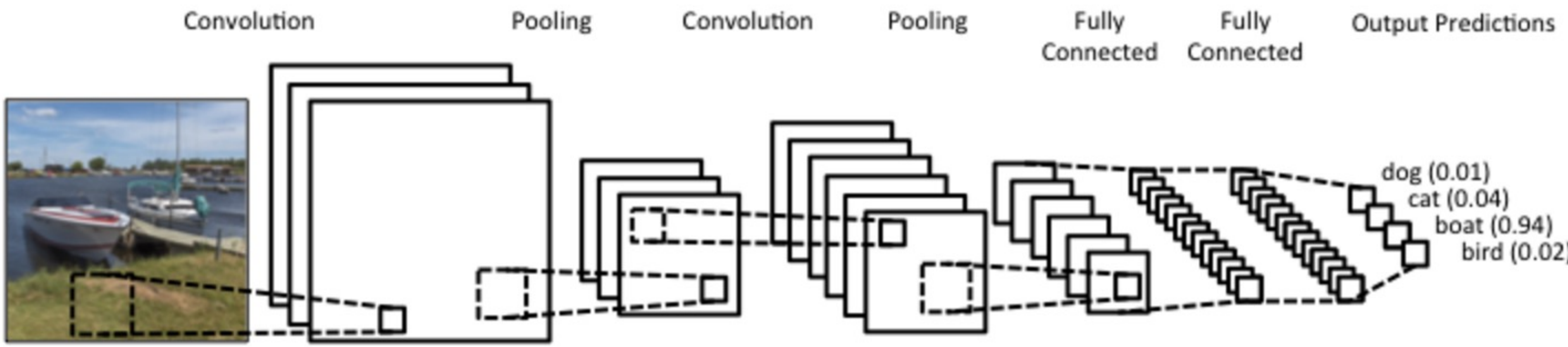
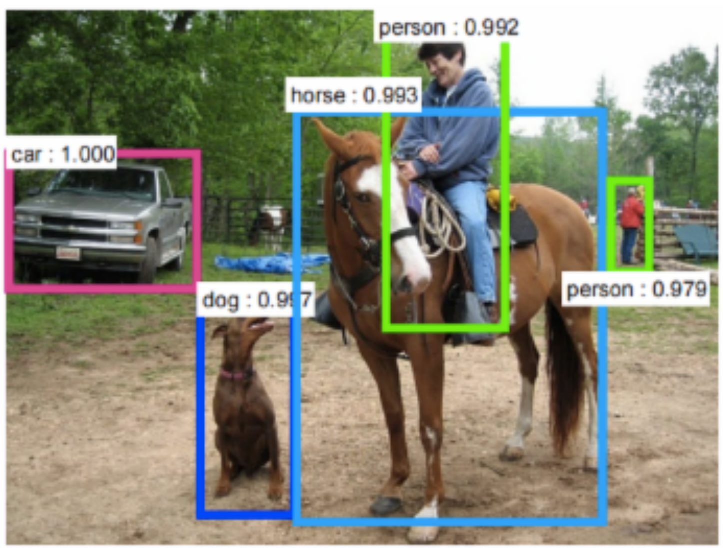
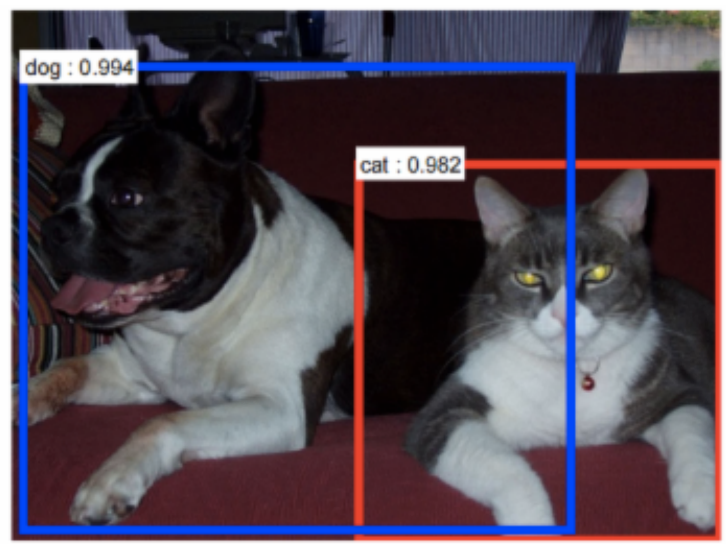
From image classification to object detection

Image classification



Object detection





Slides from L. Lazebnik

Image source

What are the challenges of object detection?

- Images may contain more than one class, multiple instances from the same class
- Bounding box localization
- Evaluation

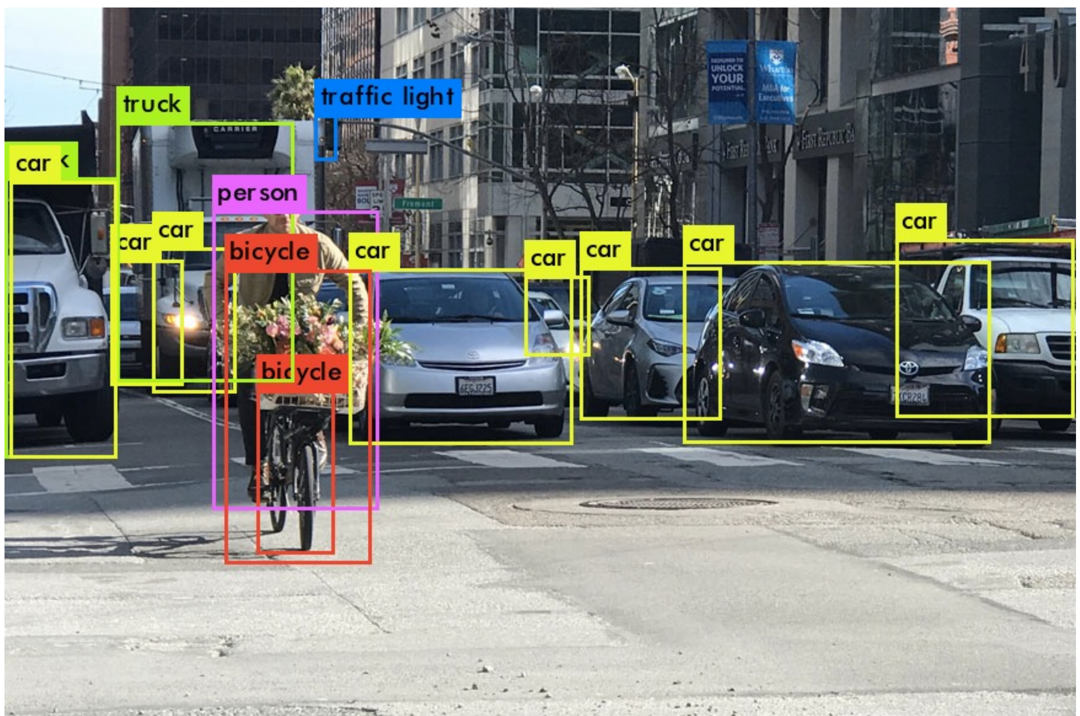


Image source

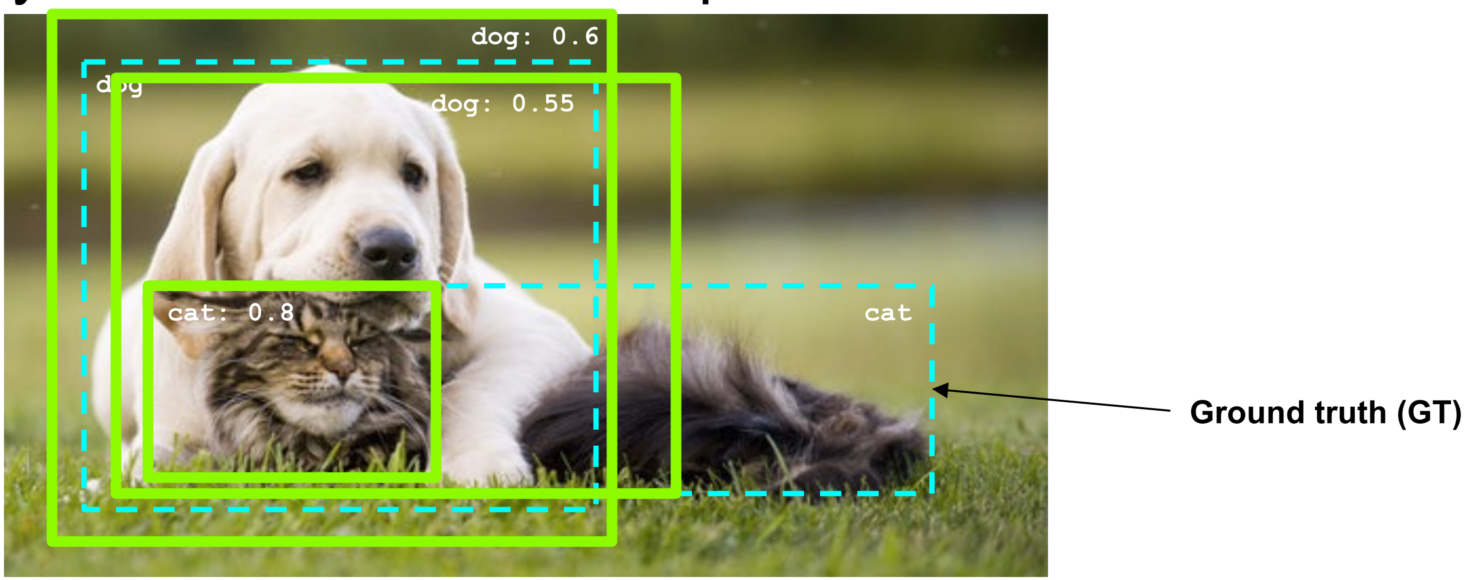
Outline

- Task definition and evaluation
- Generic object detection before deep learning
  - Sliding windows
  - HoG, DPMs (Components, Parts)
  - Region Classification Methods

- Deep detection approaches
  - R-CNN
  - Fast R-CNN
  - Faster R-CNN
  - SSD

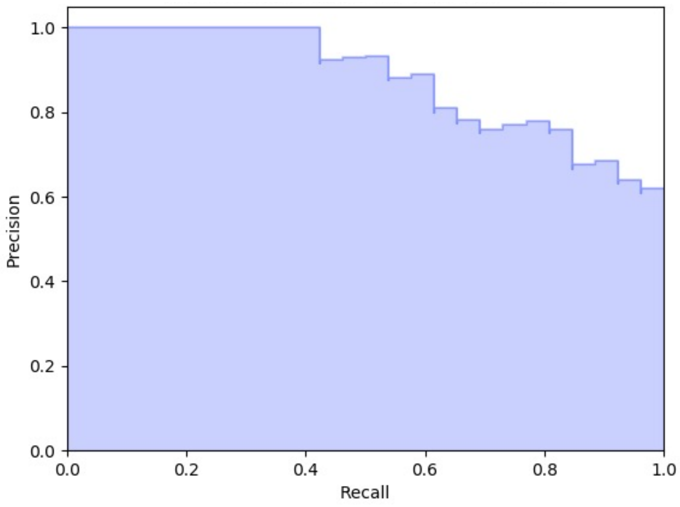
Object detection evaluation

- At test time, predict bounding boxes, class labels, and confidence scores
- For each detection, determine whether it is a true or false positive
  - PASCAL criterion: Area(GT ∩ Det) / Area(GT ∪ Det) > 0.5
  - For multiple detections of the same ground truth box, only one considered a true positive



Object detection evaluation

- At test time, predict bounding boxes, class labels, and confidence scores
- For each detection, determine whether it is a true or false positive
- For each class, plot Recall-Precision curve and compute Average Precision (area under the curve)
- Take mean of AP over classes to get mAP



Precision:
true positive detections / total detections

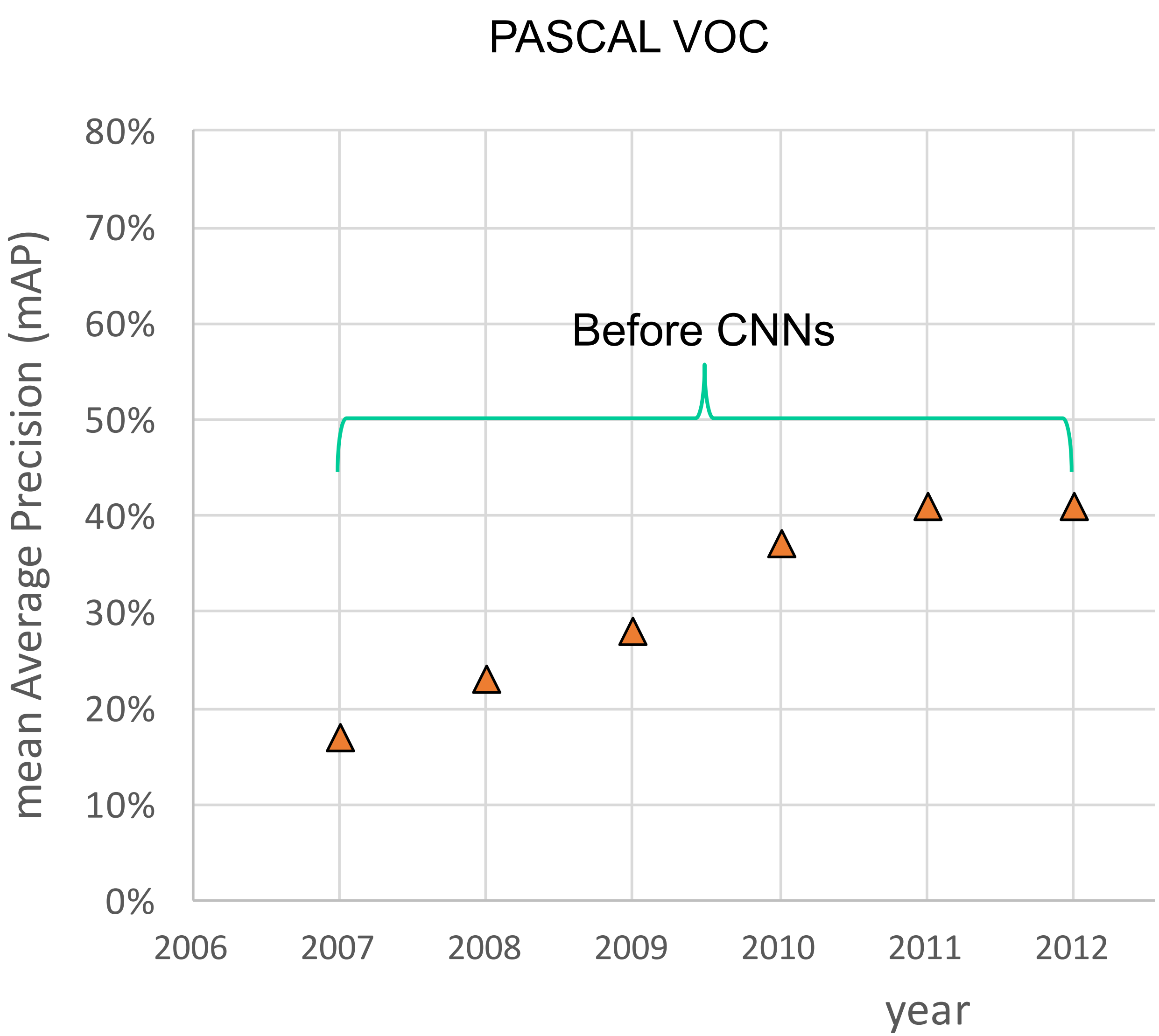
Recall:
true positive detections / total positive test instances

PASCAL VOC Challenge (2005-2012)

- 20 challenge classes:
  - *Person*
  - *Animals:* bird, cat, cow, dog, horse, sheep
  - *Vehicles:* aeroplane, bicycle, boat, bus, car, motorbike, train
  - *Indoor:* bottle, chair, dining table, potted plant, sofa, tv/monitor
- Dataset size (by 2012): 11.5K training/validation images, 27K bounding boxes, 7K segmentations

http://host.robots.ox.ac.uk/pascal/VOC/

Progress on PASCAL detection



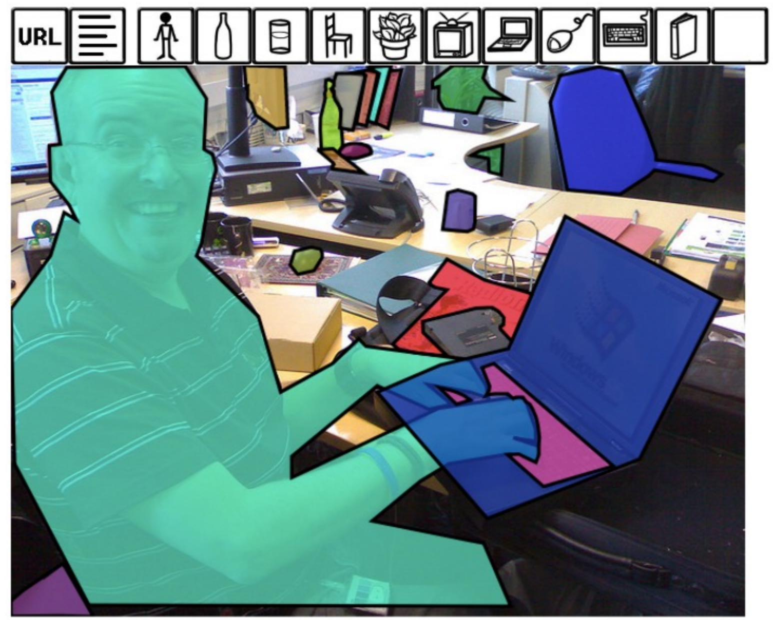
Newer benchmark: COCO

What is COCO?

