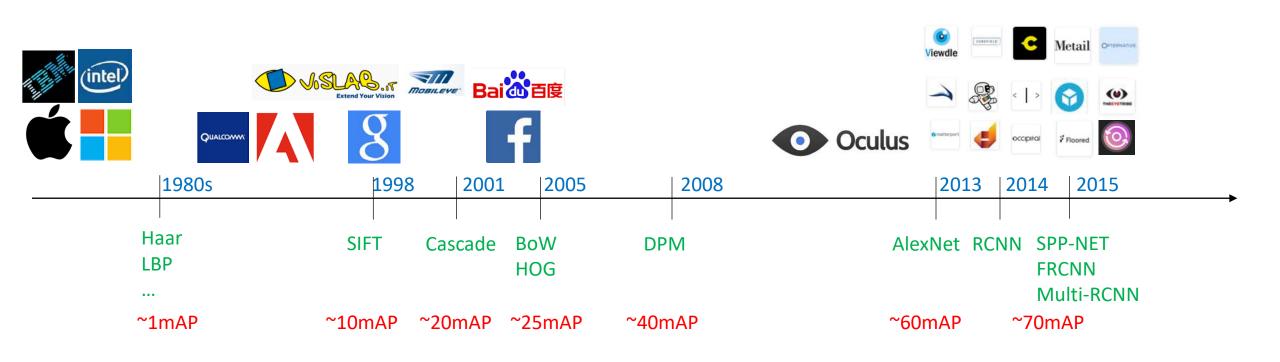
Object Detection Using CNNs

C.-C. Jay Kuo
University of Southern California

History in Object Detection

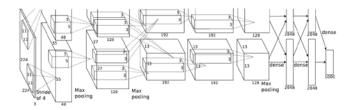


mAP: Mean Average Precision

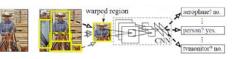
Object Detection with DNN

2013 2014 2015

AlexNet



RCNN



Caffe

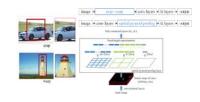
DenseNet



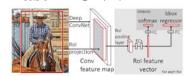
Part-Based R-CNN



SPP-Net



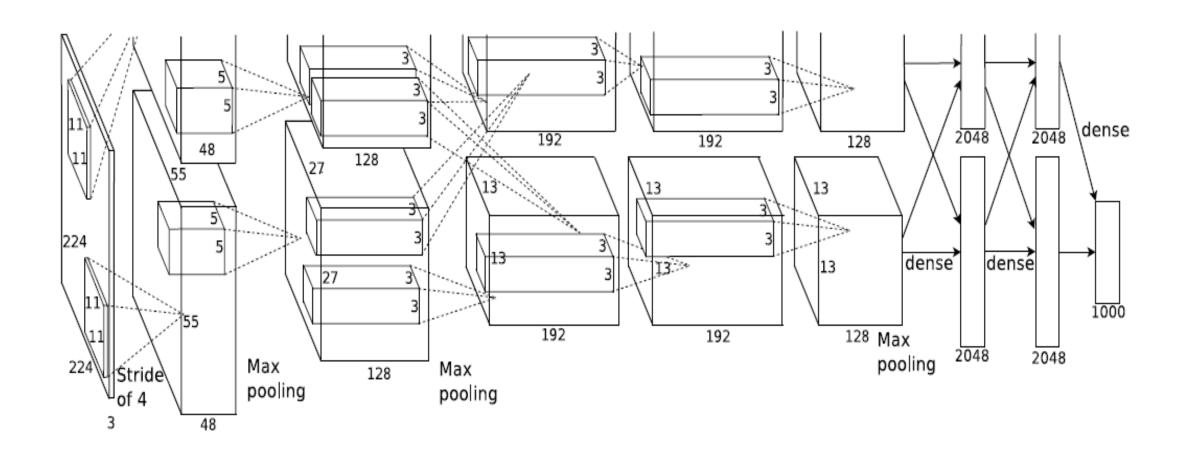
Fast R-CNN



Faster R-CNN

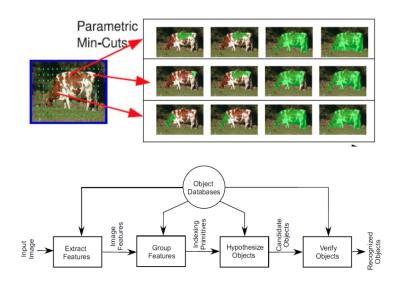


Alex Net (2013)



Region Proposal with CNN (RCNN)

Constraint Parametric Min-Cut



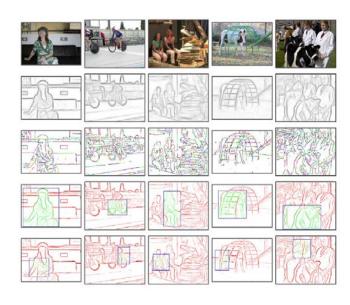
J. Carreira and C.sminchisescu. CPMC Automatic object segmentation using constrained parametric min-cust. In CVPR, 2012

