Object Detection

2019.01.21

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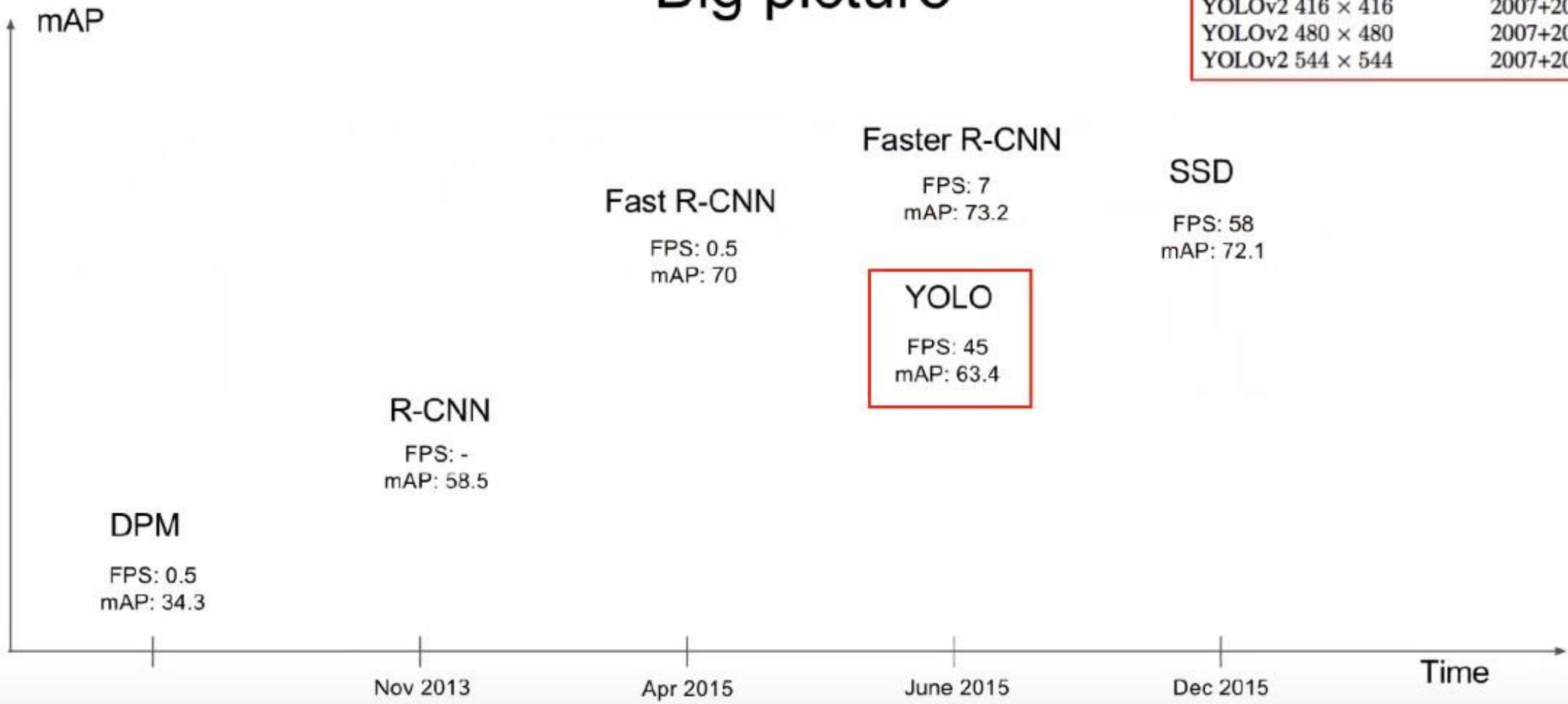
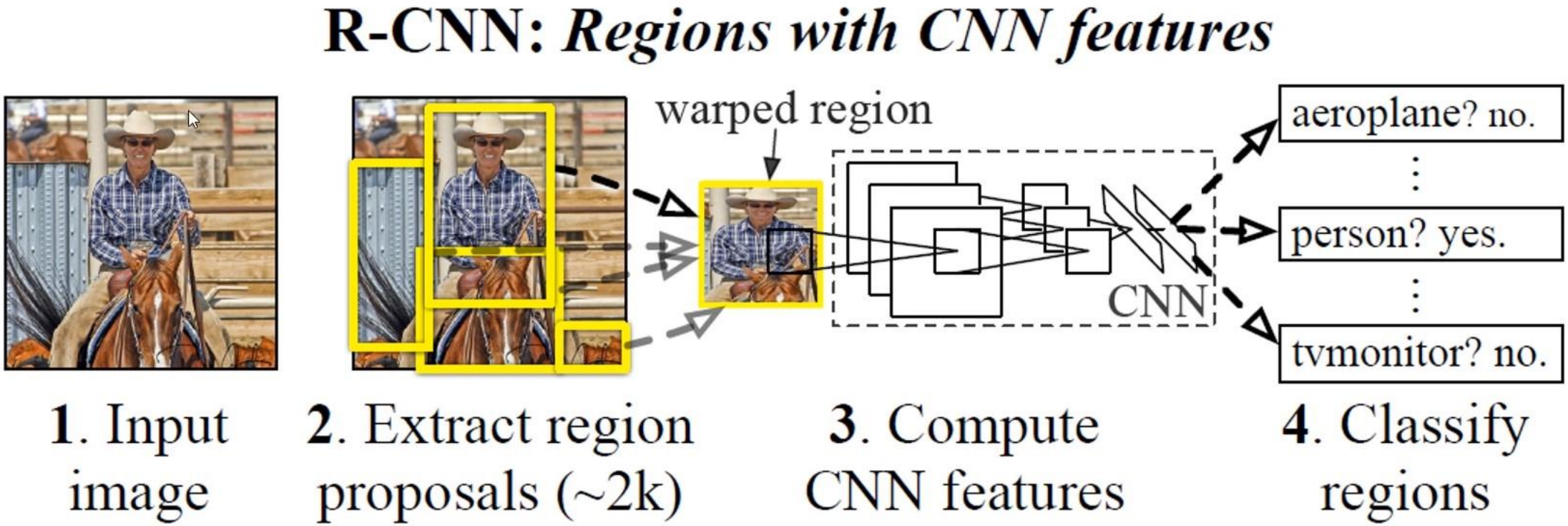
Evaluation on VOC2007

Big picture

YOLOv2 416 × 416	2007+2012	76.8	67
YOLOv2 480 × 480	2007+2012	77.8	59
YOLOv2 544 × 544	2007+2012	**78.6**	40

