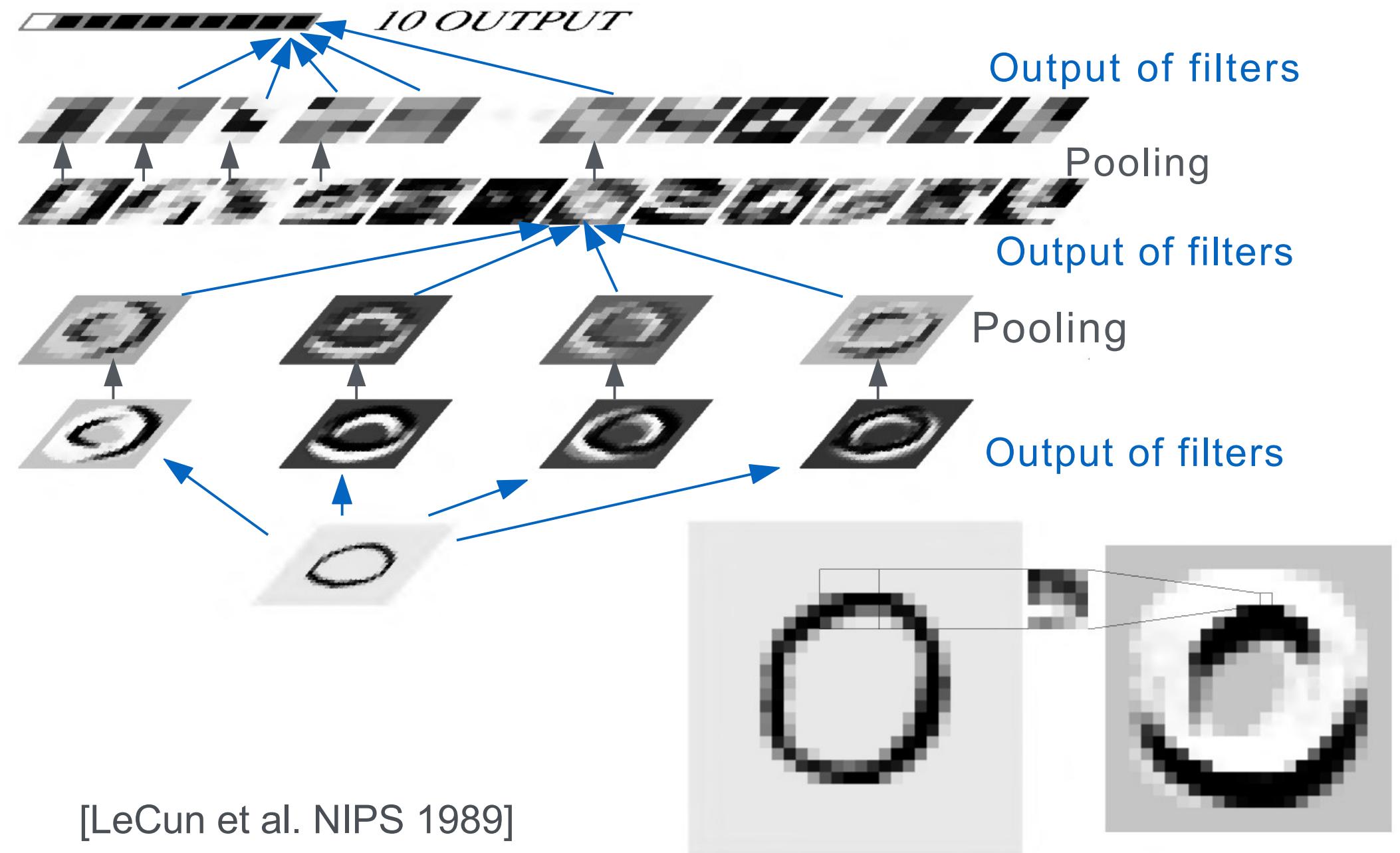
Convolutional Neural Network (CNN)

- We can use filters that focus on each color...

