Lecture 10:

Optimizing Object Detection:

A Case Study of R-CNN, *Fast* R-CNN, and *Faster* R-CNN and Single Shot Detection

Visual Computing Systems

Stanford CS348V, Winter 2018

Today's task: object detection

Image classification: what is the object in this image?

tennis racket

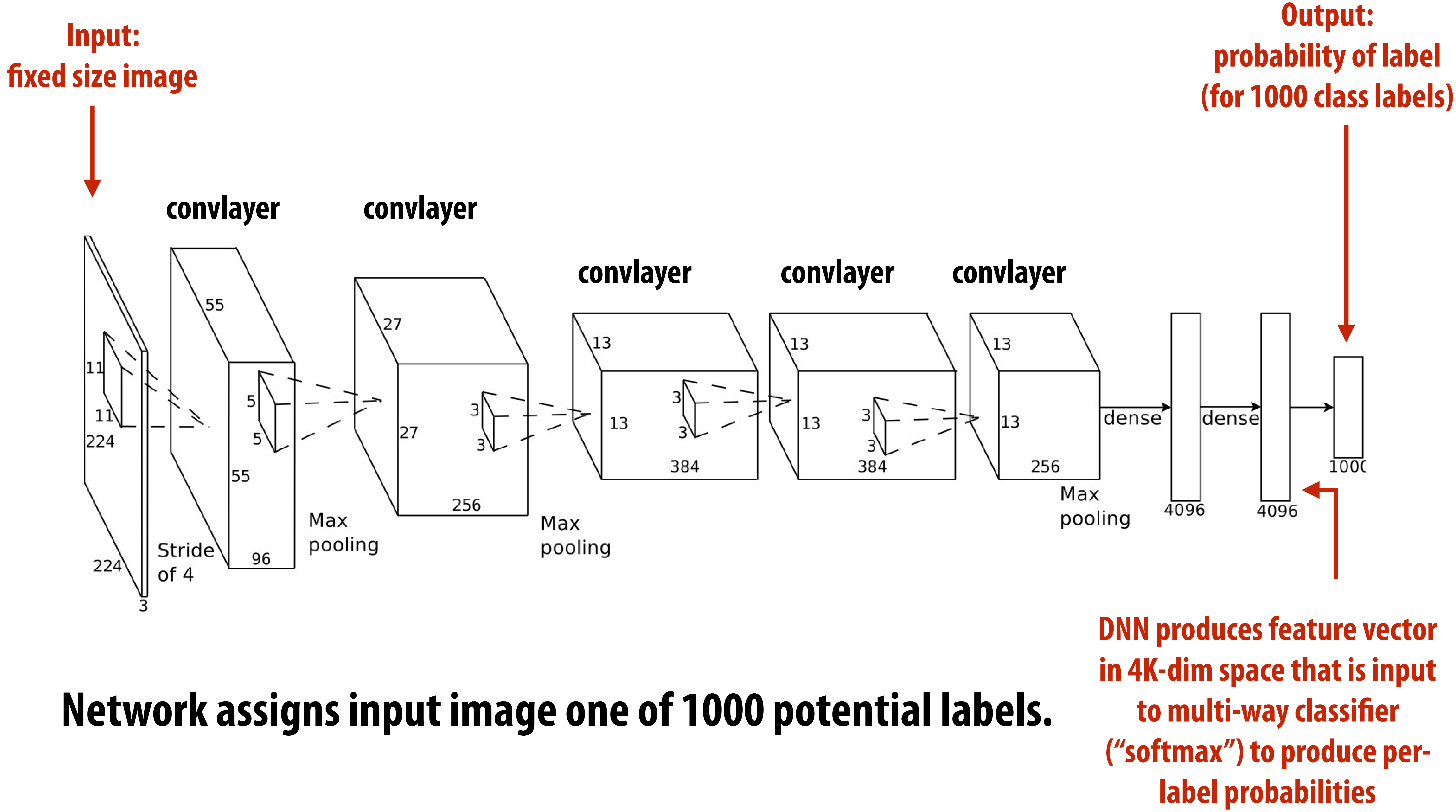
Object detection involves localization: where is the tennis racket in this image? (if there is one at all?)

Quick review

- Why did we say that DNNs learn "good features"?

Krizhevsky (AlexNet) image classification network

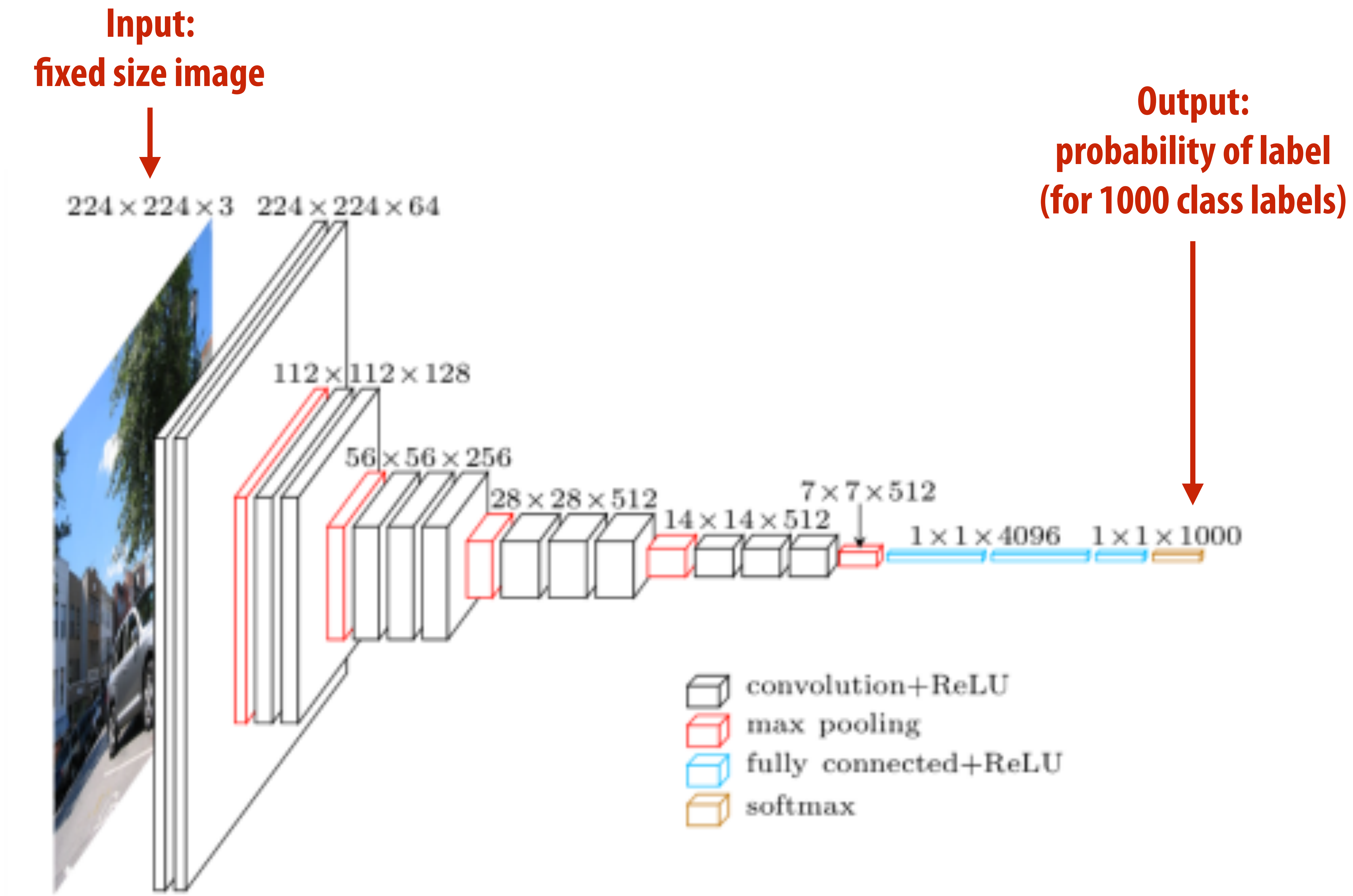
[Krizhevsky 2012]



Network assigns input image one of 1000 potential labels.

VGG-16 image classification network

[Simonyan 2015]



Network assigns input image one of 1000 potential labels.