COCO is a large-scale object detection, segmentation, and captioning dataset. COCO has several features:

- Object segmentation
- Recognition in context
- Superpixel stuff segmentation
- 330K images (>200K labeled)
- 1.5 million object instances
- 80 object categories
- 91 stuff categories
- 5 captions per image
- 250,000 people with keypoints

COCO
Common Objects in Context



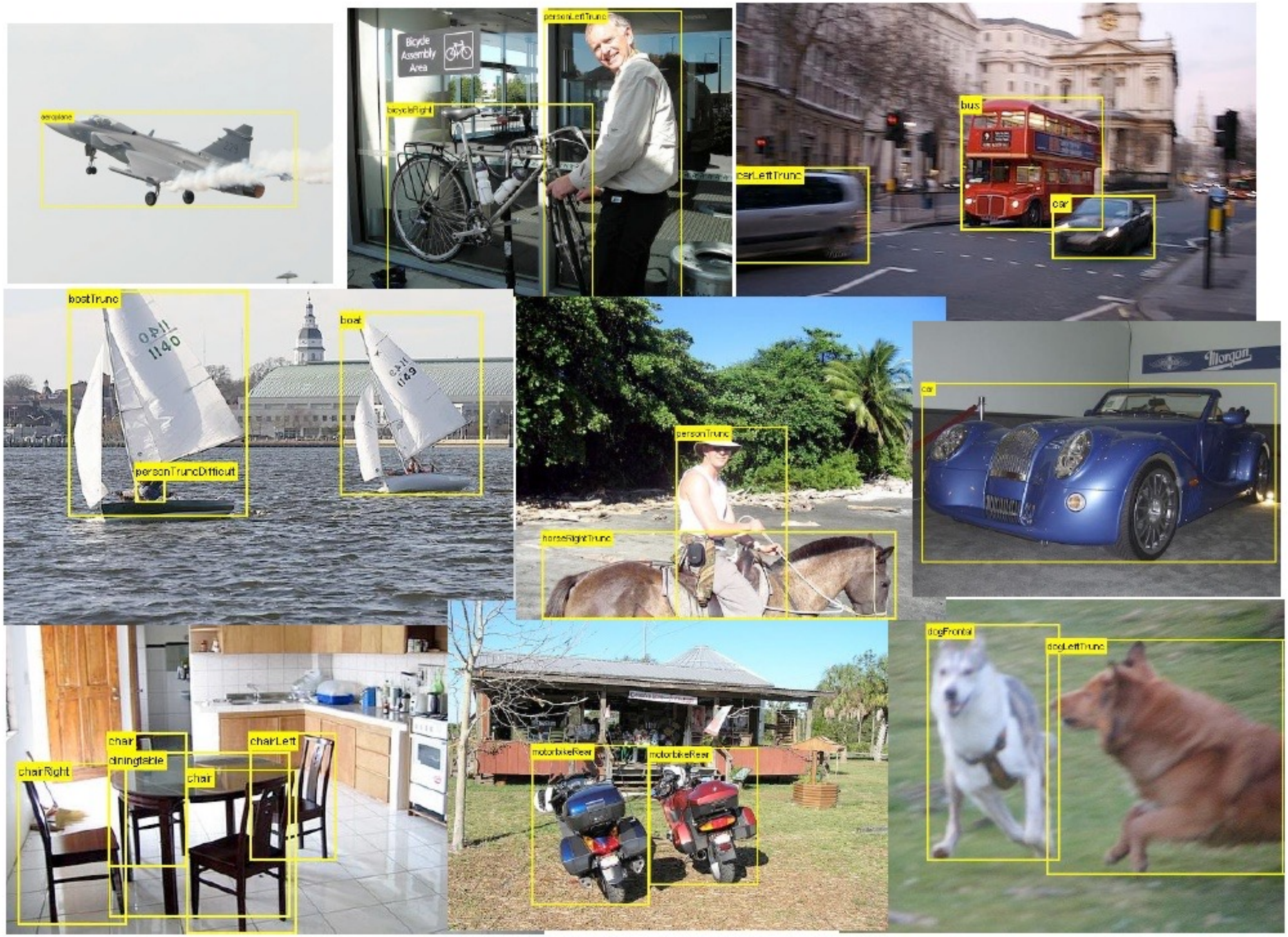
http://cocodataset.org/#home

COCO detection metrics

```
Average Precision (AP):
   AP              % AP at IoU=.50:.05:.95 (primary challenge metric)
   AP^IoU=.50      % AP at IoU=.50 (PASCAL VOC metric)
   AP^IoU=.75      % AP at IoU=.75 (strict metric)
AP Across Scales:
   AP^small        % AP for small objects: area < 32²
   AP^medium       % AP for medium objects: 32² < area < 96²
   AP^large        % AP for large objects: area > 96²
Average Recall (AR):
   AR^max=1        % AR given 1 detection per image
   AR^max=10       % AR given 10 detections per image
   AR^max=100      % AR given 100 detections per image
AR Across Scales:
   AR^small        % AR for small objects: area < 32²
   AR^medium       % AR for medium objects: 32² < area < 96²
   AR^large        % AR for large objects: area > 96²
```

- Leaderboard: http://cocodataset.org/#detection-leaderboard
  - Current best mAP: ~52%
- Official COCO challenges no longer include detection
  - More emphasis on instance segmentation and dense segmentation

Detection before deep learning

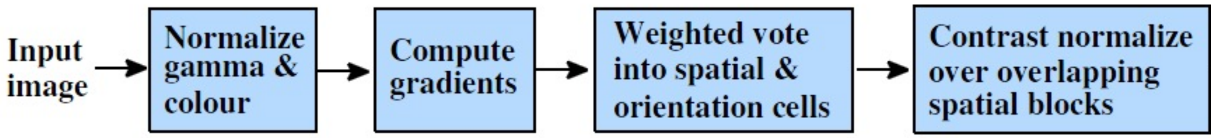


Conceptual approach: Sliding window detection

- Slide a window across the image and evaluate a detection model at each location
    - Thousands of windows to evaluate: efficiency and low false positive rates are essential
    - Difficult to extend to a large range of scales, aspect ratios

Histograms of oriented gradients (HOG)

- Partition image into blocks and compute histogram of gradient orientations in each block



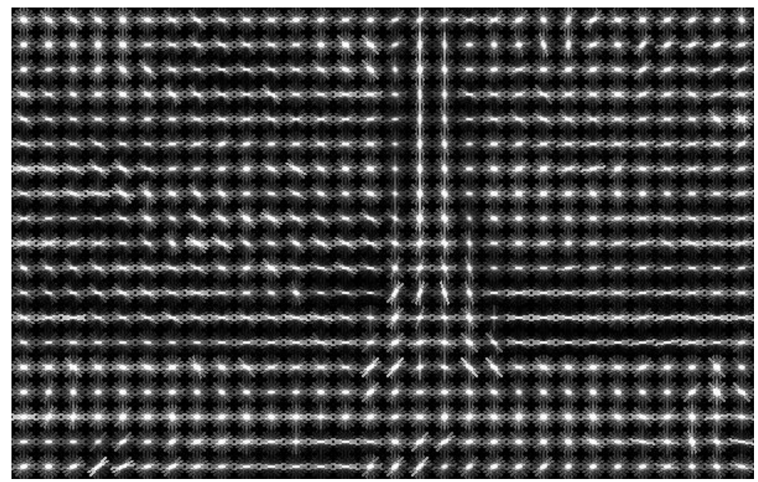


Image credit: N. Snavely

N. Dalal and B. Triggs, [Histograms of Oriented Gradients for Human Detection](), CVPR 2005

Pedestrian detection with HOG

- Train a pedestrian template using a linear support vector machine

positive training examples

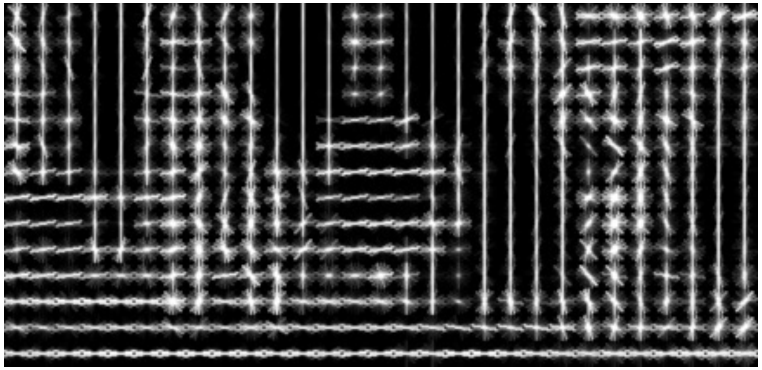
negative training examples

N. Dalal and B. Triggs, [Histograms of Oriented Gradients for Human Detection](), CVPR 2005

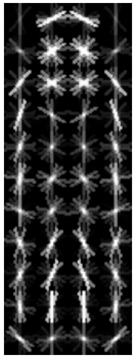
Pedestrian detection with HOG

- Train a pedestrian template using a linear support vector machine
- At test time, convolve feature map with template
- Find local maxima of response
- For multi-scale detection, repeat over multiple levels of a HOG *pyramid*

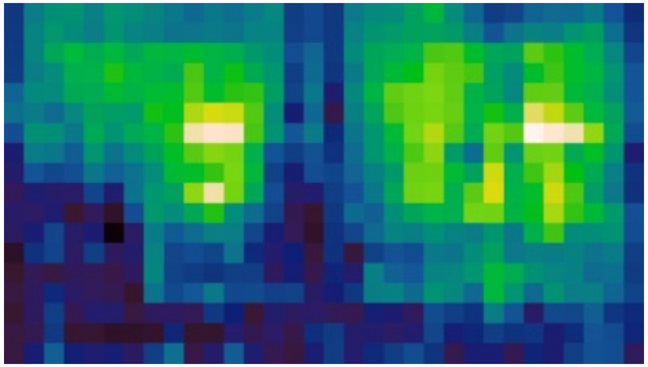
HOG feature map



Template



Detector response map



N. Dalal and B. Triggs, Histograms of Oriented Gradients for Human Detection, CVPR 2005

Discriminative part-based models

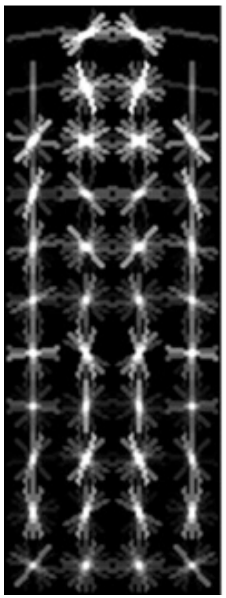
- Single rigid template usually not enough to represent a category
  - Many objects (e.g. humans) are articulated, or have parts that can vary in configuration

  - Many object categories look very different from different viewpoints, or from instance to instance

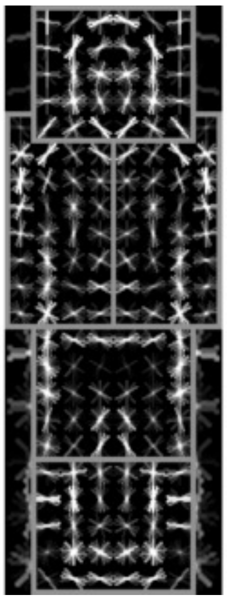
Slide by N. Snavely

Discriminative part-based models

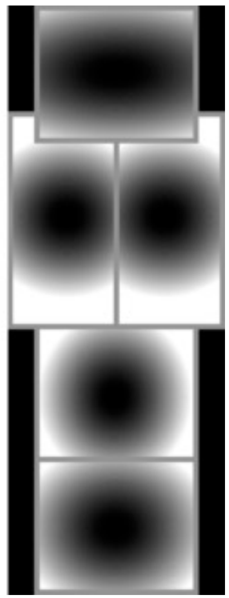
Root filter



Part filters



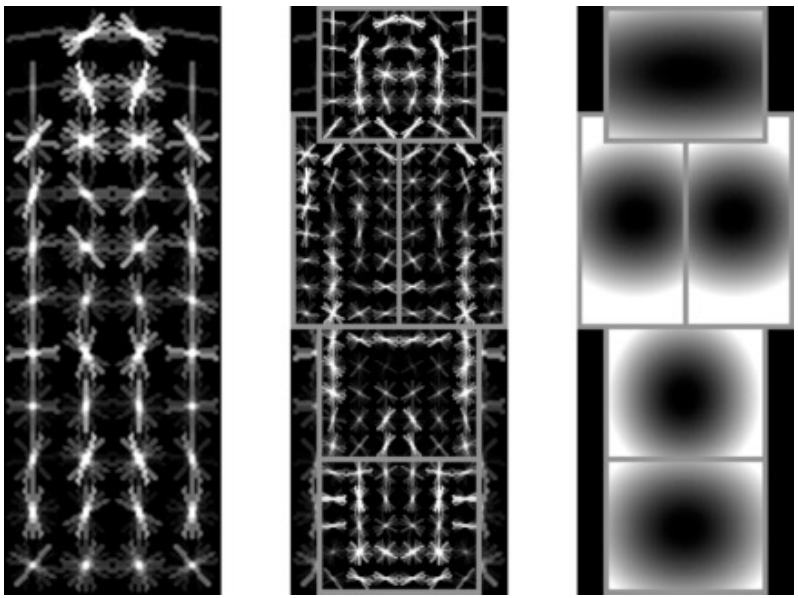
Deformation weights



P. Felzenszwalb, R. Girshick, D. McAllester, D. Ramanan, [Object Detection with Discriminatively Trained Part Based Models](), PAMI 32(9), 2010

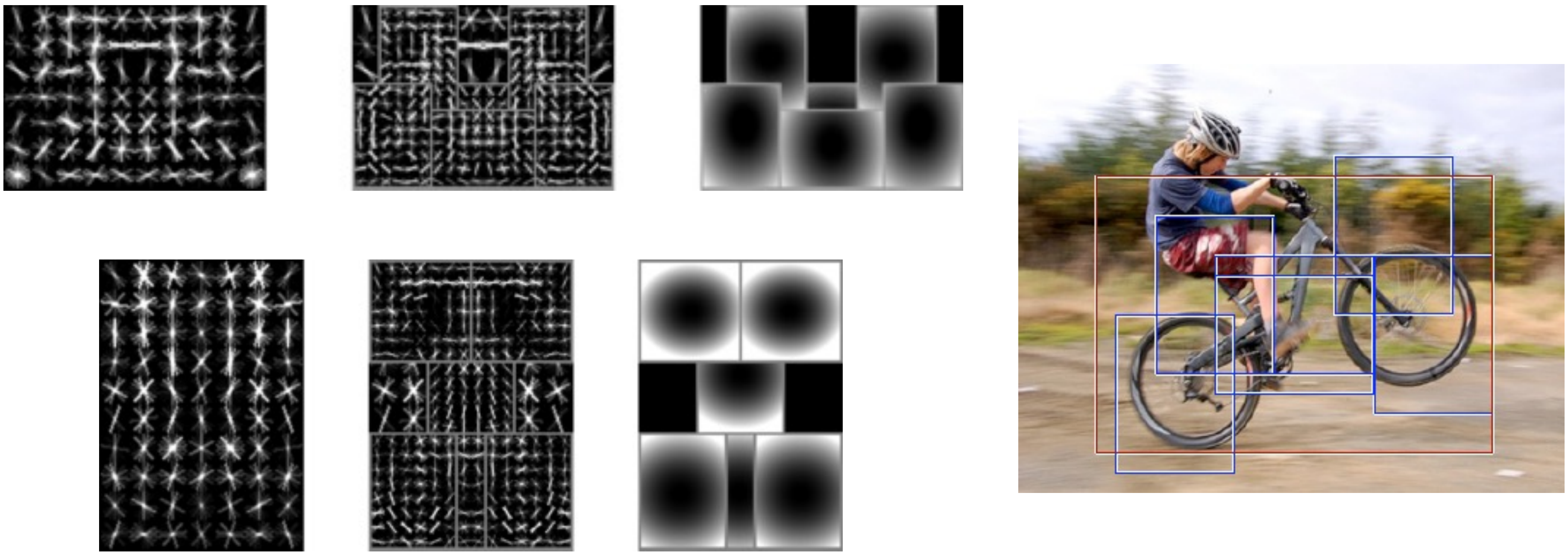
Discriminative part-based models

Multiple components



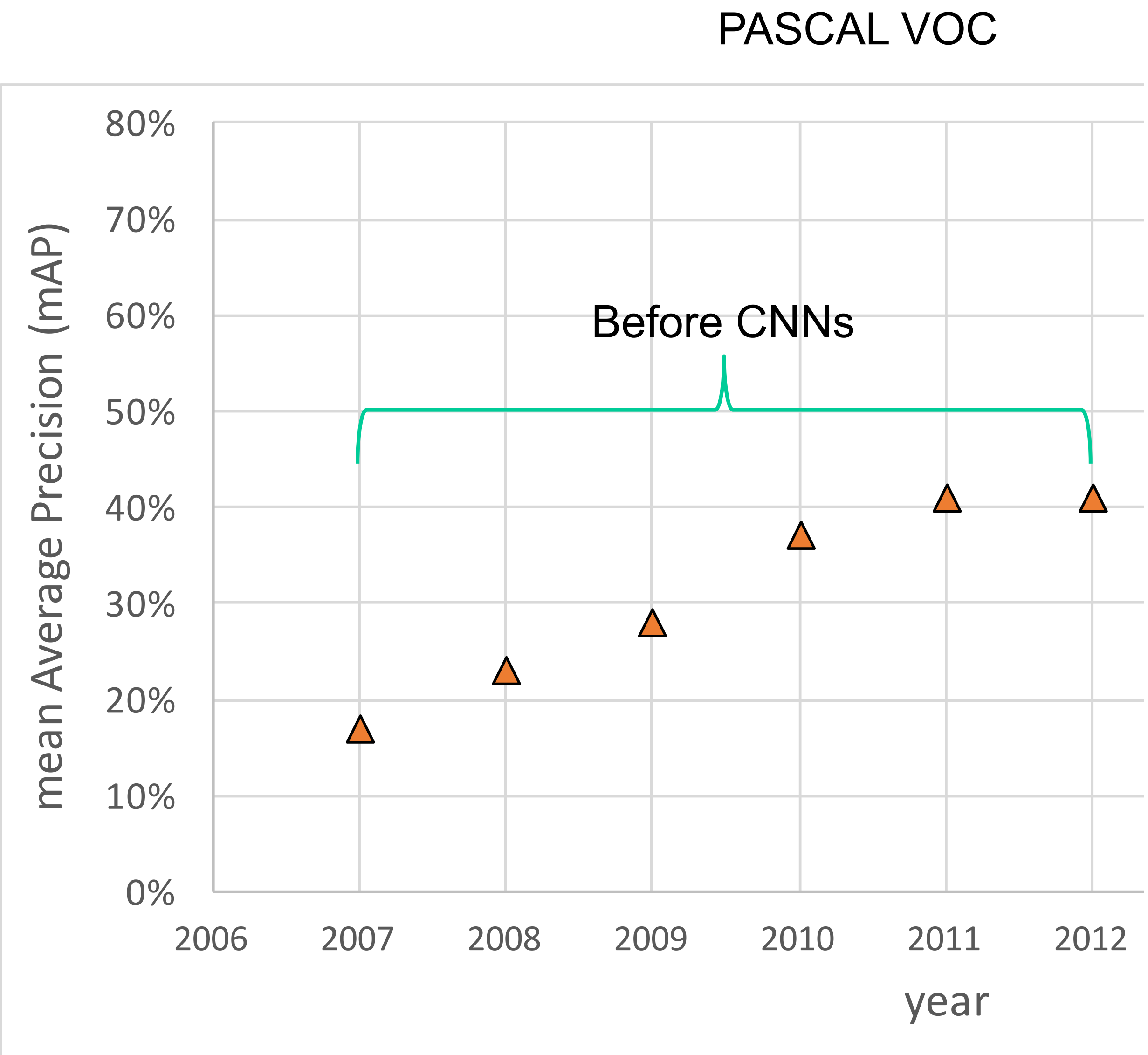
P. Felzenszwalb, R. Girshick, D. McAllester, D. Ramanan, [Object Detection with Discriminatively Trained Part Based Models](), PAMI 32(9), 2010

Discriminative part-based models

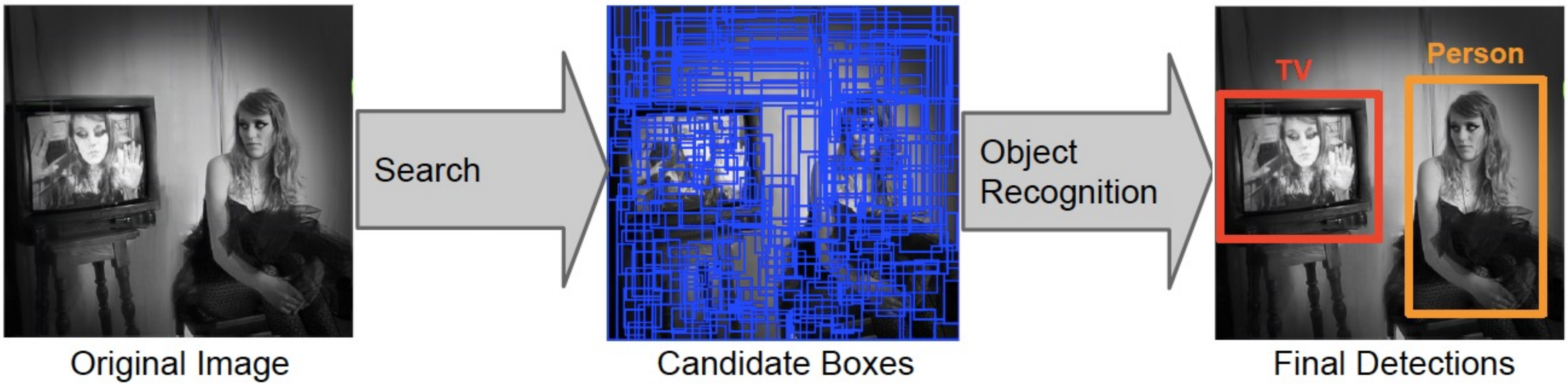


P. Felzenszwalb, R. Girshick, D. McAllester, D. Ramanan, [Object Detection with Discriminatively Trained Part Based Models](), PAMI 32(9), 2010

