



Insight to computer vision



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Overview – What is CV?

Classification



Object detection

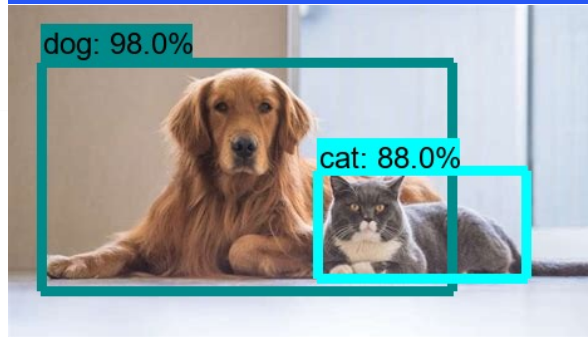


Image Segmentation (panoptic)



Keypoint detection



and many more...

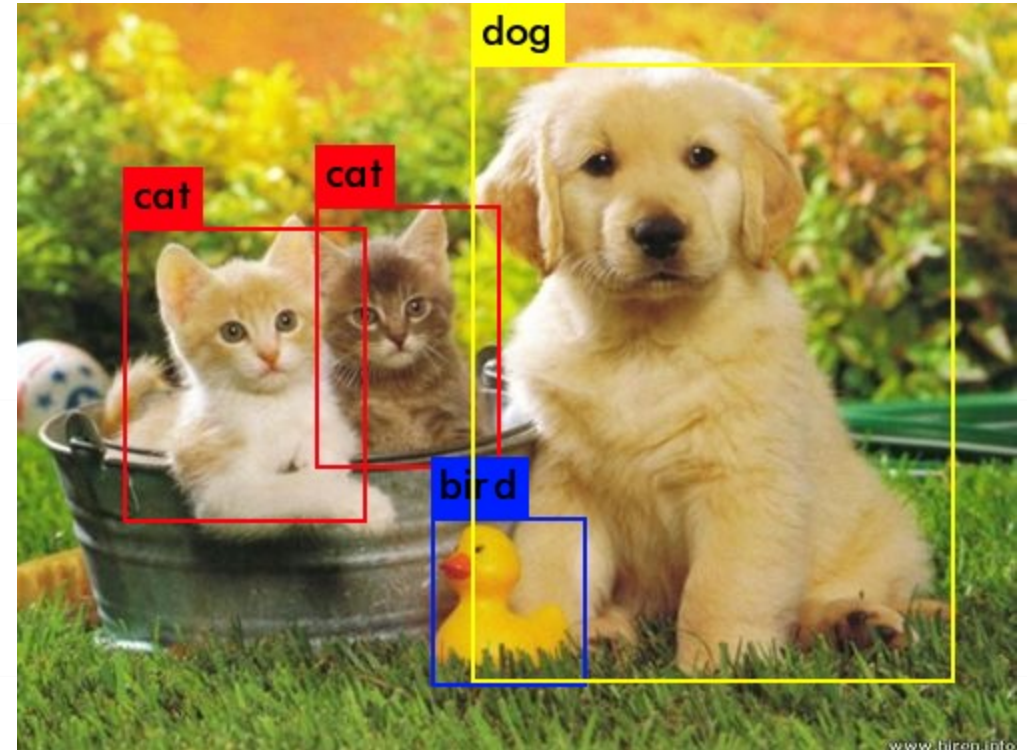
Object Detection Task

Localization (regression)

- Localized the subject in the image
- Done by drawing bounding boxes (bbox) around the subject
- Bbox described as $(x1, y1, x2, y2)$ or (x, y, w, h)

