

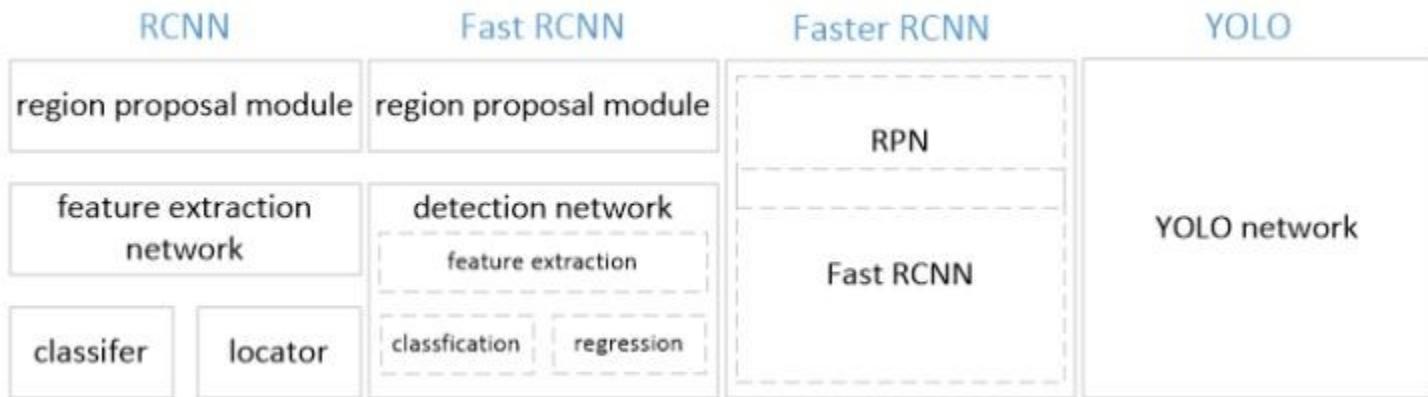
You Only Look

- 检测
- Training
- Predicting
- Non-max Suppression
- Darknet native on Windows

@ 100

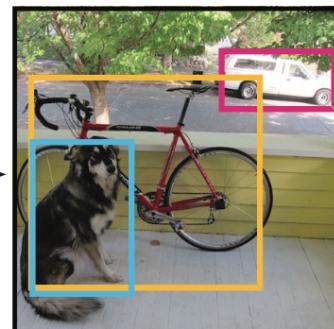
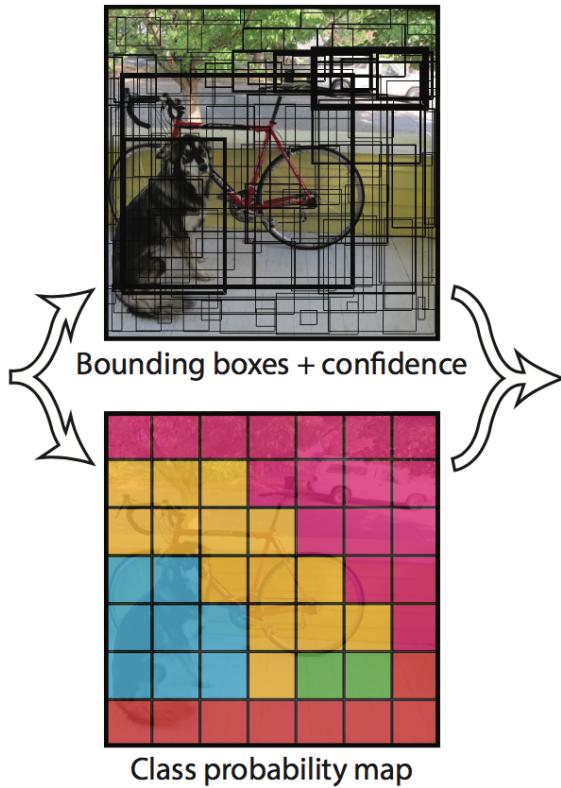
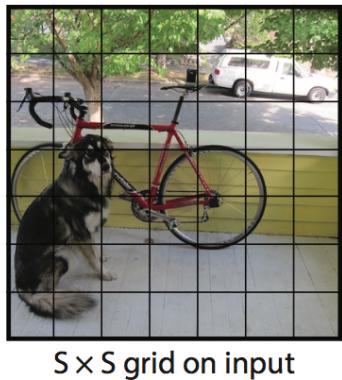


1.Review

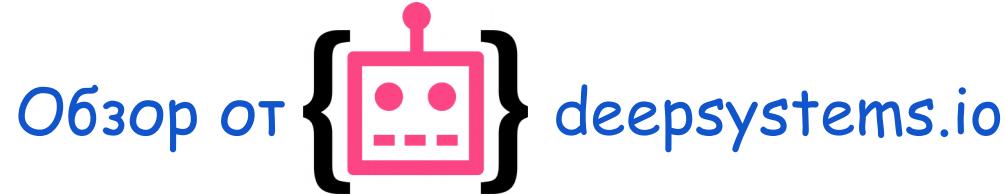


YOLO 识别框

YOLO 不需要 region proposal 框

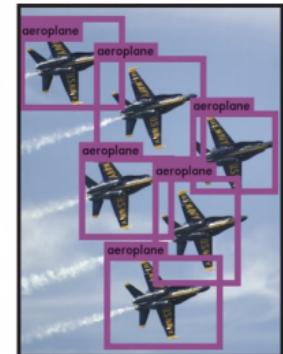
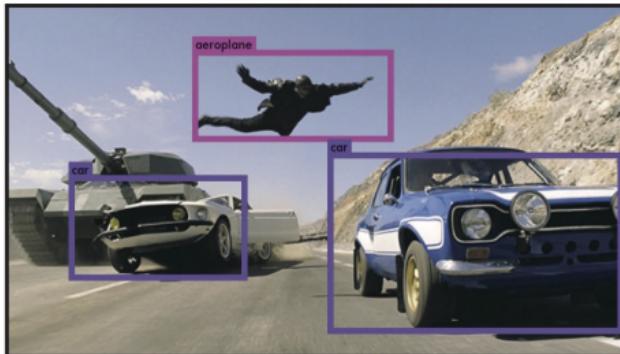
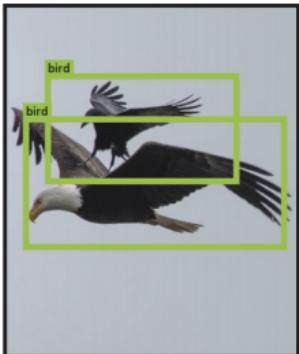


2.Training

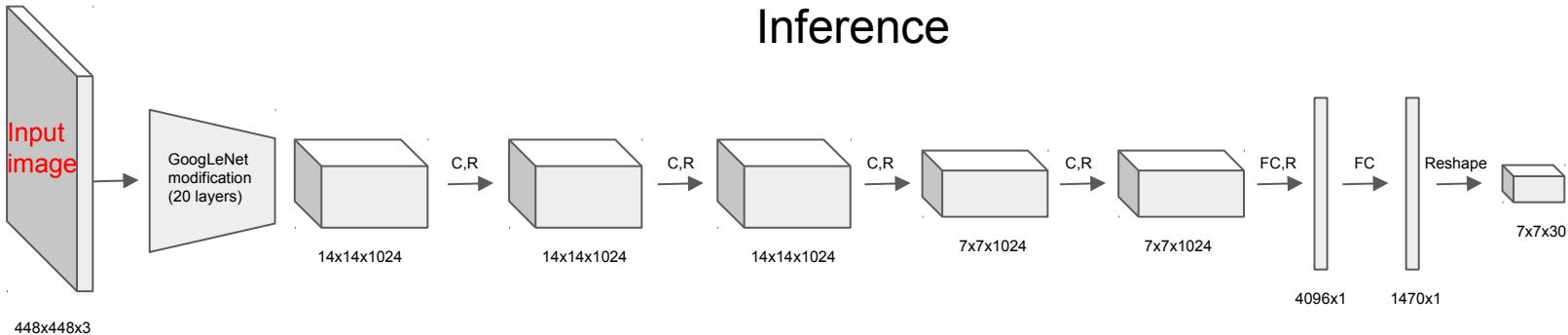


YOLO

You Only Look Once: Unified, Real-Time Object Detection
[Joseph Redmon](#), [Santosh Divvala](#), [Ross Girshick](#), [Ali Farhadi](#)



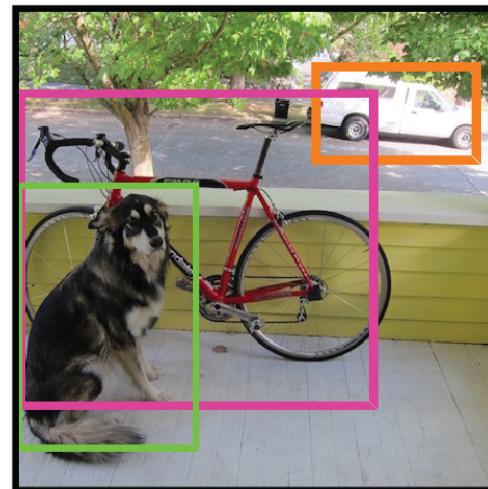
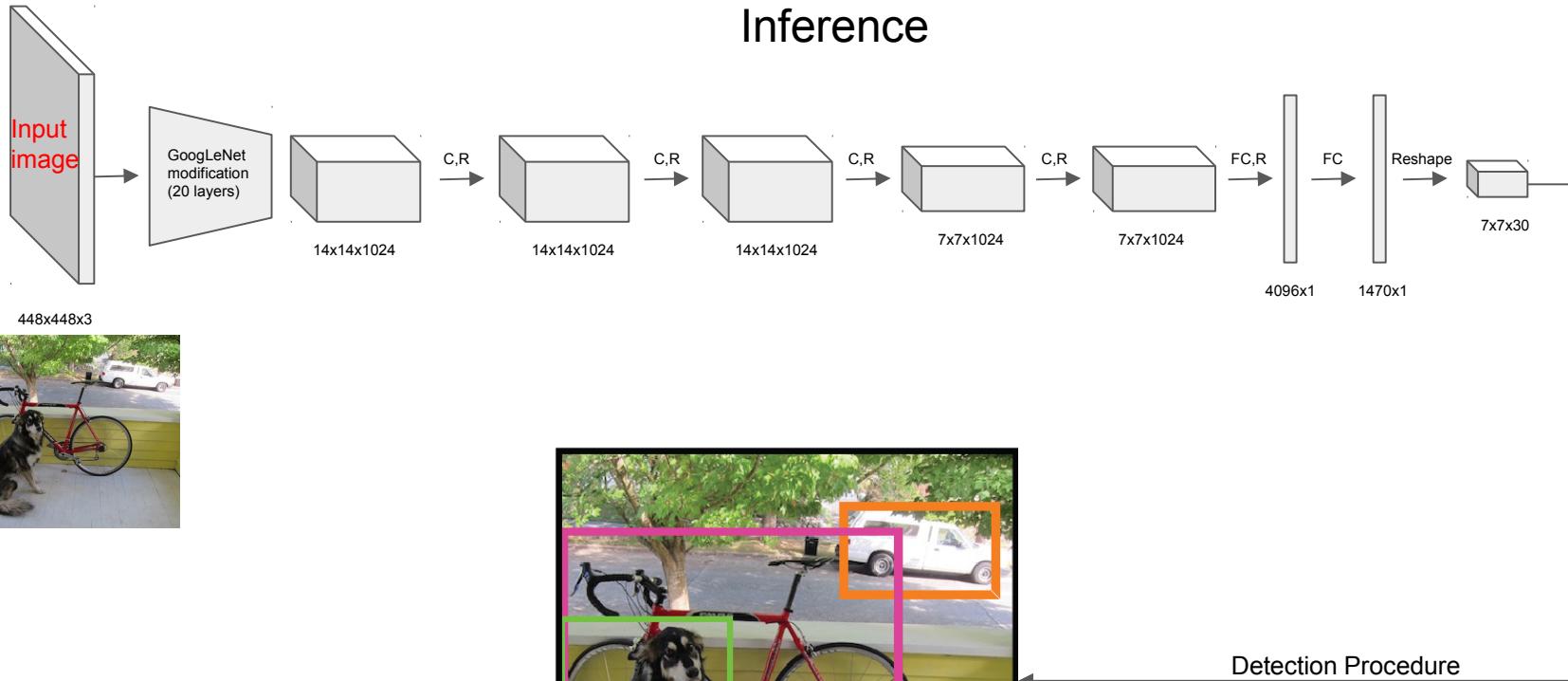
Inference



448x448x3

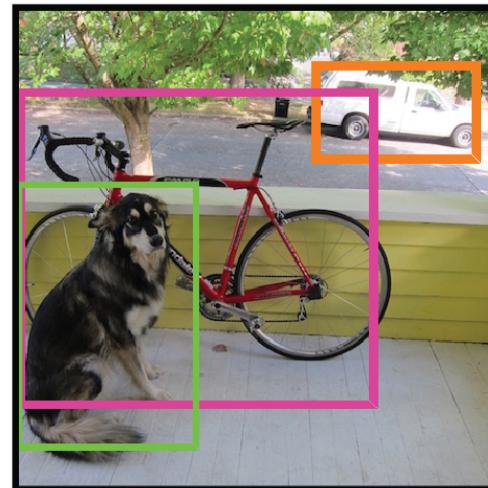
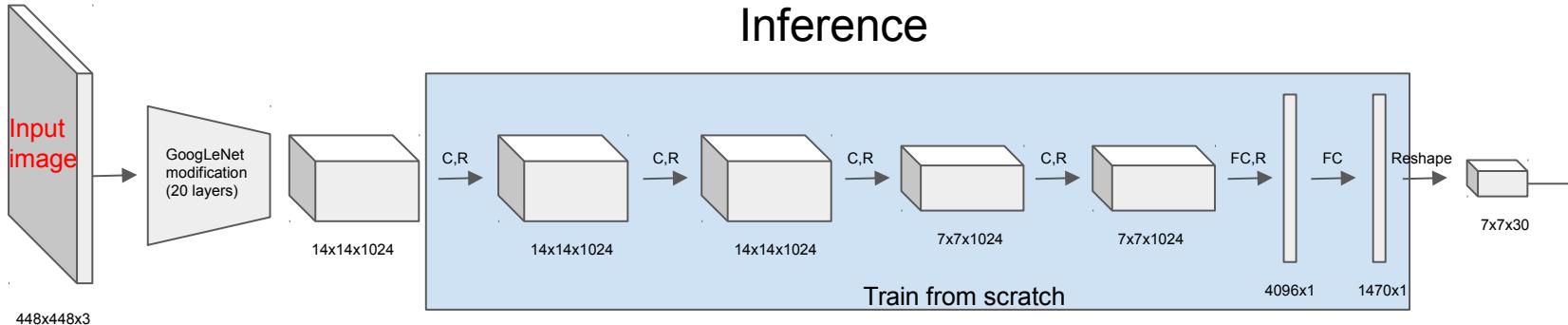


Inference



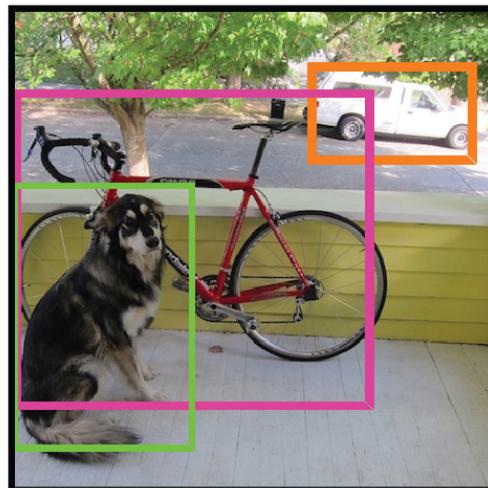
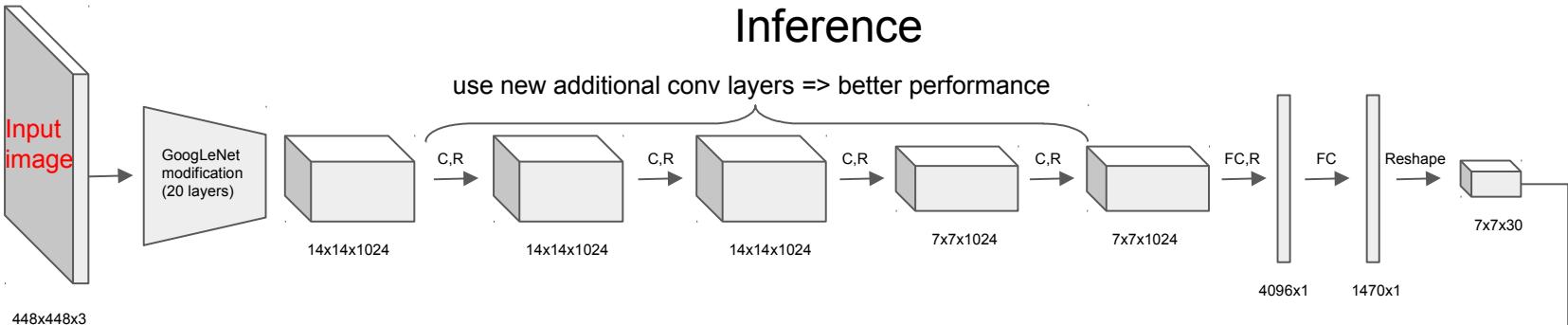
Detection Procedure