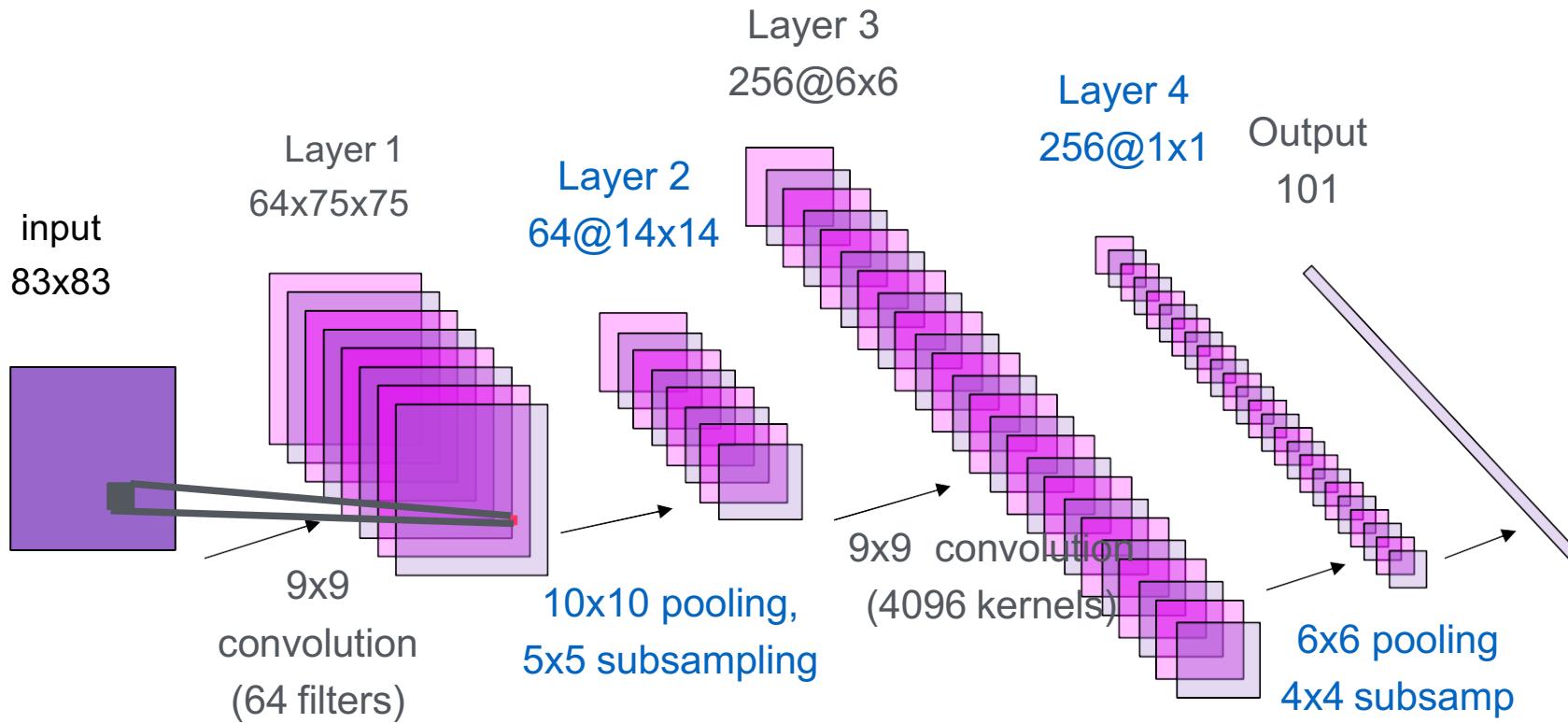


We can also have more than one filter for each color

Convolutional network



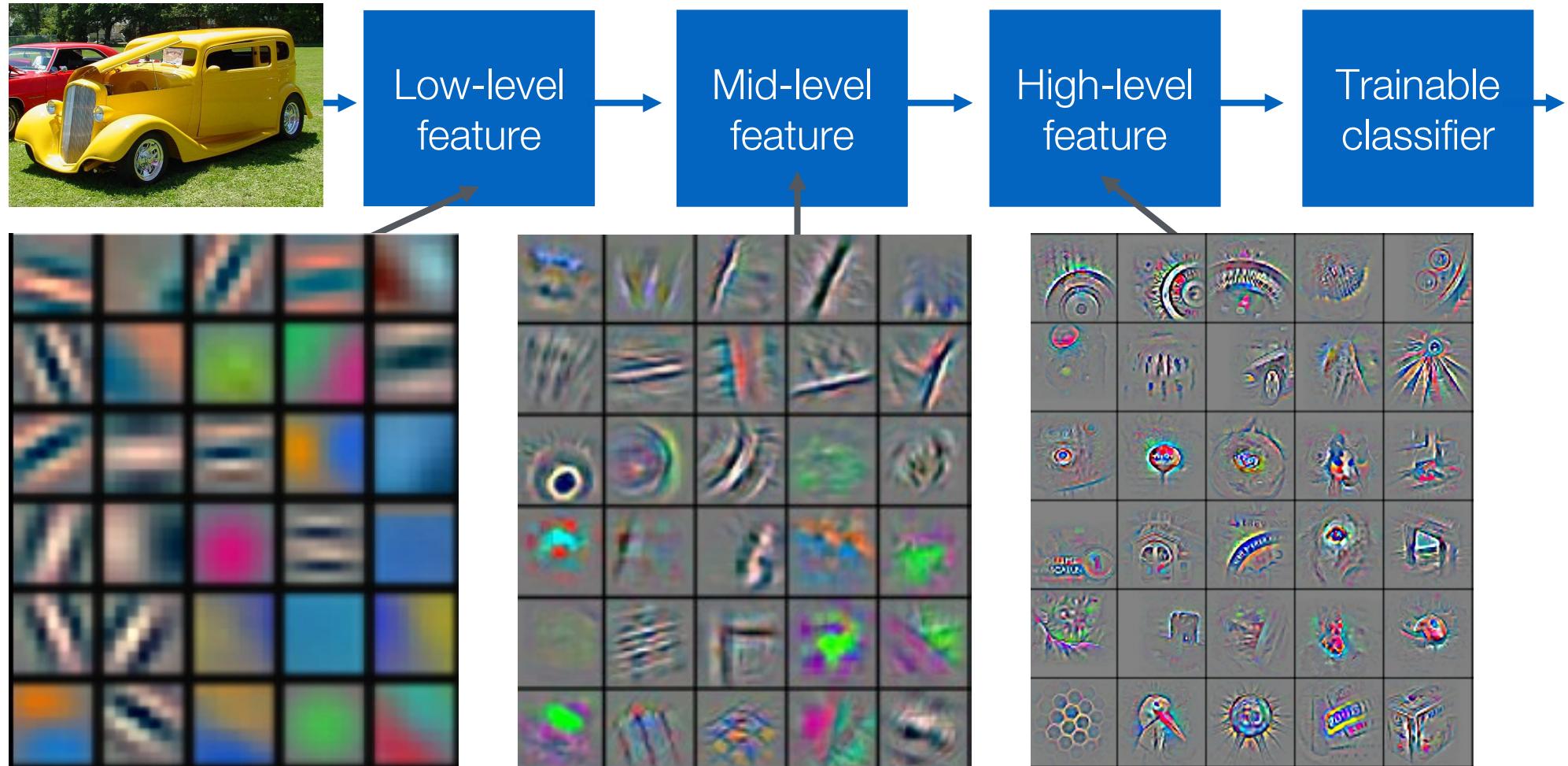
Convolutional Network (ConvNet)



- Non-Linearity: sigmoid, half-wave rectification (ReLU)
- Pooling: max, average, ...
- Training: Image labels

