



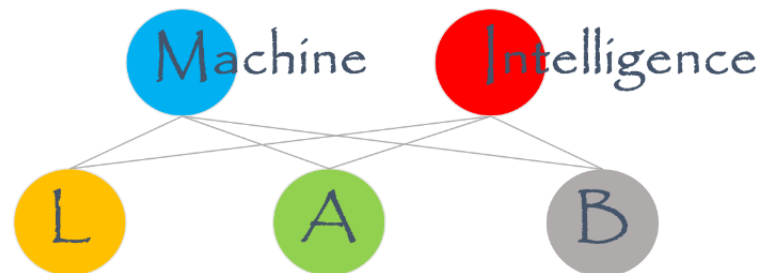
Object Detection – Part 2

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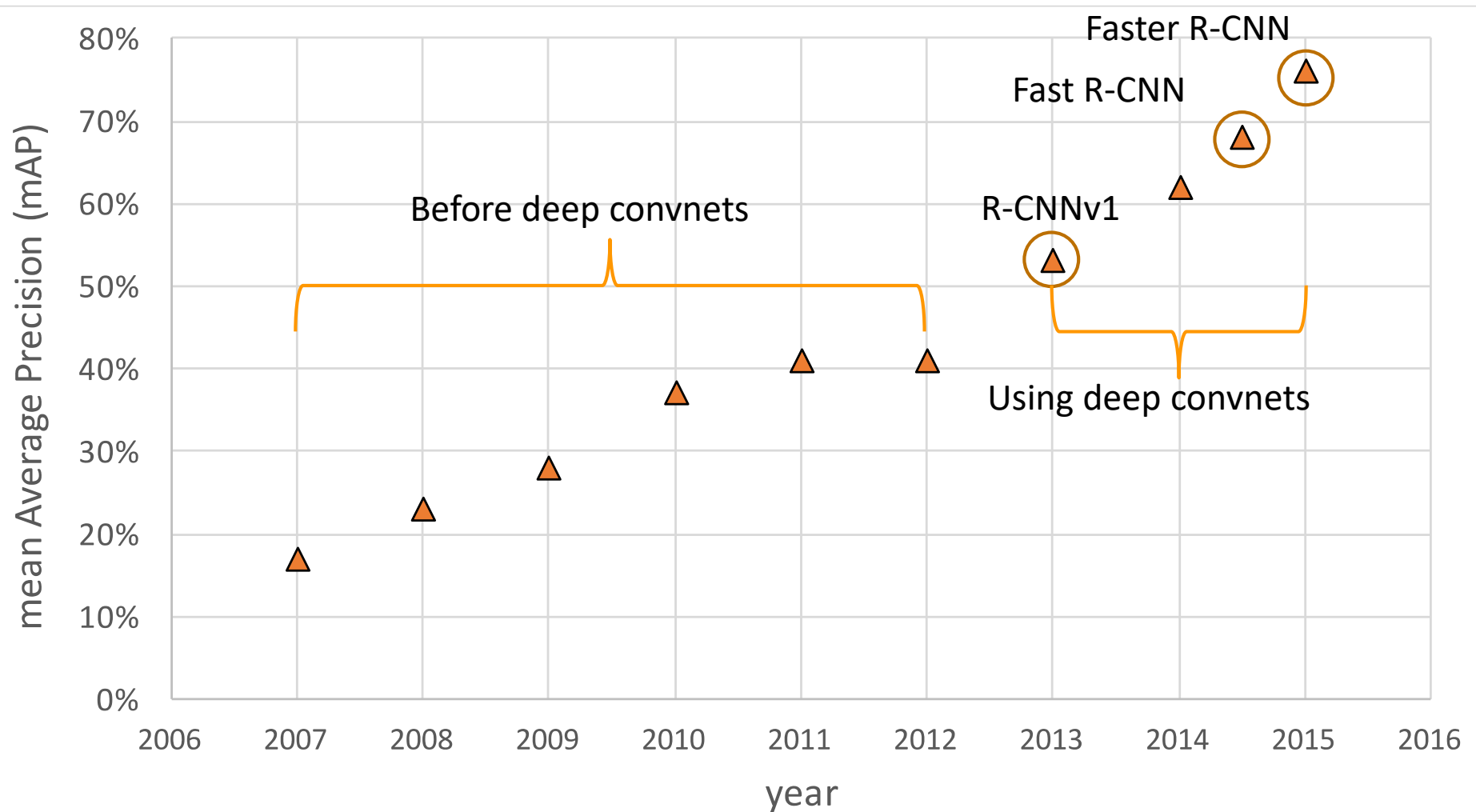


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Outline

- **R-CNN, Fast R-CNN, Faster R-CNN**
- **YOLO, SSD**
- **Other Extensions**

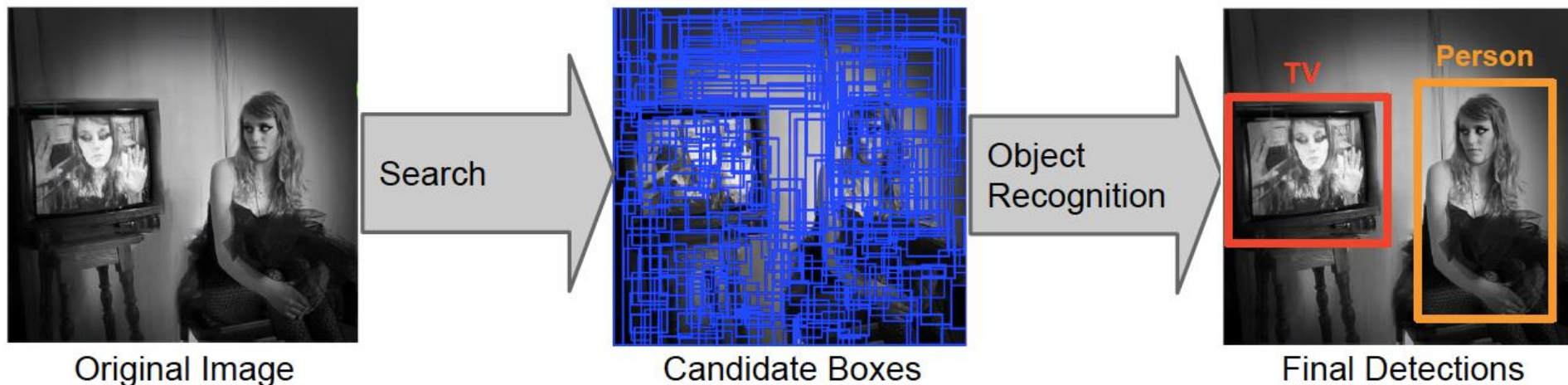
Object detection progress



Convolutional Feature Maps

- See He Kaiming's tutorial slides
- <http://mp7.watson.ibm.com/ICCV2015/ObjectDetectionICCV2015.html>