Progress on PASCAL detection



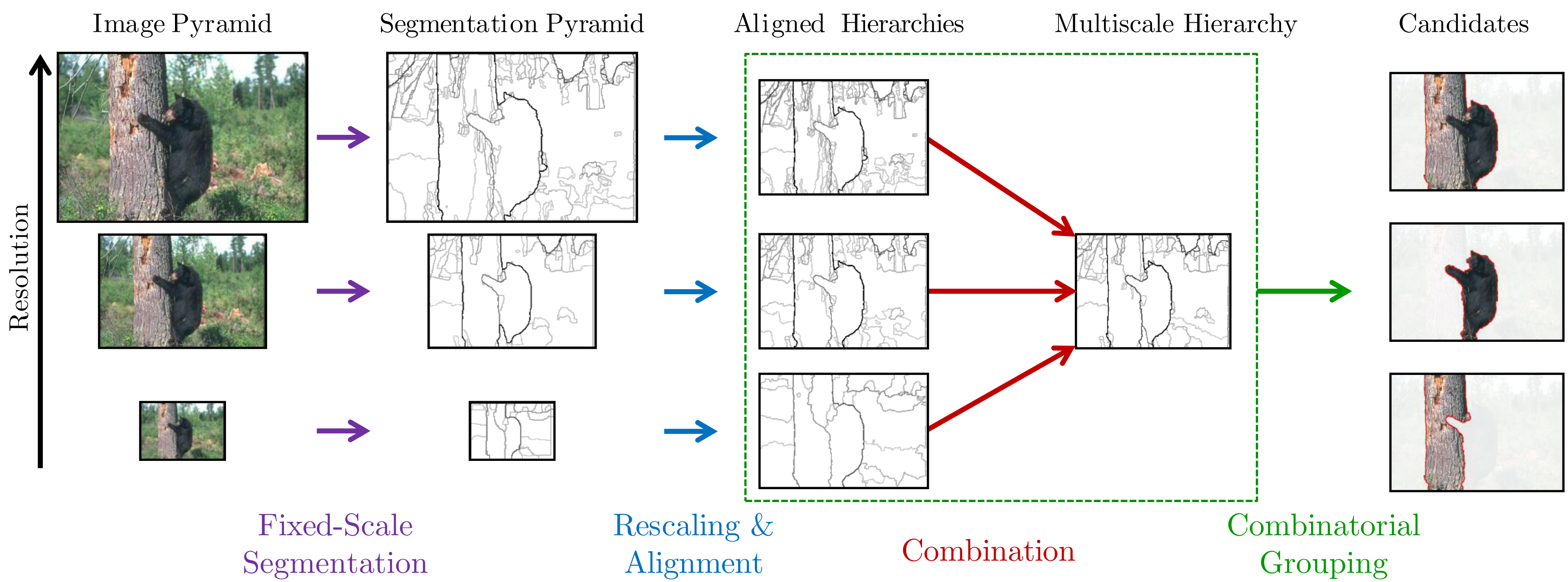
Conceptual approach: Proposal-driven detection



- Generate and evaluate a few hundred *region proposals*
  - Proposal mechanism can take advantage of low-level *perceptual organization* cues
  - Proposal mechanism can be category-specific or category-independent, hand-crafted or trained
  - Classifier can be slower but more powerful

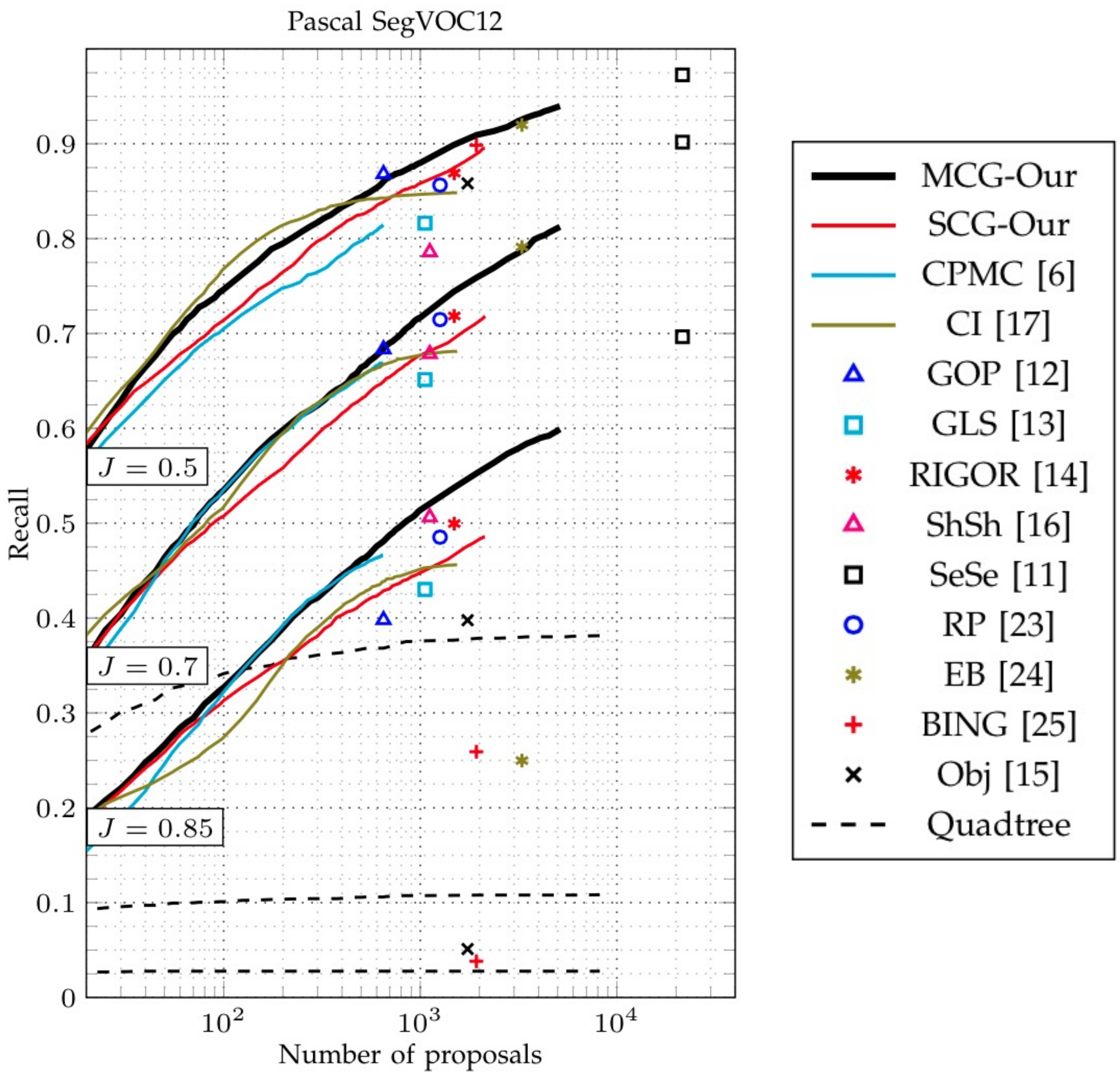
Multiscale Combinatorial Grouping

- Use hierarchical segmentation: start with small *superpixels* and merge based on diverse cues



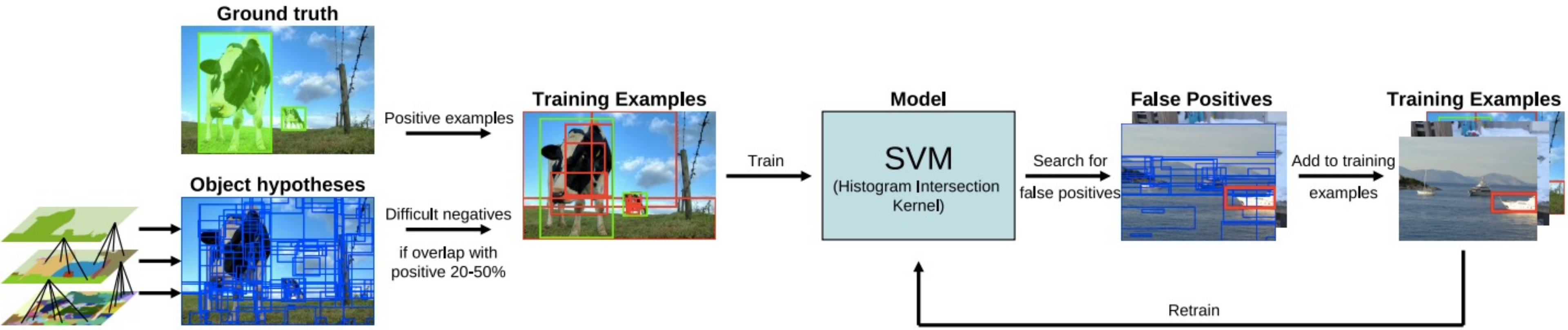
P. Arbelaez. et al., Multiscale Combinatorial Grouping, CVPR 2014

Region Proposals for Detection (Eval)



P. Arbelaez. et al., [Multiscale Combinatorial Grouping](), CVPR 2014

Region Proposals for Detection

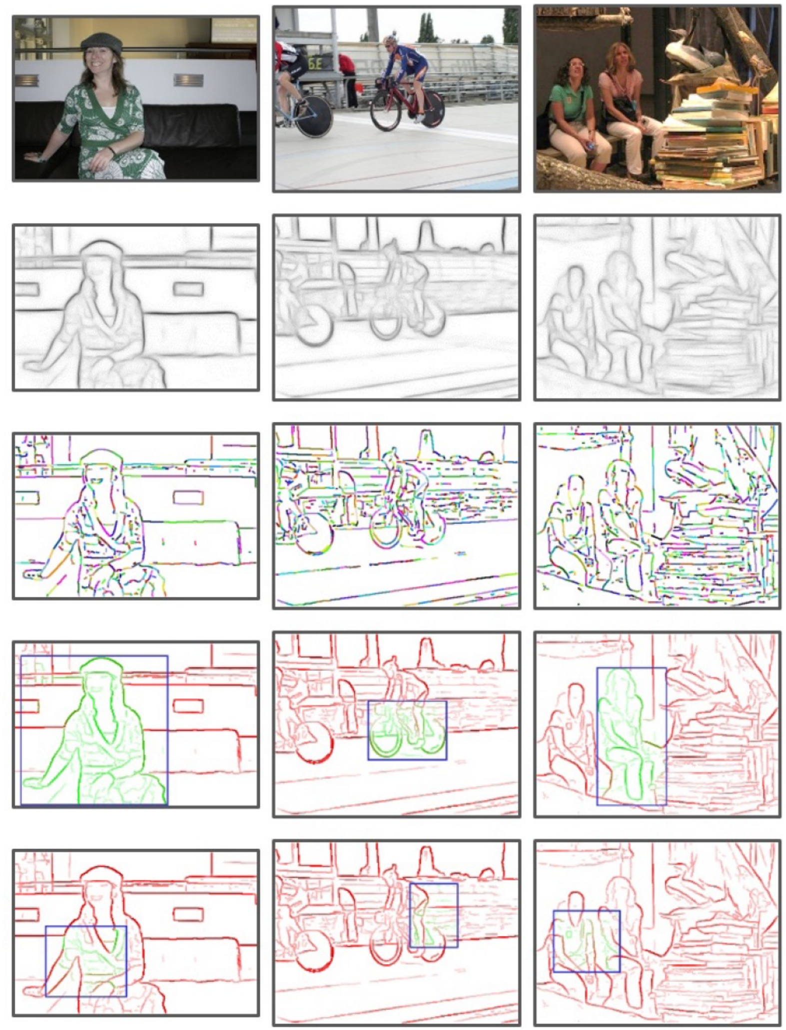


- Feature extraction: color SIFT, codebook of size 4K, spatial pyramid with four levels = 360K dimensions

J. Uijlings, K. van de Sande, T. Gevers, and A. Smeulders, [Selective Search for Object Recognition](), IJCV 2013

Another proposal method: EdgeBoxes

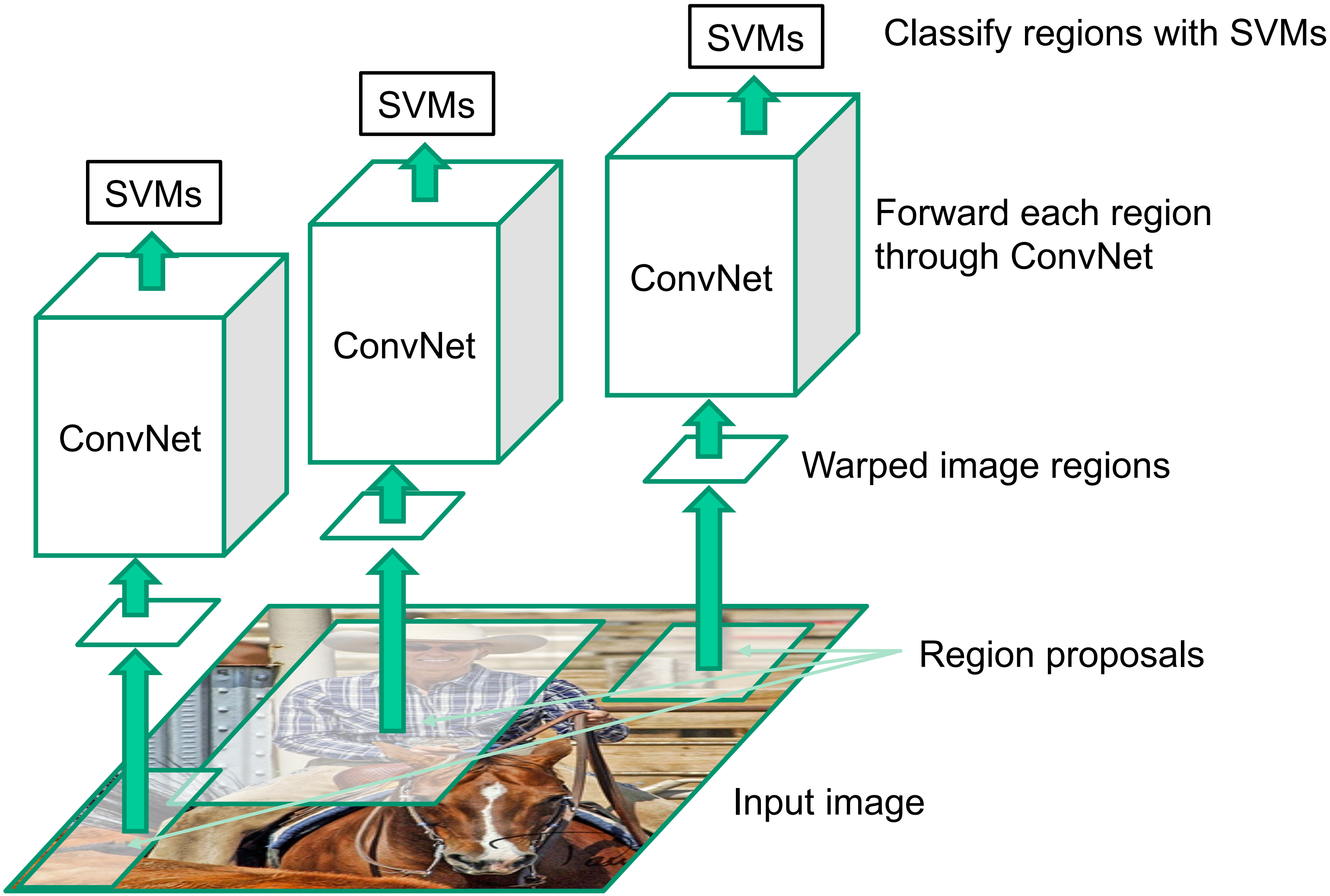
- Box score: number of edges in the box minus number of edges that overlap the box boundary
- Uses a trained edge detector
- Uses efficient data structures (incl. integral images) for fast evaluation
- Gets 75% recall with 800 boxes (vs. 1400 for Selective Search), is 40 times faster



C. Zitnick and P. Dollar, [Edge Boxes: Locating Object Proposals from Edges](), ECCV 2014

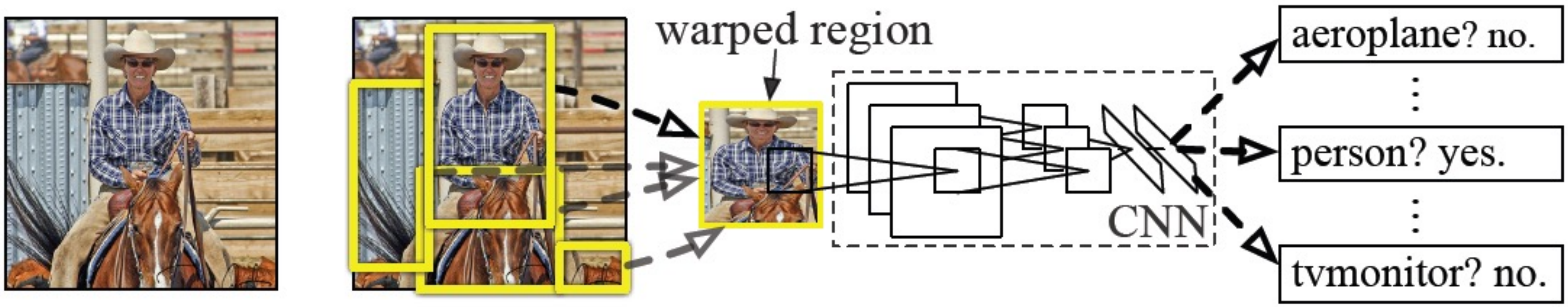
R-CNN: Region proposals + CNN features

Source: R. Girshick



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

R-CNN details

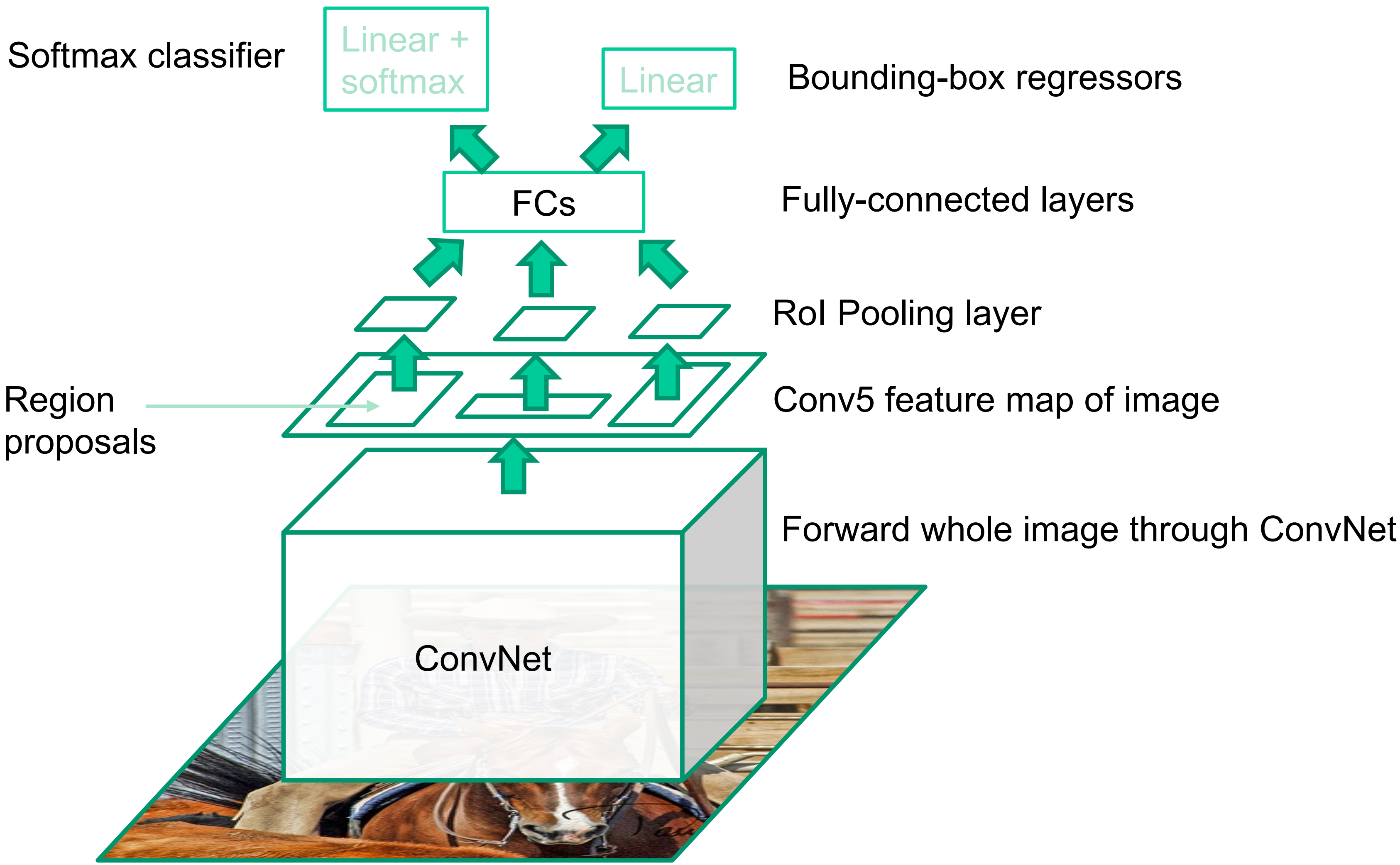


- **Regions**: ~2000 Selective Search proposals
- **Network**: AlexNet *pre-trained* on ImageNet (1000 classes), *fine-tuned* on PASCAL (21 classes)
- **Final detector**: warp proposal regions, extract fc7 network activations (4096 dimensions), classify with linear SVM
- **Bounding box regression** to refine box locations
- **Performance:** mAP of **53.7%** on PASCAL 2010 (vs. **35.1%** for Selective Search and **33.4%** for Deformable Part Models)