Inference



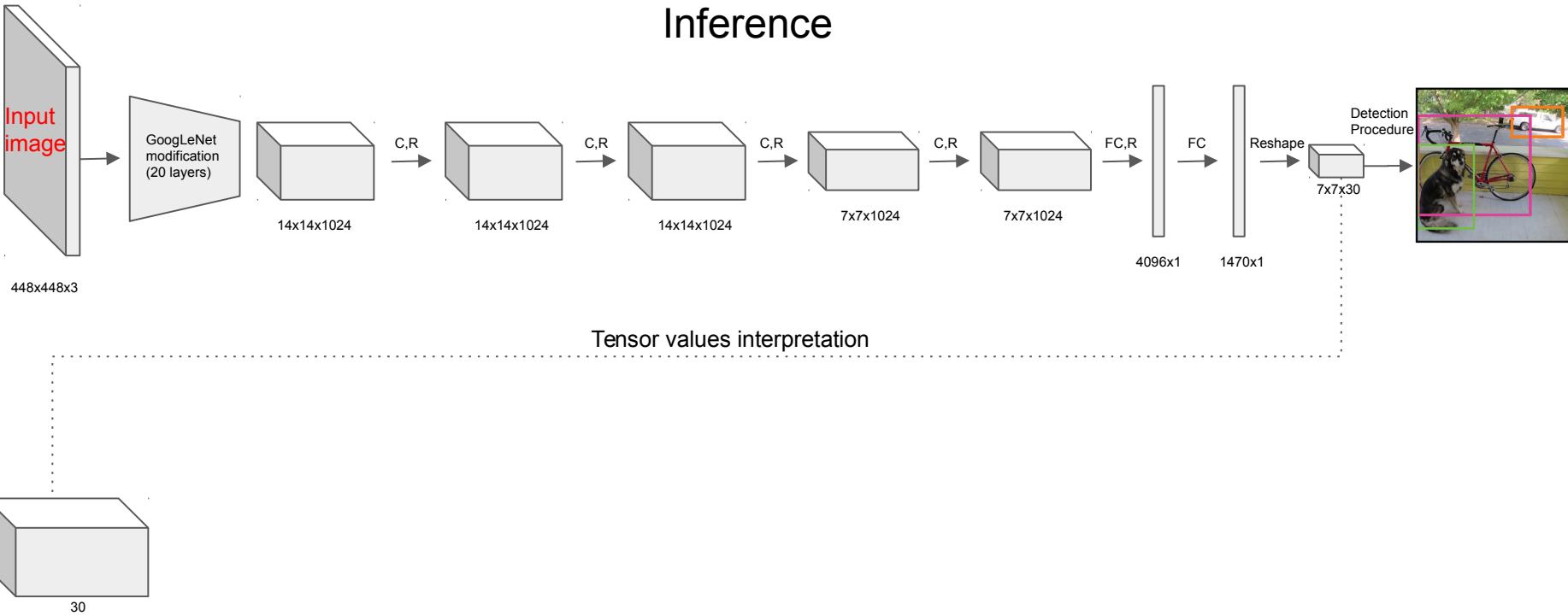
Detection Procedure

Inference

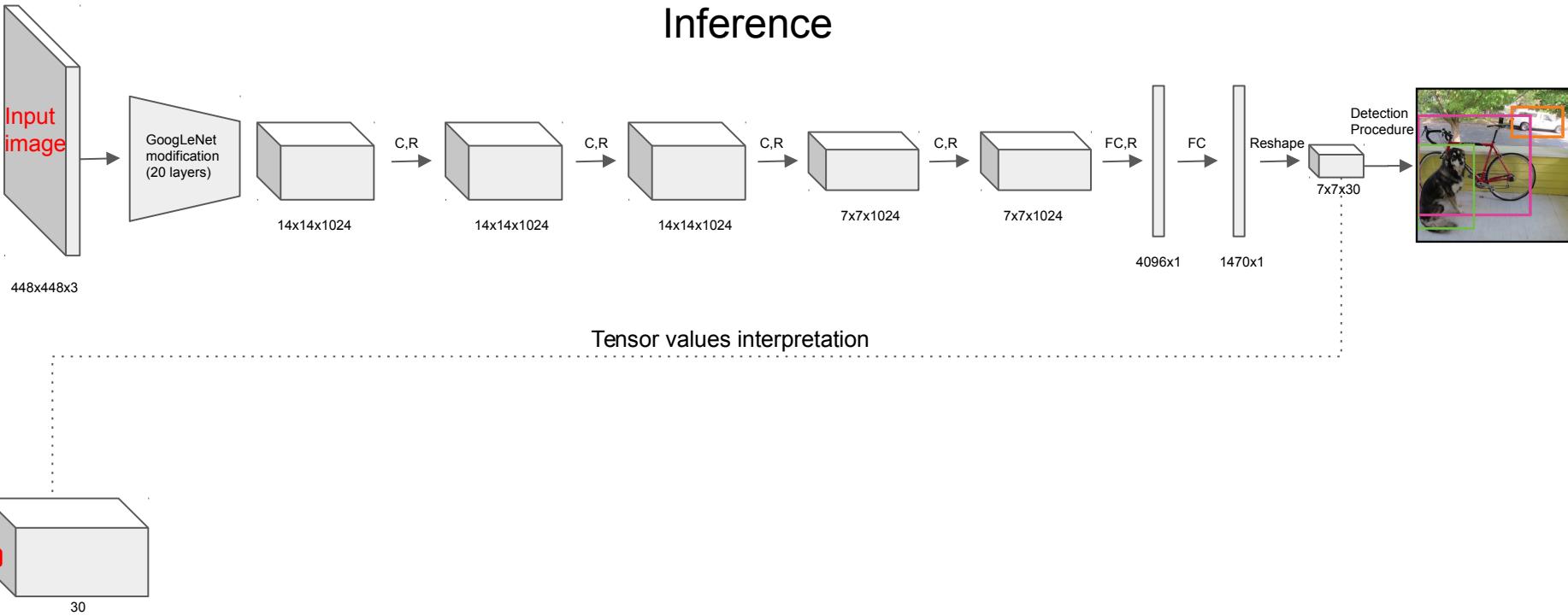


Detection Procedure

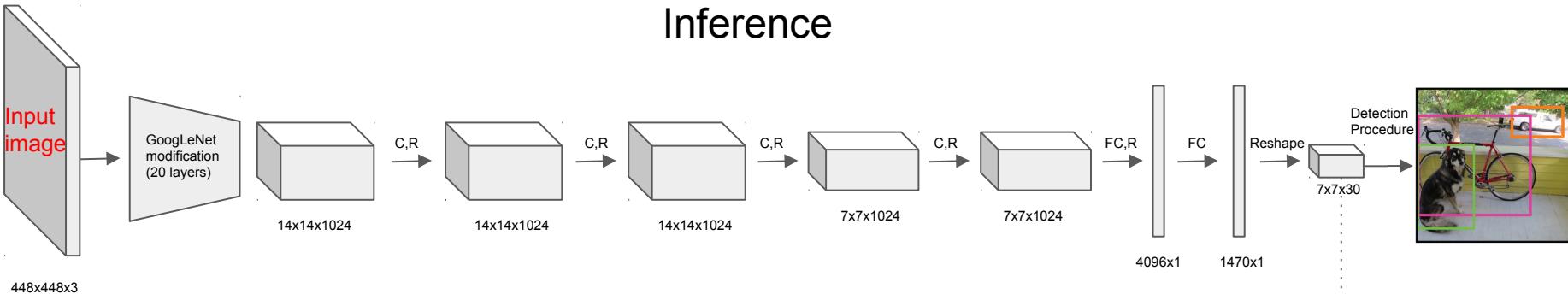
Inference



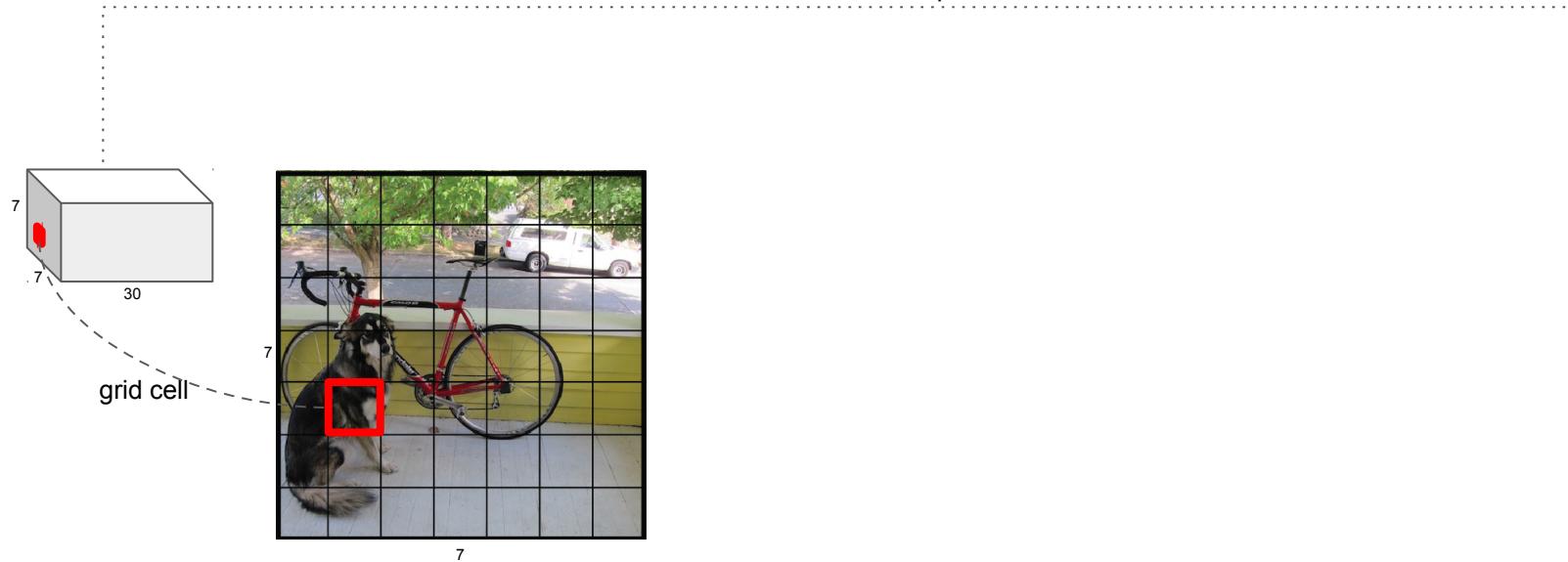
Inference



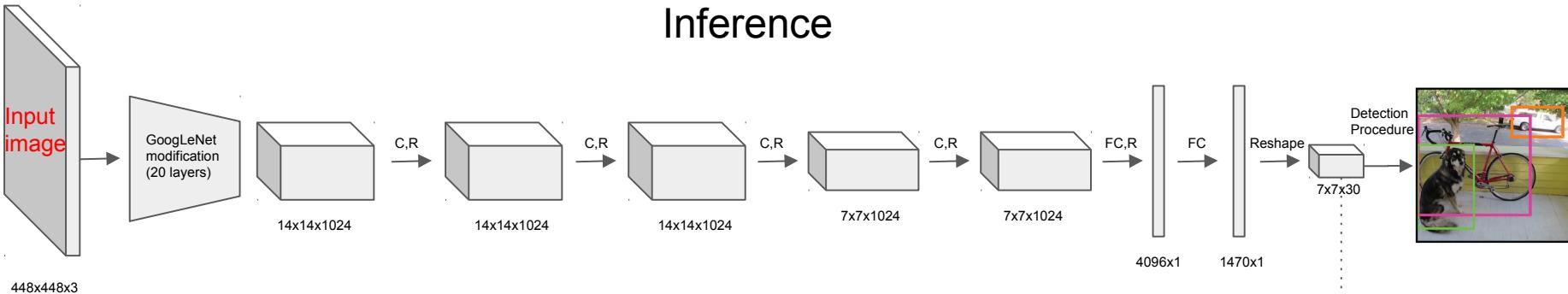
Inference



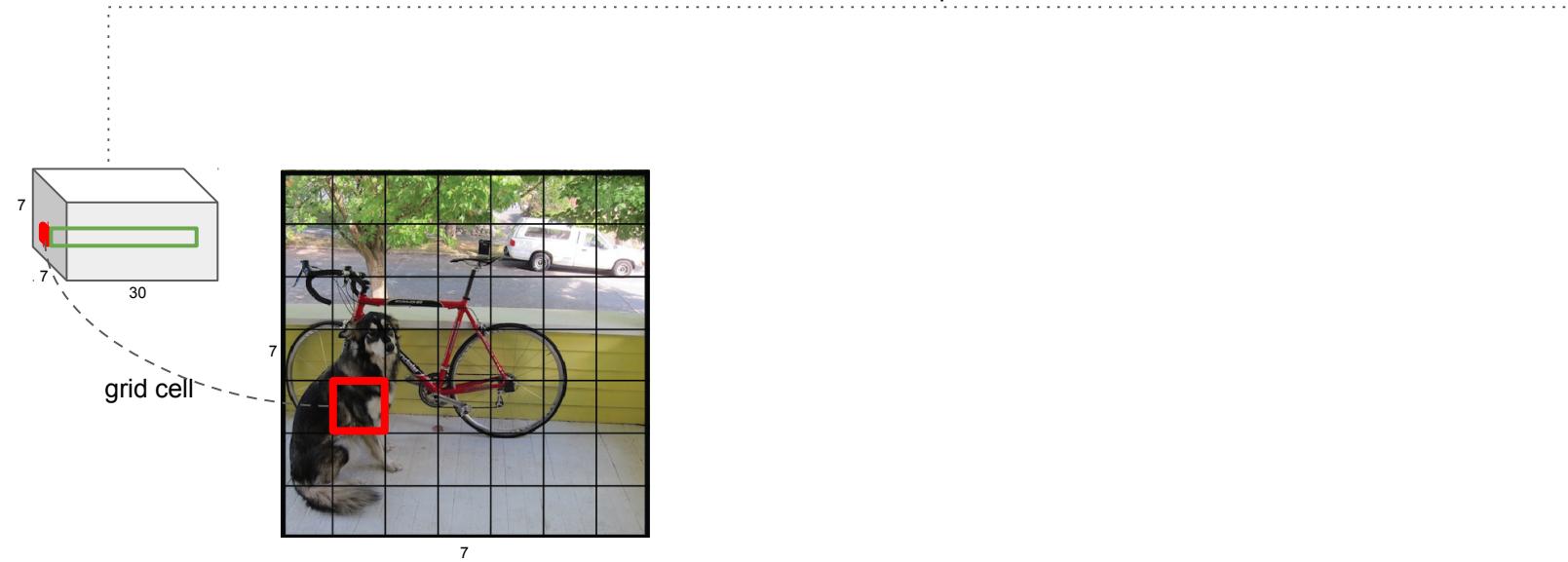
Tensor values interpretation



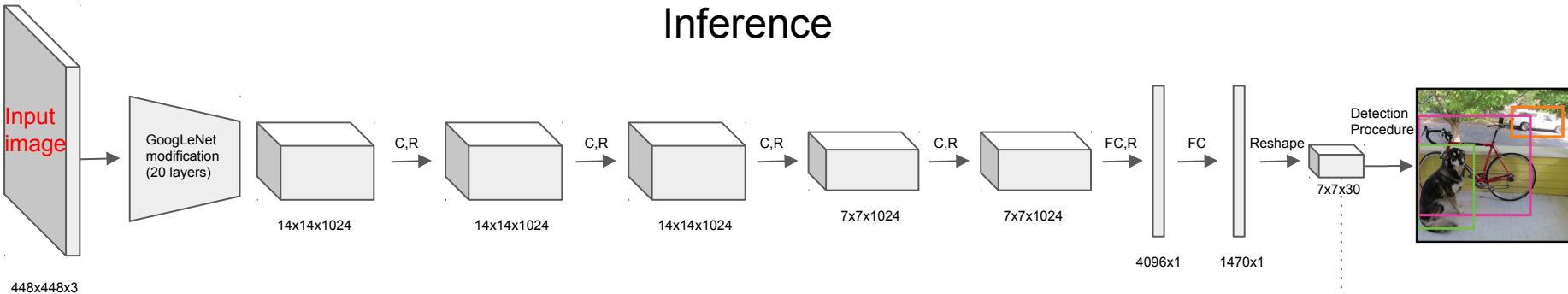
Inference



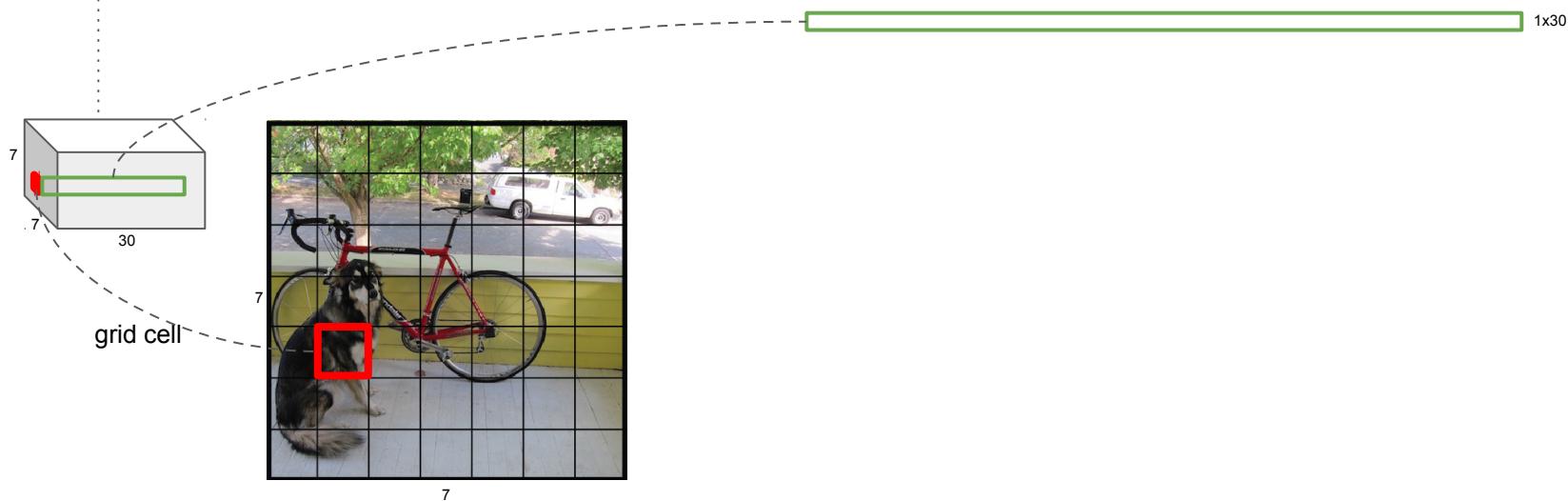
Tensor values interpretation



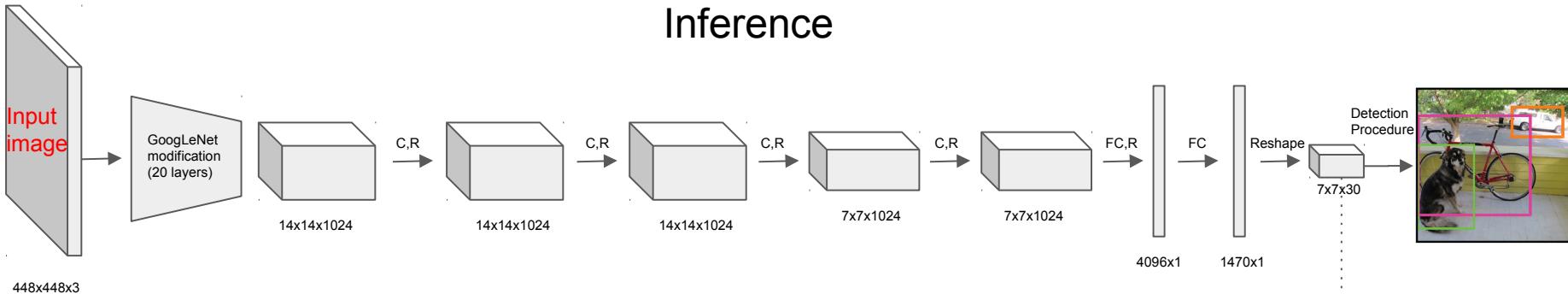
Inference



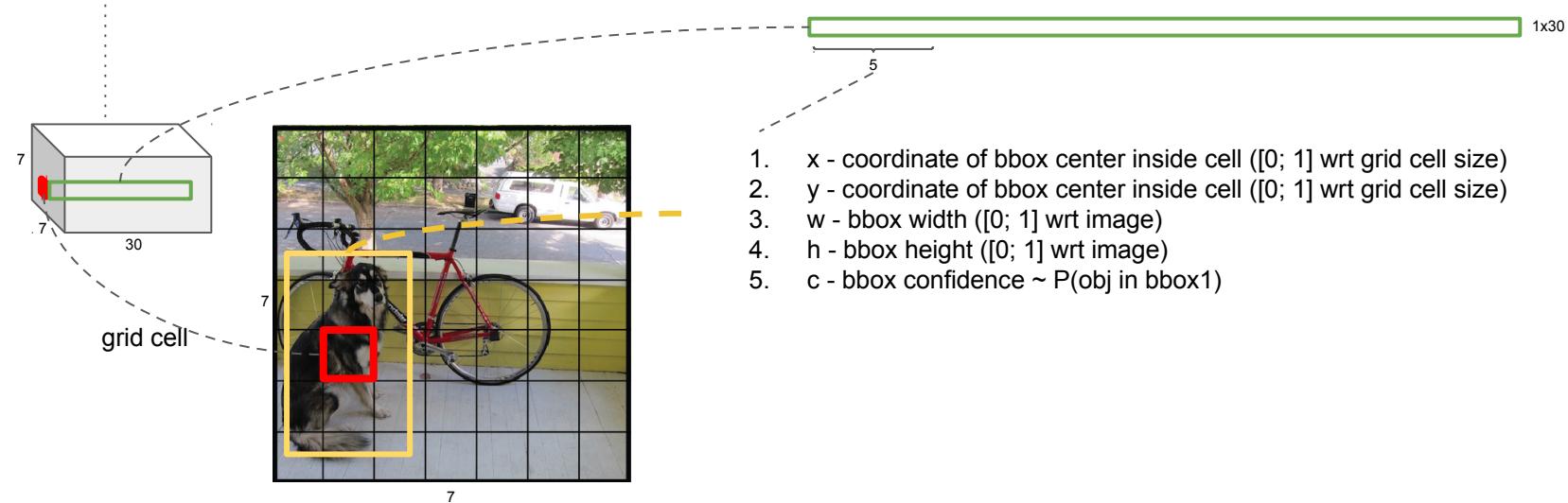
Tensor values interpretation



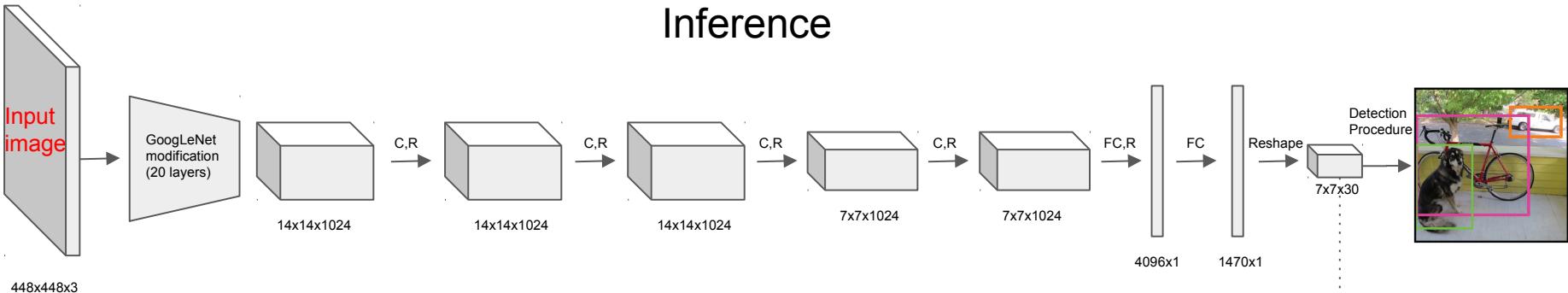
Inference



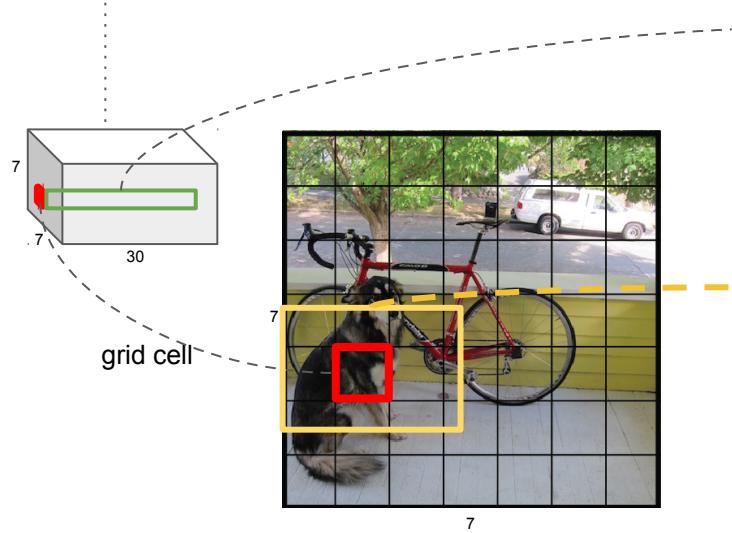
Tensor values interpretation



Inference



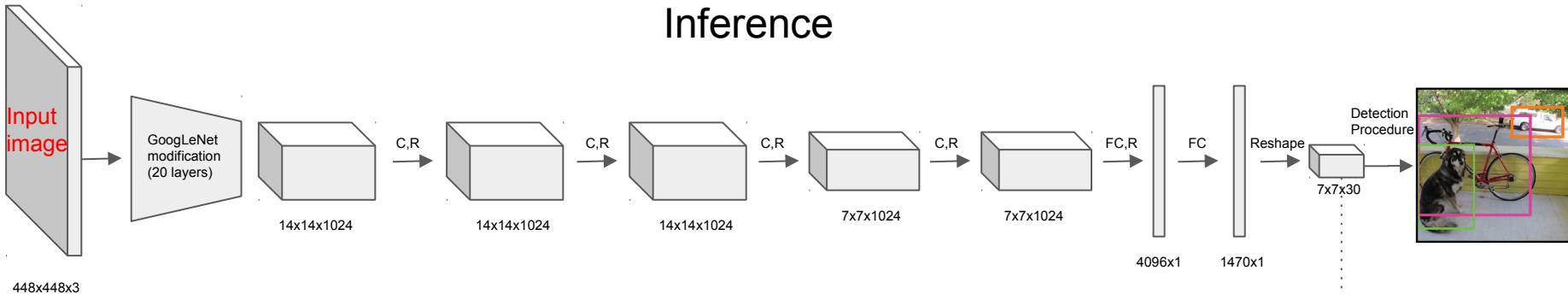
