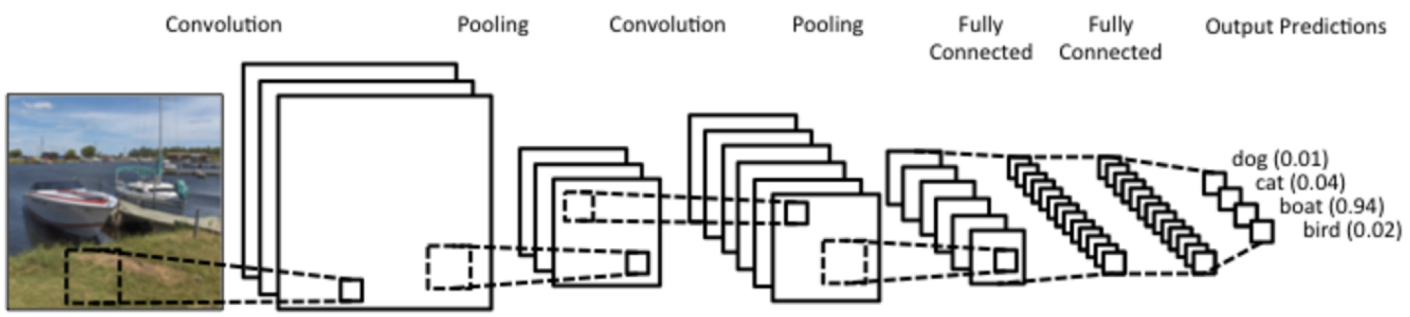
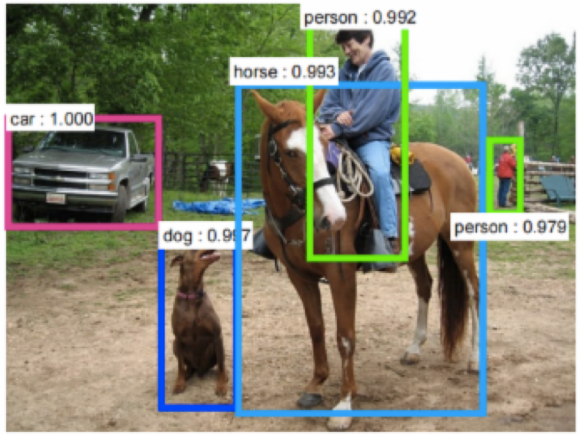
From image classification to object detection

Image classification



Object detection



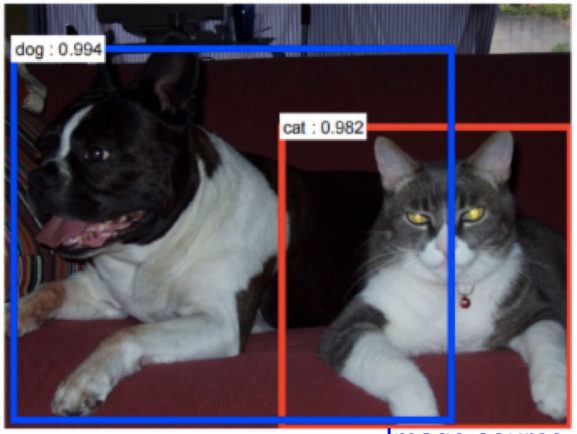


Image source

What are the challenges of object detection?

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

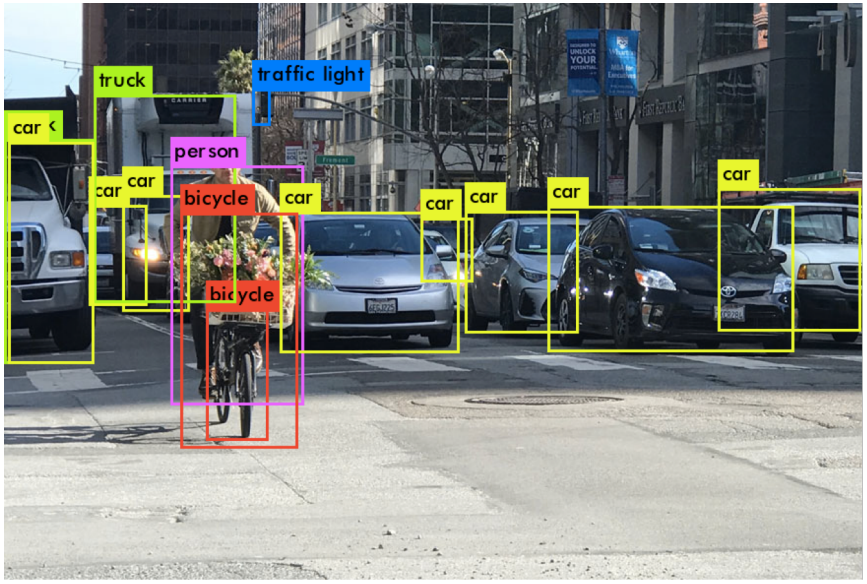


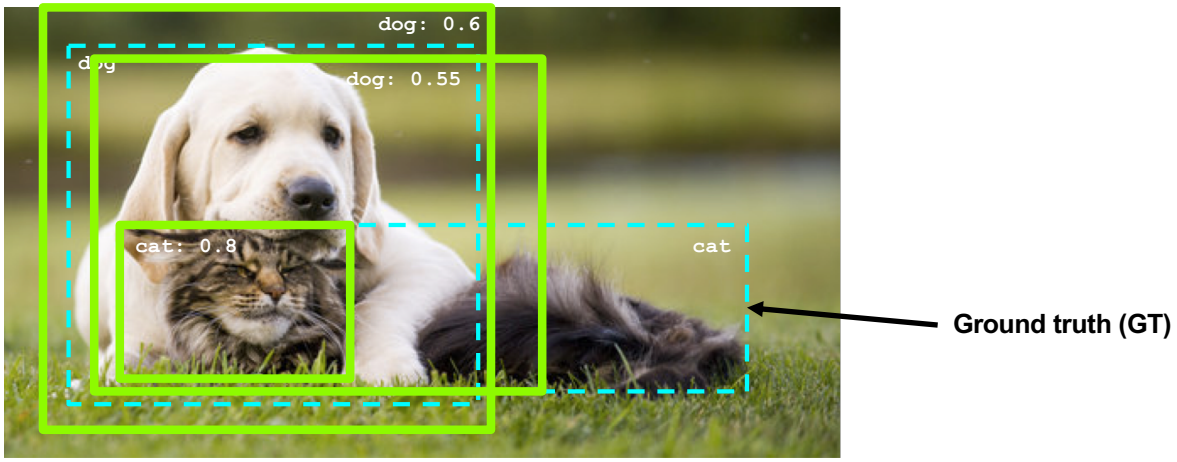
Image source

Outline

- Task definition and evaluation
- Detection strategies
- Zoo of deep detection approaches
  - R-CNN
  - Fast R-CNN
  - Faster R-CNN
  - YOLO
  - SSD
  - Some recent entries: RetinaNet, CornerNet, DETR

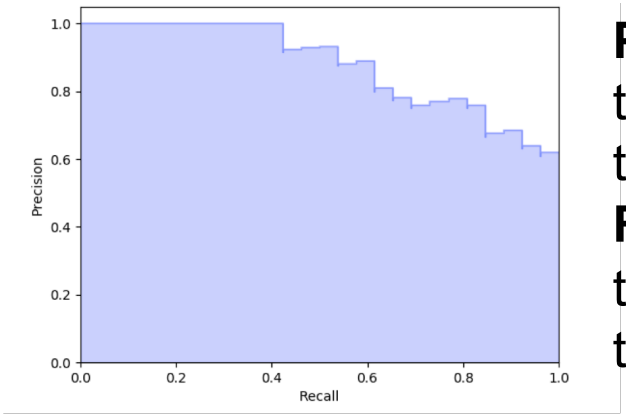
Object detection evaluation

- 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 is considered a true positive



Object detection evaluation

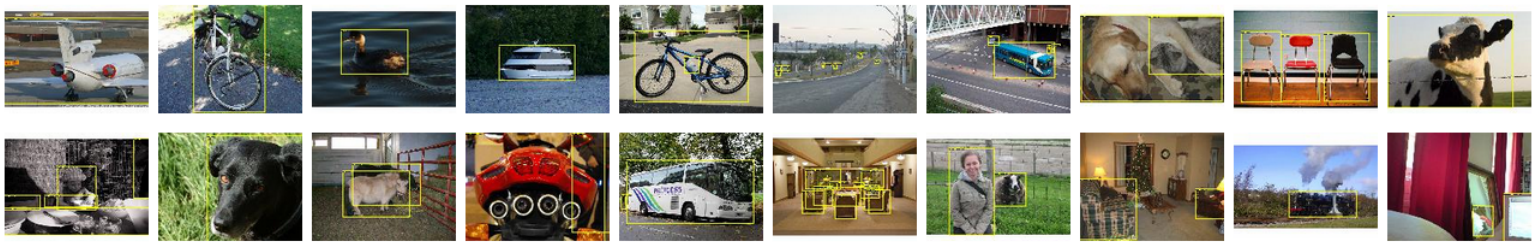
- At test time, predict bounding boxes, class labels, and confidence scores
- For each detection, determine whether it is a true or false positive
- For each class, sort detections from highest to lowest confidence, plot Recall-Precision curve and compute Average Precision (area under the curve)
- Take 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)

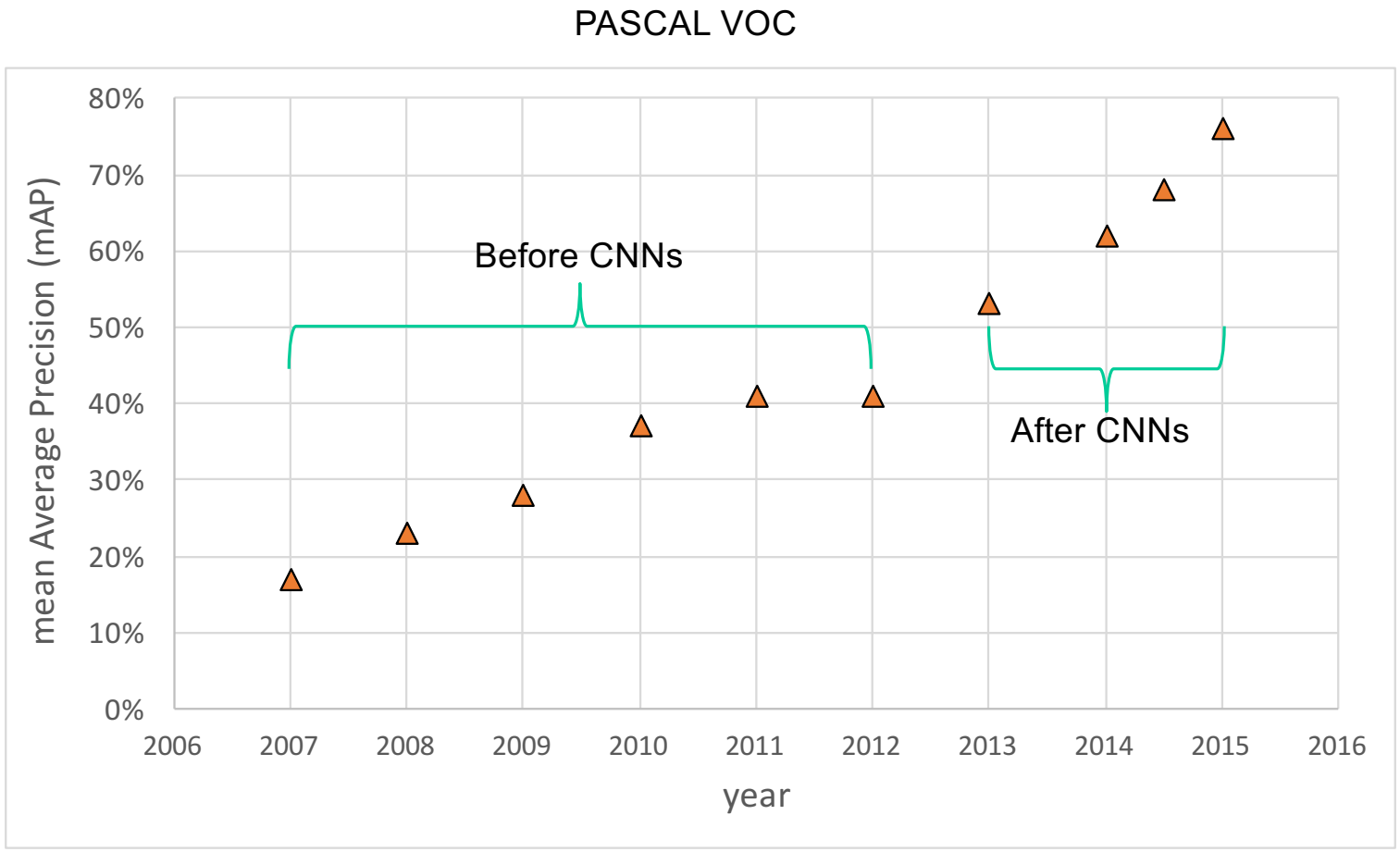


- 20 challenge classes:
  - *Person*
  - *Animals:* bird, cat, cow, dog, horse, sheep
  - *Vehicles:* airplane, bicycle, boat, bus, car, motorbike, train
  - *Indoor:* bottle, chair, dining table, potted plant, sofa, tv/monitor

- 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



Current benchmark: COCO

What is COCO?

