Deep Learning

Deeper, Better, _____ , Stronger than Machine Learning

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Universidad de Chile – DCC

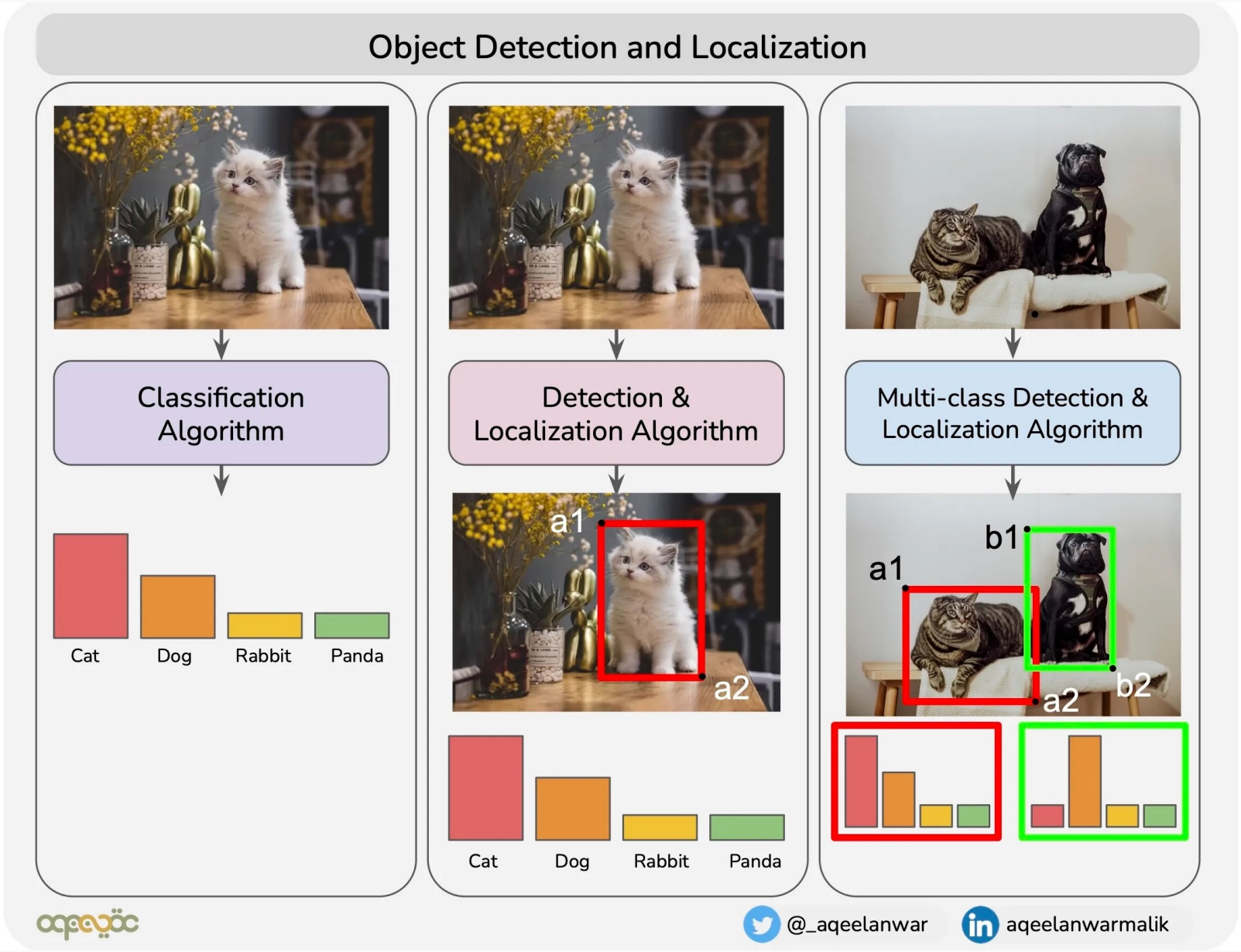
CC6204, Primavera 2024

Object Detection

Introduction

Outline : Introduction

Object Detection



How to evaluate?

How to evaluate the prediction of an bounding box?

$$IoU = \frac{\text{area of overlap}}{\text{area of union}}$$

IoU >= 0.5

The overall Object Detection model can be evaluated using a metric called Average Precision (AP) that uses:

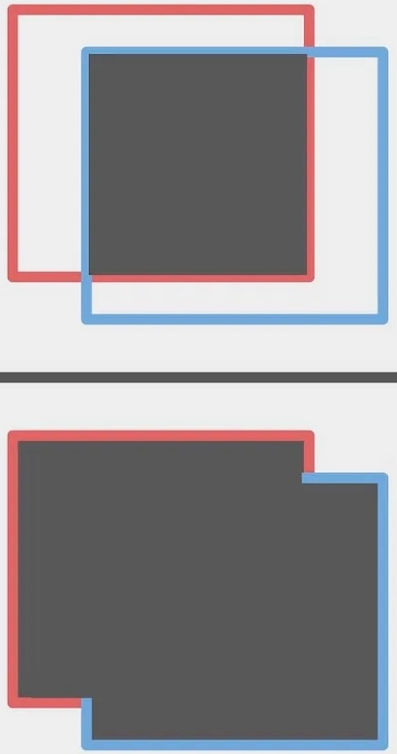
- IoU to compare bounding boxes locations
- the probability of a bounding box