Beyond sliding windows: Region proposals



- Advantages:
 - Cuts down on number of regions detector must evaluate
 - Allows detector to use more powerful features and classifiers
 - Uses low-level *perceptual organization* cues
 - Proposal mechanism can be category-independent
 - Proposal mechanism can be trained

Selective search: Basic idea

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



Input Image

Bounding Box Regression

- Input: A set of N training pairs $\{(P^i, G^i)\}_{i=1,\dots,N}$, where $P^i = (P_x^i, P_y^i, P_w^i, P_h^i)$ and $G^i = (G_x^i, G_y^i, G_w^i, G_h^i)$. (Drop superscript i for simplicity)
- Output: Four functions $d_x(P), d_y(P), d_w(P), d_h(P)$

$$\hat{G}_x = P_w d_x(P) + P_x \quad (1)$$

$$\hat{G}_y = P_h d_y(P) + P_y \quad (2)$$

$$\hat{G}_w = P_w \exp(d_w(P)) \quad (3)$$

$$\hat{G}_h = P_h \exp(d_h(P)). \quad (4)$$

- Learn model parameters by optimizing the regularized least squares objective

$$\mathbf{w}_\star = \operatorname{argmin}_{\hat{\mathbf{w}}_\star} \sum_i^N (t_\star^i - \hat{\mathbf{w}}_\star^\top \phi_5(P^i))^2 + \lambda \|\hat{\mathbf{w}}_\star\|^2. \quad (5)$$

Bounding Box Regression

- Learn model parameters by optimizing the regularized least squares objective

$$\mathbf{w}_\star = \underset{\hat{\mathbf{w}}_\star}{\operatorname{argmin}} \sum_i^N (t_\star^i - \hat{\mathbf{w}}_\star^\top \phi_5(P^i))^2 + \lambda \|\hat{\mathbf{w}}_\star\|^2. \quad (5)$$