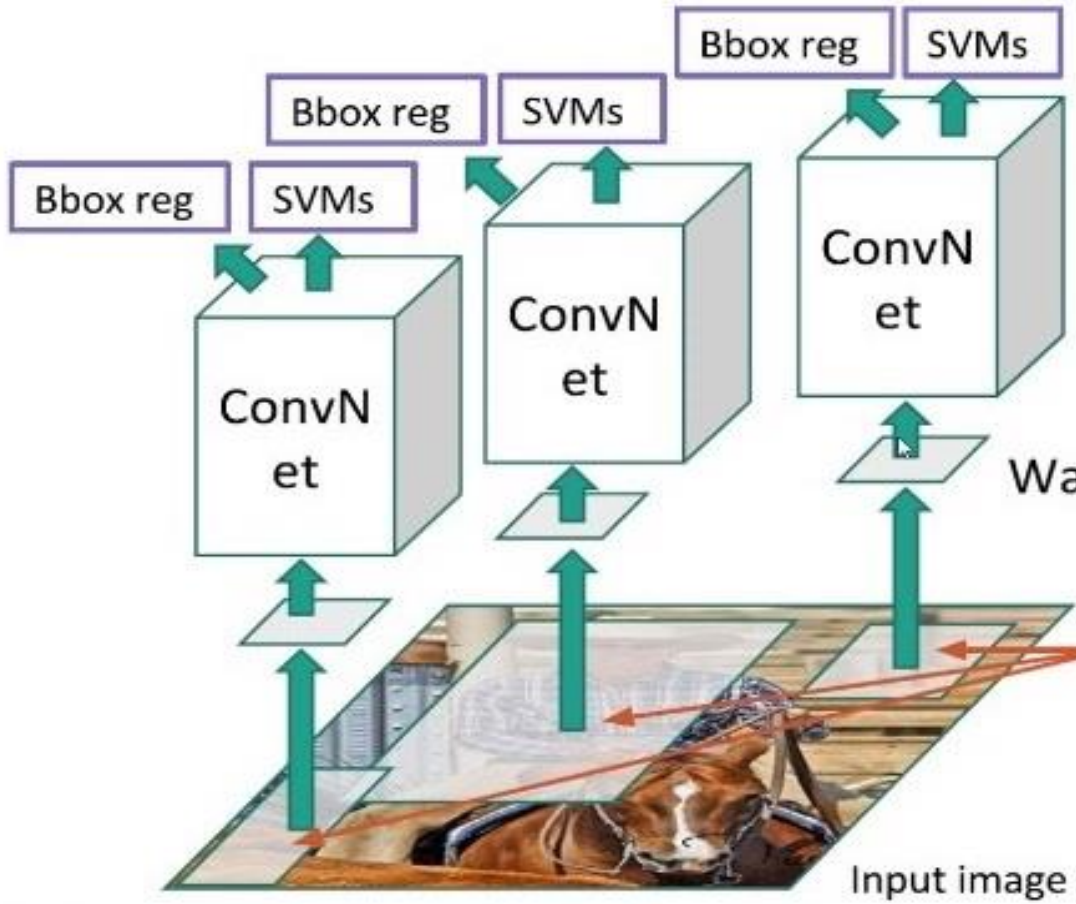


R-CNN Architecture



Input Image

R-CNN



Linear Regression for bounding box offsets

Classify regions with SVMs

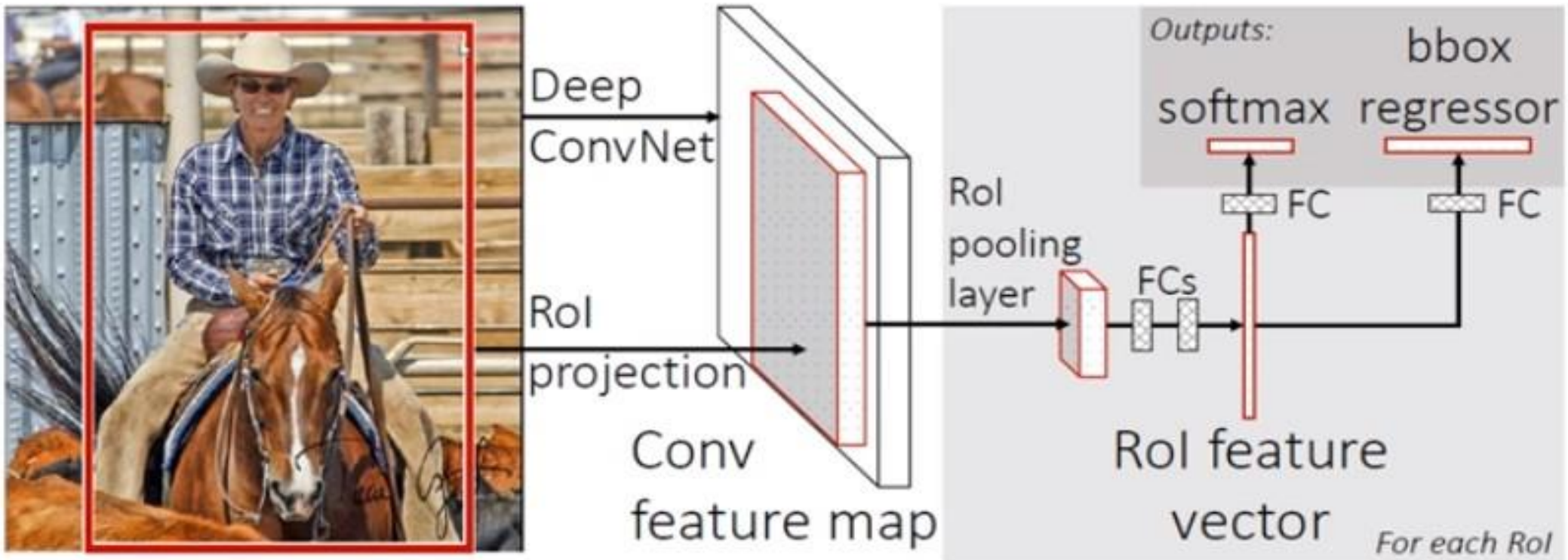
Forward each region through ConvNet

Warped image regions

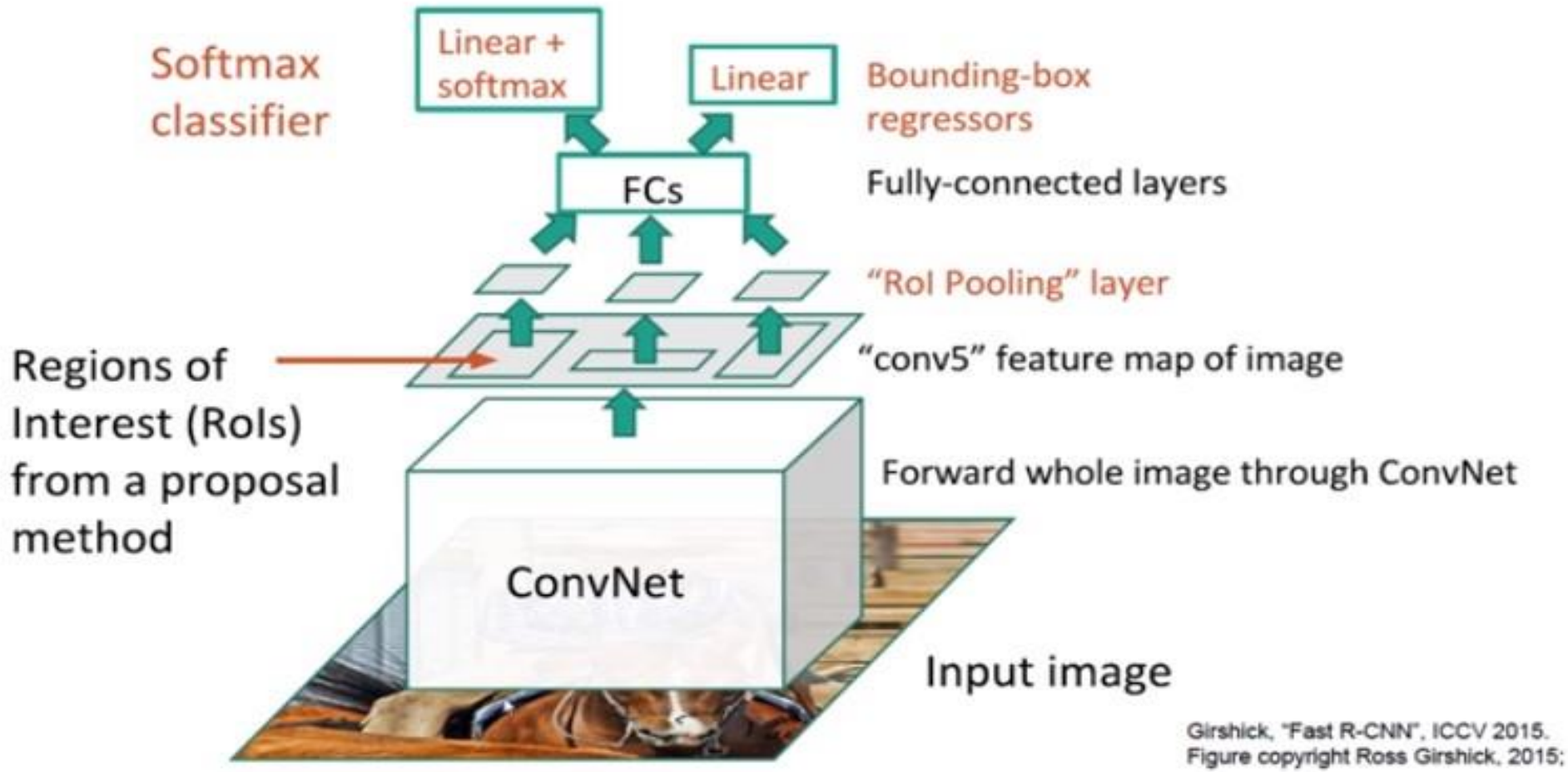
Regions of Interest (RoI) from a proposal method (~2k)

Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.

Fast R-CNN Architecture

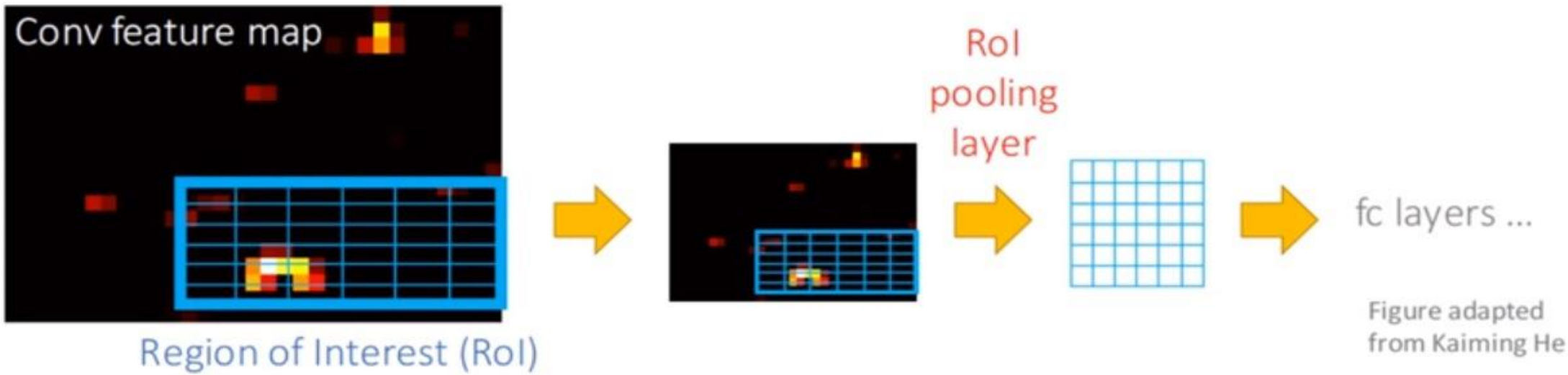


Fast R-CNN



Girshick, "Fast R-CNN", ICCV 2015.
Figure copyright Ross Girshick, 2015;

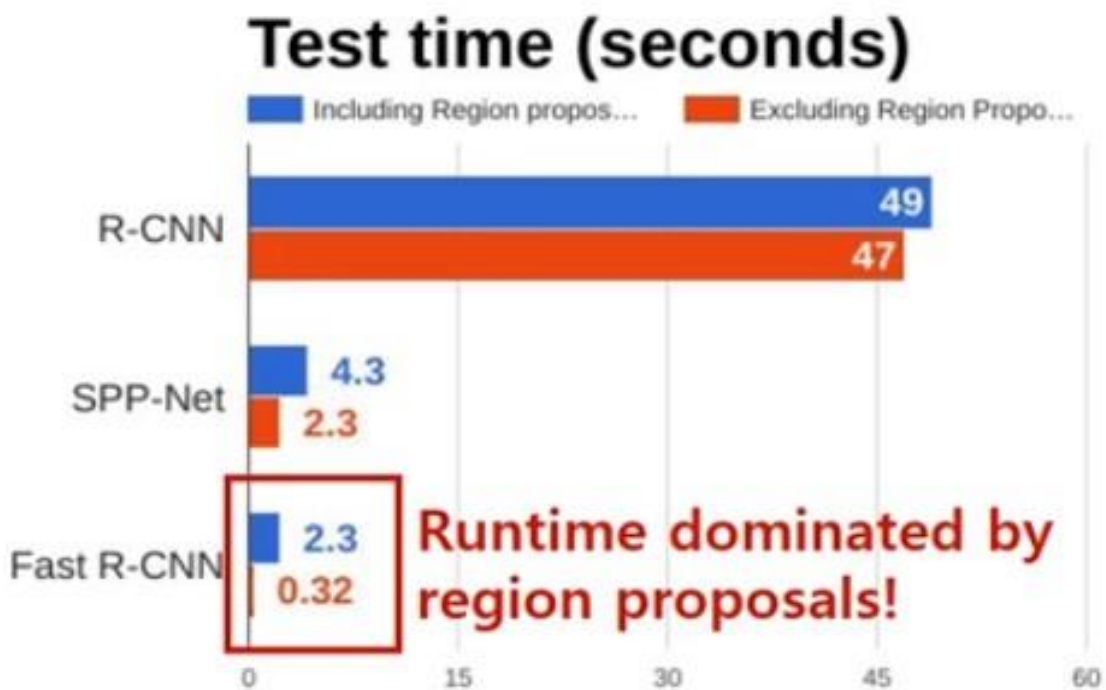
RoI Pooling



Just a special case of the SPP layer with one pyramid level

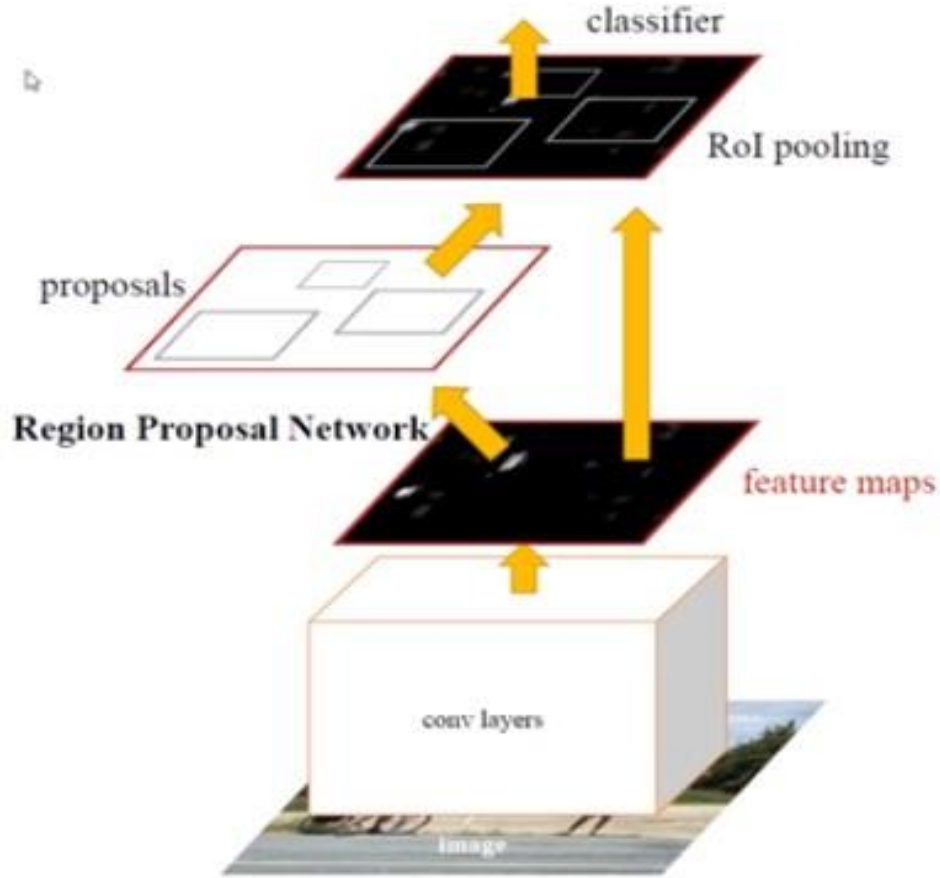
RoI in Conv feature map : 21x14 → 3x2 max pooling with stride(3, 2) → output : 7x7
RoI in Conv feature map : 35x42 → 5x6 max pooling with stride(5, 6) → output : 7x7

R-CNN vs SPP-net vs Fast R-CNN

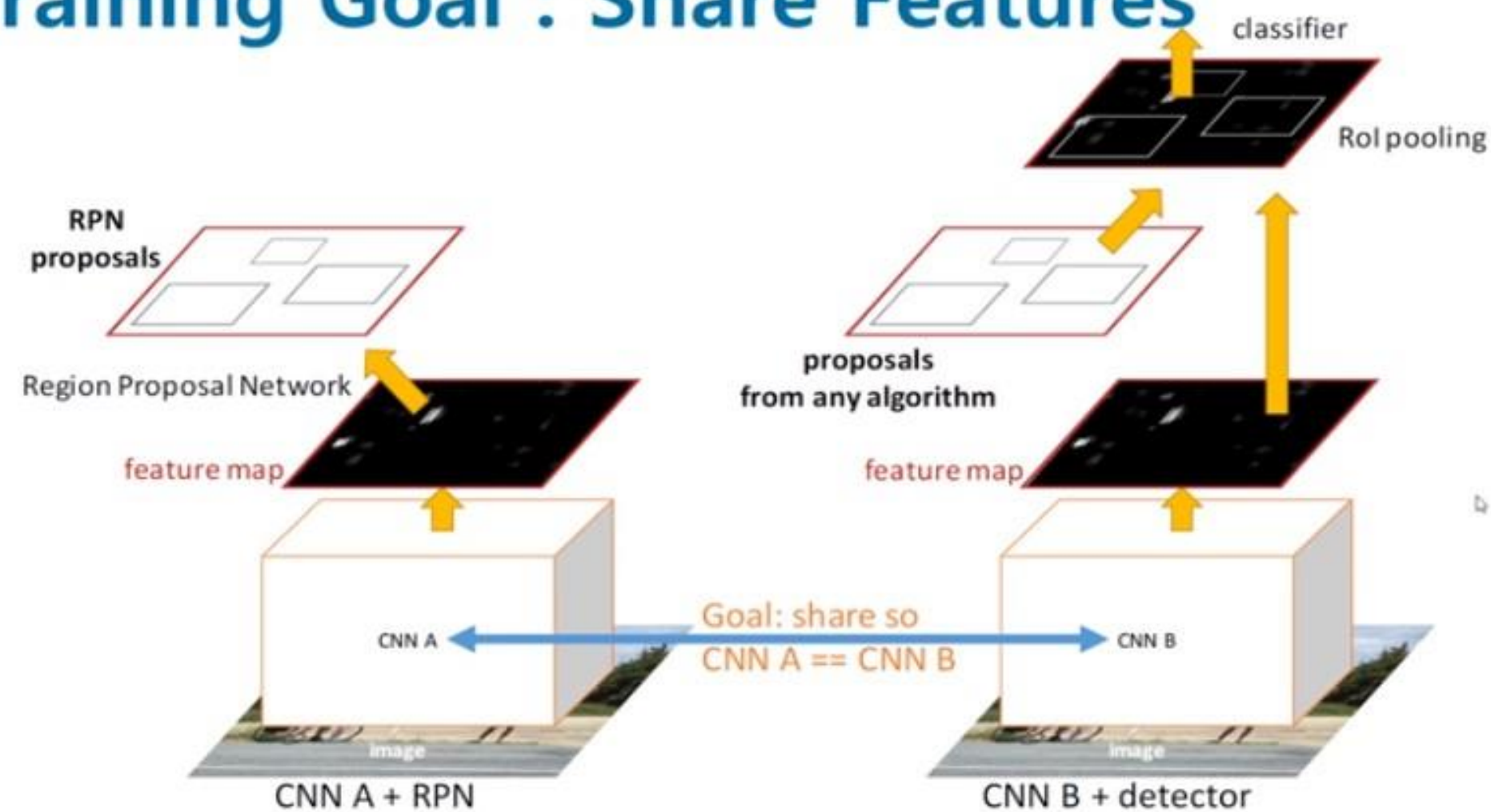


Faster R-CNN(RPN + Fast R-CNN)