R-CNN pros and cons

- Pros
  - Accurate!
  - Any deep architecture can immediately be "plugged in"
- Cons
  - Not a single end-to-end system
    - Fine-tune network with softmax classifier (log loss)
    - Train post-hoc linear SVMs (hinge loss)
    - Train post-hoc bounding-box regressions (least squares)
  - Training is slow (84h), takes a lot of disk space
    - 2000 CNN passes per image
  - Inference (detection) is slow (47s / image with VGG16)

Fast R-CNN

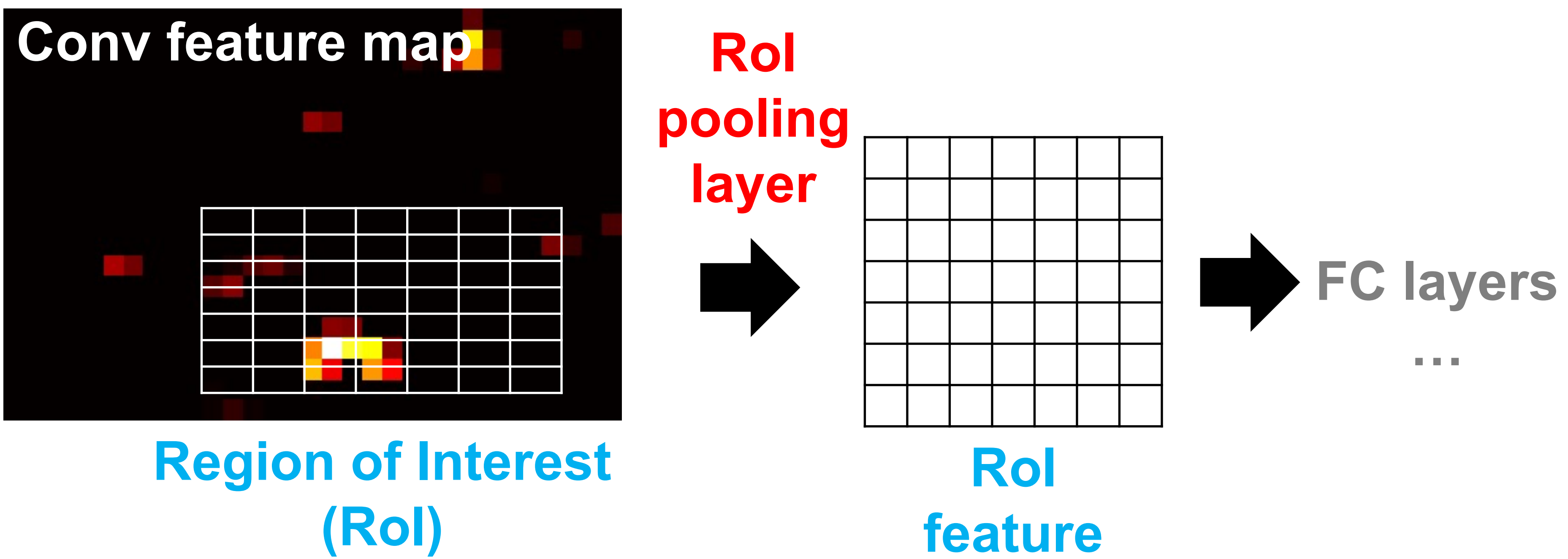


Source: R. Girshick

R. Girshick, [Fast R-CNN](), ICCV 2015

RoI pooling

- "Crop and resample" a fixed-size feature representing a region of interest out of the outputs of the last conv layer
  - Use nearest-neighbor interpolation of coordinates, max pooling



Source: R. Girshick, K. He

RoI pooling illustration

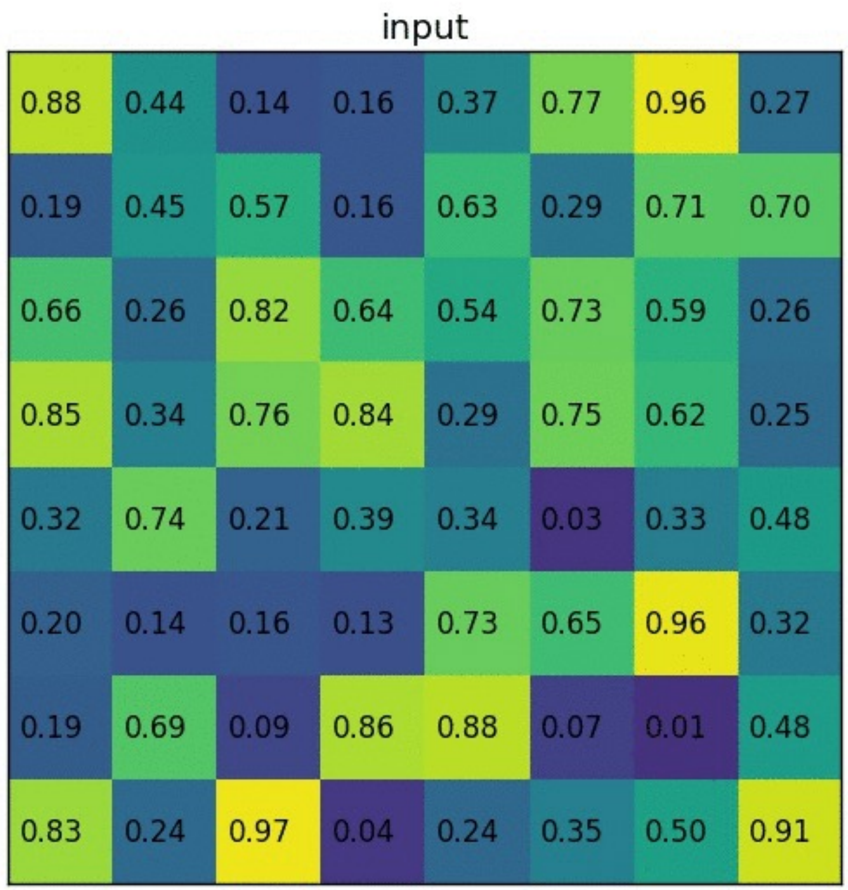
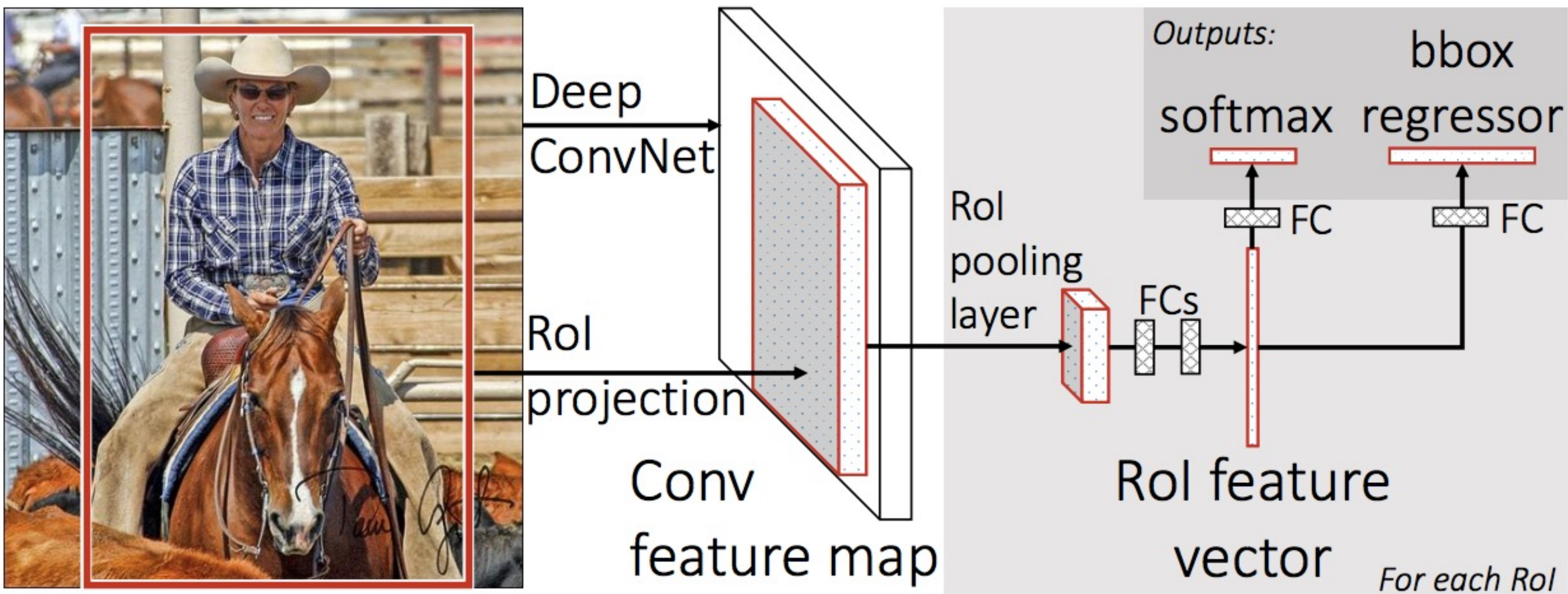


Image source

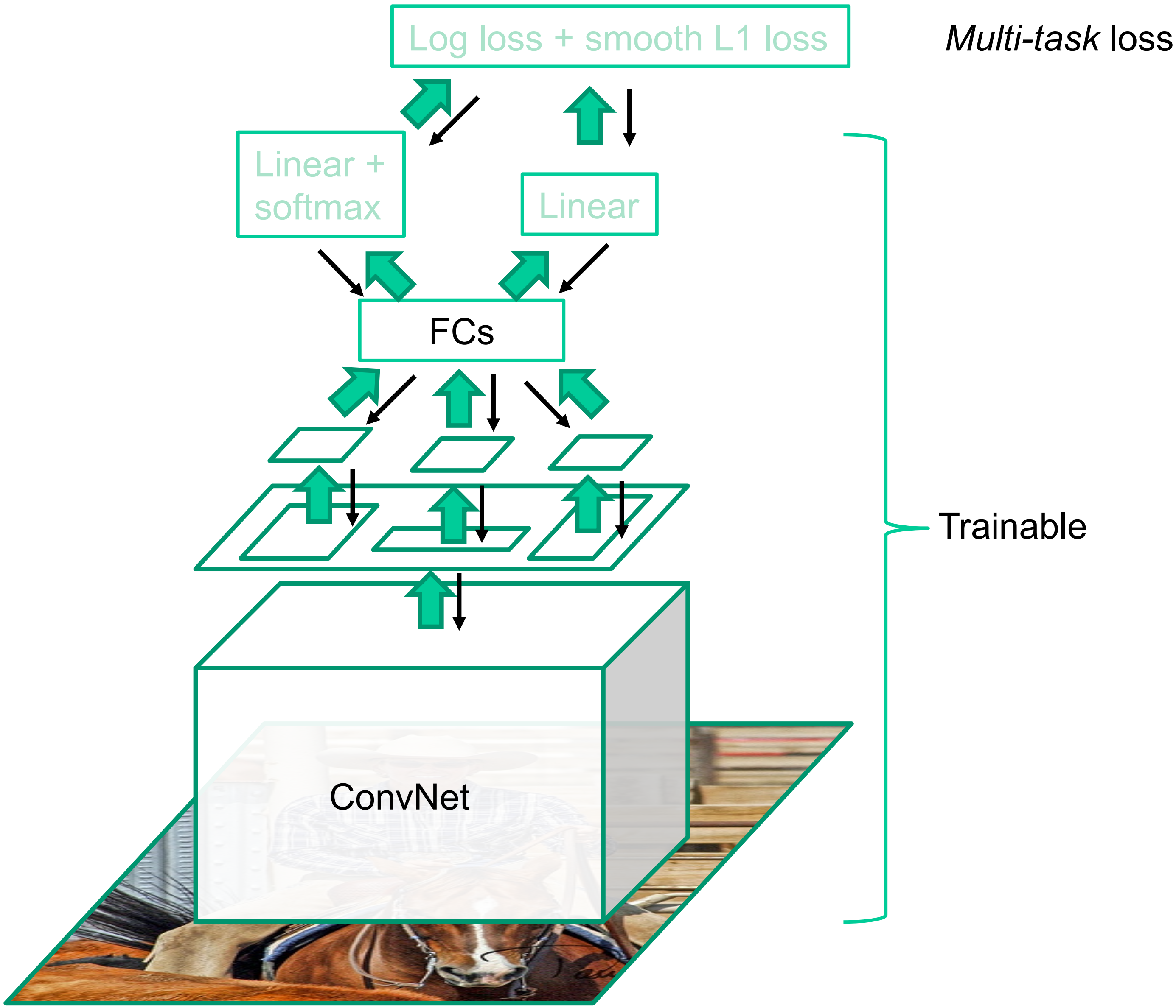
Prediction

- For each RoI, network predicts probabilities for C+1 classes (class 0 is background) and four bounding box offsets for C classes



R. Girshick, [Fast R-CNN](), ICCV 2015

Fast R-CNN training



Source: R. Girshick

R. Girshick, [Fast R-CNN](), ICCV 2015

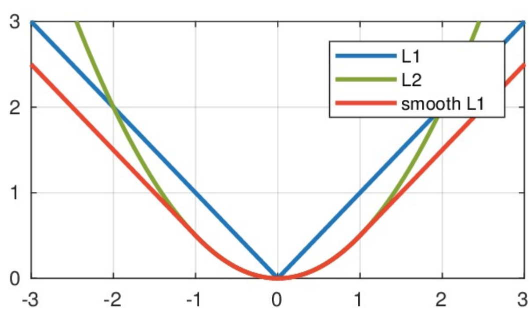
Multi-task loss

- Loss for ground truth class y, predicted class probabilities $P(y)$, ground truth box b, and predicted box $\hat{b}$:

$$L(y, P, b, \hat{b}) = \underbrace{-\log P(y)}_{\text{softmax loss}} + \lambda \mathbb{I}[y \geq 1] \underbrace{L_{\text{reg}}(b, \hat{b})}_{\text{regression loss}}$$

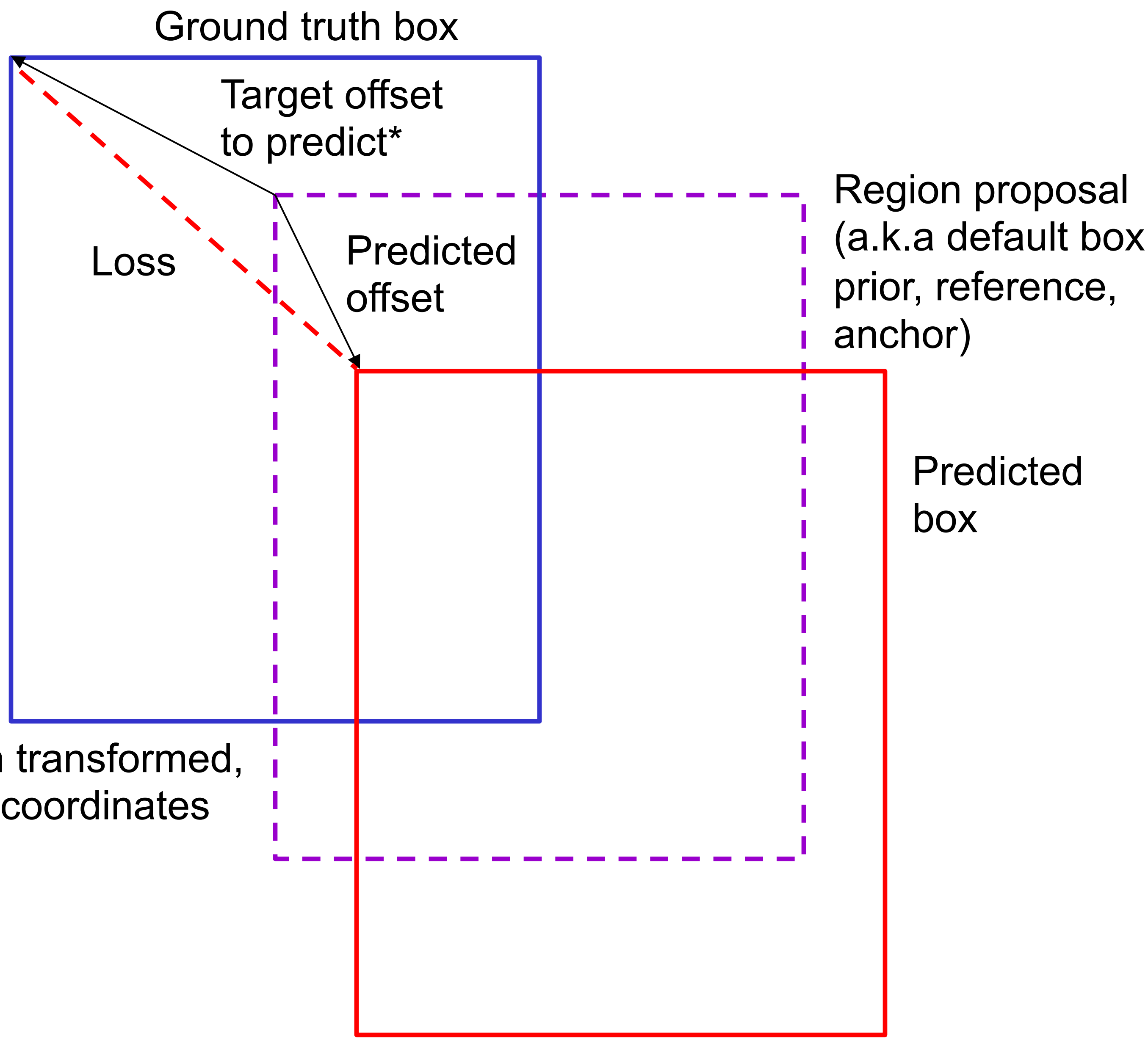
- Regression loss: *smooth L1 loss* on top of log space offsets relative to proposal

$$L_{\text{reg}}(b, \hat{b}) = \sum_{i=\{x,y,w,h\}} \text{smooth}_{L_1}(b_i - \hat{b}_i)$$



$$\text{smooth}_{L_1}(x) = \begin{cases} 0.5x^2 & \text{if } |x| < 1 \\ |x| - 0.5 & \text{otherwise} \end{cases}$$