Selective Search



J.R.R Uijlings, K.E.A. Van De Sande, T. Gevers, and A.W.M. Smeulders, Selective Search for Object Recognition. In IJCV 2013

EdgeBox



C. L. Zitnick and P. Dollar, "Edge boxes: Locating object 'proposals from edges," in ECCV, 2014.

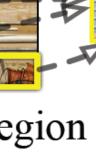
RCNN Flowchart

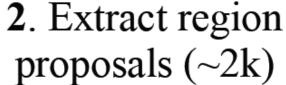


1. Input image

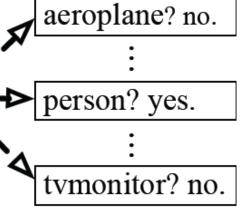








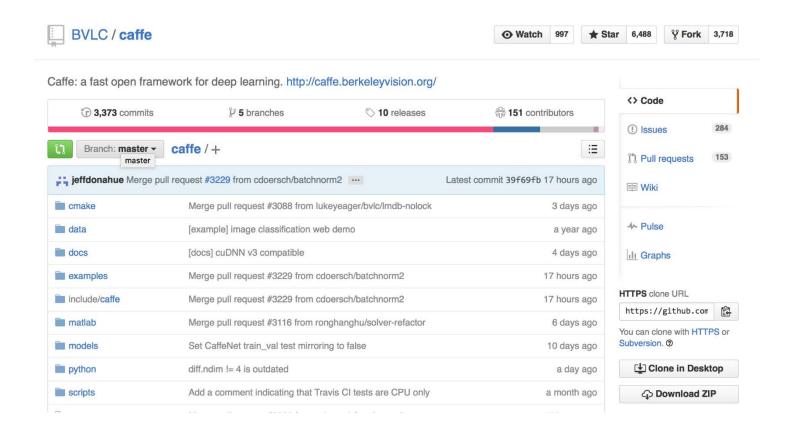




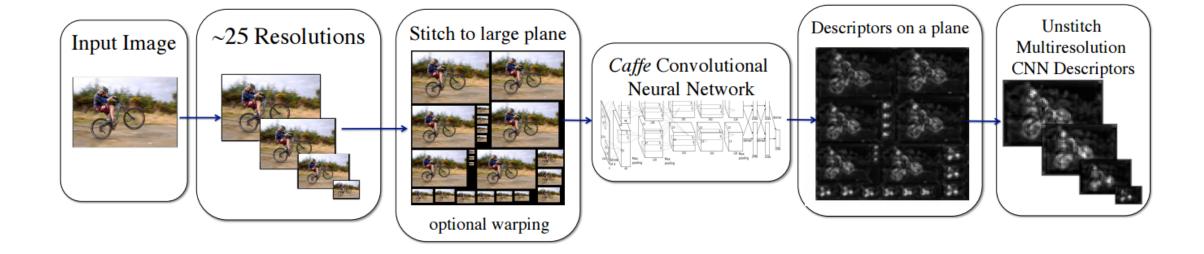
4. Classify regions

warped region

Caffe: Public Domain Software

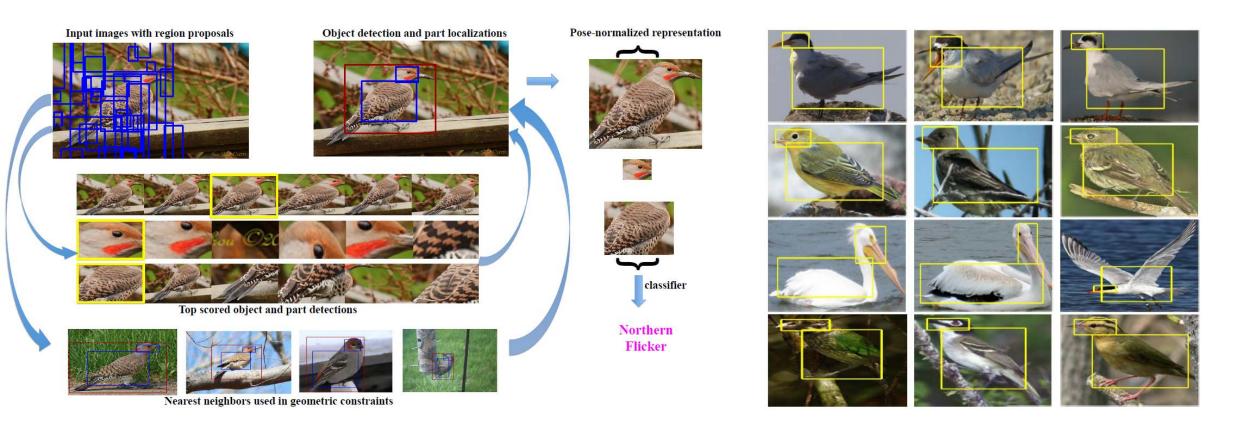


Dense Net



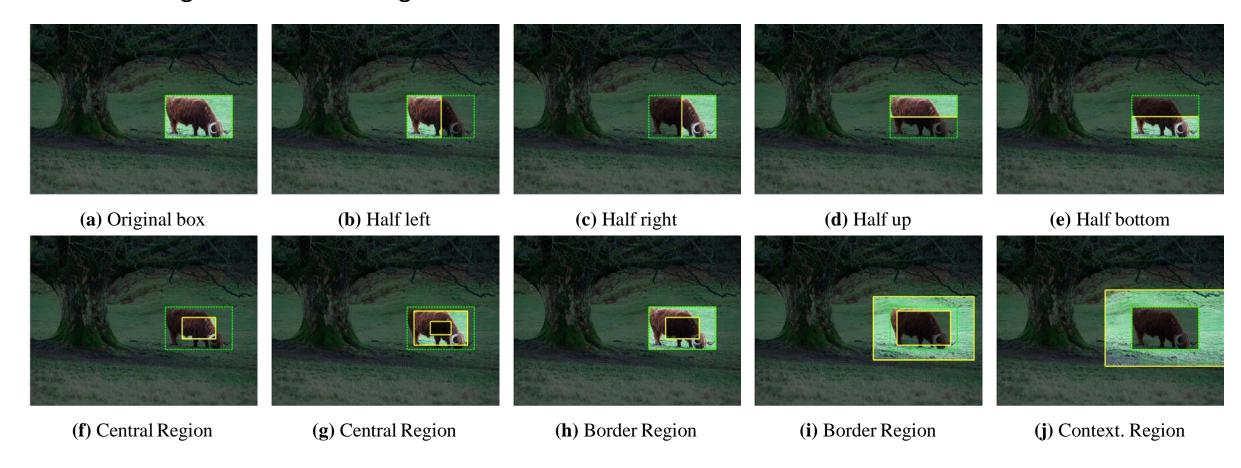
Part-based CNN

• Fine-grained Detection

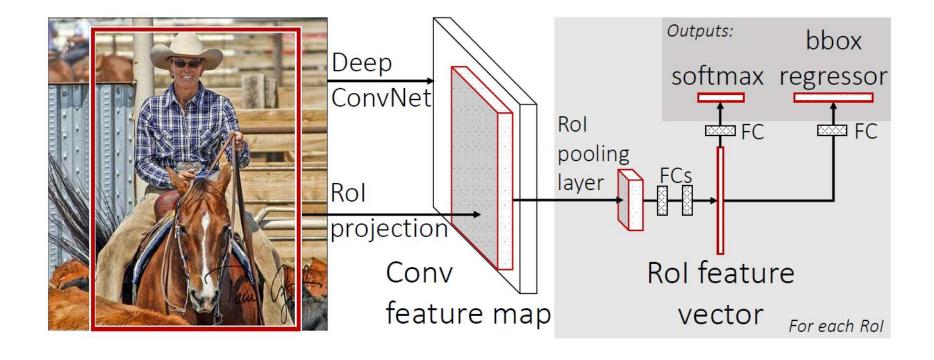


Multi-region CNN

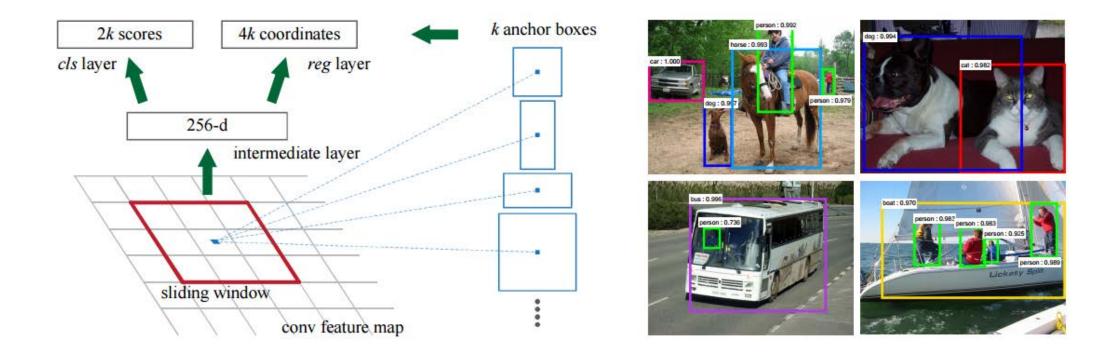
Multi-region & semantic segmentation-aware CNN model:



Fast RCNN

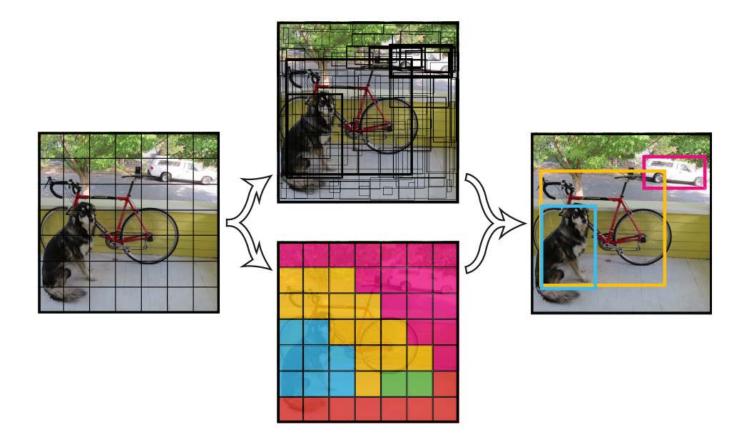


Faster RCNN



YOLO

• More improved CNN based Object Detector:



Performance Comparison

• State-of-the-art methods comparison:

Method	ROI needed?	Regression?	Accuracy	Speed
RCNN	Υ	N	62.4	0.01 fps
Fast-RCNN	Υ	Υ	68.4	0.01 fps
Faster-RCNN	N	Υ	70.4	3 fps
YOLO	N	Υ	57.9	45 fps

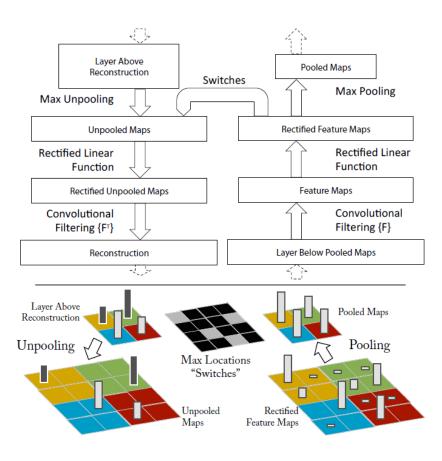
Comments

- Alex Net was the first one proposed for object detection
- Recent publications have focused on two aspects:
 - Fine-tuning for better region proposals, which serve as a critical preprocessing step for DNN
 - Seeking more applications
- Both hardware and software are accessible to the public
- However, no labeled training data are accessible to the public
- It can be implemented in the cloud platform, but not in the embedded system platform

Visualization of Deep Features

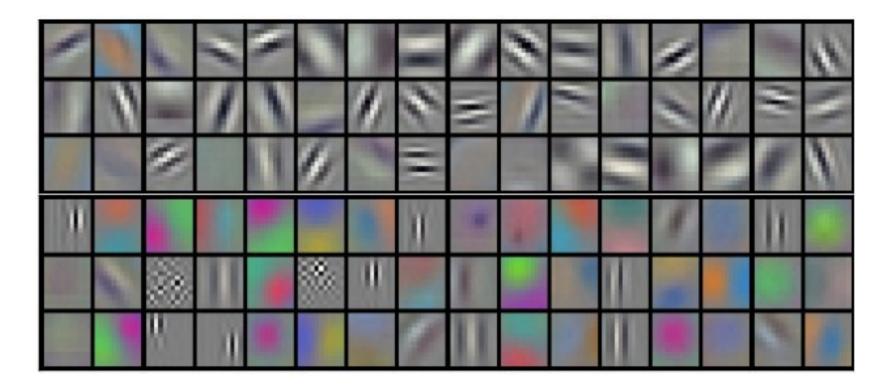
Feature Visualization

De-conv Network:



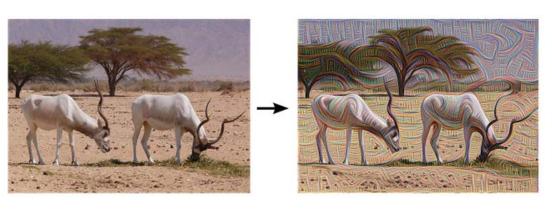
Features at Lower Layers

Conv1 Filter Response (Gabor-like filters)



Reconstruction at Lower Layers

Extracting low level features (oriented edges/contours)