- Insert a Region Proposal Network (RPN) after the last convolutional layer → using GPU!
- RPN trained to produce region proposals directly; no need for external region proposals
- After RPN, use RoI Pooling and an upstream classifier and bbox regressor just like Fast R-CNN



Training Goal : Share Features



1 YOLO

- Extremely Fast
- Global reasoning
- Generalizable representation

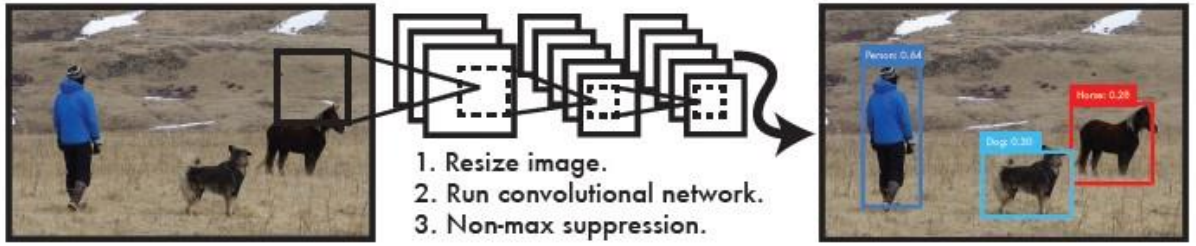


Figure 1: The YOLO Detection System. Processing images with YOLO is simple and straightforward. Our system (1) resizes the input image to 448 × 448, (2) runs a single convolutional network on the image, and (3) thresholds the resulting detections by the model's confidence.

1 YOLO

* B : Bboxes and Confidence score
  (confidence score : Pr(Object)*IOU

* C : class probabilities w.r.t # classes
  Pr(Class | Object)

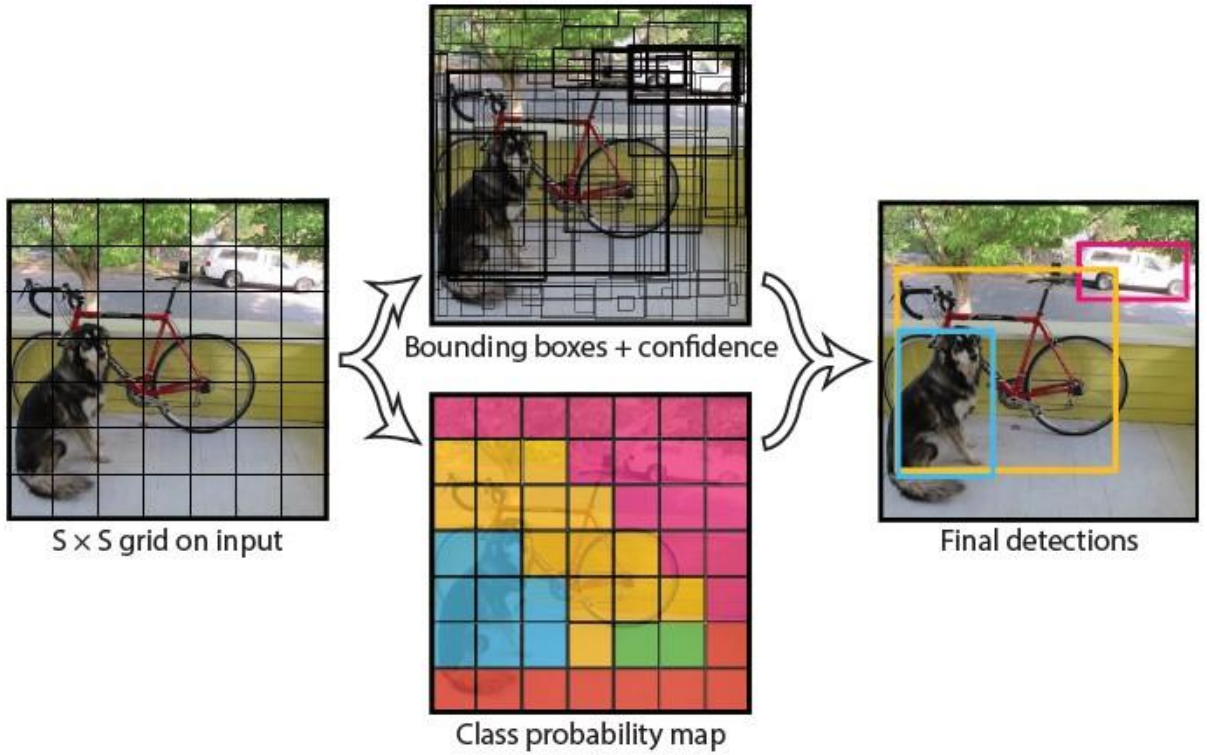


Figure 2: The Model. Our system models detection as a regression problem. It divides the image into an $S \times S$ grid and for each grid cell predicts B bounding boxes, confidence for those boxes, and C class probabilities. These predictions are encoded as an $S \times S \times (B * 5 + C)$ tensor.

1 YOLO

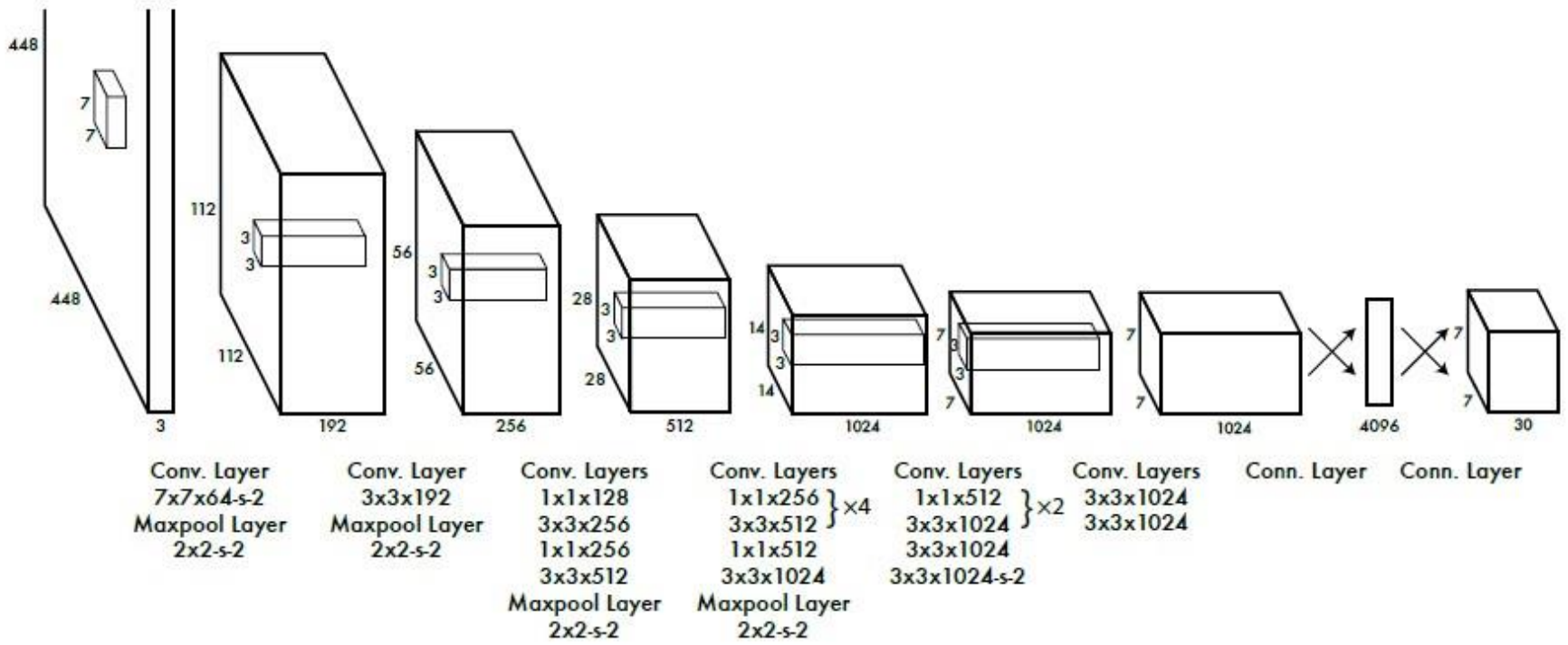
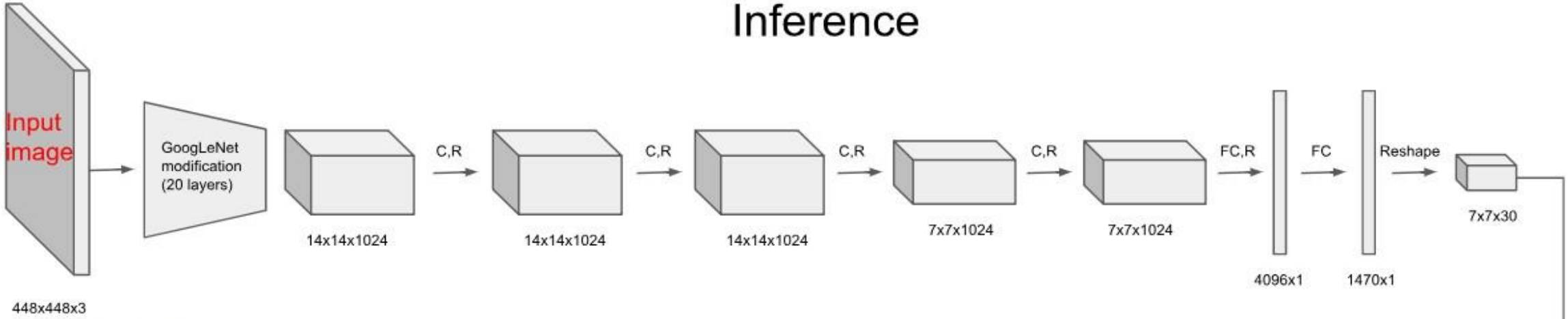
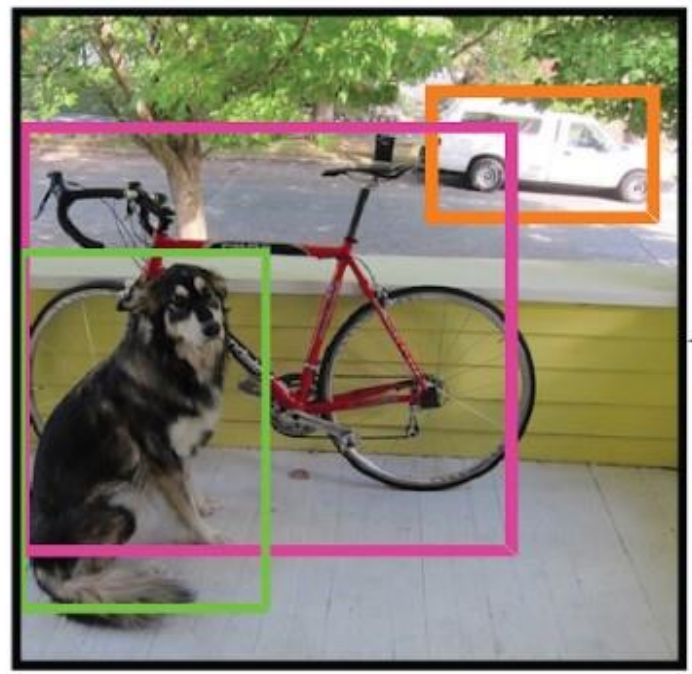


Figure 3: The Architecture. Our detection network has 24 convolutional layers followed by 2 fully connected layers. Alternating 1×1 convolutional layers reduce the features space from preceding layers. We pretrain the convolutional layers on the ImageNet classification task at half the resolution (224×224 input image) and then double the resolution for detection.