- The regression targets t_\star for the training pair (P, G) are defined as

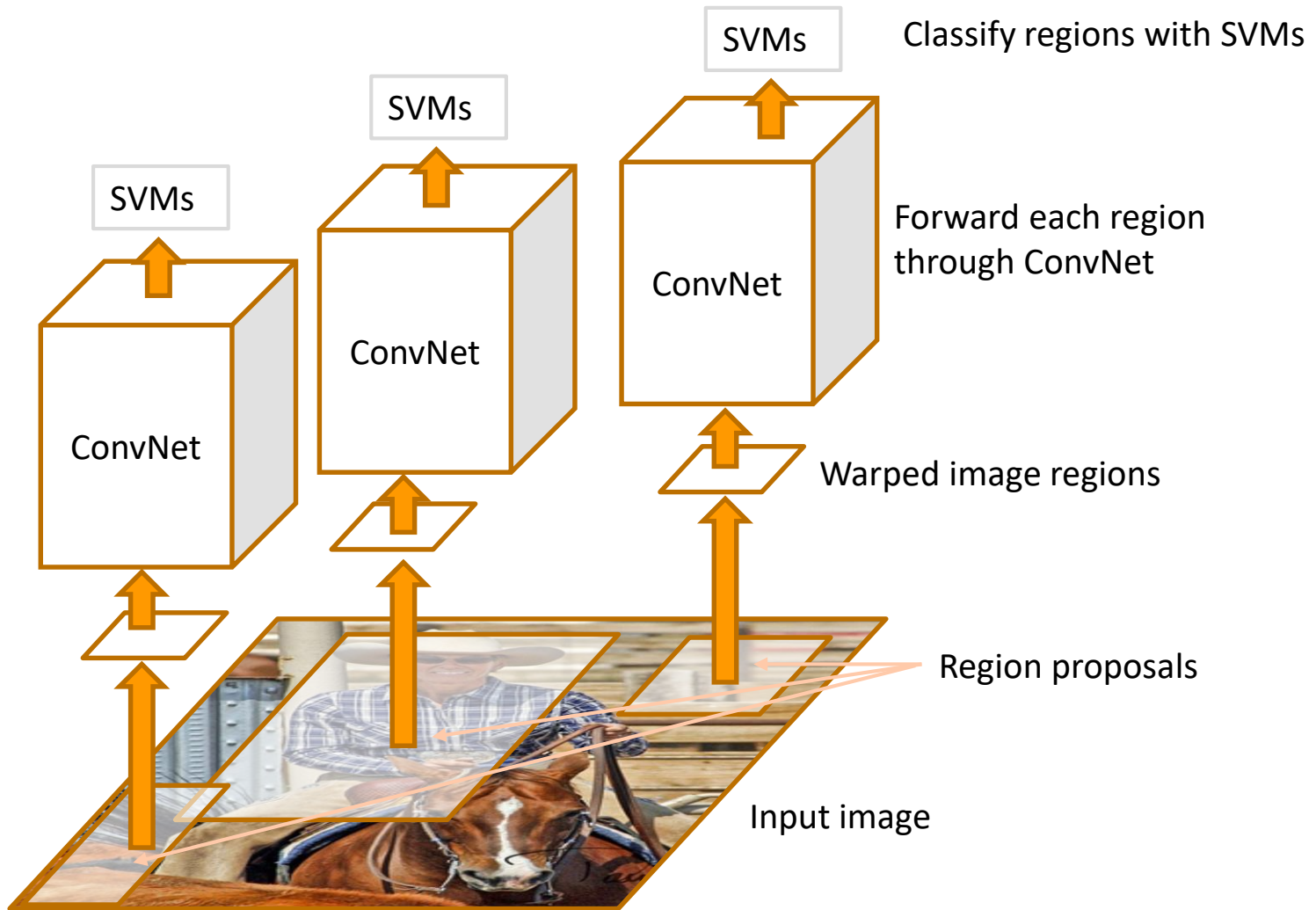
$$t_x = (G_x - P_x)/P_w \quad (6)$$

$$t_y = (G_y - P_y)/P_h \quad (7)$$

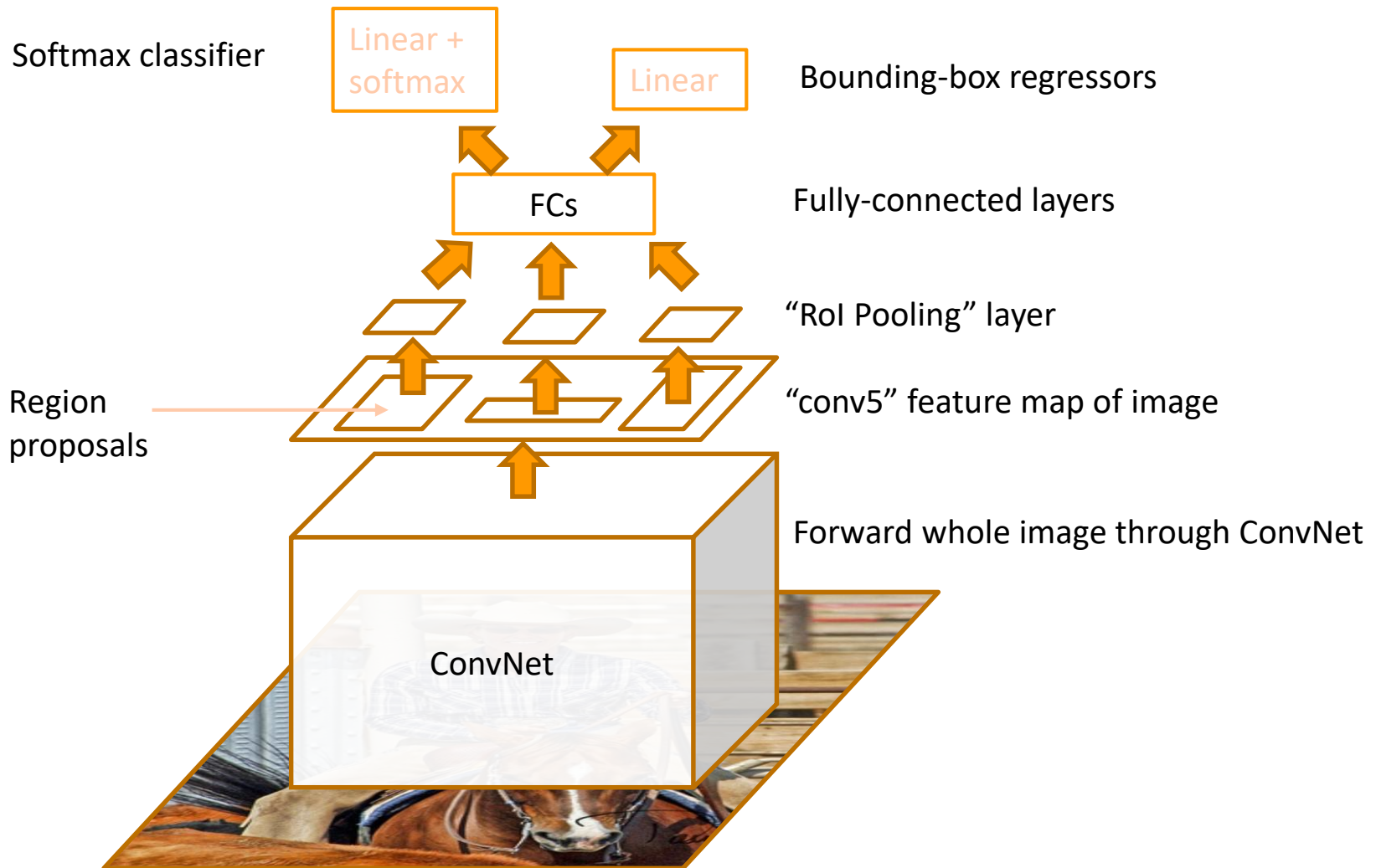
$$t_w = \log(G_w/P_w) \quad (8)$$