Today: several object detection papers

- R-CNN [Girshick 2014]
- Fast R-CNN [Girshick 2015]
- Faster R-CNN [Ren, He, Girshick, Sun 2015]
- Each paper improves on ***both*** the wall-clock performance and the detection accuracy of the previous

- Also Single Shot Detection (SSD) [Liu 2016]
- And Mask-RCNN for instance segmentation [He 2017]

Using classification network as a “subroutine for object detection

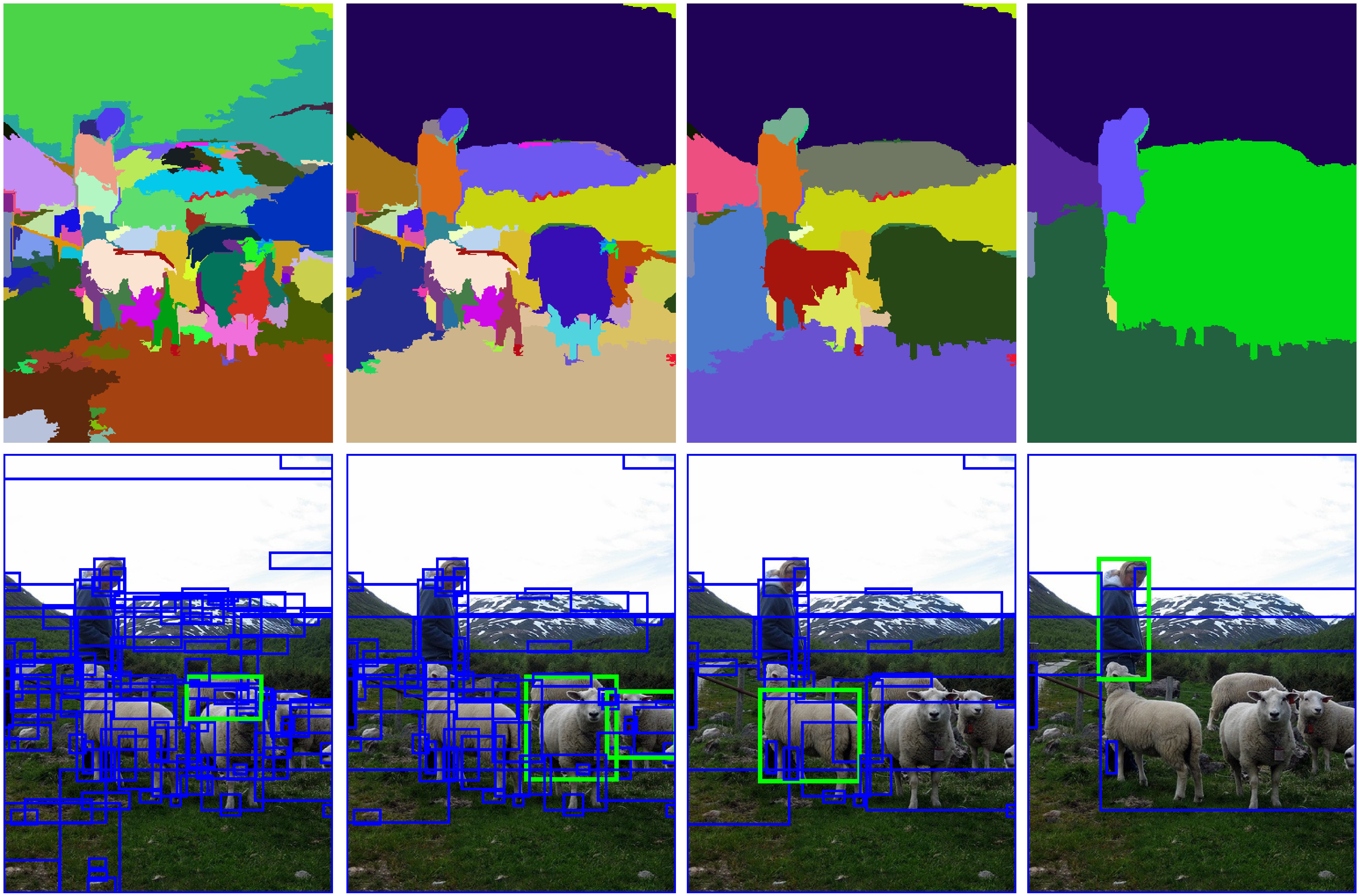
[Girshick 2014]

Search over all regions of the image and all region sizes for objects
(“Sliding window” over image, repeated for multiple potential object scales)

```
for all region top-left positions (x,y):
   for all region sizes (w,h):
      cropped = image_crop(image, bbox(x,y,w,h))
      resized = image_resize(227,227)
      label = detect_object(resized)
      if (label != background)
         // region defined by bbox(x,y,w,h) contains object
         // of class ‘label’
```

Optimization 1: filter detection work via object proposals

Selective search [Uijlings IJCV 2013]



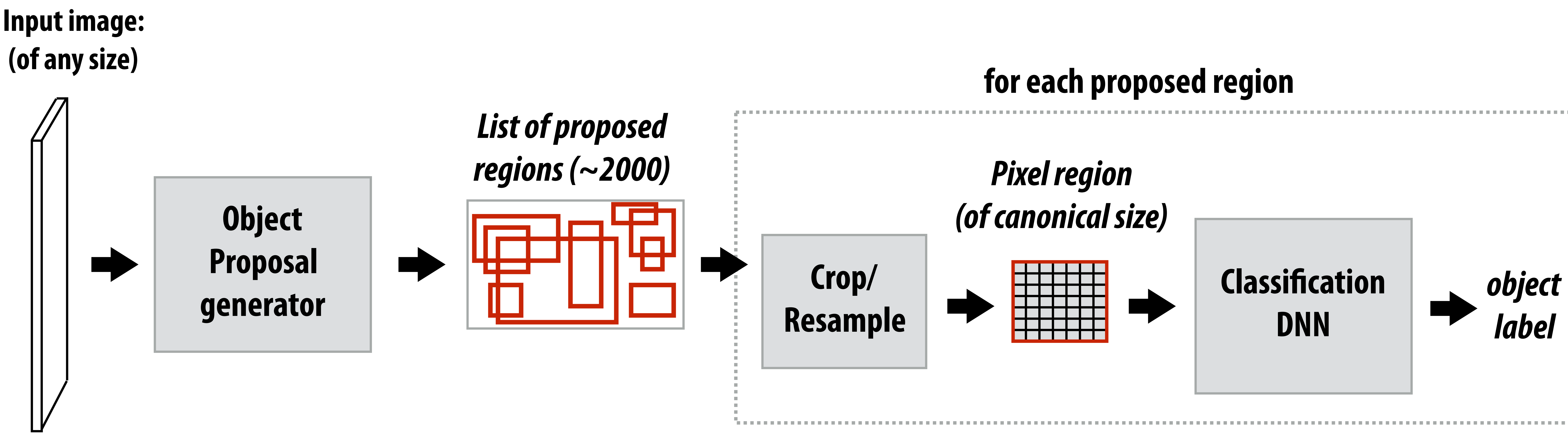
Input: image

Output: list of regions (various scales) that are likely to contain objects

Idea: proposal algorithm filters parts of the image not likely to contain objects

Object detection pipeline executed only on proposed regions

[Girshick 2014]