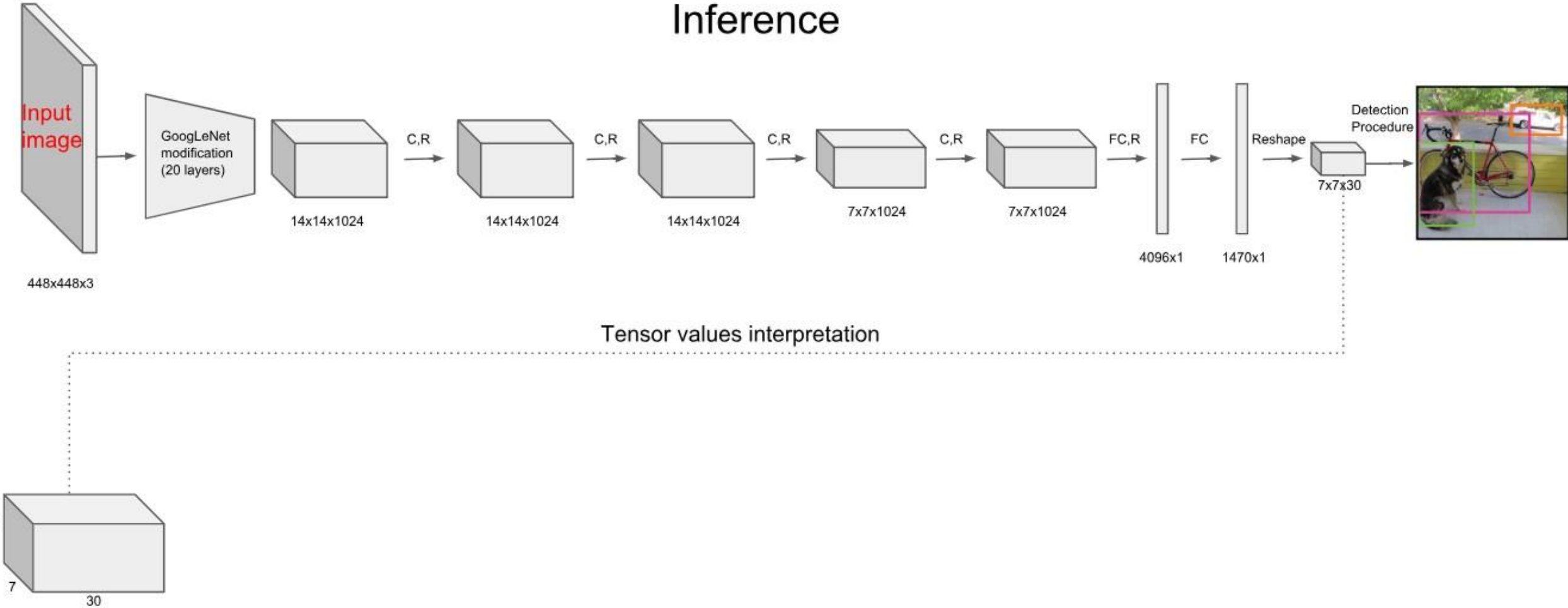
Inference



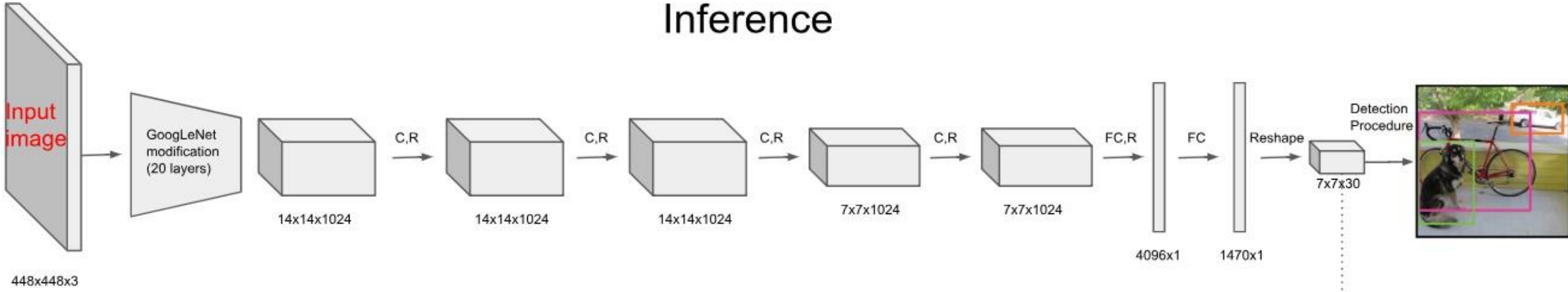
Detection Procedure



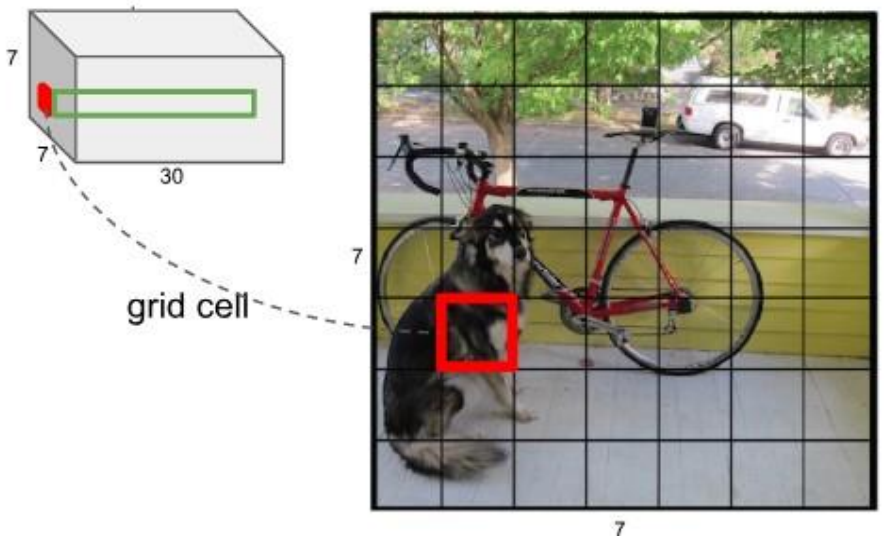
Inference


Input image
448x448x3
GoogLeNet modification (20 layers)
14x14x1024
C,R
14x14x1024
C,R
14x14x1024
C,R
7x7x1024
C,R
7x7x1024
FC,R
4096x1
FC
1470x1
Reshape
7x7x30
Detection Procedure
Tensor values interpretation
7
7
30

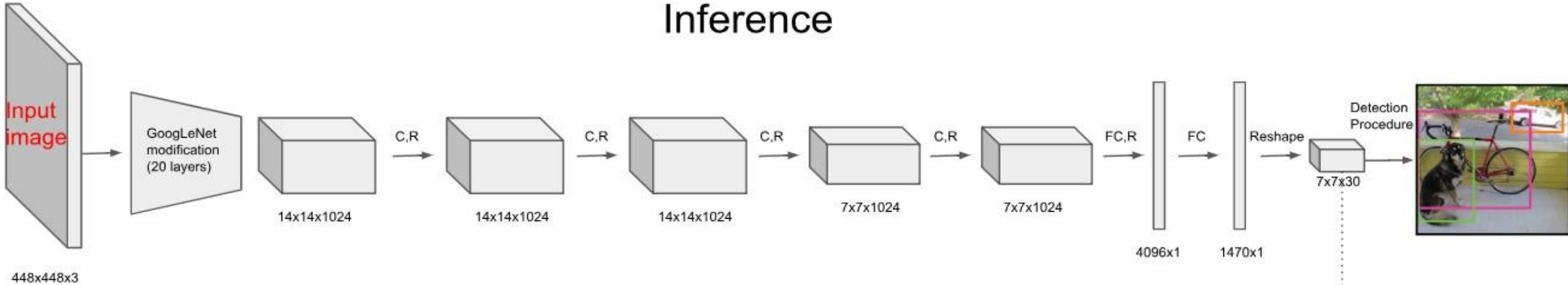
Inference



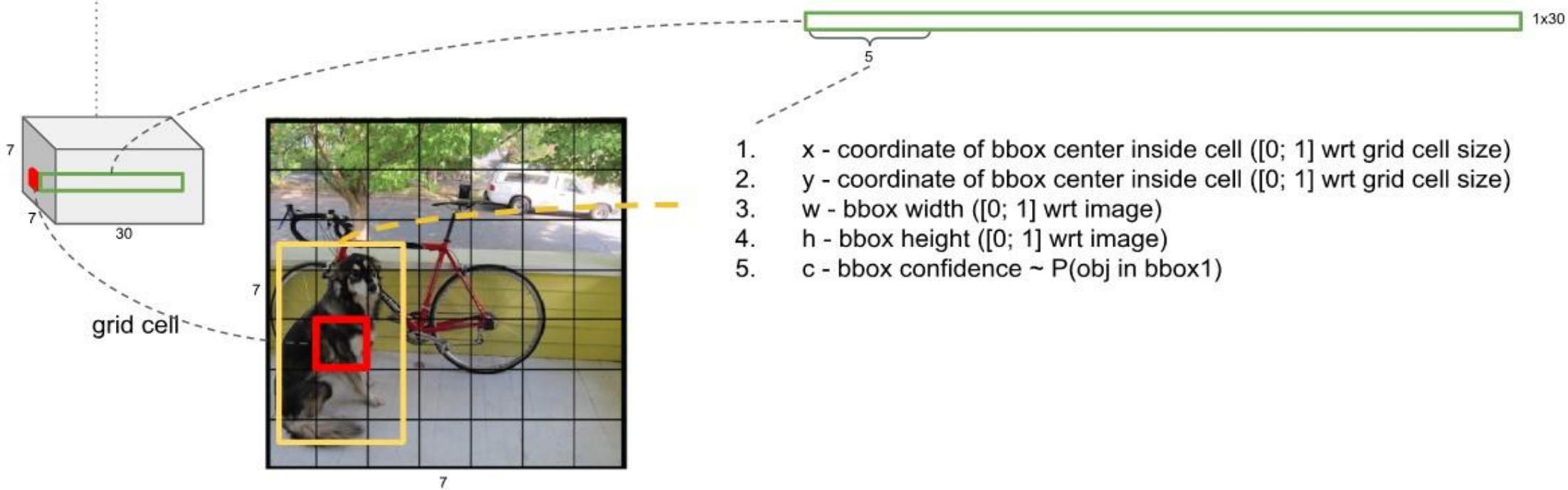
Tensor values interpretation



Inference

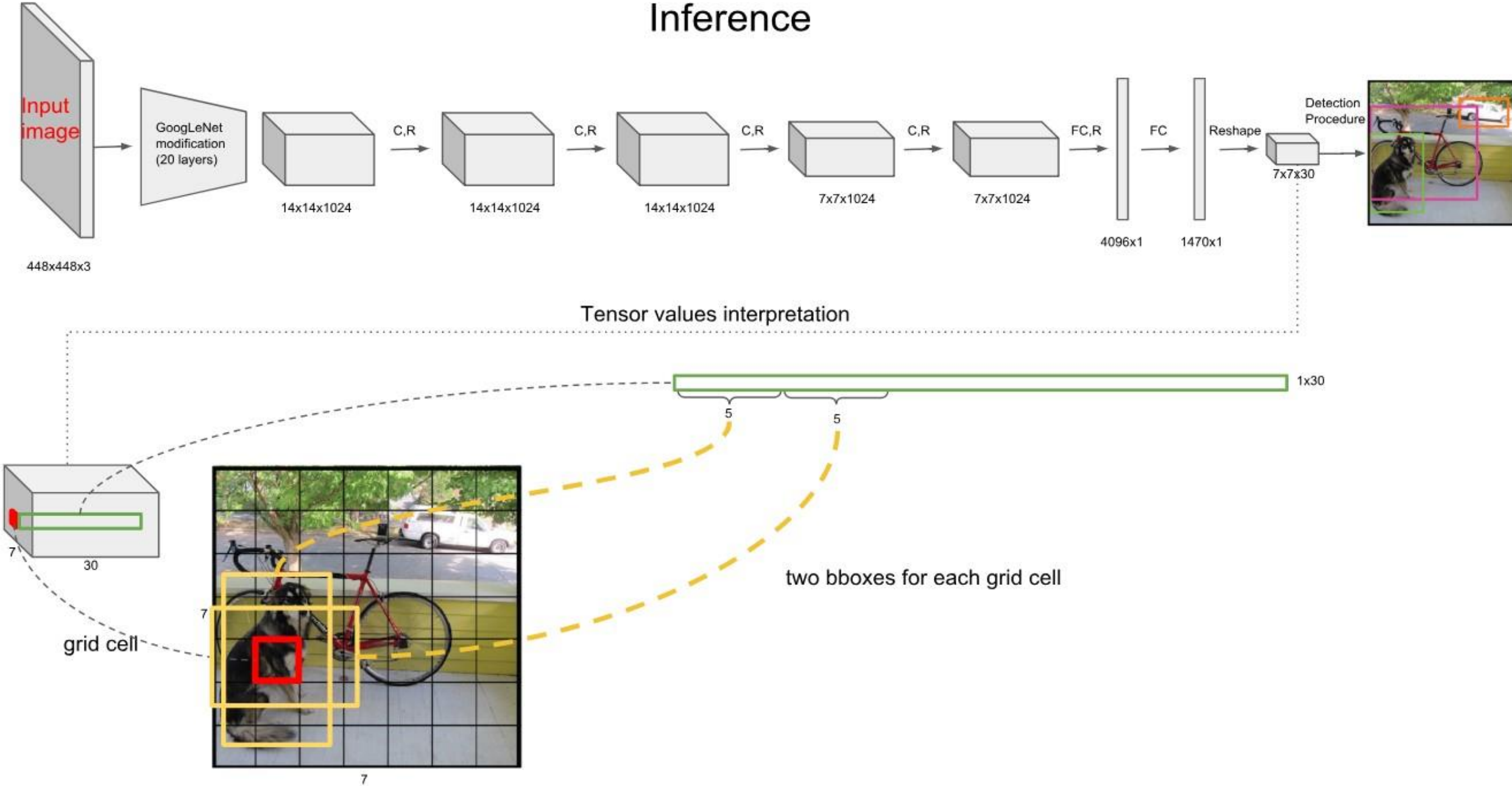


Tensor values interpretation



1. x - coordinate of bbox center inside cell ([0; 1] wrt grid cell size)
2. y - coordinate of bbox center inside cell ([0; 1] wrt grid cell size)
3. w - bbox width ([0; 1] wrt image)
4. h - bbox height ([0; 1] wrt image)
5. c - bbox confidence ~ P(obj in bbox1)