$$t_h = \log(G_h/P_h). \quad (9)$$

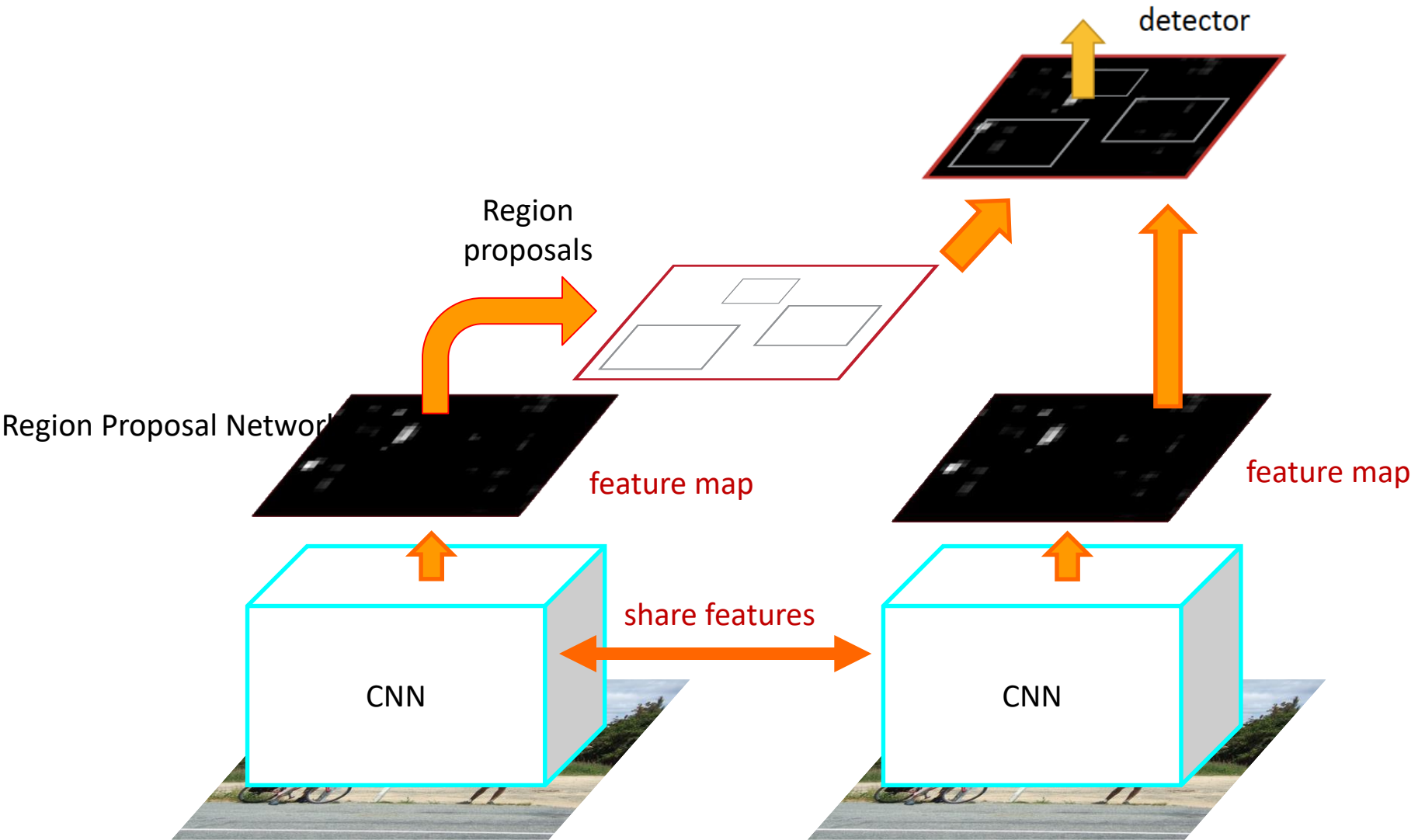
Review: R-CNN



Review: Fast R-CNN

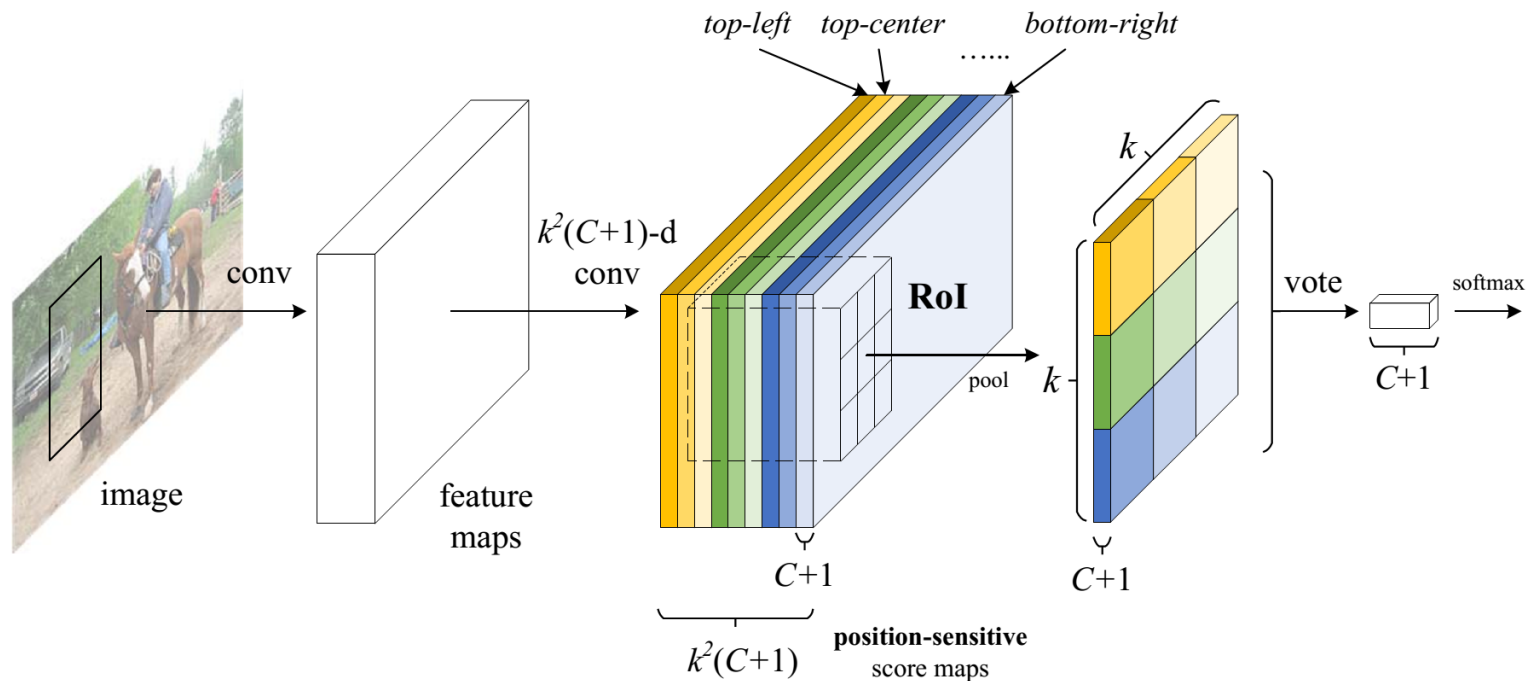


Review: Faster R-CNN



R-FCN

- Abandon FC layers. Use fully convolutional layers.



