Object detection (deep methods)

Object detection

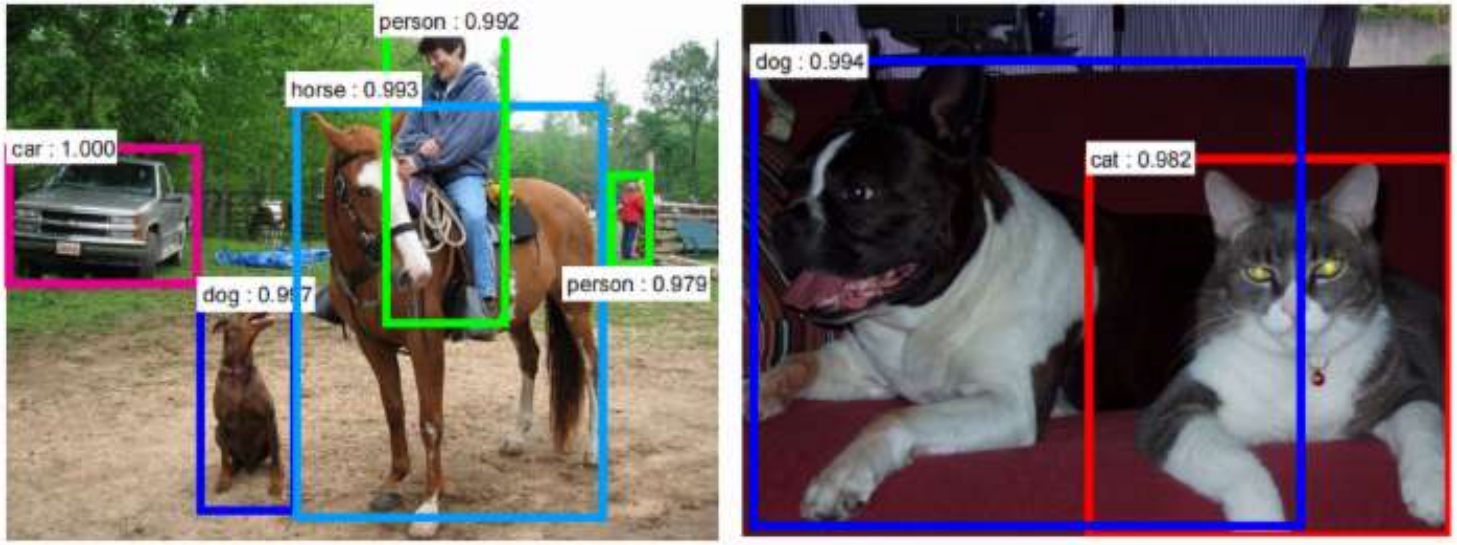
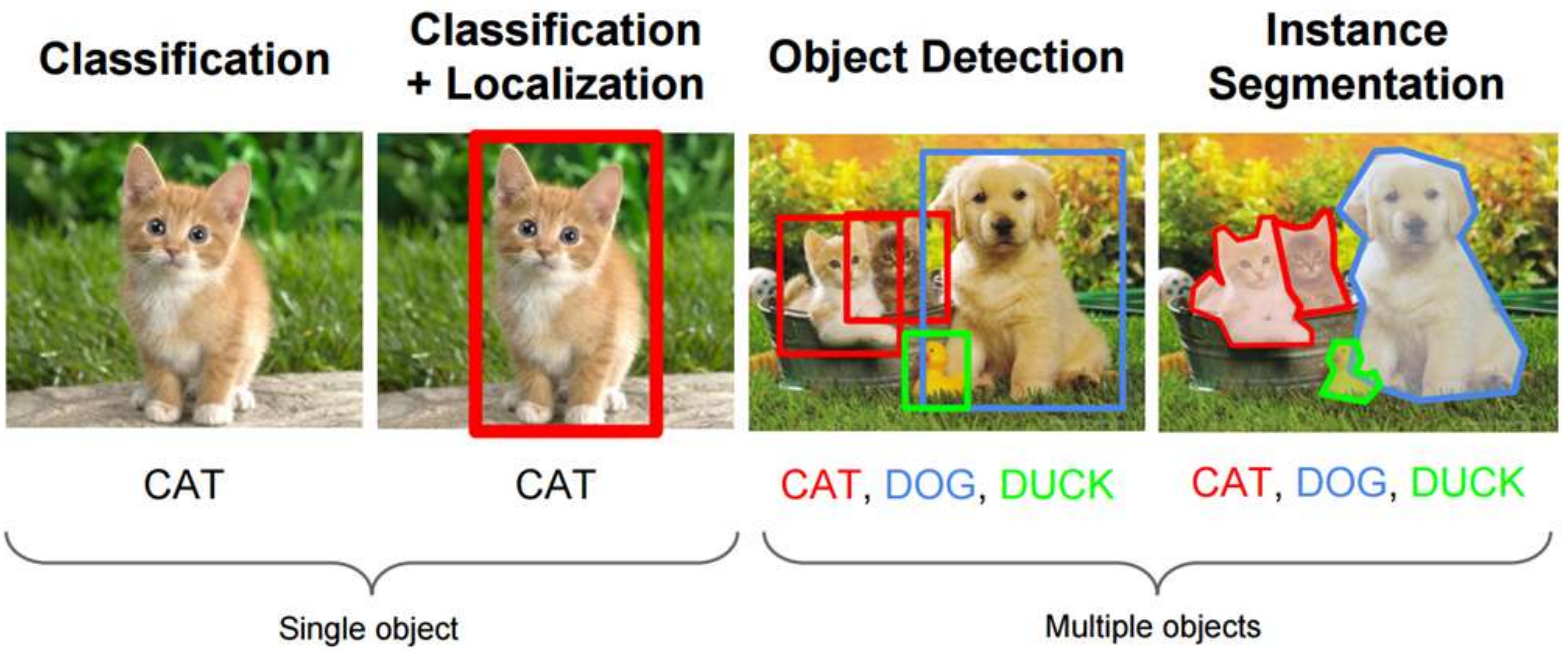


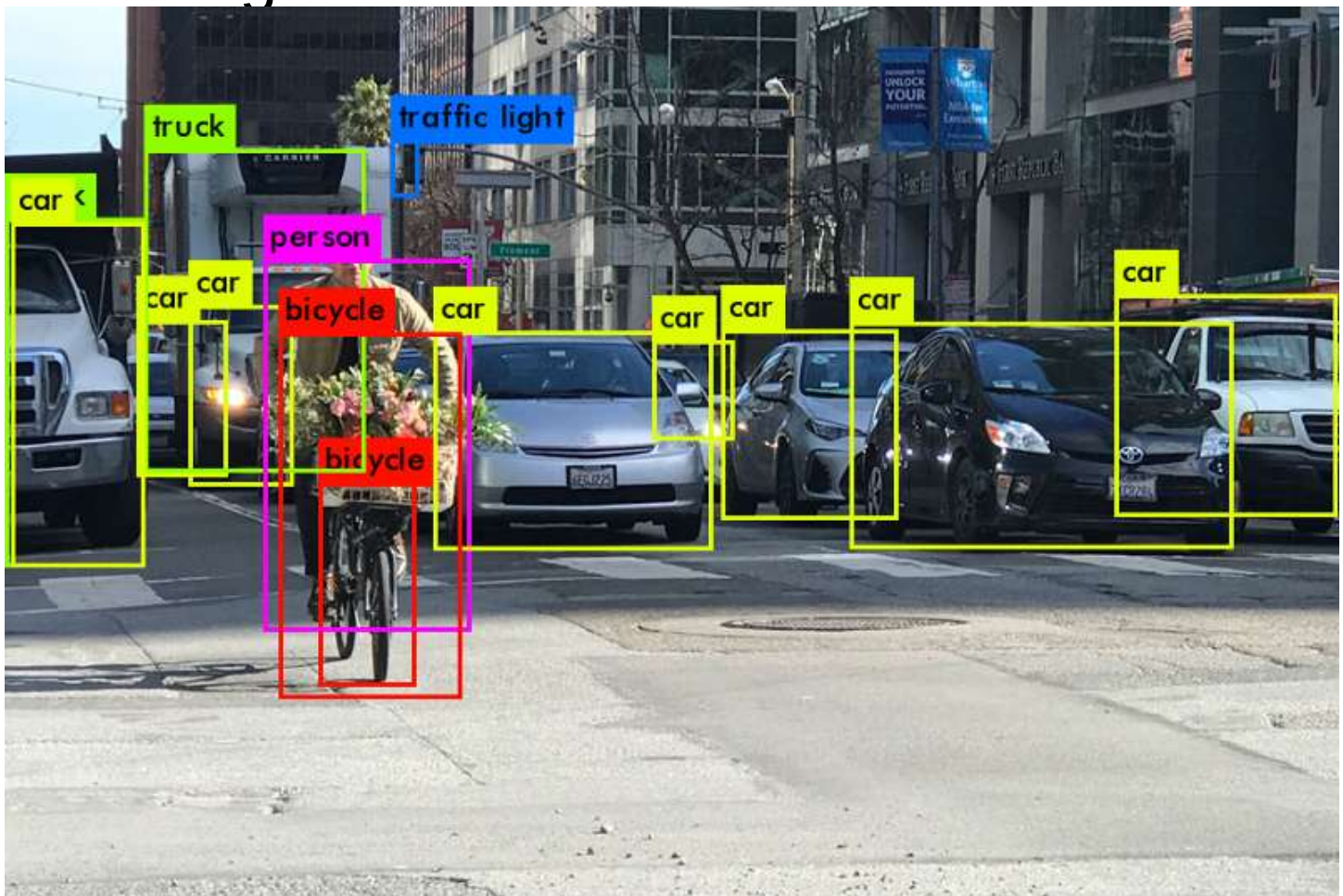
Image source

What is object detection



What are the challenges of object detection?

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

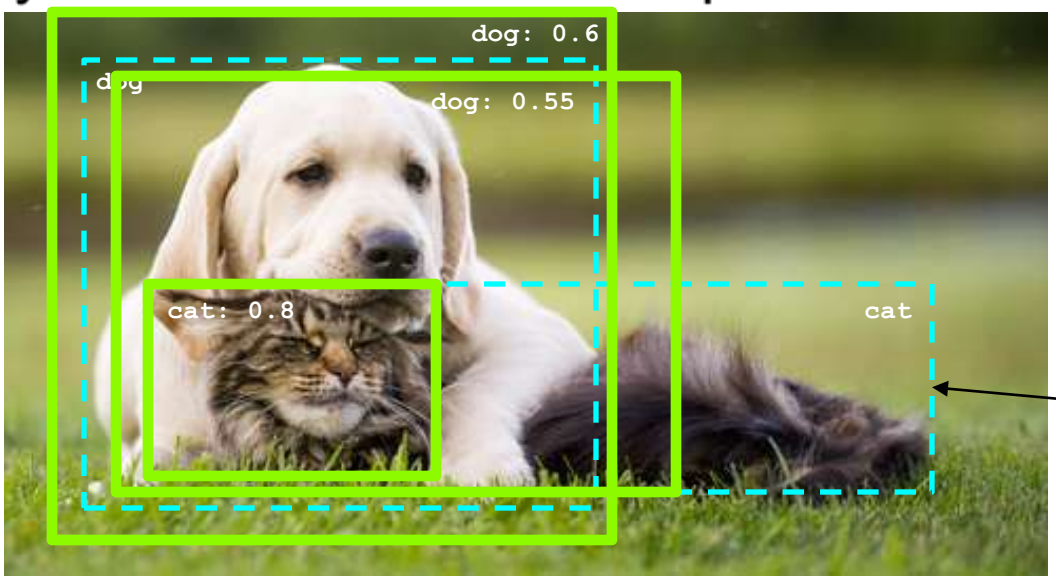


Outline

- Task definition and evaluation
- Generic object detection before deep learning
- Zoo of deep detection approaches
  - R-CNN
  - Fast R-CNN
  - Faster R-CNN
  - Yolo
  - SSD