Inference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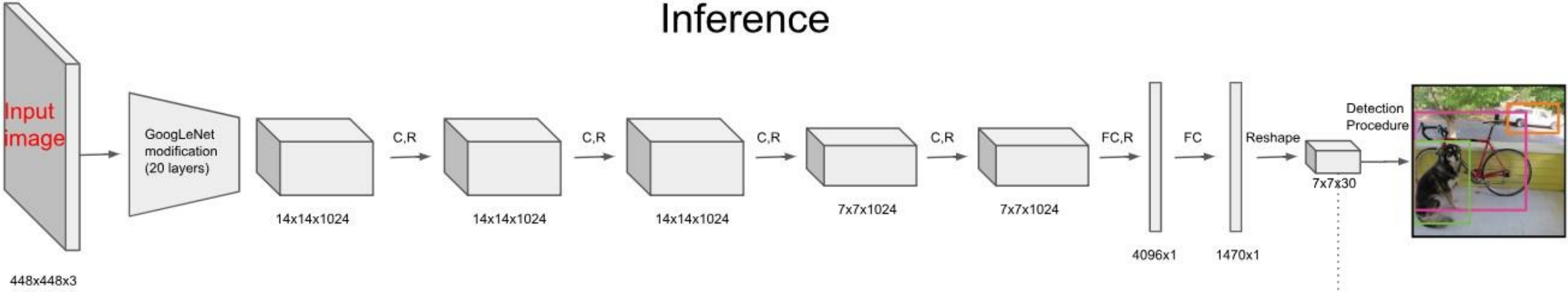
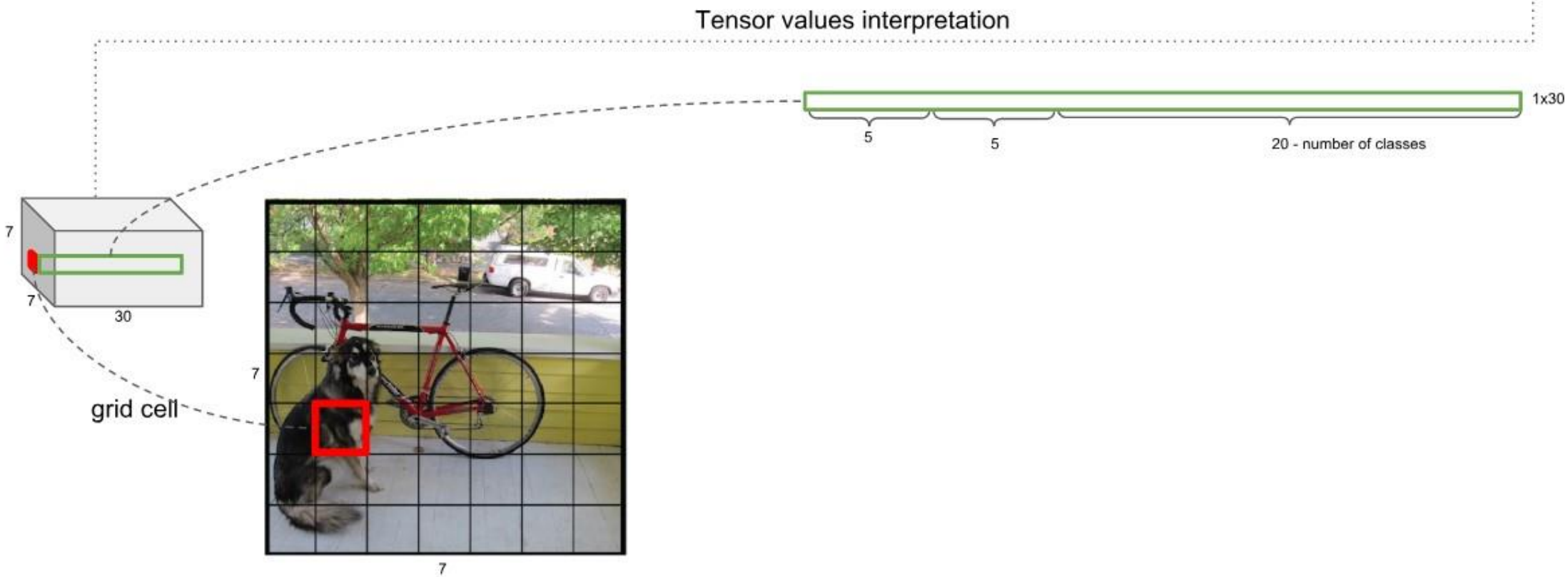
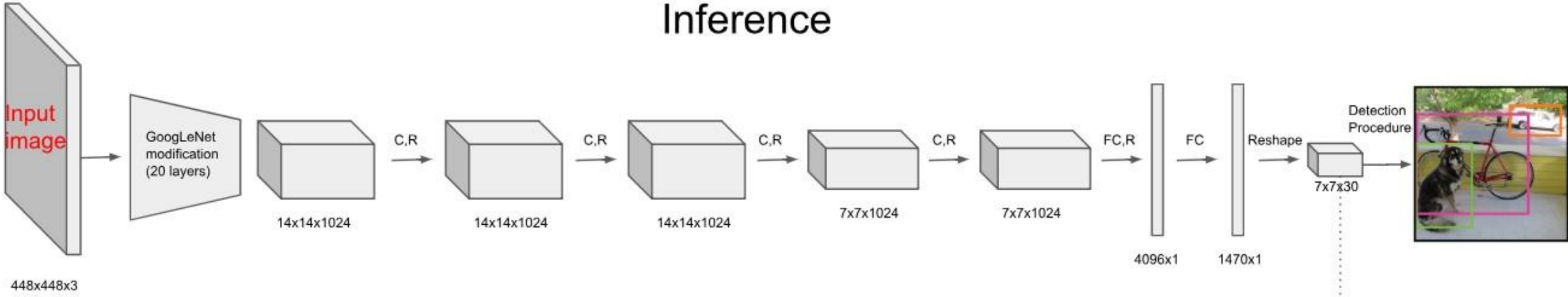
14x14x1024
C,R
14x14x1024
C,R
14x14x1024
C,R
7x7x1024
C,R
7x7x1024
FC,R
4096x1
FC
1470x1
Reshape
7x7x30
Detection Procedure
Tensor values interpretation
1x30
5
5
7
7
30
grid cell
7
7
two bboxes for each grid cell

Inference

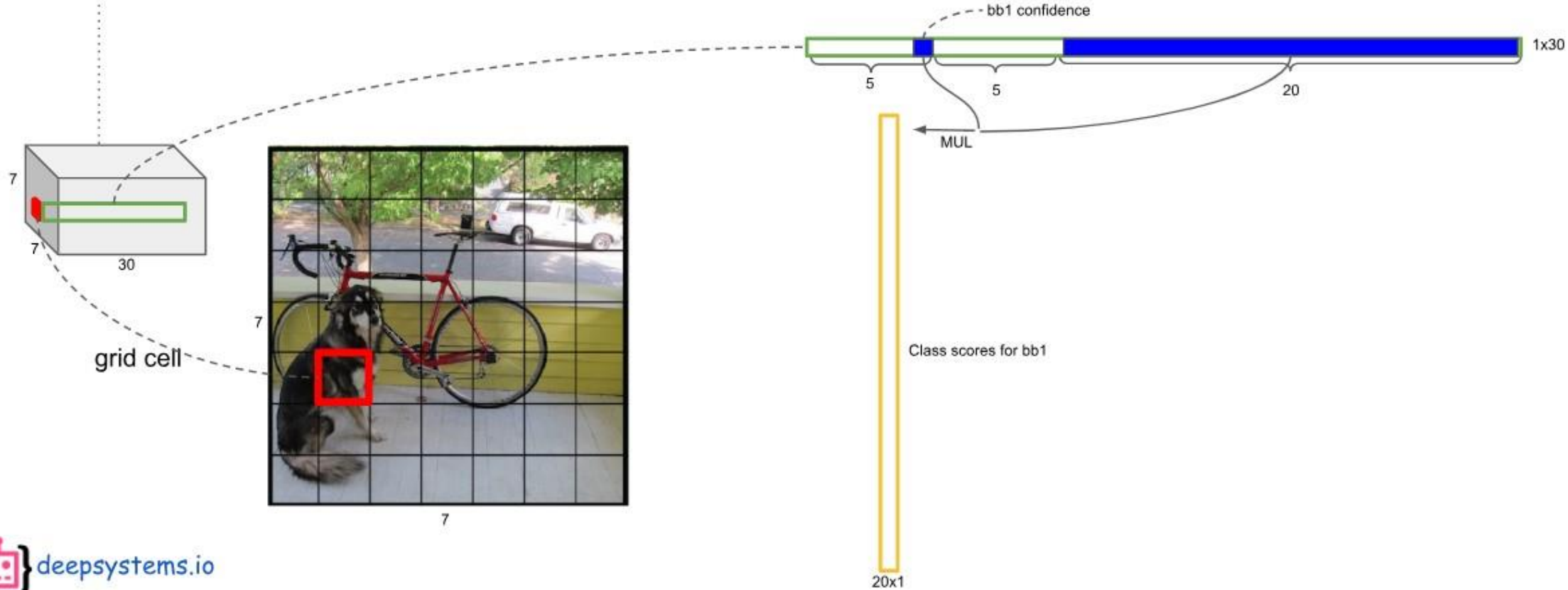

Input image
448x448x3
GoogLeNet modification (20 layers)
14x14x1024
C,R
14x14x1024
C,R
14x14x1024
C,R
7x7x1024
C,R
7x7x1024
FC,R
4096x1
FC
1470x1
Reshape
7x7x30
Detection Procedure


Tensor values interpretation
1x30
5
5
20 - number of classes
7
7
30
7
7
grid cell