Tensor values interpretation



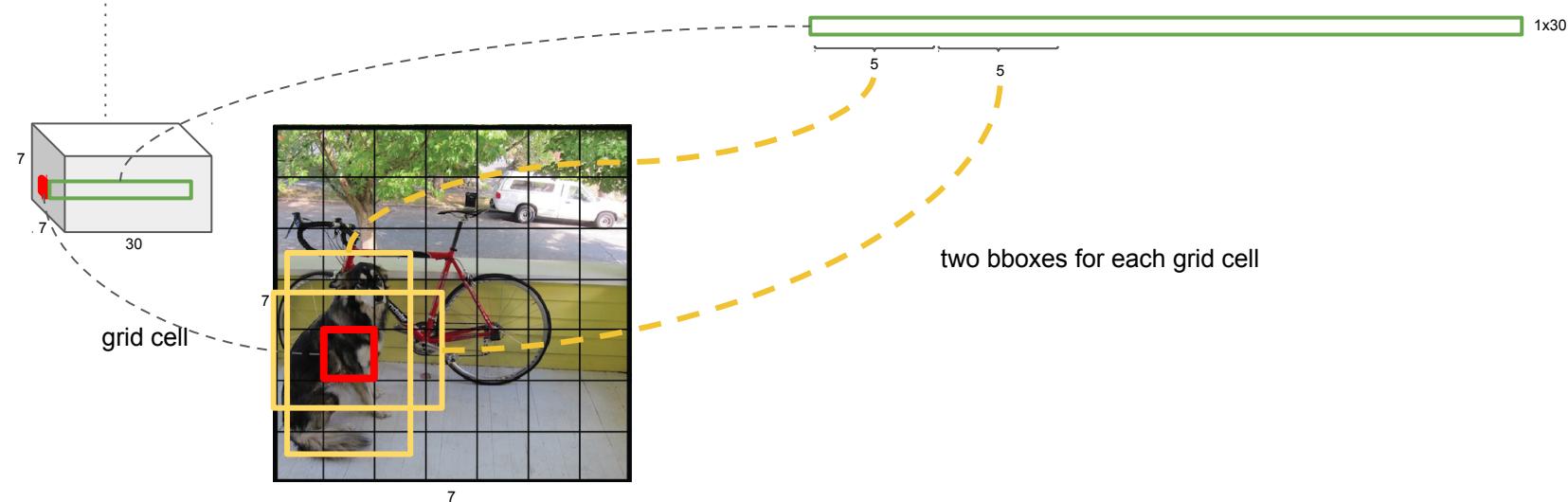
1. x - coordinate of bbox center inside cell ([0; 1] wrt grid cell size)
2. y - coordinate of bbox center inside cell ([0; 1] wrt grid cell size)
3. w - bbox width ([0; 1] wrt image)
4. h - bbox height ([0; 1] wrt image)
5. c - bbox **confidence**

$$\text{confidence} = \Pr(\text{Object}) \times \text{IoU}_{\text{pred}}^{\text{truth}}$$

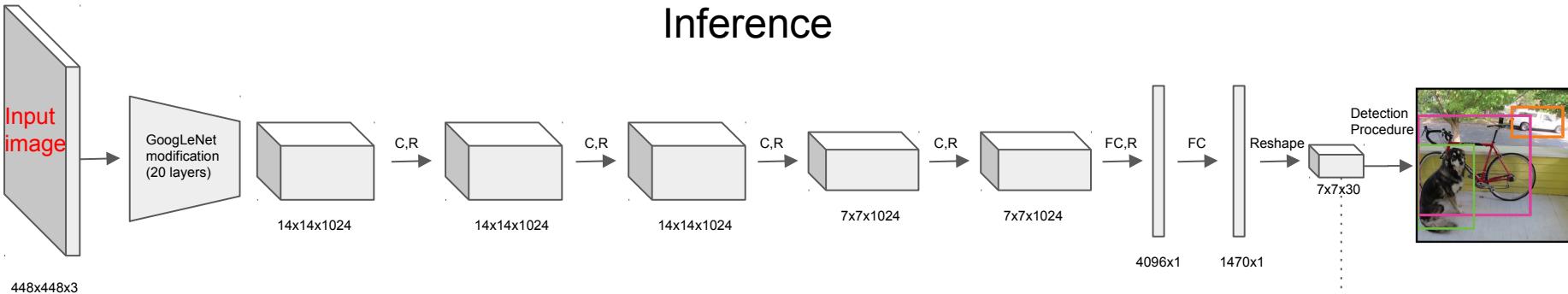
Inference



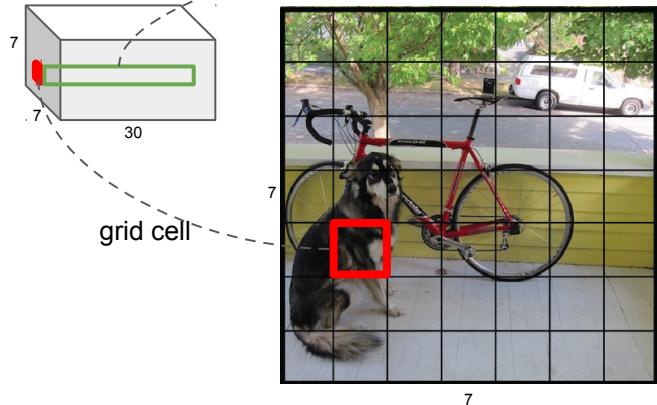
Tensor values interpretation



Inference



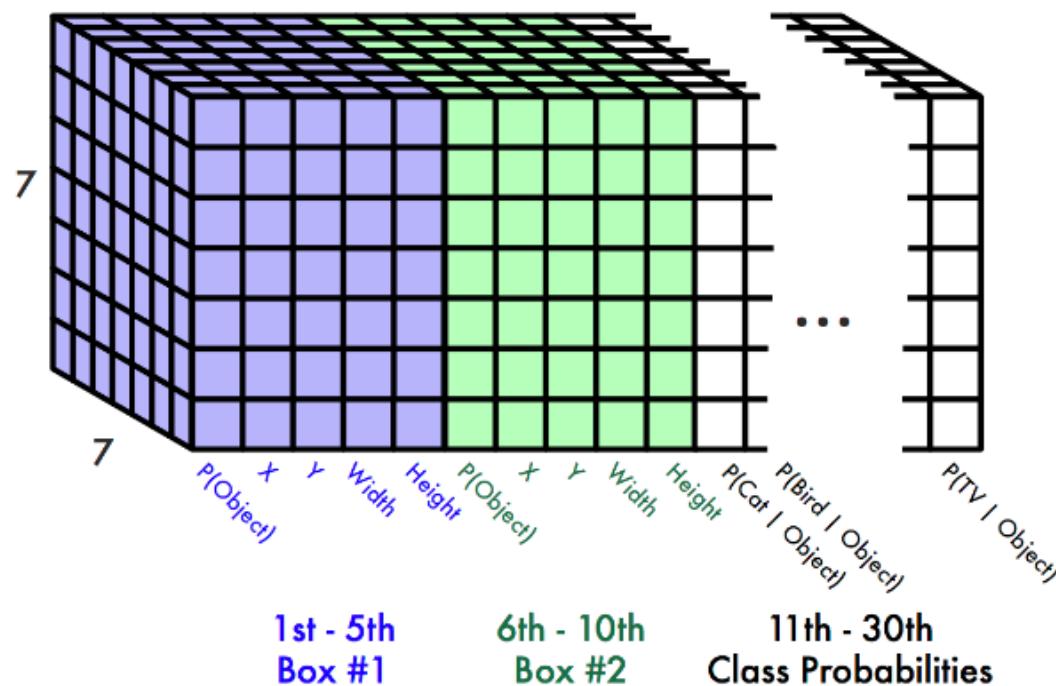
Tensor values interpretation



This parameterization fixes the output size

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

$$7 \times 7 \times (2 \times 5 + 20) = 7 \times 7 \times 30 \text{ tensor} = \mathbf{1470 \text{ outputs}}$$