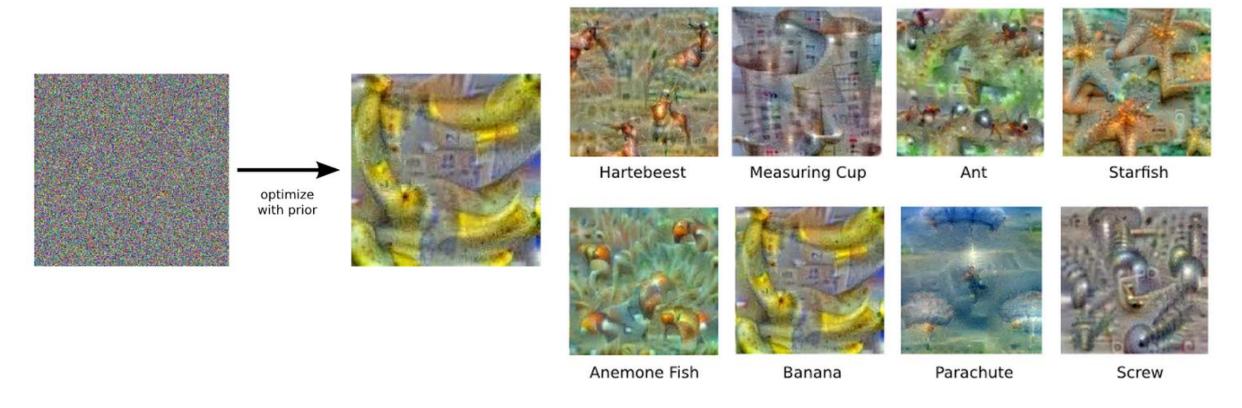






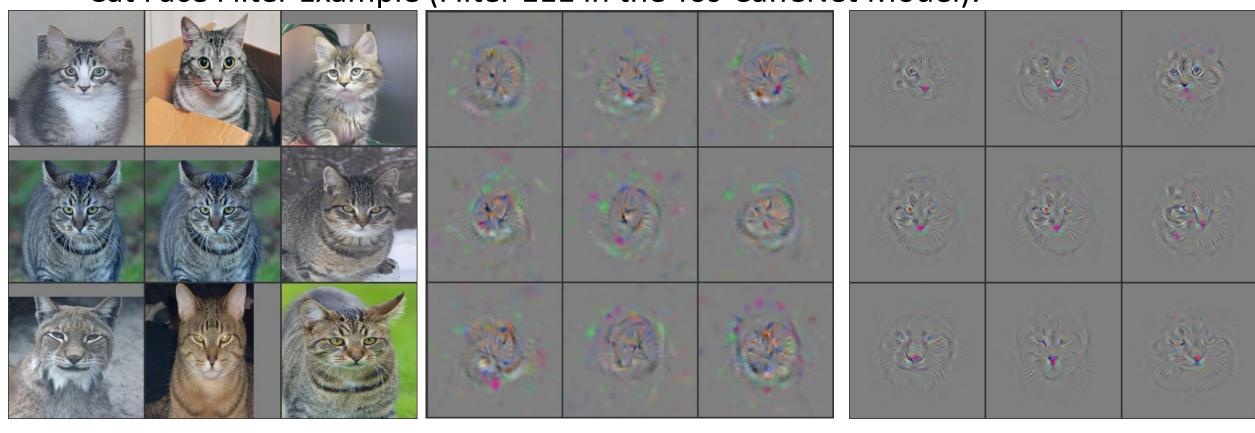
Reconstruction at Higher Layers

Random Noise Input



Deep Features at Conv5

• Cat Face Filter Example (Filter 111 in the Yos-CaffeNet Model):



Top 9 Input Activation Images

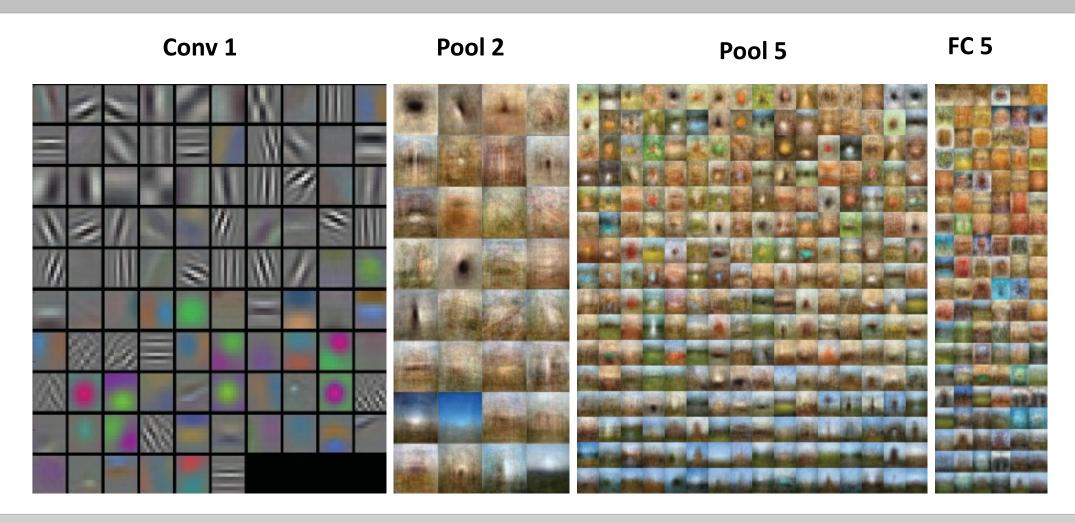
Max Reconstructed Input Activation

Deconv Image

Comments

- Deep feature visualization provides helpful insight into the role played by various layers
 - Lower layers subband-filtered images with large coverage
 - Higher layers contour-dominating images with focused coverage
 - Three general trends
 - Contour formation
 - From surfaces to contours
 - Color reduction
 - From colorful to colorless
 - Background removal
 - From larger regions (with background) to focused regions (without background)
- The whole process can be viewed as a spatial (contour) feature binding process