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

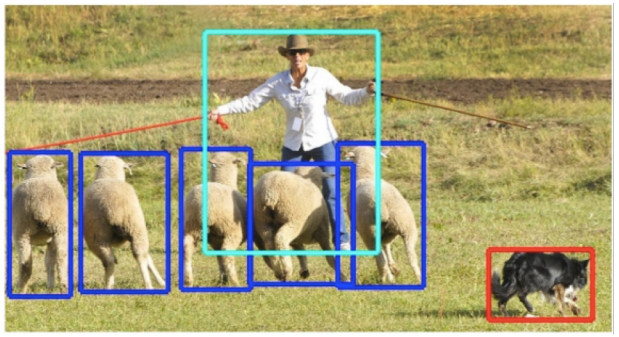
- Object segmentation
- Recognition in context
- Superpixel stuff segmentation
- 330K images (>200K labeled)
- 1.5 million object instances
- 80 object categories
- 91 stuff categories
- 5 captions per image
- 250,000 people with keypoints

COCO
Common Objects in Context

http://cocodataset.org/#home

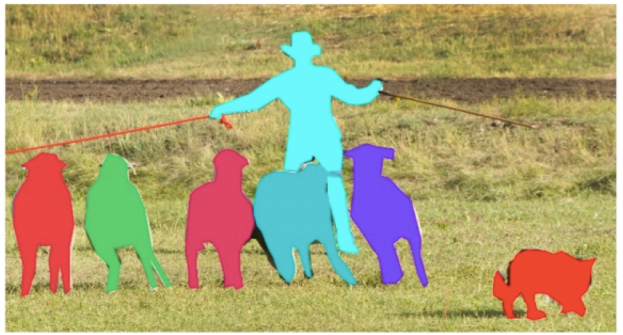
COCO dataset: Tasks

image classification



object detection

semantic segmentation



instance segmentation

- Also: keypoint prediction, captioning, question answering…

COCO detection metrics

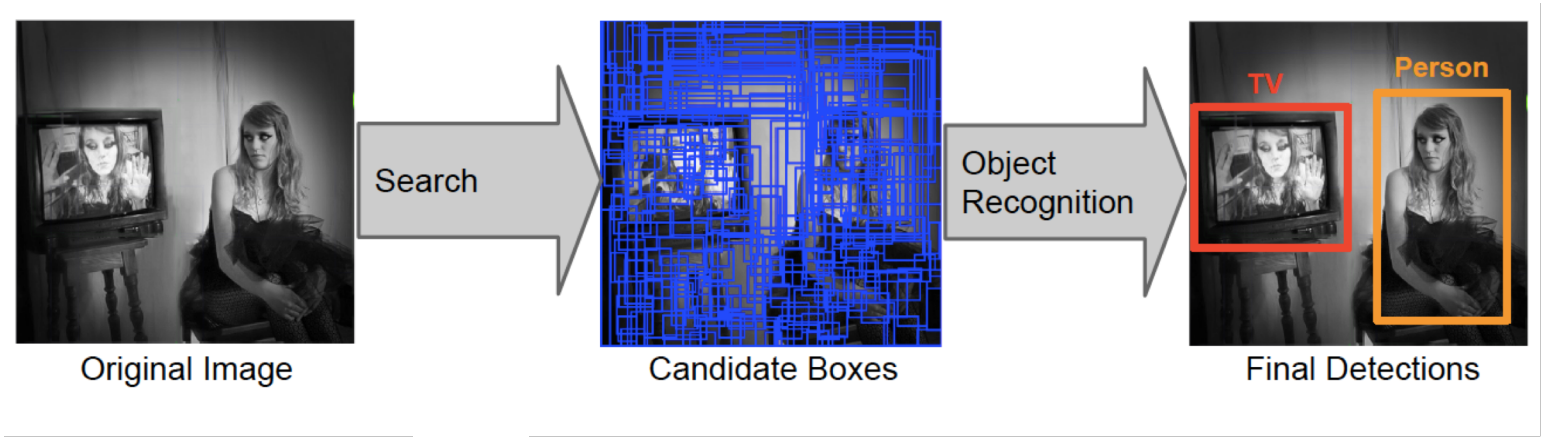
```
Average Precision (AP):
  AP                  % AP at IoU=.50:.05:.95 (primary challenge metric)
  AP^IoU=.50          % AP at IoU=.50 (PASCAL VOC metric)
  AP^IoU=.75          % AP at IoU=.75 (strict metric)
AP Across Scales:
  AP^small            % AP for small objects: area < 32^2
  AP^medium           % AP for medium objects: 32^2 < area < 96^2
  AP^large            % AP for large objects: area > 96^2
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 < 32^2
  AR^medium           % AR for medium objects: 32^2 < area < 96^2
  AR^large            % AR for large objects: area > 96^2
```

- Leaderboard: http://cocodataset.org/#detection-leaderboard
- Official COCO challenges no longer include detection
  - Emphasis has shifted to instance segmentation and dense semantic segmentation

Approaches to detection: Sliding windows

- 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

Approaches to detection: Object proposals



- 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

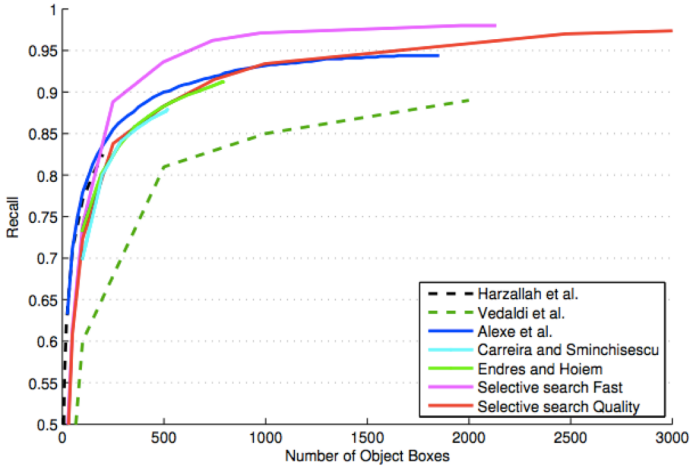
Selective search for detection

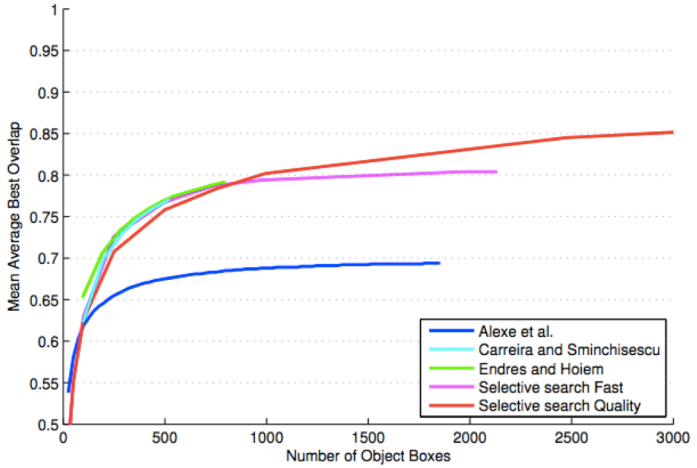
- Use hierarchical segmentation: start with small *superpixels* and merge based on diverse cues

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

Selective search for detection

Evaluation of region proposals





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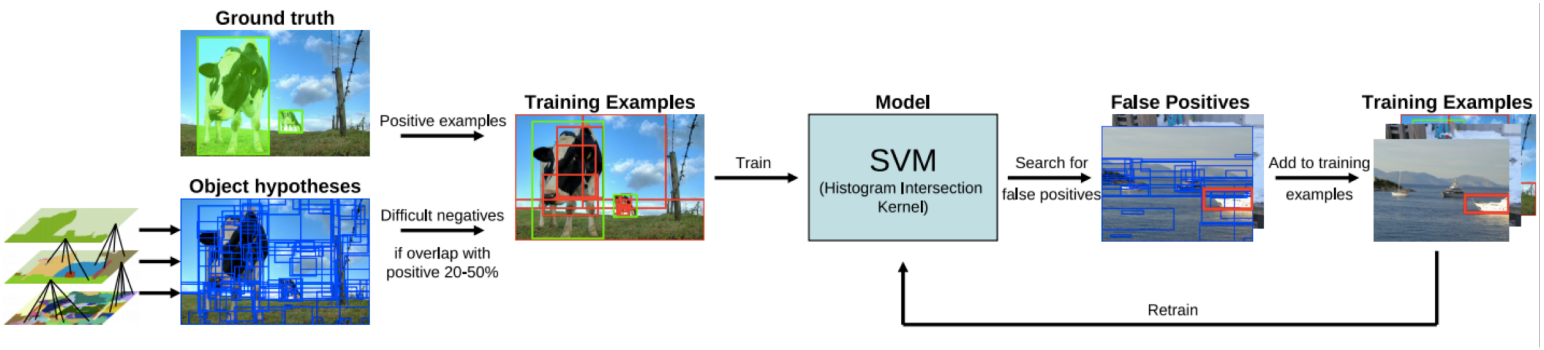
Selective search for detection



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

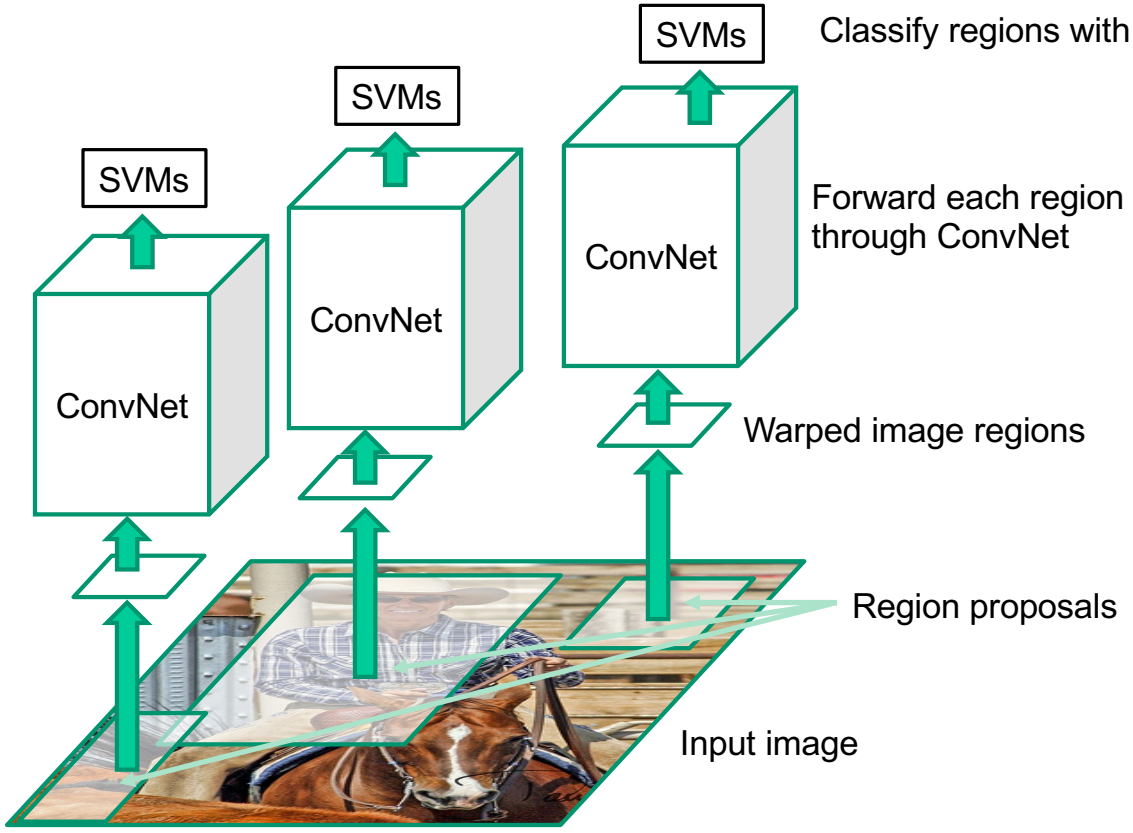
J. Uijlings, K. van de Sande, T. Gevers, and A. Smeulders, Selective Search for Object Recognition, IJCV 2013

Approaches to detection

- Before ~2010, dominated by sliding windows
- 2010-2013: proposal-driven
- Deep learning approaches started as proposal-driven, but have evolved back toward sliding windows
- Most recently, “global” methods are becoming more common

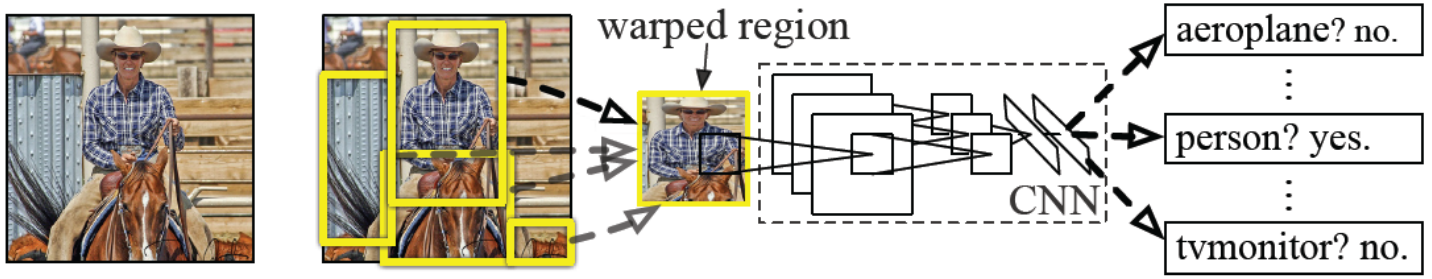
R-CNN: Region proposals + CNN features

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

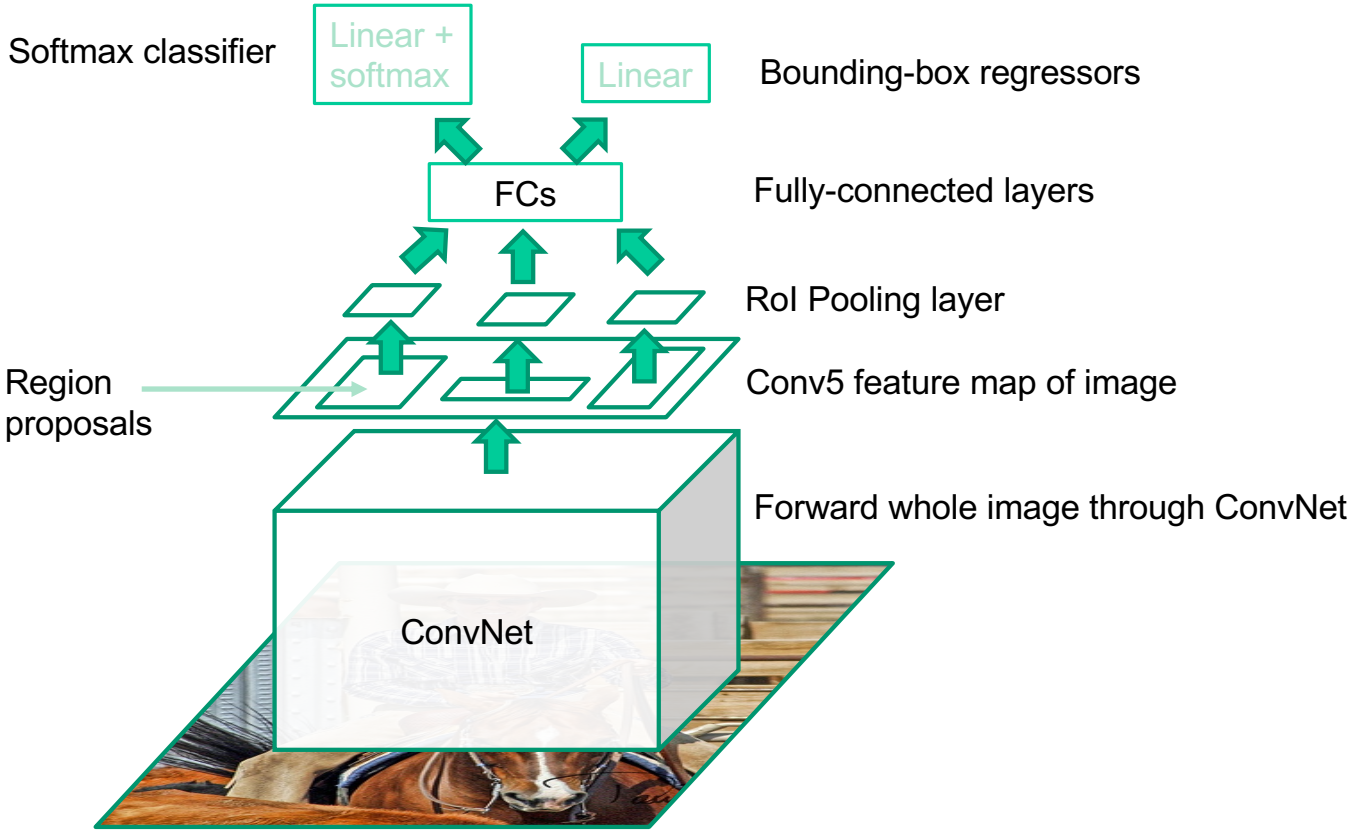


- **Regions**: ~2000 Selective Search proposals
- **Network**: AlexNet *pre-trained* on ImageNet (1000 classes), *fine-tuned* on PASCAL (21 classes)
- **Final detector**: warp proposal regions, extract fc7 network activations (4096 dimensions), classify with linear SVM
- **Bounding box regression** to 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
  - Much more accurate than previous approaches!
  - 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 was slow (84h), took up a lot of storage
    - 2000 CNN passes per image
  - Inference (detection) was slow (47s / image with VGG16)