LOSS

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

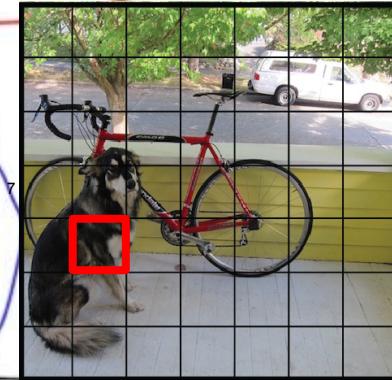
坐标误差

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

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

IOU误差

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



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

分类误差

3. Testing

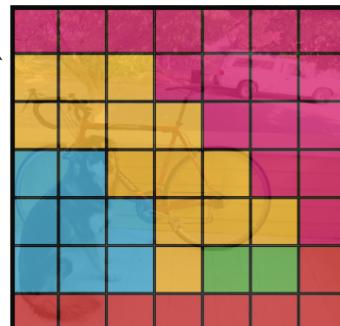
Non-max suppression NMS



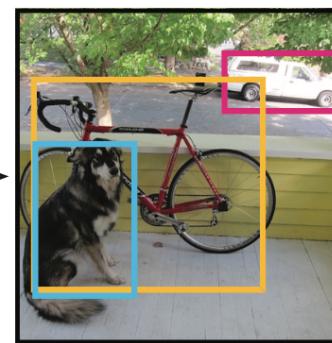
$S \times S$ grid on input



Bounding boxes + confidence

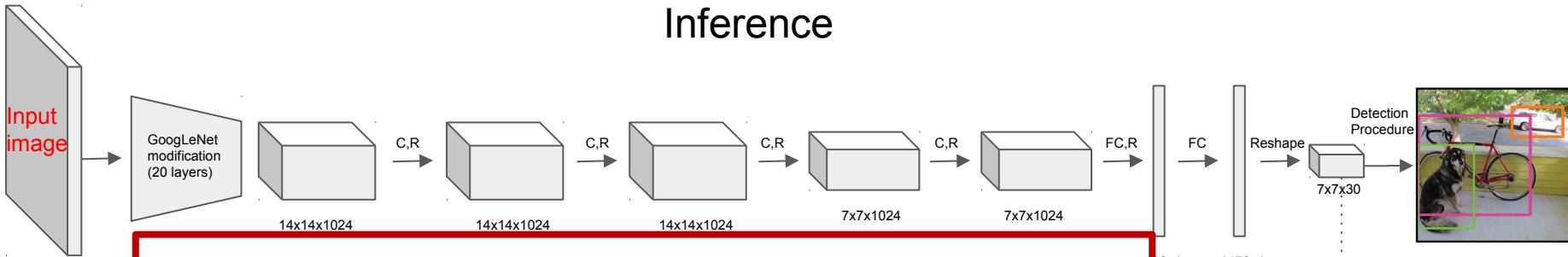


Class probability map

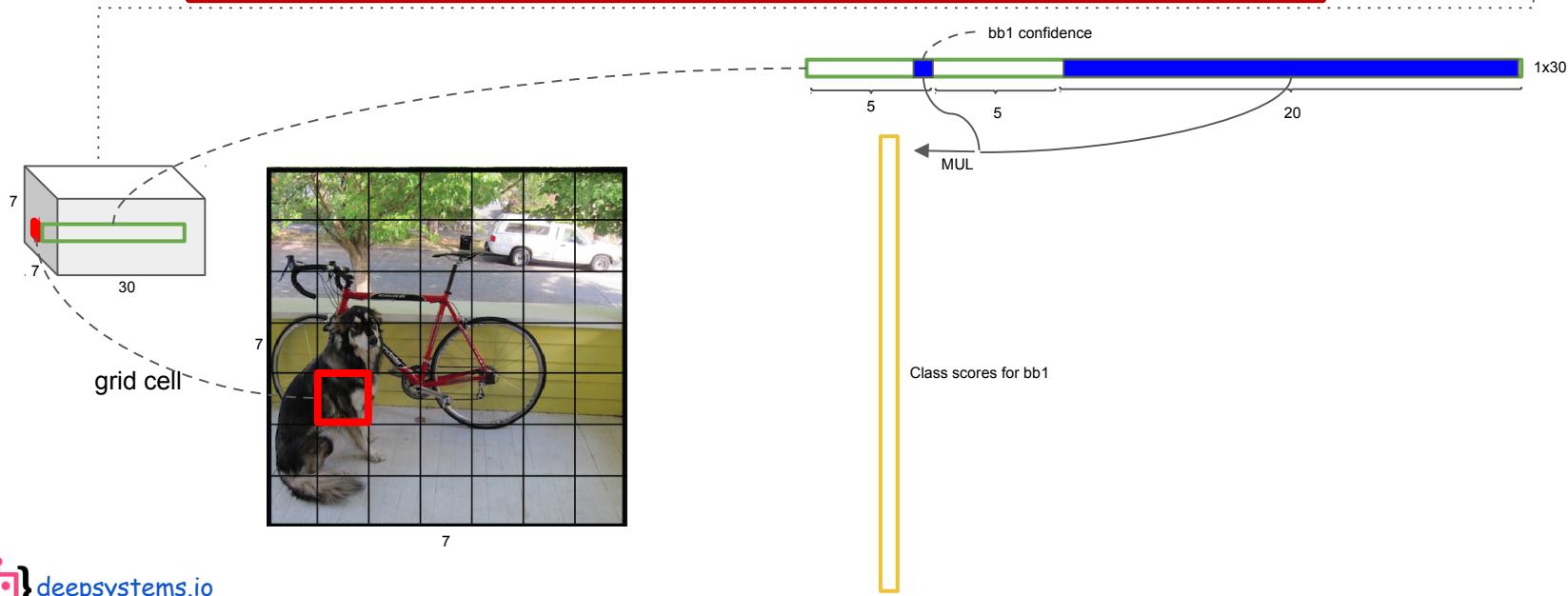


Final detections

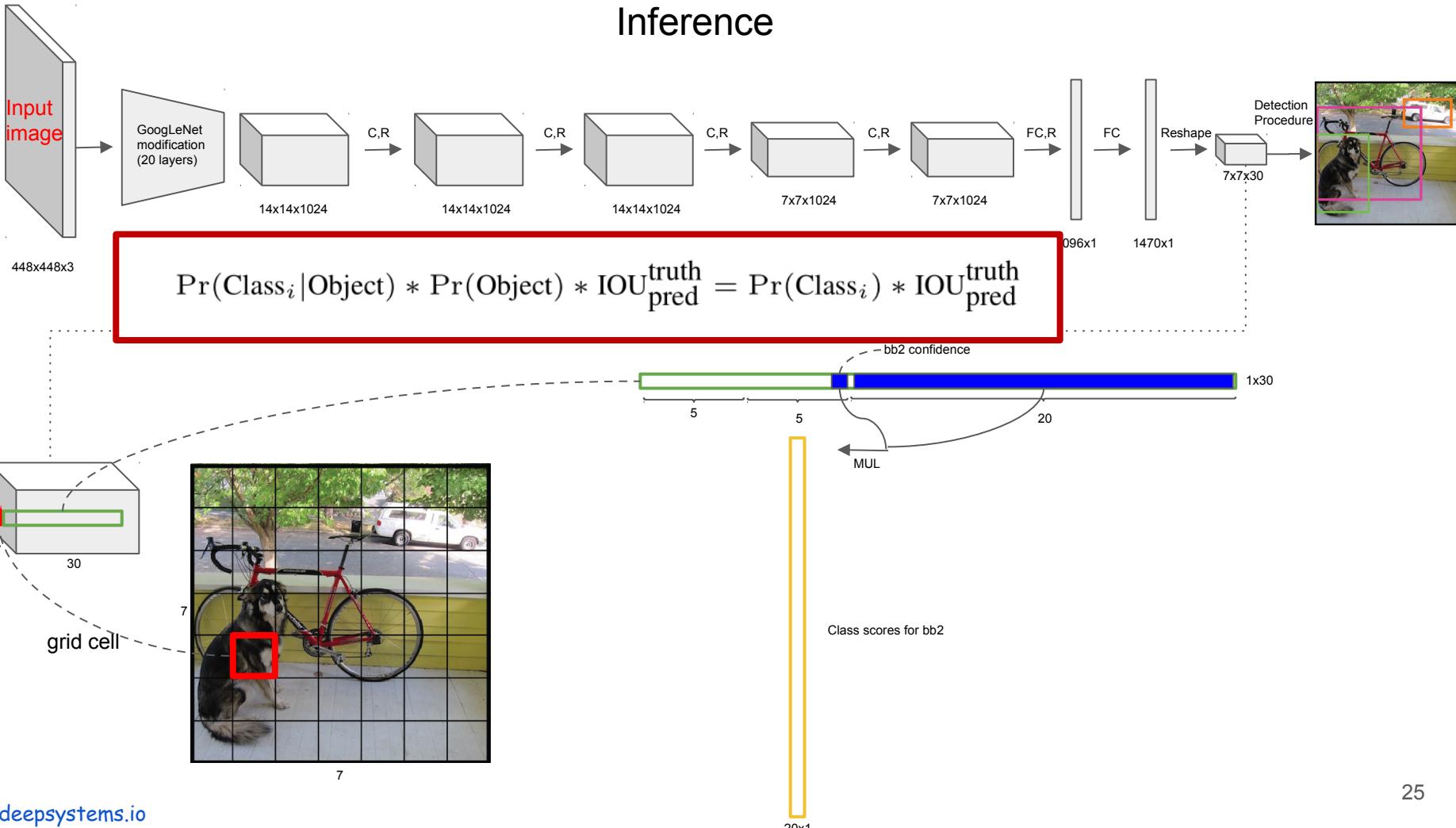
Inference



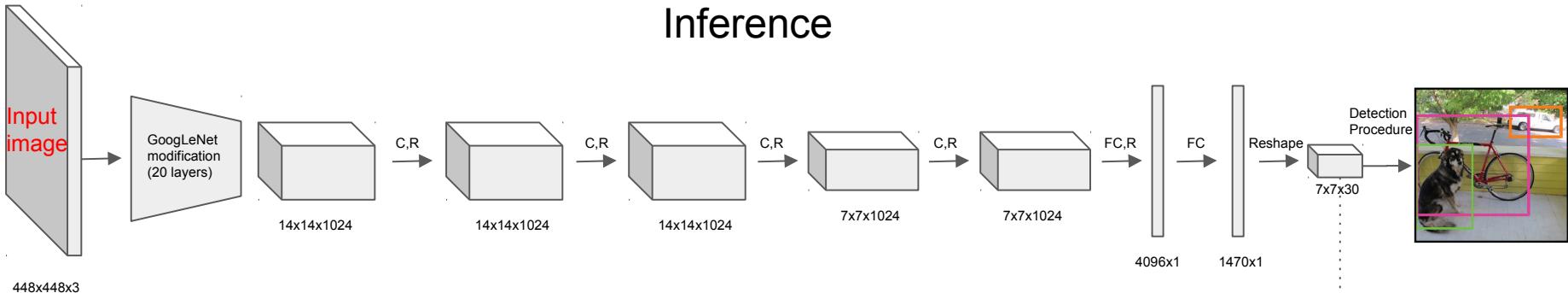
$$\Pr(\text{Class}_i \mid \text{Object}) * \Pr(\text{Object}) * \text{IOU}_{\text{pred}}^{\text{truth}} = \Pr(\text{Class}_i) * \text{IOU}_{\text{pred}}^{\text{truth}}$$