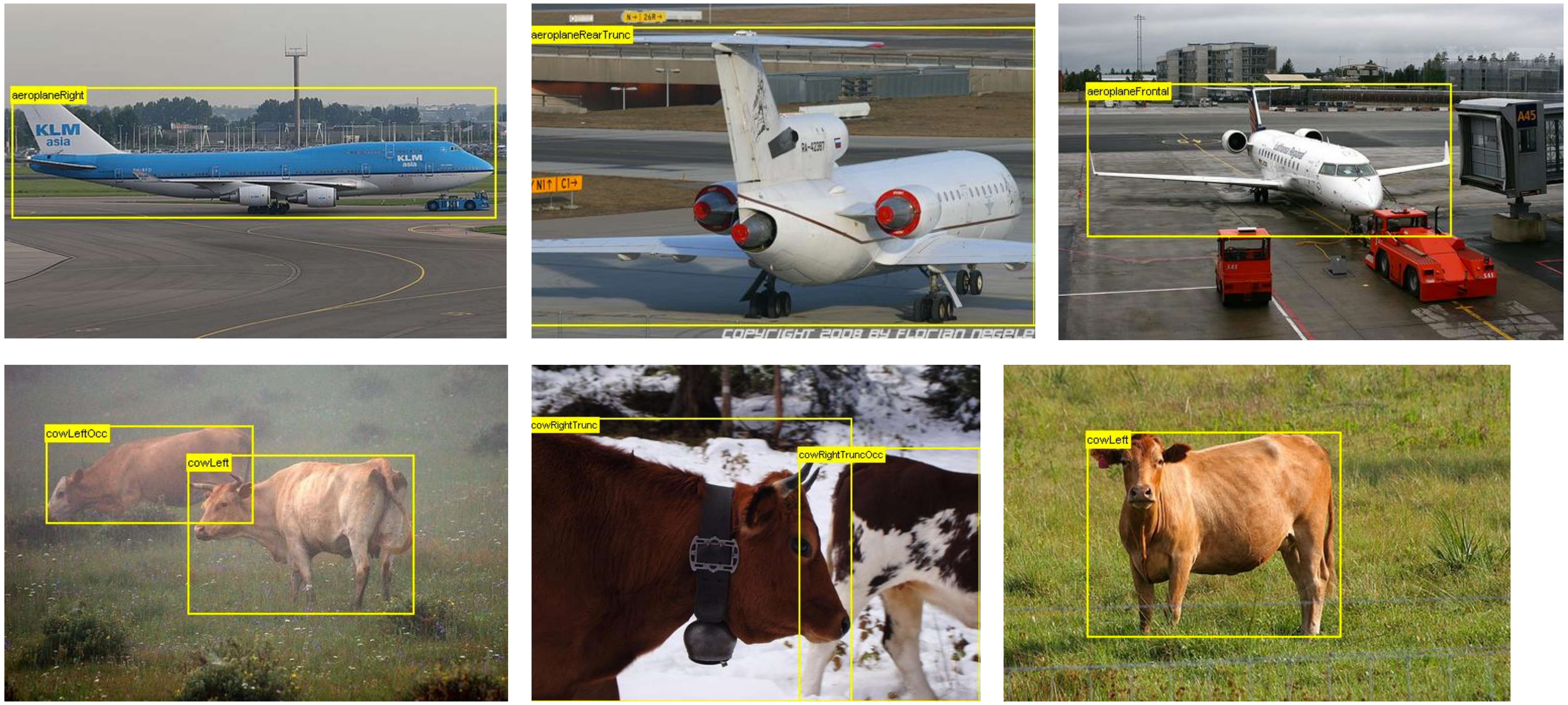


Object detection performance on Pascal VOC

Example training data

airplanes

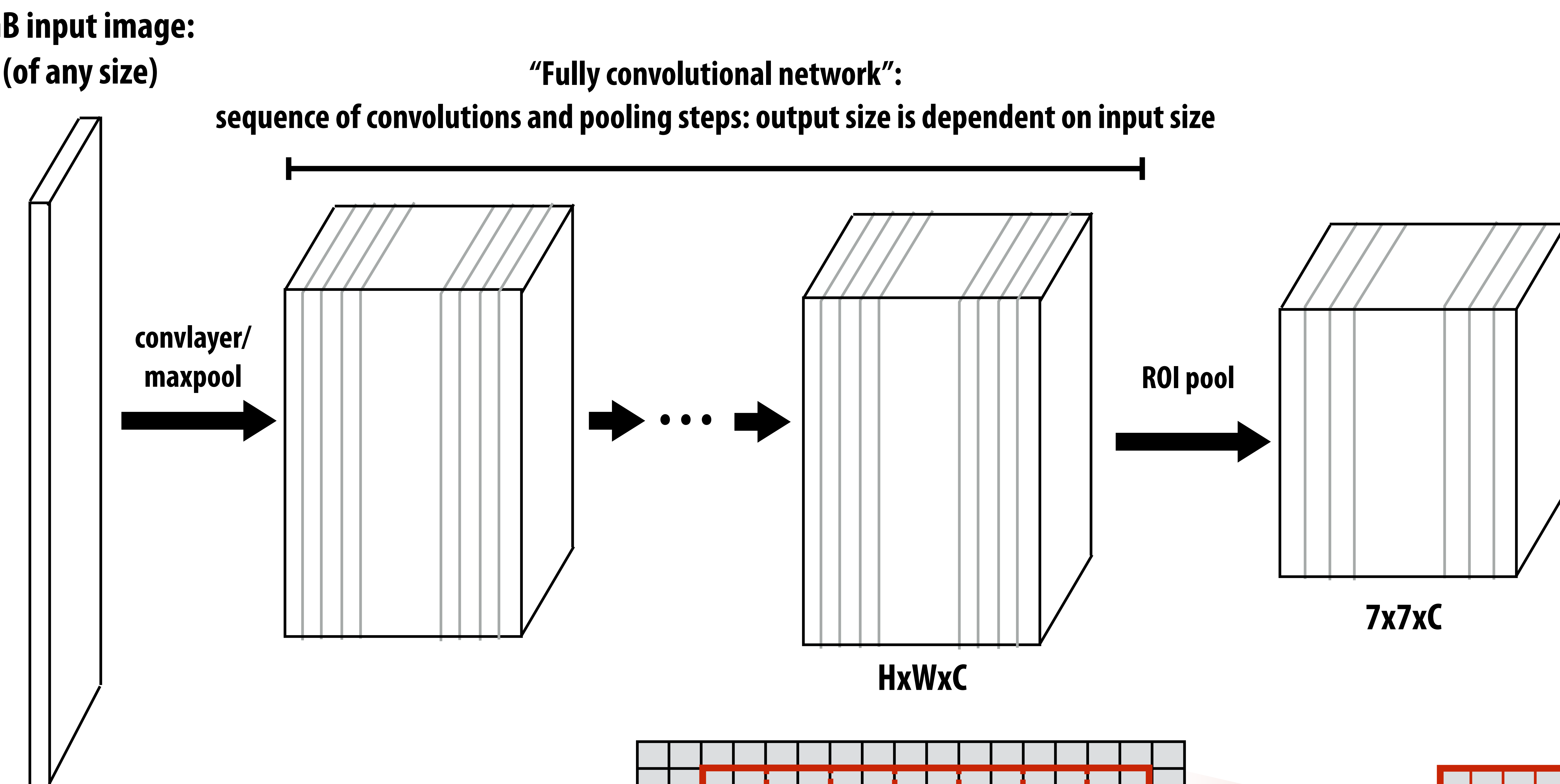
cow

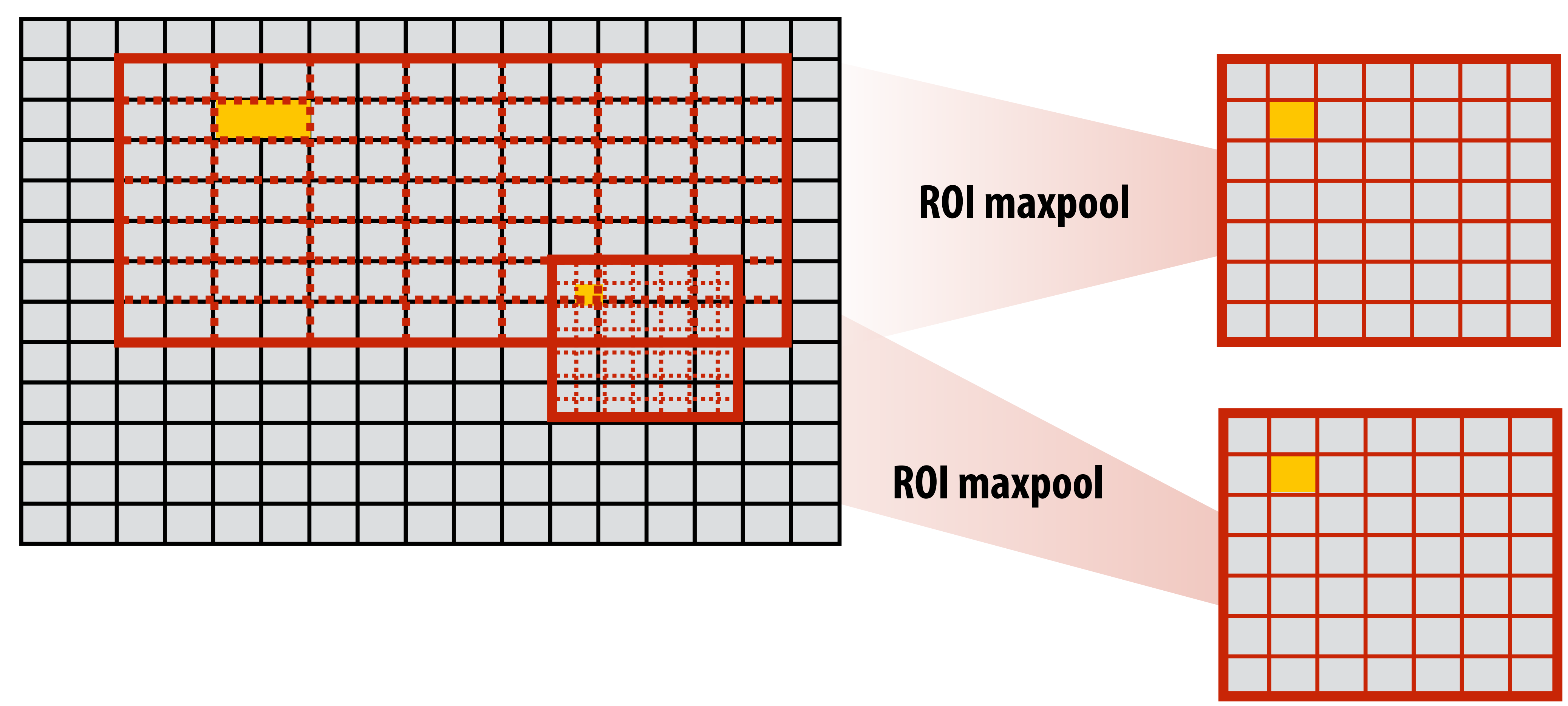


VOC 2010 test	aero	bike	bird	boat	bottle	bus	car	cat	chair	cow	table	dog	horse	mbike	person	plant	sheep	sofa	train	tv	mAP
DPM v5 [18]†	49.2	53.8	13.1	15.3	35.5	53.4	49.7	27.0	17.2	28.8	14.7	17.8	46.4	51.2	47.7	10.8	34.2	20.7	43.8	38.3	33.4
UVA [34]	56.2	42.4	15.3	12.6	21.8	49.3	36.8	46.1	12.9	32.1	30.0	36.5	43.5	52.9	32.9	15.3	41.1	31.8	47.0	44.8	35.1
Regionlets [36]	65.0	48.9	25.9	24.6	24.5	56.1	54.5	51.2	17.0	28.9	30.2	35.8	40.2	55.7	43.5	14.3	43.9	32.6	54.0	45.9	39.7
SegDPM [16]†	61.4	53.4	25.6	25.2	35.5	51.7	50.6	50.8	19.3	33.8	26.8	40.4	48.3	54.4	47.1	14.8	38.7	35.0	52.8	43.1	40.4
R-CNN	67.1	64.1	46.7	32.0	30.5	56.4	57.2	65.9	27.0	47.3	40.9	66.6	57.8	65.9	53.6	26.7	56.5	38.1	52.8	50.2	50.2

DNN weights "pre-trained" using object classification on ImageNet (lots of data, different task)
DNN weights "fine-tuned" for the 20 VOC categories + 1 "background" category (task-specific data)

Optimization 2: region of interest pooling





Idea: the output of early convolutional layers of network on downsampled input region is approximated by resampling output of fully-convolutional implementation of conv layers.