Fast R-CNN

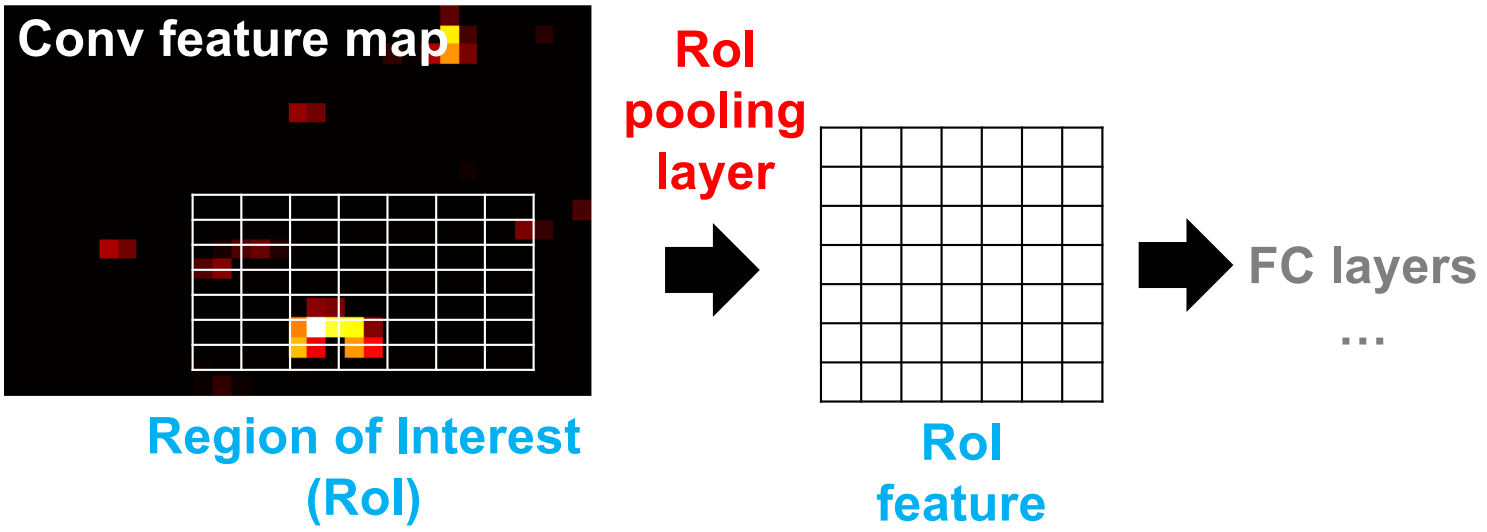


Source: R. Girshick

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

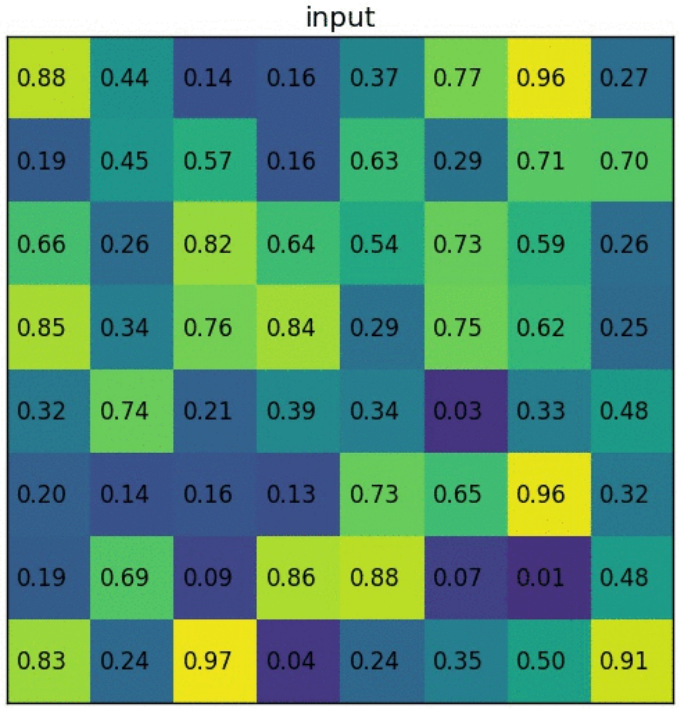
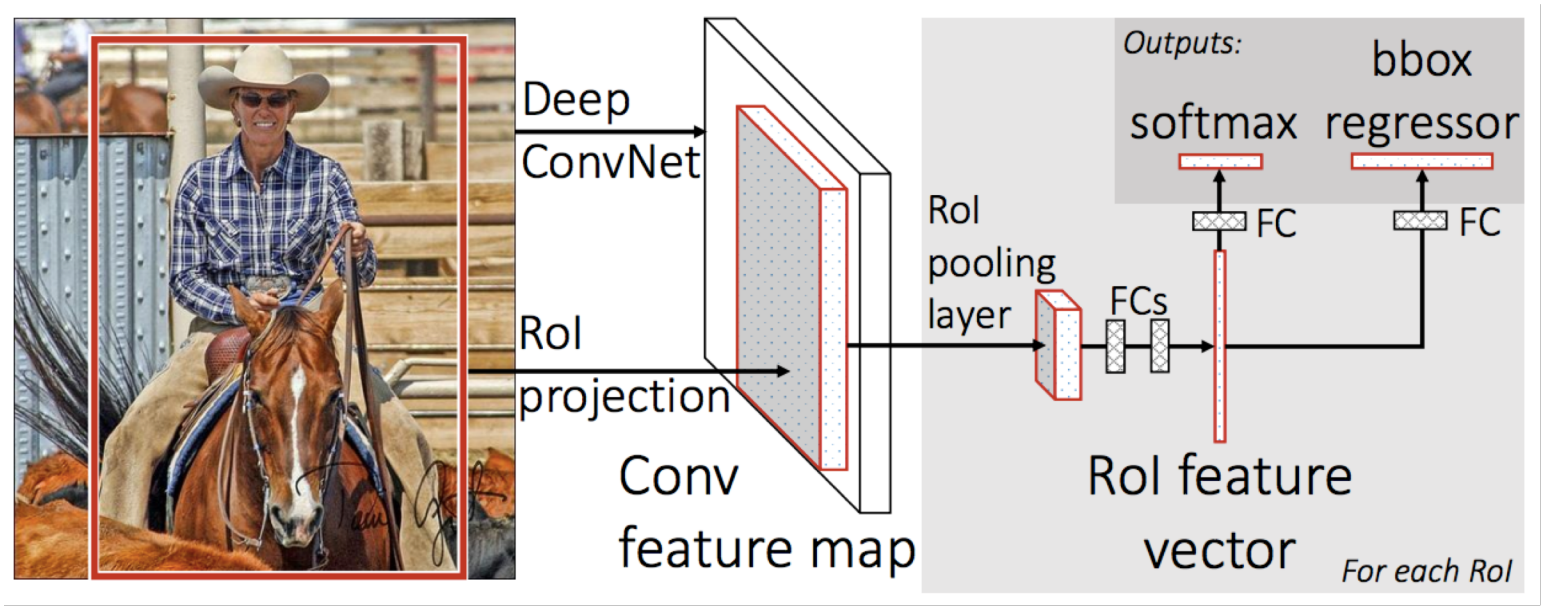


Image source

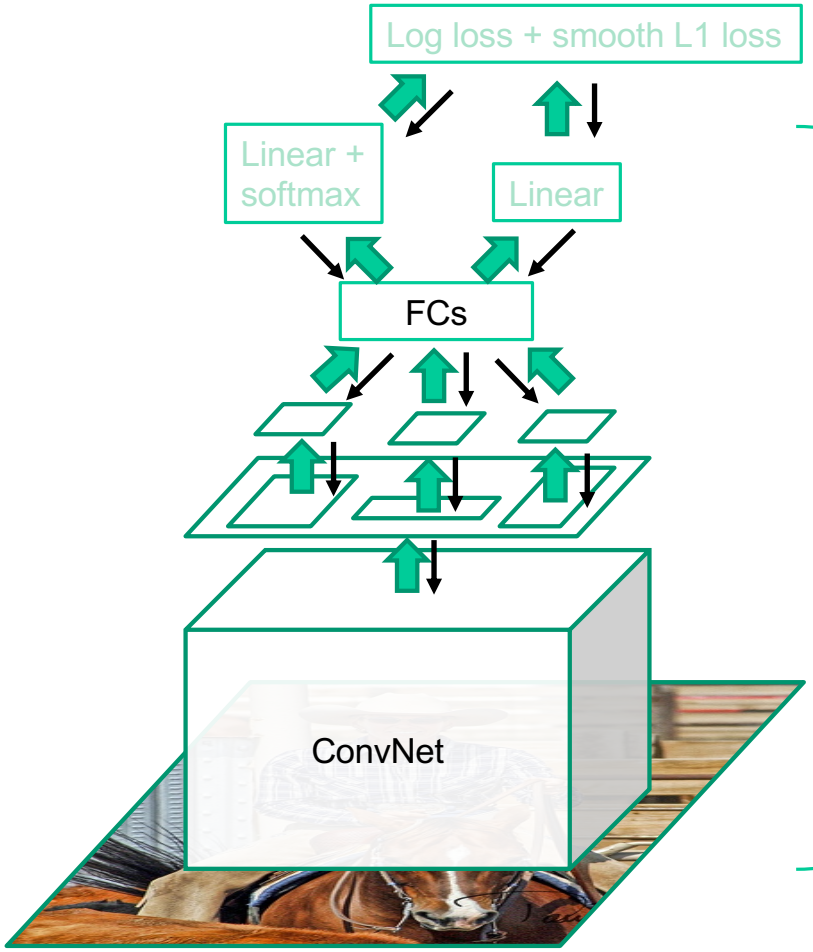
Prediction

- 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



Multi-task loss

Trainable

Source: R. Girshick

R. Girshick, Fast R-CNN, ICCV 2015

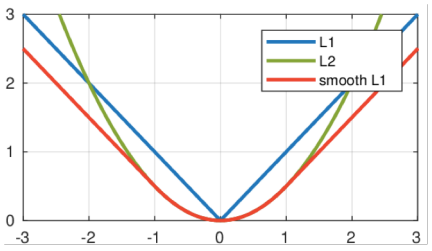
Multi-task loss

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

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

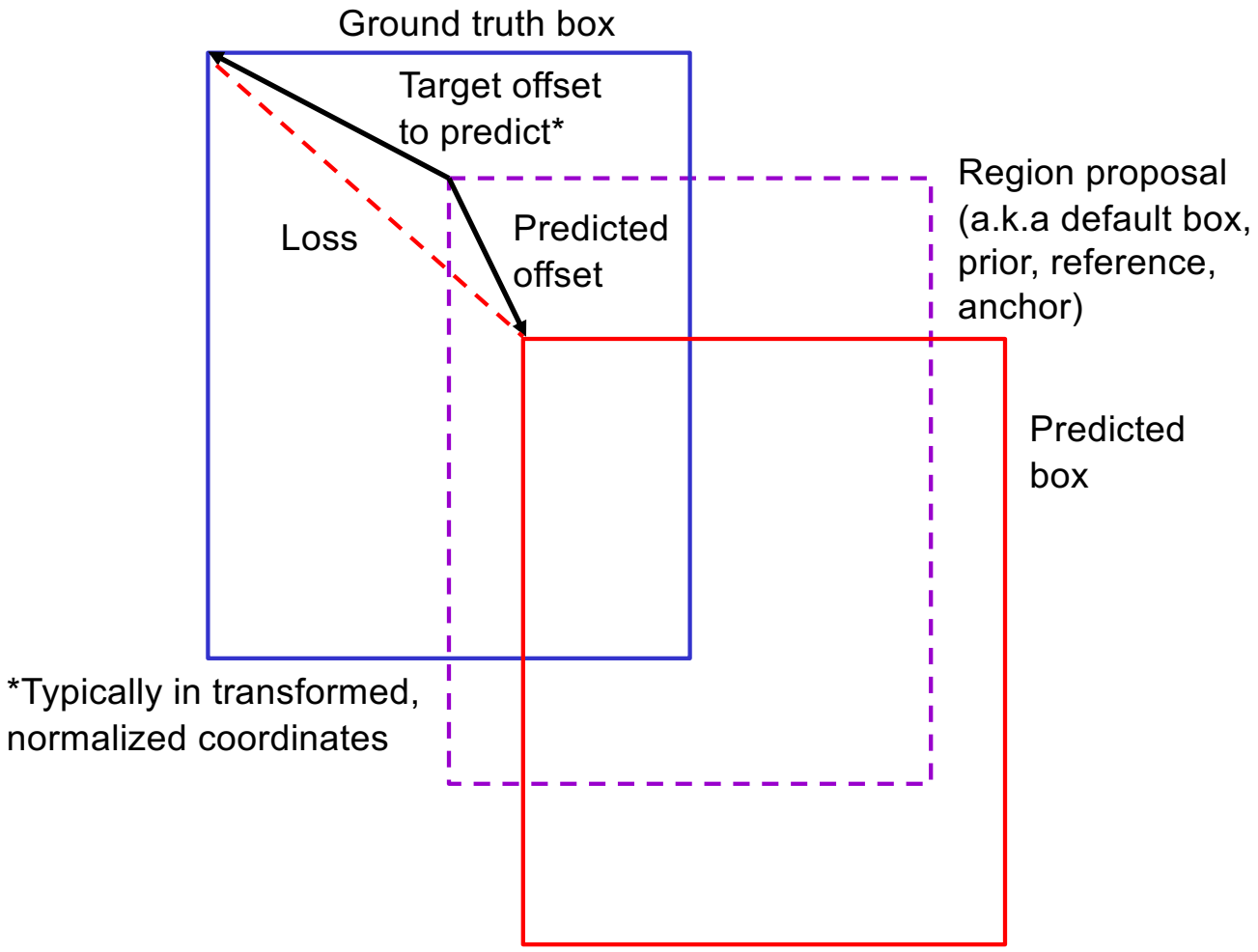
- Regression loss: *smooth* L_1 *loss* on top of log space offsets relative to proposal

