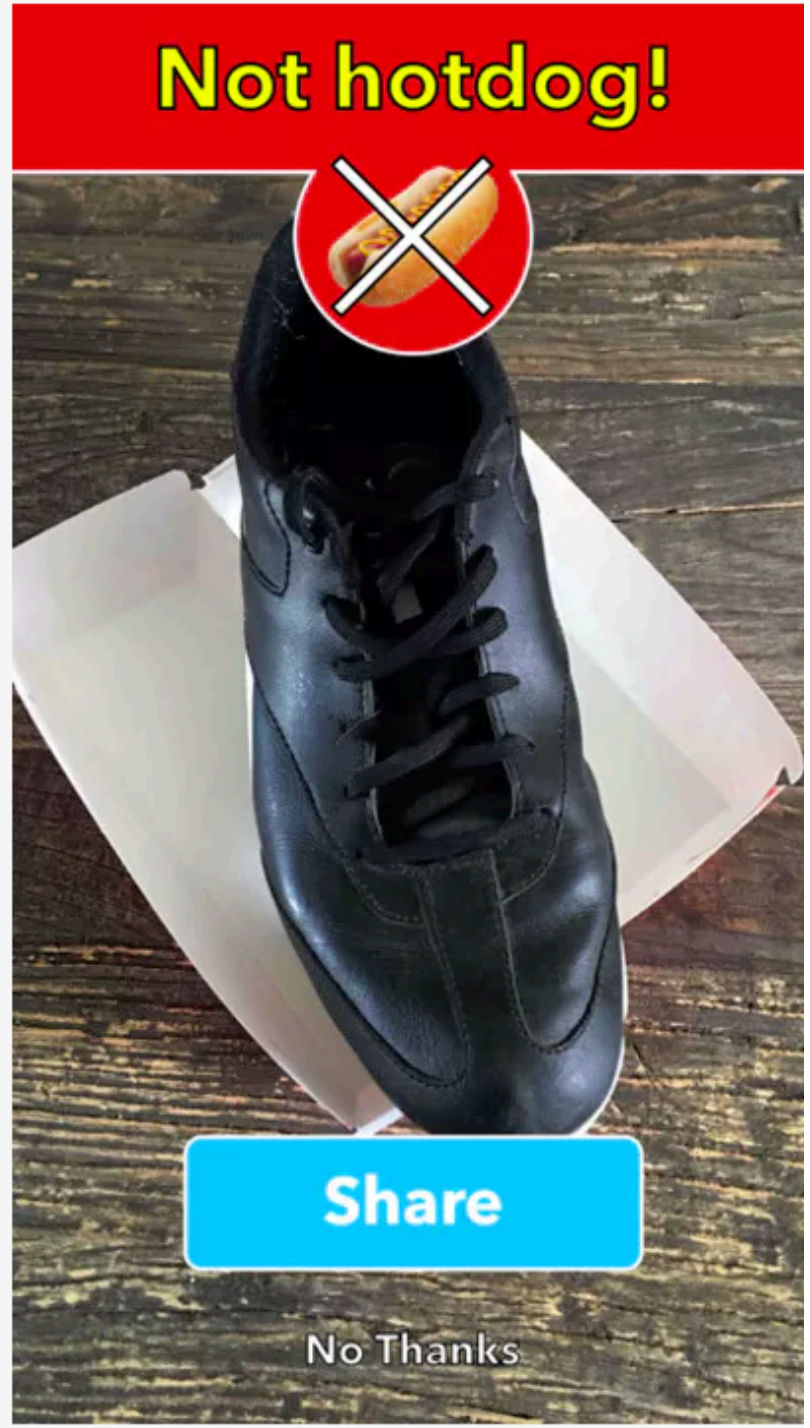
Metrics for Detection

Presentation by Hallgeir Løkken

For TDT17


Hotdog!
Share
No Thanks


Not hotdog!
Share
No Thanks

Confidence

«How certain are we that a region of interest contains a hotdog?»

TP – True Positive	FP – False Positive
TN – True Negative	FN – False Negative

Recall

$$Recall = \frac{TP}{TP + FN}$$

«Out of all the hotdogs, how many did we find?»