Inference

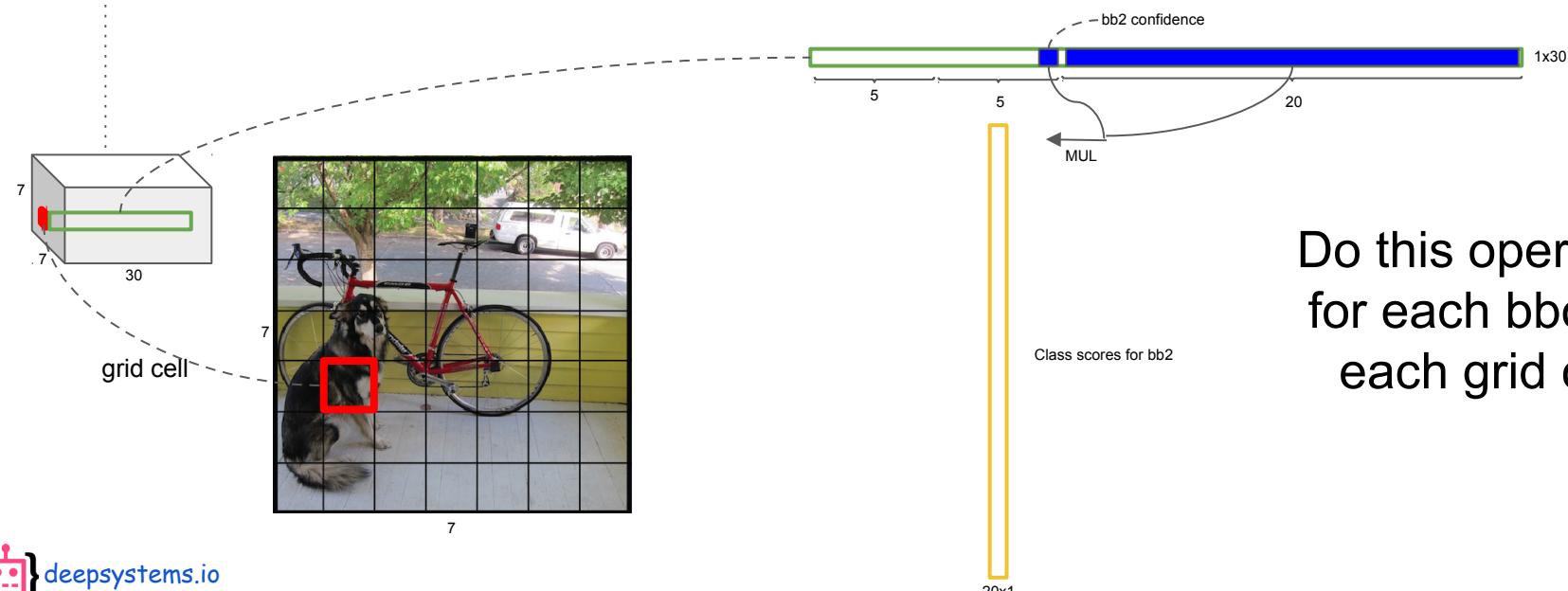


Inference



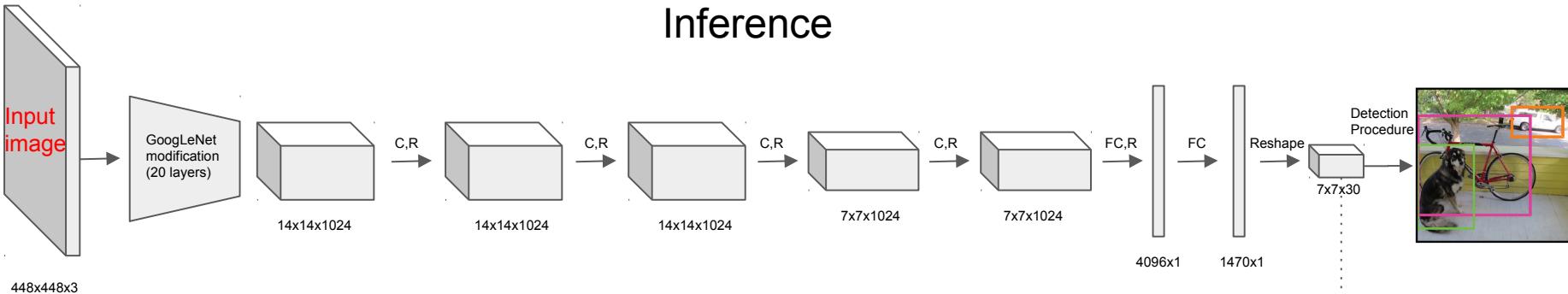
448x448x3

Tensor values interpretation

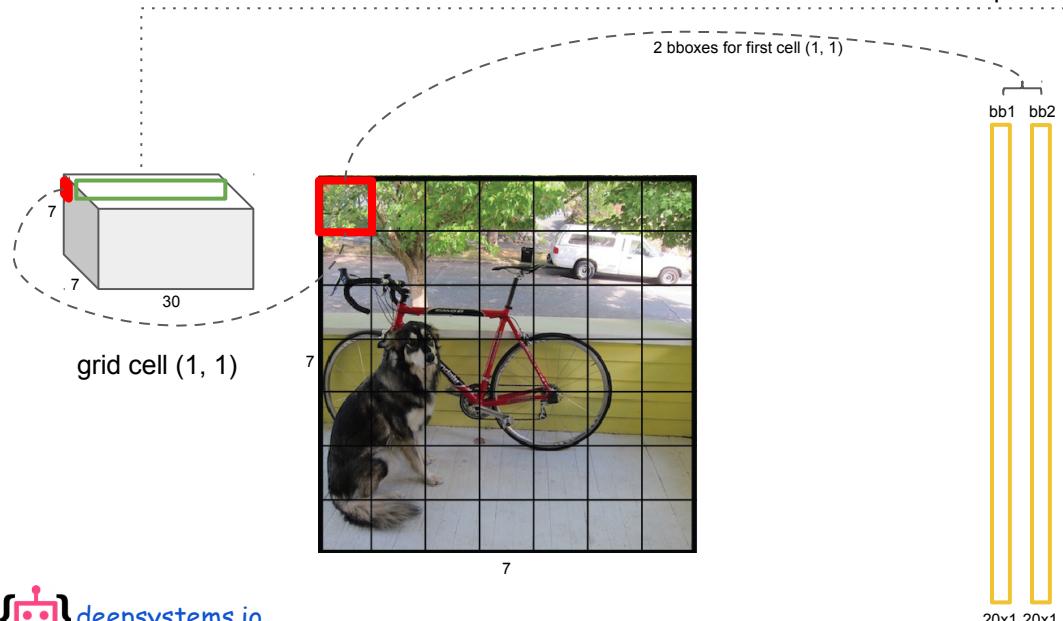


Do this operation
for each bbox in
each grid cell

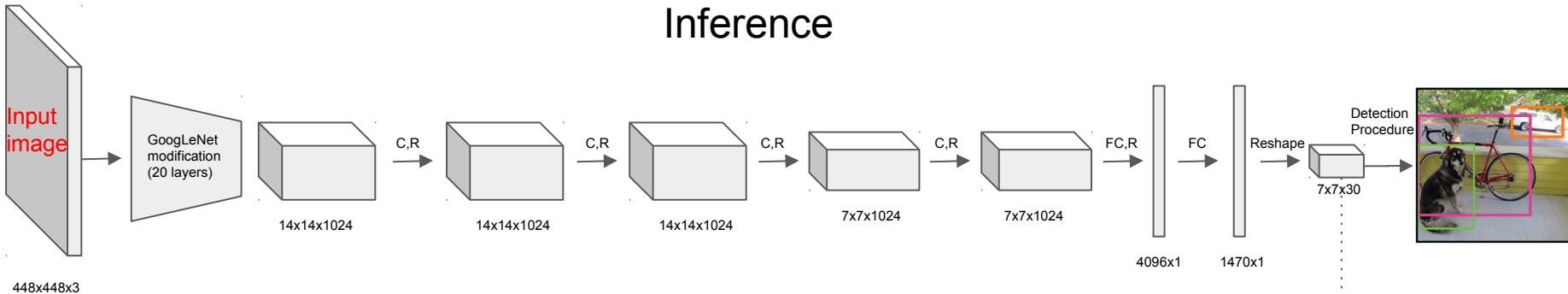
Inference



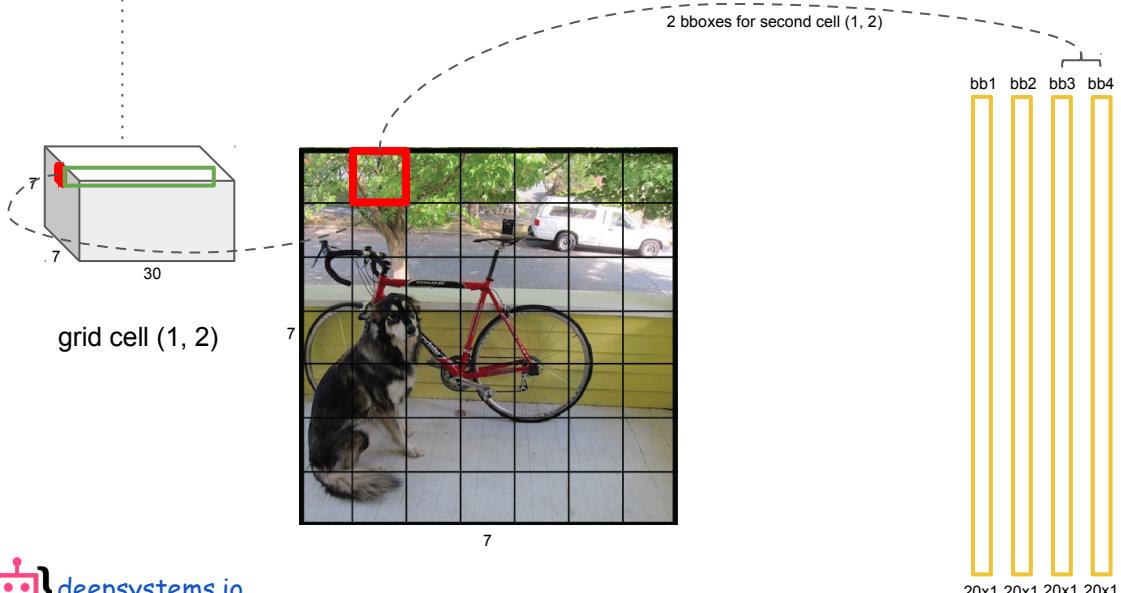
Tensor values interpretation



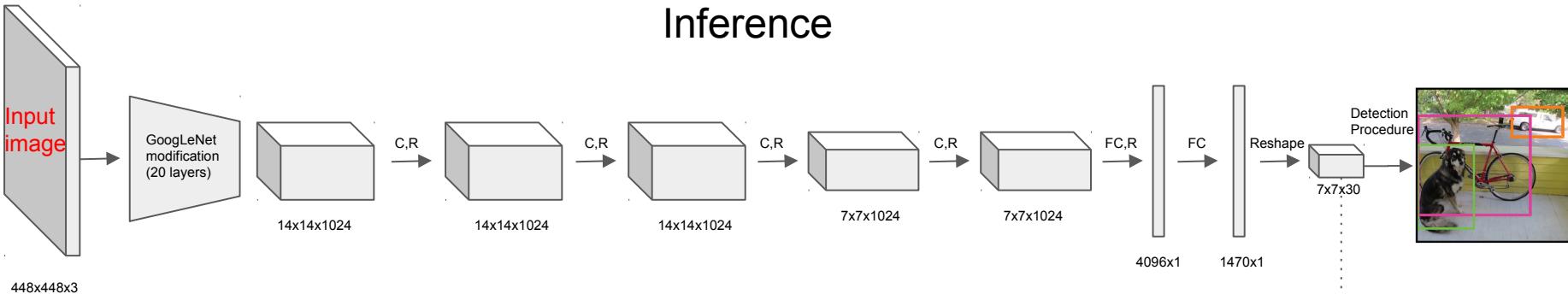
Inference



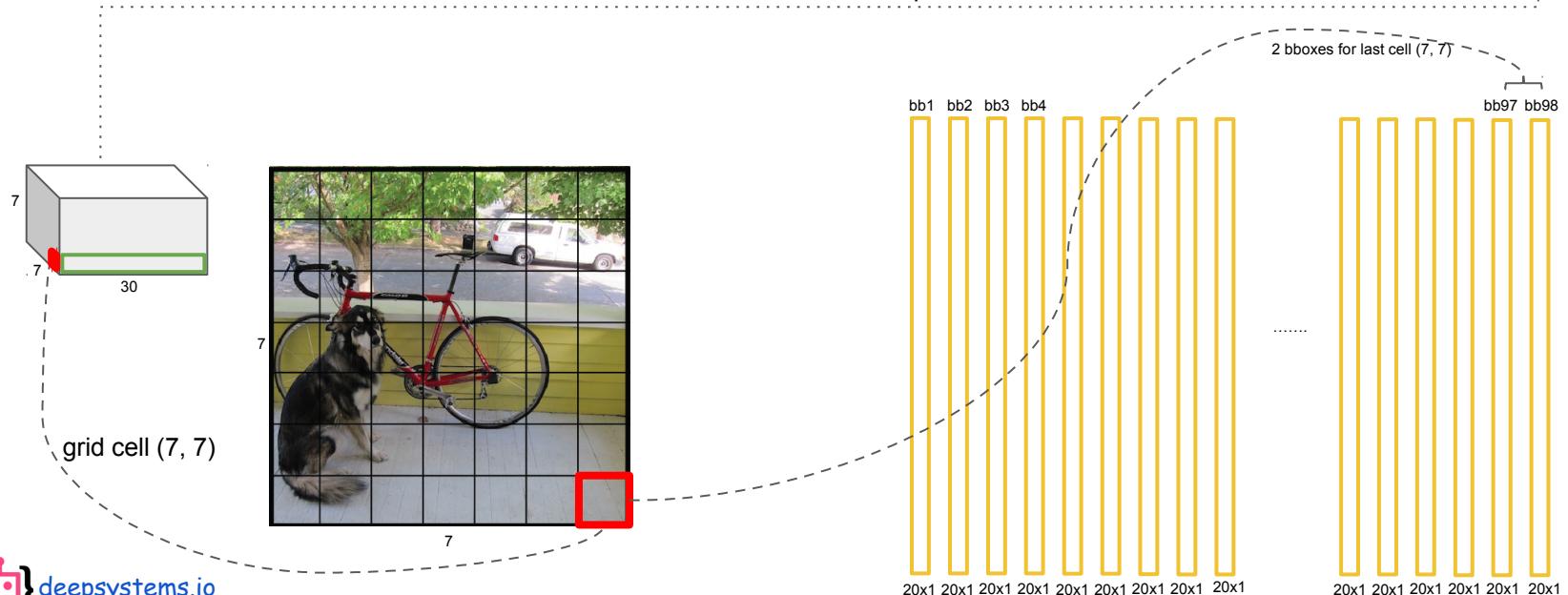
Tensor values interpretation



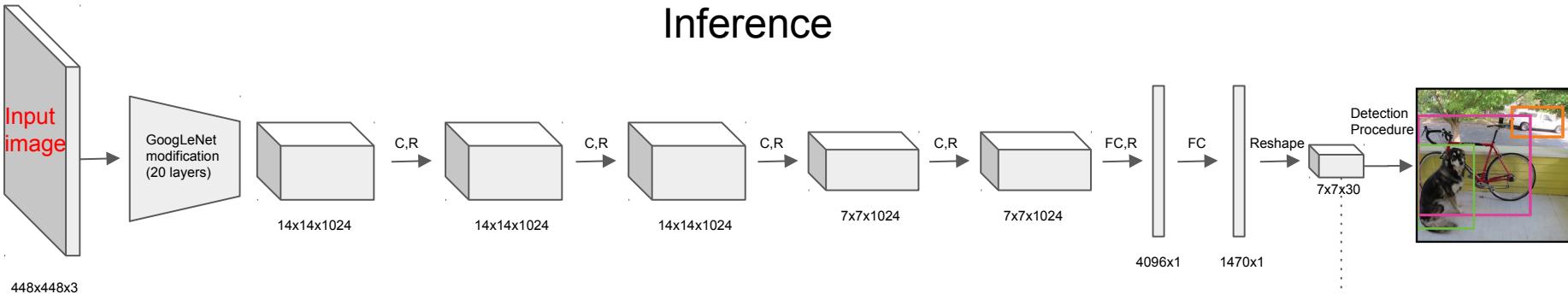
Inference



Tensor values interpretation

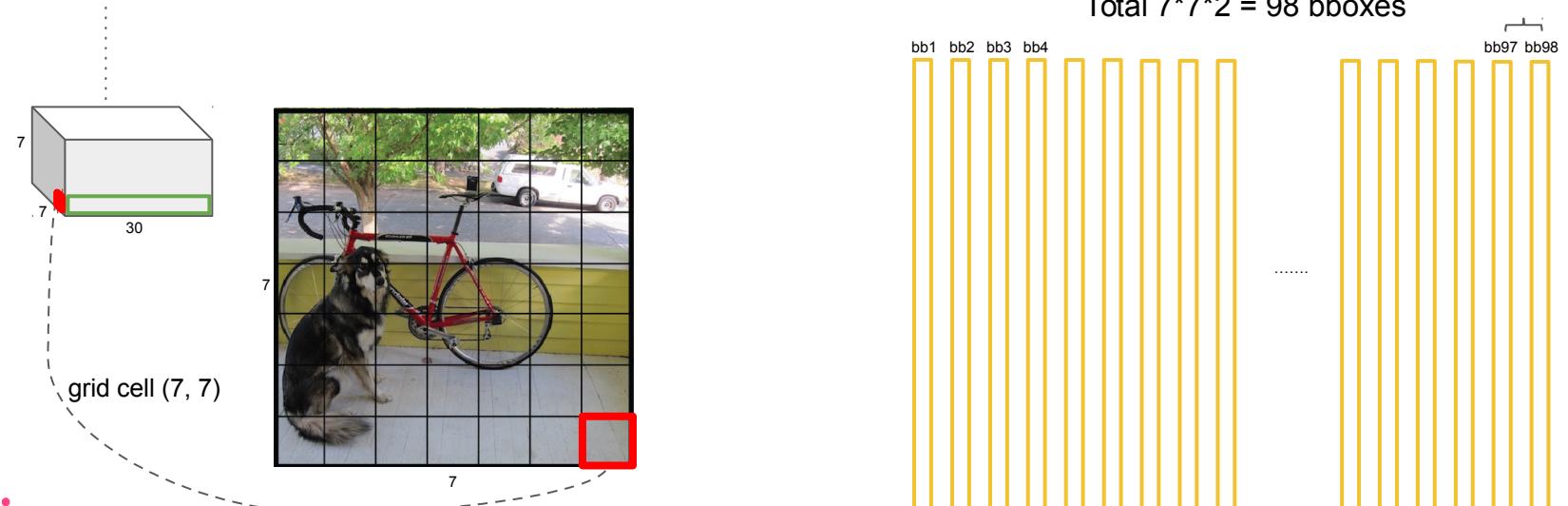


Inference

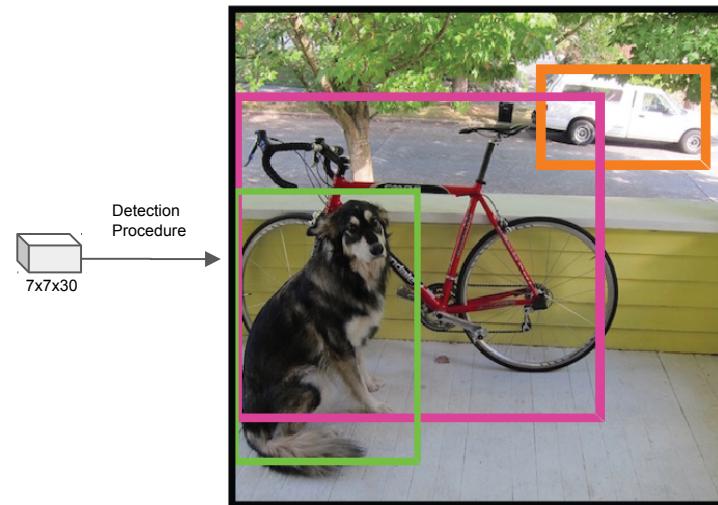


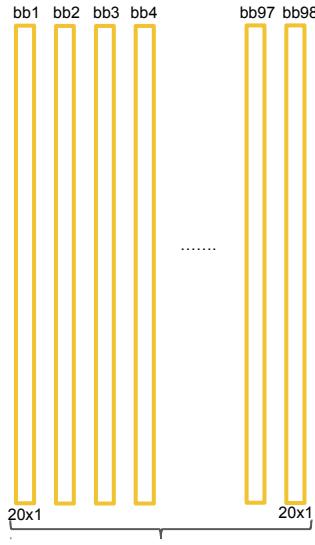
Tensor values interpretation

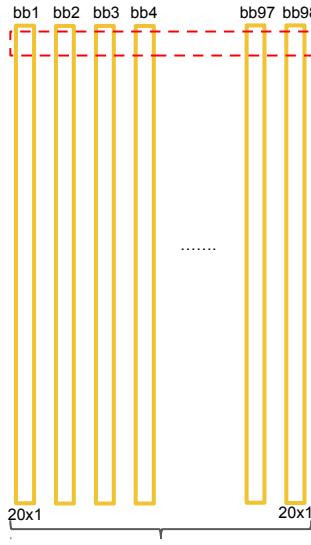
Total $7 \times 7 \times 2 = 98$ bboxes



Look at detection procedure

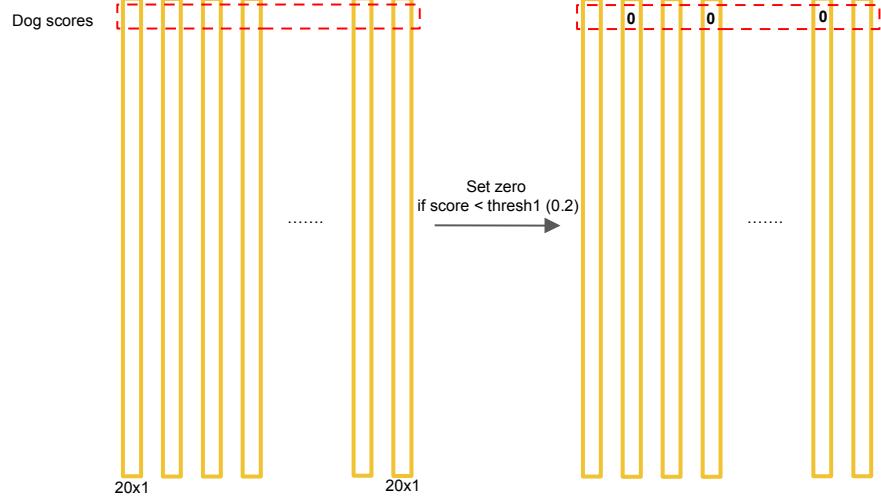


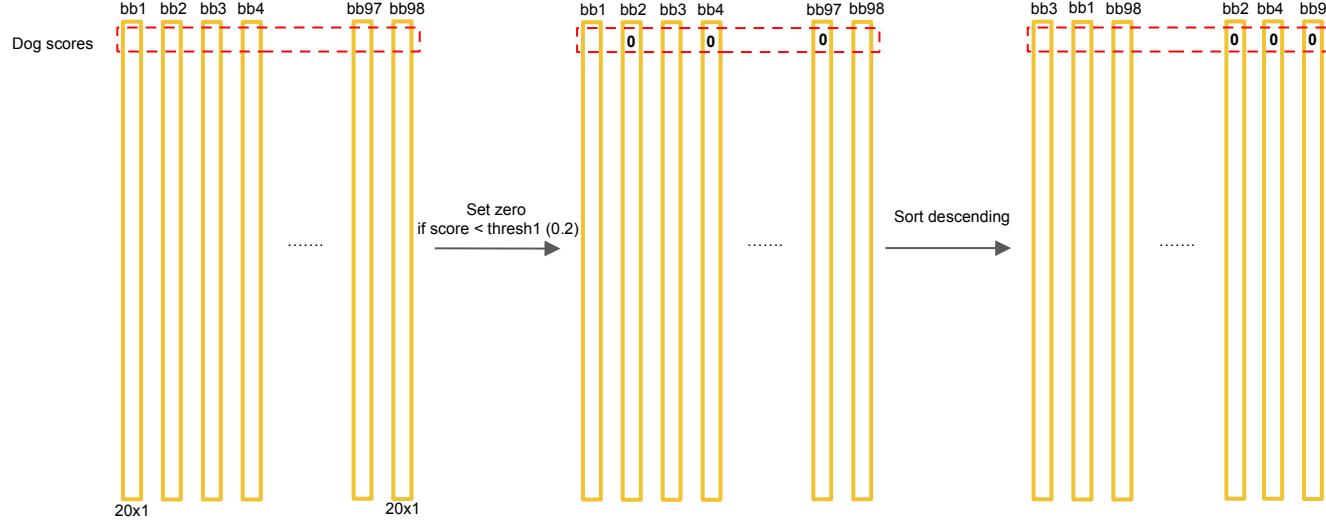


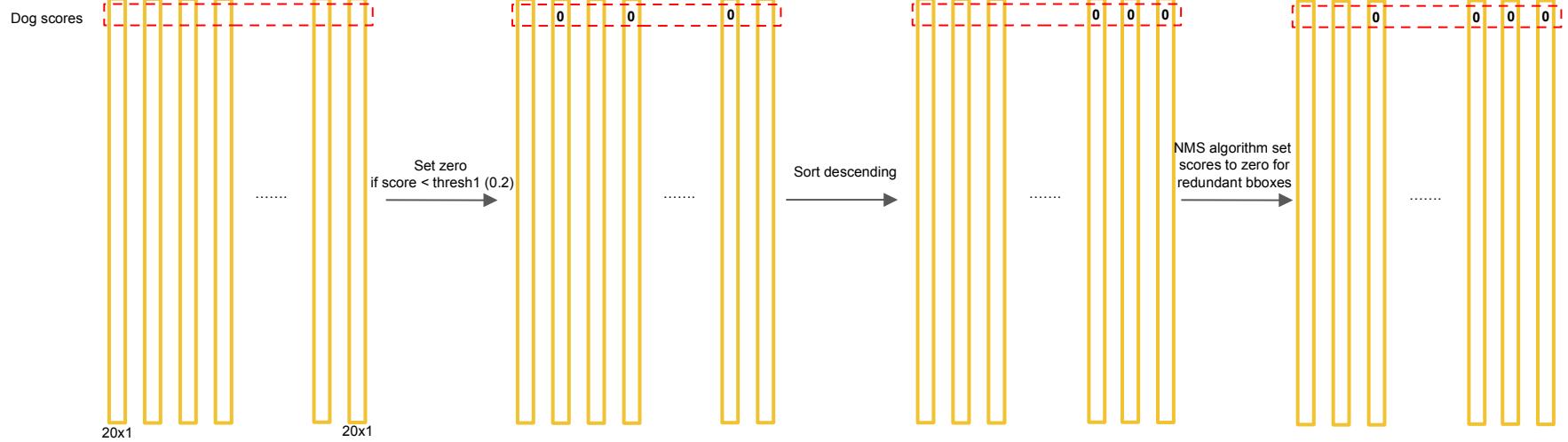


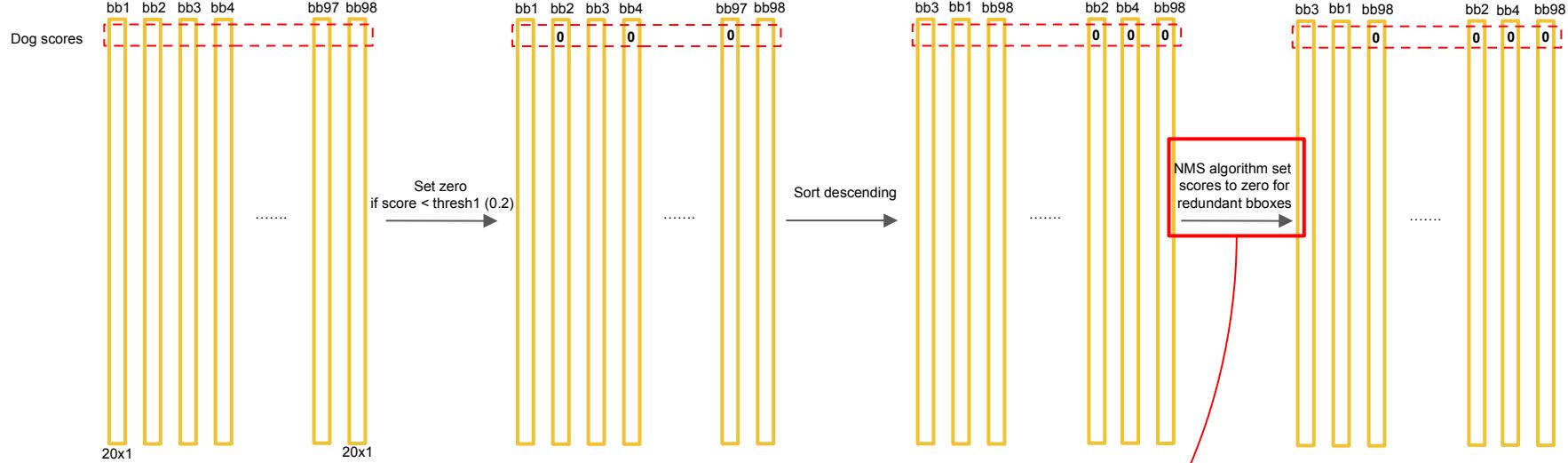
Class scores for each bbox

Get first class scores for each bbox









How it works

Non-Maximum Suppression: intuition

Non-Maximum Suppression: intuition

class (dog) scores for each bbox

class: dog

	bb47	bb20	bb15	bb7													bb1	bb4	bb8	bb98
	0.8	0.5	0.3	0.2												0	0	0	0	