Bounding box regression



*Typically in transformed, normalized coordinates

Fast R-CNN results

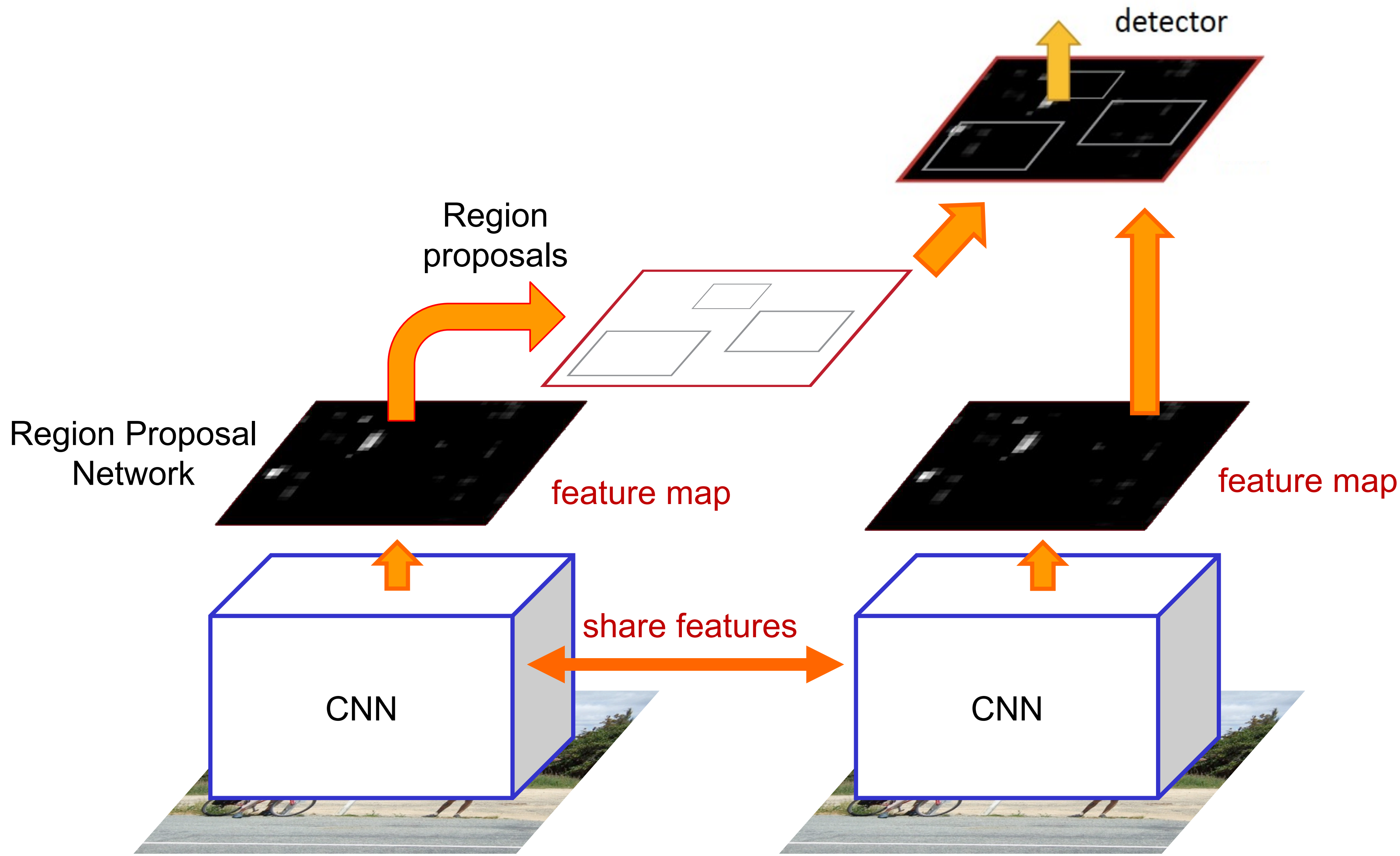
	Fast R-CNN	**R-CNN**
Train time (h)	**9.5**	84
- Speedup	**8.8x**	1x
Test time / image	**0.32s**	47.0s
Test speedup	**146x**	1x
mAP	**66.9%**	66.0%

(vs. 53.7% for AlexNet)

Timings exclude object proposal time, which is equal for all methods.
All methods use VGG16 from Simonyan and Zisserman.

Source: R. Girshick

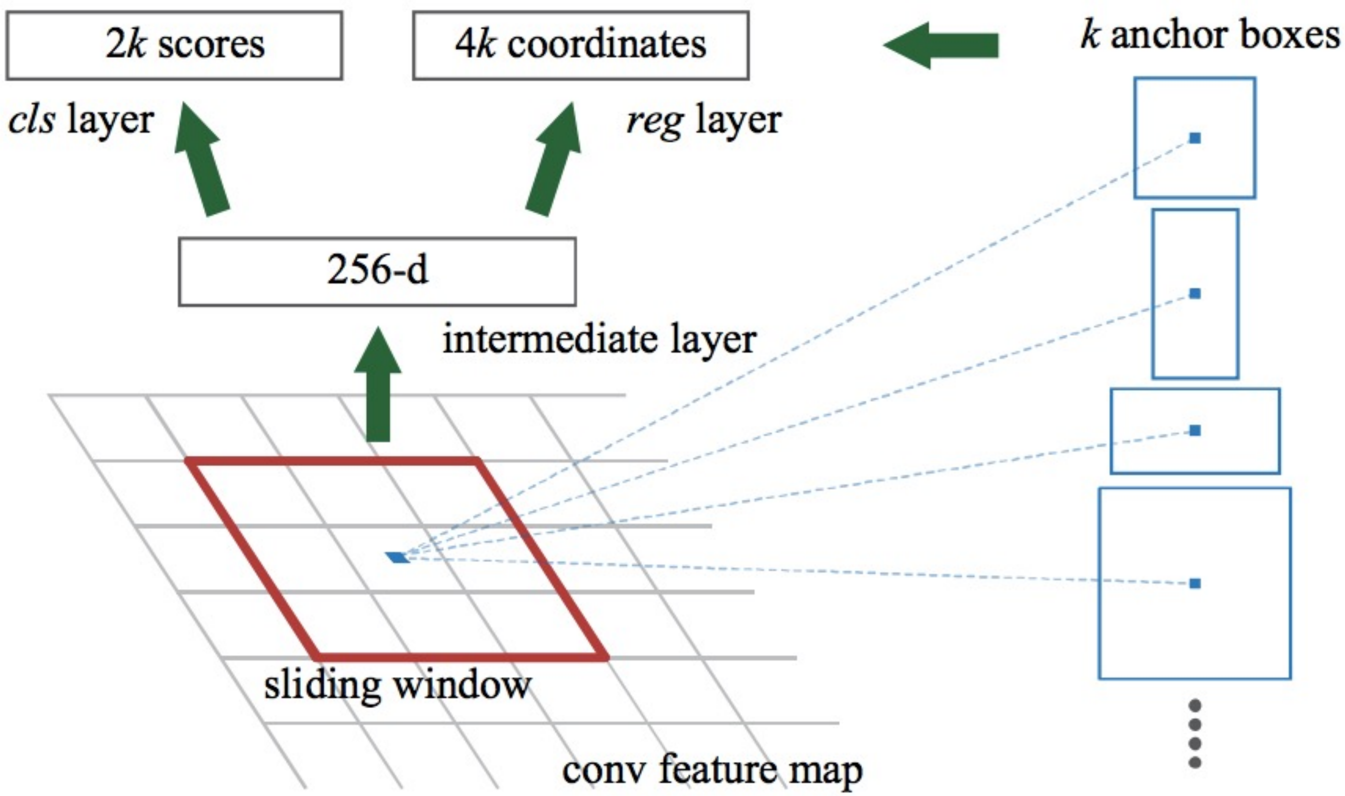
Faster R-CNN



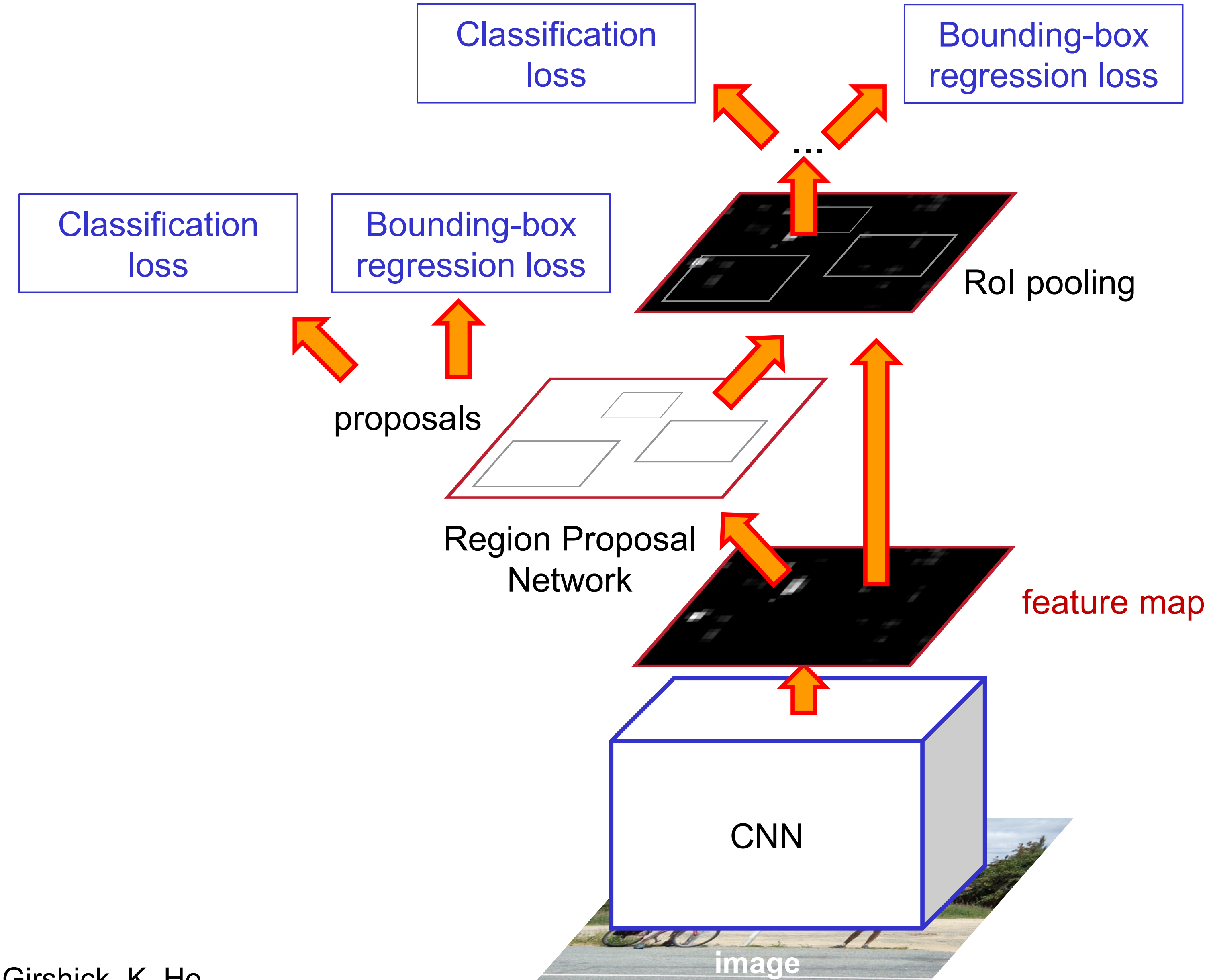
S. Ren, K. He, R. Girshick, and J. Sun, [Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks], NIPS 2015

Region proposal network (RPN)

- Slide a small window (3x3) over the conv5 layer
  - Predict object/no object
  - Regress bounding box coordinates with reference to *anchors* (3 scales x 3 aspect ratios)



One network, four losses



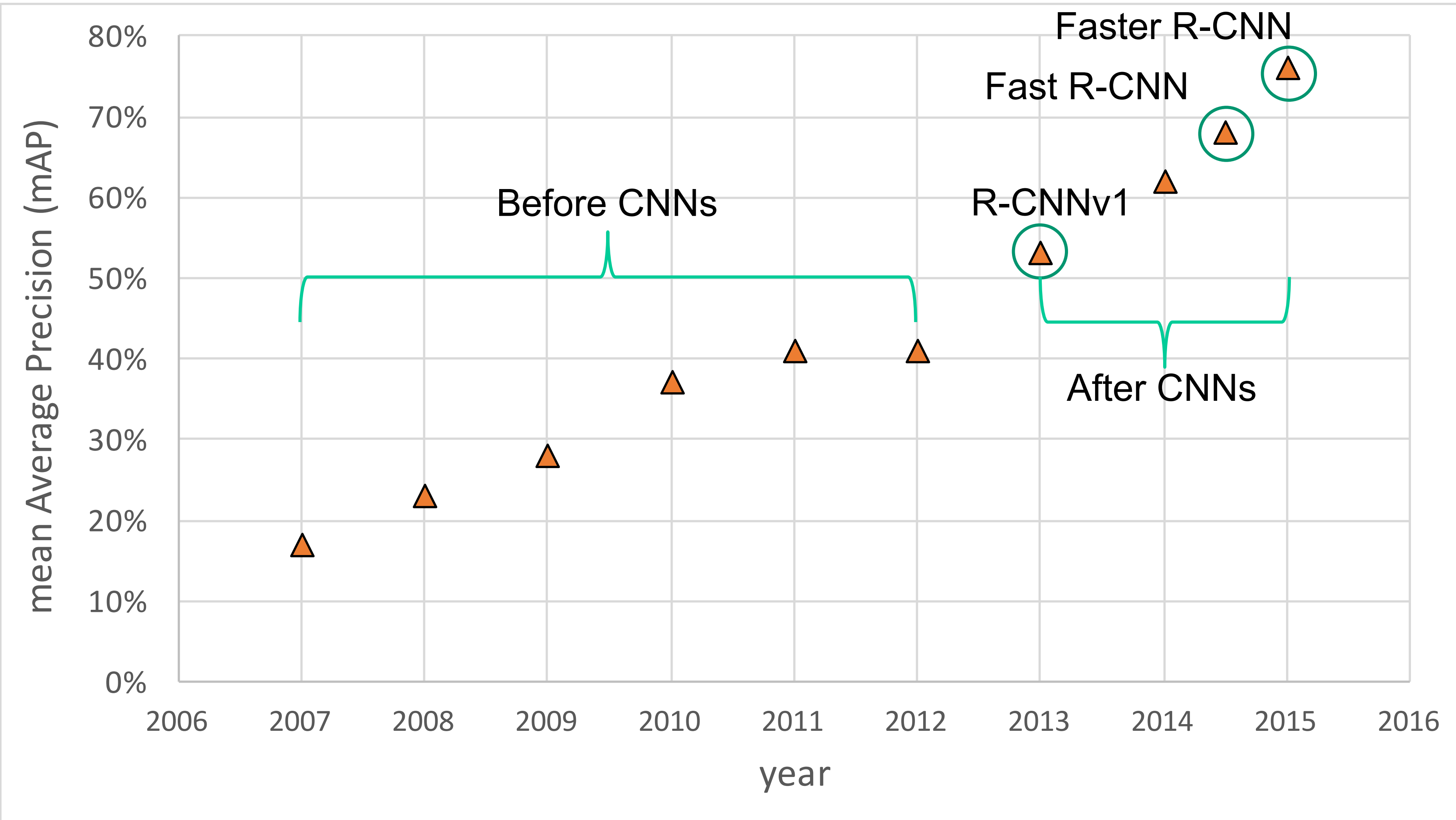
Source: R. Girshick, K. He

Faster R-CNN results

system	time	07 data	07+12 data
R-CNN	~50s	66.0	-
Fast R-CNN	~2s	66.9	70.0
Faster R-CNN	198ms	**69.9**	**73.2**

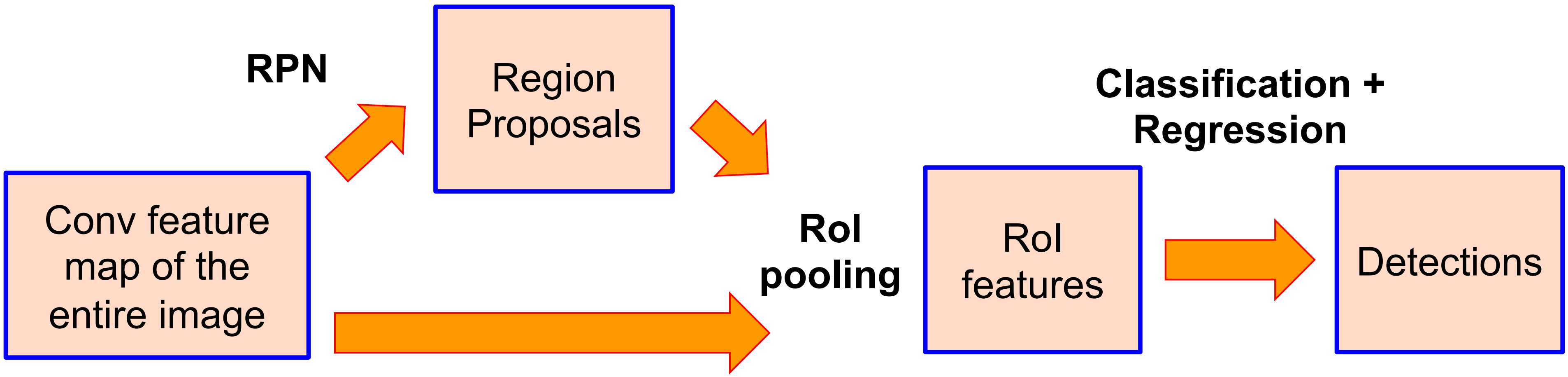
detection mAP on PASCAL VOC 2007, with VGG-16 pre-trained on ImageNet

Object detection progress



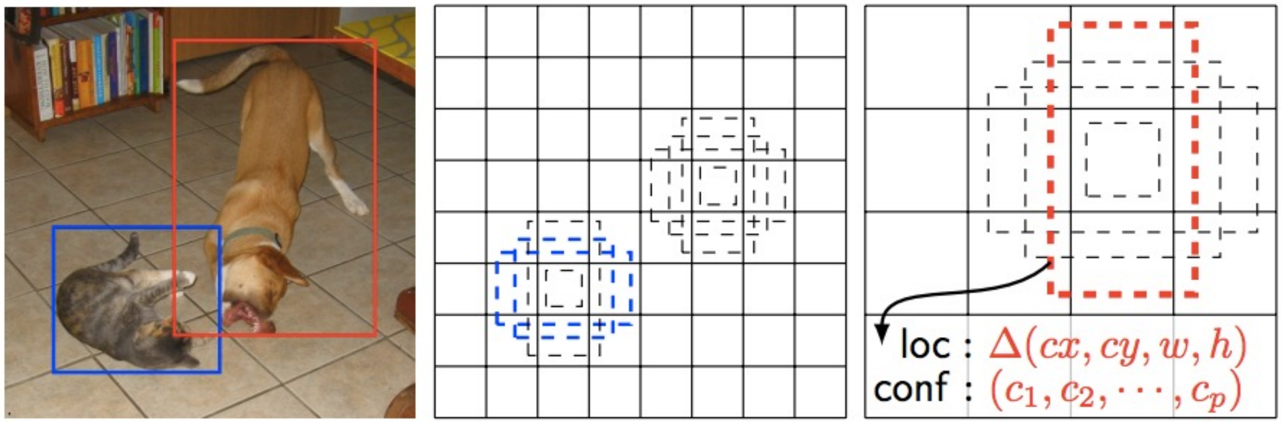
Streamlined detection architectures

- The Faster R-CNN pipeline separates proposal generation and region classification:



- Is it possible do detection in one shot?