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



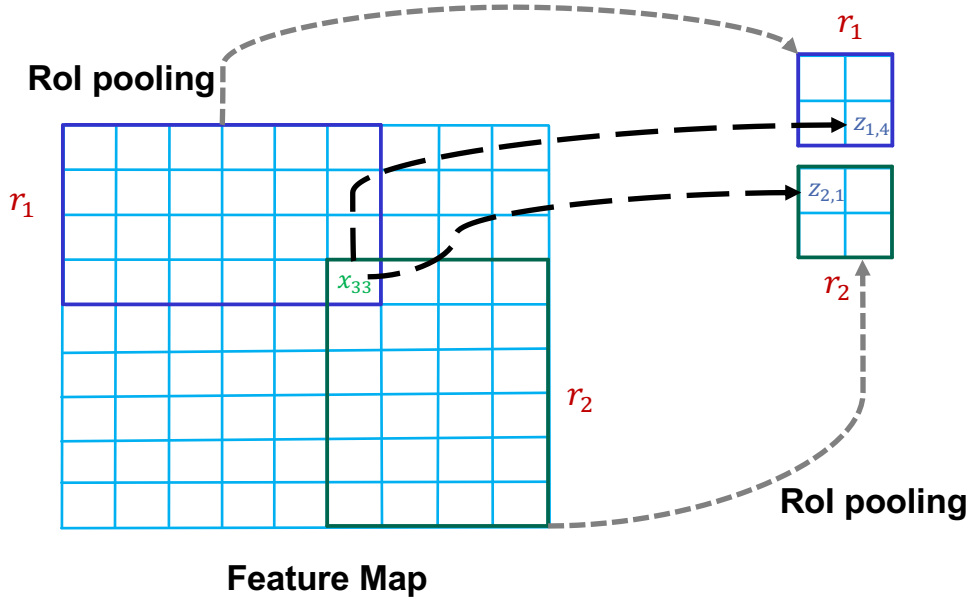
$$\text{smooth}_{L_1}(x) = \begin{cases} 0.5x^2 & \text{if } |x| < 1 \\ |x| - 0.5 & \text{otherwise} \end{cases}$$

Bounding box regression



ROI pooling: Backpropagation

- Similar to max pooling, but has to take into account overlap of pooling regions



Source: Ross Girshick

ROI pooling: Backpropagation

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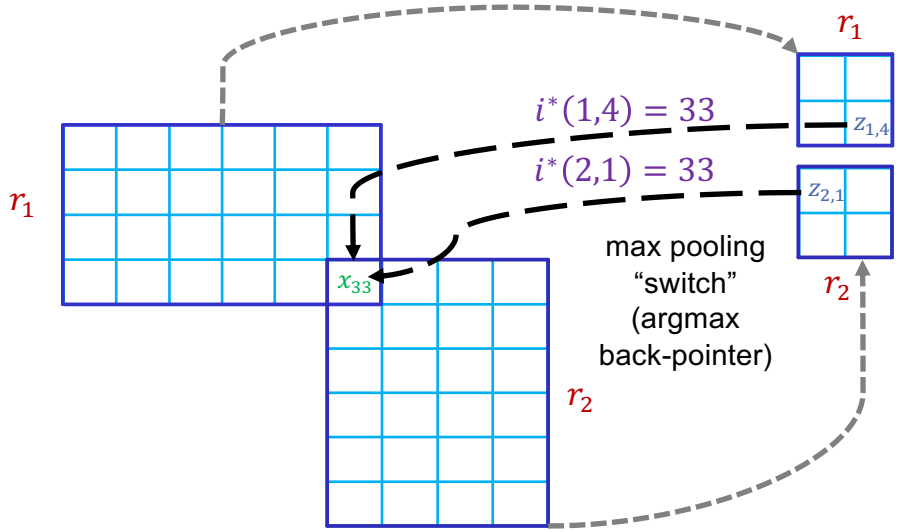


Backward Pass:
Have $\frac{\partial e}{\partial z}$,
want $\frac{\partial e}{\partial x}$

$$\frac{\partial e}{\partial x_i} = \sum_r \sum_j \frac{\partial e}{\partial z_{rj}} \frac{\partial z_{rj}}{\partial x_i} = \sum_r \sum_j \mathbb{I}[i = i^*(r,j)] \frac{\partial e}{\partial z_{rj}}$$

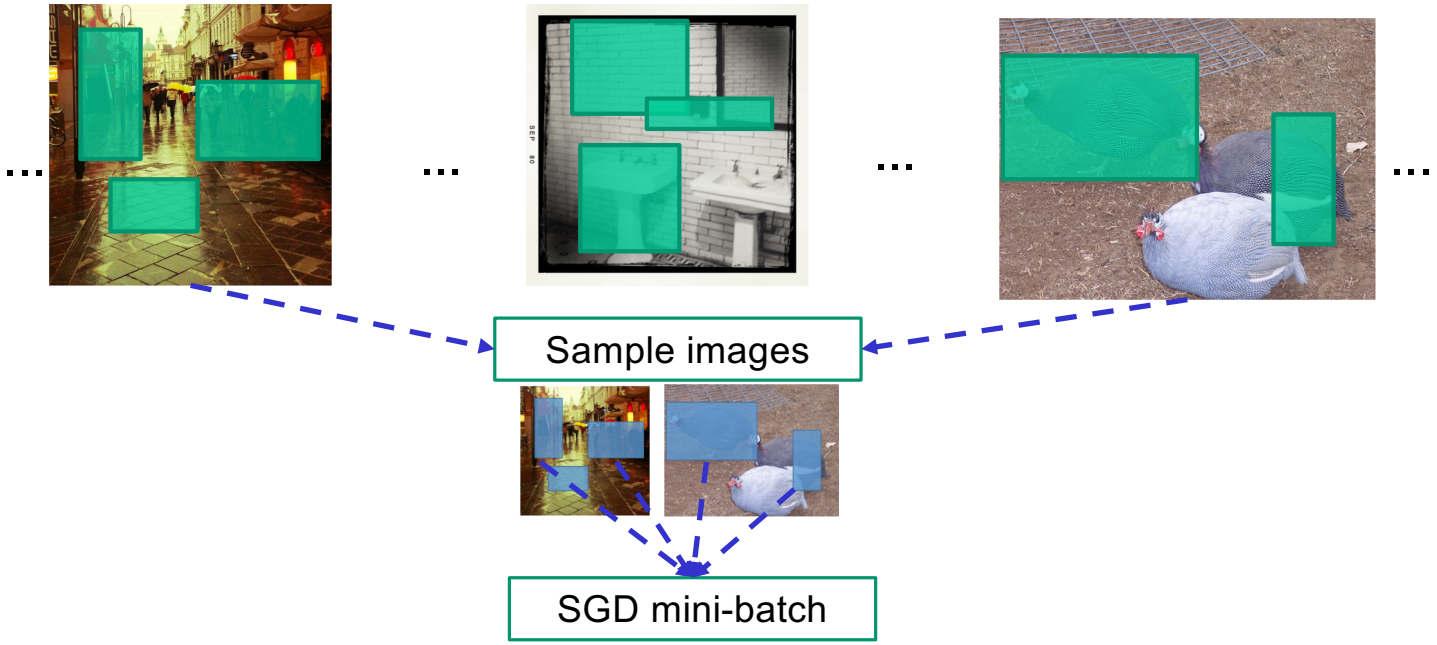
Over regions r, RoI indices j

1 if r, j "pooled" input i; 0 o/w

Source: Ross Girshick

Mini-batch sampling

- Sample a few images (e.g., 2)
- Sample many regions from each image (64)



Source: R. Girshick, K. He

Fast R-CNN results

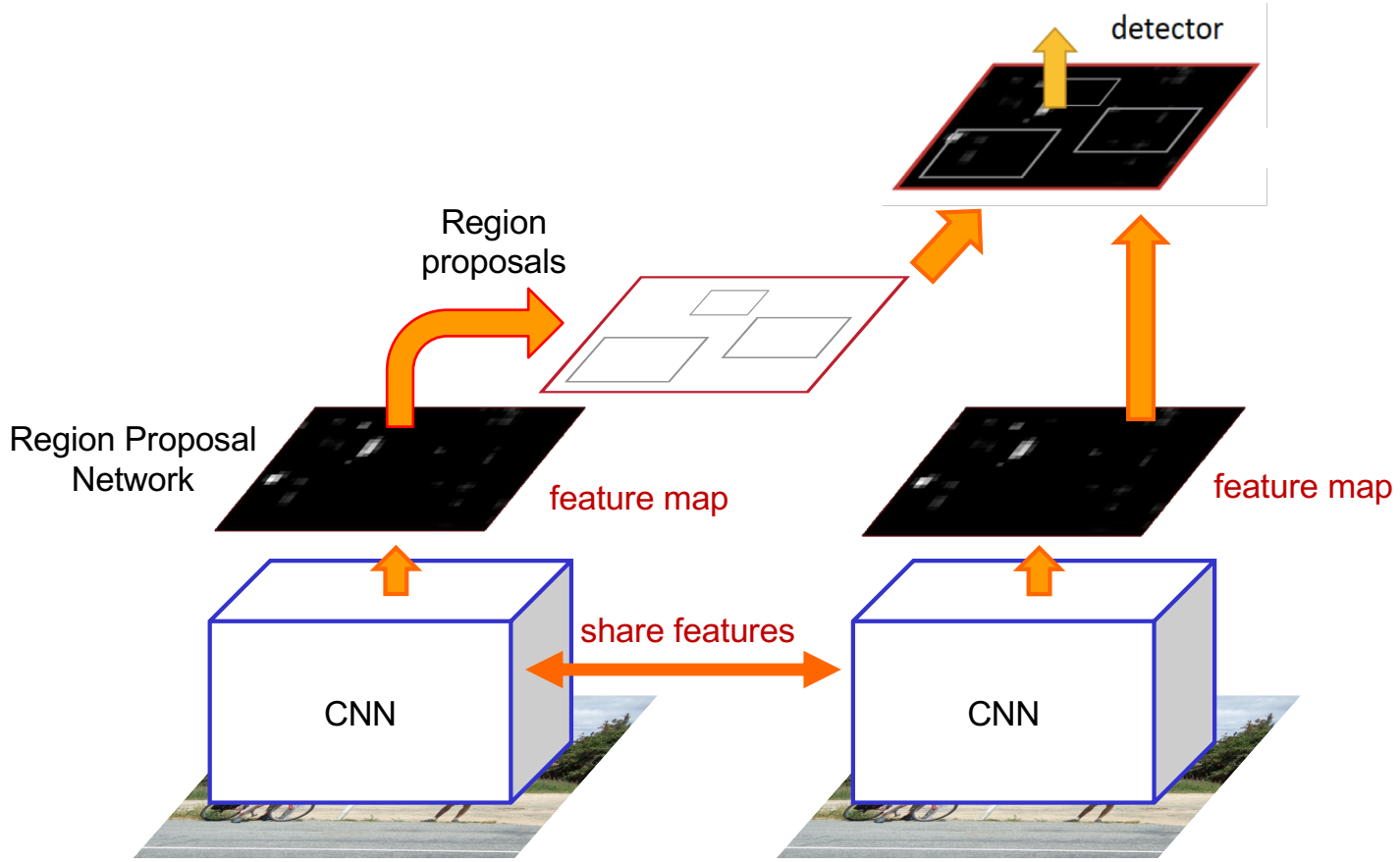
	Fast R-CNN	R-CNN
Train time (h)	**9.5**	84
- Speedup	**8.8x**	
Test time / image	**0.32s**	47.0s
- Test speedup	**146x**	
mAP	**66.9%**	66.0%

(vs. 53.7% for AlexNet)