1x98

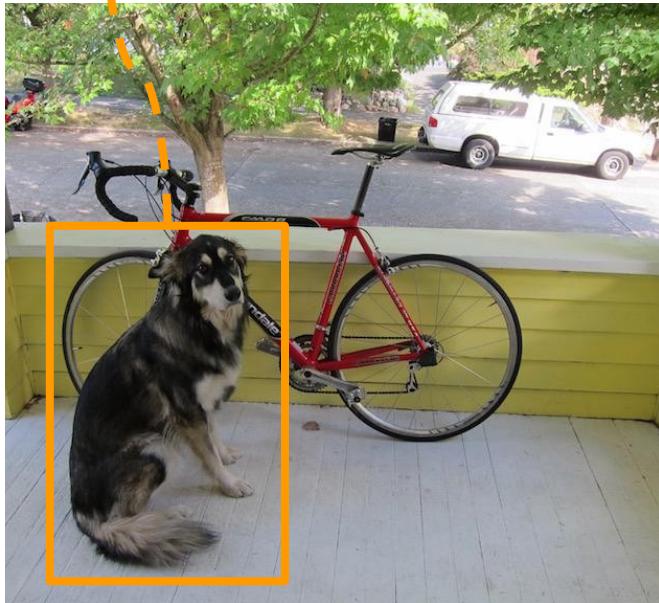
Non-Maximum Suppression: intuition

class: dog

bb47	bb20	bb15	bb7					
0.8	0.5	0.3	0.2					

bb1	bb4	bb8	bb98
0	0	0	0

1x98



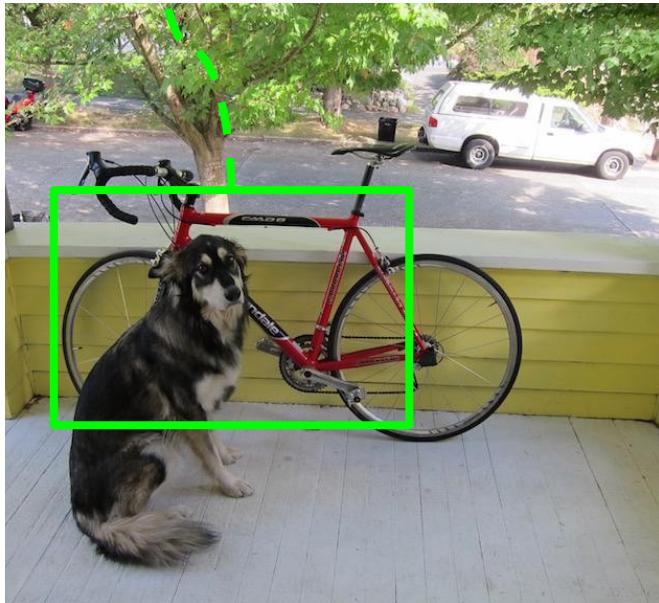
Non-Maximum Suppression: intuition

class: dog

bb47	bb20	bb15	bb7					
0.8	0.5	0.3	0.2					

bb1	bb4	bb8	bb98
0	0	0	0

1x98



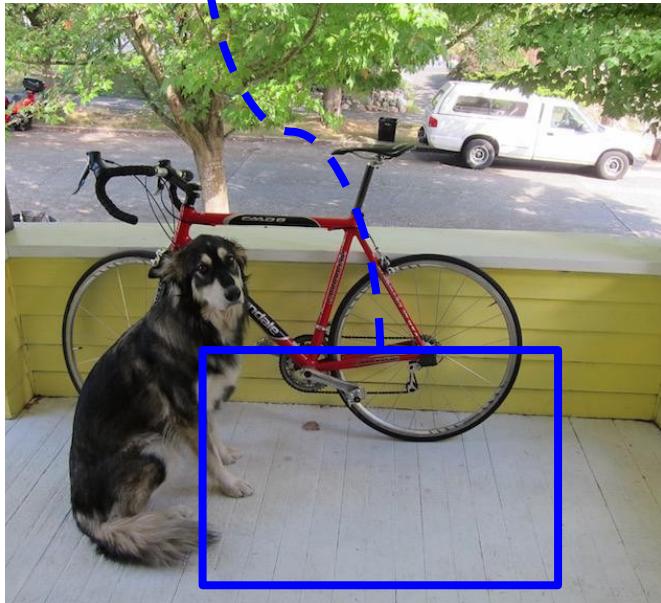
Non-Maximum Suppression: intuition

class: dog

bb47	bb20	bb15	bb7					
0.8	0.5	0.3	0.2					

bb1	bb4	bb8	bb98
0	0	0	0

1x98



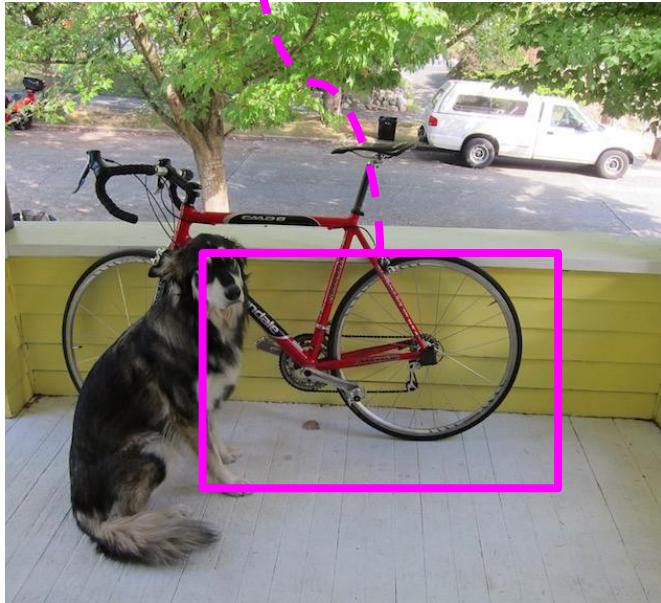
Non-Maximum Suppression: intuition

class: dog

bb47	bb20	bb15	bb7					
0.8	0.5	0.3	0.2					

bb1	bb4	bb8	bb98
0	0	0	0

1x98



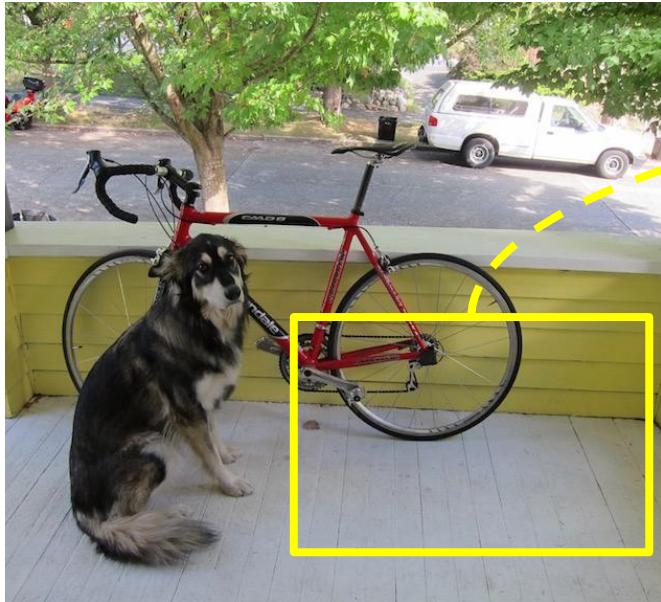
Non-Maximum Suppression: intuition

class: dog

bb47	bb20	bb15	bb7					
0.8	0.5	0.3	0.2					

bb1	bb4	bb8	bb98
0	0	0	0

1x98



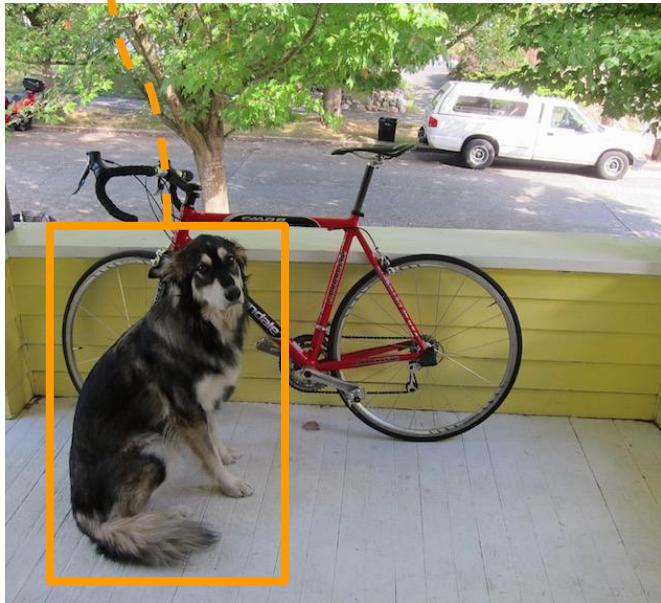
Non-Maximum Suppression: intuition

class: dog

bb47	bb20	bb15	bb7					
0.8	0.5	0.3	0.2					

bb1	bb4	bb8	bb98
0	0	0	0

1x98



Get bbox with max score. Let's denote it “bbox_max”

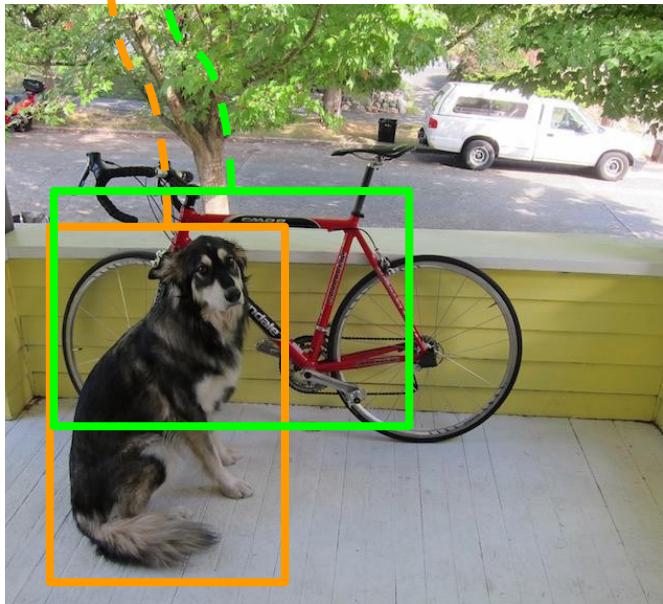
Non-Maximum Suppression: intuition

class: dog

bb47	bb20	bb15	bb7					
0.8	0.5	0.3	0.2					

bb1	bb4	bb8	bb98
0	0	0	0

1x98



Compare “`bbox_max`” with others less score (non-zero!) bboxes. Let’s denote it “`bbox_cur`”

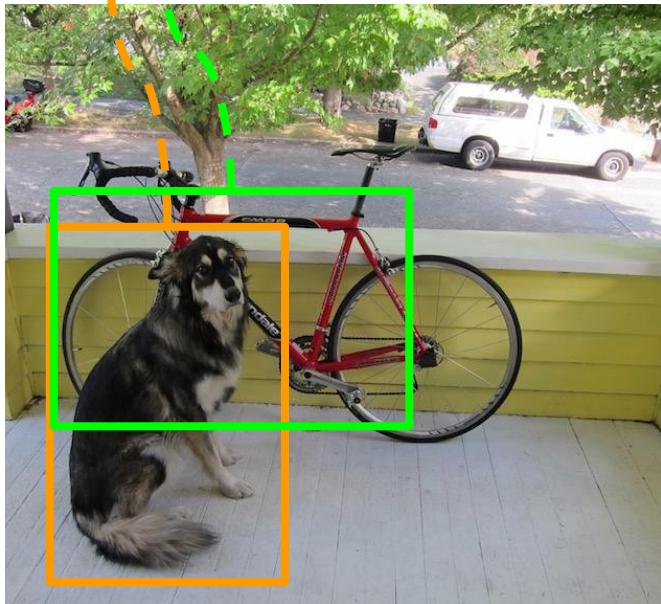
Non-Maximum Suppression: intuition

class: dog

bb47	bb20	bb15	bb7					
0.8	0.5	0.3	0.2					

bb1	bb4	bb8	bb98
0	0	0	0

1x98



If $\text{IoU}(\text{bbox_max}, \text{bbox_cur}) > 0.5$ then set 0 score to bbox_cur .

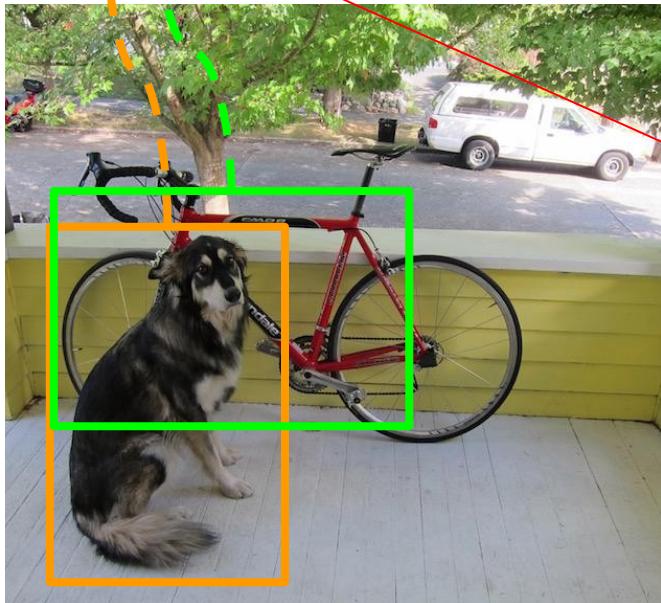
Non-Maximum Suppression: intuition

class: dog

bb47	bb20	bb15	bb7					
0.8	0	0.3	0.2					

bb1	bb4	bb8	bb98
0	0	0	0

1x98



If $\text{IoU}(\text{bbox}_{\text{max}}, \text{bbox}_{\text{cur}}) > 0.5$ then set 0 score to bbox_{cur} .

In this case: set to 0.

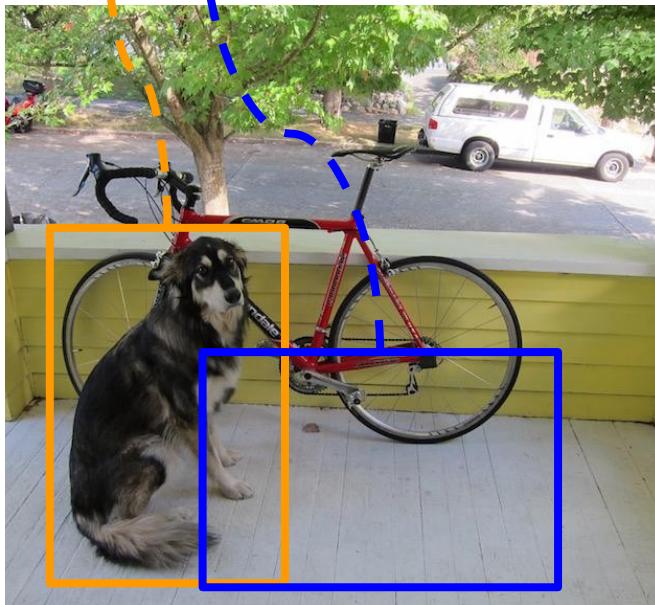
Non-Maximum Suppression: intuition

class: dog

bb47	bb20	bb15	bb7
0.8	0	0.3	0.2

bb1	bb4	bb8	bb98
0	0	0	0

1x98



Go to next `bbox_cur`.

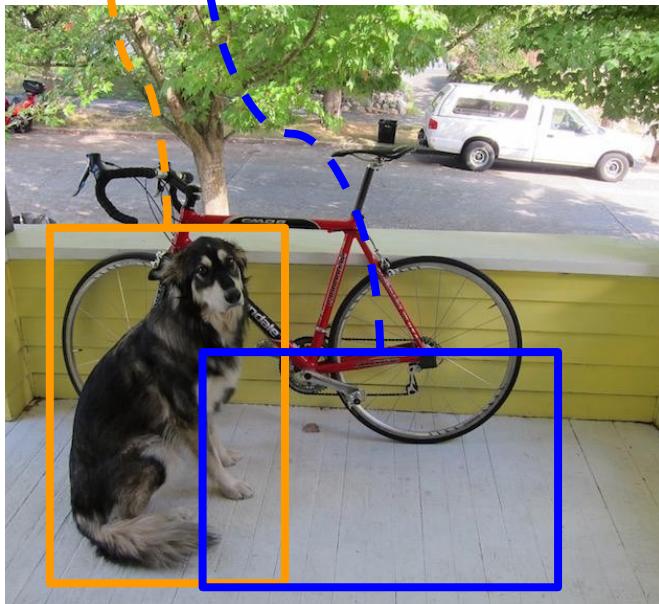
Non-Maximum Suppression: intuition

class: dog

bb47	bb20	bb15	bb7
0.8	0	0.3	0.2

bb1	bb4	bb8	bb98
0	0	0	0

1x98



Go to next `bbox_cur`.

If $\text{IoU}(\text{bbox}_{\text{max}}, \text{bbox}_{\text{cur}}) > 0.5$ then set 0 score to `bbox_cur`.

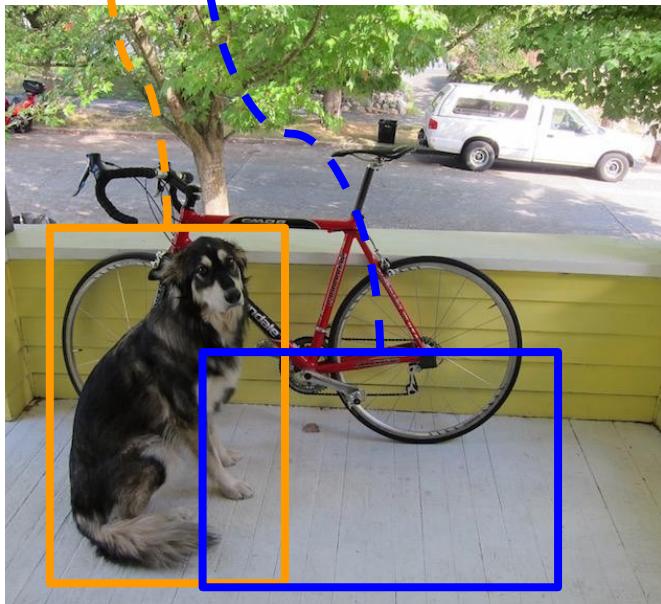
Non-Maximum Suppression: intuition

class: dog

bb47	bb20	bb15	bb7					
0.8	0	0.3	0.2					

bb1	bb4	bb8	bb98
0	0	0	0

1x98



Go to next `bbox_cur`.

If $\text{IoU}(\text{bbox_max}, \text{bbox_cur}) > 0.5$ then set 0 score to `bbox_cur`.

In this case: continue.

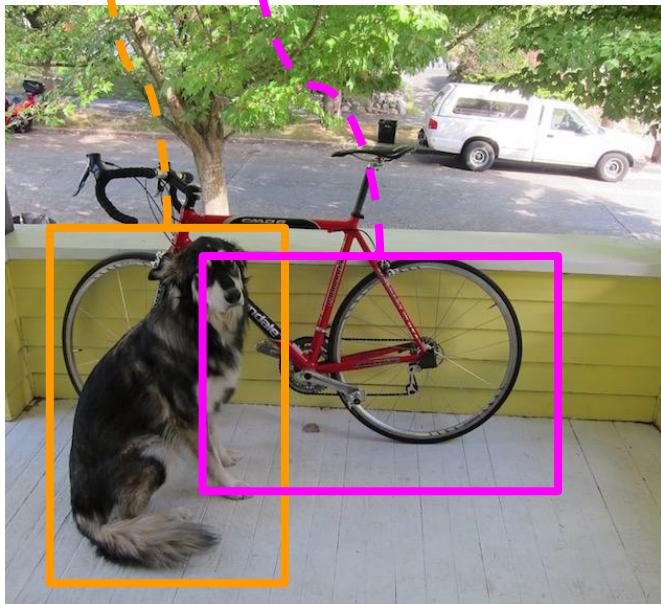
Non-Maximum Suppression: intuition

class: dog

bb47	bb20	bb15	bb7
0.8	0	0.3	0.2

bb1	bb4	bb8	bb98
0	0	0	0

1x98



Go to next `bbox_cur`.

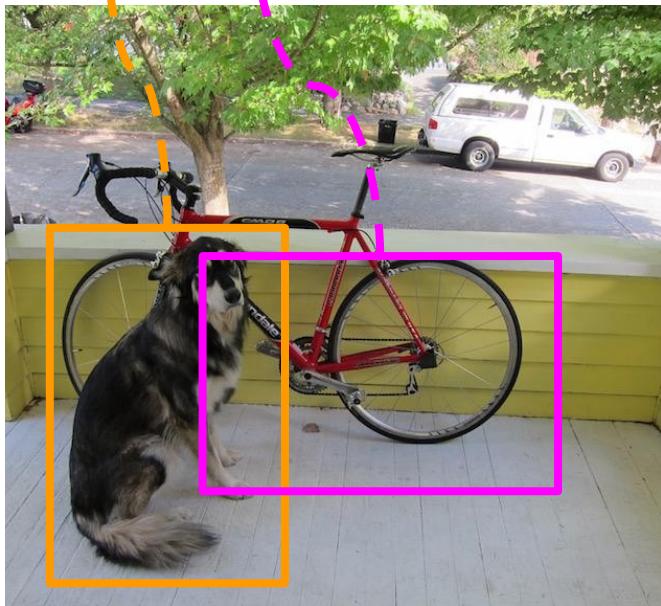
Non-Maximum Suppression: intuition

class: dog

bb47	bb20	bb15	bb7					
0.8	0	0.3	0.2					

bb1	bb4	bb8	bb98
0	0	0	0

1x98



Go to next `bbox_cur`.