Precision

$$Precision = \frac{TP}{TP + FP}$$

«Of all the images we ***thought*** *were hotdogs, how many were* ***actually*** *hotdogs?»*

Precision-recall curve

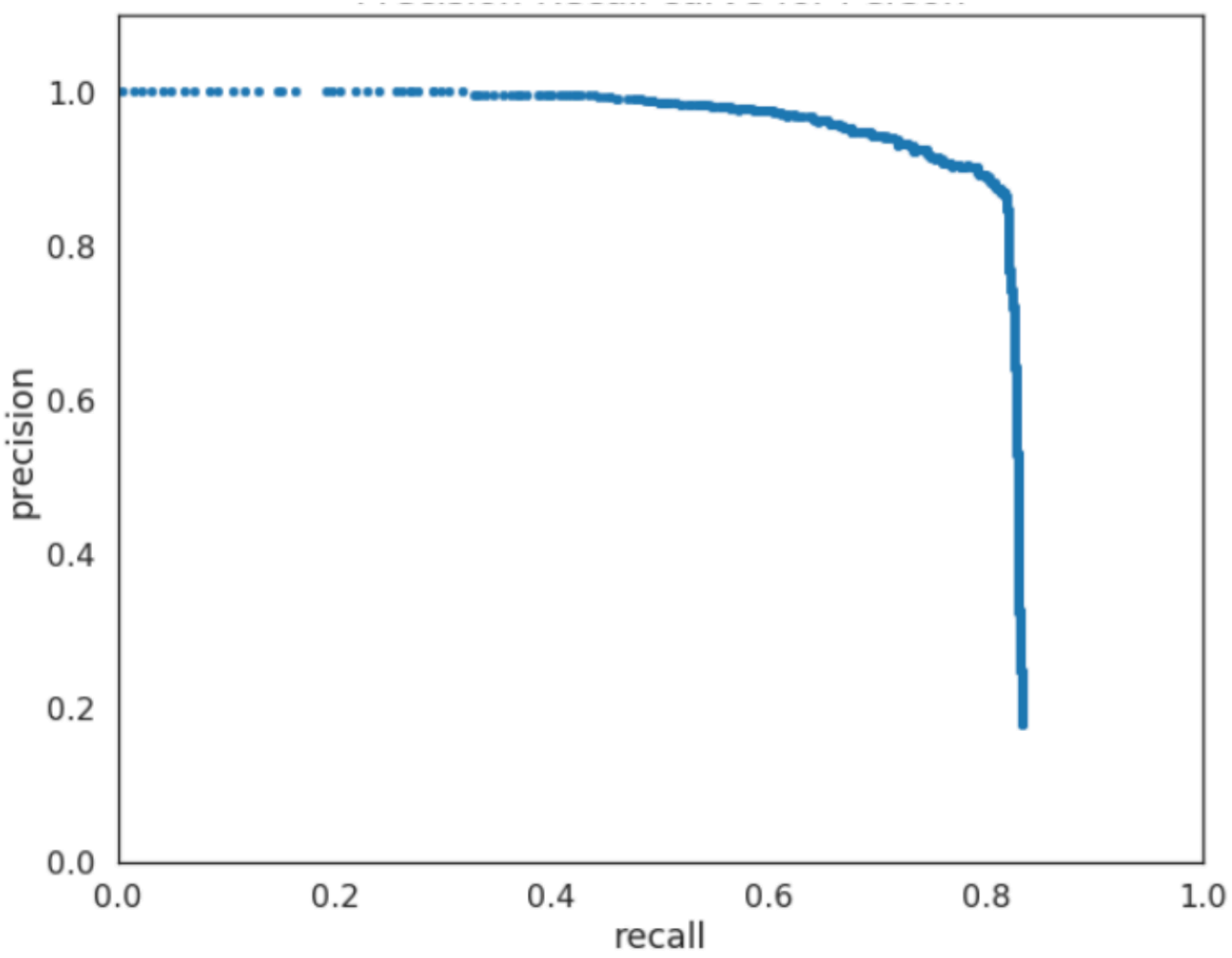


Image credits: Timothy C Arlen [1]