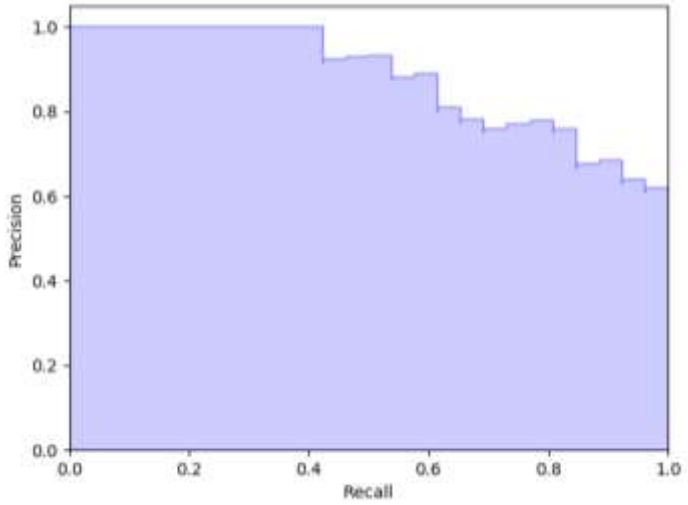
Object detection evaluation

- 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

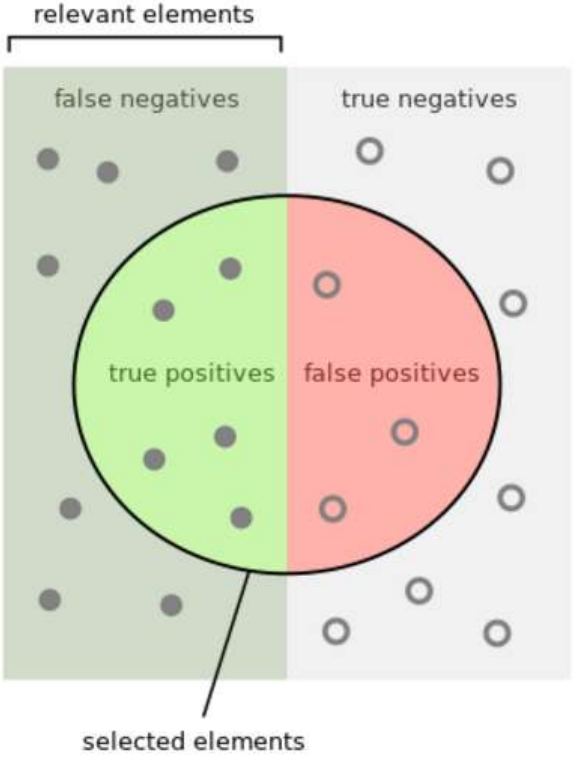
- At test time, predict bounding boxes, class labels, and confidence scores
- For each detection, determine whether it is a true or false positive
- For each class, plot Recall-Precision curve and compute Average Precision (area under the curve)
- Take mean of AP over classes to get mAP

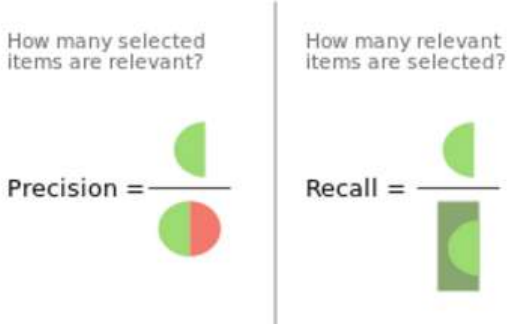


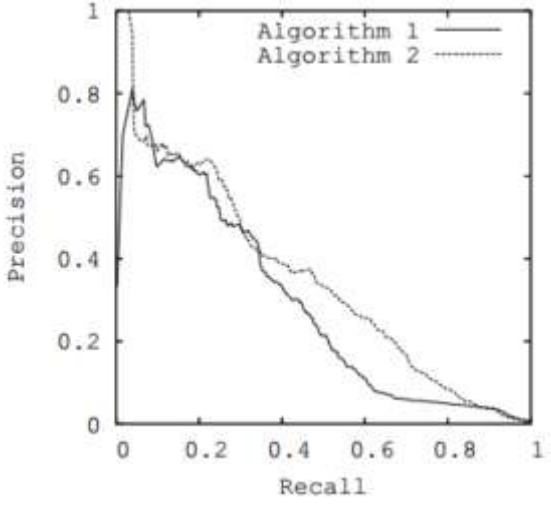
Precision:
true positive detections / total detections
Recall:
true positive detections / total positive test instances

Terms

Recall, Precision, mAP, IoU





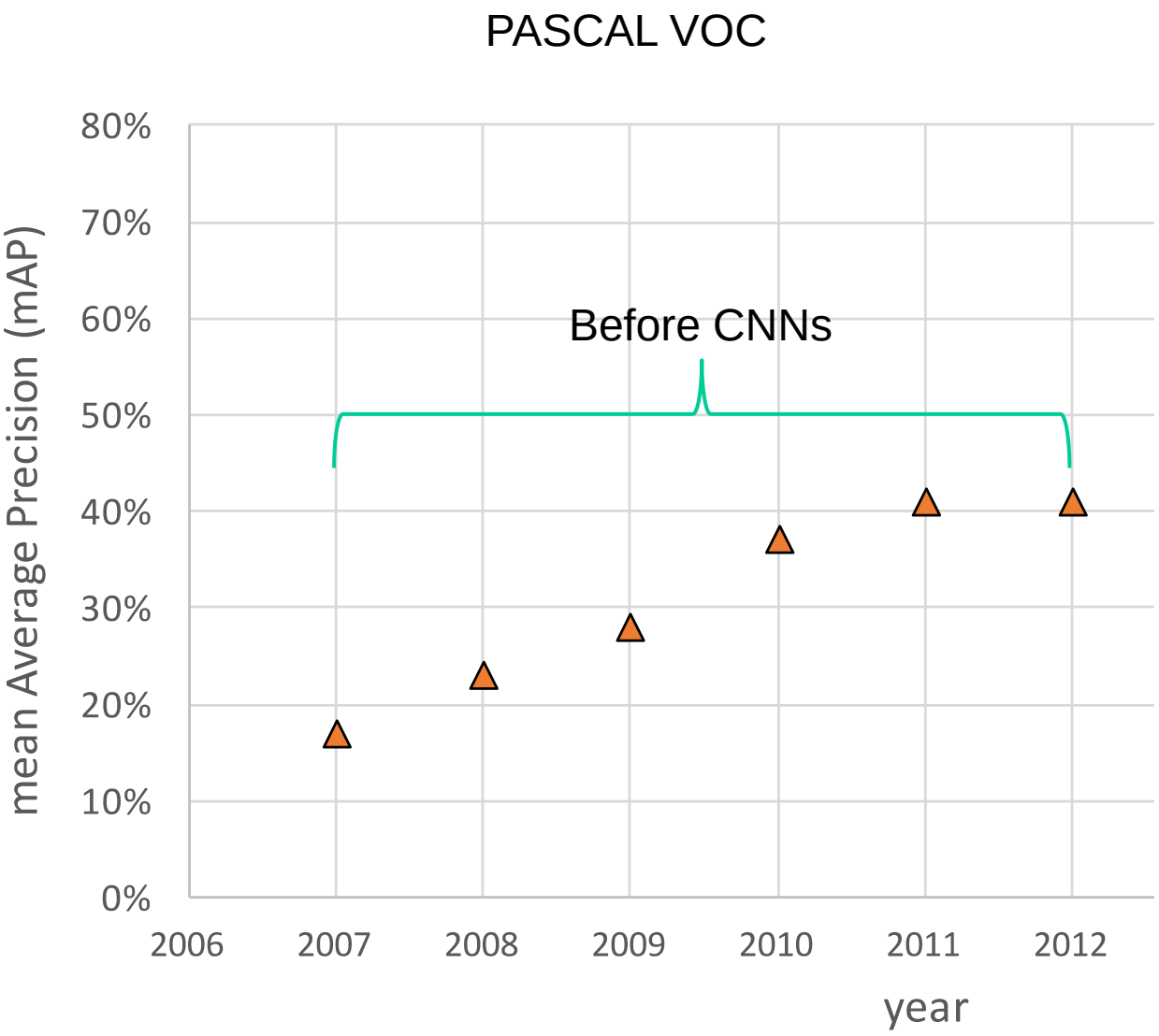


PASCAL VOC Challenge (2005-2012)

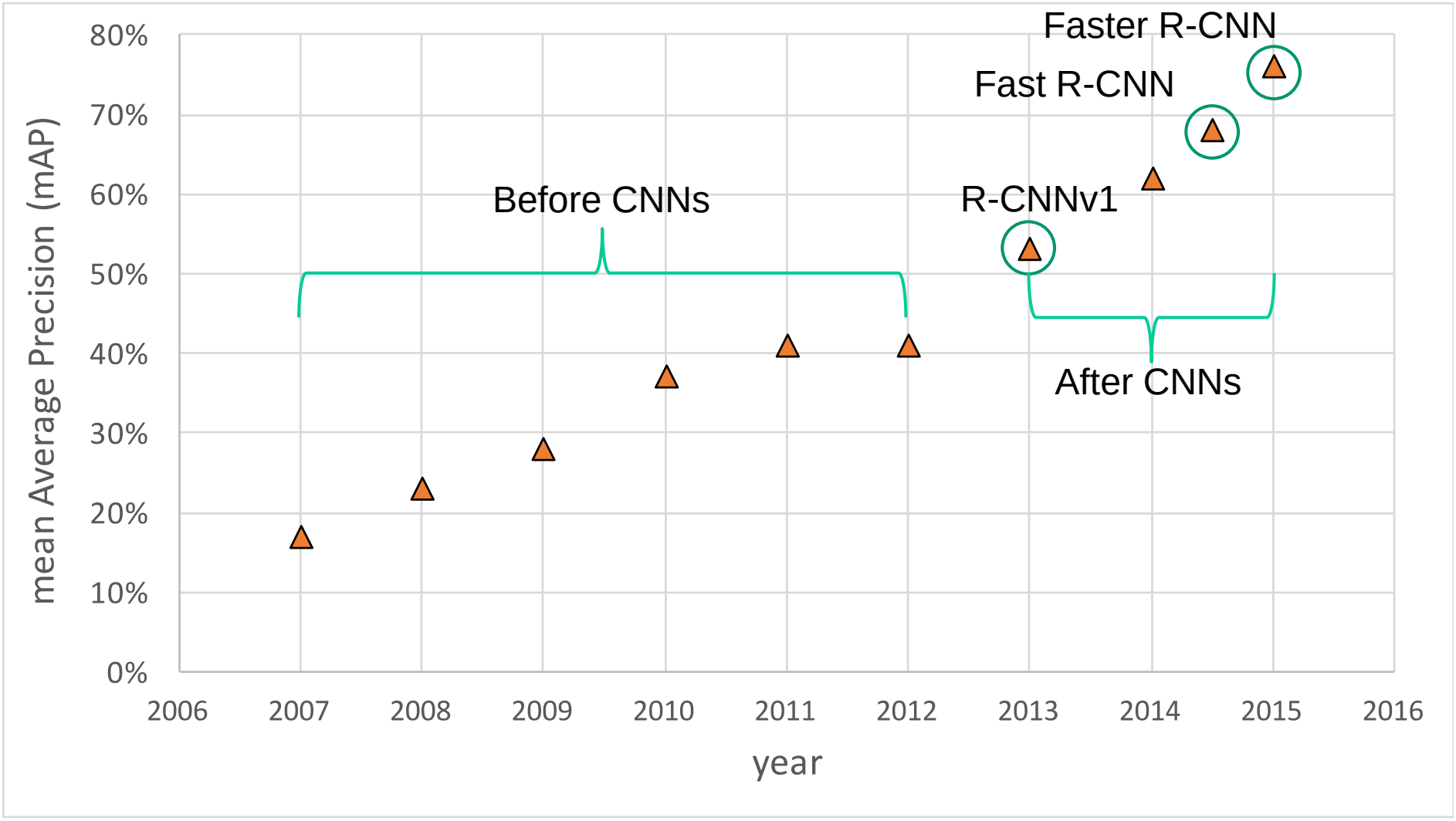
- 20 challenge classes:
  - *Person*
  - *Animals:* bird, cat, cow, dog, horse, sheep
  - *Vehicles:* aeroplane, bicycle, boat, bus, car, motorbike, train
  - *Indoor:* bottle, chair, dining table, potted plant, sofa, tv/monitor
- Dataset size (by 2012): 11.5K training/validation images, 27K bounding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