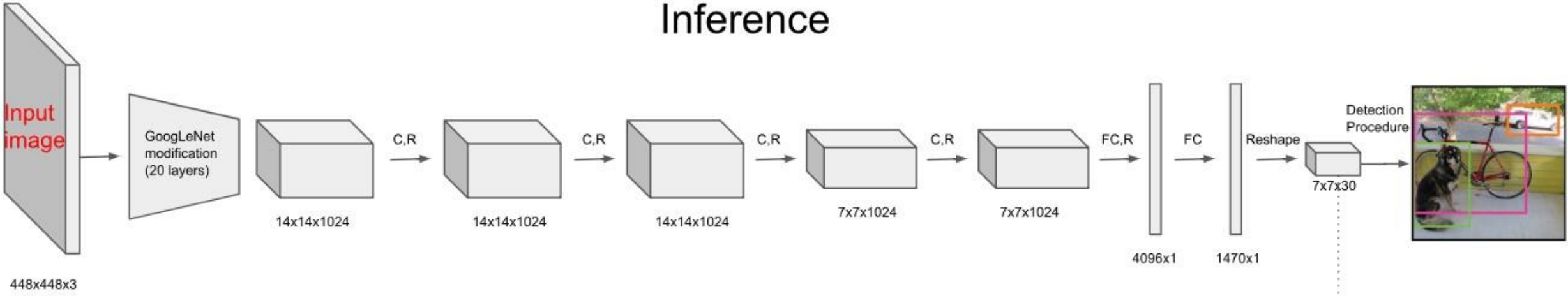
Inference



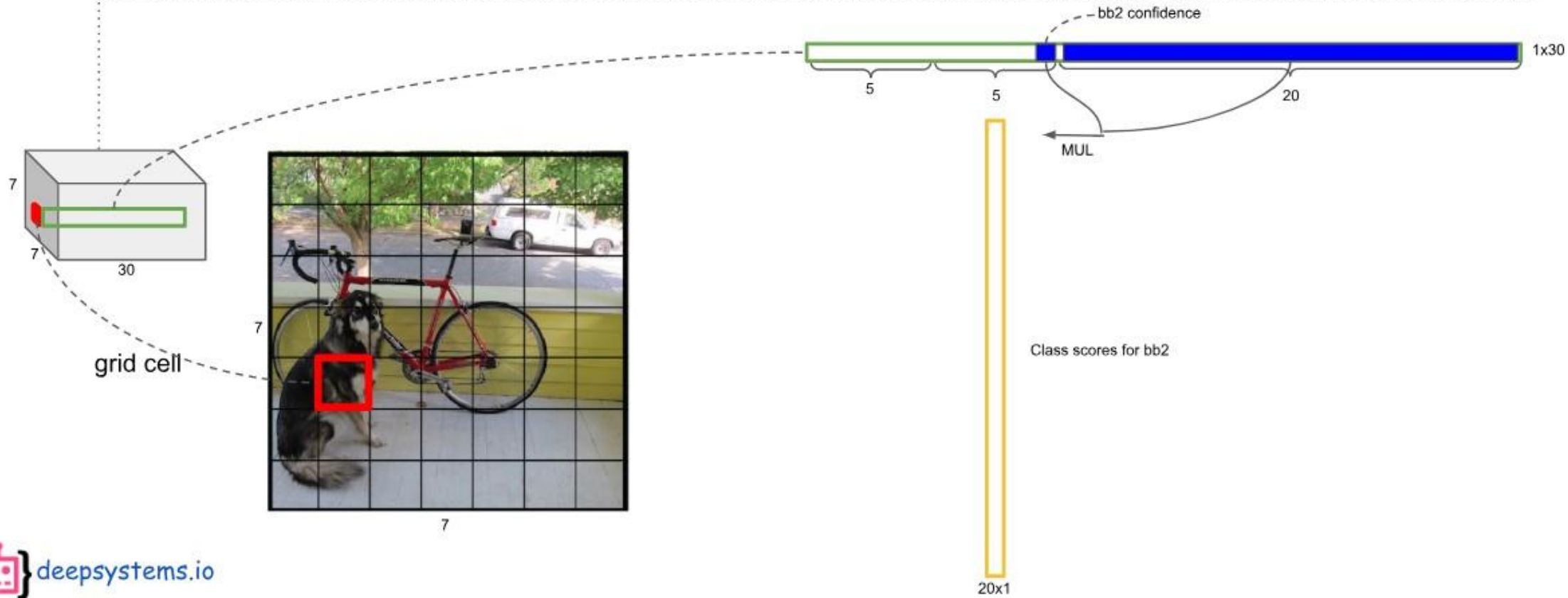
Tensor values interpretation



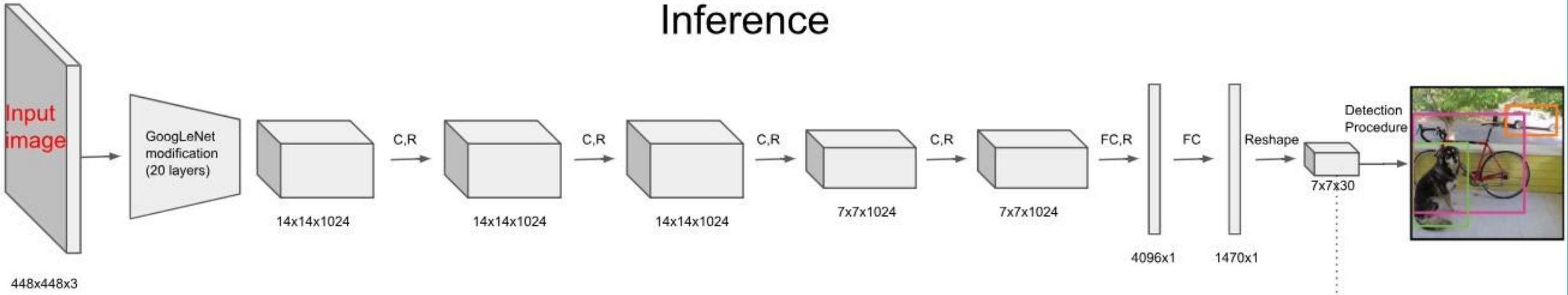
Inference



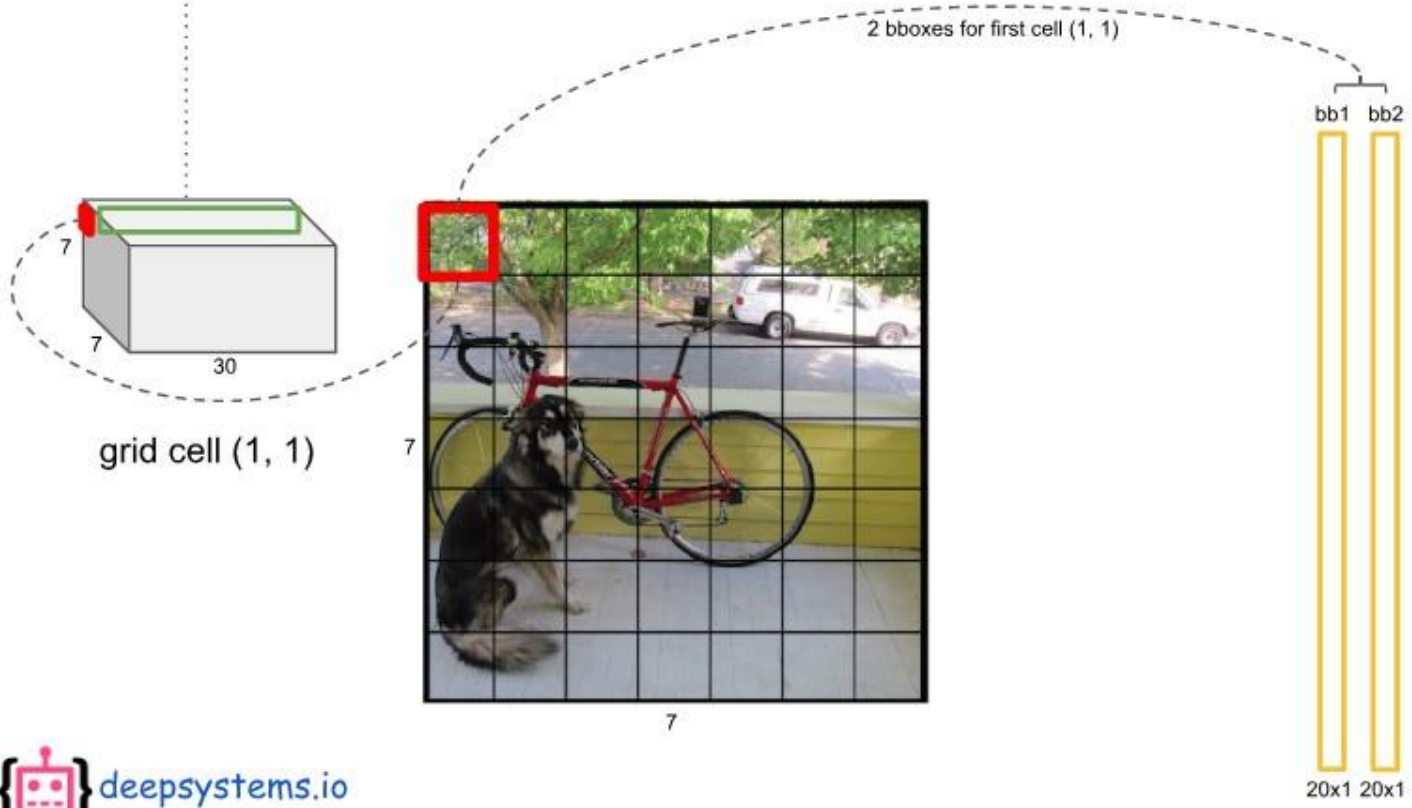
Tensor values interpretation



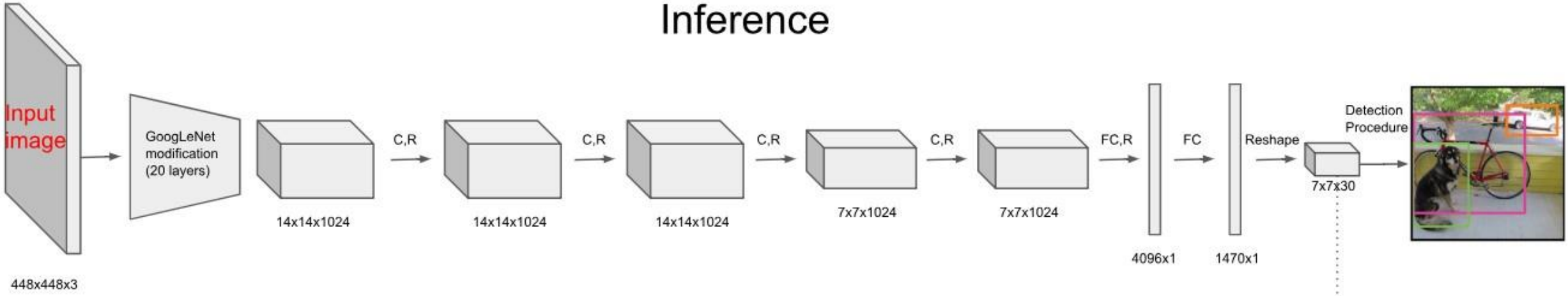
Inference



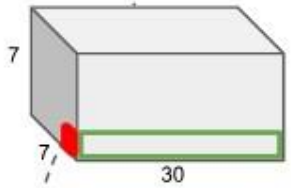
Tensor values interpretation

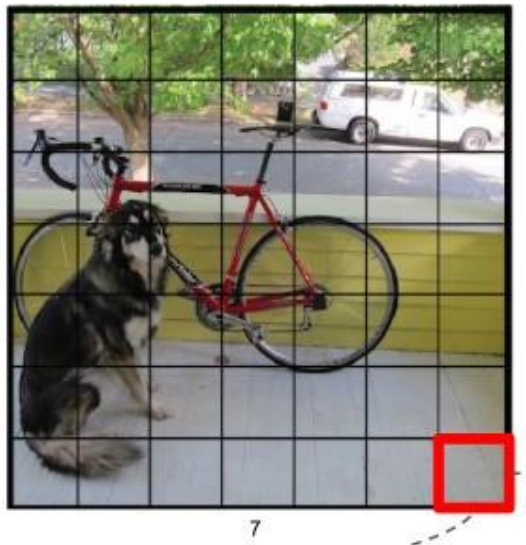


Inference



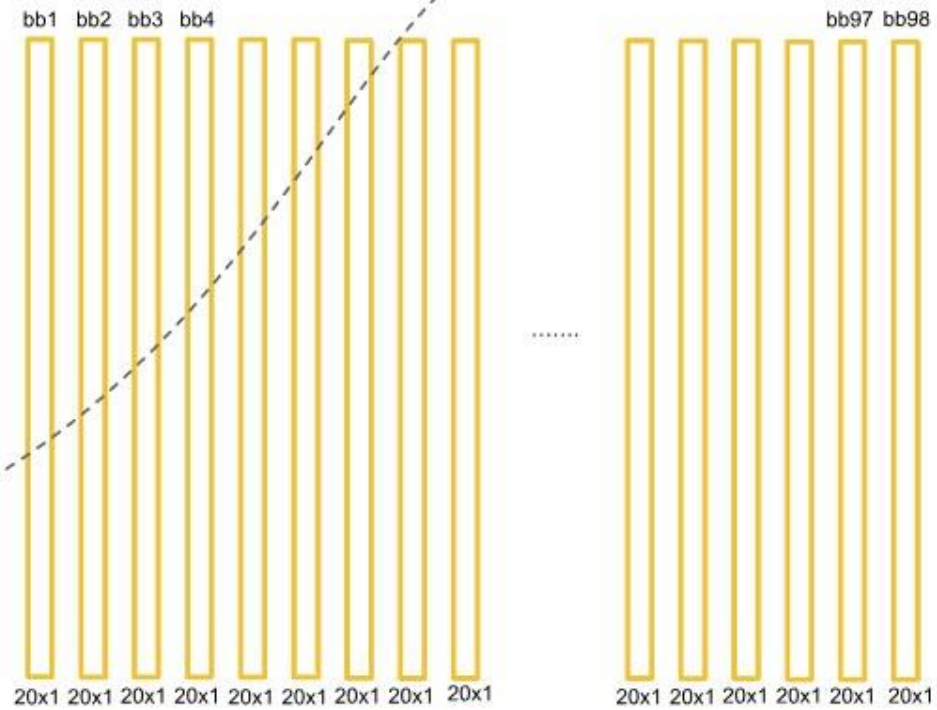
Tensor values interpretation

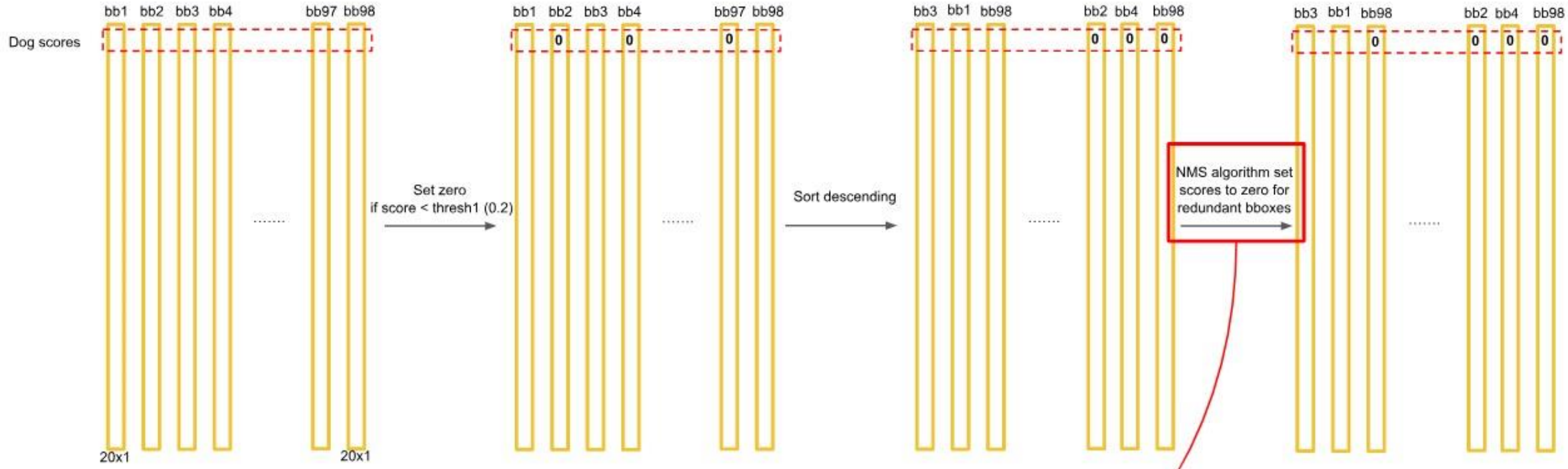




grid cell (7, 7)