Performance optimization: can evaluate convolutional layers once on large input, then reuse intermediate output many times to approximate response of a subregion of image.

Optimization 2: region of interest pooling

This is a form of "approximate common subexpression elimination"

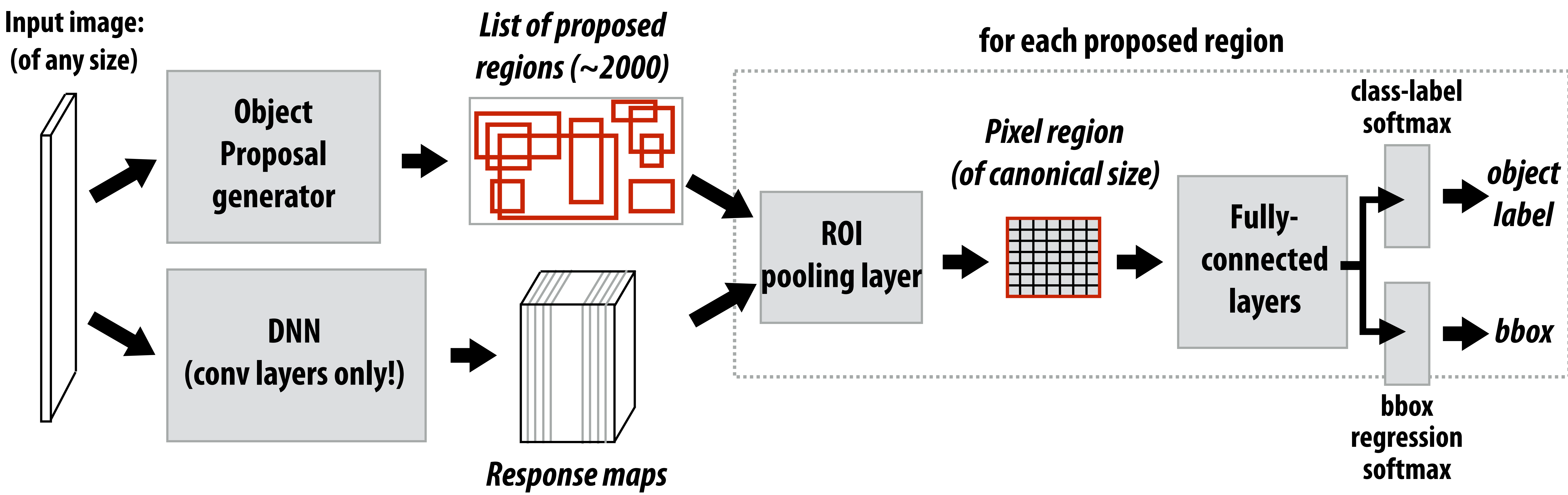
```
for all proposed regions (x,y,w,h):   // 1000's of regions/image
   cropped = image_crop(image, bbox(x,y,w,h))
   resized = image_resize(227,227)
   label = detect_object(resized)
```

redundant work (many regions overlap, so responses at lower network layers are computed many times)

```
conv5_response = evaluate_conv_layers(image)
for all proposed regions (x,y,w,h):
   region_conv5 = roi_pool(conv5_response, bbox(x,y,w,h))
   label = evaluate_fully_connected_layers(region_conv5)
```

computed once per image

Fast R-CNN pipeline [Girshick 2015]



Evaluation speed: 146x faster than R-CNN (47sec/img → 0.32 sec/img)

[This number excludes cost of proposals]

Training speed: 9x faster than R-CNN

Training mini-batch: pick N images, pick 128/N boxes from each image (allows sharing of conv-layer pre-computation for multiple image-box training samples)

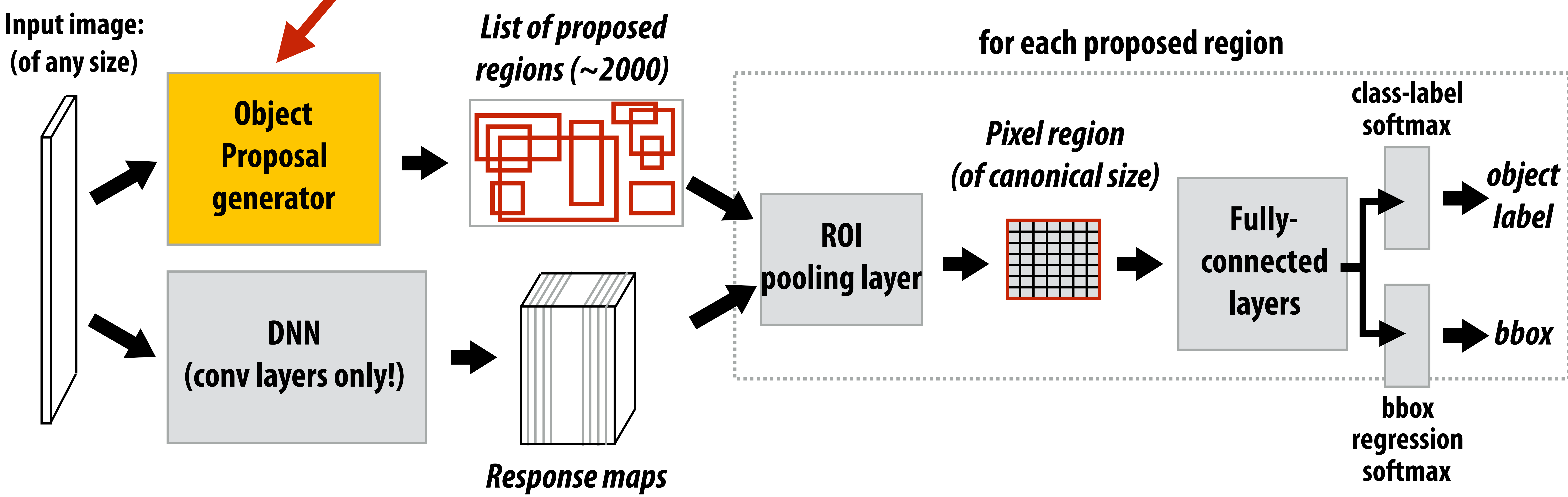
Simultaneously train class predictions and bbox predictions: joint loss = class label loss + bbox loss