Classification

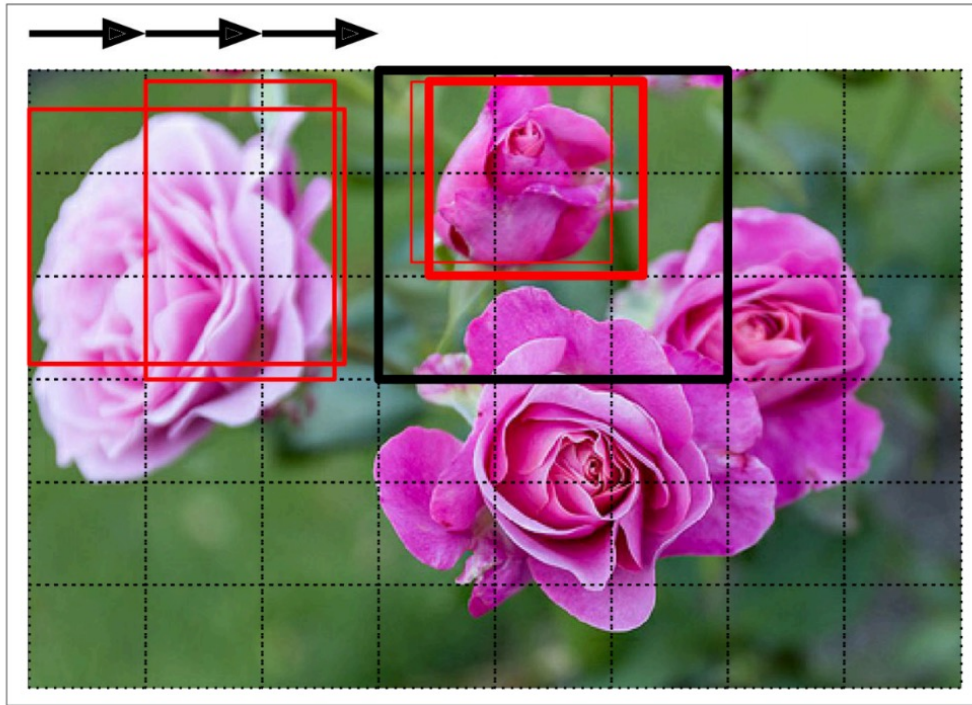
- Classify subject correctly (e.g. cat or dog)



Object detection models

Two-stage models

- Region-based CNN Family Models
 - R-CNN (2014), Fast R-CNN (2015), Faster R-CNN (2016), Mask R-CNN (2017)
- More accurate but are typically slower.



Sliding window technique

R-CNN: *Regions with CNN features*

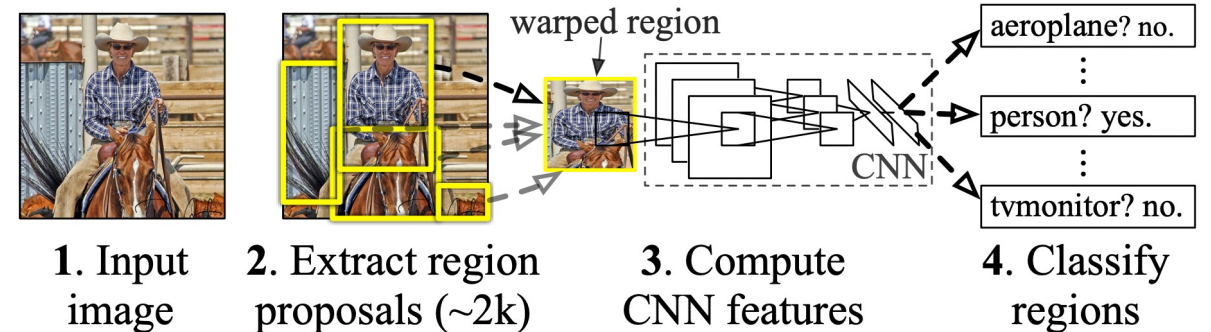


Figure 1: Object detection system overview. Our system (1) takes an input image, (2) extracts around 2000 bottom-up region proposals, (3) computes features for each proposal using a large convolutional neural network (CNN), and then (4) classifies each region using class-specific linear SVMs.