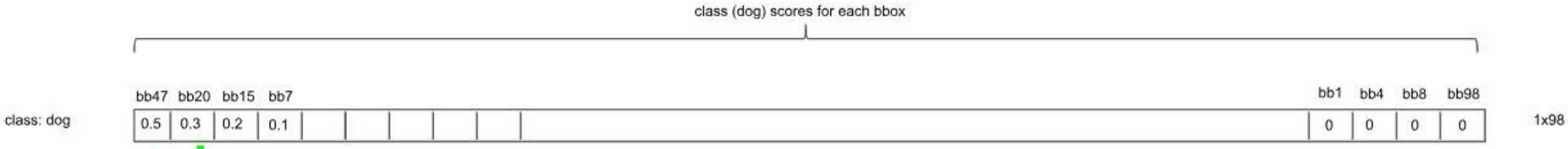
2 bboxes for last cell (7, 7)

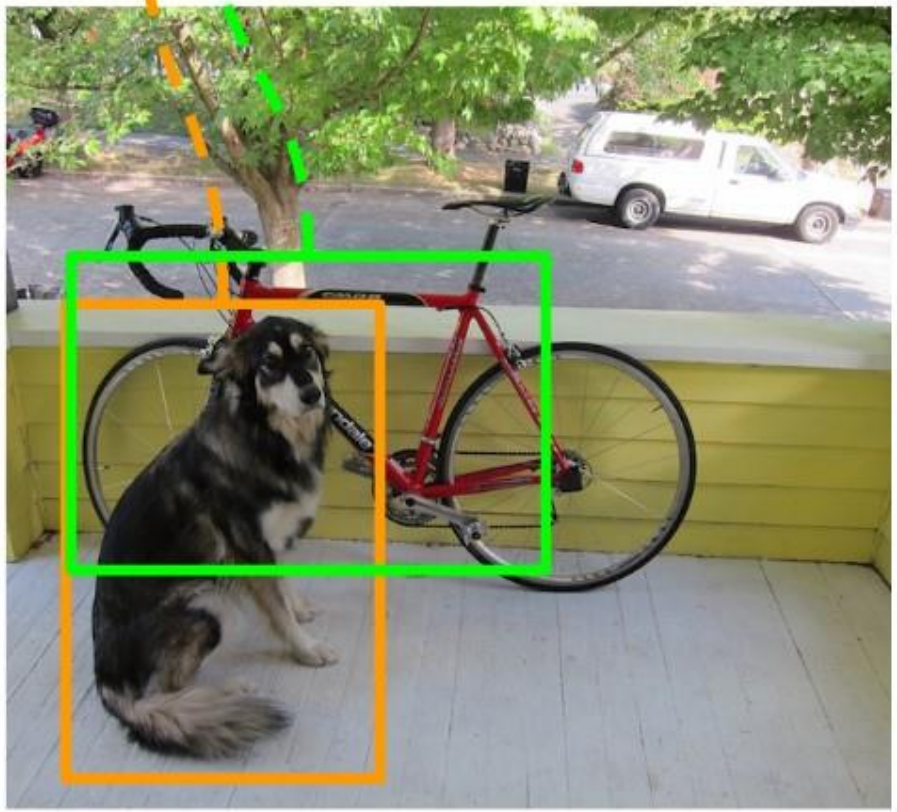



Dog scores
bb1 bb2 bb3 bb4 ..... bb97 bb98
20x1
20x1
Set zero
if score < thresh1 (0.2)
bb1 bb2 bb3 bb4 ..... bb97 bb98
0 0 0
Sort descending
bb3 bb1 bb98 ..... bb2 bb4 bb98
0 0 0
NMS algorithm set
scores to zero for
redundant bboxes
bb3 bb1 bb98 ..... bb2 bb4 bb98
0 0 0

How it works

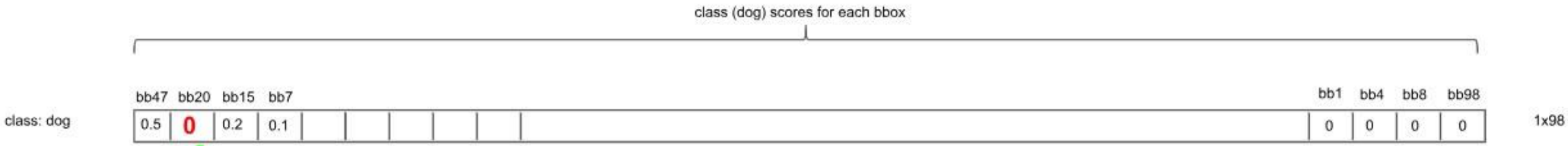
Non-Maximum Suppression: intuition

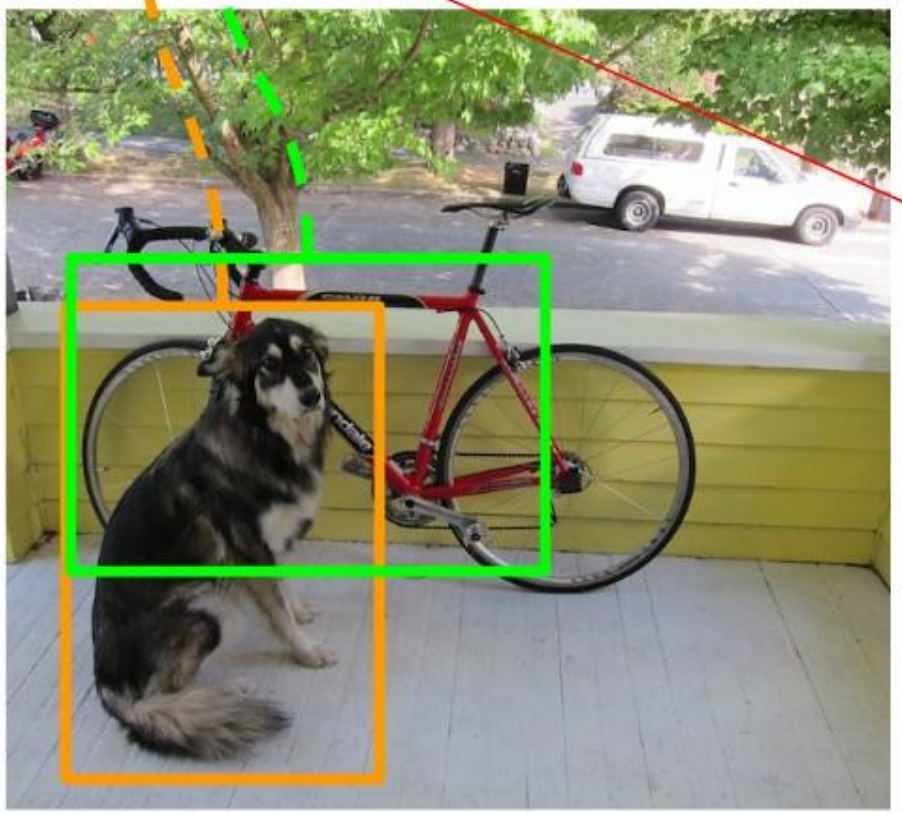




If IoU(bbox_max, bbox_cur) > 0.5 then set 0 score to bbox_cur.

Non-Maximum Suppression: intuition

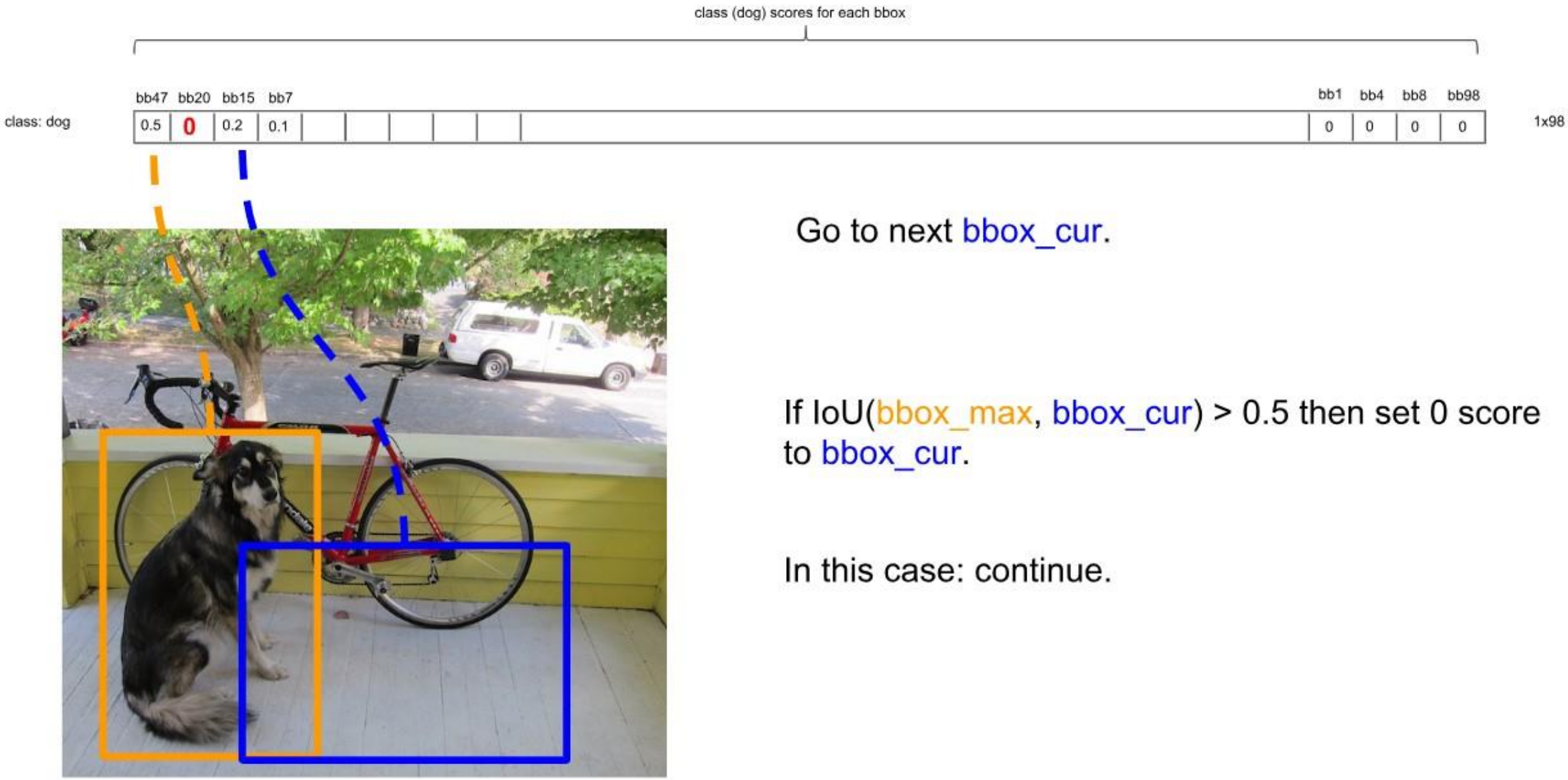




If IoU(bbox_max, bbox_cur) > 0.5 then set 0 score to bbox_cur.

In this case: set to 0.

Non-Maximum Suppression: intuition

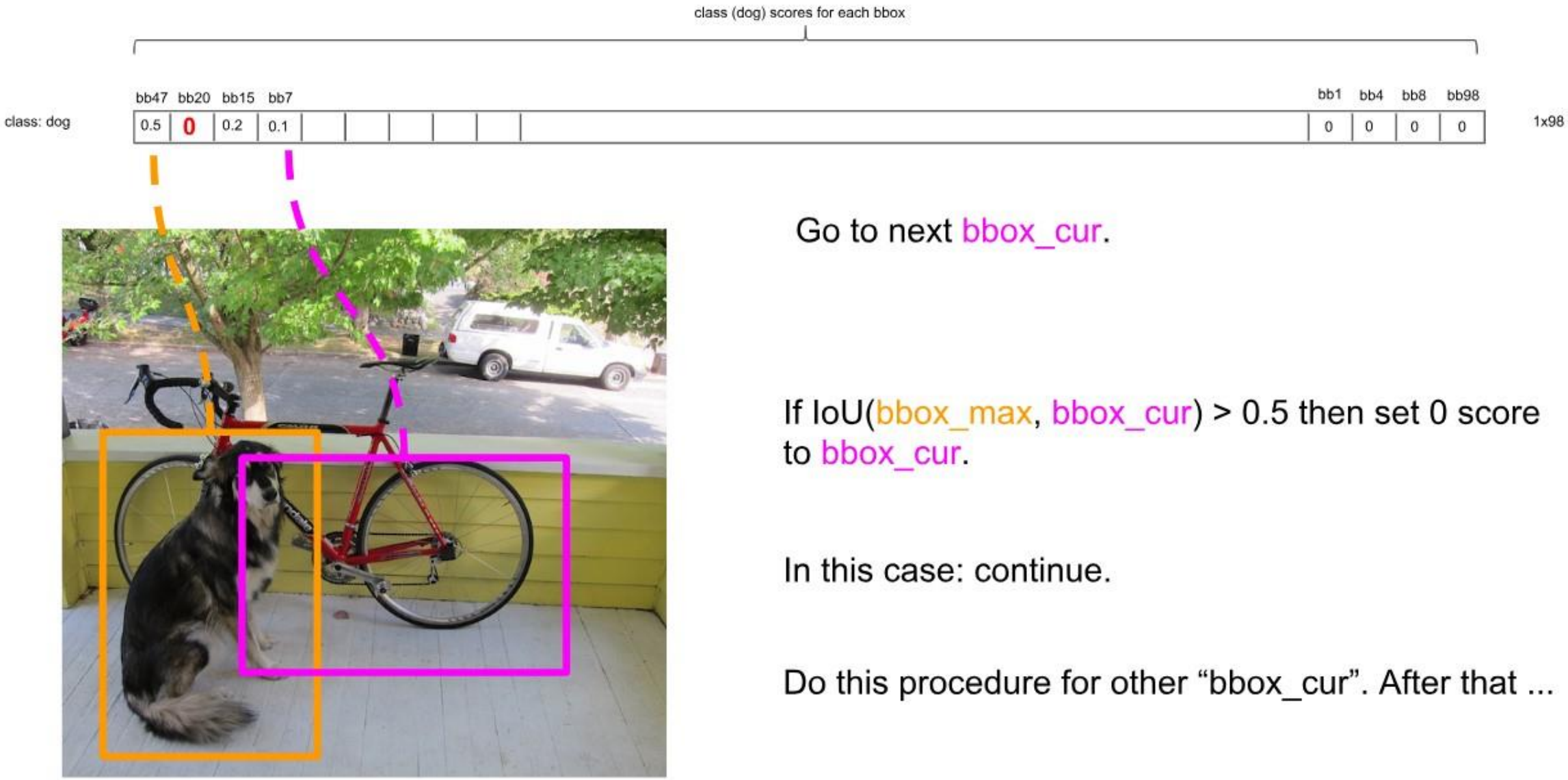


Go to next bbox_cur.