R-FCN

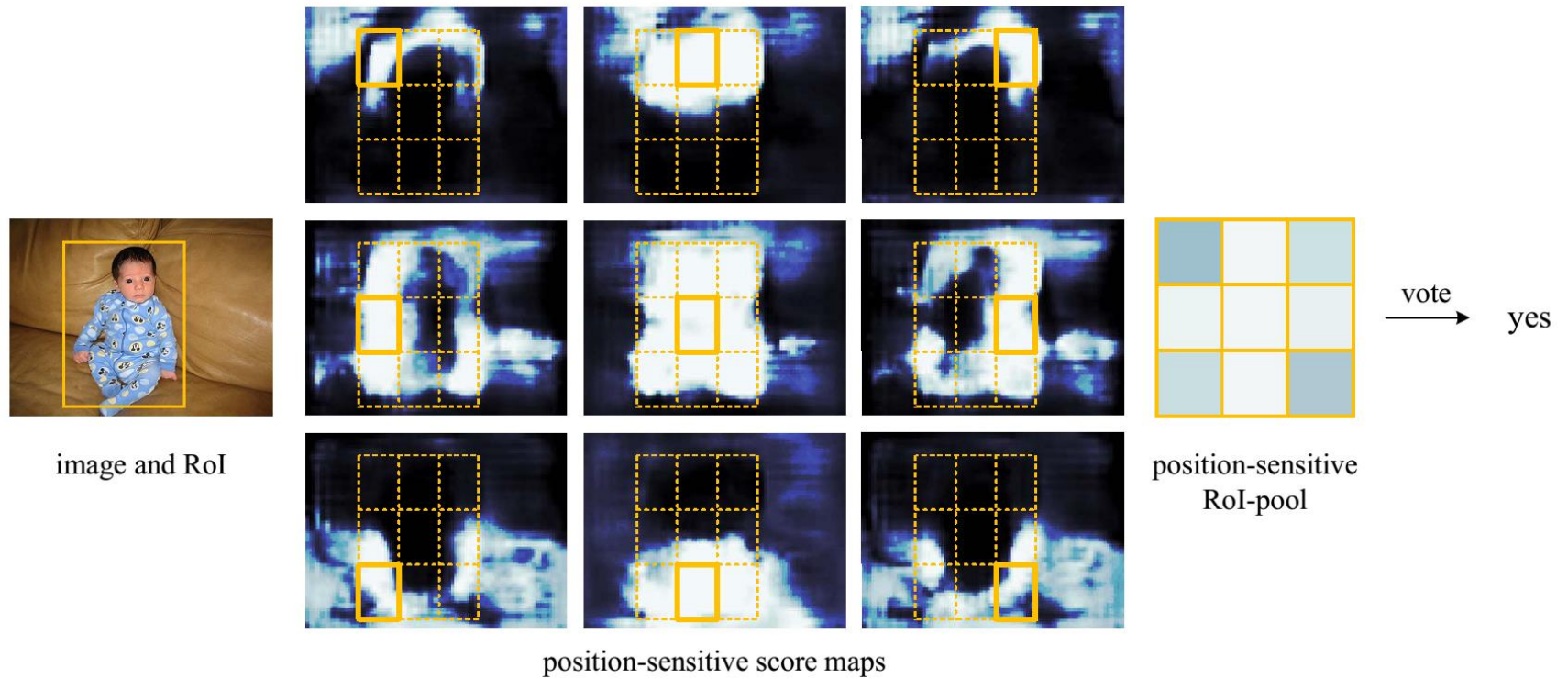
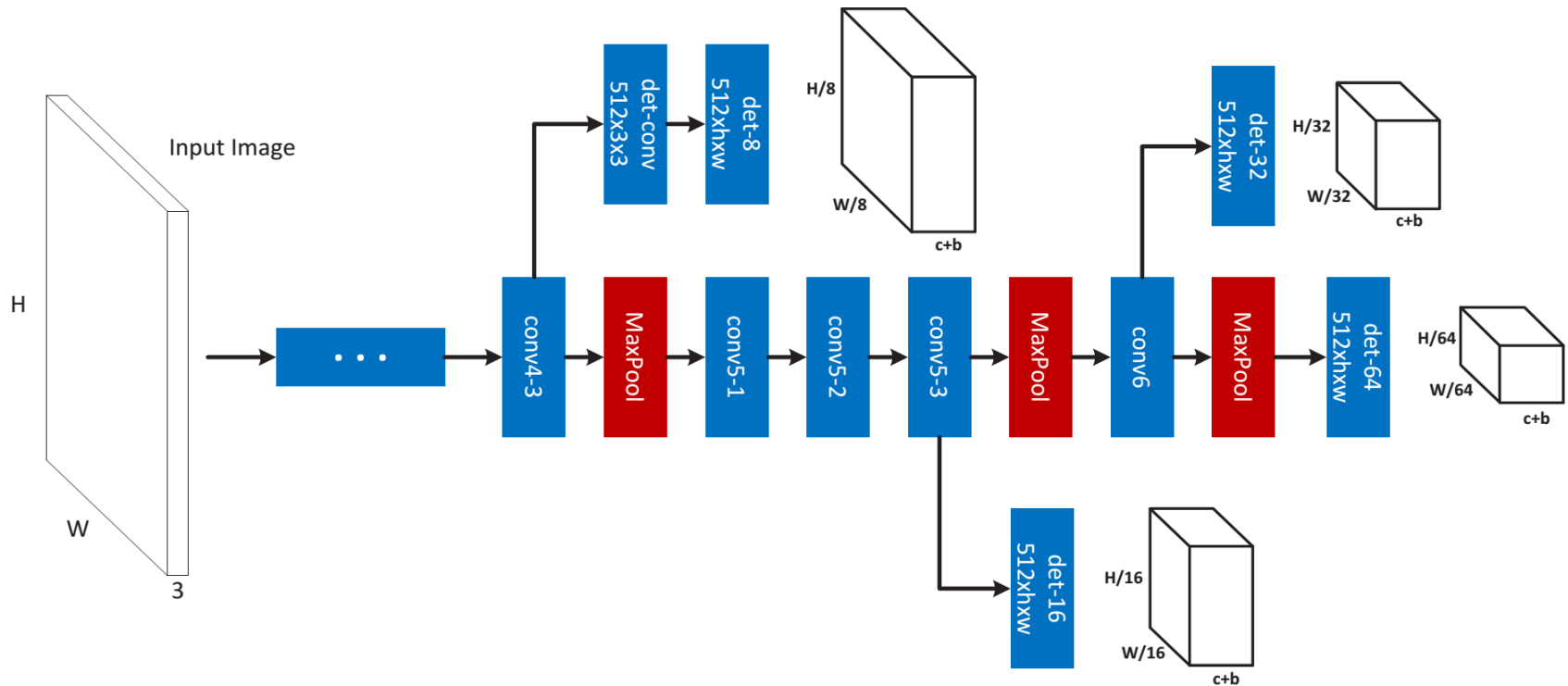