Note: training updates weights in BOTH fully connected/softmax layers AND conv layers

method	train set	aero	bike	bird	boat	bottle	bus	car	cat	chair	cow	table	dog	horse	mbike	persn	plant	sheep	sofa	train	tv	mAP
R-CNN BB [10]	12	79.3	72.4	63.1	44.0	44.4	64.6	66.3	84.9	38.8	67.3	48.4	82.3	75.0	76.7	65.7	35.8	66.2	54.8	69.1	58.8	62.9
FRCN [ours]	12	80.1	74.4	67.7	49.4	41.4	74.2	68.8	87.8	41.9	70.1	50.2	86.1	77.3	81.1	70.4	33.3	67.0	63.3	77.2	60.0	66.1

Problem: bottleneck is now generating proposals

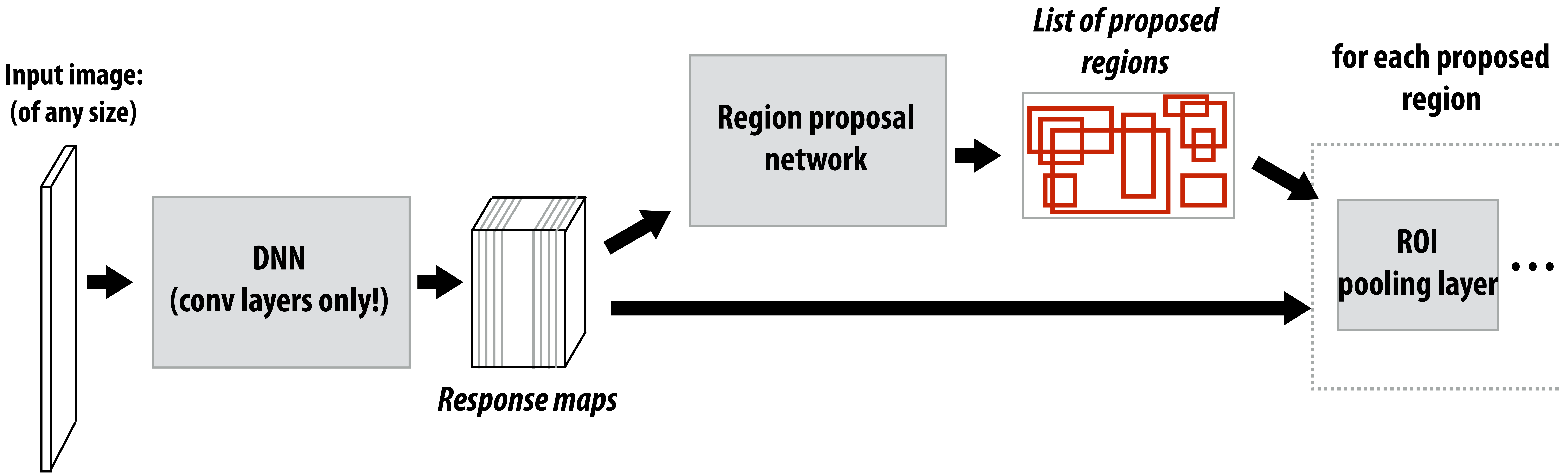
Selective search [Uijlings 13] ~ 10 sec/image on CPU
EdgeBoxes [Zitnick 14] ~ 0.2 sec/image on CPU



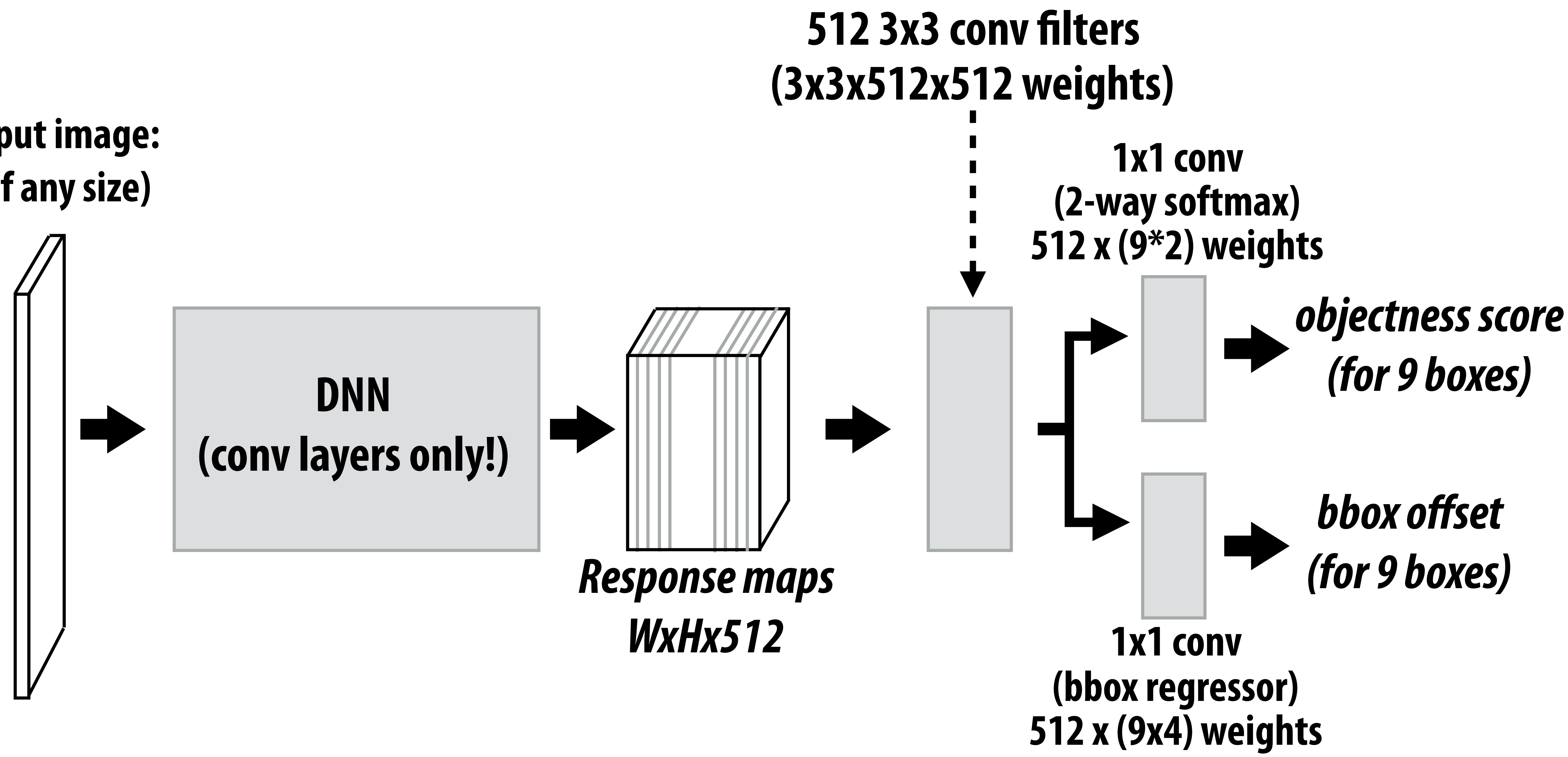
Idea: why not predict regions from the convolutional feature maps that must be computed for detection anyway? (share computation between proposals and detection)

Faster R-CNN using a region proposal network (RPN)

[Ren 2015]