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

Progress on PASCAL detection



Object detection progress

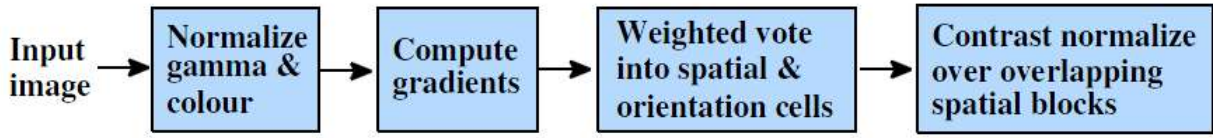


Conceptual approach: Sliding window detection

- 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



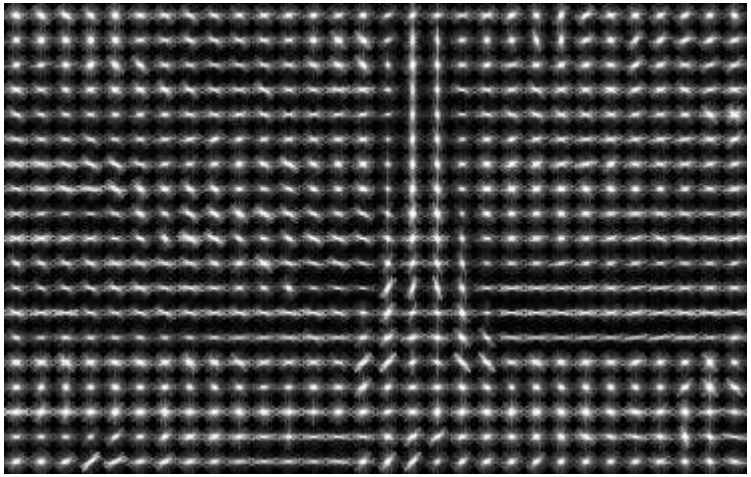


Image credit: N. Snavely

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

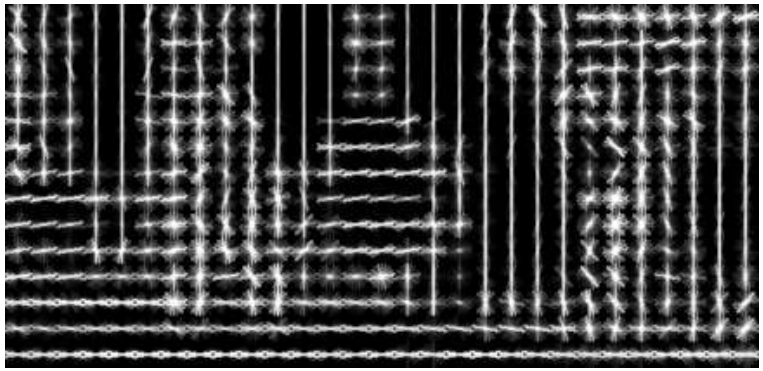
negative training examples

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

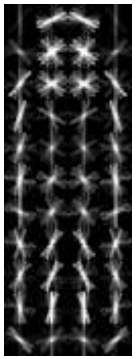
Pedestrian detection with HOG

- 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*

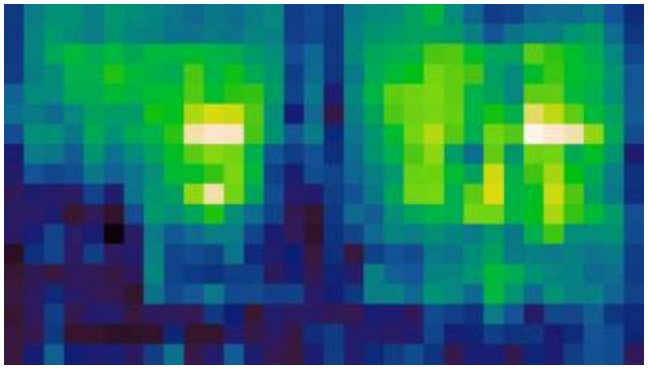
HOG feature map



Template



Detector response map



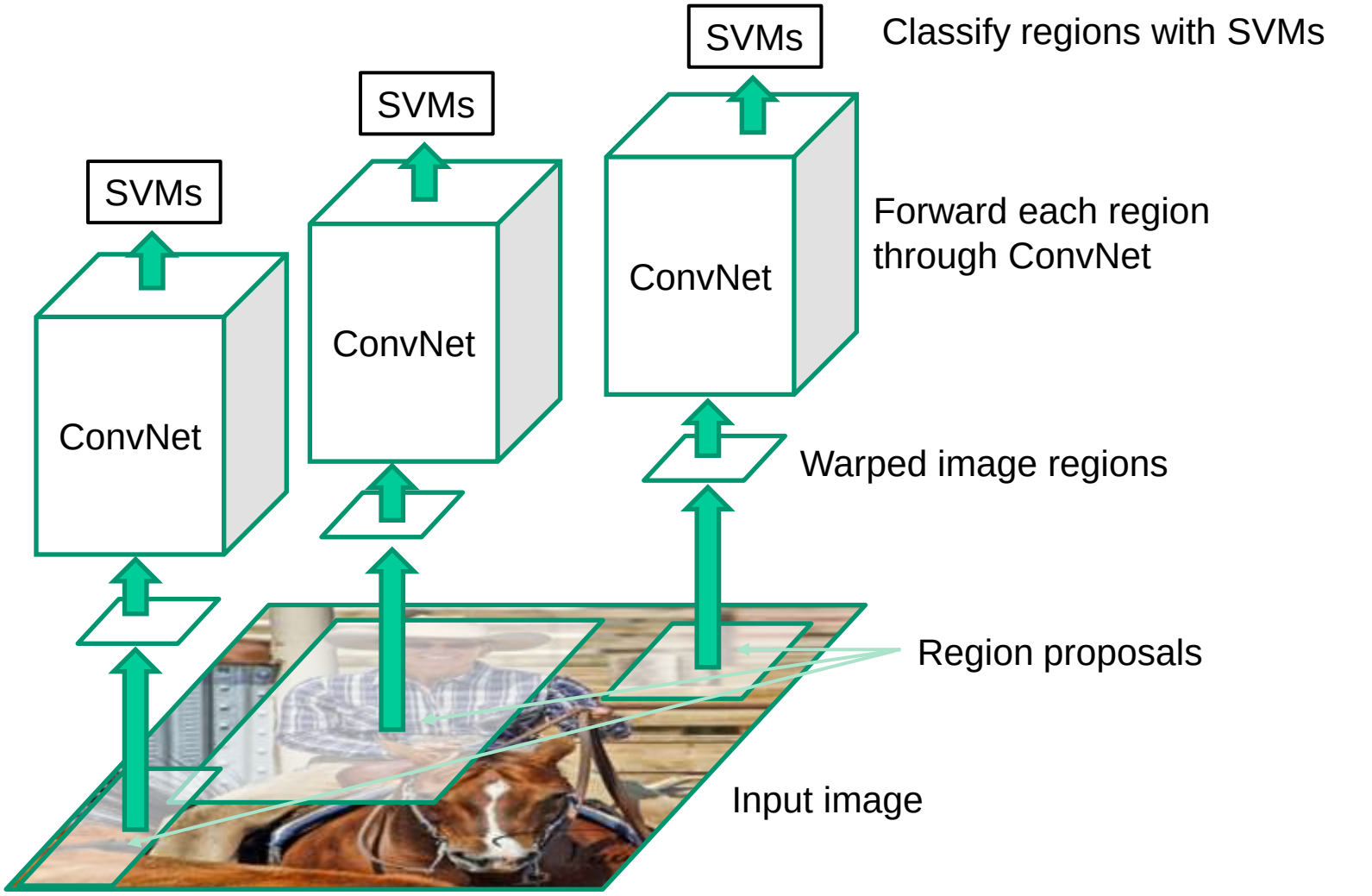
N. Dalal and B. Triggs, Histograms of Oriented Gradients for Human Detection, CVPR 2005

Example detections

[Dalal and Triggs, CVPR 2005]

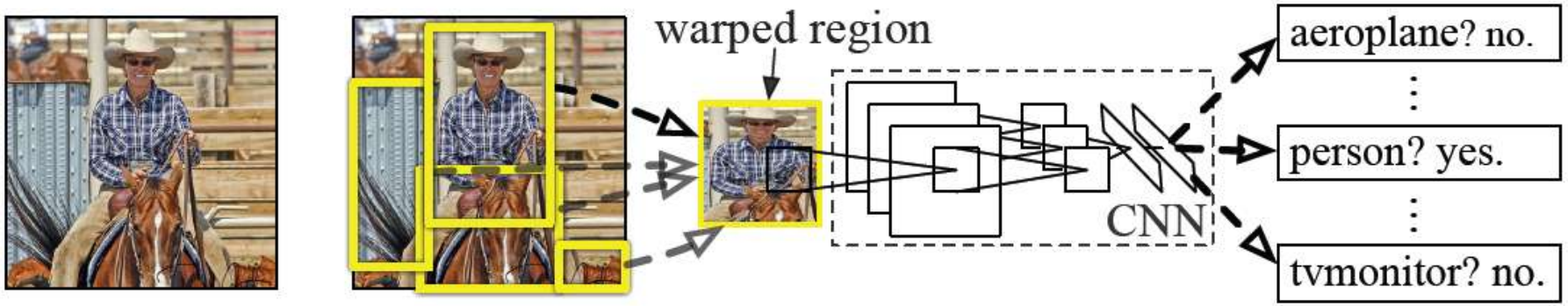
R-CNN: Region proposals + CNN features

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

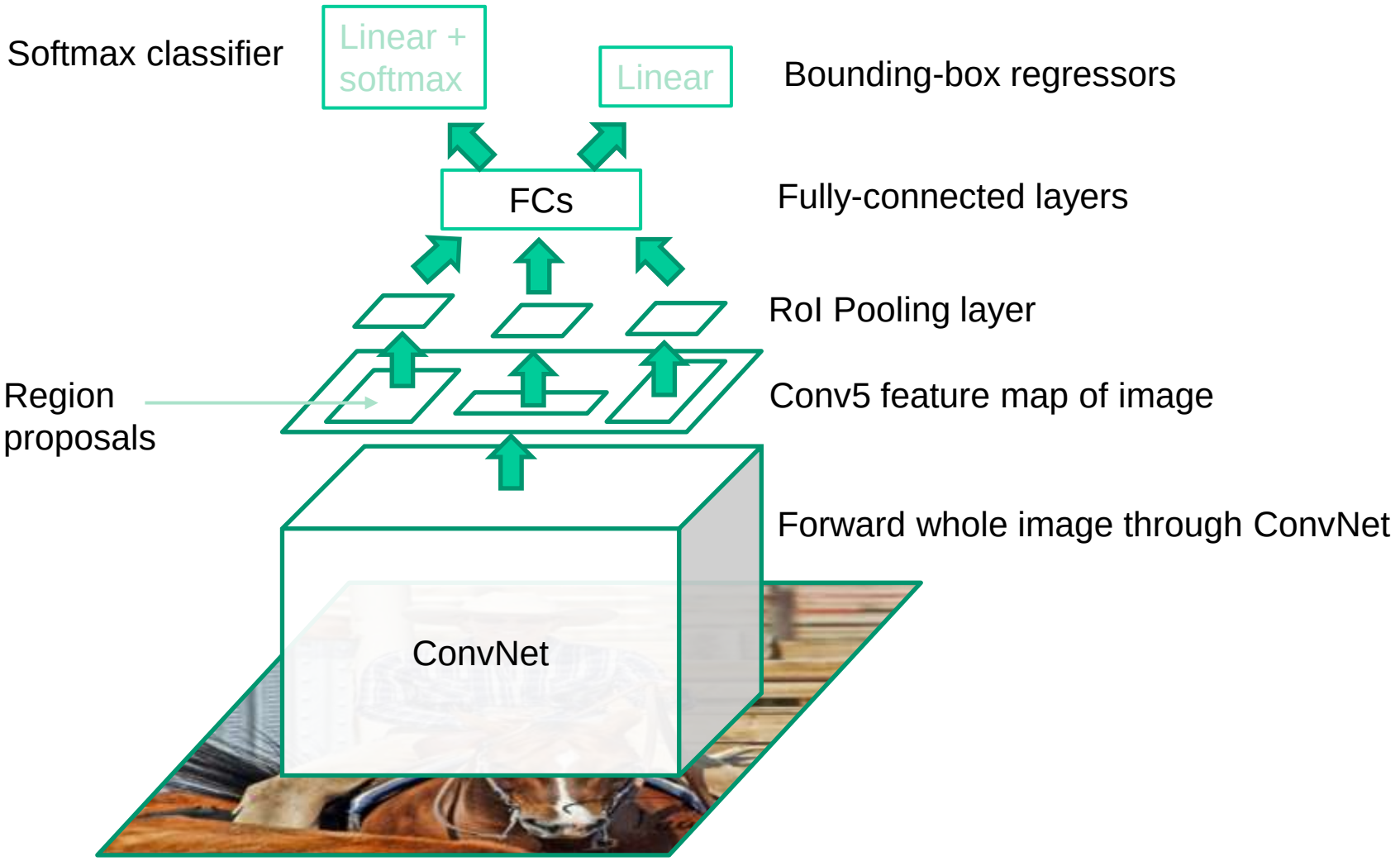


- **Regions**: ~2000 Selective Search proposals
- **Network**: AlexNet *pre-trained* on ImageNet (1000 classes), *fine-tuned* on PASCAL (21 classes)
- **Final detector**: warp proposal regions, extract fc7 network activations (4096 dimensions), classify with linear SVM
- **Bounding box regression** to 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