Figure 3: Visualization of R-FCN ($k \times k = 3 \times 3$) for the *person* category.

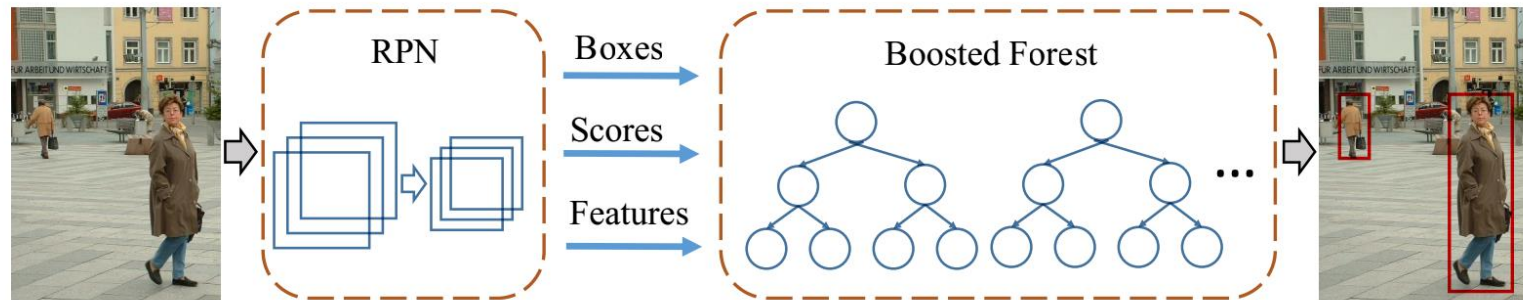
Multi-Scale R-CNN

- Objects at different scales



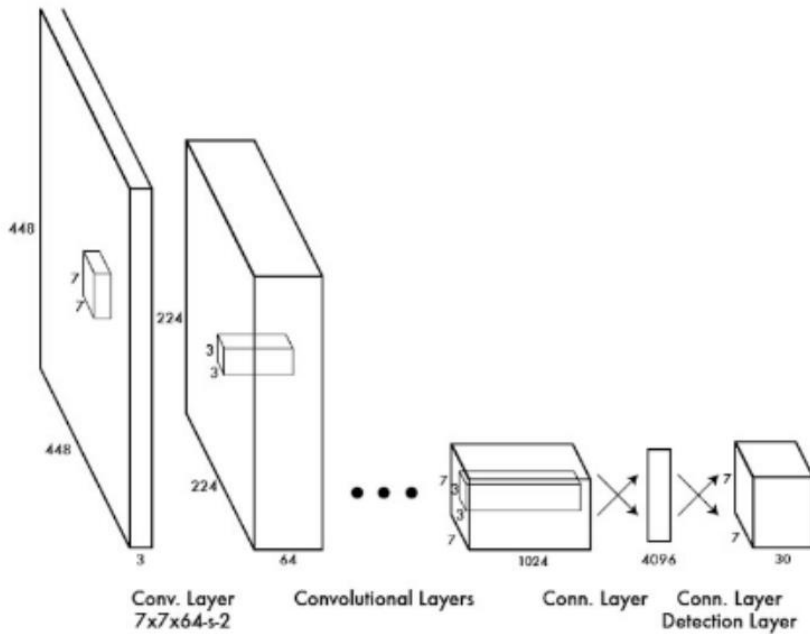
Remove Linear Classifiers

- FC layers are “weak” classifiers
- Replace with non-linear classifiers



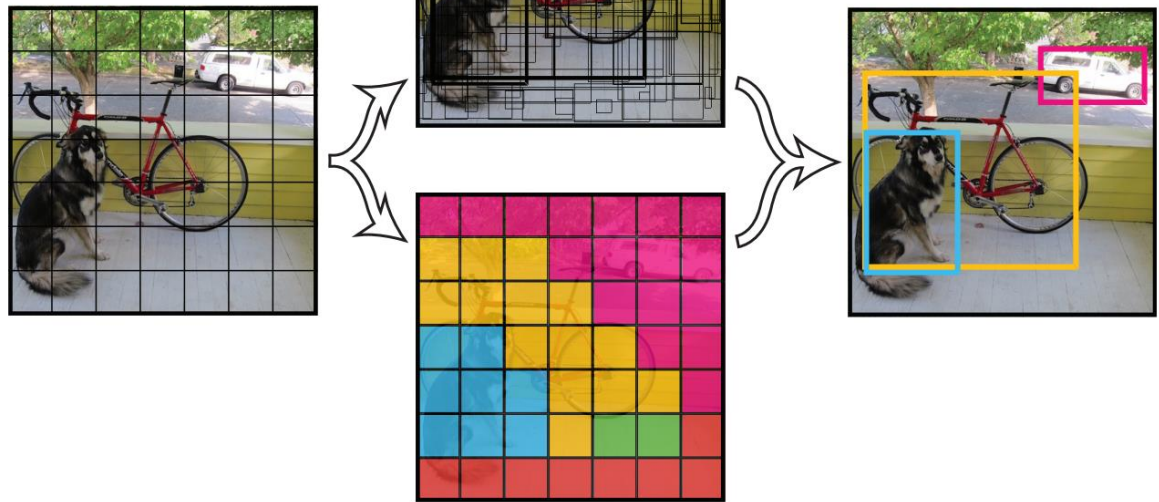
Liliang Zhang et al., Is Faster R-CNN Doing Well for Pedestrian Detection? ECCV 2016

YOLO



Regression instead of classification:

If the center of an object falls into a grid cell, that grid cell is responsible for detecting that object.