Average Precision

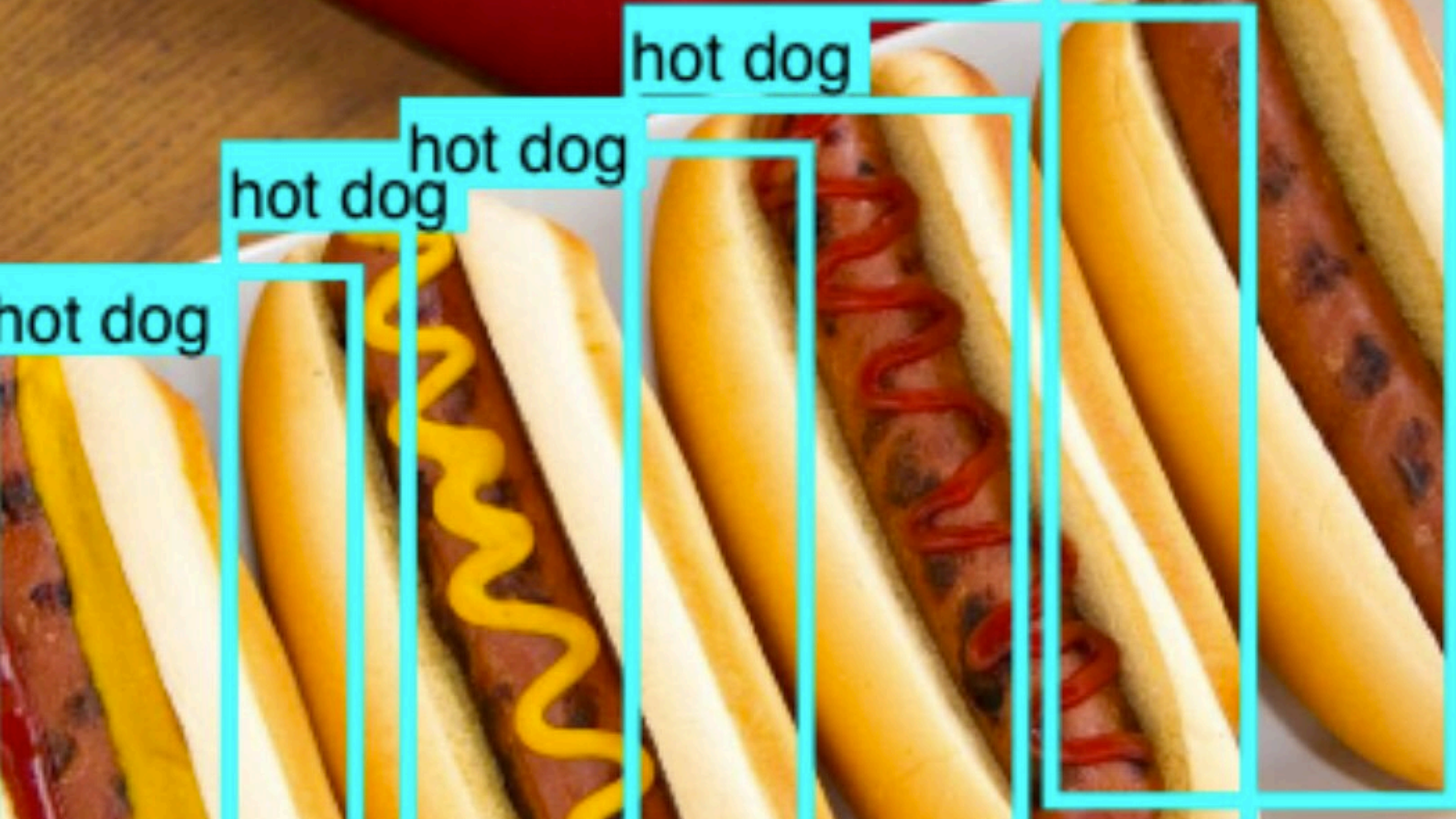
1. Calculate the precision of N evenly spaced recall values
2. Average the calculated precisions

$$AP = \frac{\sum_i^N P@R_i}{N}$$

Ref: [3]