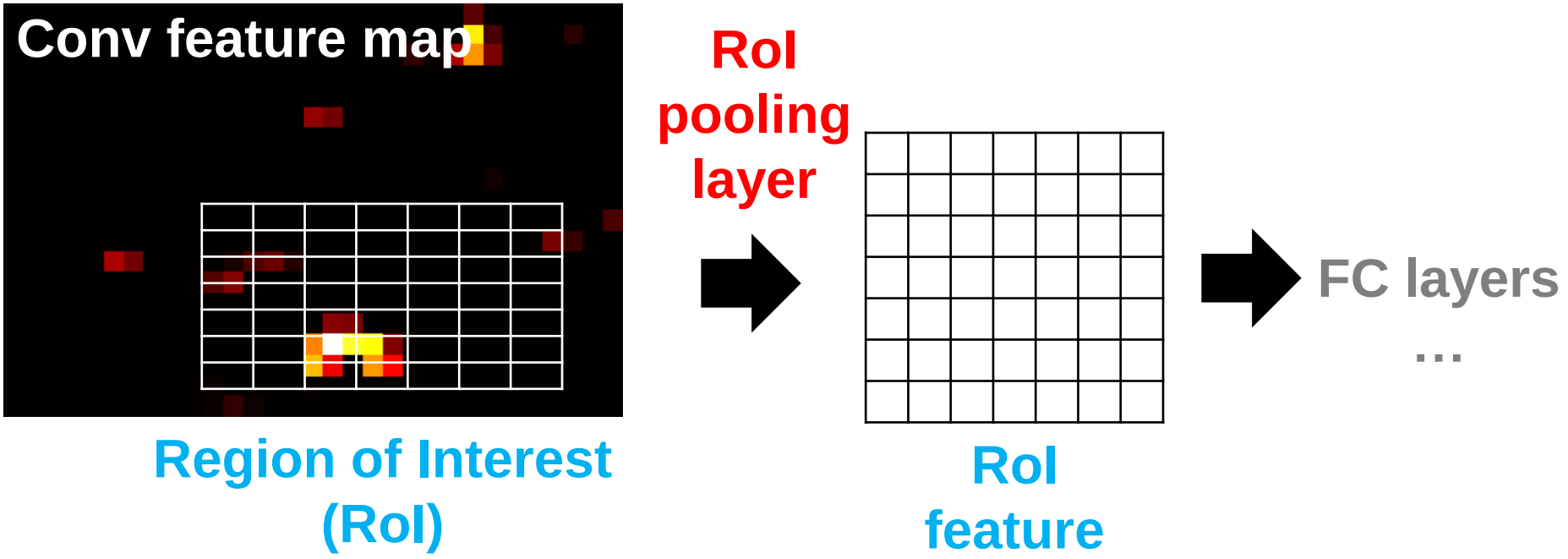


Source: R. Girshick

R. Girshick, Fast R-CNN, ICCV 2015

RoI pooling

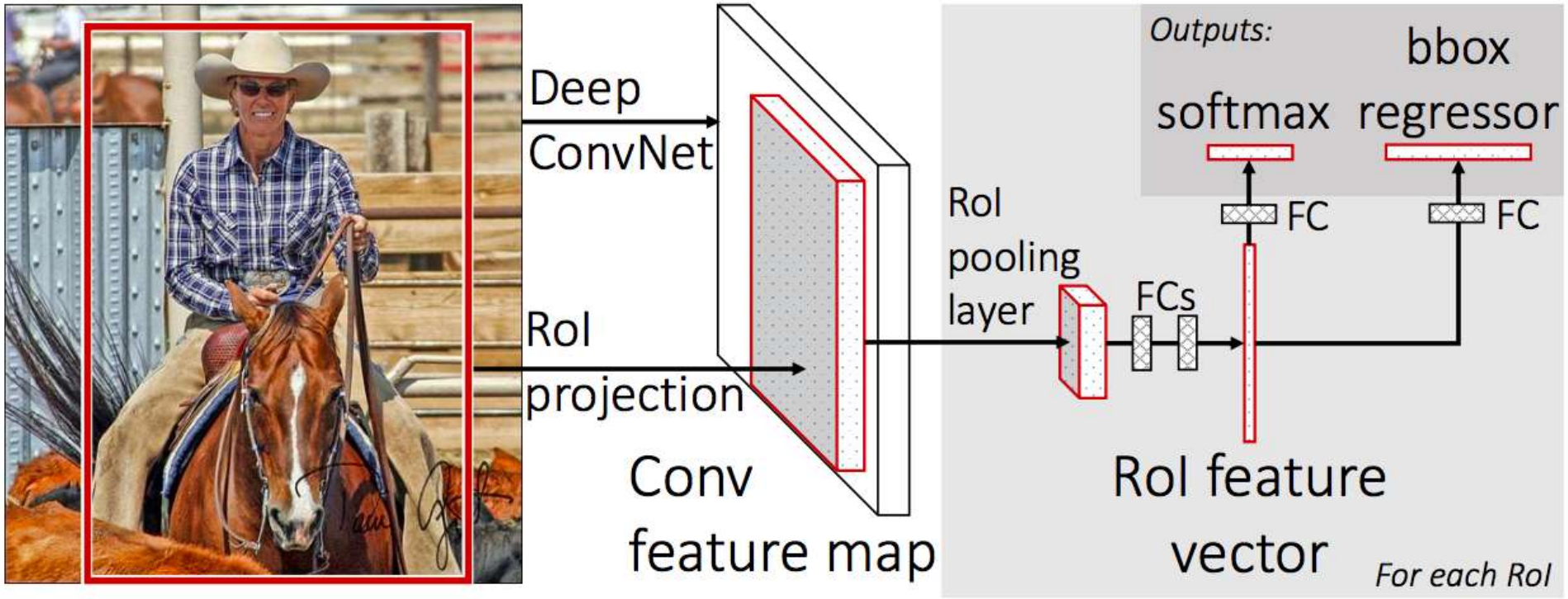
- "Crop and resample" a fixed-size feature representing a region of interest out of the outputs of the last conv layer
  - Use nearest-neighbor interpolation of coordinates, max pooling