Deep learning = learning hierarchical representations

It's **deep** if it has more than one stage of non-linear feature transformation

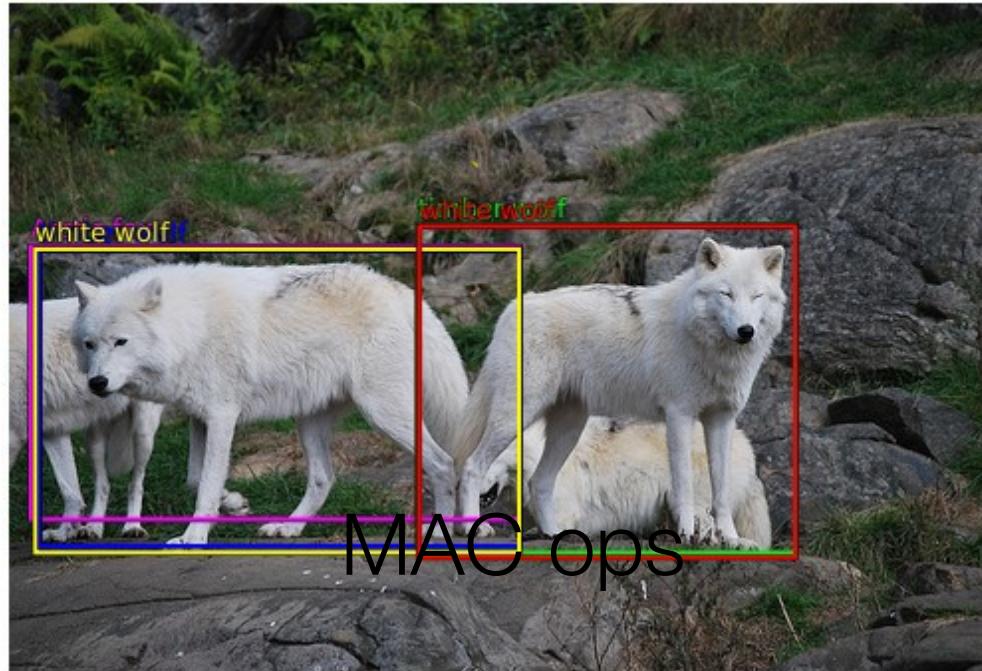


Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

Applications

Object Recognition in Images

Object Recognition



Top 5:

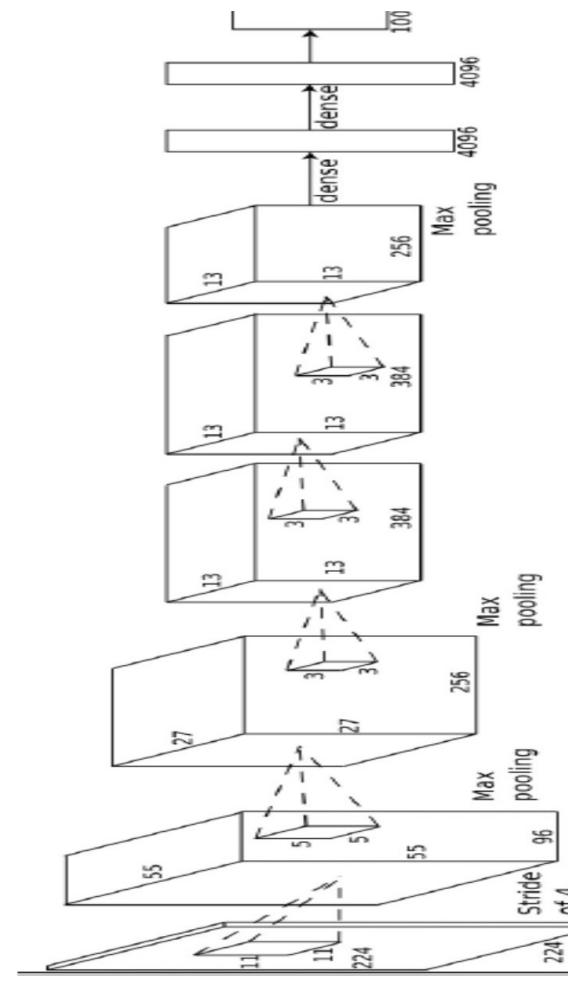
white wolf
white wolf
timber wolf
timber wolf
Arctic fox

ILSVRC2012_val_00000027.JPEG

Object Recognition [Krizhevsky, Sutskever, Hinton 2012]

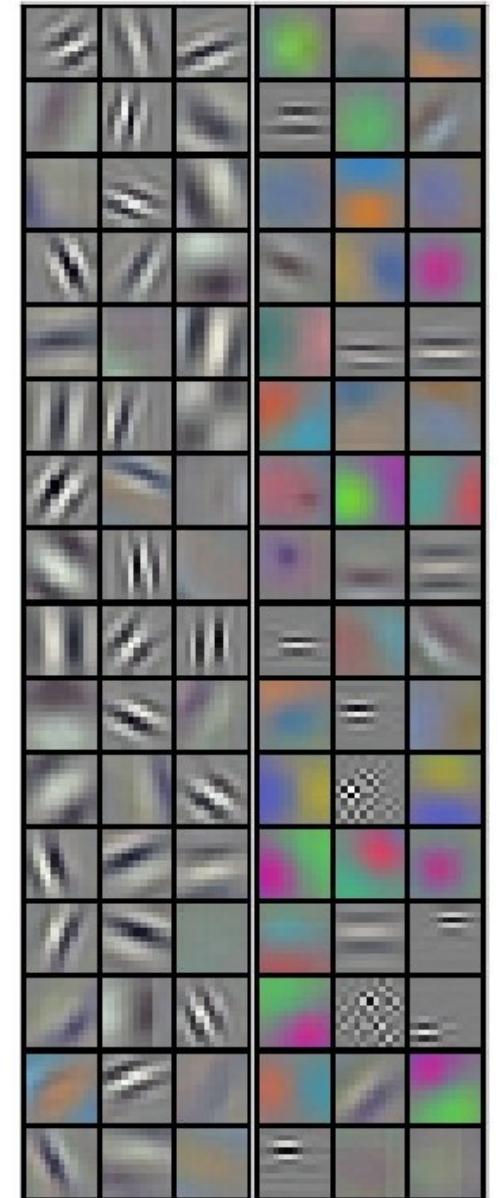
- Won the 2012 ImageNet LSVRC. 60 Million parameters, 832M Matrix multiplication + accumulation operations

