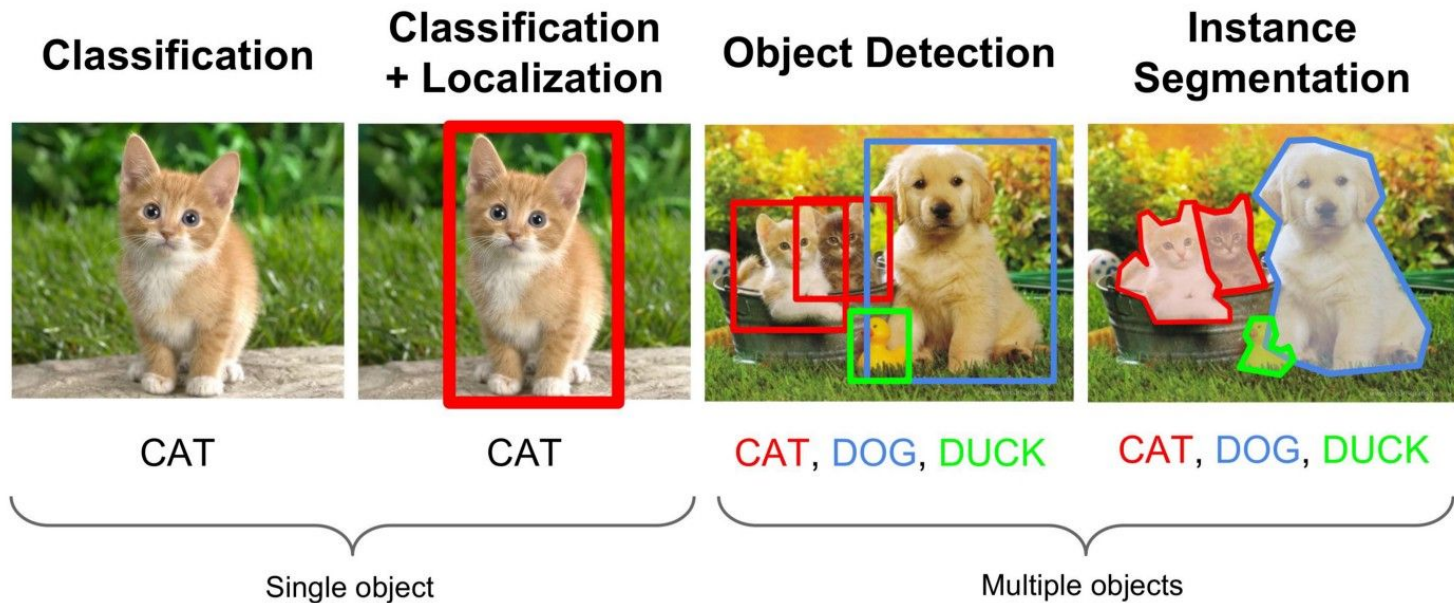


Deep Learning

Seminar 6

What are computer vision tasks?



Semantic segmentation:

- Faster / easier than instance segm
- Allows “complete” explanation
- Merges instances
- Suitable for “stuff” and things

Next lecture

Object detection:

- Faster / easier than instance segm
- Distinguishes instances
- Inaccurate for some classes
- Incomplete
- Suitable for things

This time

Instance / Panoptic segmentation:

- Complete
- Distinguish instances
- Accurate
- Harder/slower

Next lecture

Object detection



Object detection



As data we have:

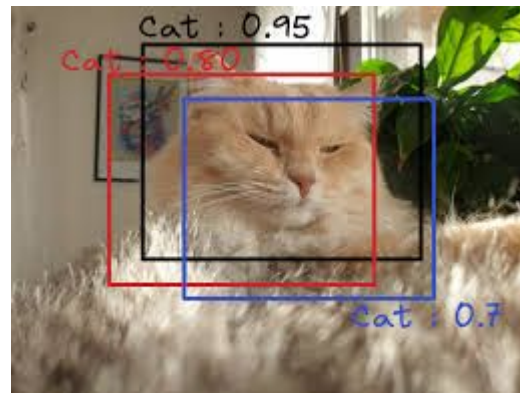
```
{  
    class: id  
    left up x: int  
    left up y: int  
    right bottom x: int  
    right bottom y: int  
}
```

Our task is to predict both class and bounding box for image

Metrics

How to measure performance?