Source: R. Girshick, K. He

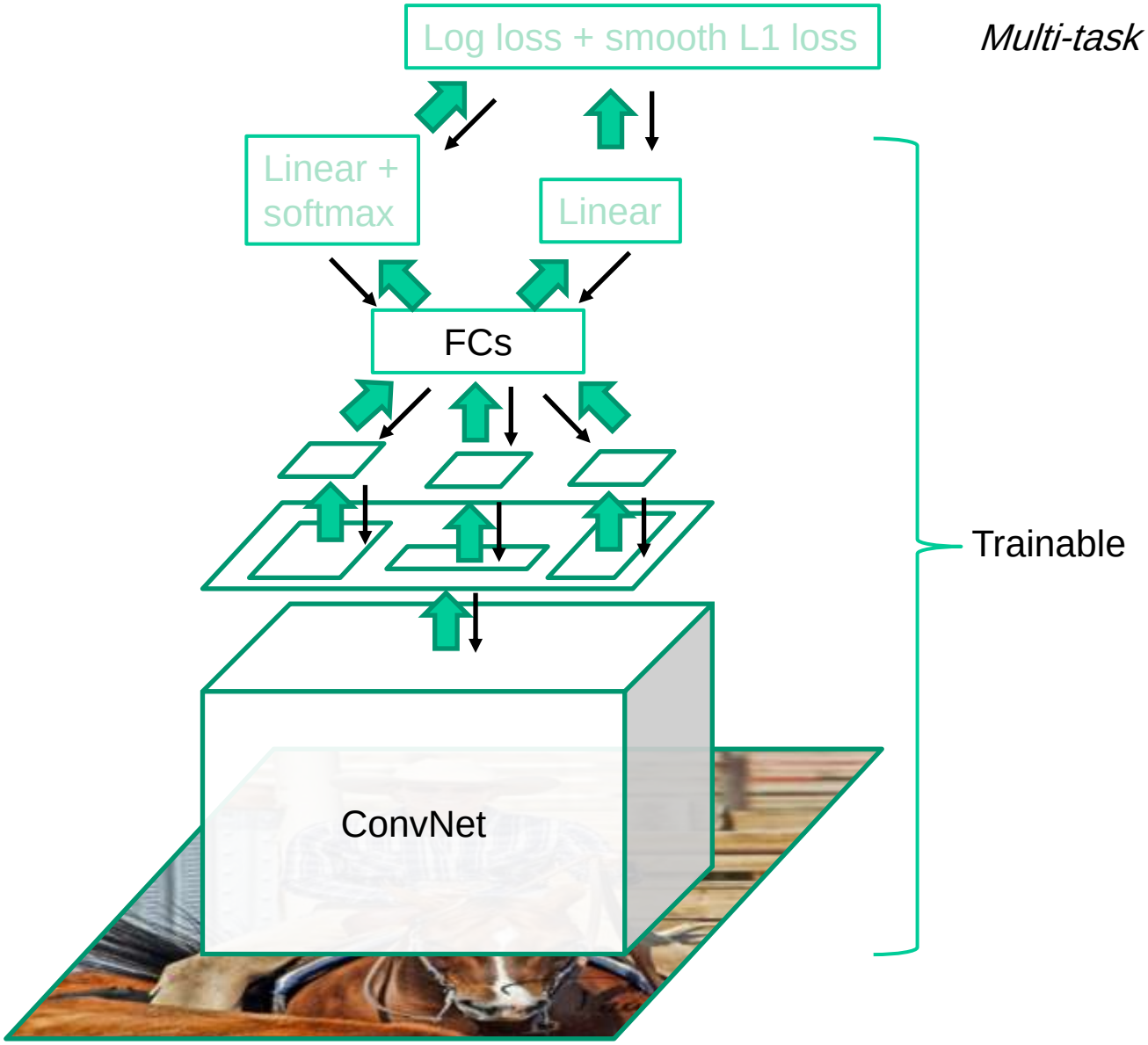
Prediction

- 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

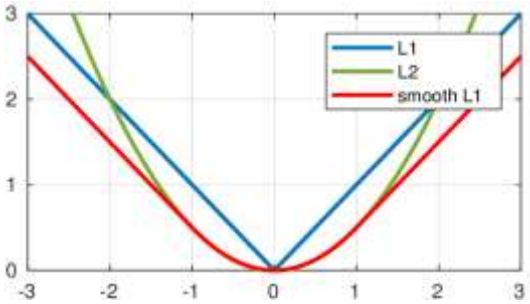
Multi-task loss

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

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

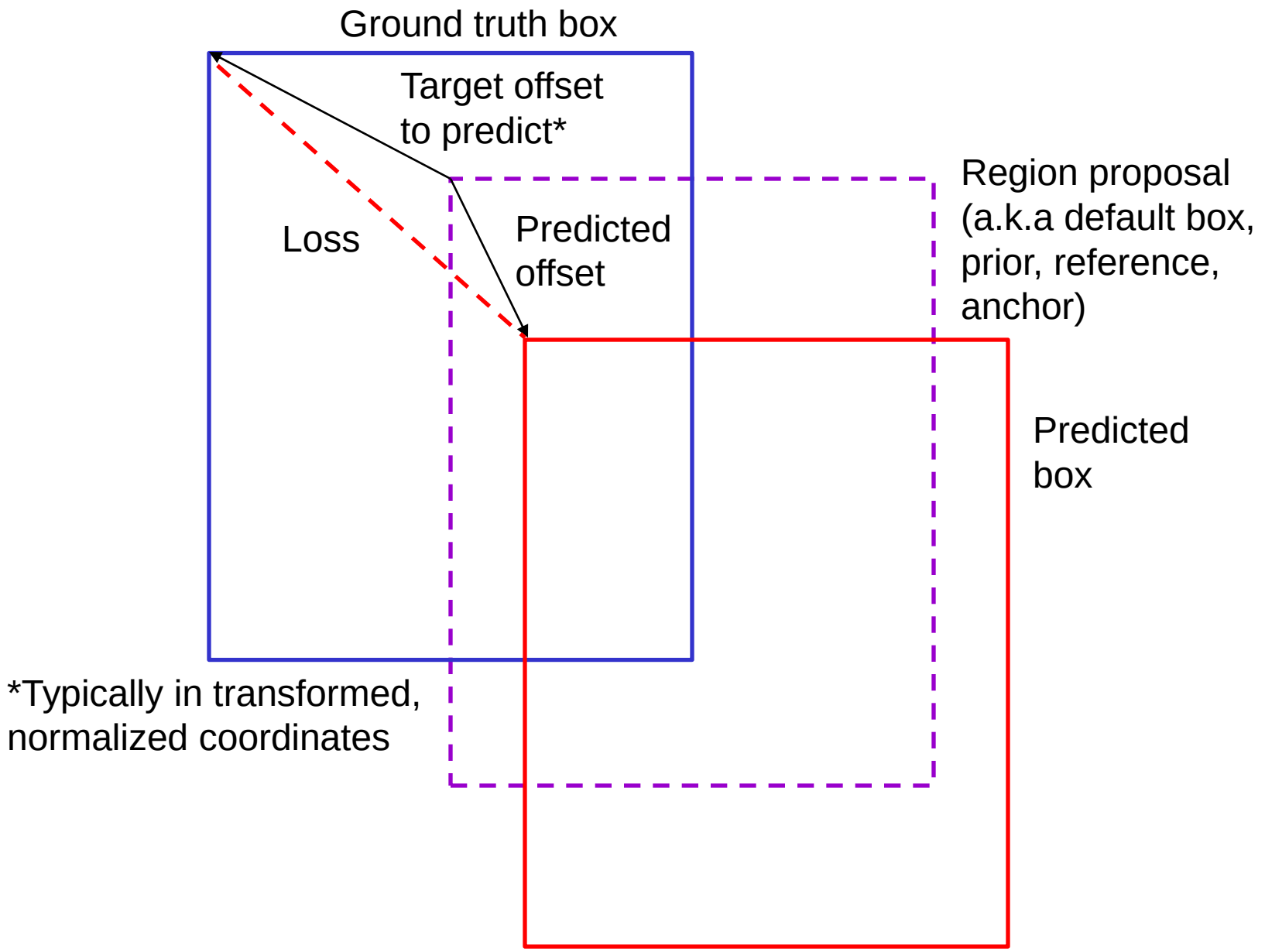
- Regression loss: *smooth L1 loss* on top of log space offsets relative to proposal

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



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

Bounding box regression



Fast R-CNN results

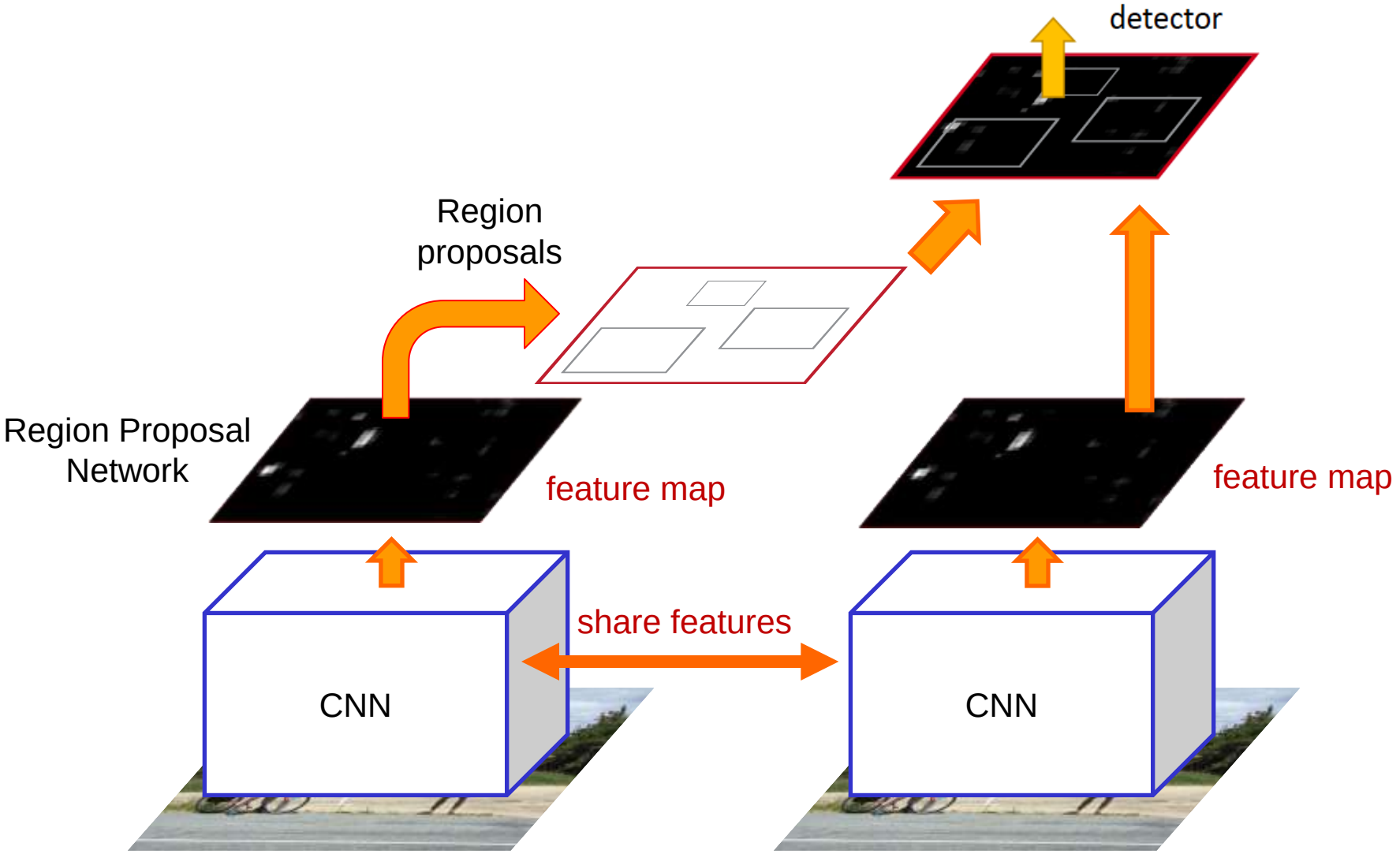
	Fast R-CNN	R-CNN
Train time (h)	**9.5**	84
- Speedup	**8.8x**	1x
Test time / image	**0.32s**	47.0s
Test speedup	**146x**	1x
mAP	**66.9%**	66.0%