Region proposal technique

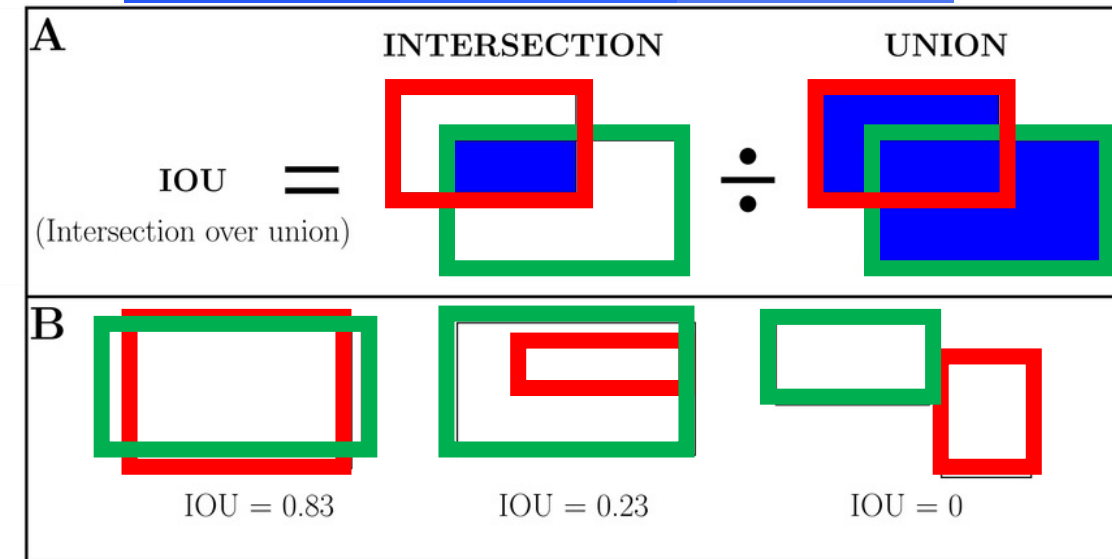
object detection models

One-stage models

- YOLO Family Models
 - YOLO (2015), YOLOv2 (2016), YOLOv3 (2018), YOLOv4 (2020), YOLOv5 (2021)
- SSD (2016)
- Fast inference speed, but not as good at recognizing a group of small objects

Evaluation metric: Intersection over Union (IoU)

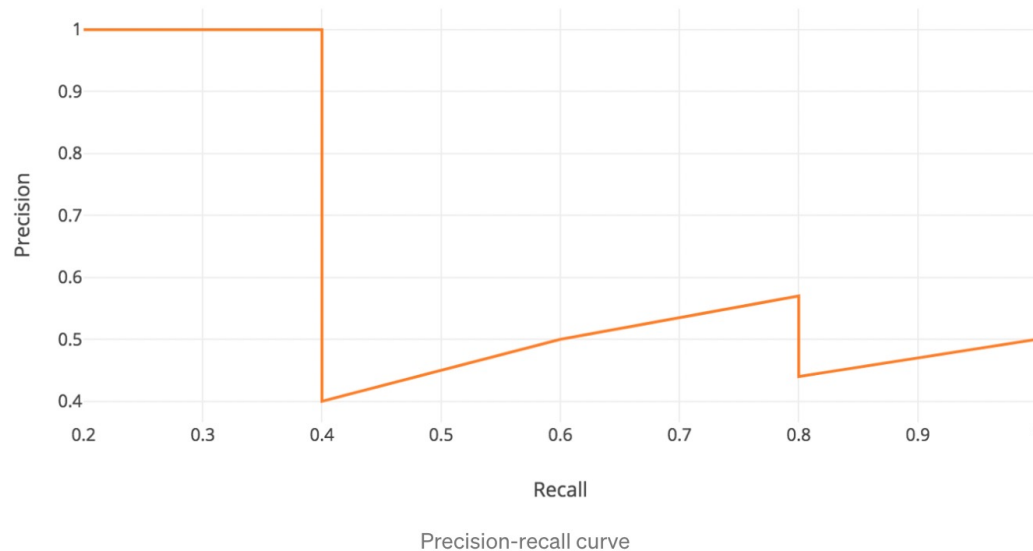
- IoU quantify the amount of overlap area between predicted bbox overlapped with ground-truth bbox
- Range from 0 (prediction totally off) to 1 (perfect prediction)
- If prediction has $\text{IoU} > 0.5$, correct classification -> TP
- If prediction has $\text{IoU} < 0.5$, correct classification -> FP
- If no prediction when there is a target -> FN (0.5 is an arbitrary threshold)