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

Source: R. Girshick

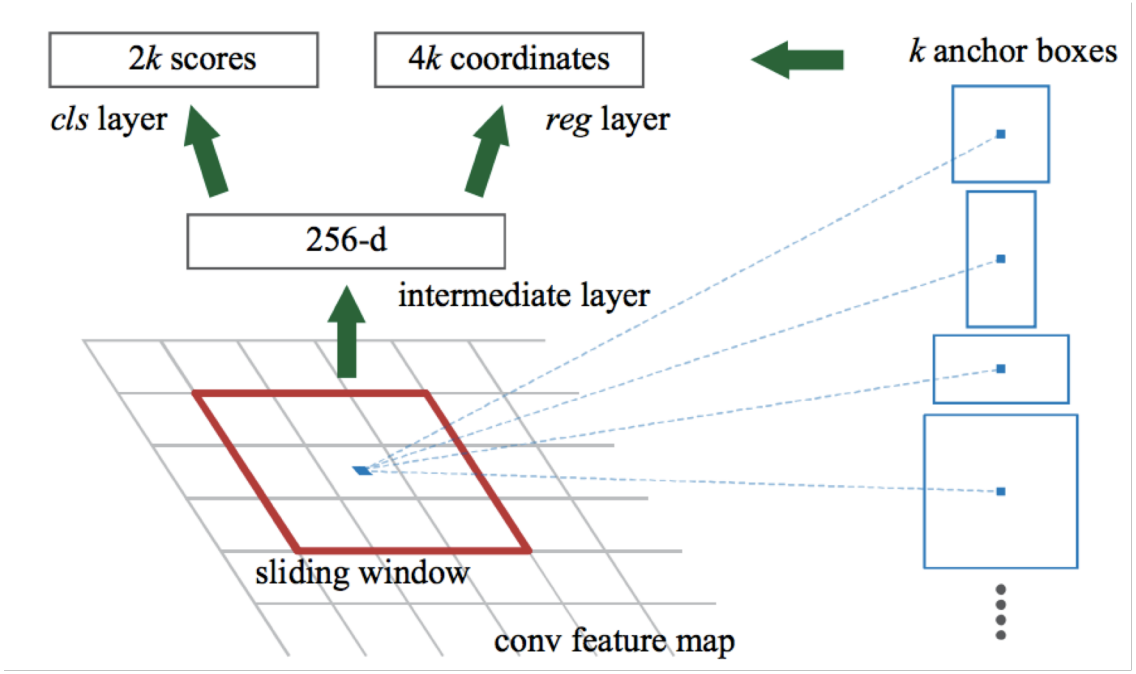
Faster R-CNN



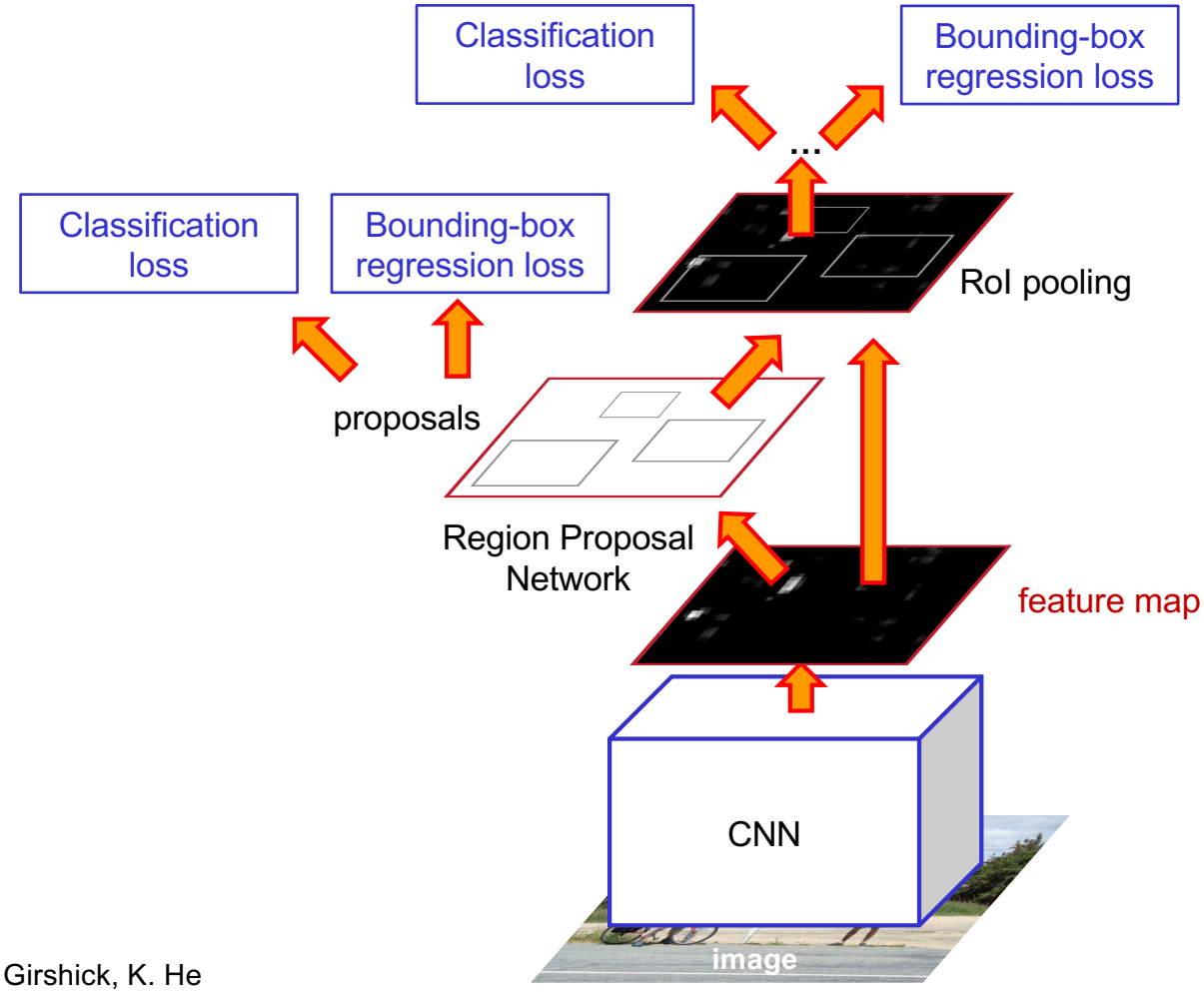
S. Ren, K. He, R. Girshick, and J. Sun, Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks, NIPS 2015

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



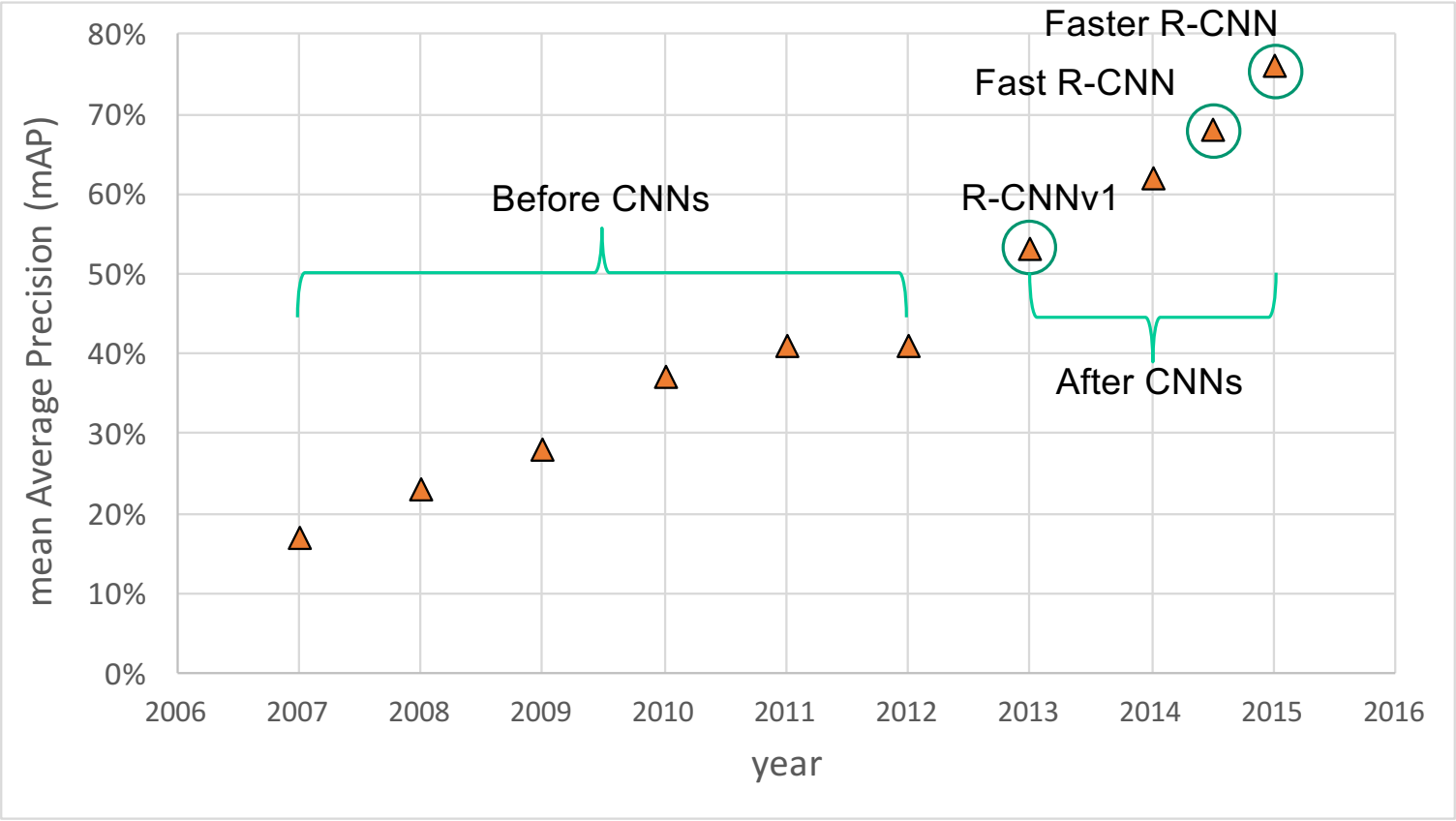
Source: R. Girshick, K. He

Faster R-CNN results

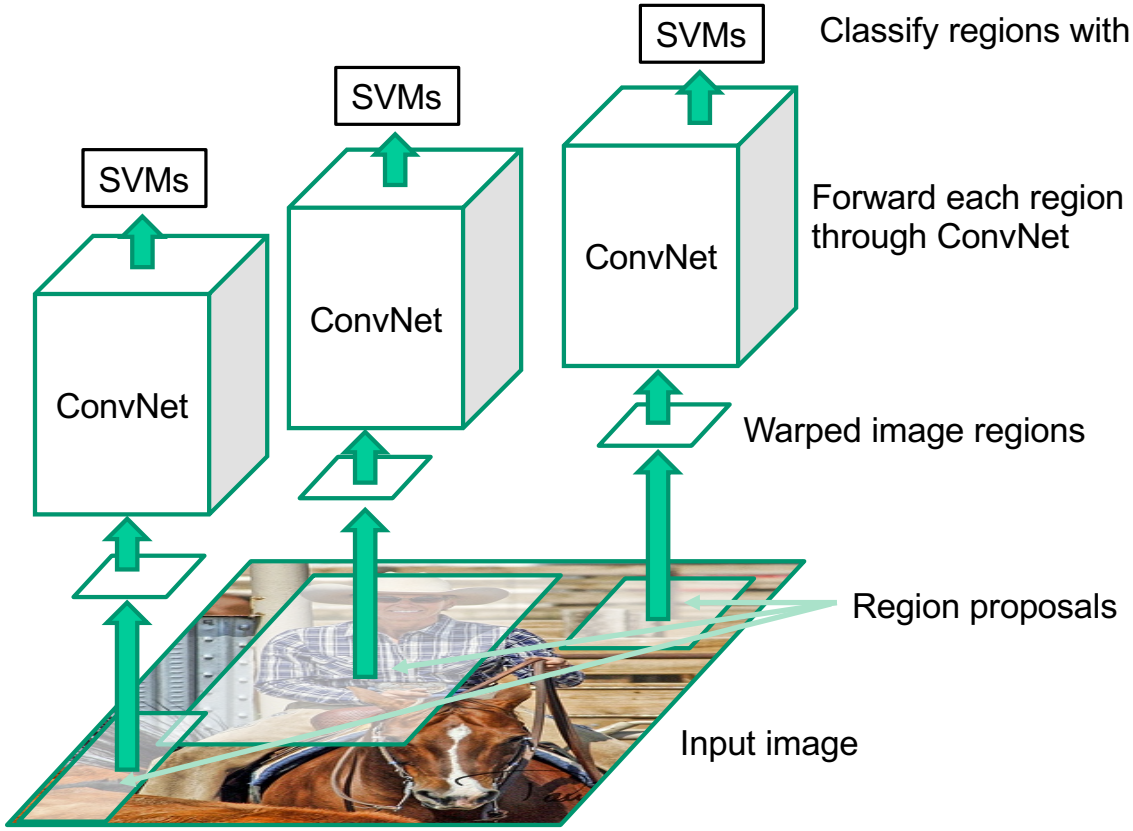
system	time	07 data	07+12 data
R-CNN	~50s	66.0	-
Fast R-CNN	~2s	66.9	70.0
Faster R-CNN	198ms	**69.9**	**73.2**

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

Object detection progress



Review: R-CNN



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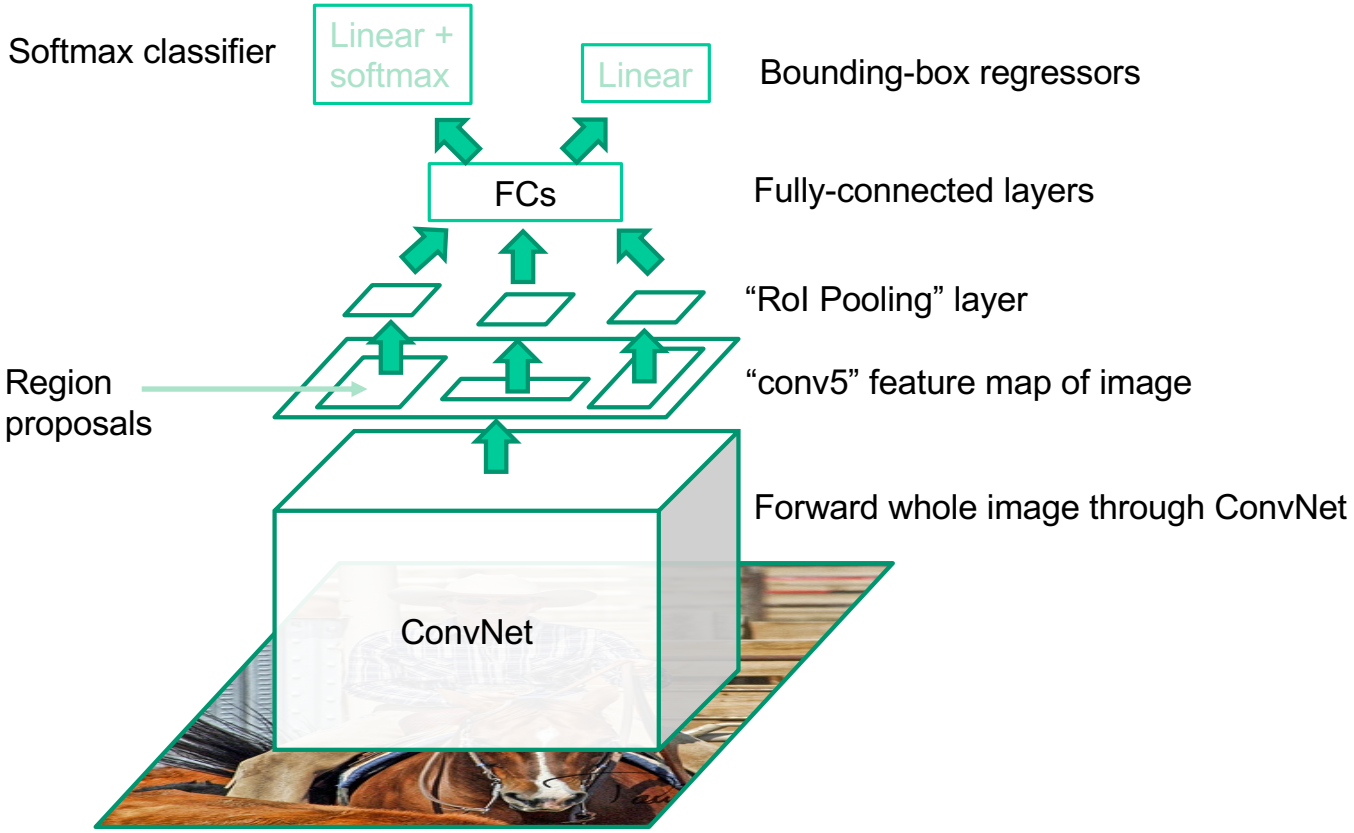
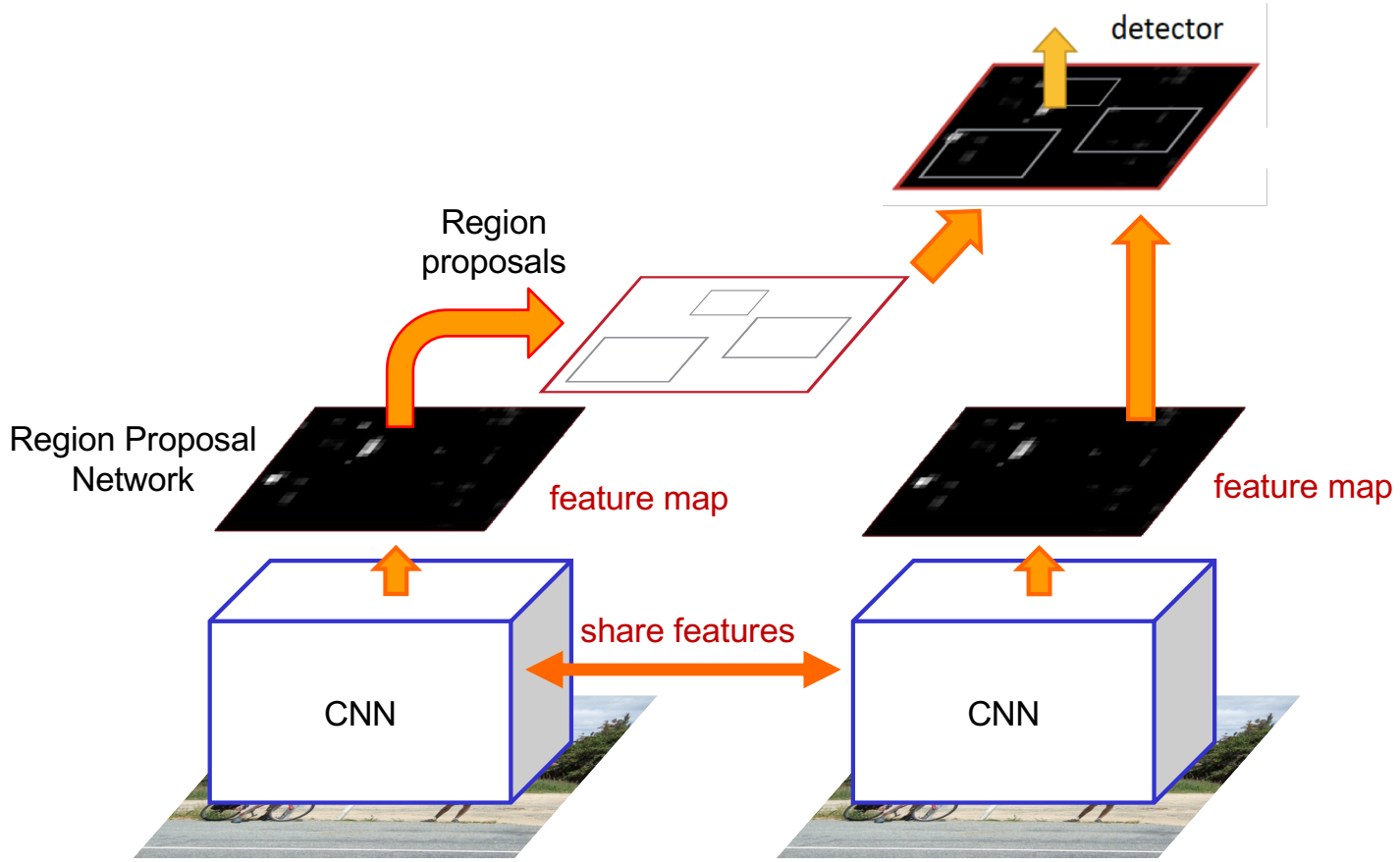
Review: Fast R-CNN