(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

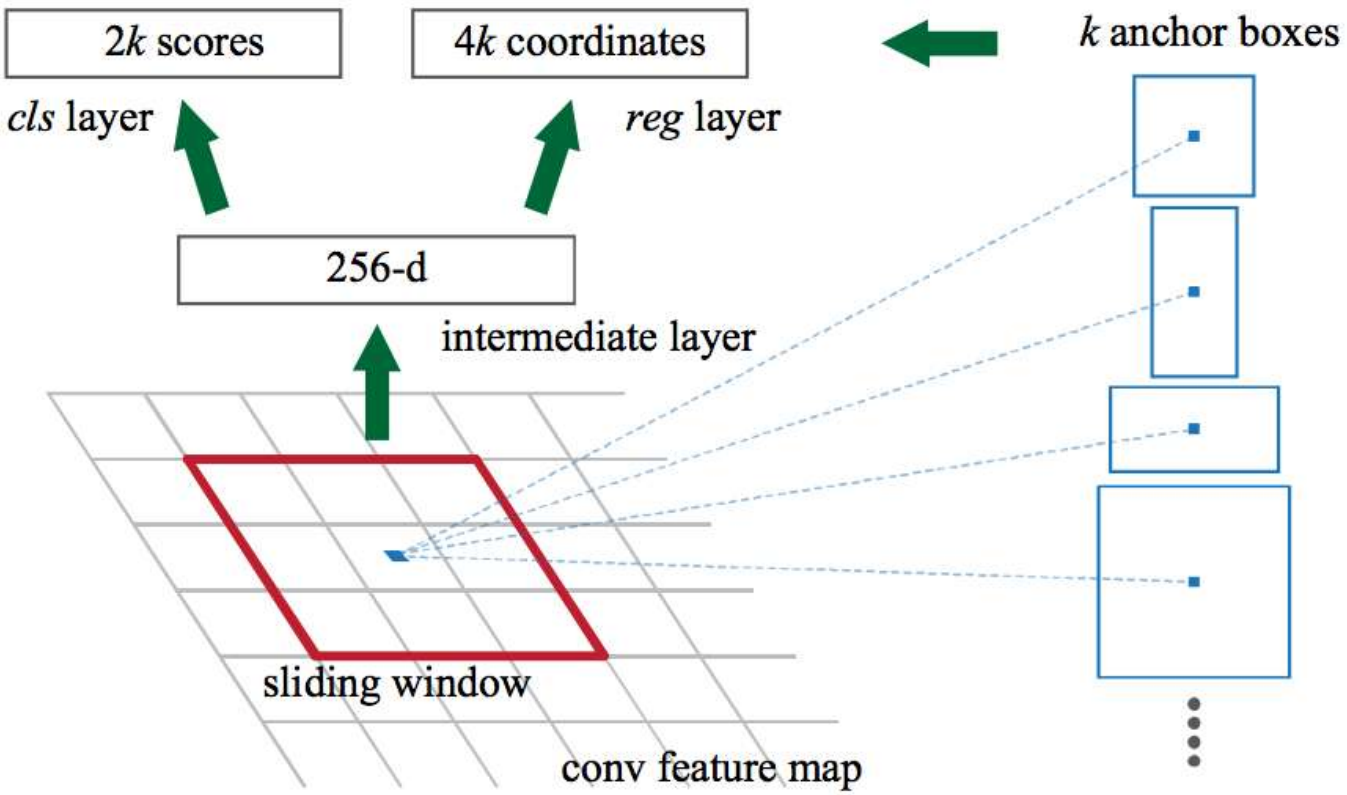
Faster R-CNN



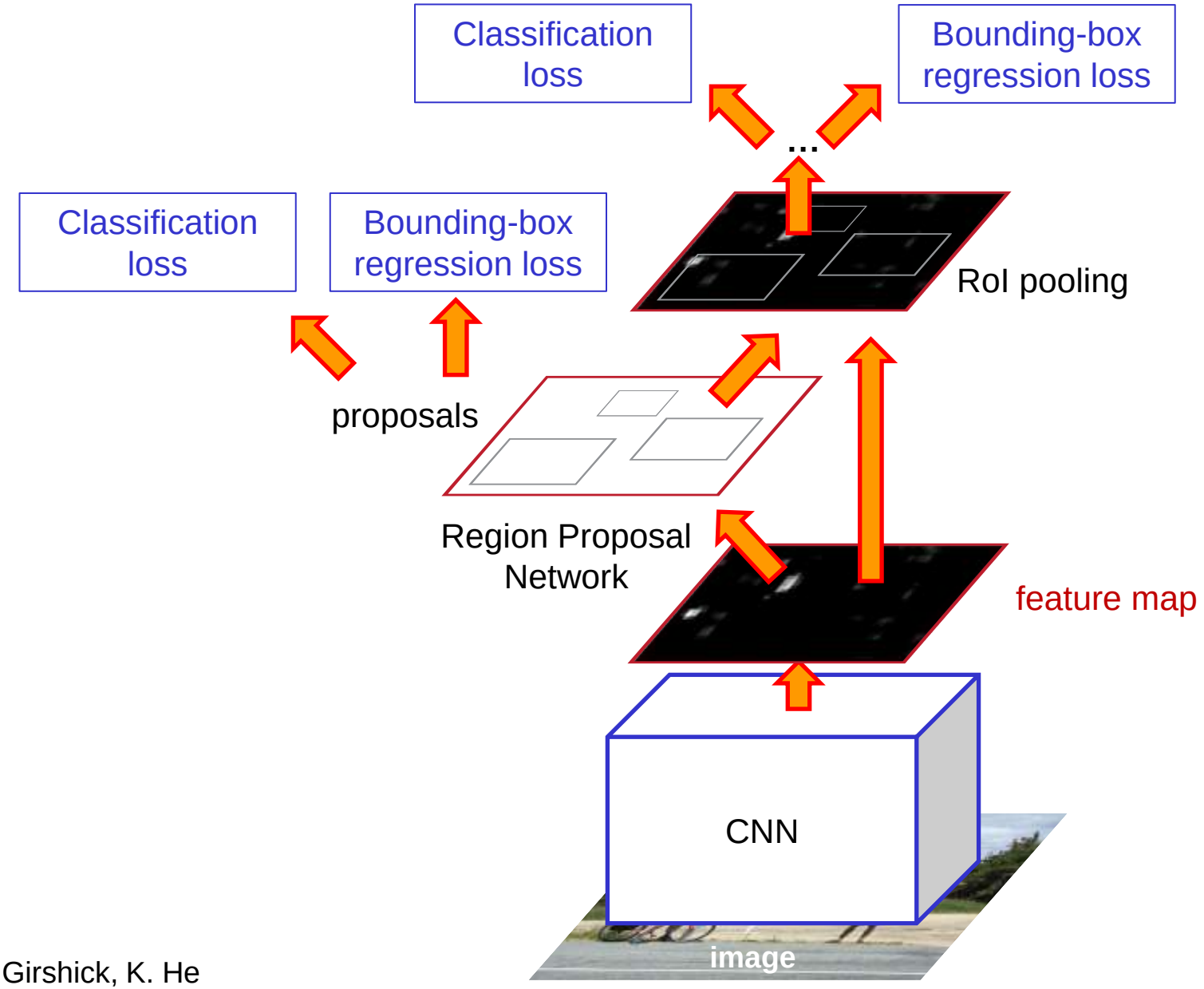
S. Ren, K. He, R. Girshick, and J. Sun, Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks, NIPS 2015

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

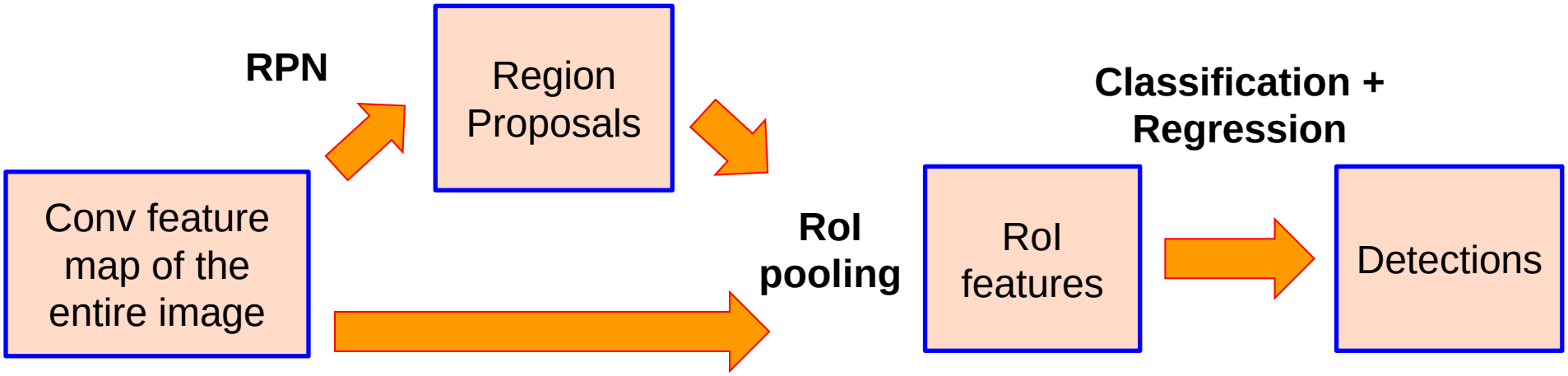
Faster R-CNN results

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**

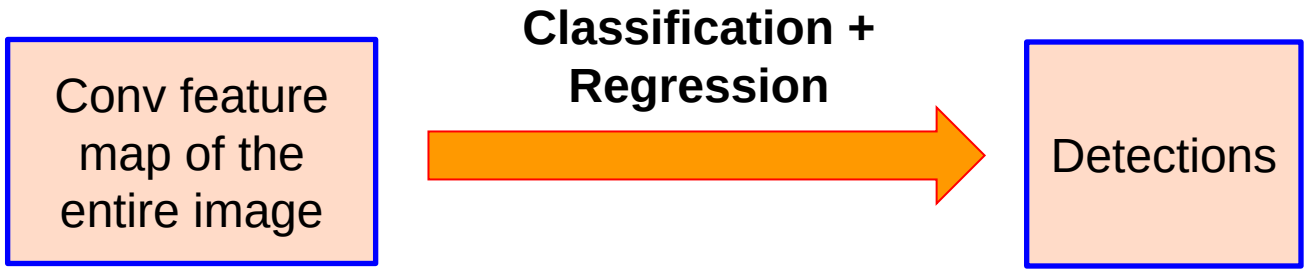
detection mAP on PASCAL VOC 2007, with VGG-16 pre-trained on ImageNet

Streamlined detection architectures

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

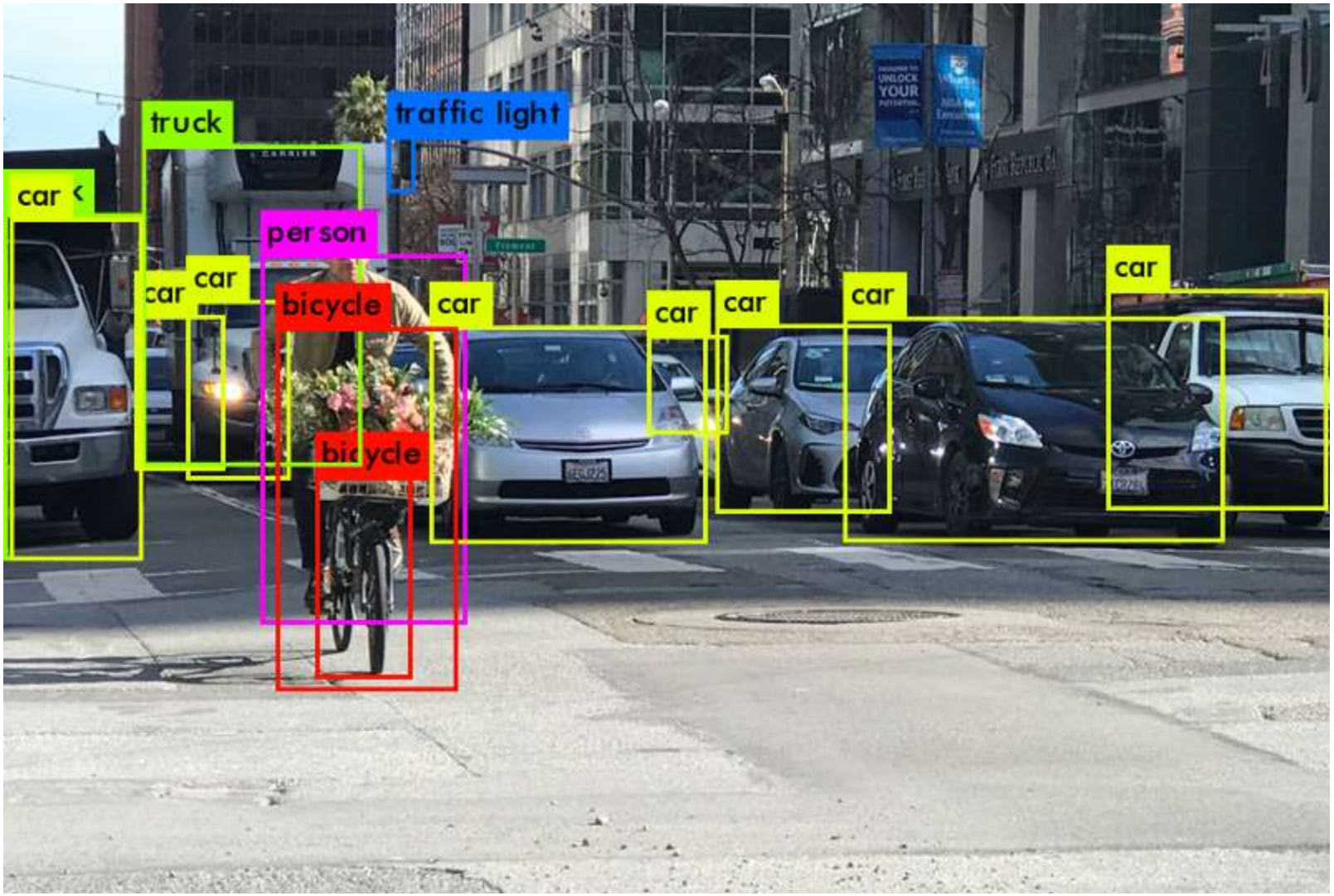


- Is it possible do detection in one shot?



You Only Look Once

Objects detected by YOLO



Grid cell

YOLO divides the input image into an S×S grid. Each grid cell predicts only one object.
The yellow grid cell tries to predict the “person” object whose center (the blue dot) falls inside the grid cell.

For each grid cell,

- it predicts **B** boundary boxes and each box has one box **confidence score**,
- it detects one object only regardless of the number of boxes **B**,
- it predicts **C conditional class probabilities** (one per class for the likeliness of the object class).

YOYO make **S x S** predictions with **B** boundary boxes.

YOLO

(x, y, w, h) + confidence score (objectness+box)

(x, y, w, h) + confidence score (objectness+box)

car: 0.05
person: 0.10
...
truck : 0.02

...

cell(1, 1)

...

...

cell(S, S)

Boundary box

- Each boundary box contains 5 elements:

  (*x, y, w, h*) and a **box confidence score**.

- The confidence score reflects how likely the box contains an object (**objectness**) and how accurate is the boundary box.

- We normalize the bounding box width *w* and height *h* by the image width and height. *x* and *y* are offsets to the corresponding cell.

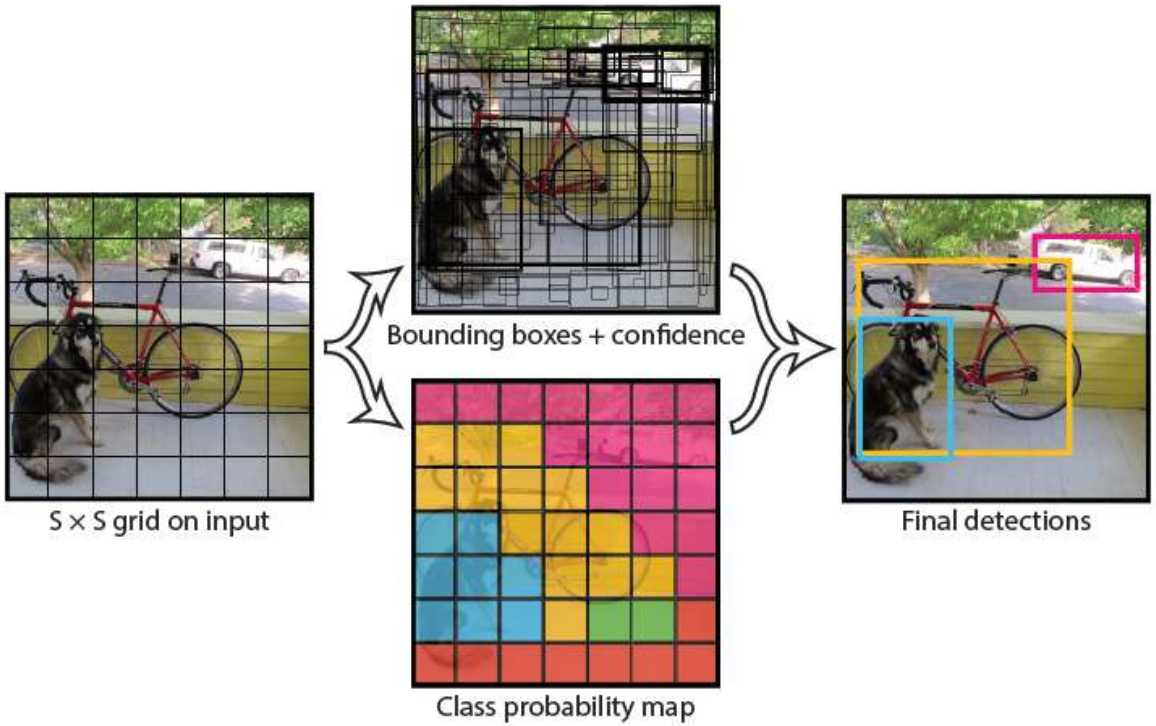
$$
\begin{aligned}
\text{box confidence score} &\equiv P_r(object) \cdot IoU \\
\text{conditional class probability} &\equiv P_r(class_i|object) \\
\text{class confidence score} &\equiv P_r(class_i) \cdot IoU \\
&= \text{box confidence score} \times \text{conditional class probability}
\end{aligned}
$$