SSD

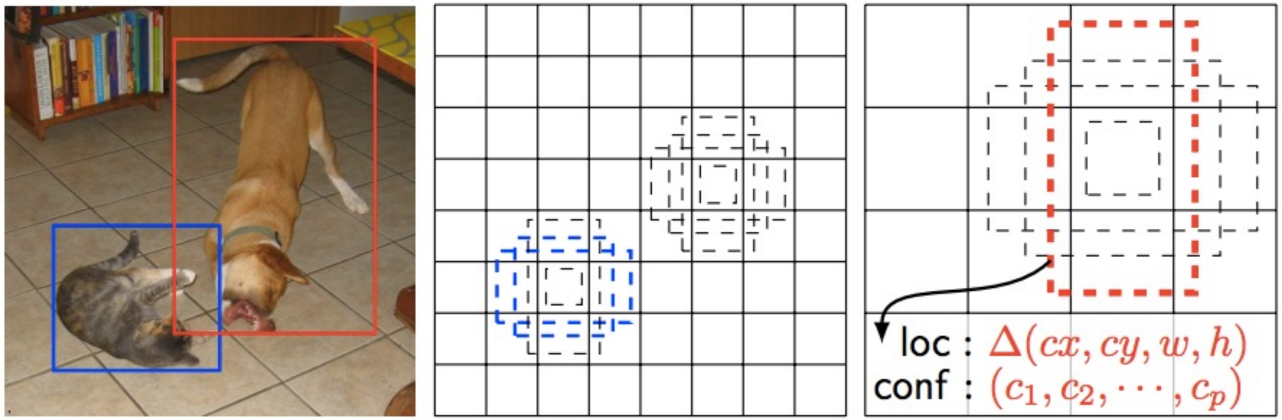


(a) Image with GT boxes (b) 8×8 feature map (c) 4×4 feature map

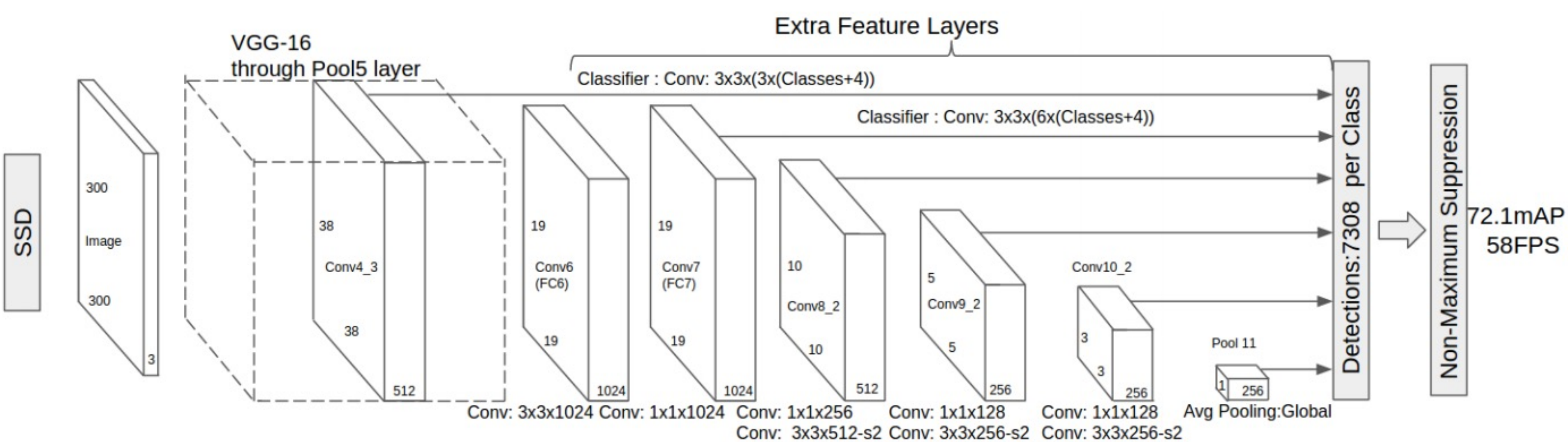
- Similarly to RPN, use anchors and directly predict class-specific bounding boxes.

W. Liu, D. Anguelov, D. Erhan, C. Szegedy, S. Reed, C.-Y. Fu, and A. Berg, [SSD: Single Shot MultiBox Detector](), ECCV 2016.

SSD



(a) Image with GT boxes (b) 8×8 feature map (c) 4×4 feature map



W. Liu, D. Anguelov, D. Erhan, C. Szegedy, S. Reed, C.-Y. Fu, and A. Berg, SSD: Single Shot MultiBox Detector, ECCV 2016.

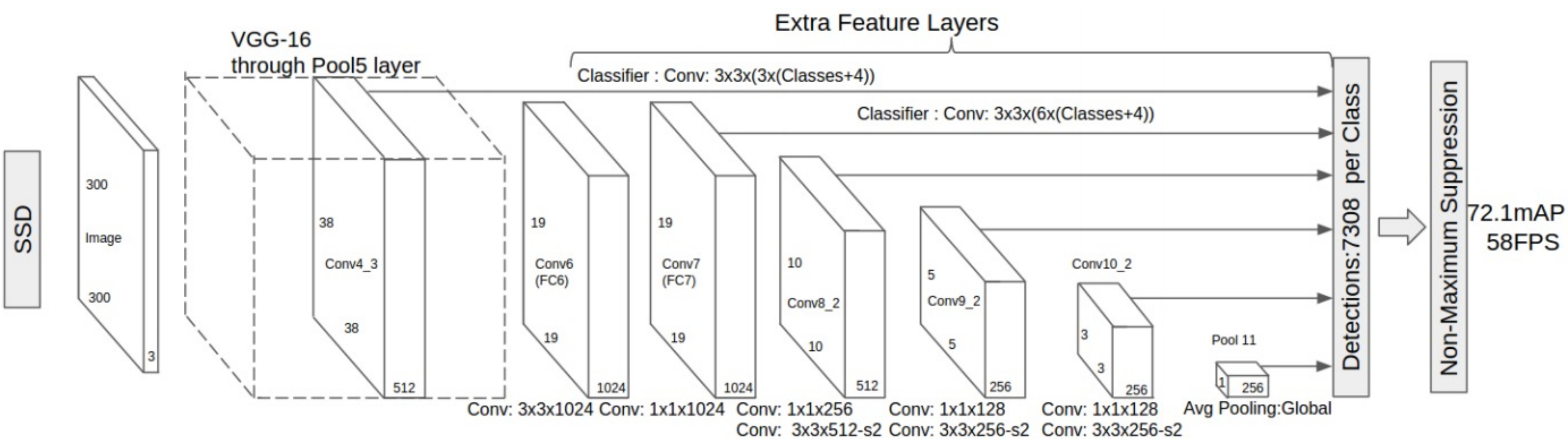
SSD: Results (PASCAL 2007)

- More accurate *and* faster than YOLO and Faster R-CNN

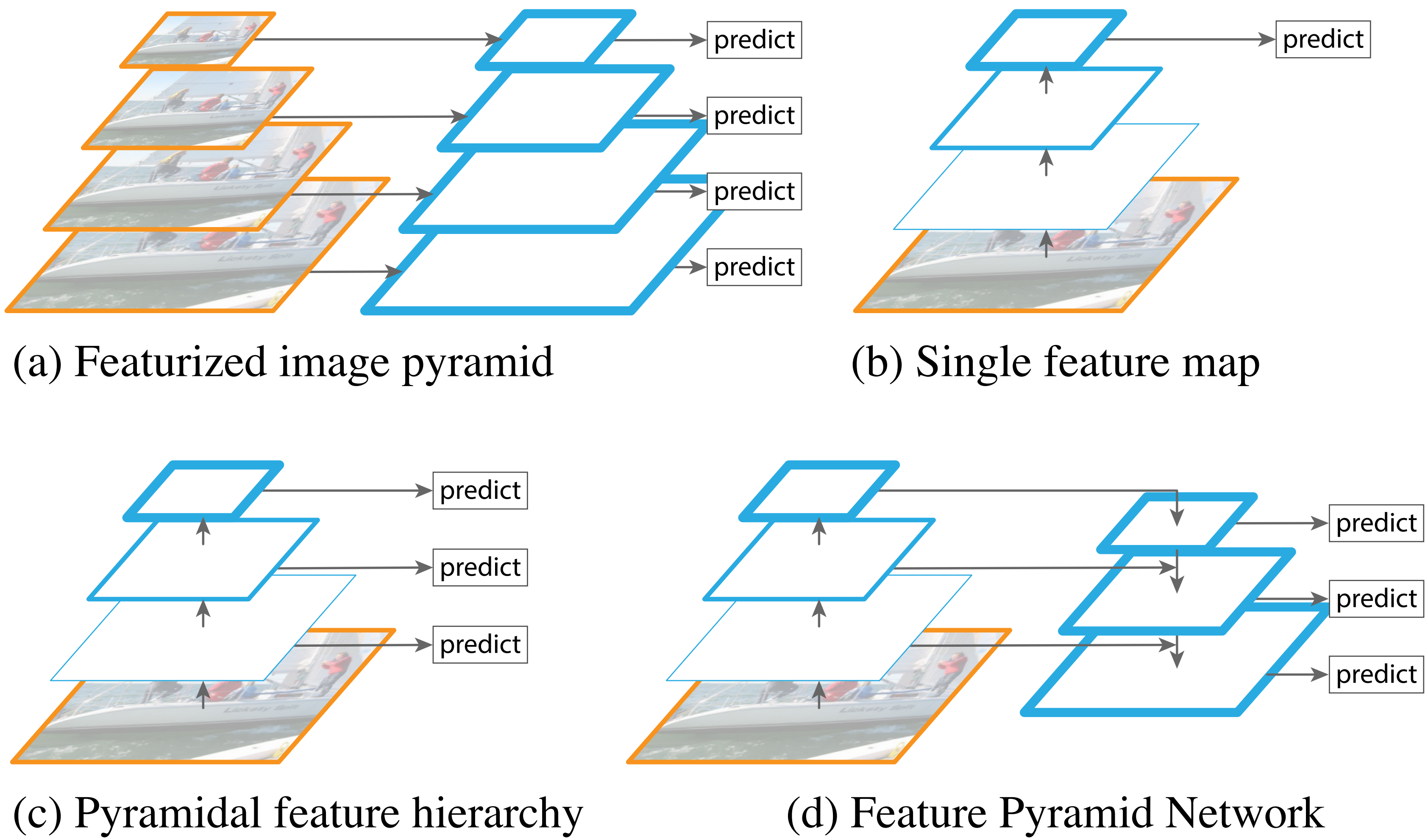
Method	mAP	FPS	batch size	# Boxes	Input resolution
Faster R-CNN (VGG16)	73.2	7	1	~ 6000	$\sim 1000 \times 600$
Fast YOLO	52.7	155	1	98	448×448
YOLO (VGG16)	66.4	21	1	98	448×448
SSD300	74.3	46	1	8732	300×300
SSD512	76.8	19	1	24564	512×512
SSD300	74.3	59	8	8732	300×300
SSD512	76.8	22	8	24564	512×512

Multi-resolution prediction

- SSD predicts boxes of different size from different conv maps, but each level of resolution has its own predictors and higher-level context does not get propagated back to lower-level feature maps
- Can we have a more elegant multi-resolution prediction architecture?



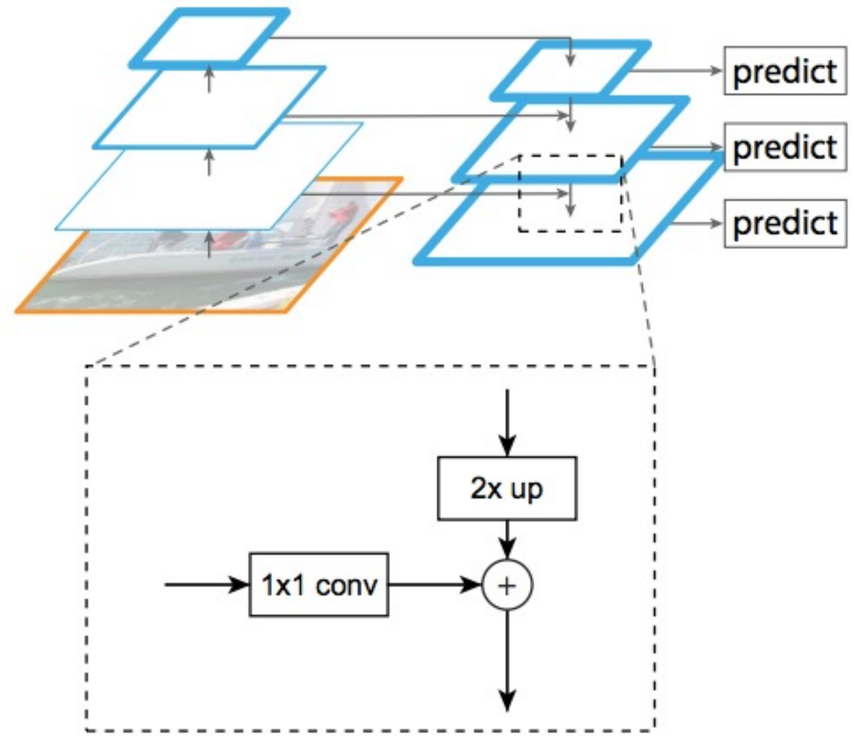
Feature Pyramid Networks



Tsung-Yi Lin, Piotr Dollar, Ross Girshick, Kaiming He, Bharath Hariharan, and Serge Belongie, [Feature Pyramid Networks for Object Detection](), CVPR 2017.

Feature pyramid networks

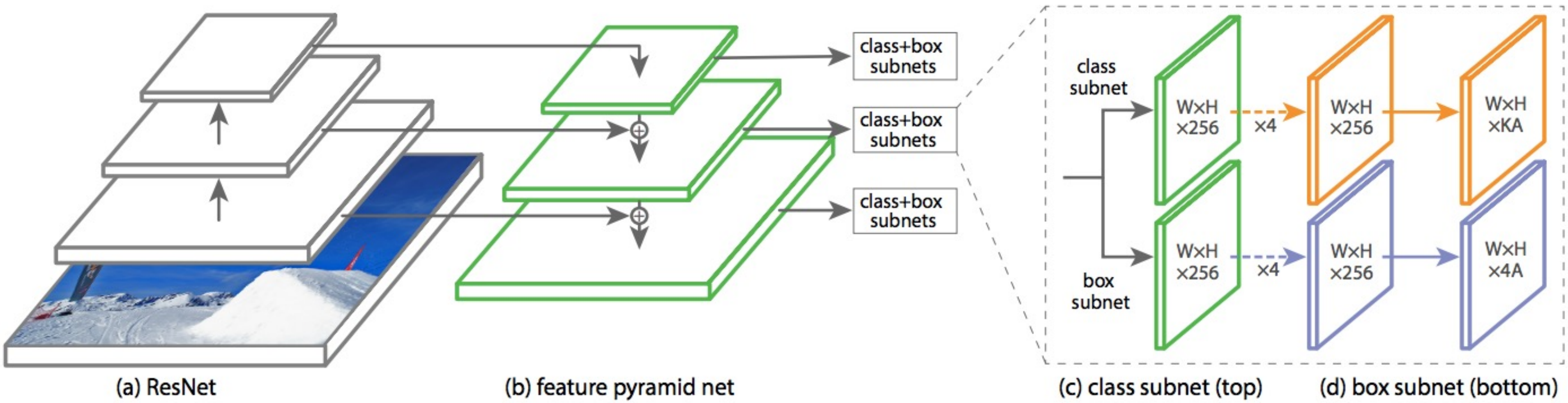
- Improve predictive power of lower-level feature maps by adding contextual information from higher-level feature maps
- Predict different sizes of bounding boxes from different levels of the pyramid (but share parameters of predictors)



T.-Y. Lin, P. Dollar, R. Girshick, K. He, B. Hariharan, and S. Belongie, [Feature pyramid networks for object detection](), CVPR 2017.

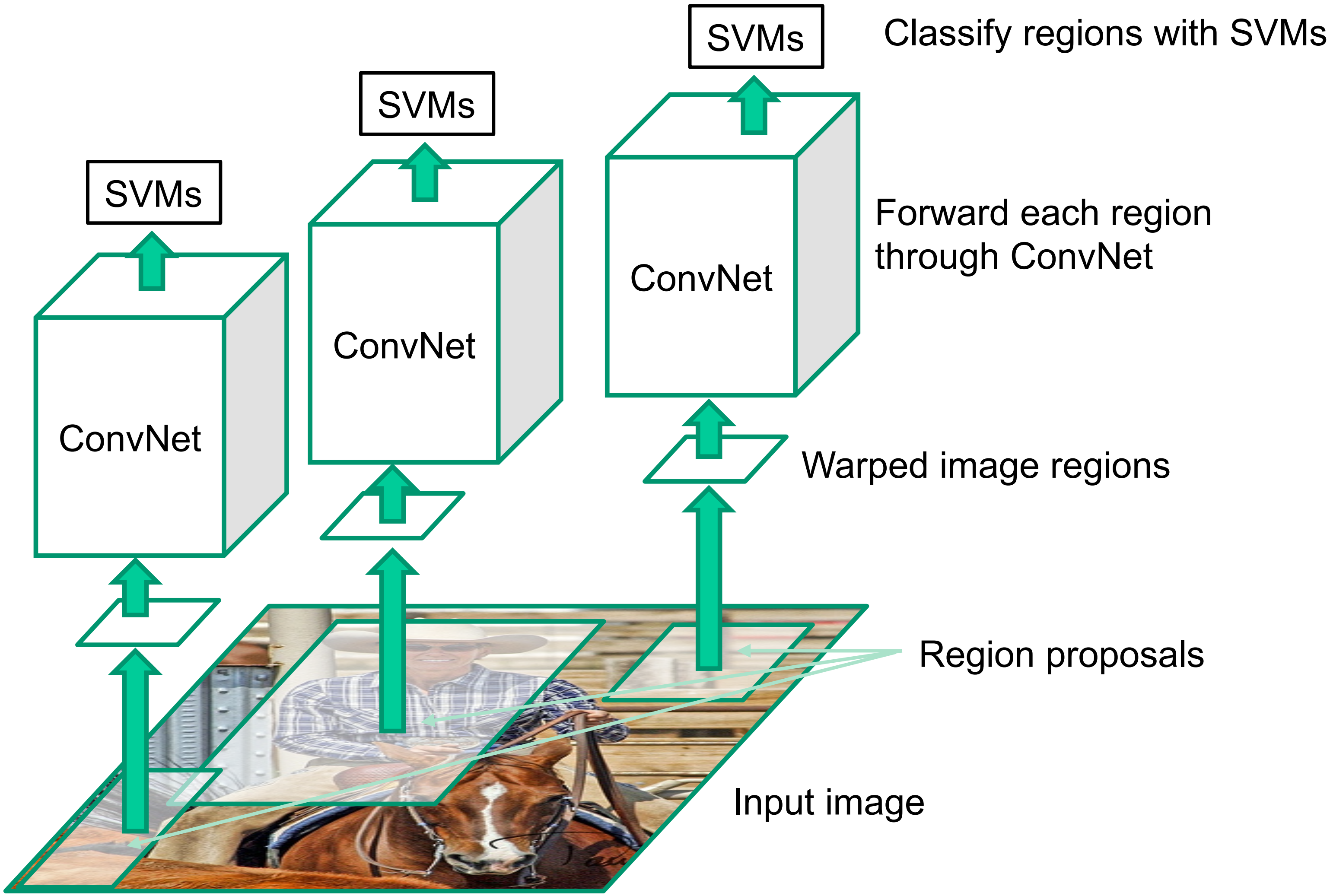
RetinaNet

- Combine feature pyramid network with *focal loss* to reduce the standard cross-entropy loss for well-classified examples



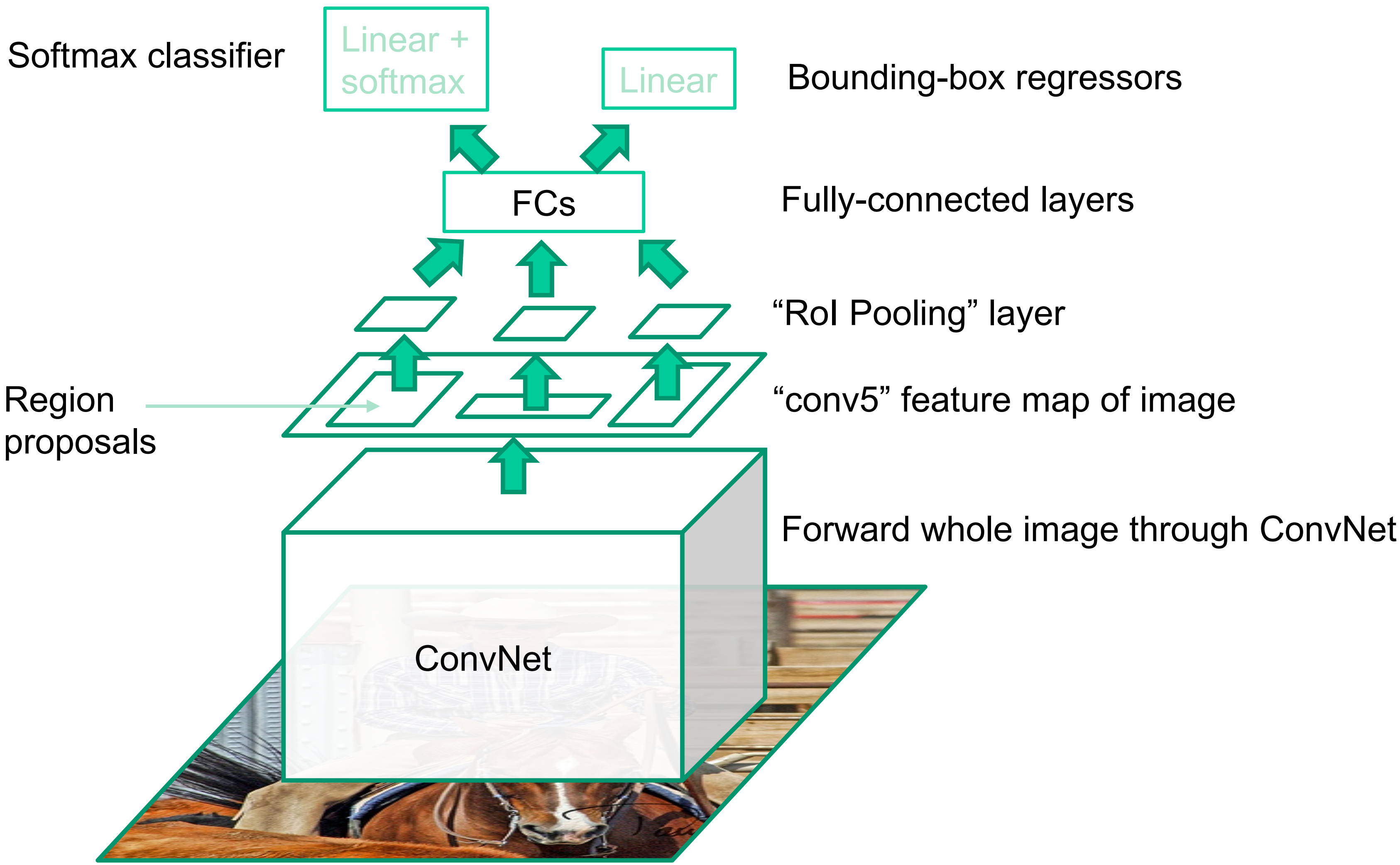
T.-Y. Lin, P. Goyal, R. Girshick, K. He, P. Dollar, [Focal loss for dense object detection](), ICCV 2017.