R. Girshick, Fast R-CNN, ICCV 2015

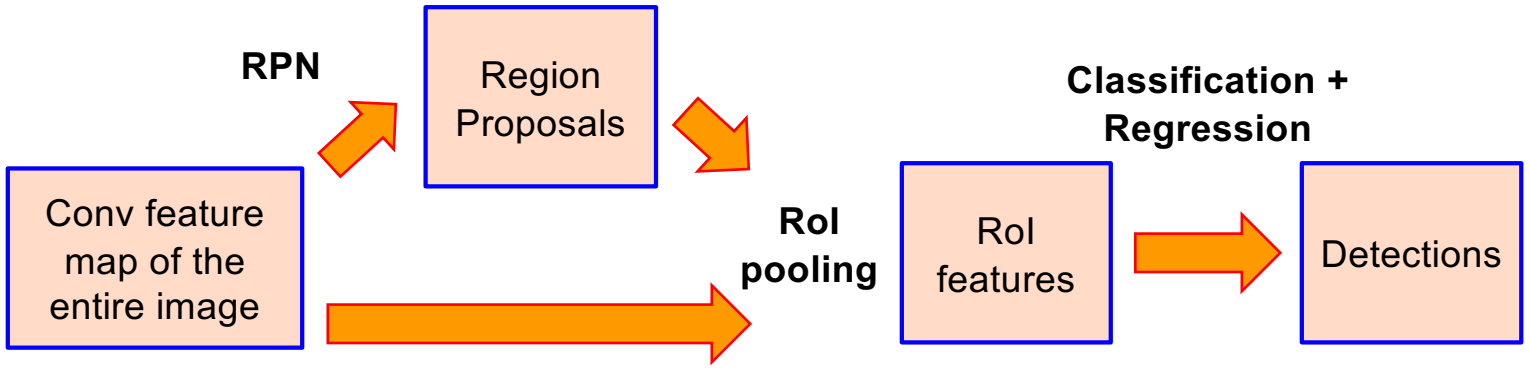
Review: Faster R-CNN



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

Streamlined detection architectures

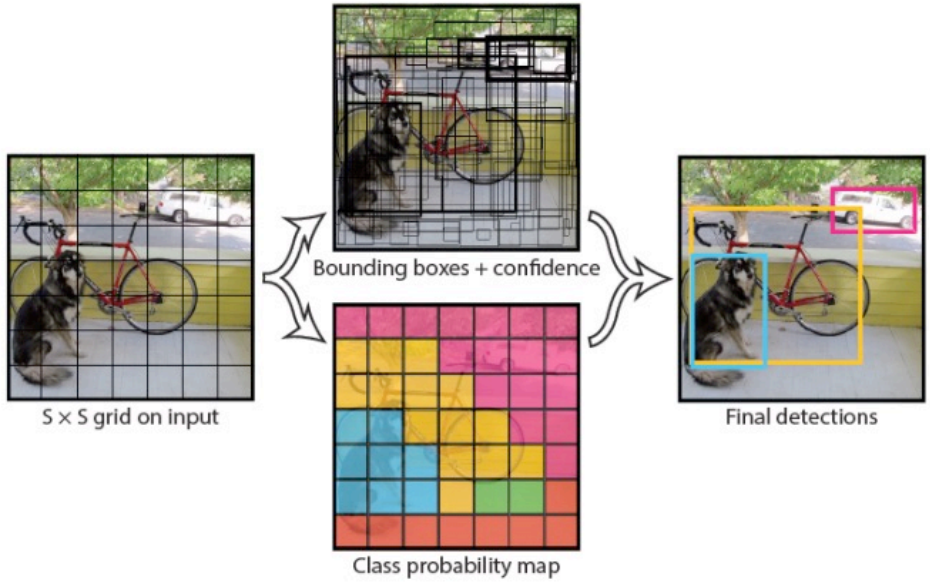
- The Faster R-CNN pipeline separates proposal generation and region classification:



- Is it possible do detection in one shot?

YOLO

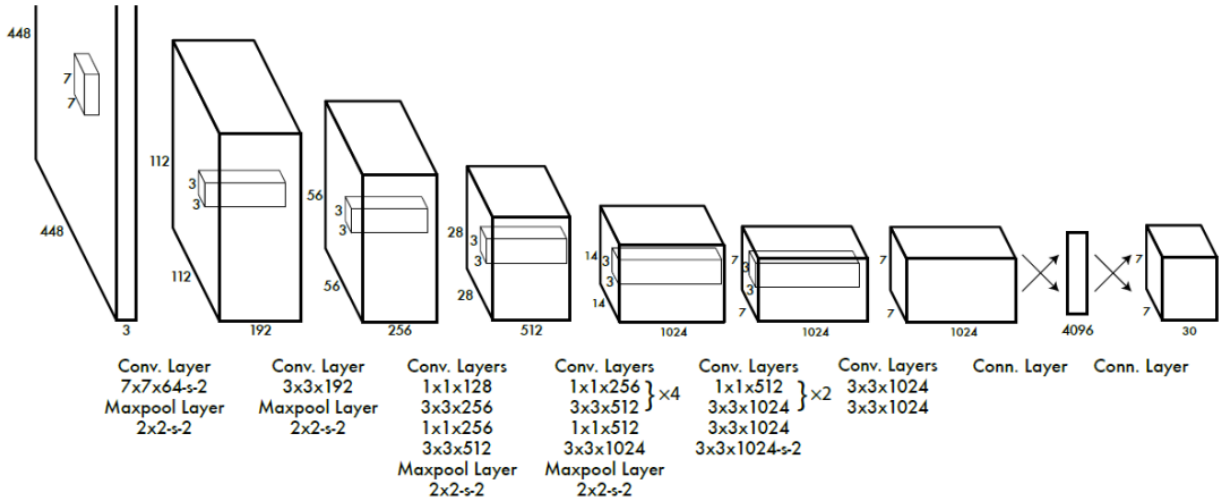
- Divide the image into a coarse grid and directly predict class label and a few candidate boxes for each grid cell



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

YOLO

1. Take conv feature maps at 7x7 resolution
2. Add two FC layers to predict, at each location, a score for each class and 2 bboxes w/ confidences
   - For PASCAL, output is 7x7x30 (30 = 20 + 2*(4+1))



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

YOLO

- Objective function:

$$\lambda_{\text{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left[(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 \right]$$

$$+ \lambda_{\text{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left[\left(\sqrt{w_i} - \sqrt{\hat{w}_i} \right)^2 + \left(\sqrt{h_i} - \sqrt{\hat{h}_i} \right)^2 \right]$$

Regression

$$+ \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left(C_i - \hat{C}_i \right)^2$$

$$+ \lambda_{\text{noobj}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{noobj}} \left(C_i - \hat{C}_i \right)^2$$

Object/no object confidence

$$+ \sum_{i=0}^{S^2} \mathbb{1}_{i}^{\text{obj}} \sum_{c \in \text{classes}} \left(p_i(c) - \hat{p}_i(c) \right)^2$$

Class prediction

YOLO

- Objective function:

Cell i contains object, predictor j is responsible for it

$$\lambda_{\text{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left[(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 \right]$$

$$+ \lambda_{\text{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left[\left(\sqrt{w_i} - \sqrt{\hat{w}_i} \right)^2 + \left(\sqrt{h_i} - \sqrt{\hat{h}_i} \right)^2 \right]$$

Small deviations matter less for larger boxes than for smaller boxes

$$+ \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left(C_i - \hat{C}_i \right)^2$$

Confidence for object

$$+ \lambda_{\text{noobj}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{noobj}} \left(C_i - \hat{C}_i \right)^2$$

Confidence for no object

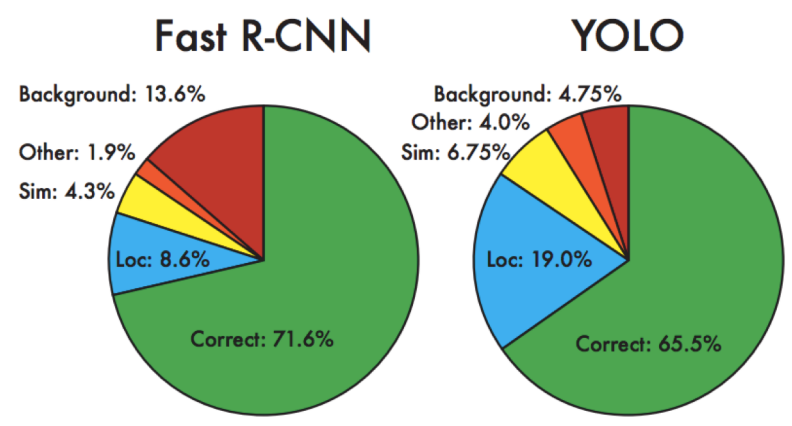
Down-weight loss from boxes that don't contain objects ($\lambda_{\text{noobj}} = 0.5$)

$$+ \sum_{i=0}^{S^2} \mathbb{1}_{i}^{\text{obj}} \sum_{c \in \text{classes}} \left(p_i(c) - \hat{p}_i(c) \right)^2$$

Class probability

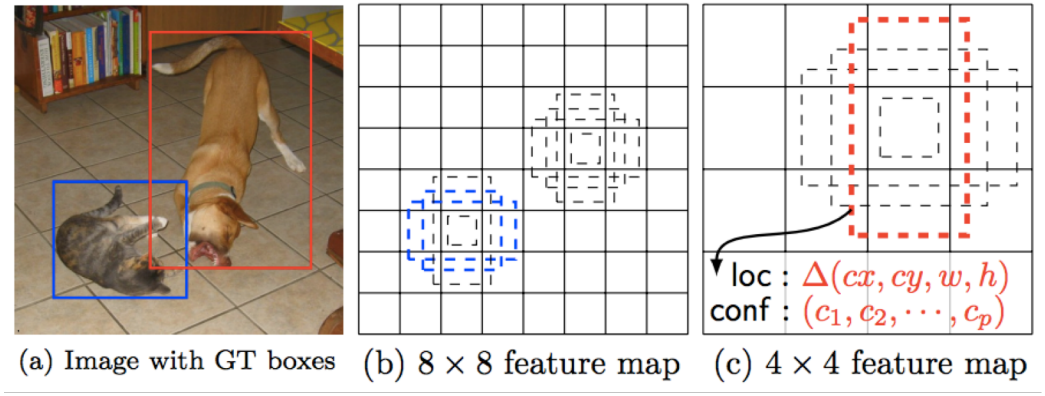
YOLO: Results

- Each grid cell predicts only two boxes and can only have one class – this limits the number of nearby objects that can be predicted
- Localization accuracy suffers compared to Fast(er) R-CNN due to coarser features, errors on small boxes
- 7x speedup over Faster R-CNN (45-155 FPS vs. 7-18 FPS)