Deep Features for Scene Recognition

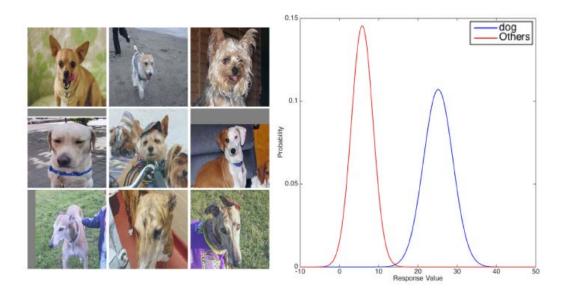


Zhou et al. "Learning deep features for scene recognition using places database", NIPS 2014.

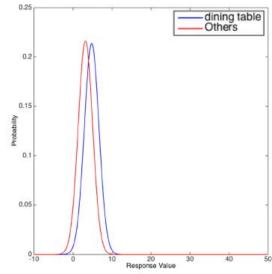
Gaussian Confusion Measure (GCM)

Conv5 Filter Response

Gaussian Confusion Measure



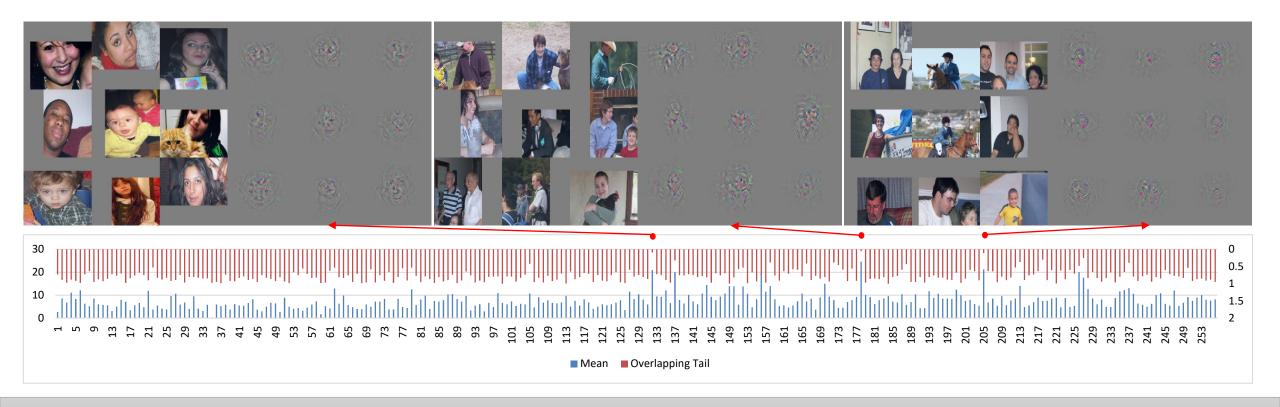




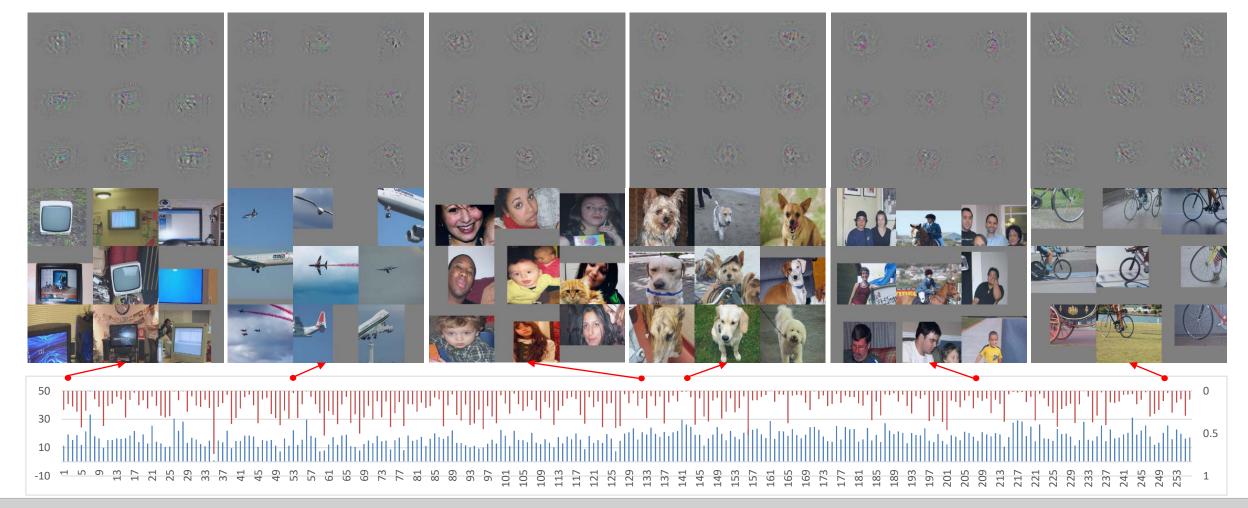
Detection Error and Mean of Conv5 Filter Responses