Review: R-CNN



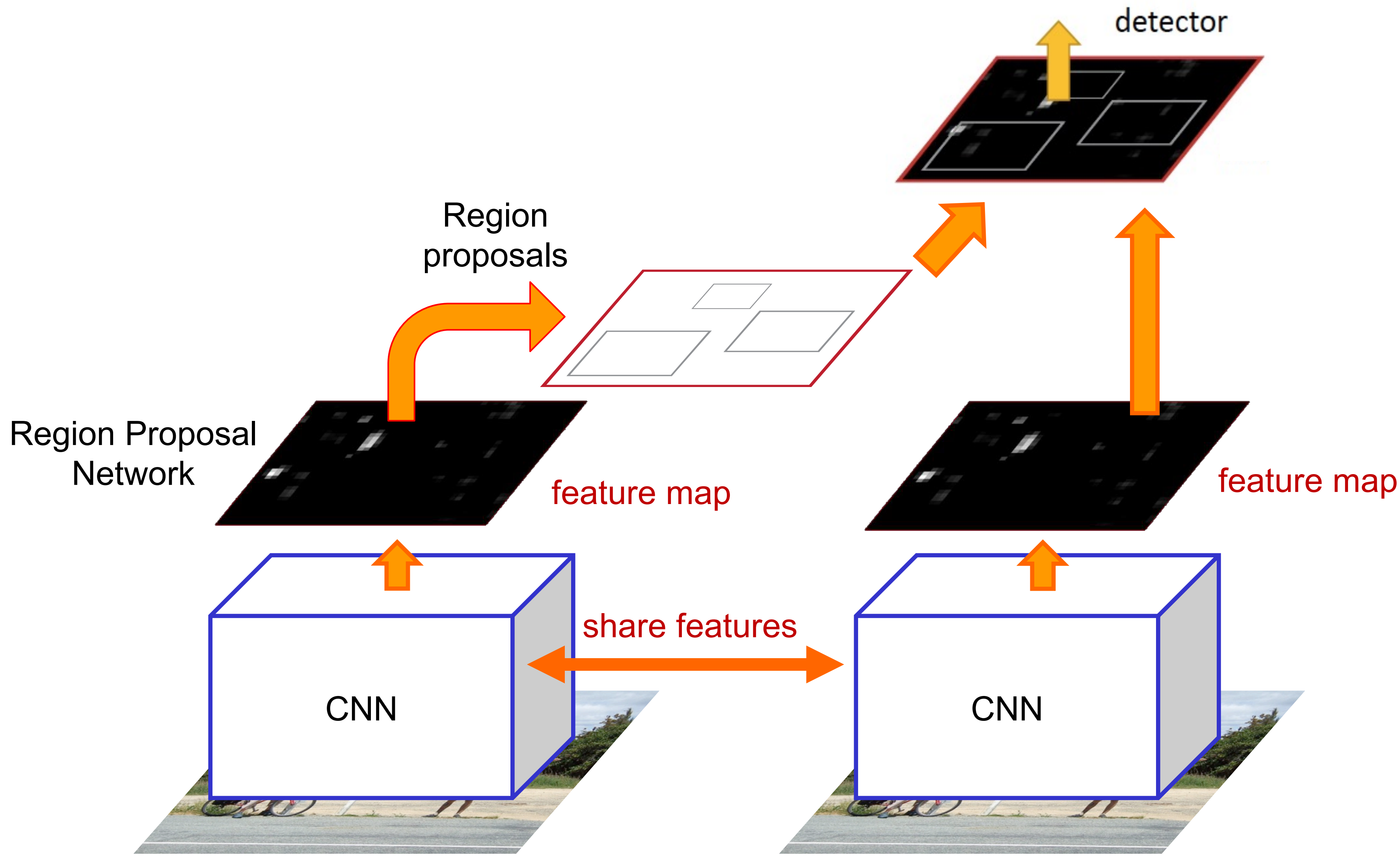
R. Girshick, J. Donahue, T. Darrell, and J. Malik, **Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation**, CVPR 2014.

Review: Fast R-CNN



R. Girshick, Fast R-CNN, ICCV 2015

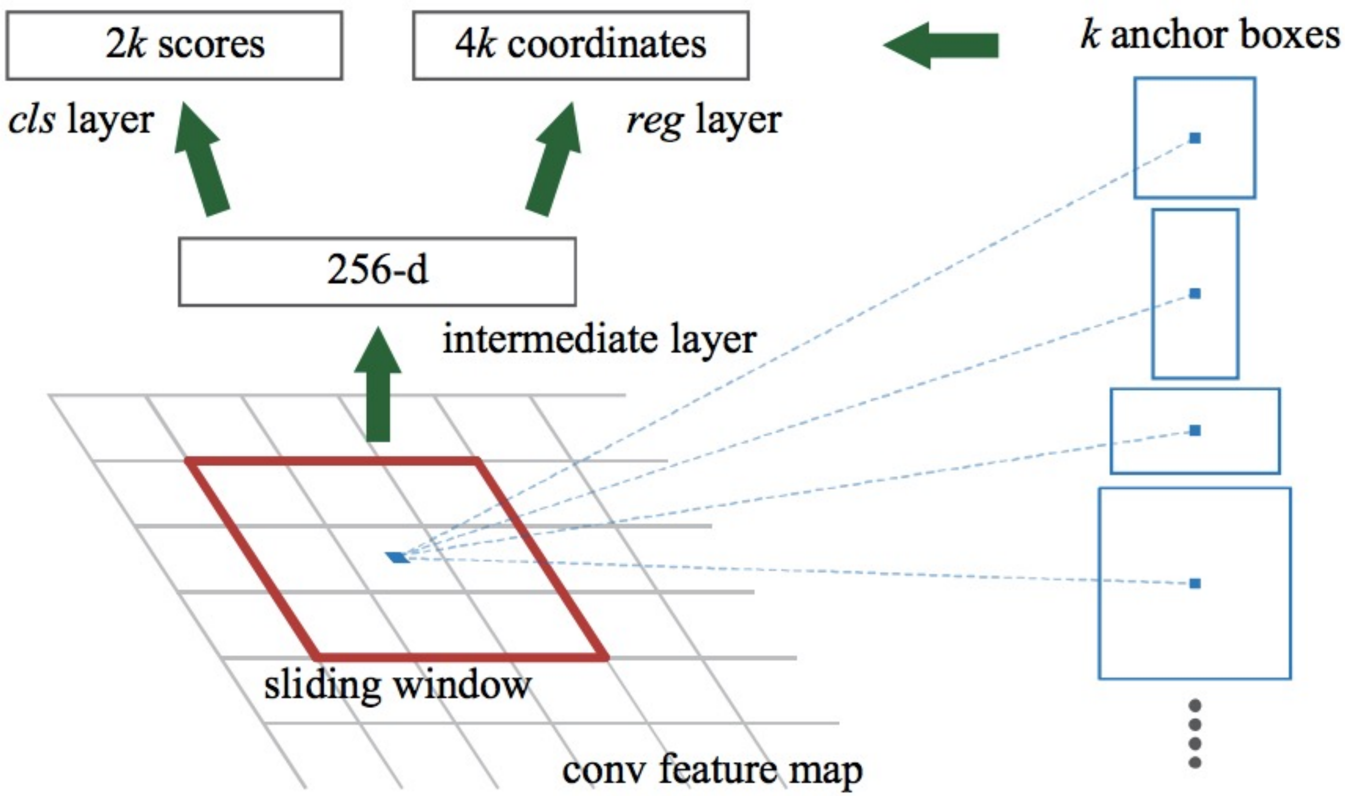
Review: Faster R-CNN



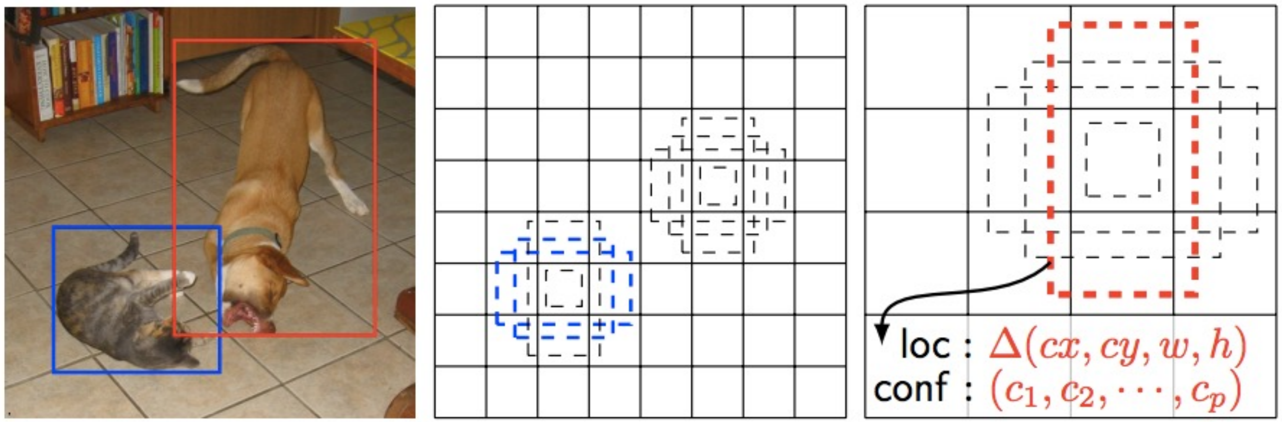
S. Ren, K. He, R. Girshick, and J. Sun, [Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks](), NIPS 2015

Review: RPN

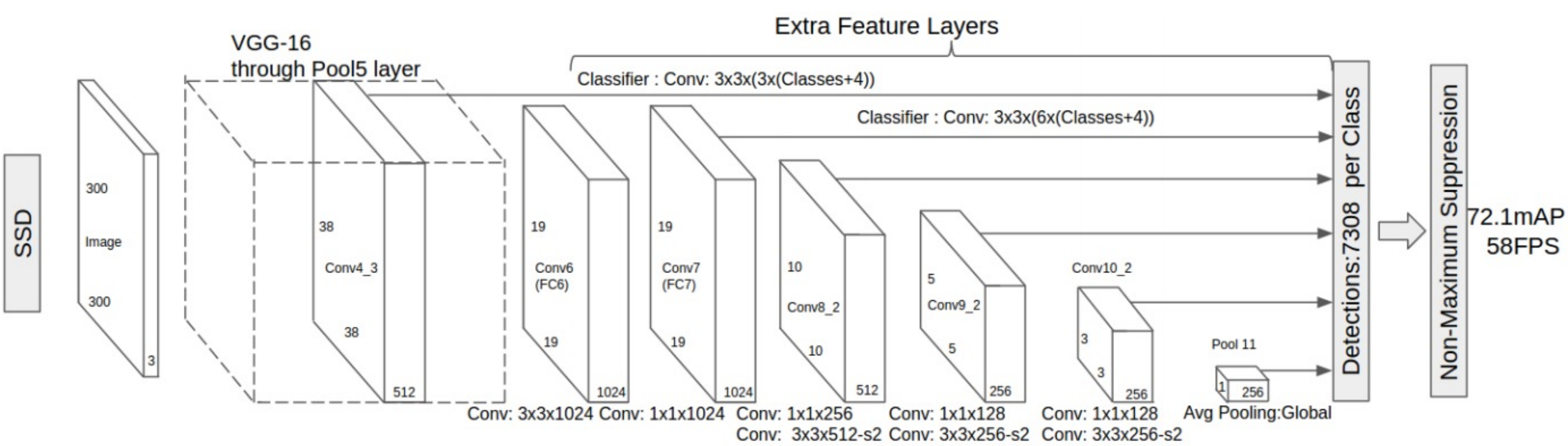
- Slide a small window (3x3) over the conv5 layer
  - Predict object/no object
  - Regress bounding box coordinates with reference to *anchors* (3 scales x 3 aspect ratios)



Review: SSD



(a) Image with GT boxes (b) 8×8 feature map (c) 4×4 feature map

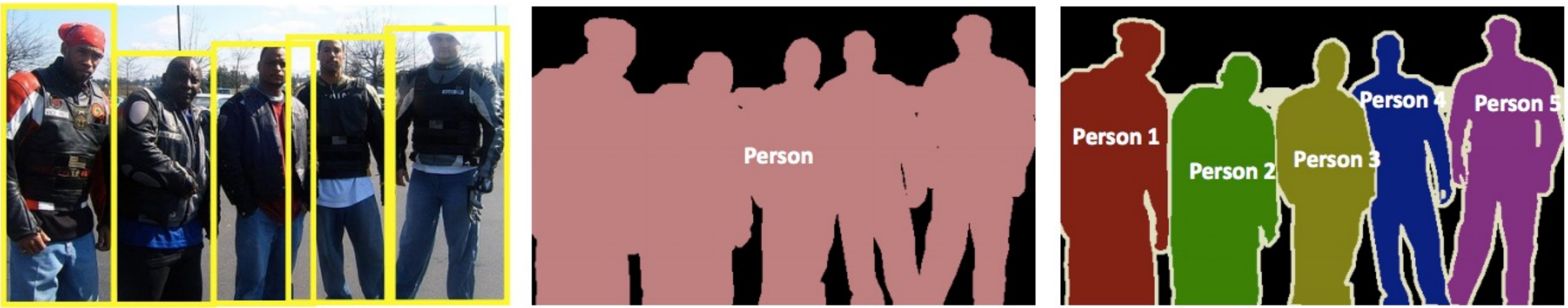


W. Liu, D. Anguelov, D. Erhan, C. Szegedy, S. Reed, C.-Y. Fu, and A. Berg, [SSD: Single Shot MultiBox Detector], ECCV 2016.

Summary: Object detection with CNNs

- R-CNN: region proposals + CNN on cropped, resampled regions
- Fast R-CNN: region proposals + RoI pooling on top of a conv feature map
- Faster R-CNN: RPN + RoI pooling
- Next generation of detectors
  - Direct prediction of BB offsets, class scores on top of conv feature maps
  - Get better context by combining feature maps at multiple resolutions

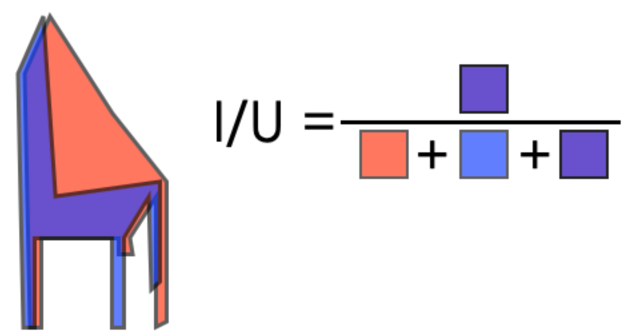
Instance segmentation



Object Detection | Semantic Segmentation | **Instance Segmentation**

Evaluation

- Average Precision like detection, except region IoU as opposed to box IoU.