If $\text{IoU}(\text{bbox}_{\text{max}}, \text{bbox}_{\text{cur}}) > 0.5$ then set 0 score to `bbox_cur`.

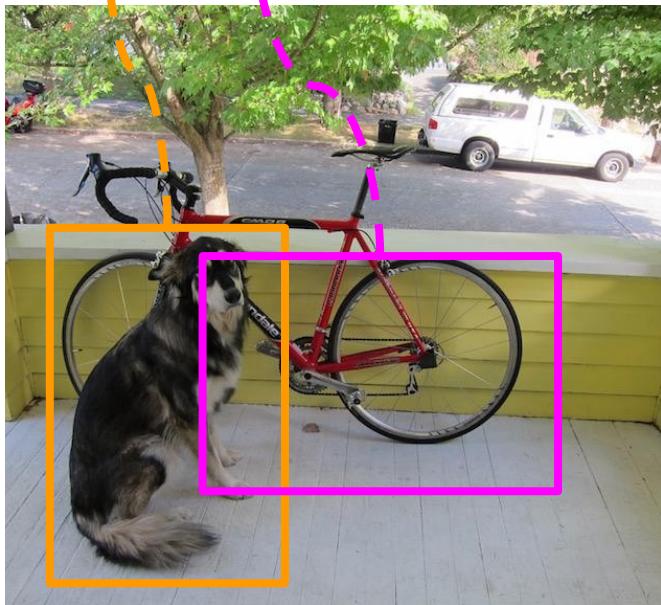
Non-Maximum Suppression: intuition

class: dog

bb47	bb20	bb15	bb7					
0.8	0	0.3	0.2					

bb1	bb4	bb8	bb98
0	0	0	0

1x98



Go to next `bbox_cur`.

If $\text{IoU}(\text{bbox}_{\text{max}}, \text{bbox}_{\text{cur}}) > 0.5$ then set 0 score to `bbox_cur`.

In this case: continue.

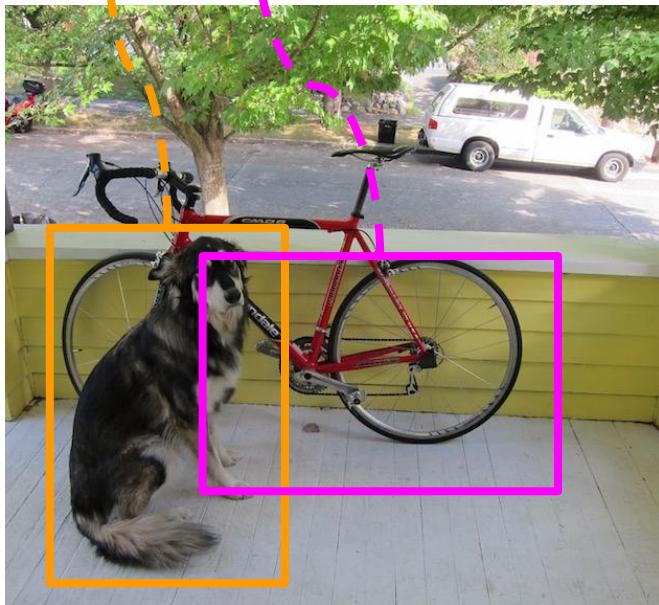
Non-Maximum Suppression: intuition

class: dog

bb47	bb20	bb15	bb7					
0.8	0	0.3	0.2					

bb1	bb4	bb8	bb98
0	0	0	0

1x98



Go to next `bbox_cur`.

If $\text{IoU}(\text{bbox}_{\text{max}}, \text{bbox}_{\text{cur}}) > 0.5$ then set 0 score to `bbox_cur`.

In this case: continue.

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

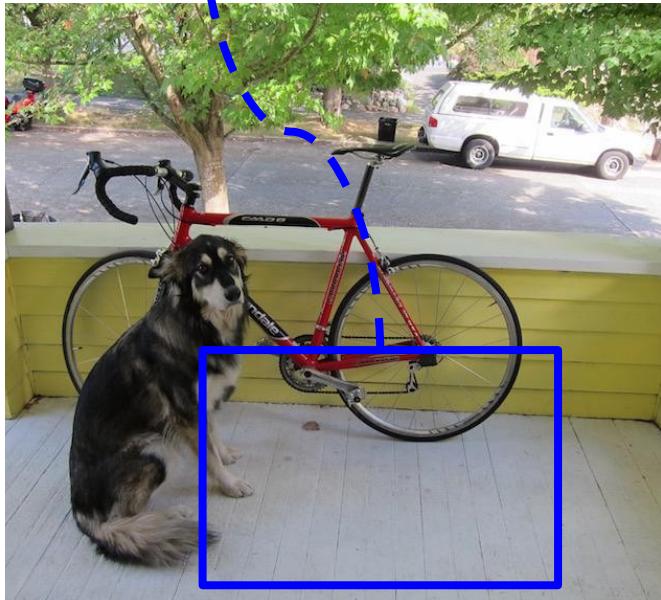
Non-Maximum Suppression: intuition

class: dog

bb47	bb20	bb15	bb7
0.8	0	0.3	0.2

bb1	bb4	bb8	bb98
0	0	0	0

1x98



Go to next bbox with big score. Let's denote it “bbox_max”

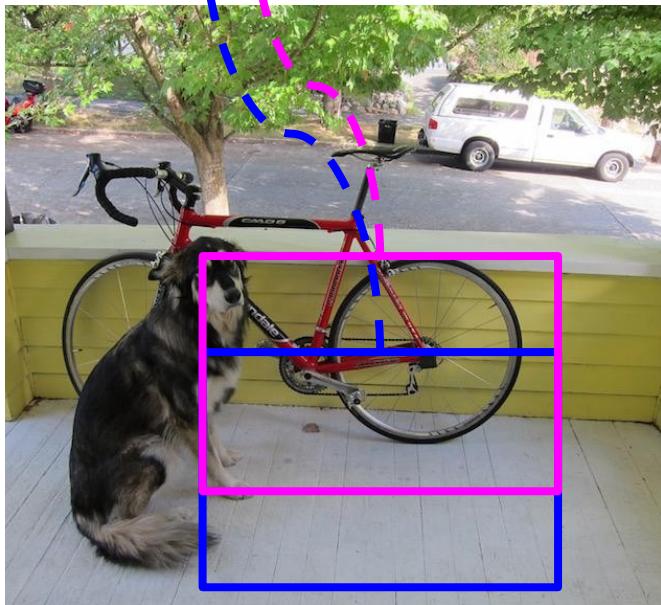
Non-Maximum Suppression: intuition

class: dog

bb47	bb20	bb15	bb7
0.8	0	0.3	0.2

bb1	bb4	bb8	bb98
0	0	0	0

1x98



Go to next `bbox_cur`.

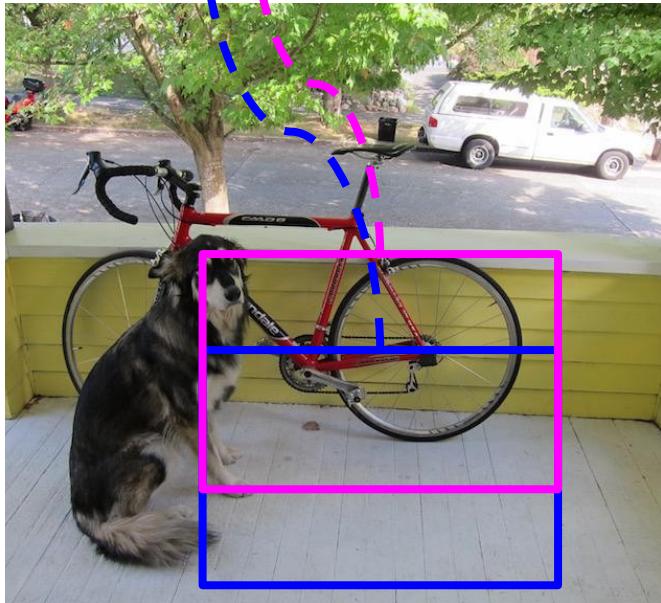
Non-Maximum Suppression: intuition

class: dog

bb47	bb20	bb15	bb7
0.8	0	0.3	0.2

bb1	bb4	bb8	bb98
0	0	0	0

1x98



Go to next `bbox_cur`.

If $\text{IoU}(\text{bbox}_{\text{max}}, \text{bbox}_{\text{cur}}) > 0.5$ then set 0 score to `bbox_cur`.

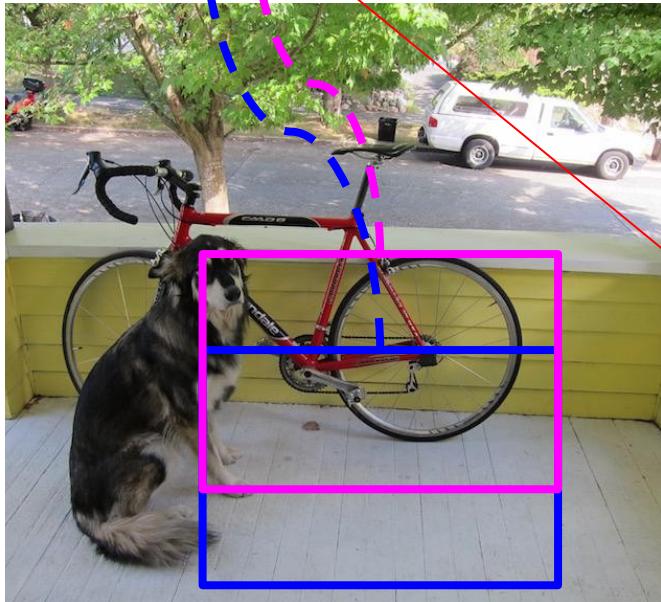
Non-Maximum Suppression: intuition

class: dog

bb47	bb20	bb15	bb7						
0.8	0	0.3	0						

bb1	bb4	bb8	bb98
0	0	0	0

1x98



Go to next `bbox_cur`.

If $\text{IoU}(\text{bbox}_{\text{max}}, \text{bbox}_{\text{cur}}) > 0.5$ then set 0 score to `bbox_cur`.

In this case: set to 0.

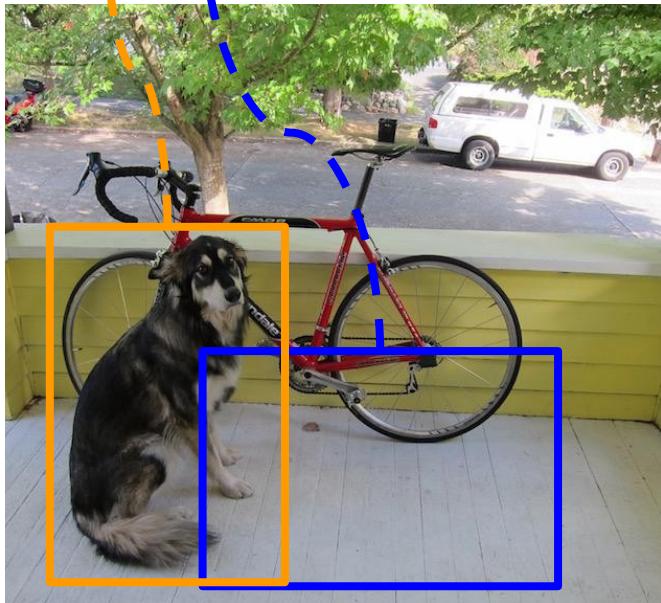
Do this procedure for other “`bbox_max`” and for other corresponding “`bbox_cur`”.

Non-Maximum Suppression: intuition

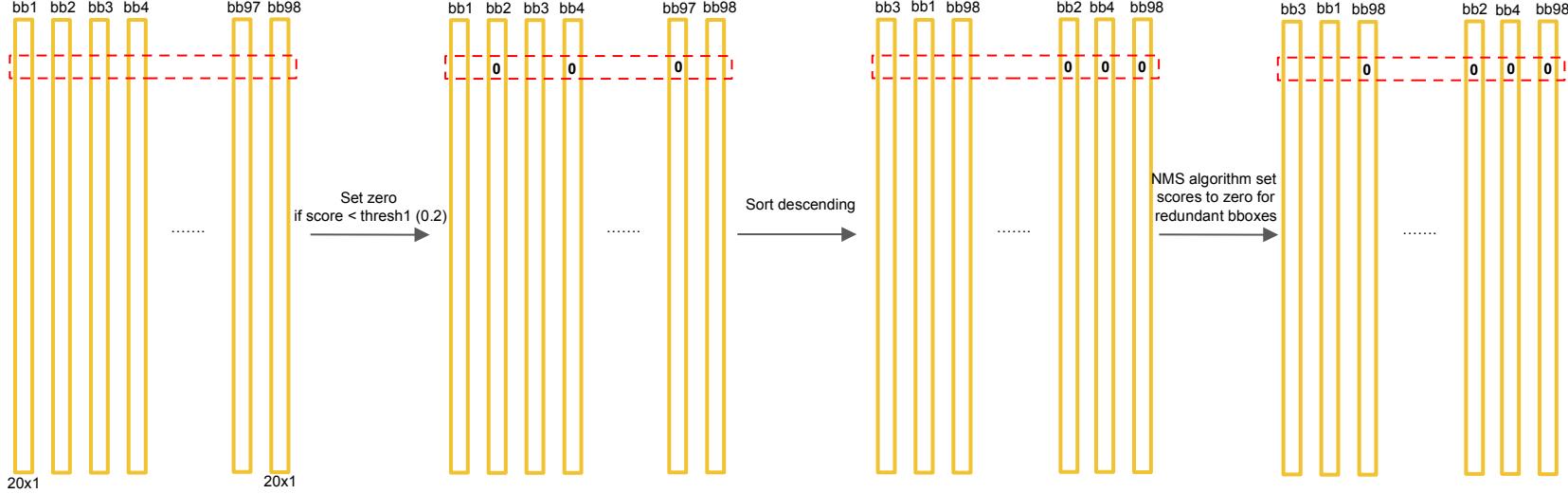
class: dog

bb47	bb20	bb15	bb7					
0.8	0	0.3	0					

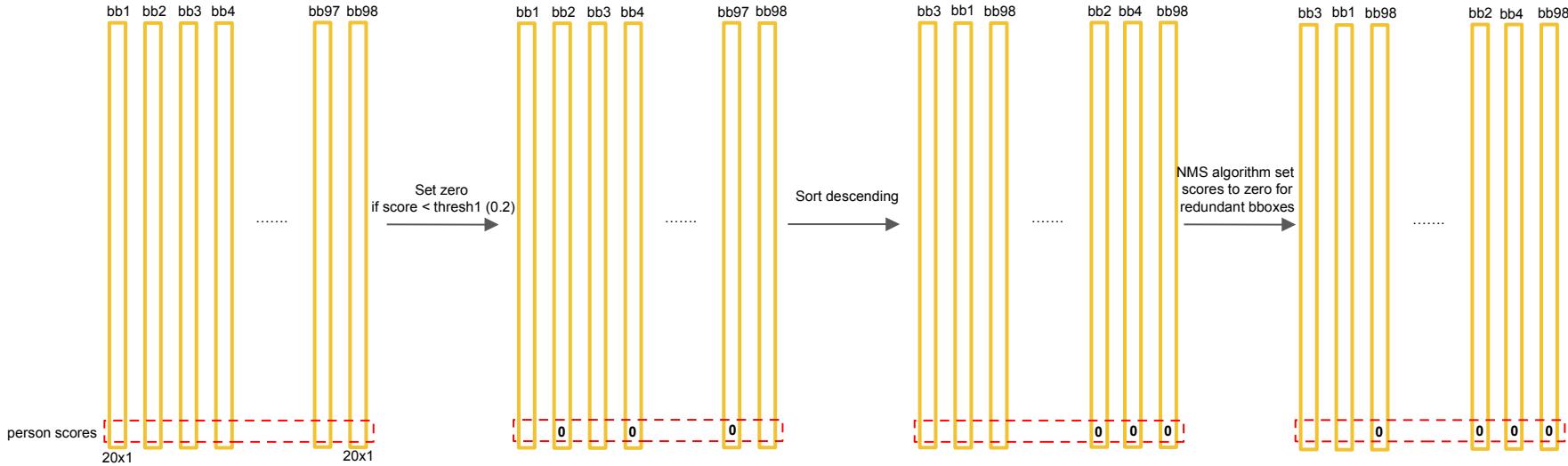
bb1	bb4	bb8	bb98
0	0	0	0



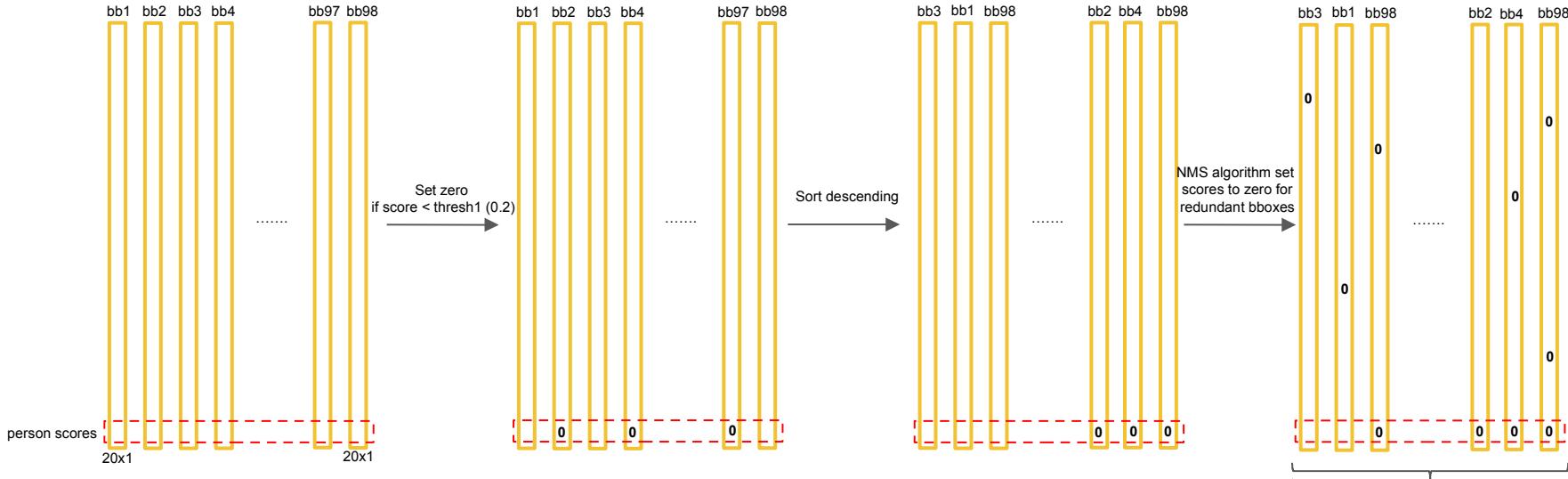
After comparison almost all pairs of bboxes the only two bboxes left with non-zero class score value.