4M	FULL CONNECT	4Mflop
16M	FULL 4096/ReLU	16M
37M	FULL 4096/ReLU	37M
	MAX POOLING	
442K	CONV 3x3/ReLU 256fm	74M
1.3M	CONV 3x3ReLU 384fm	224M
884K	CONV 3x3/ReLU 384fm	149M
	MAX POOLING 2x2sub	
	LOCAL CONTRAST NORM	
307K	CONV 11x11/ReLU 256fm	223M
	MAX POOL 2x2sub	
	LOCAL CONTRAST NORM	
35K	CONV 11x11/ReLU 96fm	105M



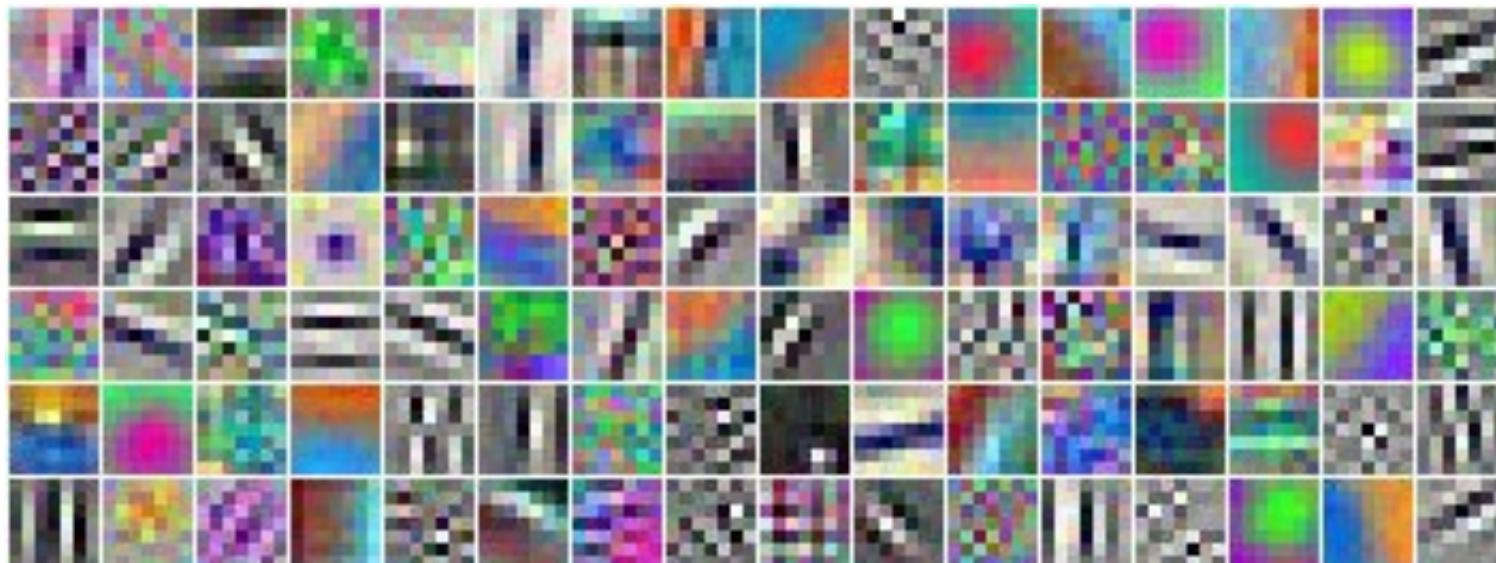
Object Recognition [Krizhevsky, Sutskever, Hinton 2012]

- Method: large convolutional net
 - 650K neurons, 832M synapses, 60M parameters
 - Trained with backprop on NVIDIA GPU
 - Trained “with all the tricks Yann came up with in the last 20 years, plus dropout” (Hinton, NIPS 2012)
 - Rectification, contrast normalization,...
- Error rate: 15% (whenever correct class isn't in top 5) Previous state of the art: 25% error
- **A revolution in computer vision**
- Acquired by Google in Jan 2013
- Deployed in Google+ Photo Tagging in May 2013



Filters: Layer 1 (7x7) and Layer 2 (7x7)