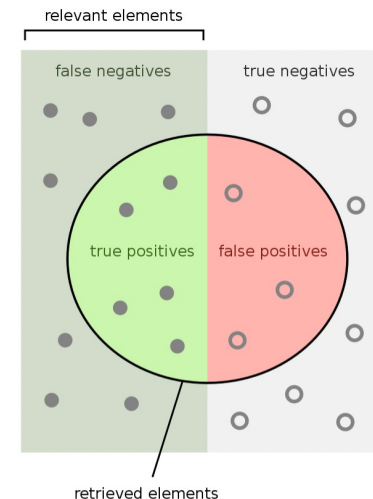
Evaluation metric: Mean Average Precision (mAP)

5 total cases in this e.g.

- Based on the concept of IoU, calculate TP, FP, FN to build a precision-recall curve
- STEPS :
 - Sort the predictions by confidence level
 - Compute the precision and recall for each row sequentially
 - Plot graph
- Calculate area under graph and you get AP!
- Repeat this for diff classes and average them e.g. AP_{CAT} , AP_{DOG}
- Hence mean AP



Rank	Correct?	Precision	Recall
1	True	1.0 $1/1$	0.2 $1/5$
2	True	1.0 $2/2$	0.4 $2/5$
3	False	0.67 $2/3$	0.4 $2/5$
4	False	0.5 $2/4$	0.4 $2/5$
5	False	0.4	0.4
6	True	0.5	0.6
7	True	0.57	0.8
8	False	0.5	0.8
9	False	0.44	0.8
10	True	0.5	1.0



How many retrieved items are relevant?

$$\text{Precision} = \frac{\text{true positives}}{\text{true positives} + \text{false positives}}$$

How many relevant items are retrieved?

$$\text{Recall} = \frac{\text{true positives}}{\text{true positives} + \text{false negatives}}$$

Evaluation metric: Mean Average Precision (mAP)

COCO Object Detection Challenge

Average Precision (AP):

```
AP % AP at IoU=.50:.05:.95 (primary challenge metric)
APIoU=.50 % AP at IoU=.50 (PASCAL VOC metric)
APIoU=.75 % AP at IoU=.75 (strict metric)
```

AP Across Scales:

```
APsmall % AP for small objects: area < 322
APmedium % AP for medium objects: 322 < area < 962
APlarge % AP for large objects: area > 962
```

Average Recall (AR):