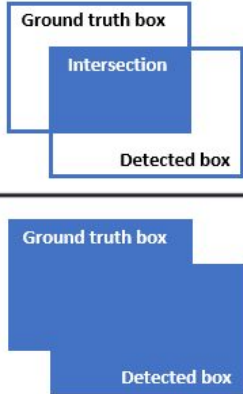
- IoU (Intersection over Union)
- mAP (mean average precision)

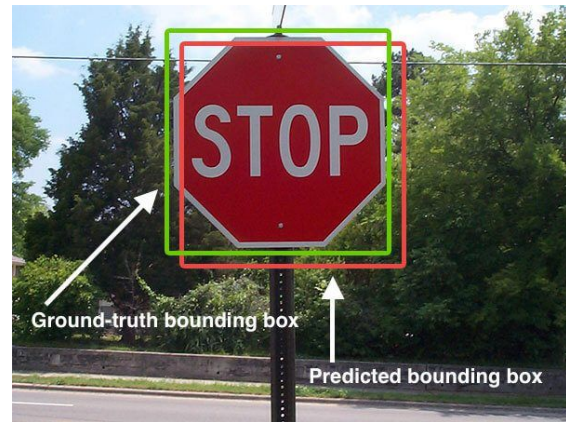


IoU (Intersection over Union)

Motivation:

- How does bounding boxes located? Good or bad?

$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}} = \frac{\text{Intersection}}{\text{Union}}$$


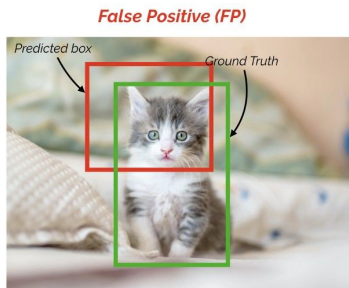


mAP (mean averaged precision)

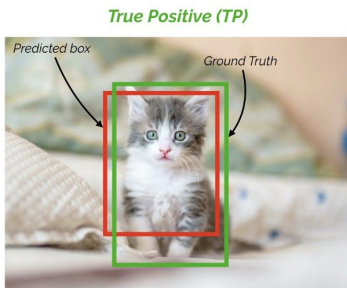
Motivation:

- Different IoU threshold gives us different predictions

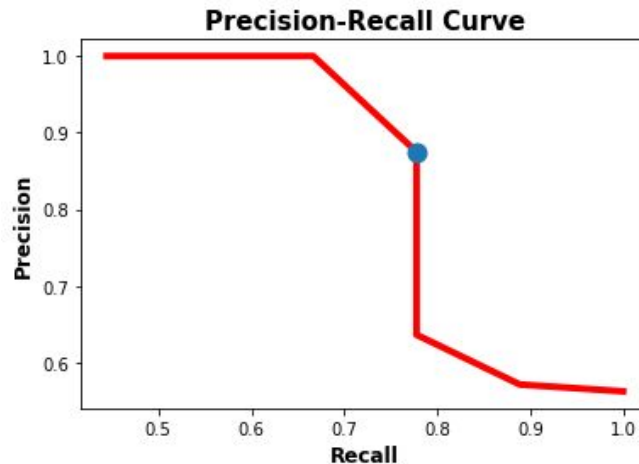
If IoU threshold = 0.5



$IoU \sim 0.3$



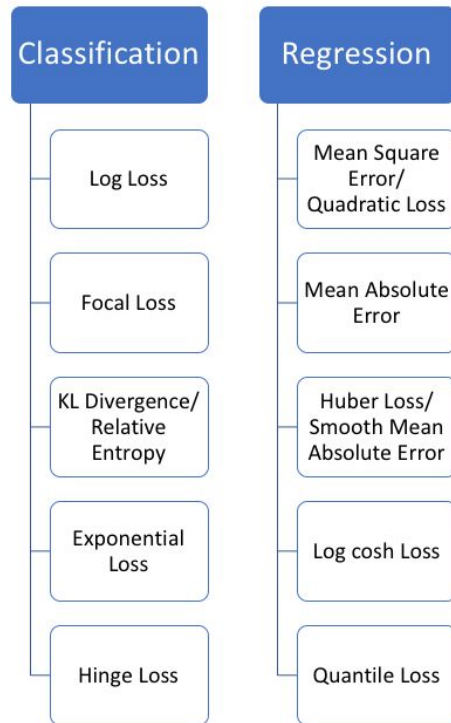
$IoU \sim 0.7$



Loss function

What is the loss function for this task?

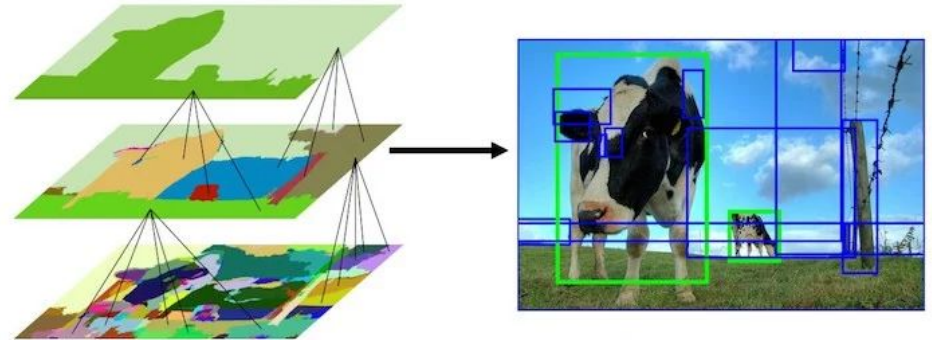
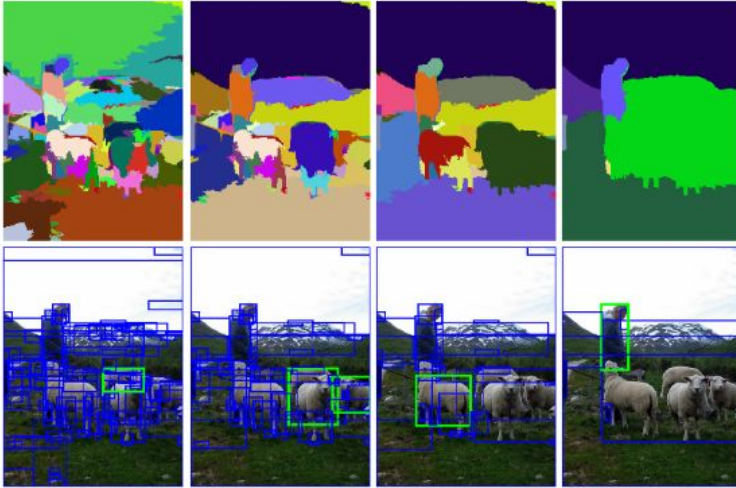
$$\mathcal{L} = \mathcal{L}_{cls} + \mathcal{L}_{reg}$$