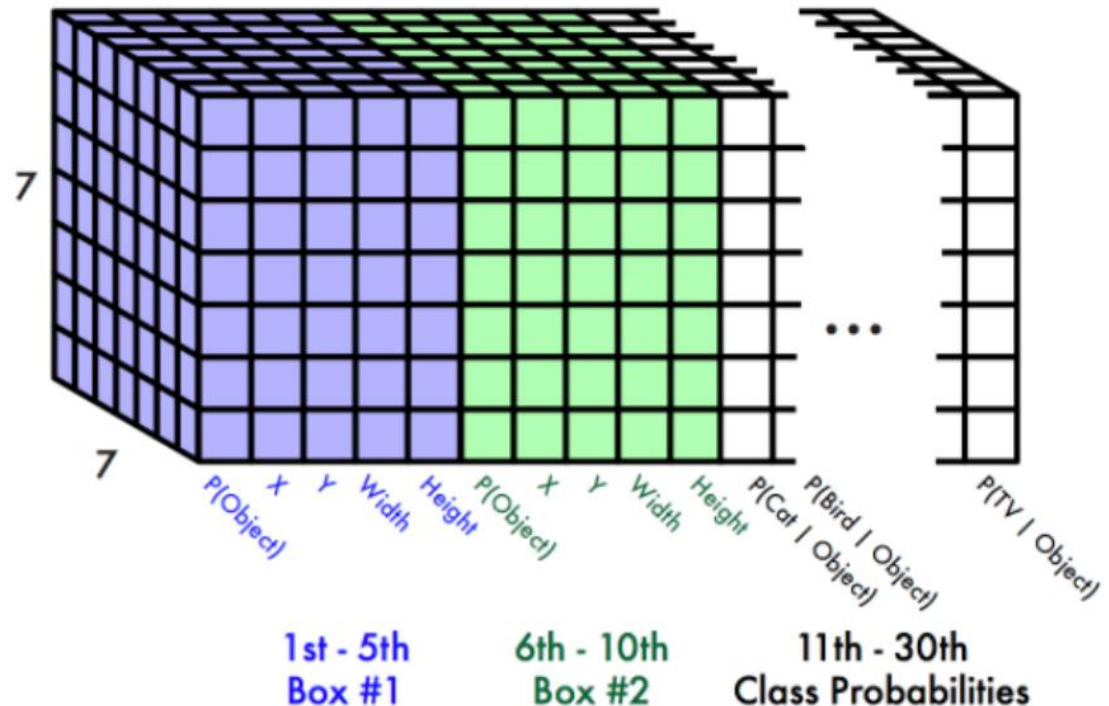


Redmon J, et al. You only look once: Unified, real-time object detection. CVPR2016

YOLO

Each cell predicts:

- For each bounding box:
 - 4 coordinates (x, y, w, h)
 - 1 confidence value
- Some number of class probabilities



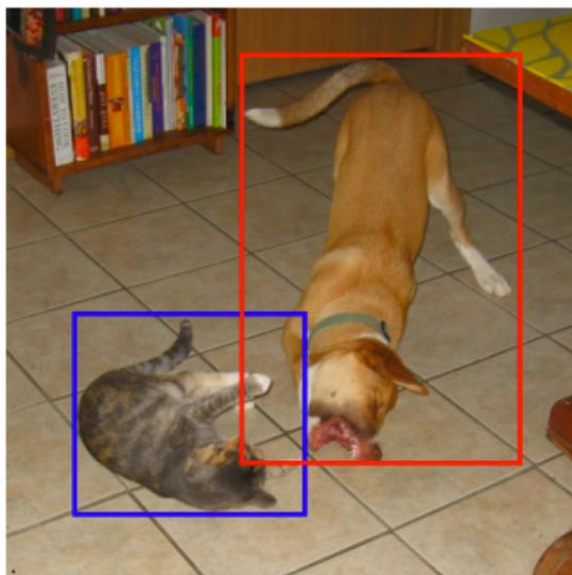
For Pascal VOC:

- 7x7 grid
- 2 bounding boxes / cell
- 20 classes

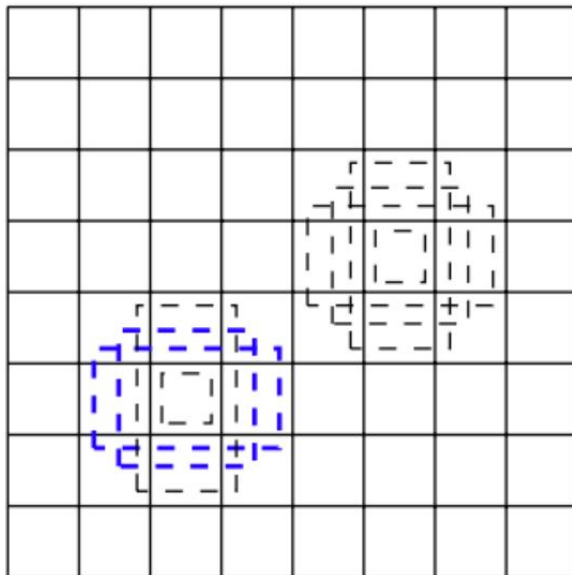
$7 \times 7 \times (2 \times 5 + 20) = 7 \times 7 \times 30$ tensor = **1470 outputs**