– Layer 1: 3x96 filters, RGB->96 feature maps, 7x7 Filters, stride 2



– Layer 2: 96x256 filters, 7x7

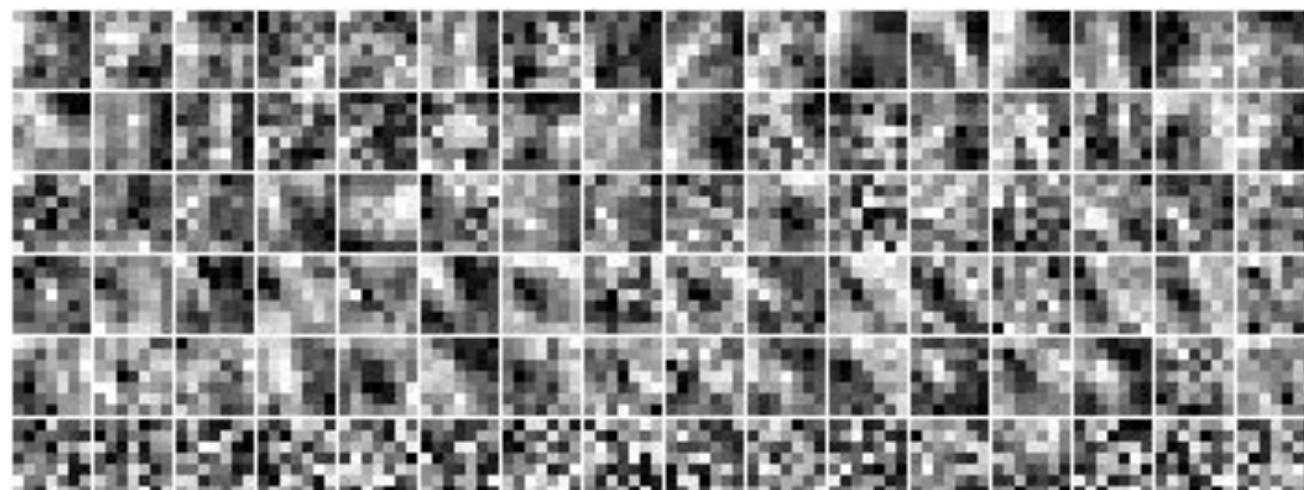
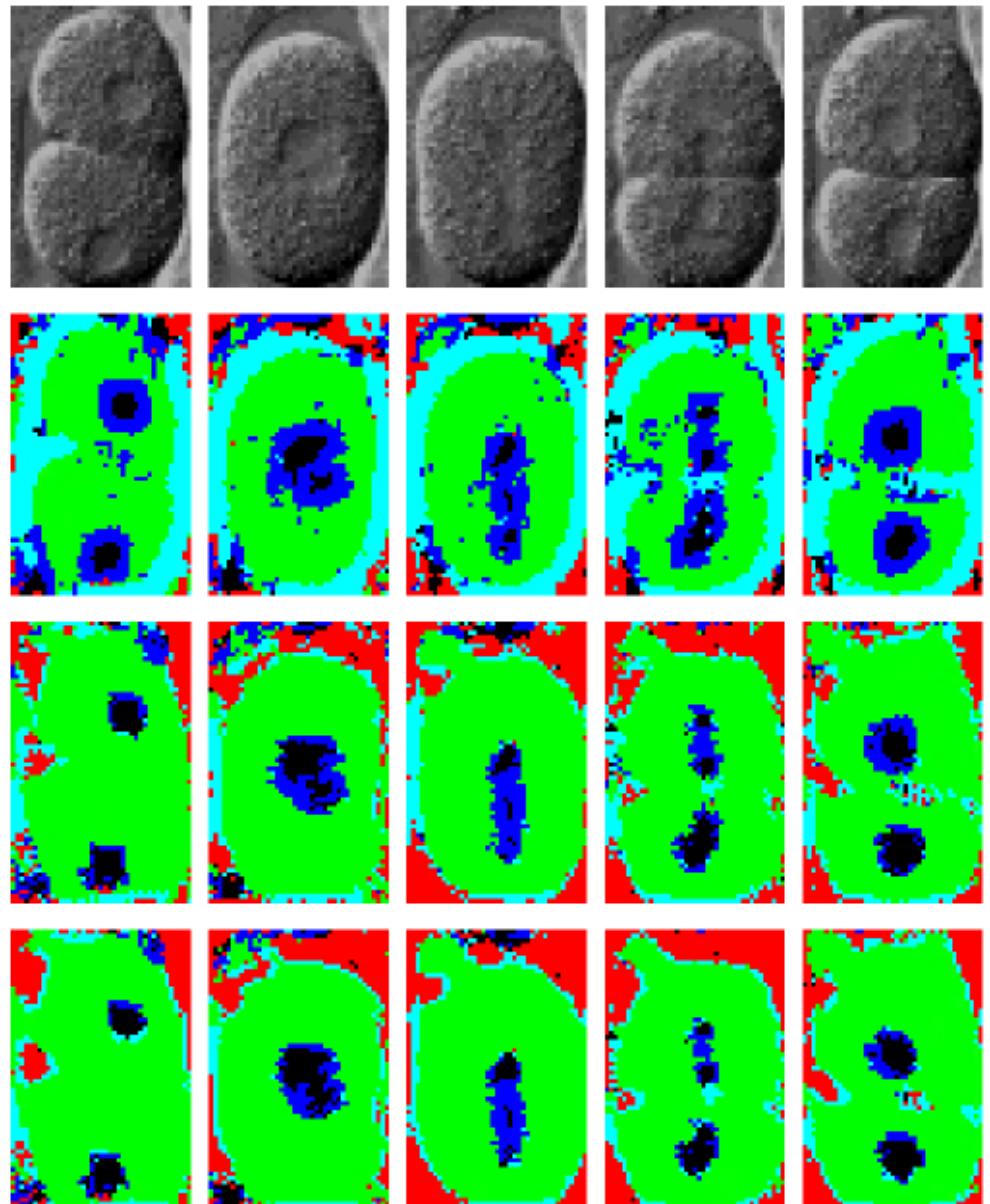