mAP – Mean Average Precision

Simply average the AP of all classes


hot dog
hot dog
hot dog
hot dog

Object Localization

- Bounding boxes
- Bounding polygons
- Pixel mask

IoU – Intersection over Union

$$IoU = \frac{area(B_p \cap B_{gt})}{area(B_p \cup B_{gt})}$$

Simple, but useful

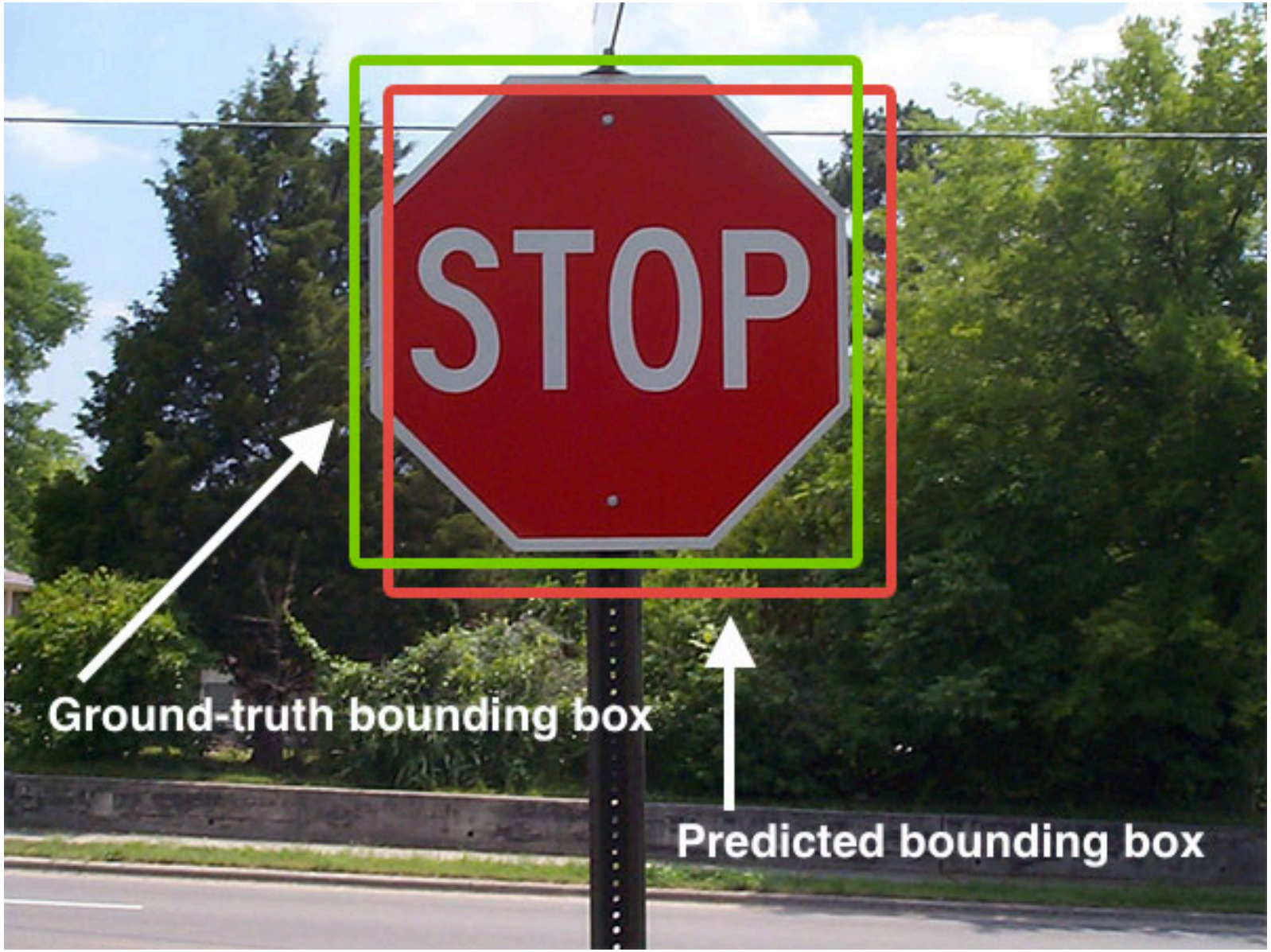
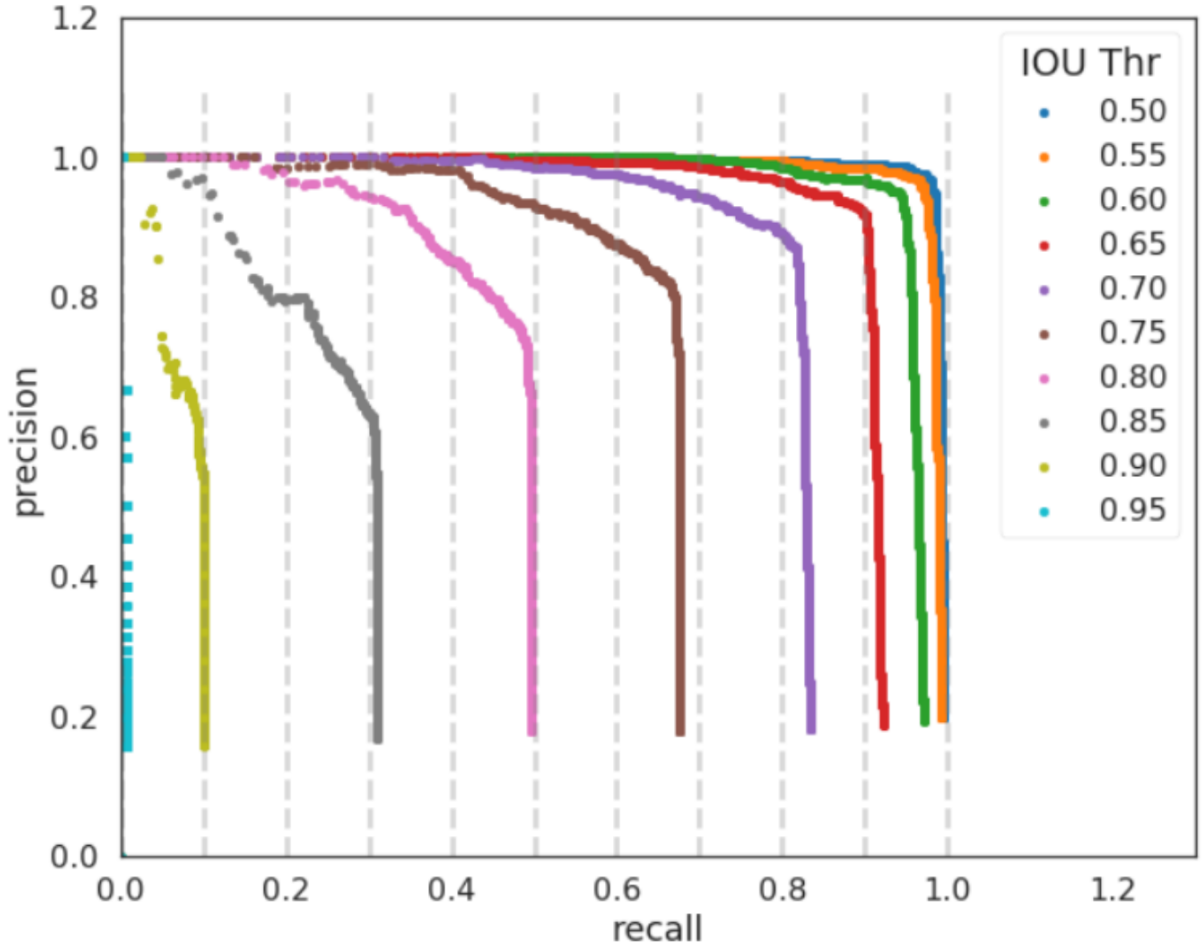


Image credits: Adrian Rosebrock [2]

IoU thresholds

We can reuse our classification metrics for localization



Summary

- Object detection consists of classification and localization
- mAP is for evaluating classification
- IoU is for evaluating object localization
- IoU thresholds makes mAP useful for evaluating the full object detector

References

- [1] : https://medium.com/@timothycarlen/understanding-the-map-evaluation-metric-for-object-detection-a07fe6962cf3
- [2] : https://www.pyimagesearch.com/2016/11/07/intersection-over-union-iou-for-object-detection/
- [3] : Zhang E., Zhang Y. (2009) Average Precision. In: LIU L., ÖZSU M.T. (eds) Encyclopedia of Database Systems. Springer, Boston, MA
- [4] : https://blog.zenggyu.com/en/post/2018-12-16/an-introduction-to-evaluation-metrics-for-object-detection/