where

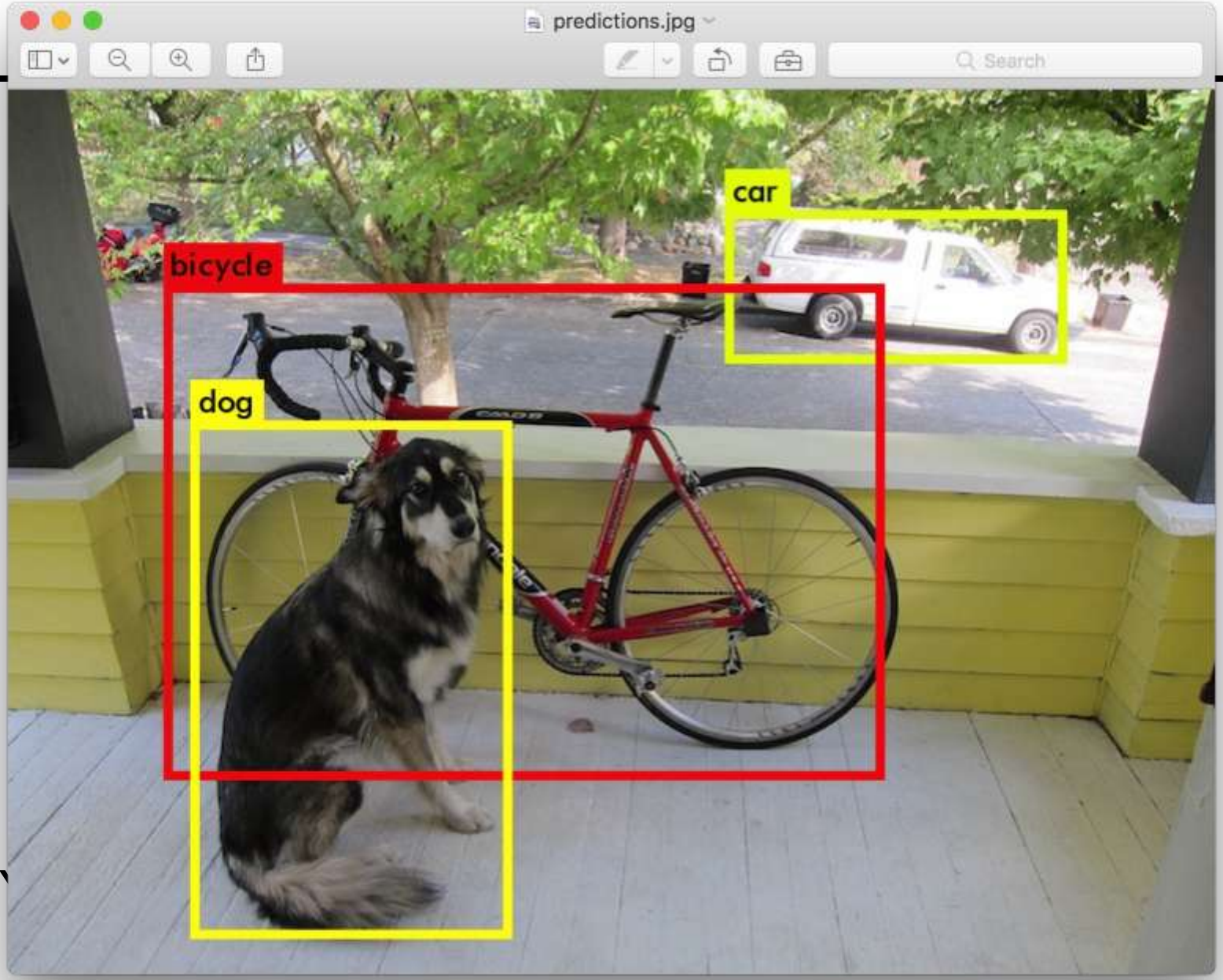
$P_r(object)$ is the probability the box contains an object.
IoU is the IoU (intersection over union) between the predicted box and the ground truth.
$P_r(class_i|object)$ is the probability the object belongs to $class_i$ given an object is presence.
$P_r(class_i)$ is the probability the object belongs to $class_i$

YOLO

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

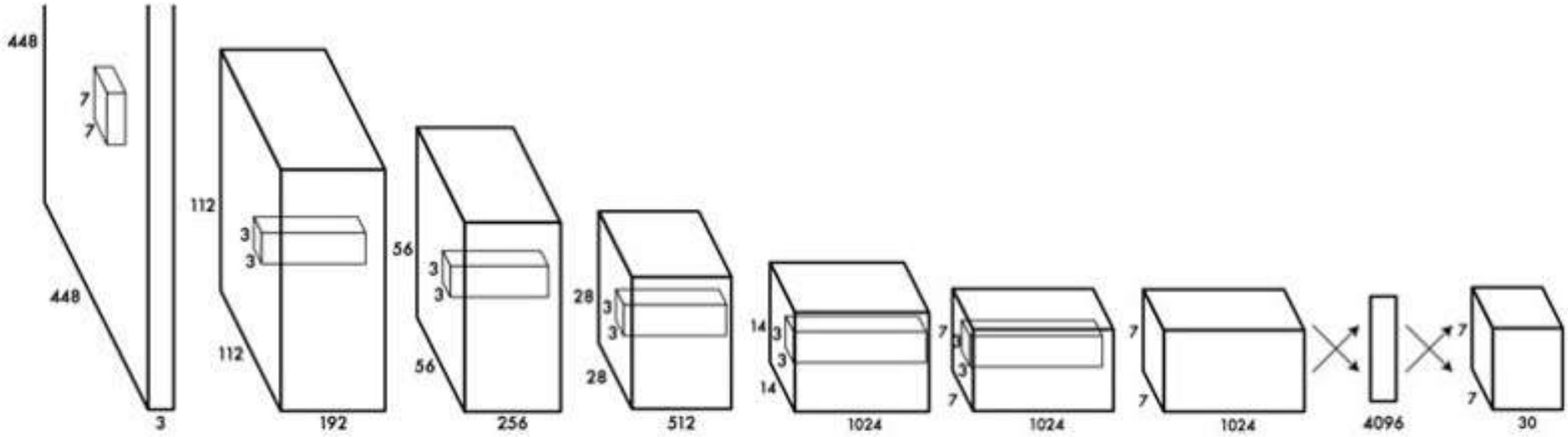


J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, You Only Look Once: Unified, Real-Time Object Detection, CVPR 2016


predictions.jpg
Search
car
bicycle
dog

YOLO

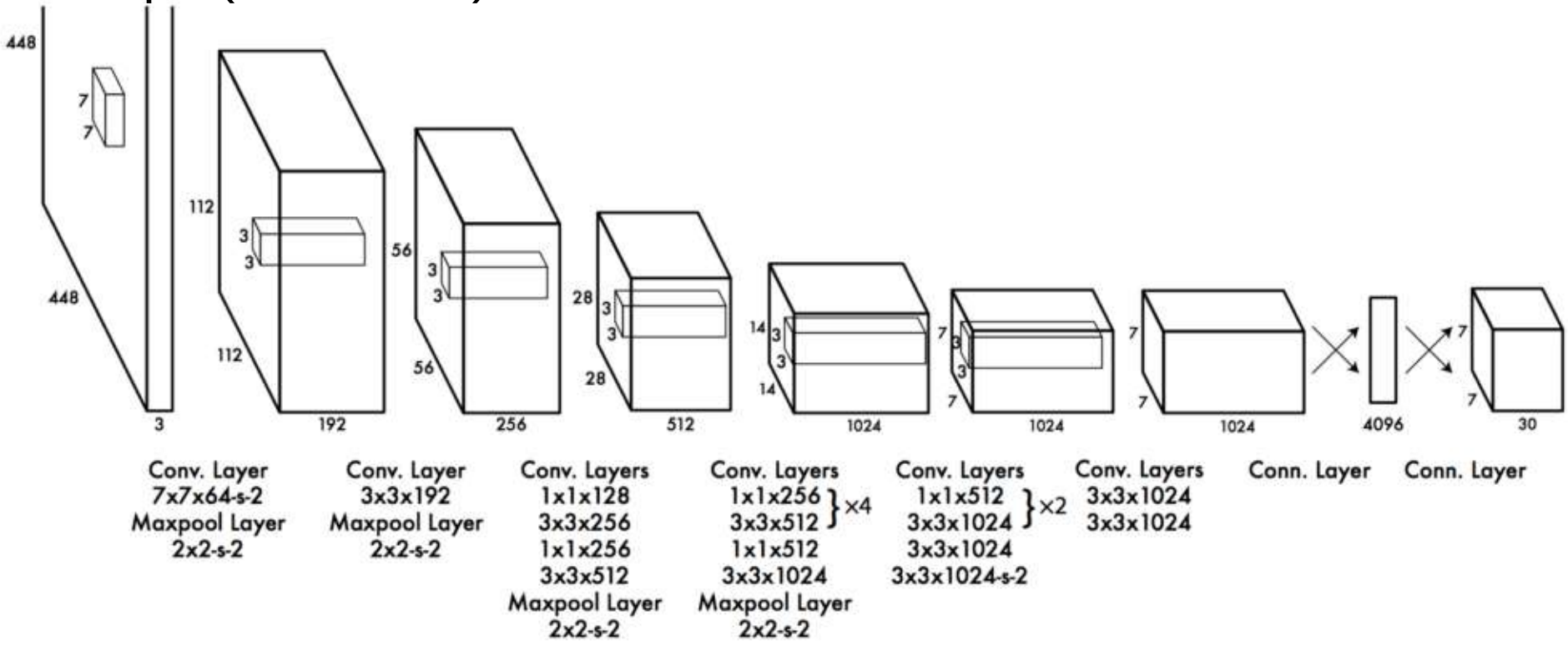
1. Take conv feature maps at 7x7 resolution
2. Add two FC layers to predict, at each location, a score for each class and 2 bboxes w/ confidences
   - For PASCAL, output is 7x7x30 (30 = 20 + 2*(4+1))



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

Network design

YOLO has 24 convolutional layers followed by 2 fully connected layers (FC). The last convolution layer outputs a tensor with shape (7, 7, 1024)



Loss function

YOLO predicts multiple bounding boxes per grid cell. To compute the loss for the true positive, we only want one of them to be **responsible** for the object. For this purpose, we select the one with the highest IoU (intersection over union) with the ground truth.

YOLO uses sum-squared error between the predictions and the ground truth to calculate loss. The loss function composes of:

- the **classification loss**.
- the **localization loss** (errors between the predicted boundary box and the ground truth).
- the **confidence loss** (the objectness of the box).

Localization loss

The localization loss measures the errors in the predicted boundary box **locations** and **sizes**.

We do not want to weight absolute errors in large boxes and small boxes equally. i.e. a 2-pixel error in a large box is the same for a small box. To partially address this, YOLO predicts the square root of the bounding box width and height instead of the width and height.

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

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

where

$\mathbb{1}_{ij}^{obj} = 1$ if the j th boundary box in cell i is responsible for detecting the object, otherwise 0.

λ_{coord} increase the weight for the loss in the boundary box coordinates.

Confidence loss

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

If an object is detected in the box, the confidence loss (measuring the objectness of the box)

where

$\hat{C}_i$ is the box confidence score of the box j in cell i.

$\mathbb{1}_{ij}^{obj} = 1$ if the j th boundary box in cell i is responsible for detecting the object, otherwise 0.

If an object is not detected in the box, the confidence loss is:

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

where

$\mathbb{1}_{ij}^{noobj}$ is the complement of $\mathbb{1}_{ij}^{obj}$.

$\hat{C}_i$ is the box confidence score of the box j in cell i.

λ_{noobj} weights down the loss when detecting background.