Image Segmentation

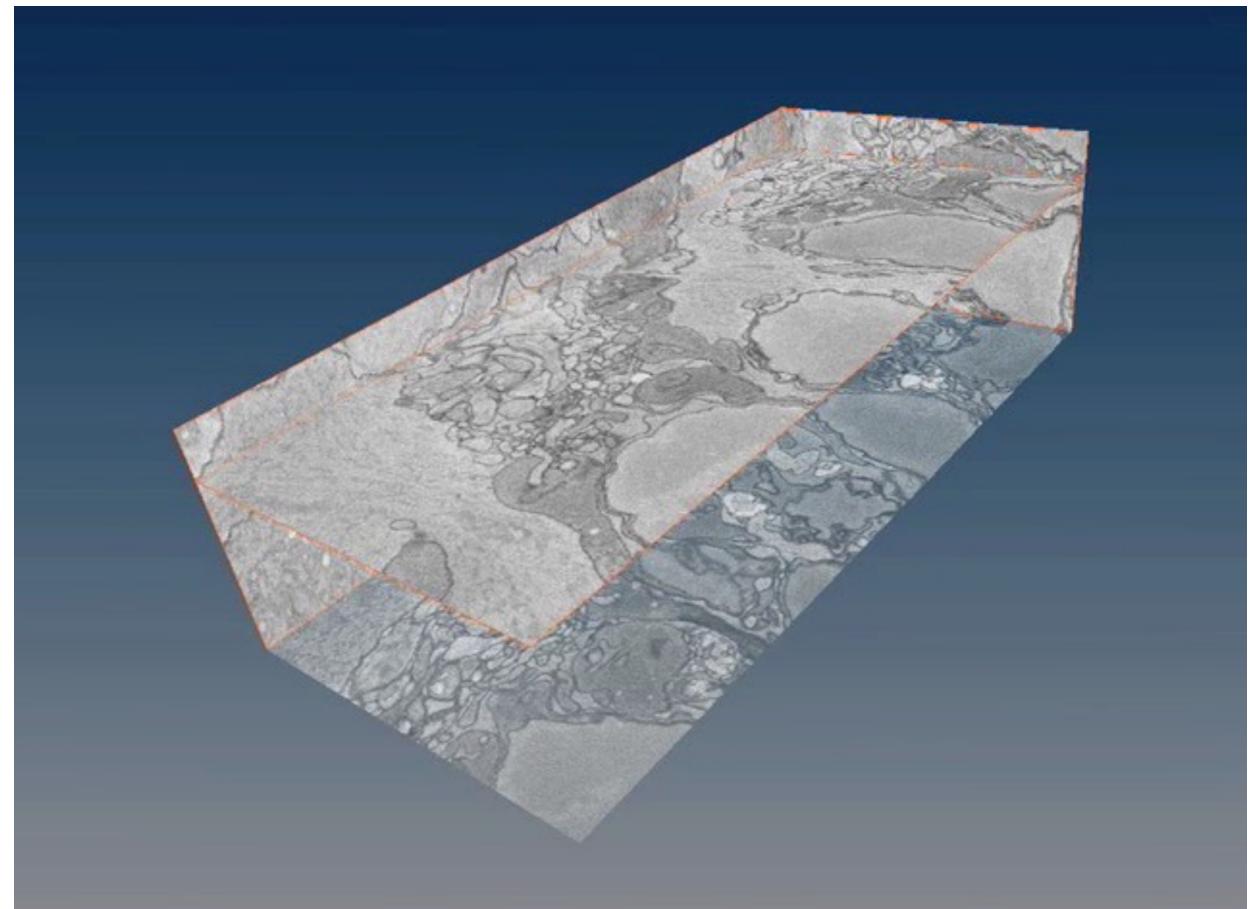
ConvNets for image segmentation

- Biological Image Segmentation
 - [Ning et al. IEEE-TIP 2005]
- Pixel labeling with large context using a convnet
- ConvNet takes a window of pixels and produces a label for the central pixel