Responses w.r.t. human objects

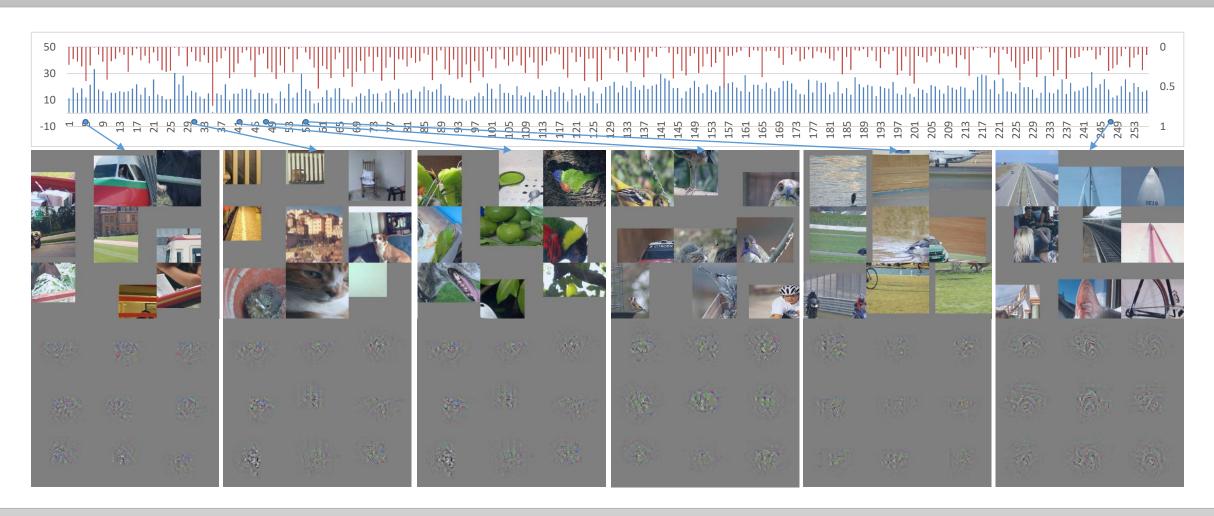
-- Known as "Grandmother Cell (GMC)" like features for human objects



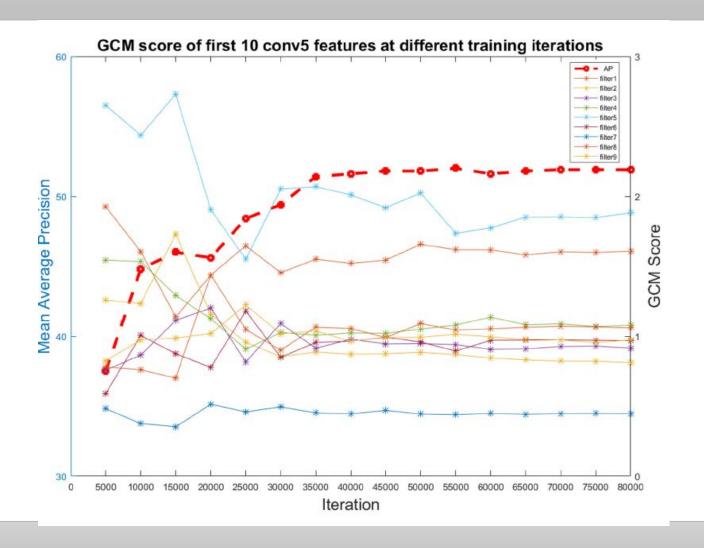
Optimal Conv5 Filters Against Multiple Object Classes (Good Examples)



Optimal Conv5 Filters Against Multiple Object Classes (Bad Examples)