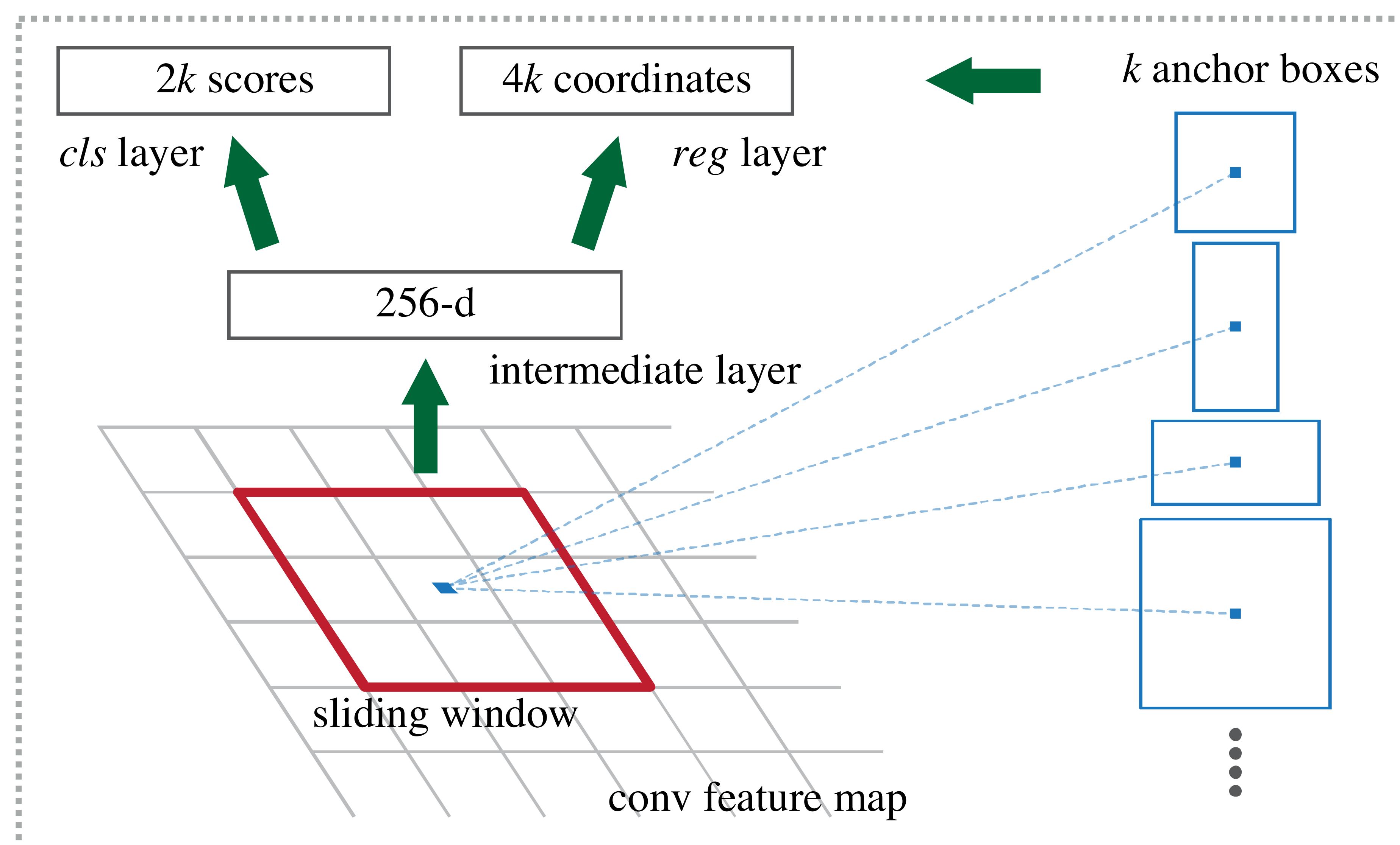
Faster R-CNN using a region proposal network (RPN)



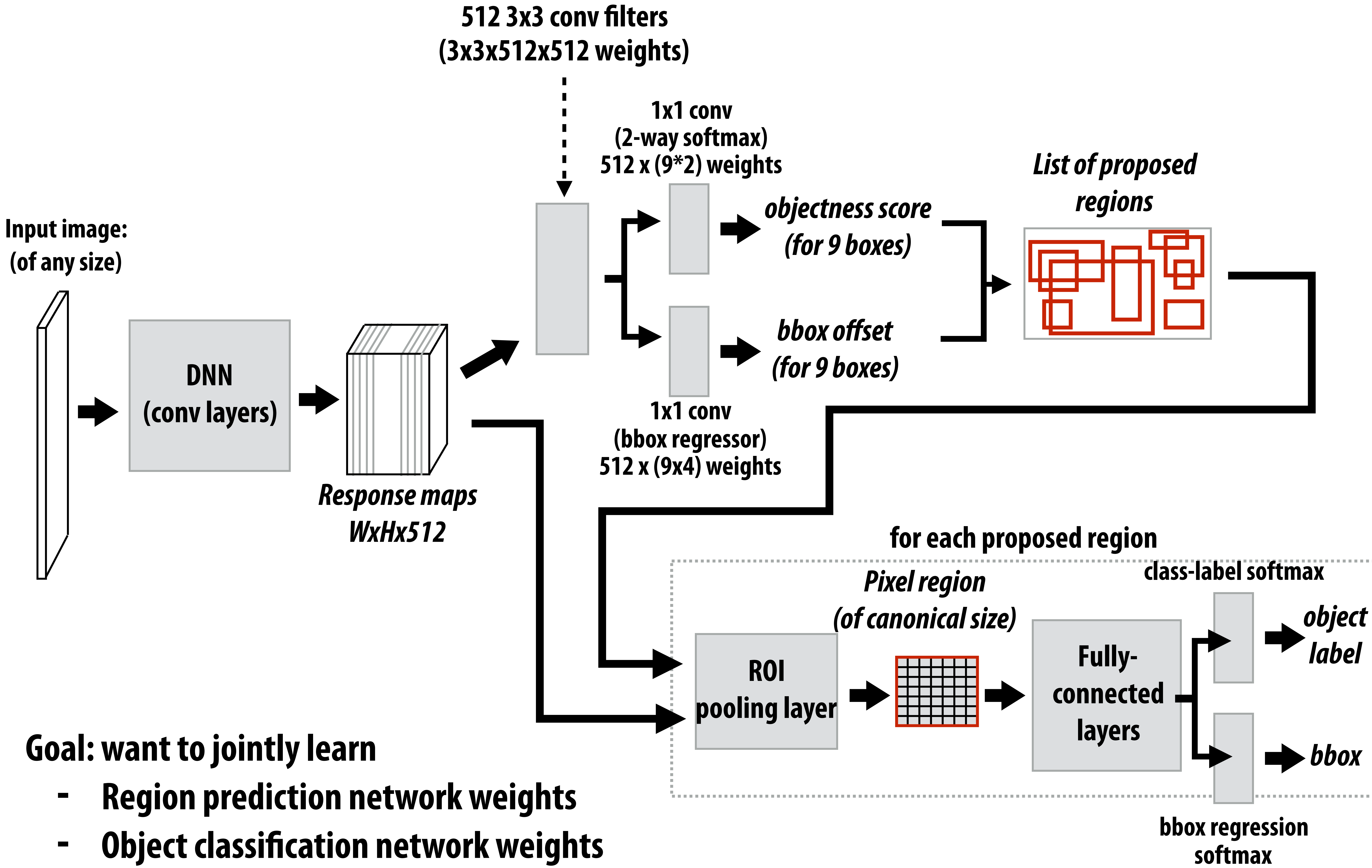
3x3 conv projects into 512-element vector per spatial position (assuming VGG input conv layers, receptive field for each output is ~228x228 pixels)

At each point assume 9 "anchor boxes" of various aspect ratios and scales

Given 512-element vector predict "objectness score" of each anchor + bbox correction to anchor



Training faster R-CNN



Goal: want to jointly learn

- Region prediction network weights
- Object classification network weights
- While constraining initial conv layers to be the same (for efficiency)

Alternating training strategy

- Train region proposal network (RPN)
  - Using loss based on ground-truth object bounding boxes
  - Positive example: intersection over union with ground truth box above threshold
  - Negative example: interestion over union less than threshold
- Then use trained RPN to train Fast R-CNN
  - Using loss based on detections and bbox regression
- Use conv layers from R-CNN to initialize RPN
- Fine-tune RPN
  - Using loss based on ground-truth boxes
- Use updated RPN to fine tune Fast R-CNN
  - Using loss based on detections and bbox regression
- Repeat…

- Notice: solution learns to predict boxes that are "good for object-detection task"
  - "End-to-end" optimization for object-detection task
  - Compare to using off-the-shelf object-proposal algorithm

Faster R-CNN results

Specializing region proposals for object-detection task yields better accuracy.

SS = selective search for object proposals

method	# proposals	data	mAP (%)
SS	2000	12	65.7
SS	2000	07++12	68.4
RPN+VGG, shared†	300	12	67.0
RPN+VGG, shared‡	300	07++12	**70.4**

Shared convolutions improve algorithm performance:

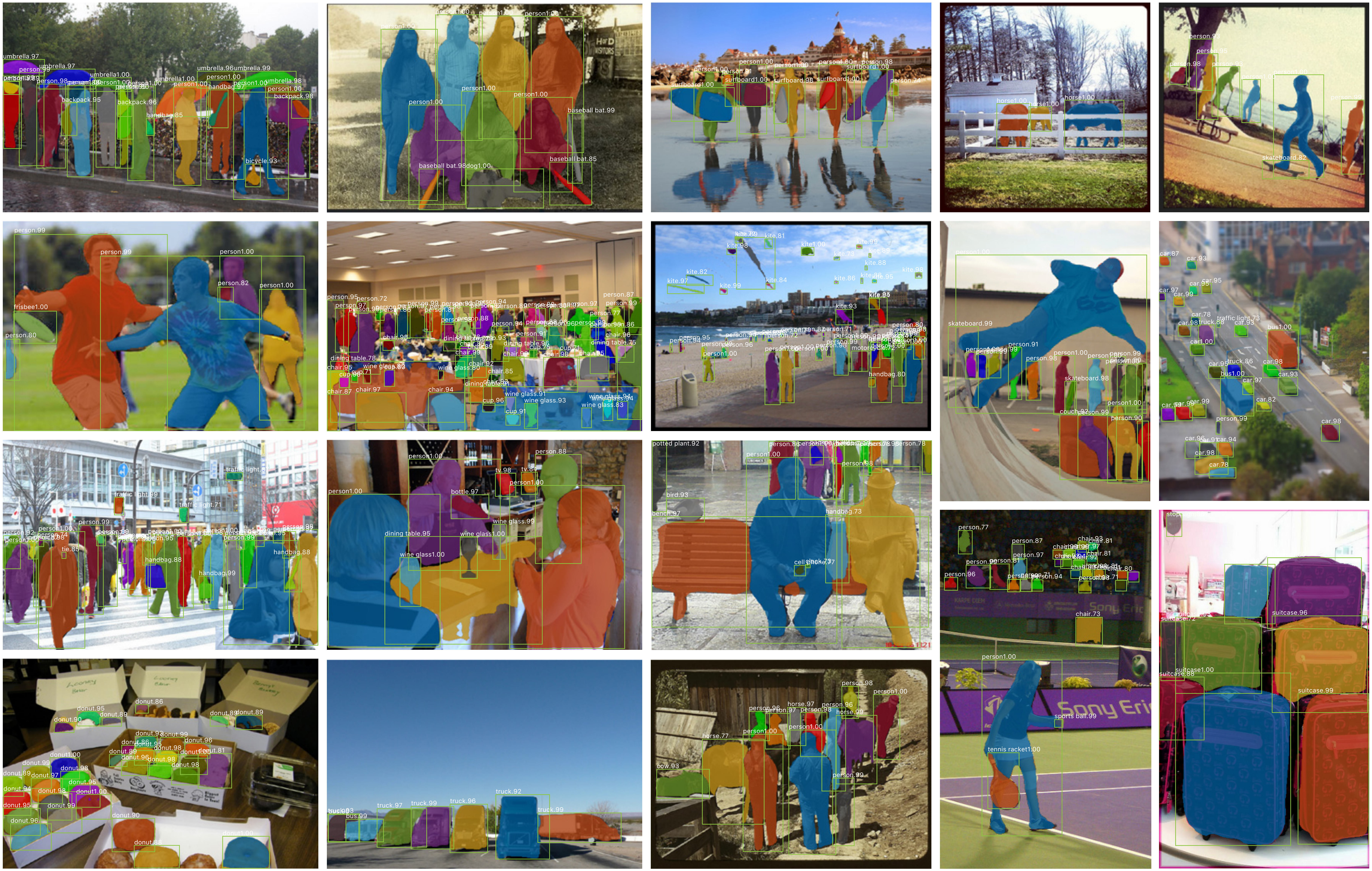
Values are times in ms

model	system	conv	proposal	region-wise	total	rate
VGG	SS + Fast R-CNN	146	1510	174	1830	0.5 fps
VGG	RPN + Fast R-CNN	141	**10**	47	**198**	**5 fps**

Summary

- **Knowledge of algorithm and properties of DNN used to gain algorithmic speedups**
  - Not just "modify the schedule of the loops"
- **Key insight: sharing results of convolutional layer computations:**
  - Between different proposed regions (proposed object bboxes)
  - Between region proposal logic and detection logic
- **Example of "end-to-end" training**
  - Back-propagate through entire algorithm to train all components at once
  - Better accuracy: globally optimize the various parts of the algorithm to be optimal for given task (Faster R-CNN: how to propose boxes learned simultaneously with detection logic)
  - Can constrain learning to preserve performance characteristics (Faster R-CNN: conv layer weights shared across RPN and detection task)

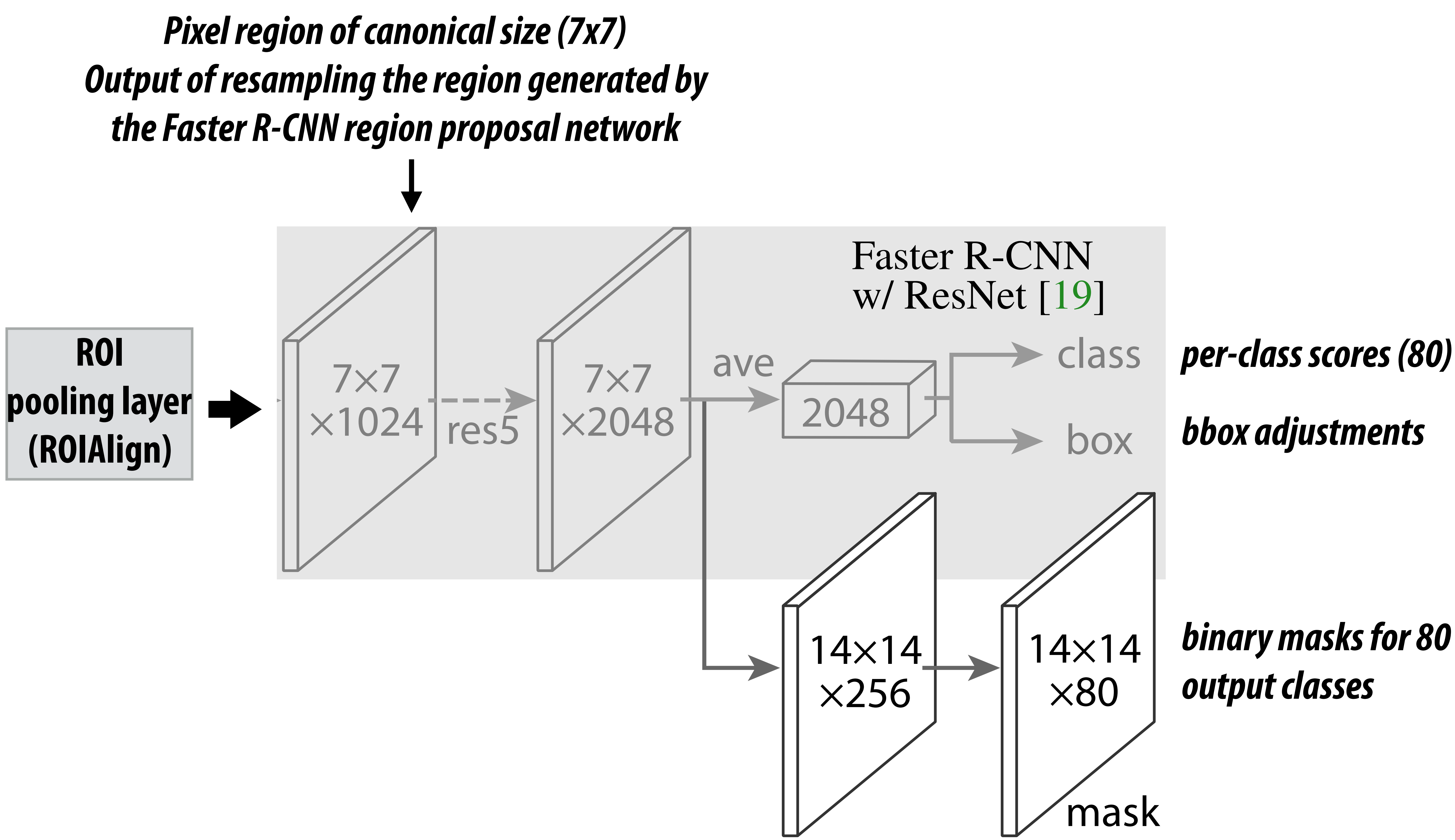
Extending to instance segmentation



[Image credit: He et al. 2017]

Mask RCNN

- **Extend Faster R-CNN to also emit a segmentation per box**
  - **Previously: box and class emitted in parallel**
  - **Now: box, class, and segmentation emitted in parallel**



Mask R-CNN for human pose

- **Loss based on bitmapped with hot pixels at joint keypoint locations rather than segmentation masks**

An alternative approach to object detection

Recall structure of algorithms so far: (reduce detection to classification)

```
for all proposed regions (x,y,w,h):
   cropped = image_crop(image, bbox(x,y,w,h))
   resized = image_resize(classifier_width,classifier_height)
   label = classify_object(resized)
   bbox_adjustment = adjust_bbox(resized)
```

New approach to detection:

```
for each level l of network:
  for each (x,y) position in output:
     use region around (l,x,y) to directly predict which anchor boxes
     centered at (x,y) are valid and class score for that box
```