Object detection

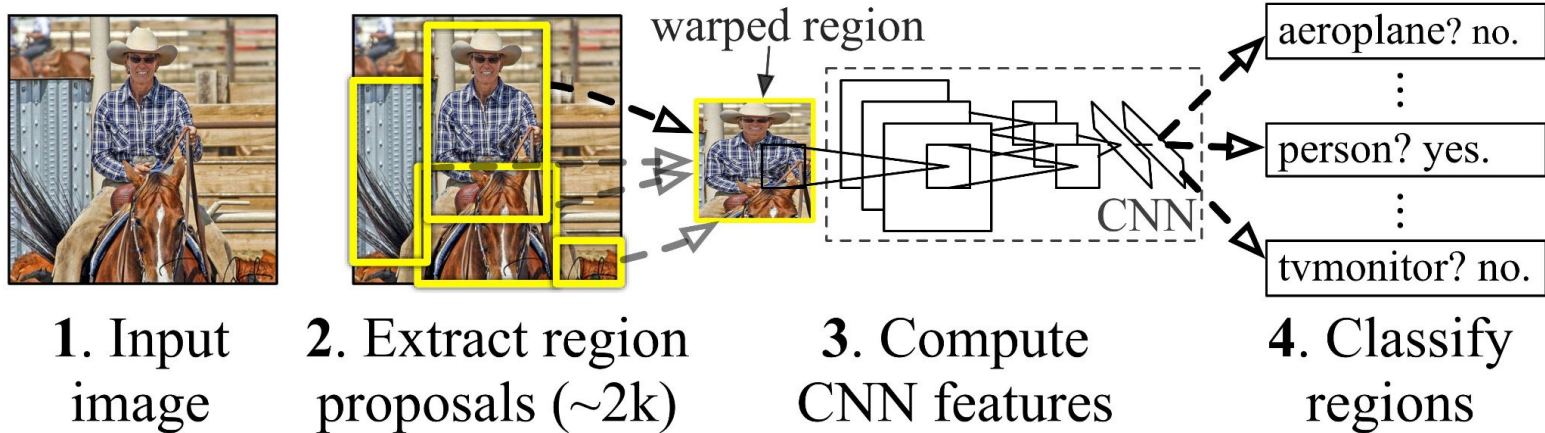
How do you approach the object detection task?

Standard method of boxes generation



R-CNN

R-CNN: *Regions with CNN features*



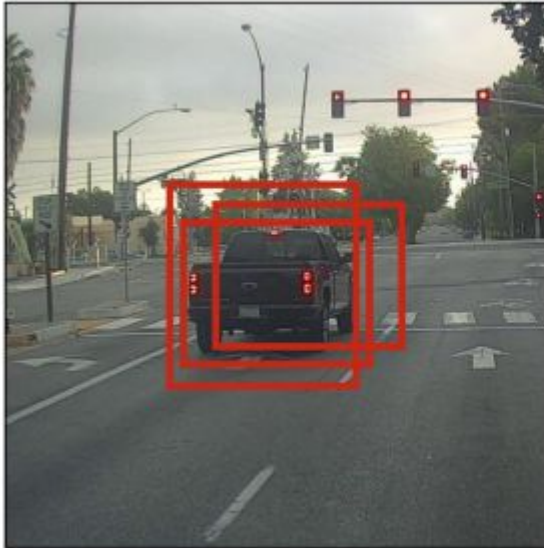
Non-maximum suppression (NMS)

Algorithm 1 Non-Max Suppression

```
1: procedure NMS( $B, c$ )
2:    $B_{nms} \leftarrow \emptyset$    Initialize empty set
3:   for  $b_i \in B$  do  $\Rightarrow$  Iterate over all the boxes
                        Take boolean variable and set it as false. This variable indicates whether b(i)
4:      $discard \leftarrow \text{False}$    should be kept or discarded
5:     for  $b_j \in B$  do   Start another loop to compare with b(i)
6:       if  $\text{same}(b_i, b_j) > \lambda_{nms}$  then   If both boxes having same IOU
7:         if  $\text{score}(c, b_j) > \text{score}(c, b_i)$  then
8:            $discard \leftarrow \text{True}$    Compare the scores. If score of b(i) is less than that
                                     of b(j), b(i) should be discarded, so set the flag to
                                     True.
9:         if not  $discard$  then   Once b(i) is compared with all other boxes and still the
                                discarded flag is False, then b(i) should be considered. So
10:           $B_{nms} \leftarrow B_{nms} \cup b_i$    add it to the final list.
11:   return  $B_{nms}$    Do the same procedure for remaining boxes and return the final list
```

Non-maximum suppression (NMS)