GCM Scores of Top 10 Conv5 Features versus Iteration Number

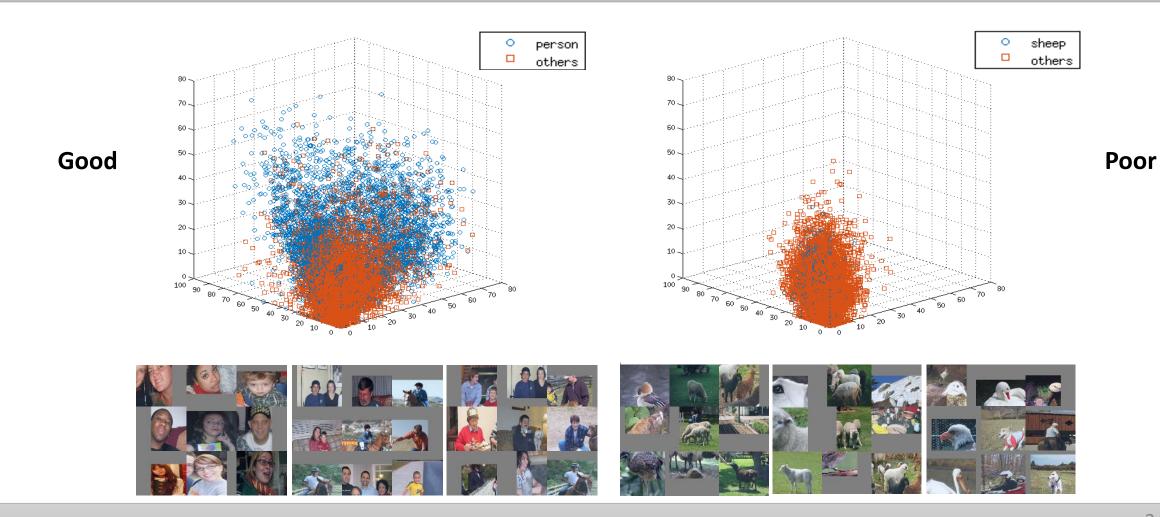


Number of GMC-like Features versus Iteration Number

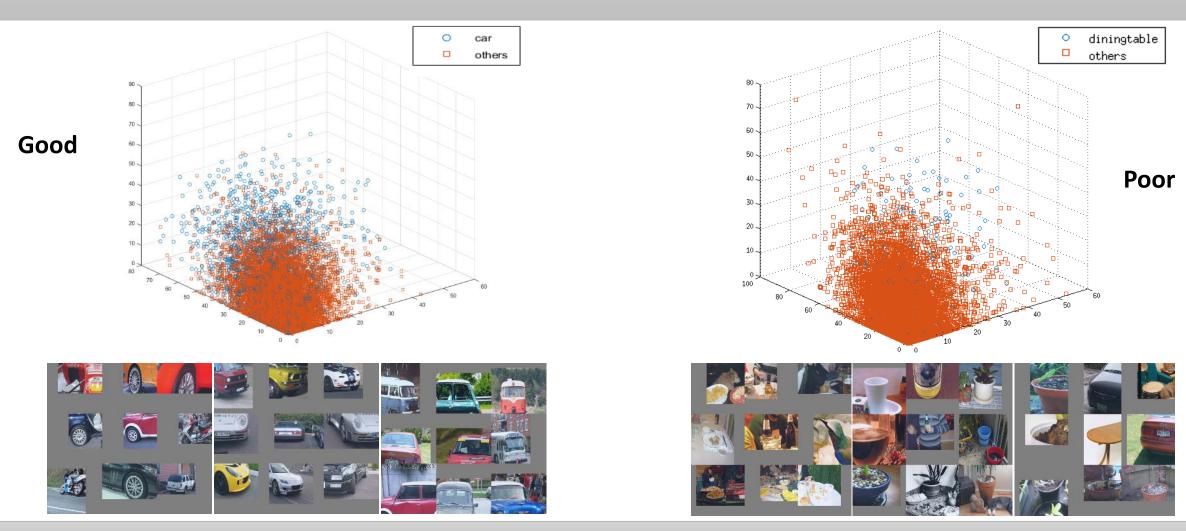
Network	Iteration	aeroplane	bicycle	bird	boat	bottle	bus	Car	cat	chair	cow	table	dog	horse	motorbike	person	plant	sheep	sofa	train	tv	sum
Caffe	10000	4	2	0	1	0	5	0	4	0	2	1	4	4	9	3	1	1	2	1	5	49
	20000	6	3	0	0	0	5	0	8	0	2	2	9	6	10	3	1	1	2	2	5	65
	30000	6	2	0	0	0	6	0	8	0	2	3	5	4	8	3	1	1	2	1	5	57
	40000	6	2	0	1	0	8	2	7	0	2	3	6	5	9	3	2	1	3	3	5	68
	80000	5	2	0	1	0	7	2	9	0	2	5	6	5	10	3	2.	1	4	4	5	73
VGG	10000	8	5	0	1	2	11	3	8	0	3	2	6	6	2	4	2	1	3	6	6	79
	20000	6	2	1	1	2	9	3	9	0	2	2	11	3	8	4	1	1	2	4	5	76
	30000	6	3	1	1	1	6	3	4	0	1	2	7	1	1	4	1	1	1	1	4	49
	40000	7	3	1	1	2	9	3	5	0	2	2	6	4	3	3	1	1	1	2	4	60
	80000	8	3	1	1	2	10	3	7	0	3	2	7	5	4	4	2	1	1	2	4	70

Cluster Purity Measure (CPM)

Examples of Cluster Purity Measure (1)



Examples of Cluster Purity Measure (2)



Comments

- Besides feature visualization, we can quantify the power of a particular filter in discriminating an object class
 - 1-D case case: A smaller "Gaussian Confusion Measure (GCM)"
 - Multiple-Dimensional case: A higher "Cluster Purity Measure (CPM)"
- GCM works for a class of objects with a similar setting
- CPM works for a class of objects with multiple settings