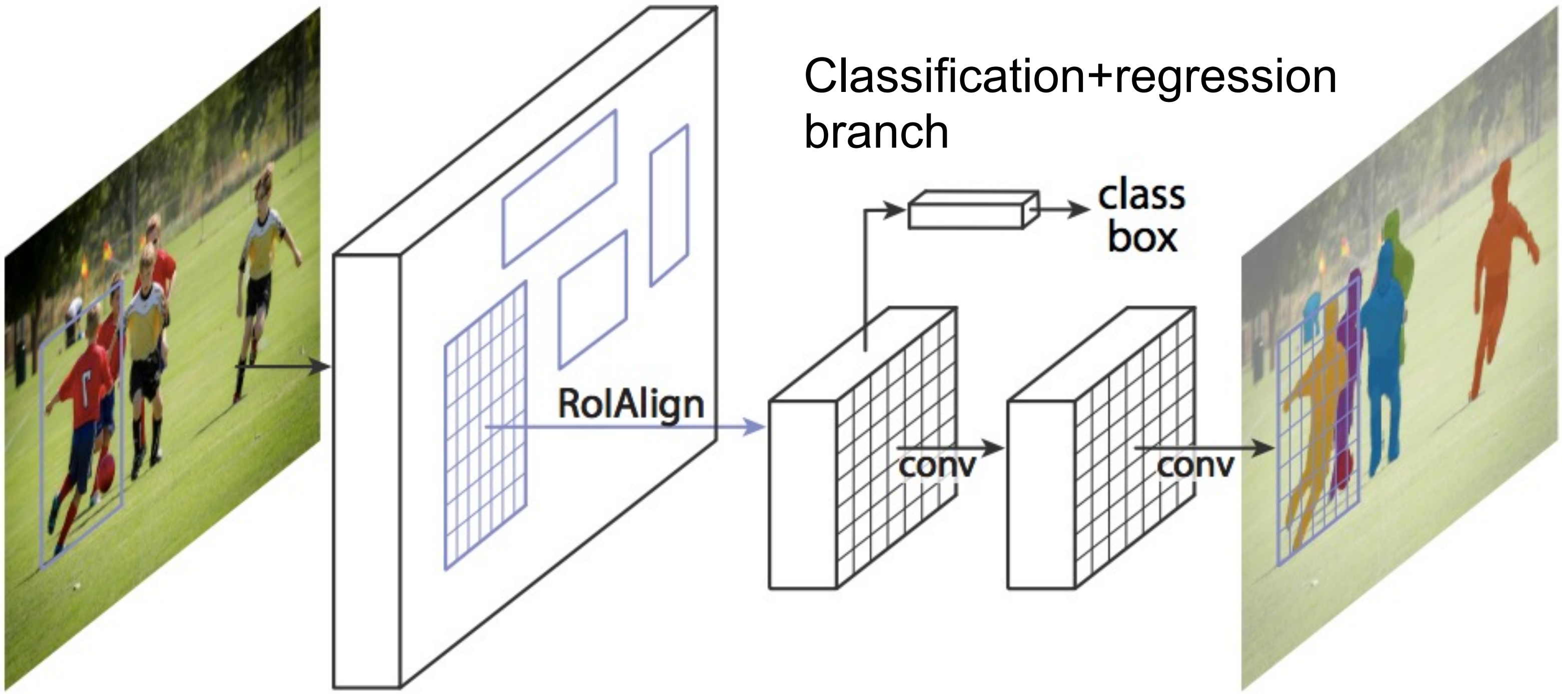


B. Hariharan et al., [Simultaneous Detection and Segmentation](), ECCV 2014

Mask R-CNN

- Mask R-CNN = Faster R-CNN + FCN on RoIs

Classification+regression branch

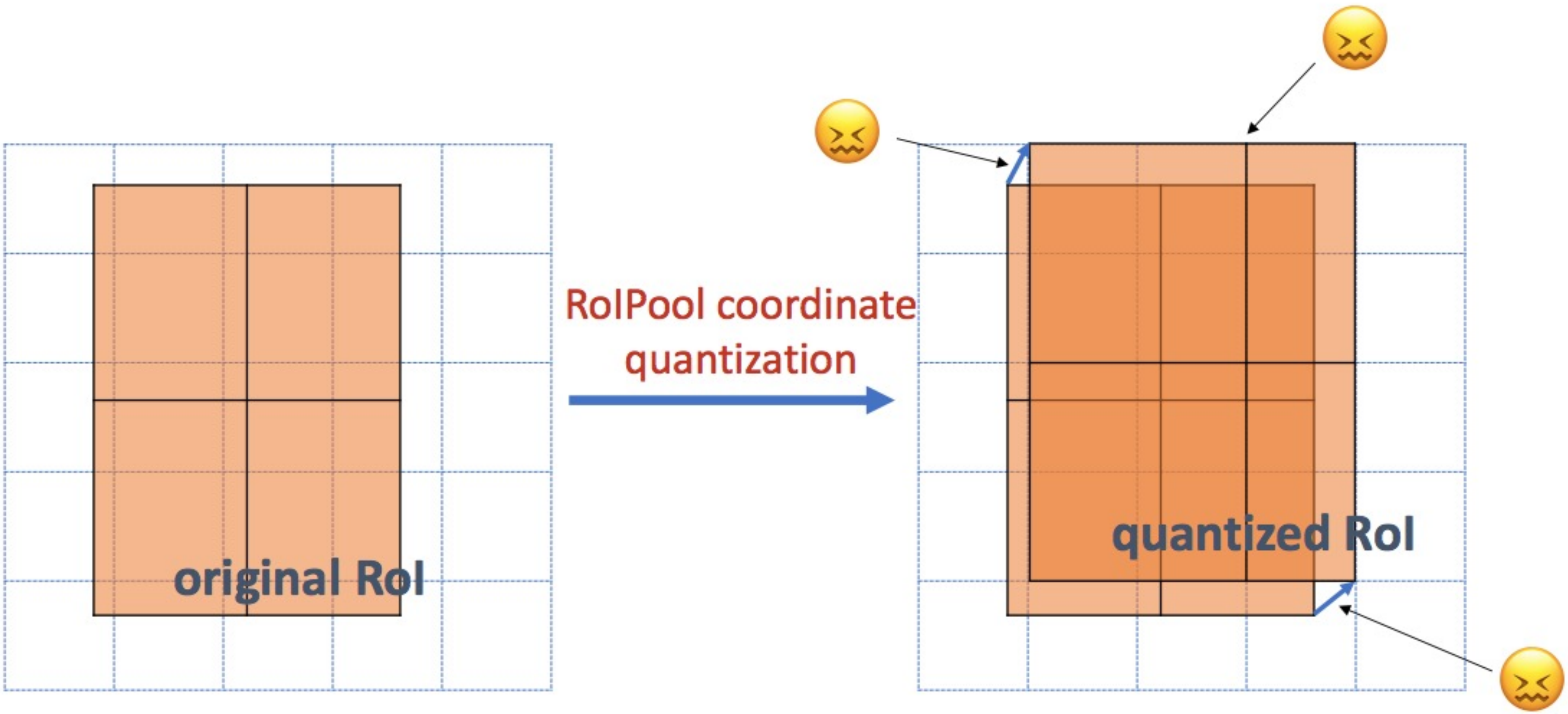


Mask branch: separately predict segmentation for each possible class

K. He, G. Gkioxari, P. Dollar, and R. Girshick, [Mask R-CNN](), ICCV 2017 (Best Paper Award)

RoIAlign vs. RoIPool

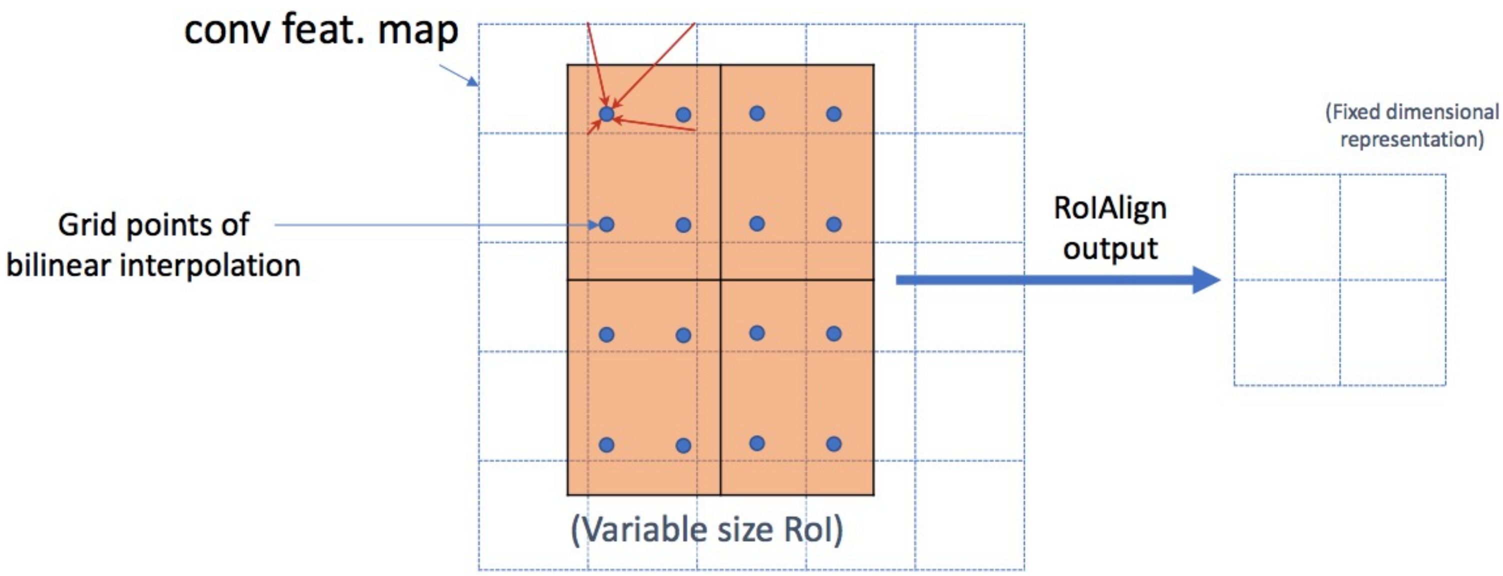
- RoIPool: nearest neighbor quantization



K. He, G. Gkioxari, P. Dollar, and R. Girshick, [Mask R-CNN](), ICCV 2017 (Best Paper Award)

RoIAlign vs. RoIPool

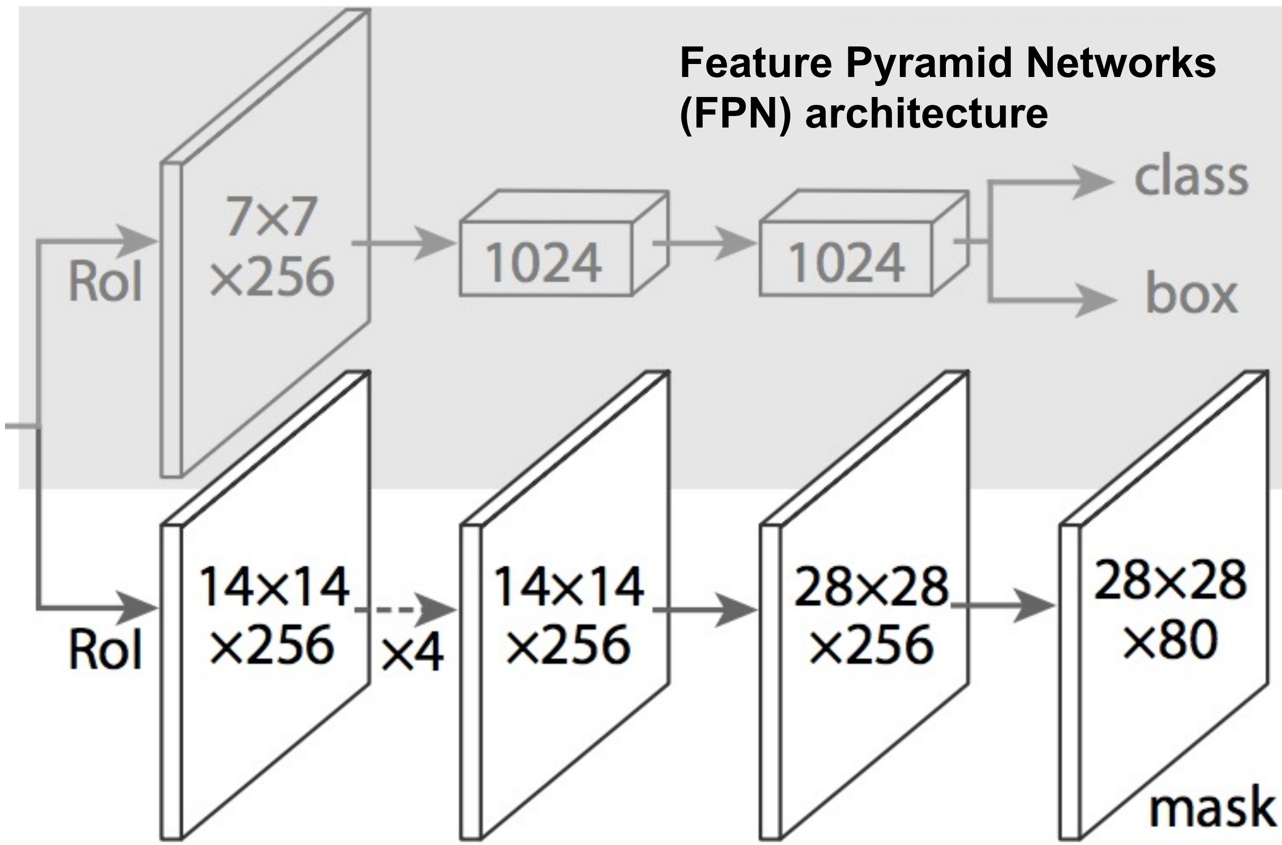
- RoIPool: nearest neighbor quantization
- RoIAlign: bilinear interpolation



K. He, G. Gkioxari, P. Dollar, and R. Girshick, [Mask R-CNN](), ICCV 2017 (Best Paper Award)

Mask R-CNN

- From RoIAlign features, predict class label, bounding box, and segmentation mask

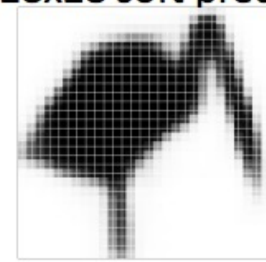


K. He, G. Gkioxari, P. Dollar, and R. Girshick, [Mask R-CNN](), ICCV 2017 (Best Paper Award)

Mask R-CNN

Validation image with box detection shown in red

28x28 soft prediction



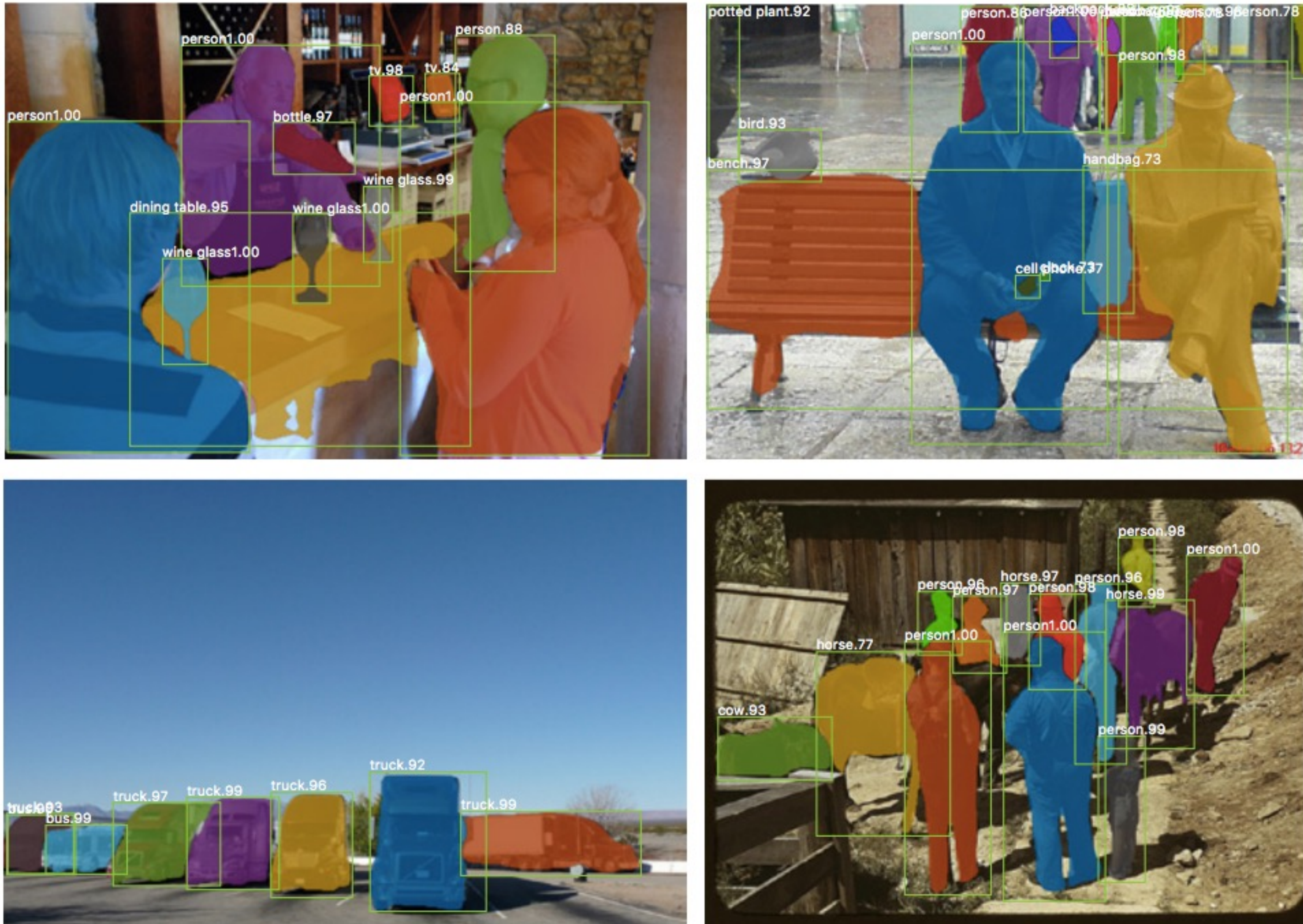
Resized Soft prediction

Final mask

K. He, G. Gkioxari, P. Dollar, and R. Girshick, Mask R-CNN,
ICCV 2017 (Best Paper Award)

Example results

Example results



Instance segmentation results on COCO

	backbone	AP	AP_{50}	AP_{75}	AP_S	AP_M	AP_L
MNC [10]	ResNet-101-C4	24.6	44.3	24.8	4.7	25.9	43.6
FCIS [26] +OHEM	ResNet-101-C5-dilated	29.2	49.5	-	7.1	31.3	50.0
FCIS+++ [26] +OHEM	ResNet-101-C5-dilated	33.6	54.5	-	-	-	-
Mask R-CNN	ResNet-101-C4	33.1	54.9	34.8	12.1	35.6	51.1
Mask R-CNN	ResNet-101-FPN	35.7	58.0	37.8	15.5	38.1	52.4
Mask R-CNN	ResNeXt-101-FPN	**37.1**	**60.0**	**39.4**	**16.9**	**39.9**	**53.5**

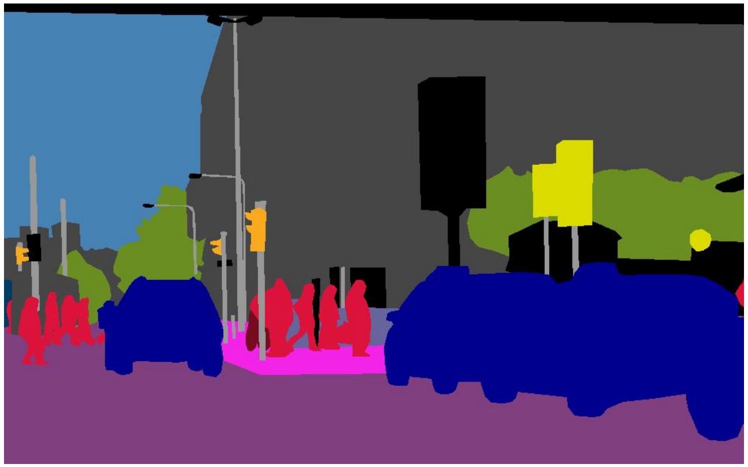
AP at different IoU thresholds

AP for different size instances

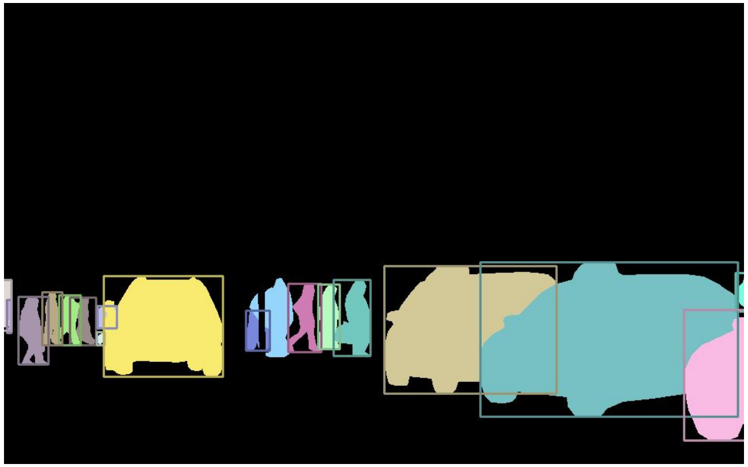
K. He, G. Gkioxari, P. Dollar, and R. Girshick, Mask R-CNN, ICCV 2017 (Best Paper Award)

Unifying Semantic and Instance Segm.

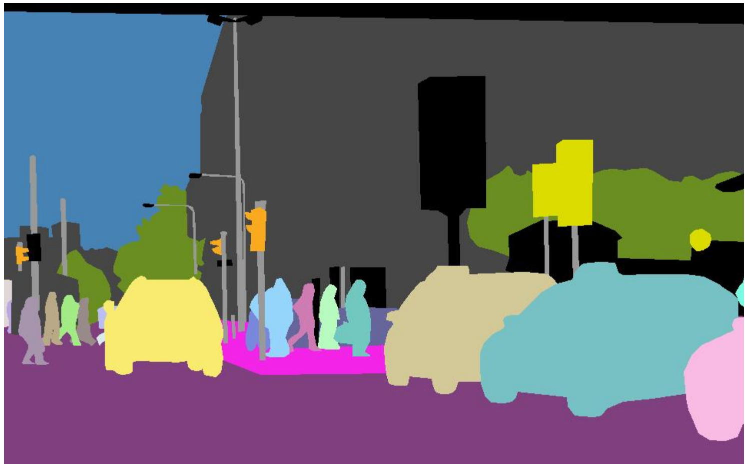
(a) image



(b) semantic segmentation



(c) instance segmentation



(d) panoptic segmentation

Alexander Kirillov, Kaiming He, Ross Girshick, Carsten Rother, Piotr Dollár, [Panoptic Segmentation](), CVPR 2019.

Keypoint prediction

- Given K keypoints, train model to predict K m x m *one-hot* maps