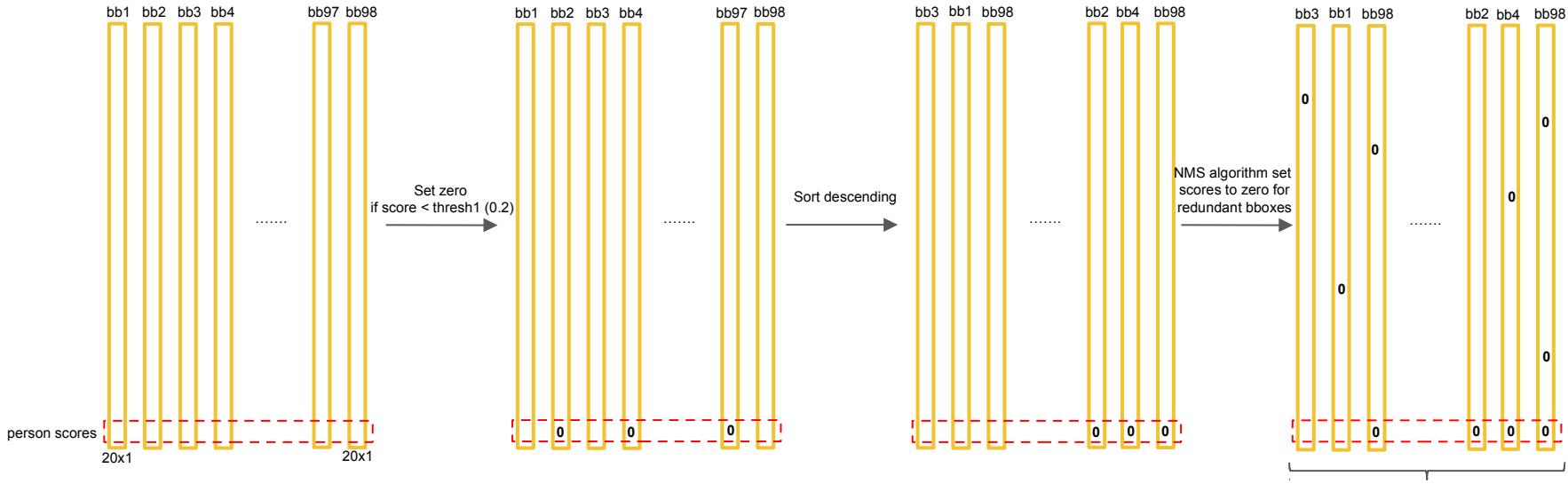
Do this procedure for next class



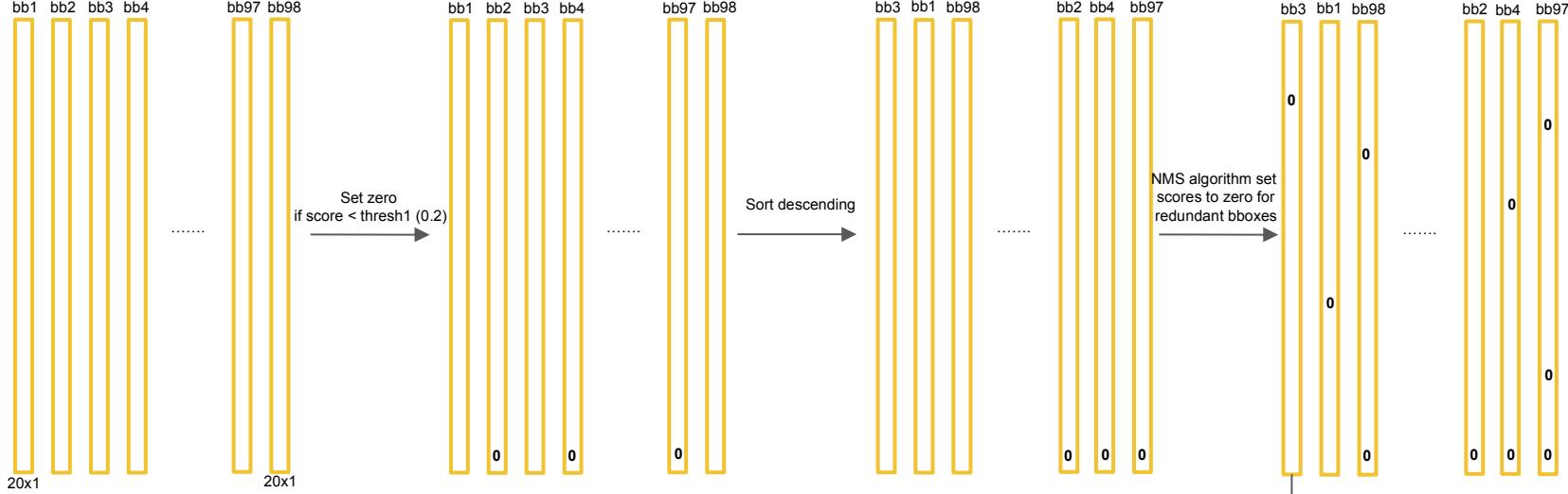
Do this procedure for all classes



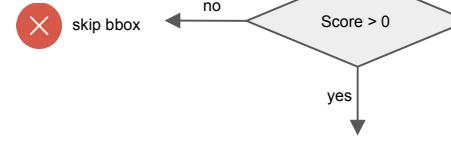
After this procedure -
a lot of zeros

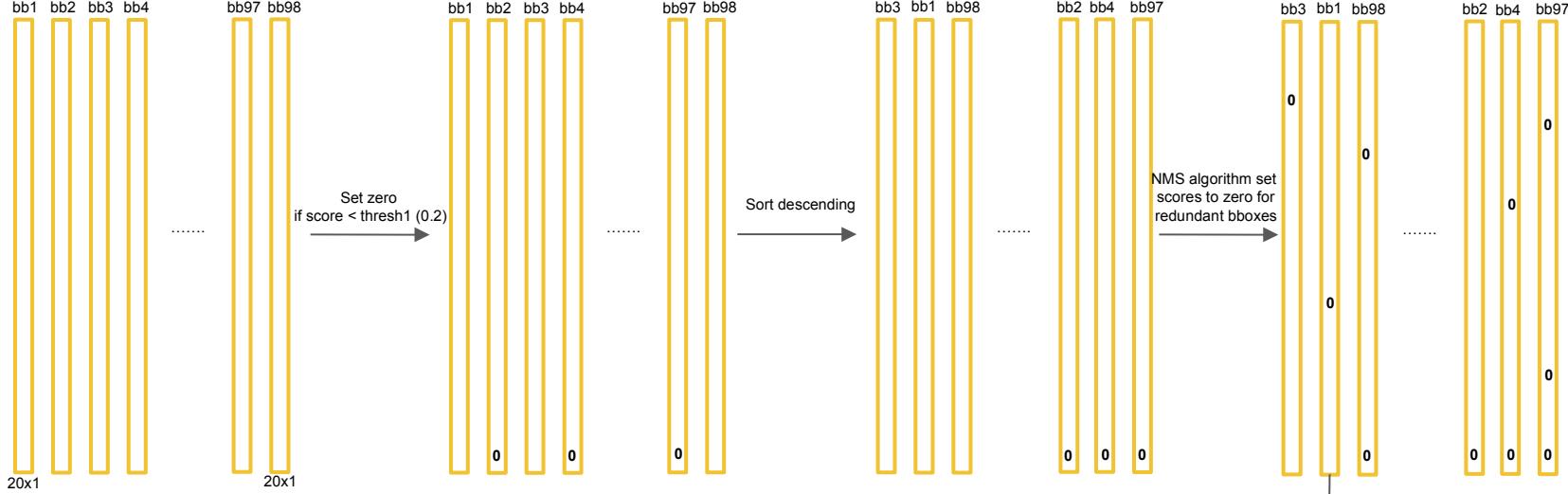


Select bboxes to draw by
class score values

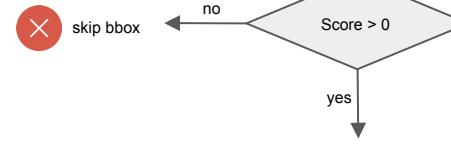


```
class = max_index(scores for bb3);
score = max(scores for bb3);
```



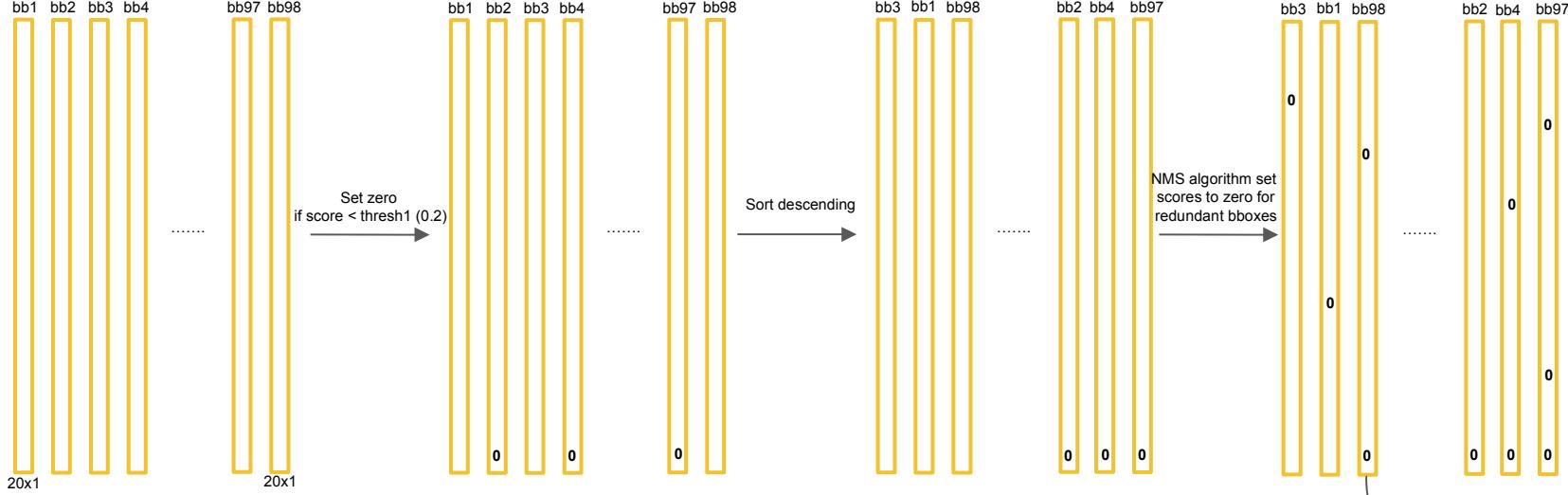


```
class = max_index(scores for bb1);
score = max(scores for bb1);
```

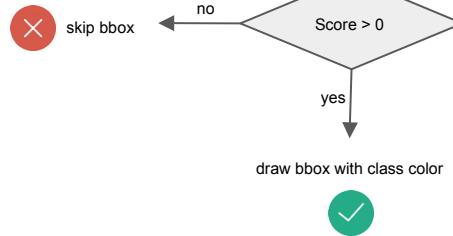


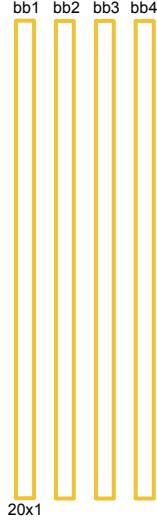
draw bbox with class color





```
class = max_index(scores for bb98);
score = max(scores for bb98);
```





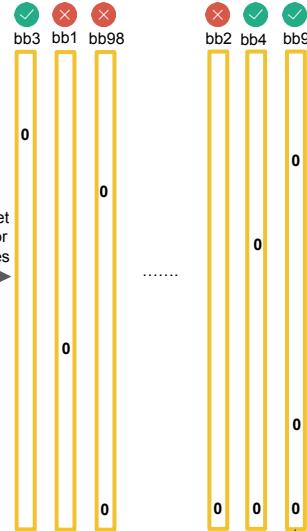
Set zero
if score < thresh1 (0.2)



Sort descending



NMS algorithm set
scores to zero for
redundant bboxes



```
class = max_index(scores for bb97);
score = max(scores for bb97);
```

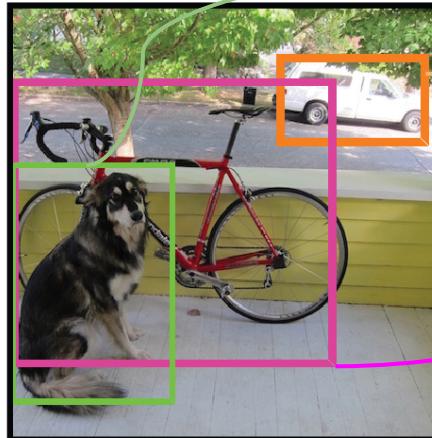
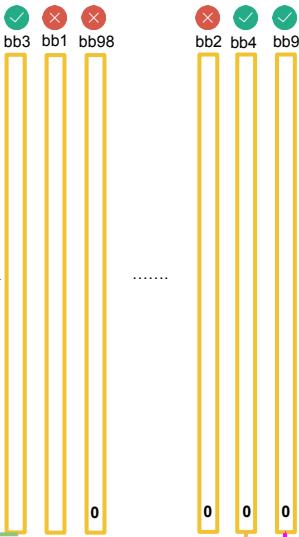
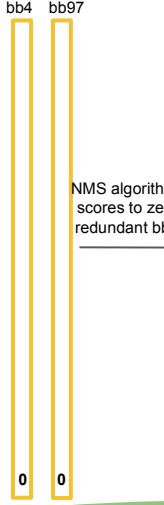
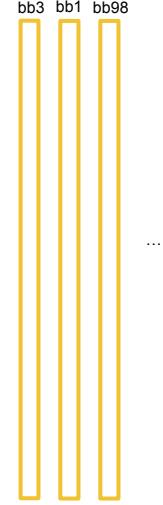
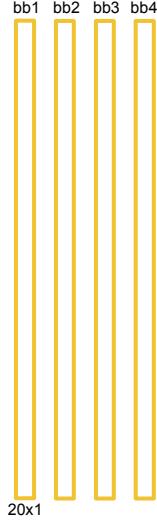
✗ skip bbox

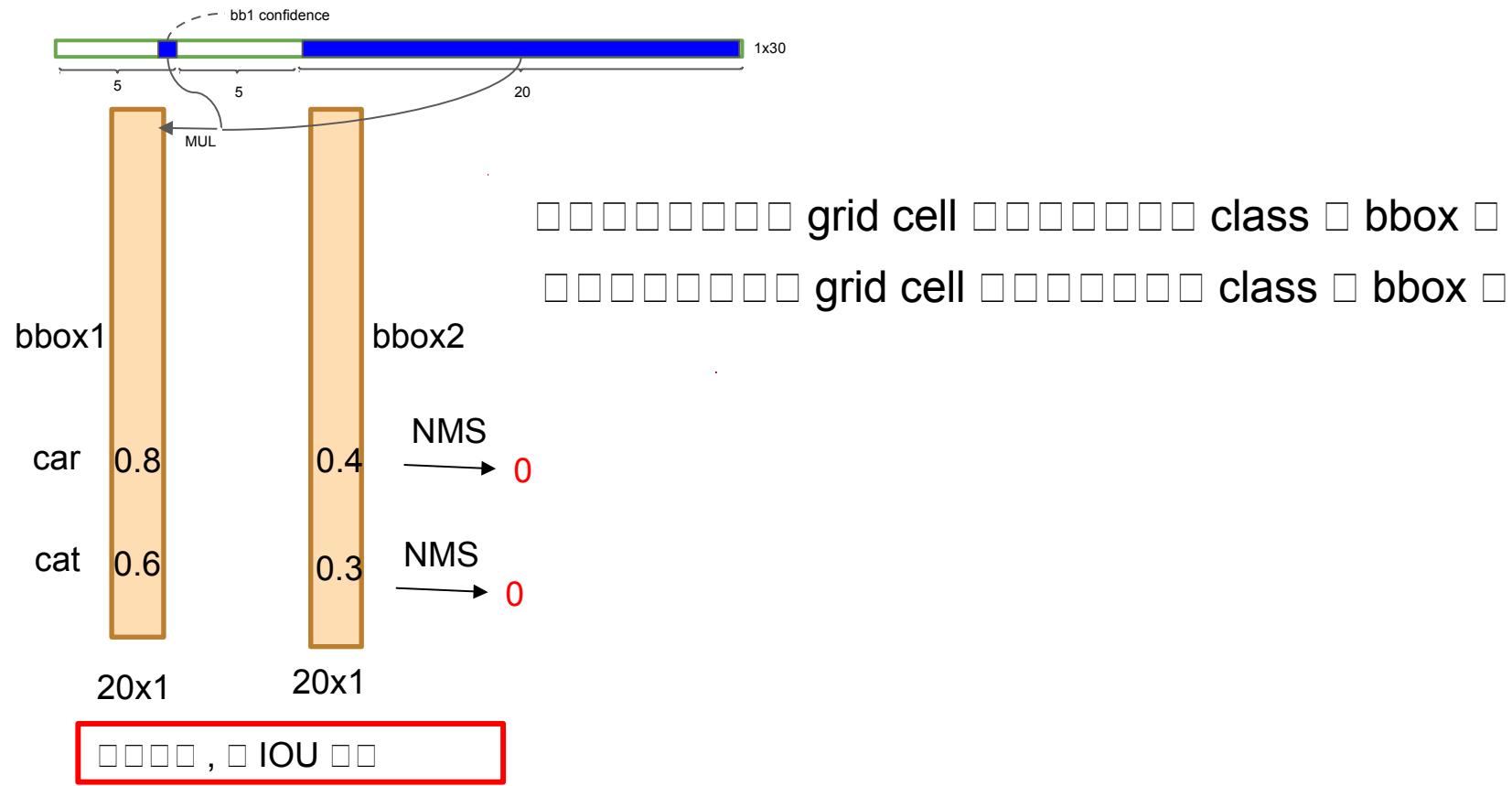
Score > 0

yes

draw bbox with class color

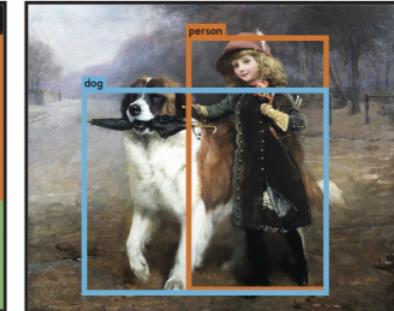
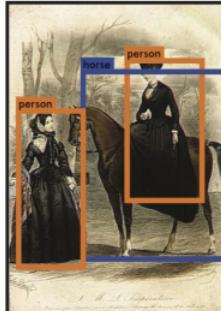






Key Points

1. Fast: YOLO - 45 fps, YOLO-tiny - 155 fps.
2. End-to-end training.
3. Makes more localization errors but is less likely to predict false positives on background
4. Performance is lower than the current state of the art.
5. Combined Fast R-CNN + YOLO model is one of the highest performing detection methods.
6. Learns very general representations of objects: it outperforms other detection methods, including DPM and R-CNN, when generalizing from natural images to other domains like artwork.



Darknet on Windows

Darknet <https://github.com/pjreddie/darknet>

Darknet for Windows <https://github.com/AlexeyAB/yolo-windows>

Darknet for Win tricks <https://github.com/pjreddie/darknet/issues/721>

Darknet install <https://pjreddie.com/darknet/install/>

Yolo v1 <https://pjreddie.com/darknet/yolov1/>

Yolo v2 <https://pjreddie.com/darknet/yolov2/>

Yolo v3 <https://pjreddie.com/darknet/yolo/>