Performance on PASCAL 2007

SSD

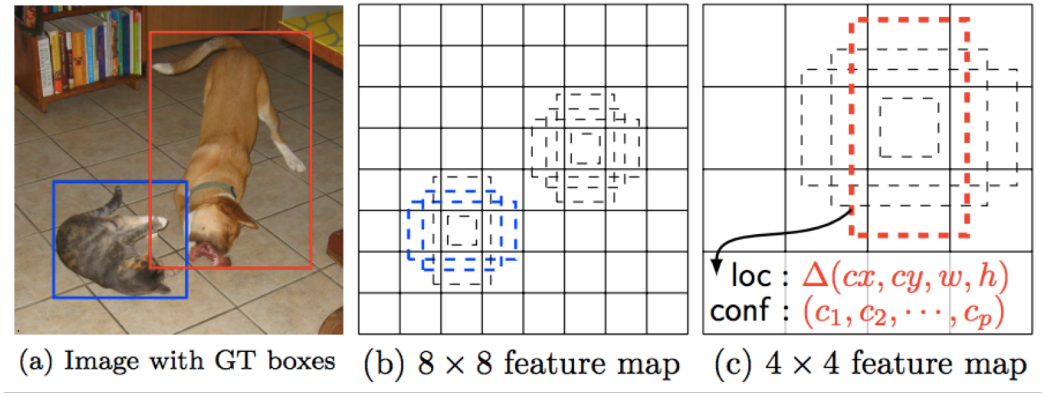


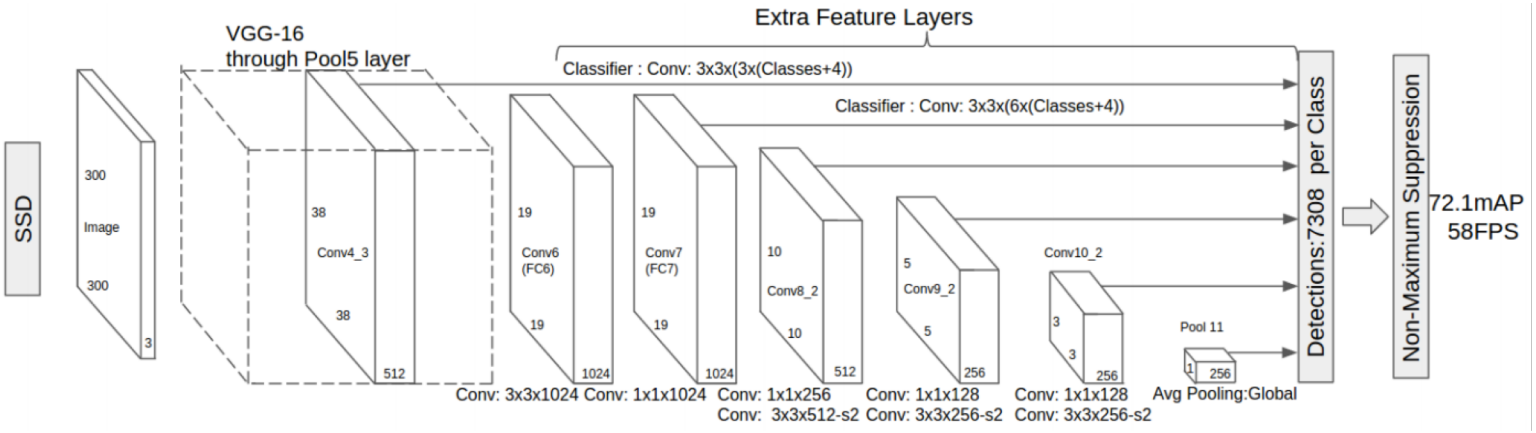
(a) Image with GT boxes (b) 8×8 feature map (c) 4×4 feature map

- Similarly to YOLO, predict bounding boxes directly from conv maps
- Unlike YOLO, do not use FC layers and predict different size boxes from conv maps at different resolutions
- Similarly to RPN, use anchors

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

SSD





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)

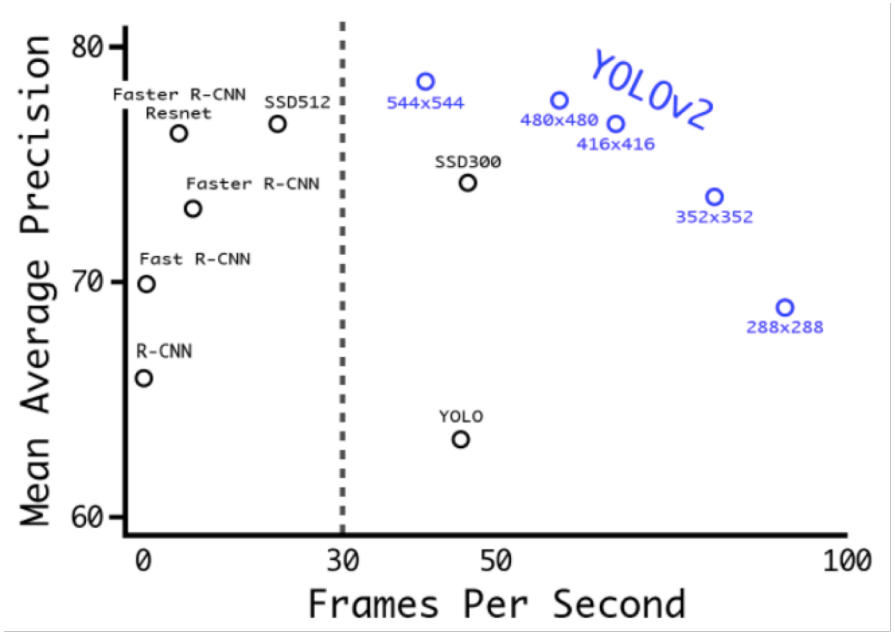
- More accurate *and* faster than YOLO and Faster R-CNN

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

YOLO v2

- Remove FC layer, do convolutional prediction with anchor boxes instead
- Increase resolution of input images and conv feature maps
- Improve accuracy using batch normalization and other tricks

VOC 2007 results

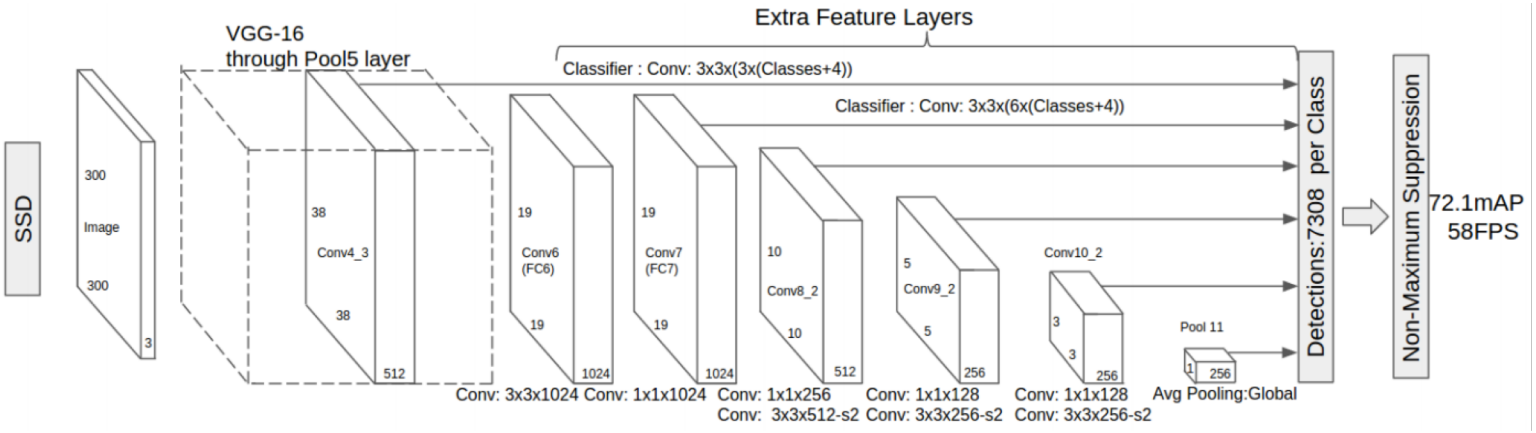


YouTube demo

J. Redmon and A. Farhadi, YOLO9000: Better, Faster, Stronger, CVPR 2017

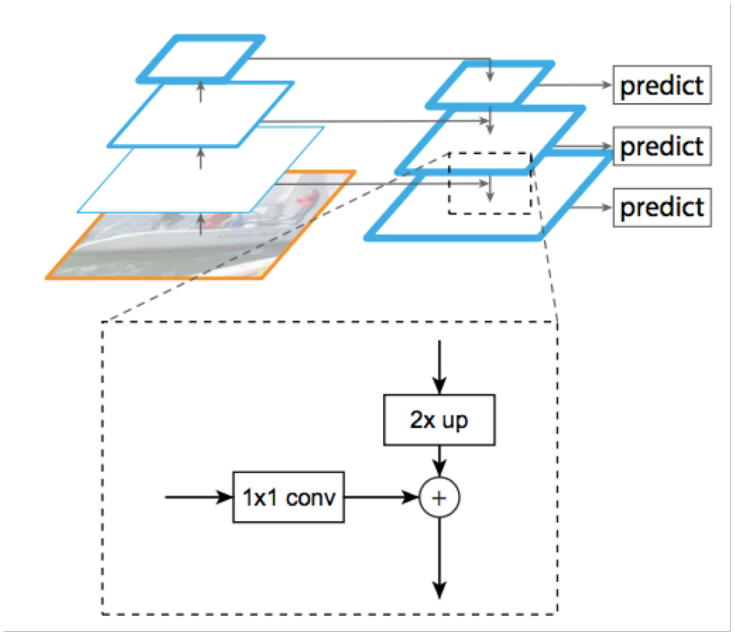
Multi-resolution prediction

- 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

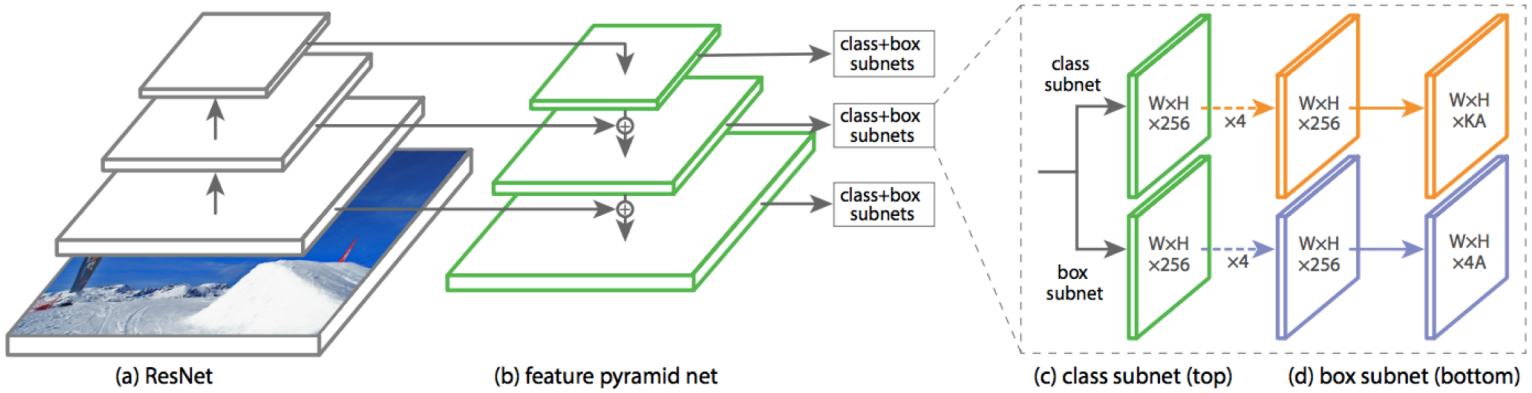
- Improve predictive power of lower-level feature maps by adding contextual information from higher-level feature maps
- Predict different sizes of bounding boxes from different levels of the pyramid (but share parameters of predictors)



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

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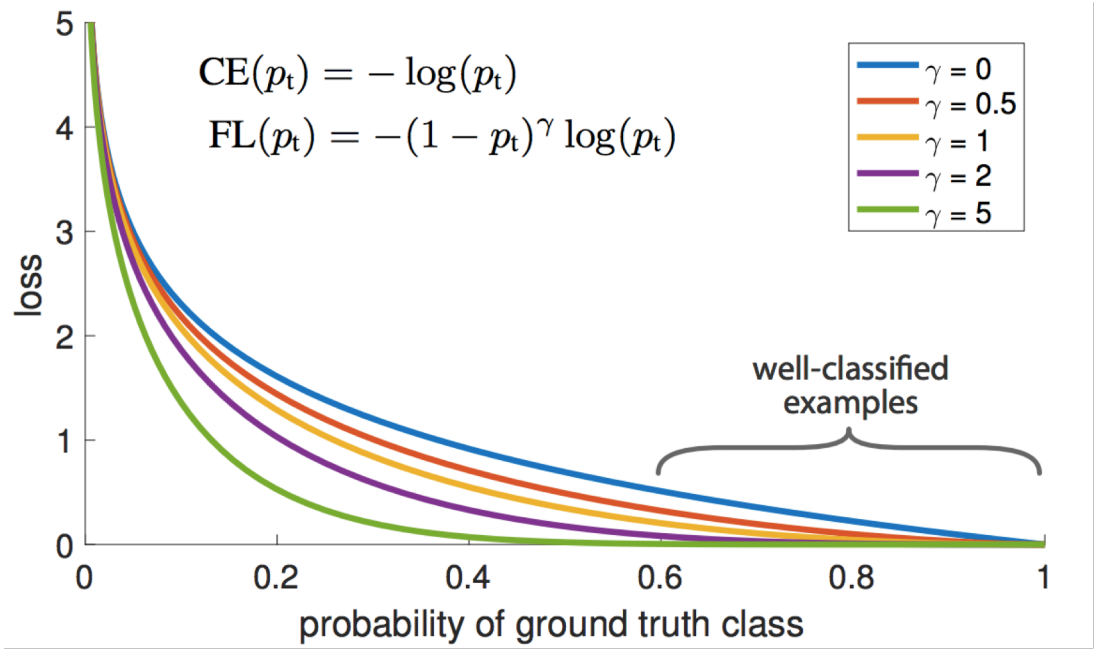
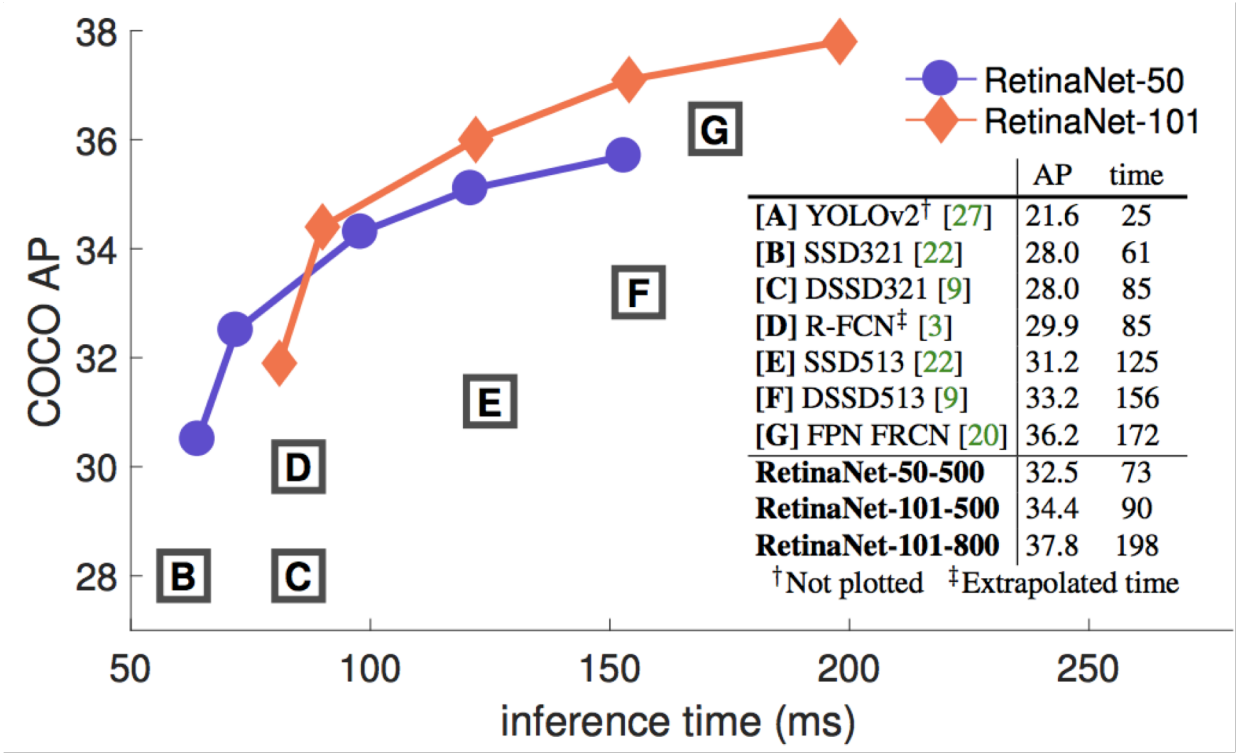