Before non-max suppression



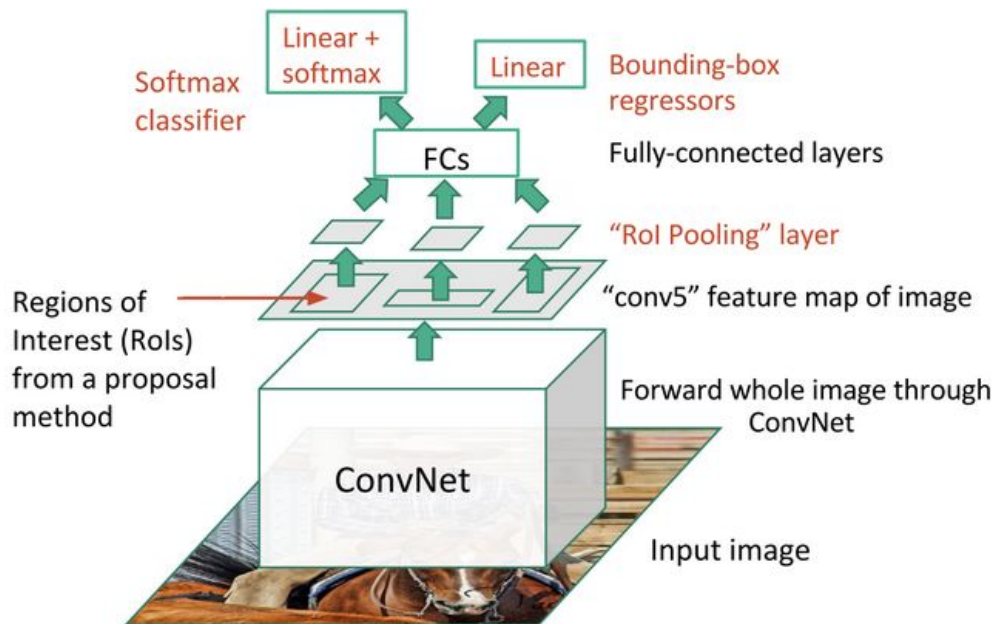
**Non-Max
Suppression**



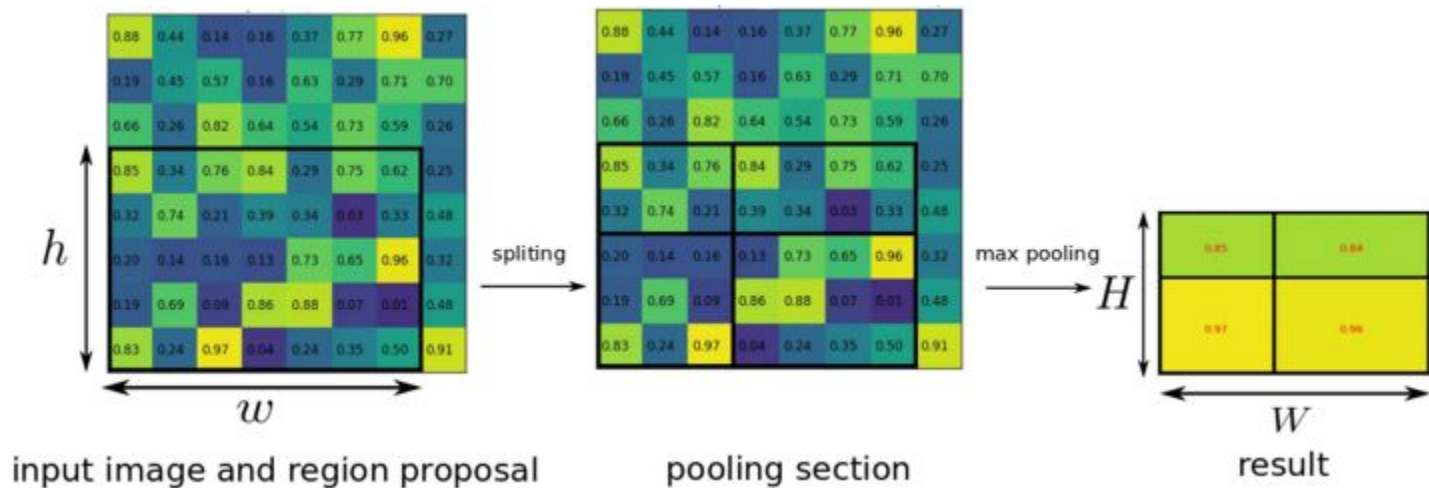