If there are B anchor boxes and C classes, then…

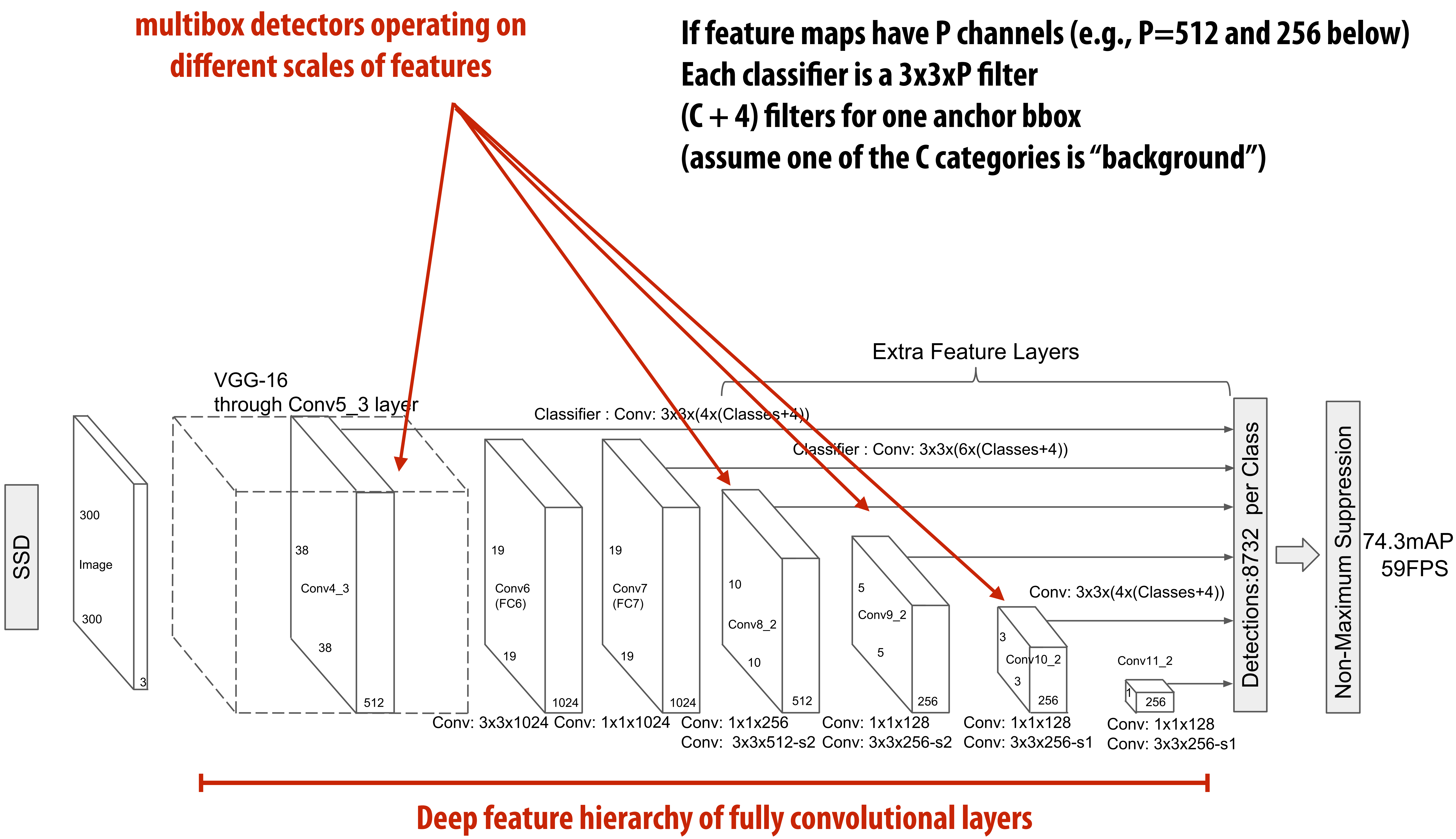
```
At each (l,x,y), prediction network has B(C + 4) outputs
```

For each anchor B, there are C class probabilities + 4 values to adjust the anchor box

SSD: Single shot multi box detector

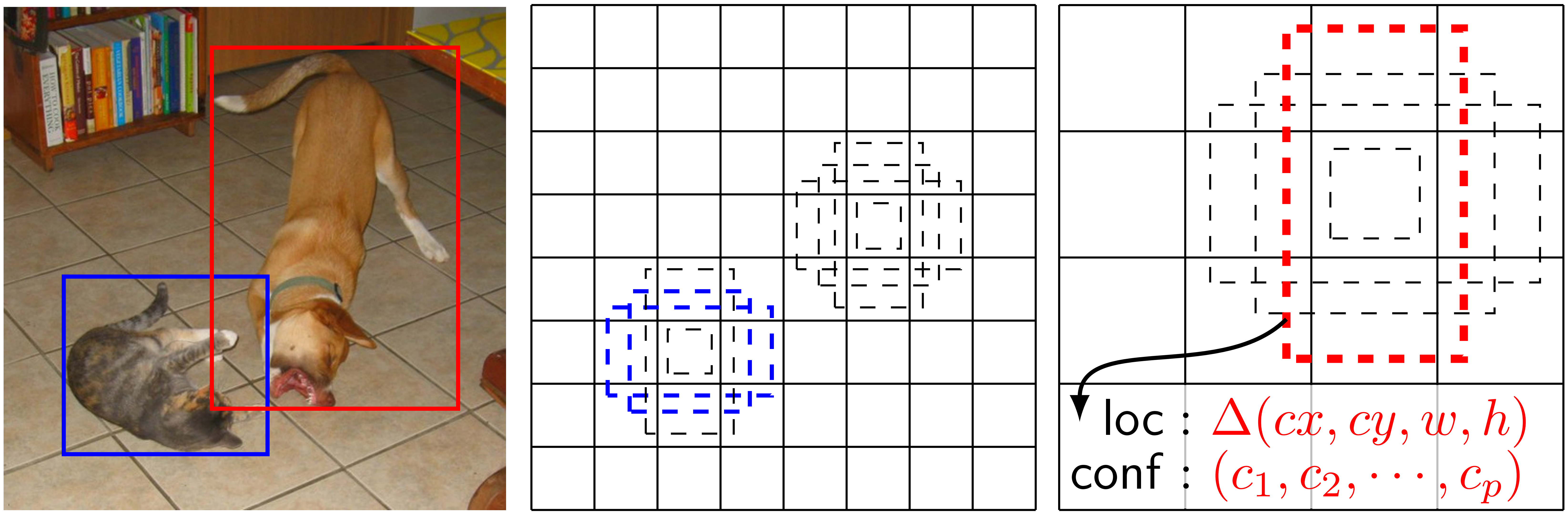
[Lui ECCV 2016]

If feature maps have P channels (e.g., P=512 and 256 below)
Each classifier is a 3x3xP filter
(C + 4) filters for one anchor bbox
(assume one of the C categories is "background")



Note: diagram shows only the feature maps

SSD anchor boxes



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

Anchor boxes at each feature map level are of different sizes

Intuition: receptive field of cells at higher levels of the network (lower resolution feature maps) is a larger fraction of the image, have information to make predictions for larger boxes

Object detection performance

600x600 input images

COCO-trained models {#coco-models}

Model name	Speed (ms)	COCO mAP[^1]	Outputs
ssd_mobilenet_v1_coco	30	21	Boxes
ssd_inception_v2_coco	42	24	Boxes
faster_rcnn_inception_v2_coco	58	28	Boxes
faster_rcnn_resnet50_coco	89	30	Boxes
faster_rcnn_resnet50_lowproposals_coco	64		Boxes
rfcn_resnet101_coco	92	30	Boxes
faster_rcnn_resnet101_coco	106	32	Boxes
faster_rcnn_resnet101_lowproposals_coco	82		Boxes
faster_rcnn_inception_resnet_v2_atrous_coco	620	37	Boxes
faster_rcnn_inception_resnet_v2_atrous_lowproposals_coco	241		Boxes
faster_rcnn_nas	1833	43	Boxes
faster_rcnn_nas_lowproposals_coco	540		Boxes

[Credit: Tensorflow detection model zoo]

Discussion

- Why did we say that DNNs learn “good features”?

- Consider Mask R-CNN

Discussion

- Today we saw our first examples of end-to-end learning
  - Idea: globally optimize all parts of a topology for specific task at hand
  - Empirically: often enables better accuracy (and also better performance)

- Interesting to consider effects on interpretability of these models (modularity is typically a favorable property of software)

Emerging theme

(from today's lecture and the Inception, MobileNet, and related readings)

- **Computer vision practitioners are "programming" via low-level manipulation of DNN topology**
  - See shift from reasoning about individual layers to writing up of basic "microarchitecture" modules (e.g., Inception module)
  - Differentiable programming

- **Interesting question: what programming model constructs or "automated compilation" tools could help raise the level of abstraction?**