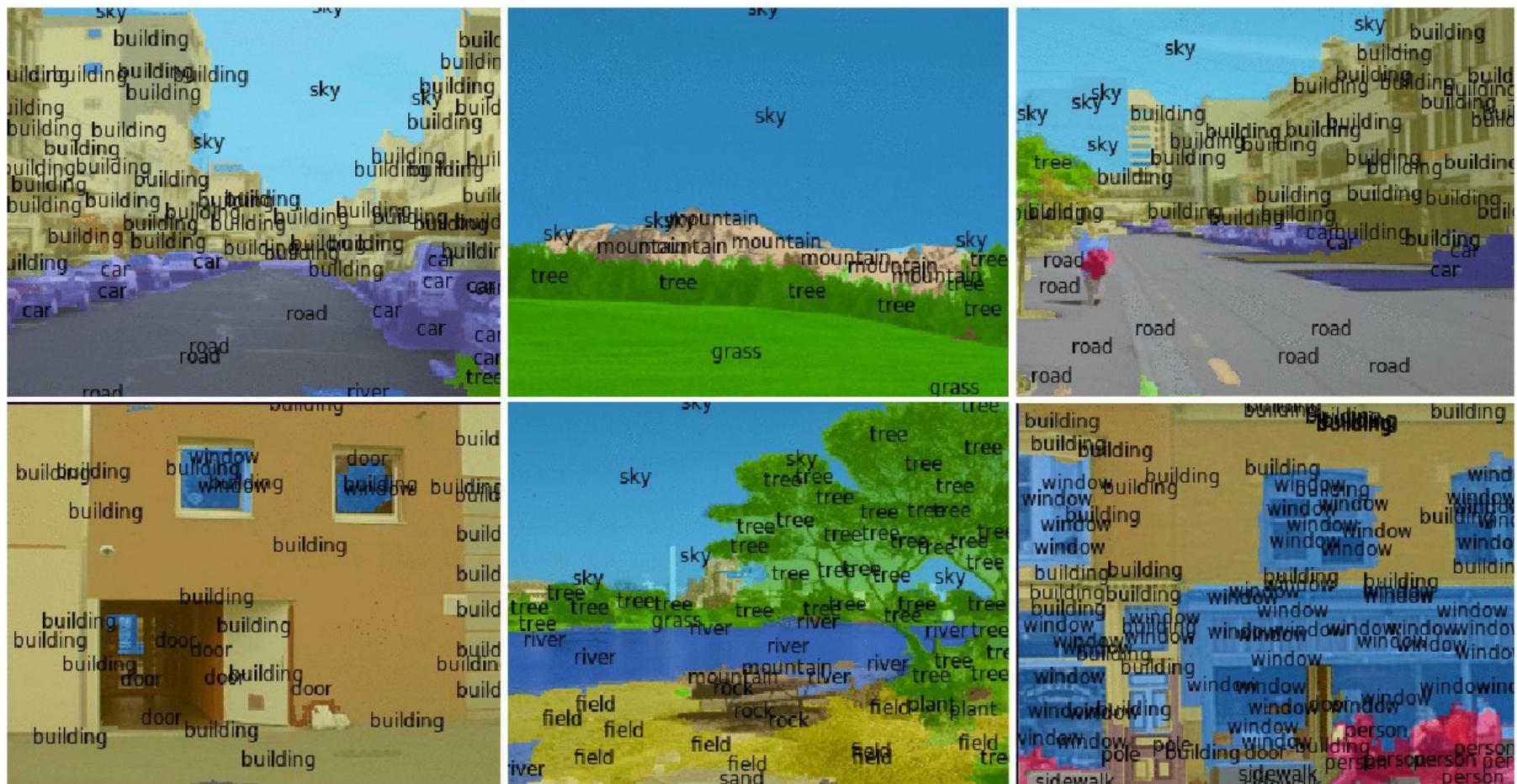
ConvNet in Connectomics [Jain, Turaga, Seung 2007-present]

- 3D ConvNet Volumetric Images
- Each voxel labeled as “membrane” or “non-membrane using a 7x7x7 voxel neighborhood
- Has become a standard method in connectomics



Semantic labeling / scene parsing: Labeling every pixel with the object it belongs to

- Would help identify obstacles, targets, landing sites, dangerous areas
- Would help line up depth map with edge maps



[Farabet et al. ICML 2012, PAMI 2013]