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

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

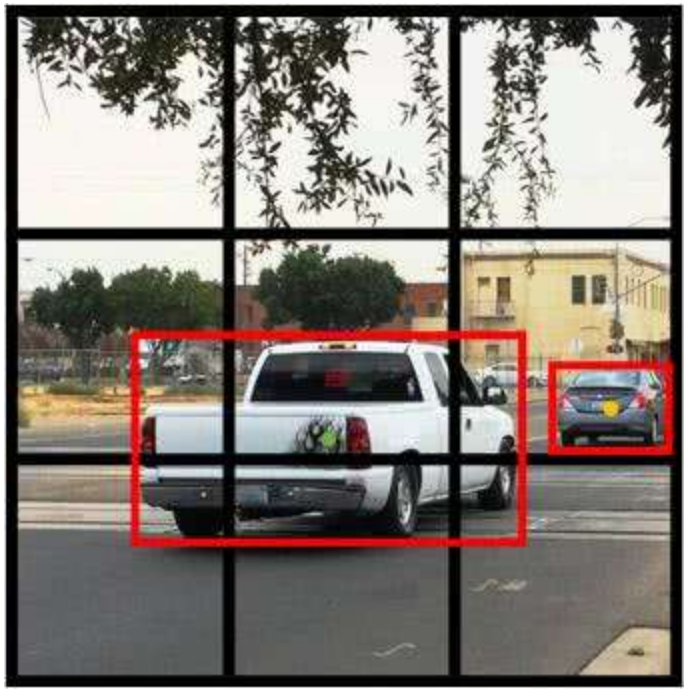
Confidence for no object

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

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

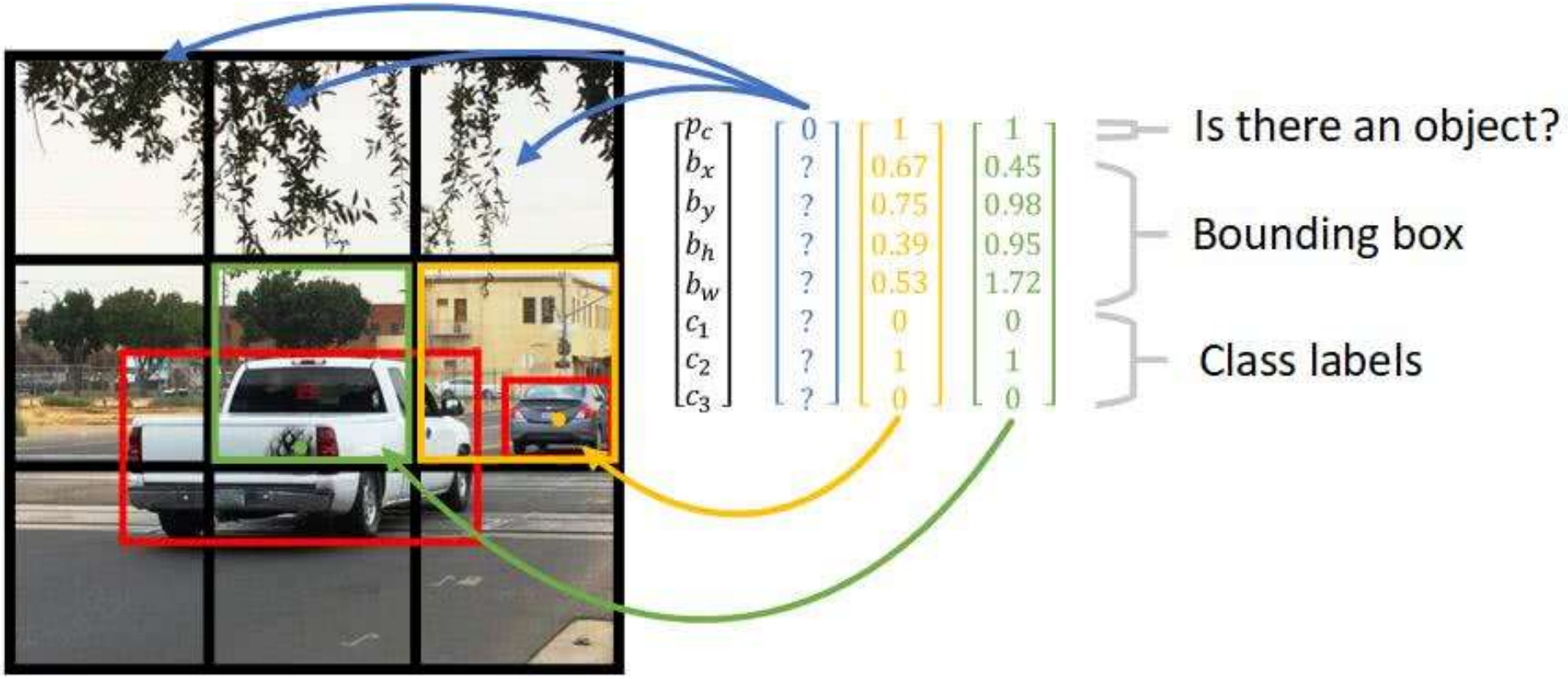
Class probability

YOLO Training



$$y = \begin{bmatrix} p_c \\ b_x \\ b_y \\ b_h \\ b_w \\ c_1 \\ c_2 \\ c_3 \\ c_4 \end{bmatrix}$$

Training


p_c
b_x
b_y
b_h
b_w
c_1
c_2
c_3
0 ? ? ? ? ? ? ?
1 0.67 0.75 0.39 0.53 0 1 0
1 0.45 0.98 0.95 1.72 0 1 0
Is there an object?
Bounding box
Class labels

Training

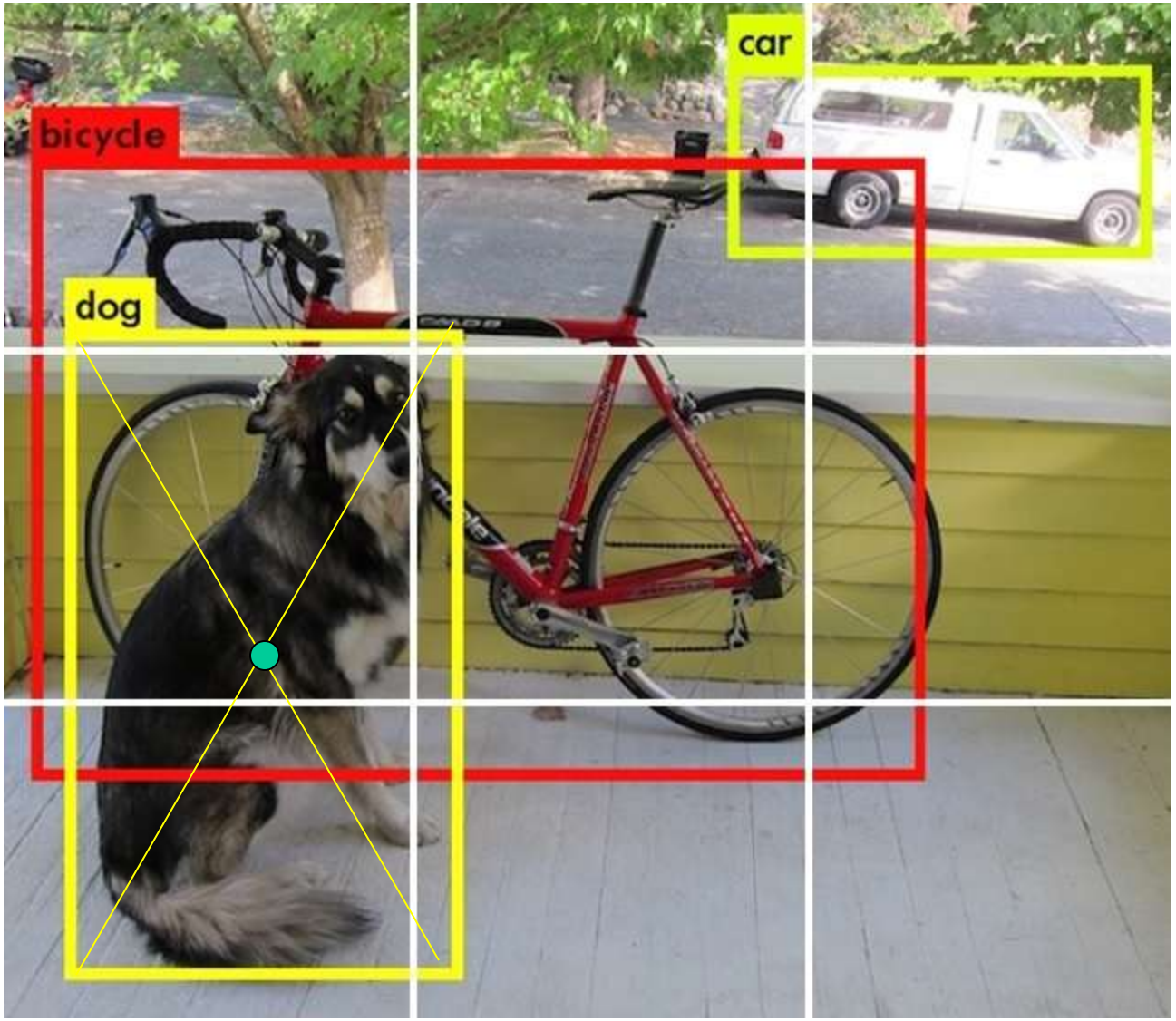
(b_x b_y): center of the object corresponding to the upper left corner of the grid cell

b_h: height of the bounding box
b_w: width of the bounding box

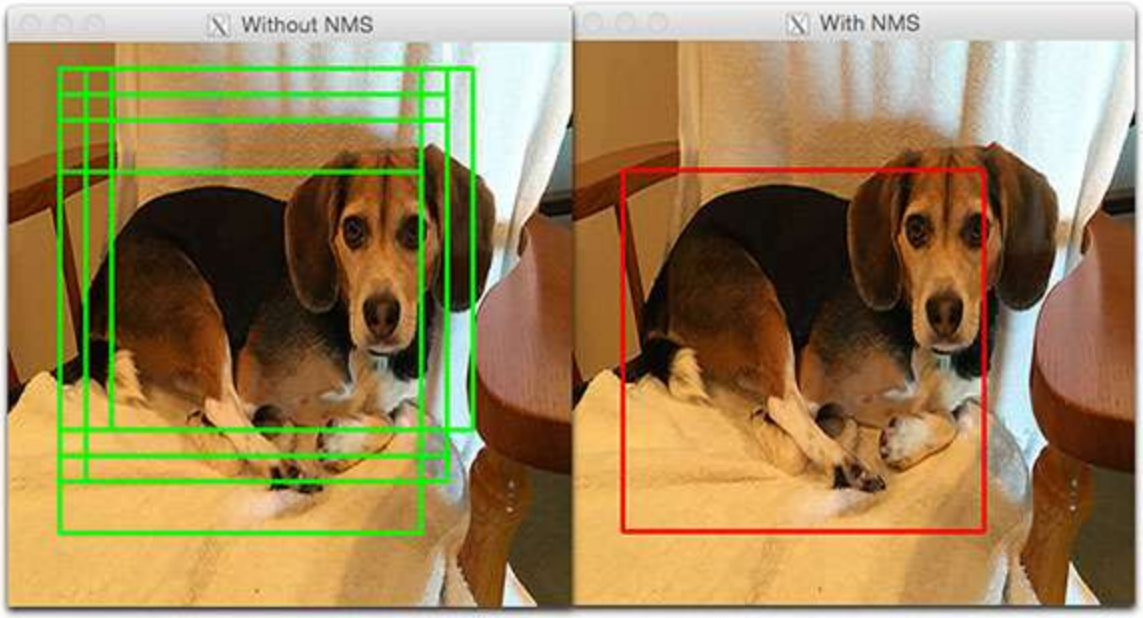
value c is corresponding to a class of an object (f.e. we have 3 types of targets to detect: car, bicycle, dog) Respectively.

$$y = \begin{bmatrix} p_c \\ b_x \\ b_y \\ b_h \\ b_w \\ c_1 \\ c_2 \\ c_3 \end{bmatrix}$$

Three objects marked with their bounding boxes.
Give the labels (y) for training for each of the 3 x 3 grid cells.



Non-max suppression



Even though we ignored weak detections, YOLO can make duplicate detections for the same object. To fix this, YOLO applies non-maximal suppression to remove duplications with lower confidence. Non-maximal suppression adds 2-3% in mAP.