T.-Y. Lin, P. Goyal, R. Girshick, K. He, P. Dollar, Focal loss for dense object detection, ICCV 2017

RetinaNet: Results



	AP	time
[A] YOLOv2† [27]	21.6	25
[B] SSD321 [22]	28.0	61
[C] DSSD321 [9]	28.0	85
[D] R-FCN‡ [3]	29.9	85
[E] SSD513 [22]	31.2	125
[F] DSSD513 [9]	33.2	156
[G] FPN FRCN [20]	36.2	172
RetinaNet-50-500	32.5	73
RetinaNet-101-500	34.4	90
RetinaNet-101-800	37.8	198

†Not plotted ‡Extrapolated time

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

YOLO v3

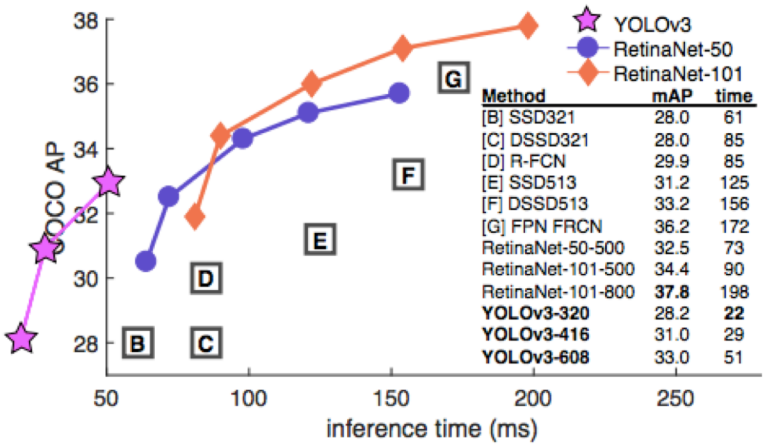
YOLOv3: An Incremental Improvement

Joseph Redmon, Ali Farhadi
University of Washington

Abstract

We present some updates to YOLO! We made a bunch of little design changes to make it better. We also trained this new network that's pretty swell. It's a little bigger than last time but more accurate. It's still fast though, don't worry. At 320 × 320 YOLOv3 runs in 22 ms at 28.2 mAP, as accurate as SSD but three times faster. When we look at the old .5 IOU mAP detection metric YOLOv3 is quite good. It achieves 57.9 AP_{50} in 51 ms on a Titan X, compared to 57.5 AP_{50} in 198 ms by RetinaNet, similar performance but 3.8× faster. As always, all the code is online at https://pjreddie.com/yolo/.

1. Introduction



Method	mAP	time
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[G] FPN FRCN	36.2	172
RetinaNet-50-500	32.5	73
RetinaNet-101-500	34.4	90
RetinaNet-101-800	**37.8**	198
YOLOv3-320	28.2	**22**
YOLOv3-416	31.0	29
YOLOv3-608	33.0	51

Figure 1. We adapt this figure from the Focal Loss paper [9]. YOLOv3 runs significantly faster than other detection methods with comparable performance. Times from either an M40 or Titan X, they are basically the same GPU.

https://pjreddie.com/media/files/papers/YOLOv3.pdf

Summary so far

- 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: YOLO, SSD, RetinaNet
  - Direct prediction of BB offsets, class scores on top of conv feature maps
  - Get better context by combining feature maps at multiple resolutions
- Most recent developments: architectures borrowed from dense prediction, transformers

CornerNet

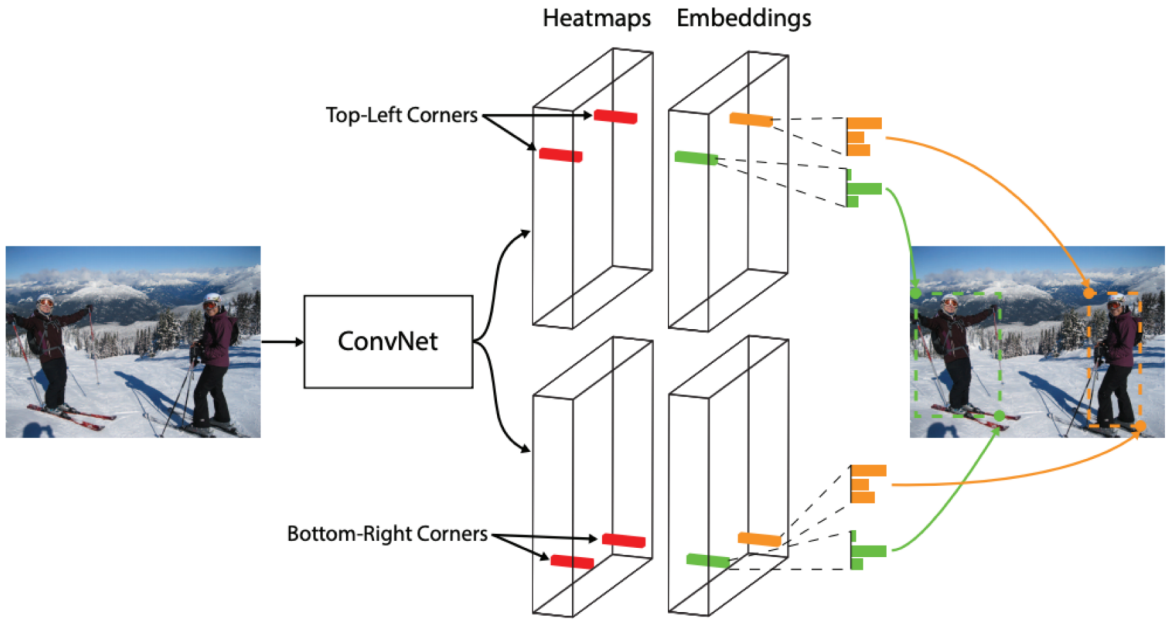
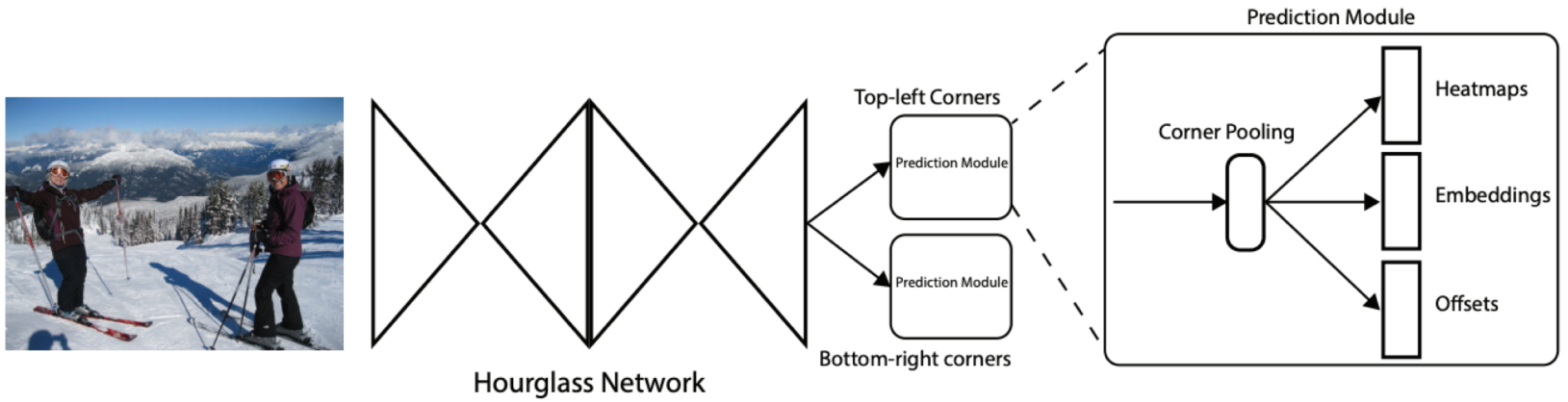


Fig. 1. We detect an object as a pair of bounding box corners grouped together. A convolutional network outputs a heatmap for all top-left corners, a heatmap for all bottom-right corners, and an embedding vector for each detected corner. The network is trained to predict similar embeddings for corners that belong to the same object.

H. Law and J. Deng, CornerNet: Detecting Objects as Paired Keypoints, ECCV 2018

CornerNet



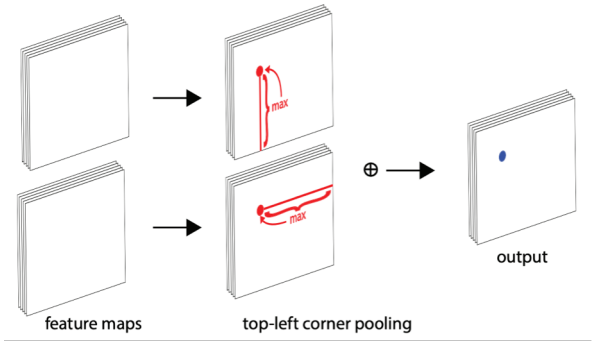
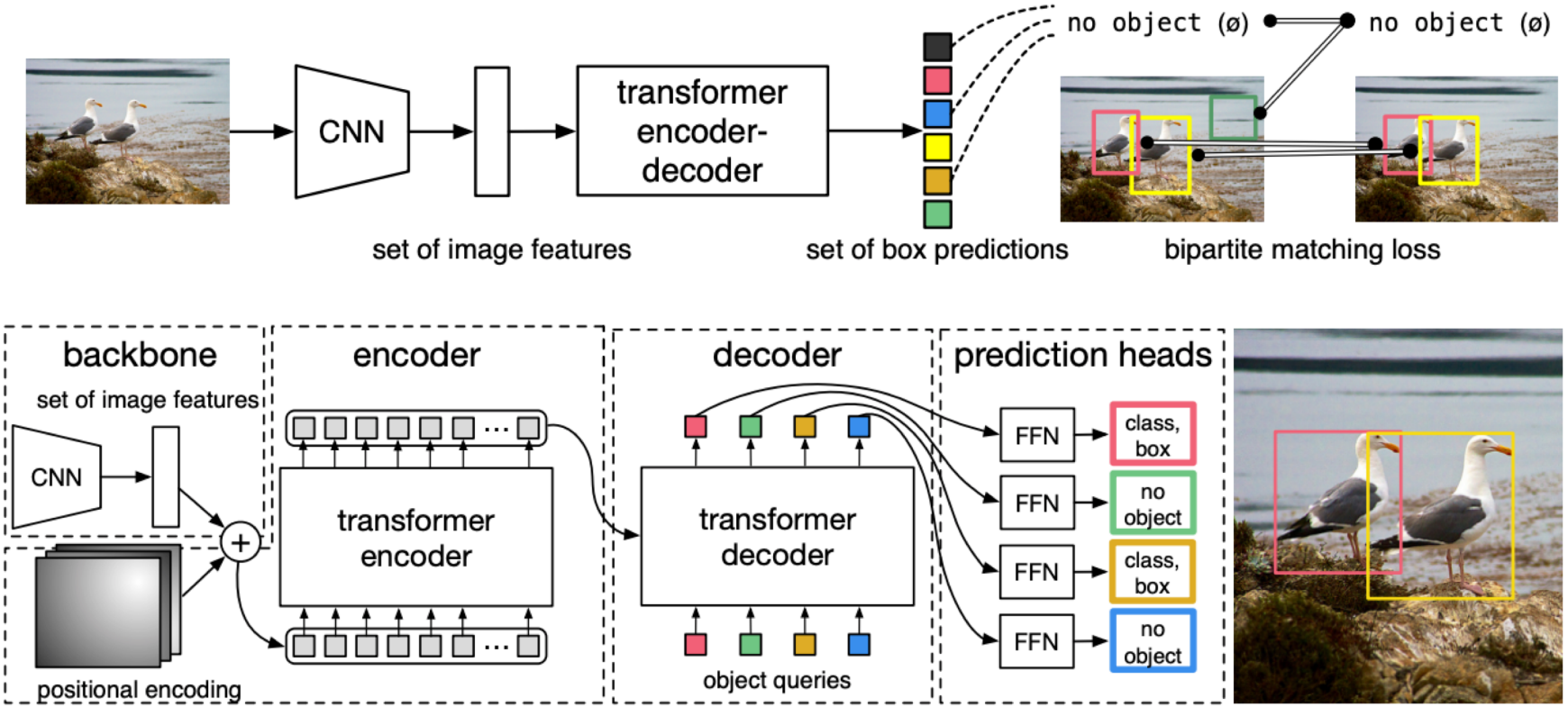


Fig. 2. Often there is no local evidence to determine the location of a bounding box corner. We address this issue by proposing a new type of pooling layer.

H. Law and J. Deng, CornerNet: Detecting Objects as Paired Keypoints, ECCV 2018

Detection Transformer (DETR)



N. Carion et al. End-to-end object detection with transformers. arXiv 2020