After non-max suppression



Fast R-CNN

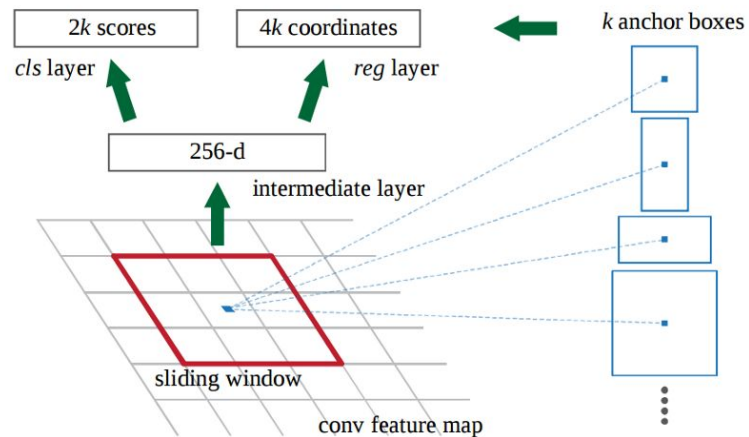
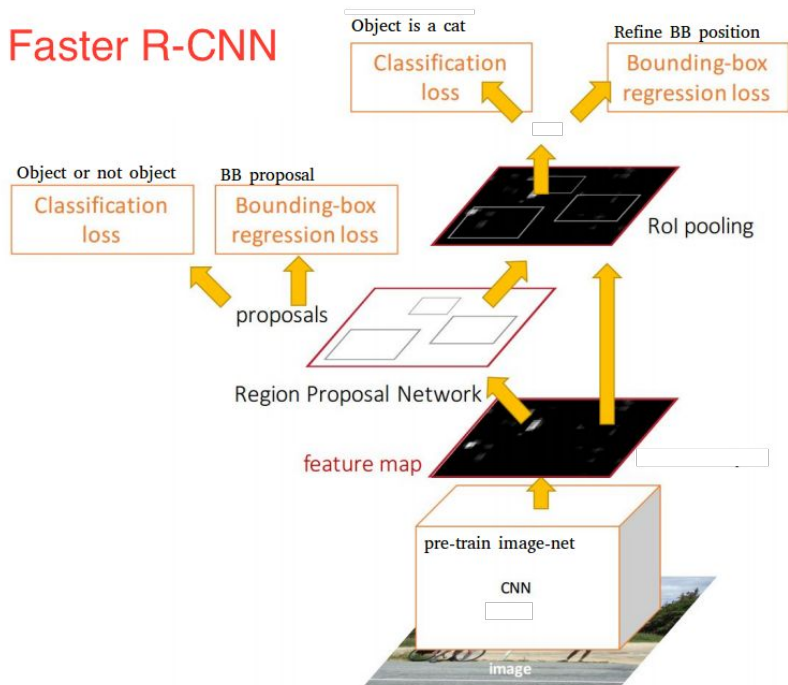