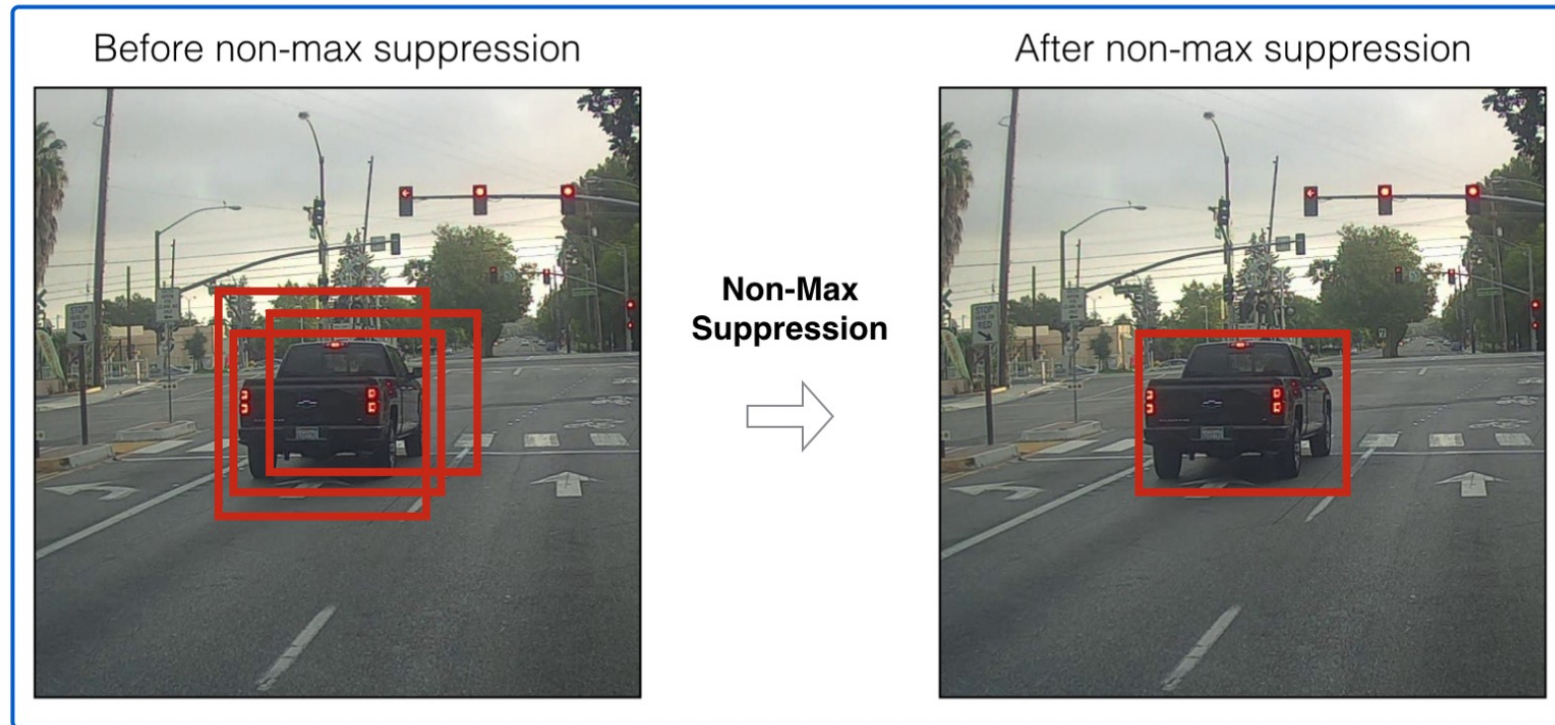
```
ARmax=1 % AR given 1 detection per image
ARmax=10 % AR given 10 detections per image
ARmax=100 % AR given 100 detections per image
```

AR Across Scales:

```
ARsmall % AR for small objects: area < 322
ARmedium % AR for medium objects: 322 < area < 962
ARlarge % AR for large objects: area > 962
```