SSD

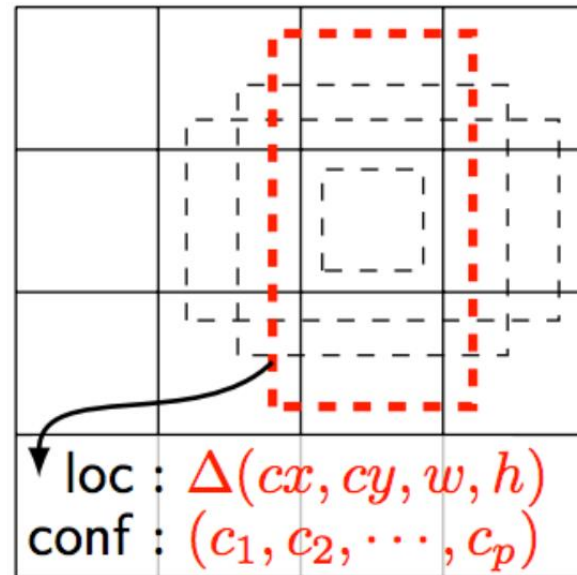
- SSD: YOLO + default box shape + multi-scale



(a) Image with GT boxes



(b) 8×8 feature map

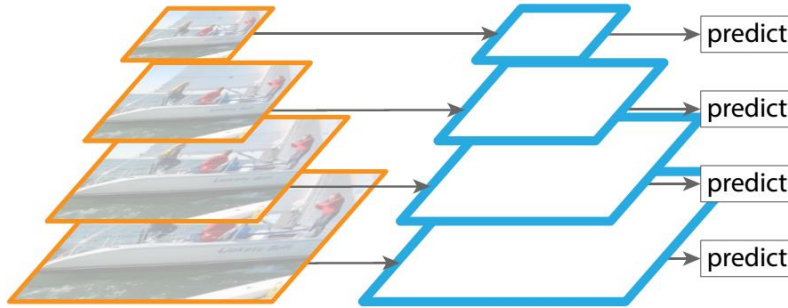


loc : $\Delta(cx, cy, w, h)$
conf : (c_1, c_2, \dots, c_p)

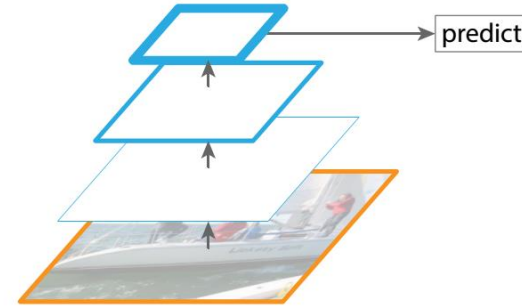
(c) 4×4 feature map

FPN (Feature Pyramid Network)

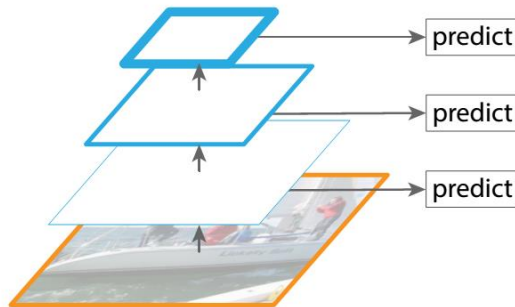
- Explore the power of multiple scales



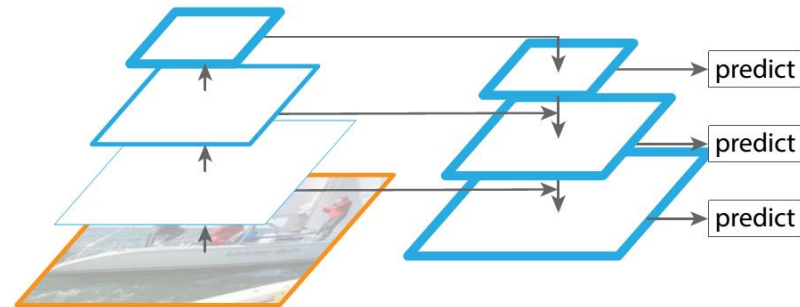
(a) Featurized image pyramid



(b) Single feature map



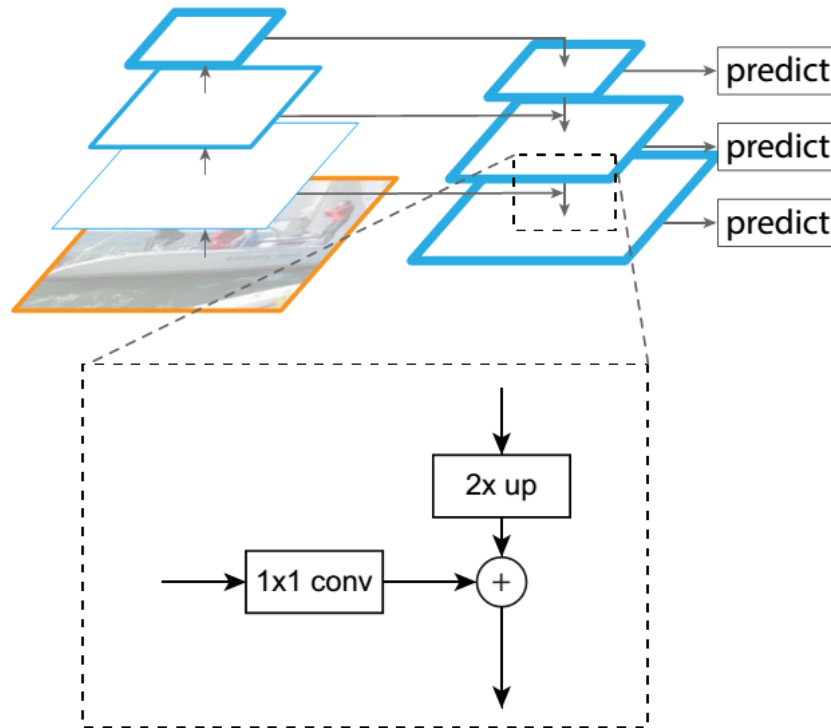
(c) Pyramidal feature hierarchy



(d) Feature Pyramid Network

FPN (Feature Pyramid Network)

- The top-down pathway



Question?