RoI pooling

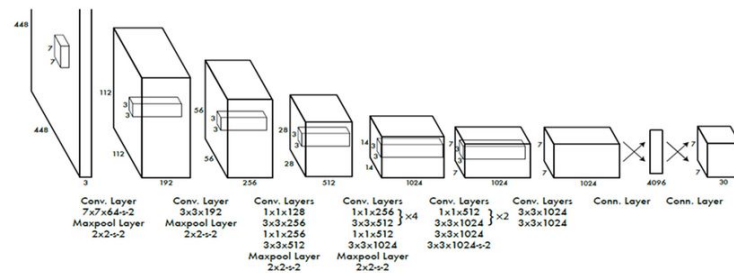
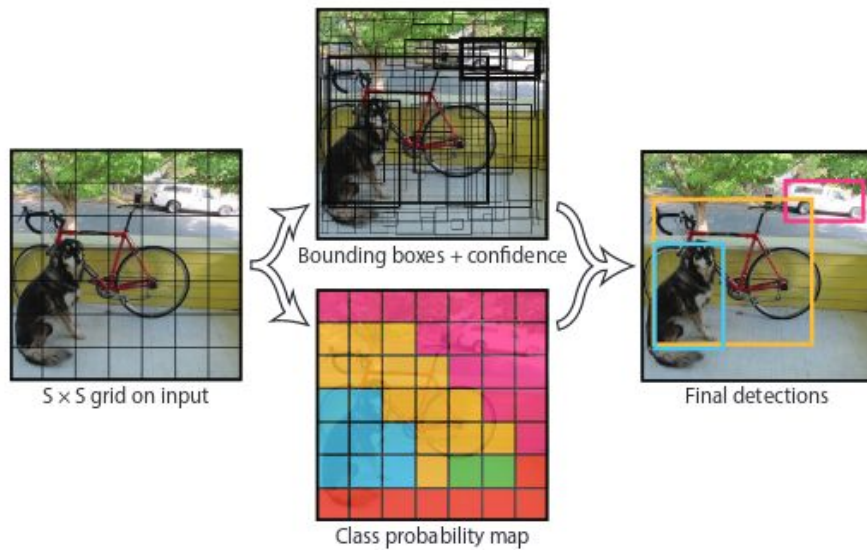


Faster R-CNN

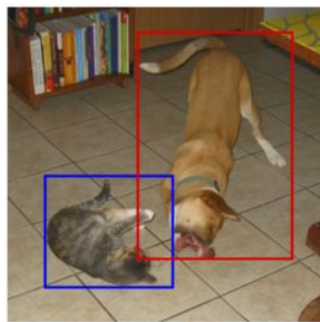
Faster R-CNN



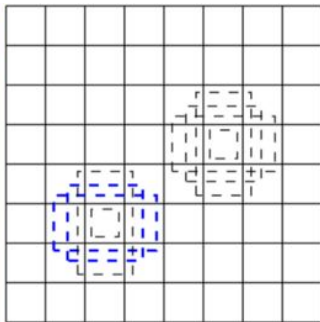
YOLO



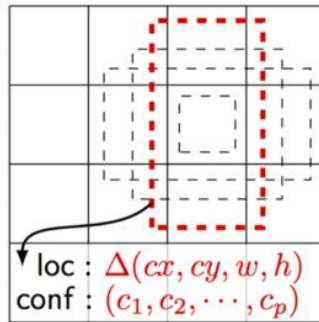
SSD



(a) Image with GT boxes

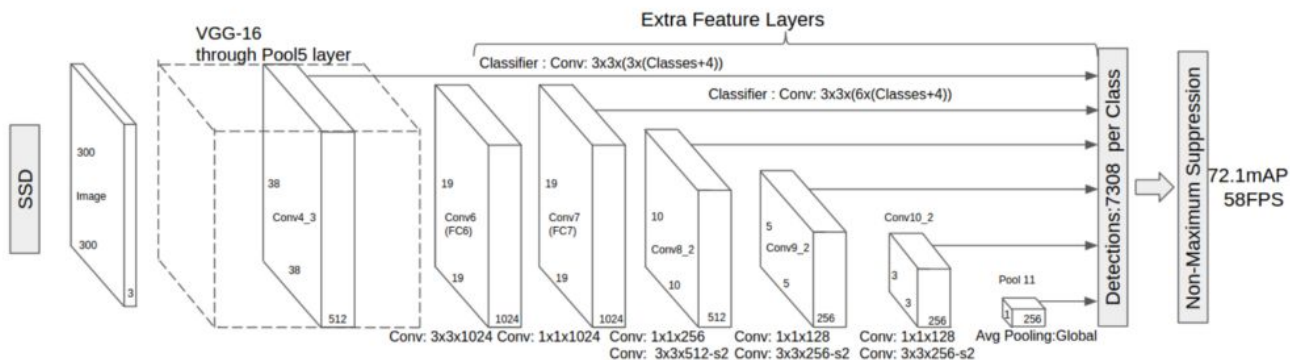


(b) 8×8 feature map



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

(c) 4×4 feature map



Recap

- Object detection
- RCNN
- Fast RCNN
- Faster RCNN
- YOLO
- SSD