If IoU(bbox_max, bbox_cur) > 0.5 then set 0 score to bbox_cur.

In this case: continue.

Non-Maximum Suppression: intuition



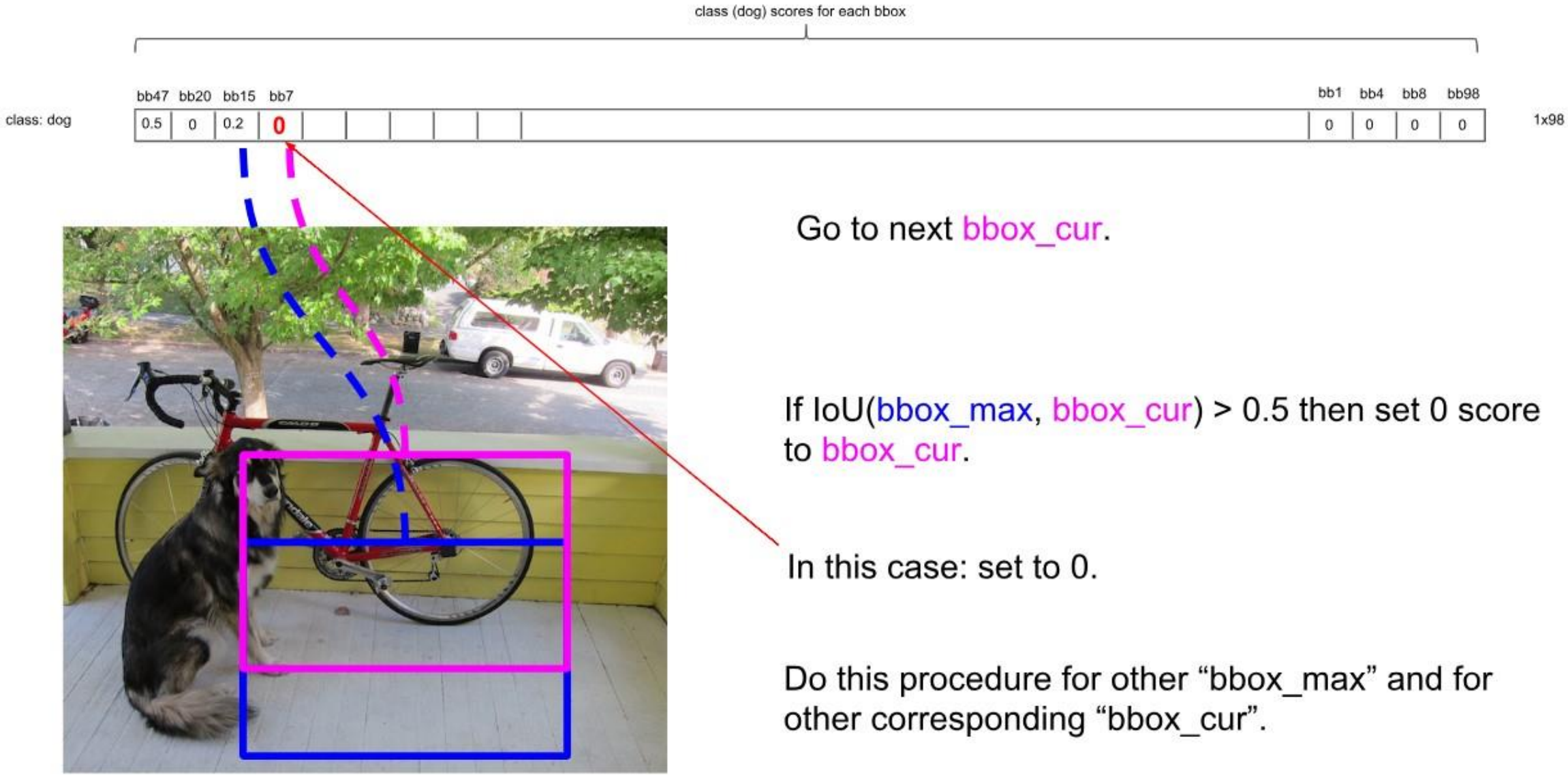
Go to next bbox_cur.

If IoU(bbox_max, bbox_cur) > 0.5 then set 0 score to bbox_cur.

In this case: continue.

Do this procedure for other “bbox_cur”. After that ...

Non-Maximum Suppression: intuition

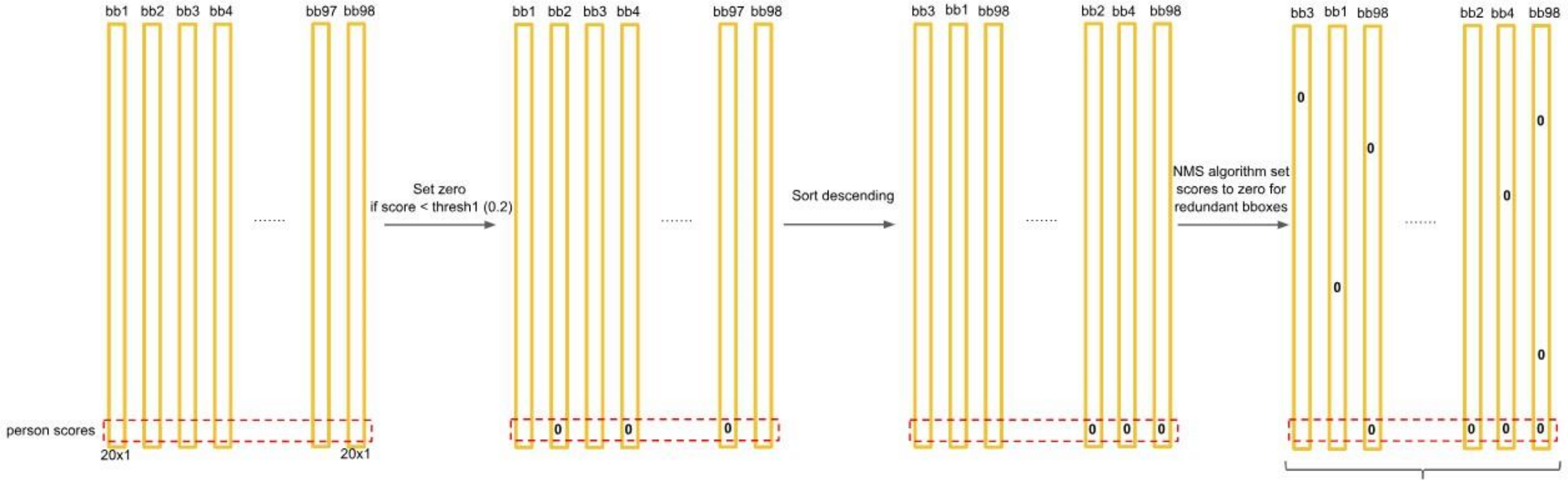


Go to next bbox_cur.

If IoU(bbox_max, bbox_cur) > 0.5 then set 0 score to bbox_cur.

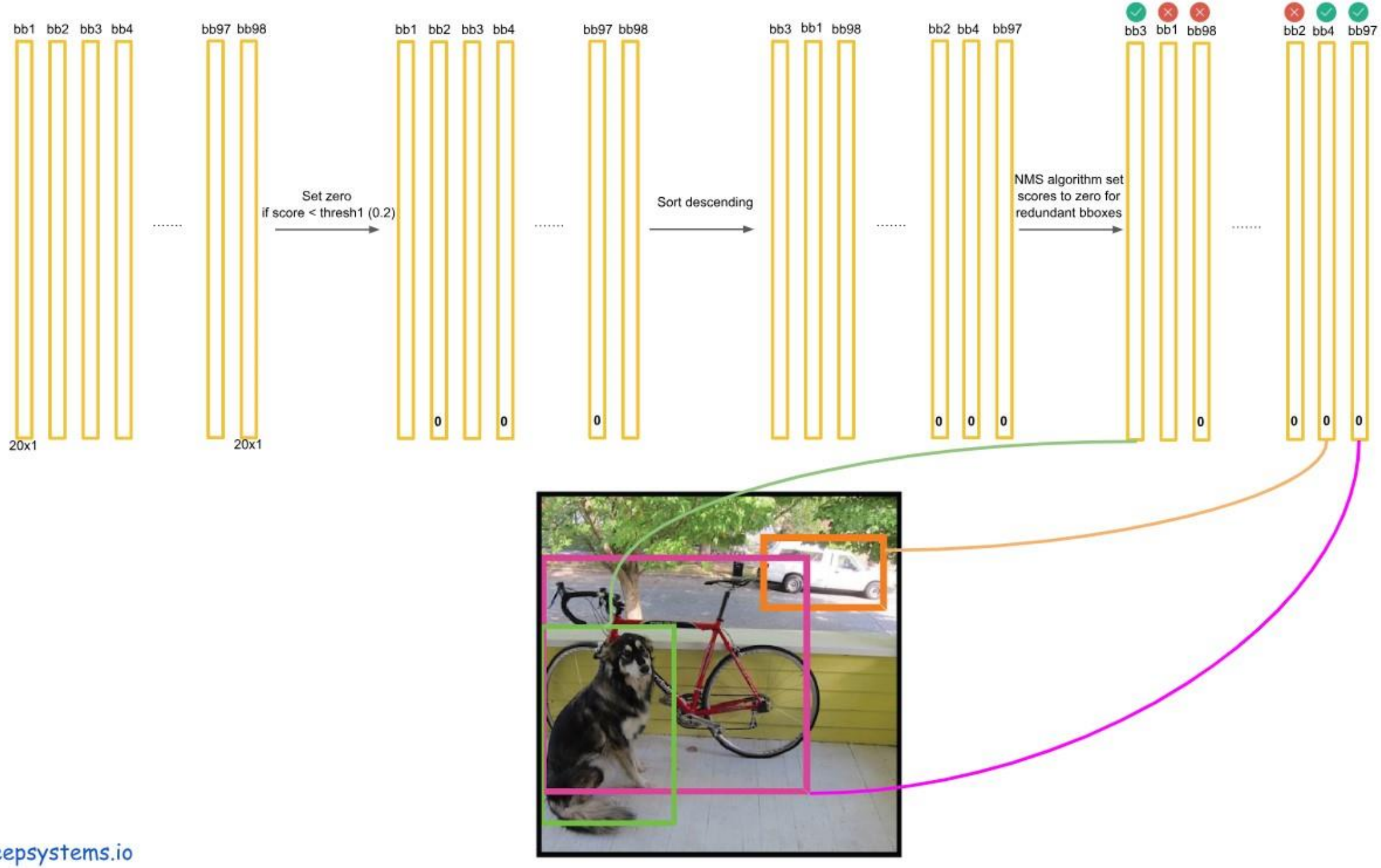
In this case: set to 0.

Do this procedure for other “bbox_max” and for other corresponding “bbox_cur”.



After this procedure -
a lot of zeros


bb1 bb2 bb3 bb4
20x1
bb97 bb98
20x1
Set zero
if score < thresh1 (0.2)
bb1 bb2 bb3 bb4
0 0
bb97 bb98
0
Sort descending
bb3 bb1 bb98
bb2 bb4 bb97
0 0 0
NMS algorithm set
scores to zero for
redundant bboxes
bb3 bb1 bb98
0 0 0
bb2 bb4 bb97
0 0 0 0
class = max_index(scores for bb97);
score = max(scores for bb97);
Score > 0
no
skip bbox
yes
draw bbox with class color


bb1 bb2 bb3 bb4
bb97 bb98
20x1
20x1
Set zero
if score < thresh1 (0.2)
bb1 bb2 bb3 bb4
0 0
bb97 bb98
0
Sort descending
bb3 bb1 bb98
bb2 bb4 bb97
0 0 0
NMS algorithm set
scores to zero for
redundant bboxes
bb3 bb1 bb98
0
bb2 bb4 bb97
0 0 0

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

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

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

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

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

Regression problem : SSE

$\lambda_{\text{coord}} = 5$ and $\lambda_{\text{noobj}} = .5.$

Classification based cell