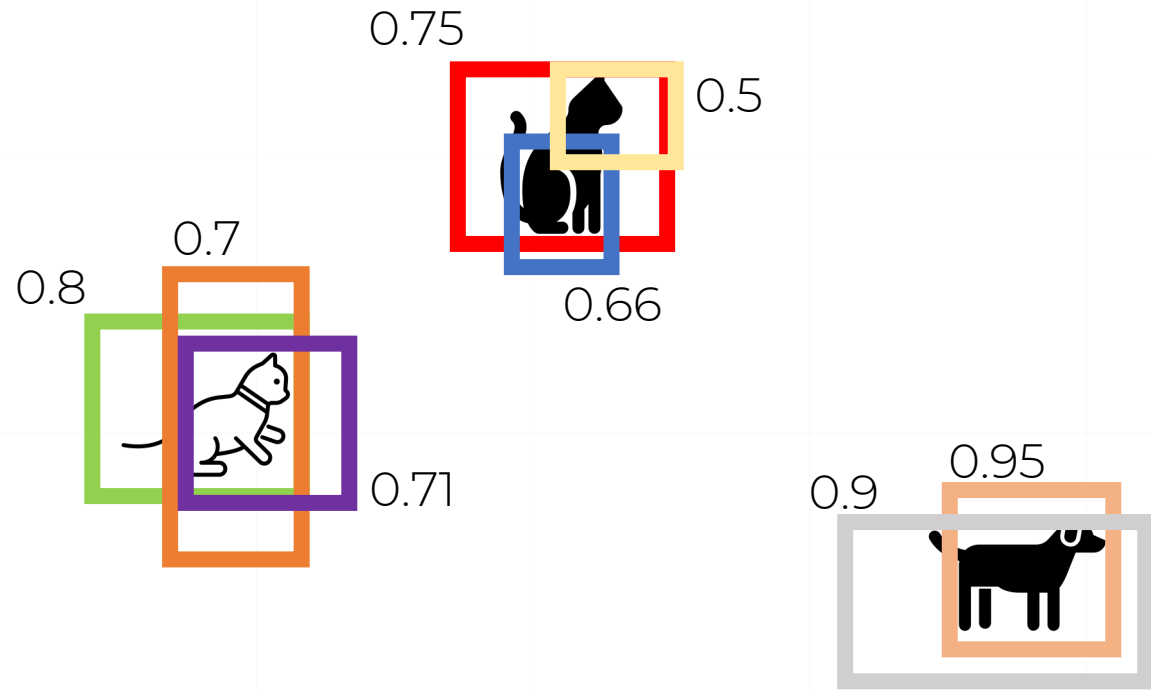
Non-max suppression (NMS)

- Most obj detection models proposed multiple bbox around the target.
- NMS is a technique to remove all except one bbox proposal



Steps:

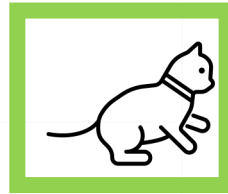
1. Start from one class
2. Select the bbox with the highest confidence score.
3. Check the IOU score of other bboxes.
4. Discard the bbox if $\text{IOU} > 0.7$ (arbitrary threshold)
5. Select the second highest confidence score and repeat step 3 and 4.
6. Repeat step 1 to 5 for other classes.



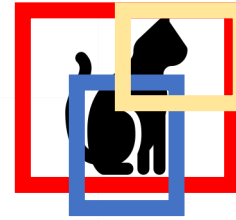
Steps:

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0.8



0.75

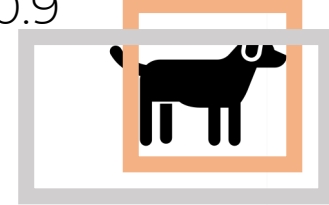


0.5

0.66

0.9

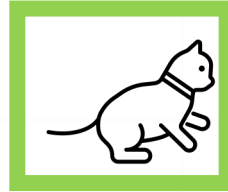
0.95



Steps:

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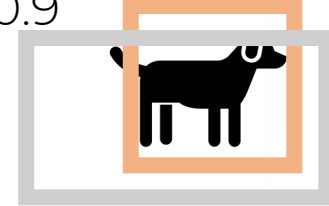


0.75



0.9

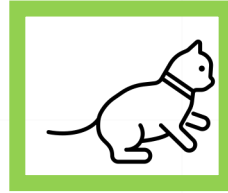
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Steps:

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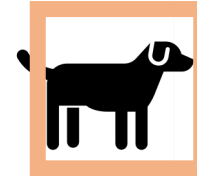
0.8



0.75



0.95

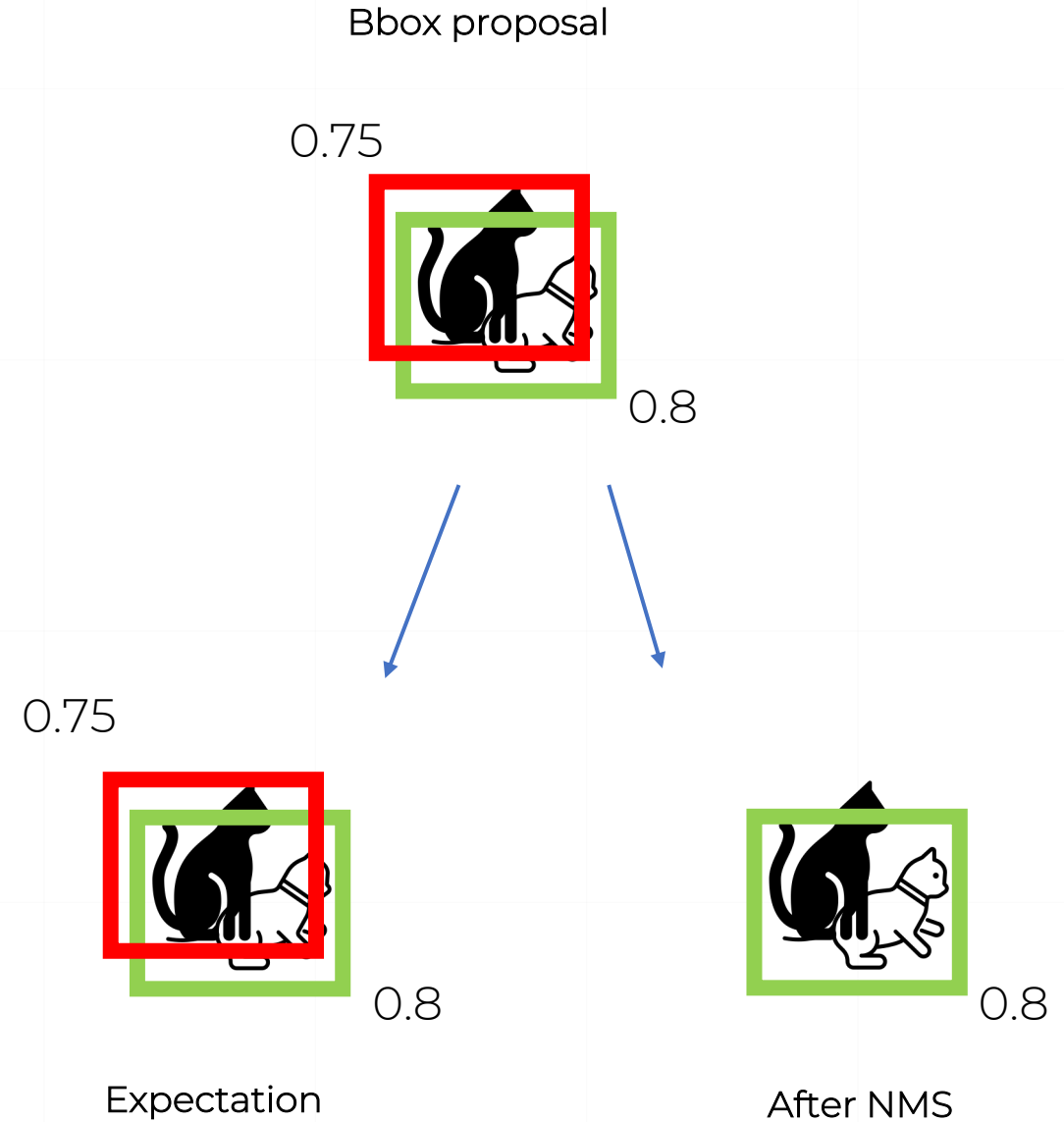


Steps:

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Problem?

NMS performed poorly if targets are close



Thanks !