Intersection over Union

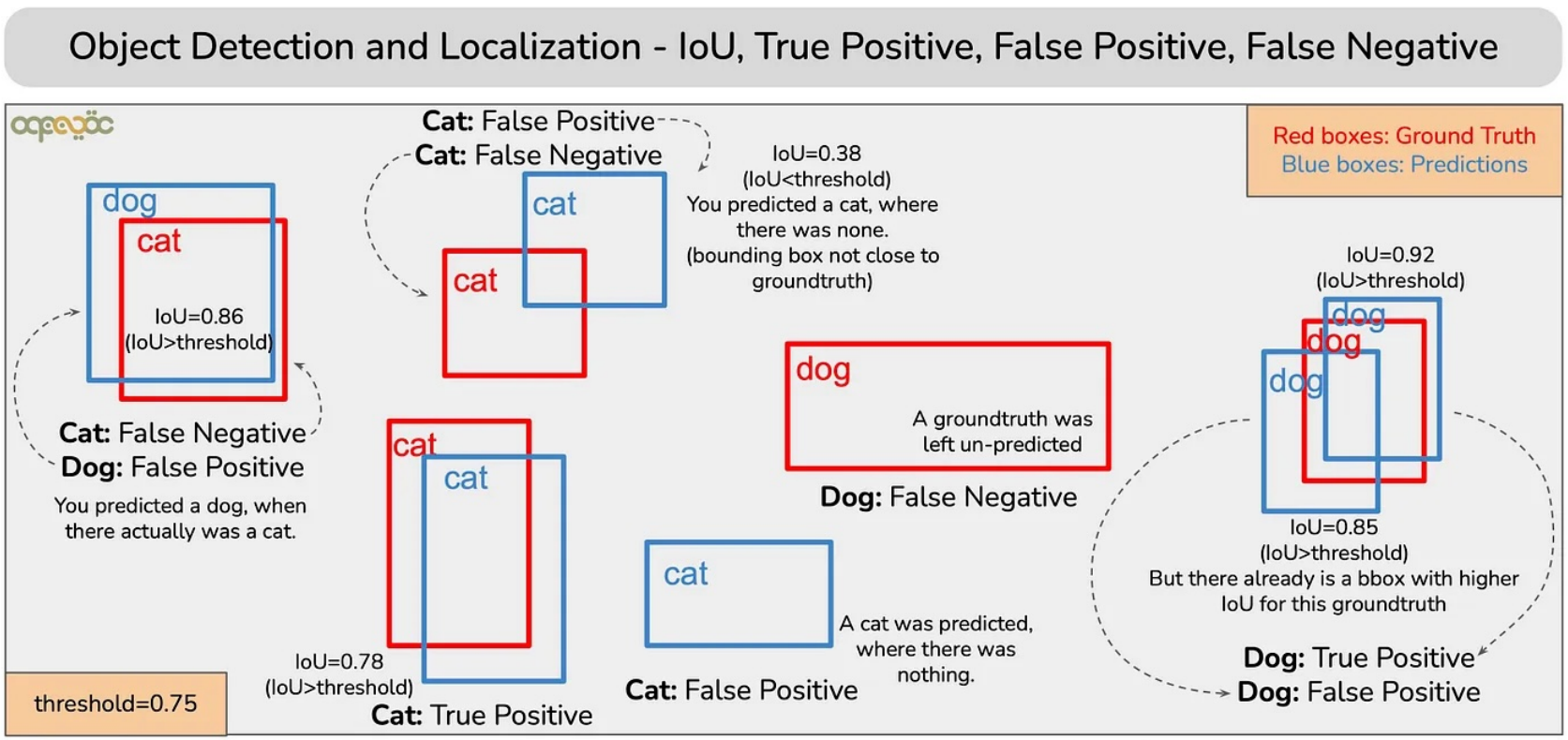
Intersection over Union (IoU)

Ratio between the area of intersection and the area of union of 2 bounding boxes

$$IoU = \frac{\text{area of intersection}}{\text{area of union}}$$



Intersection over Union: how to define a True or False



Threshold	Class	# GroundTruth	# predictions	TP	FP	FN	Precision	Recall
0.75	Cat	3	3	1	2	2	1/3	1/3
	Dog	2	3	1	2	1	1/3	1/2
0.35	Cat	3	3	2	1	1	2/3	2/3
	Dog	2	3	1	2	1	1/3	1/2

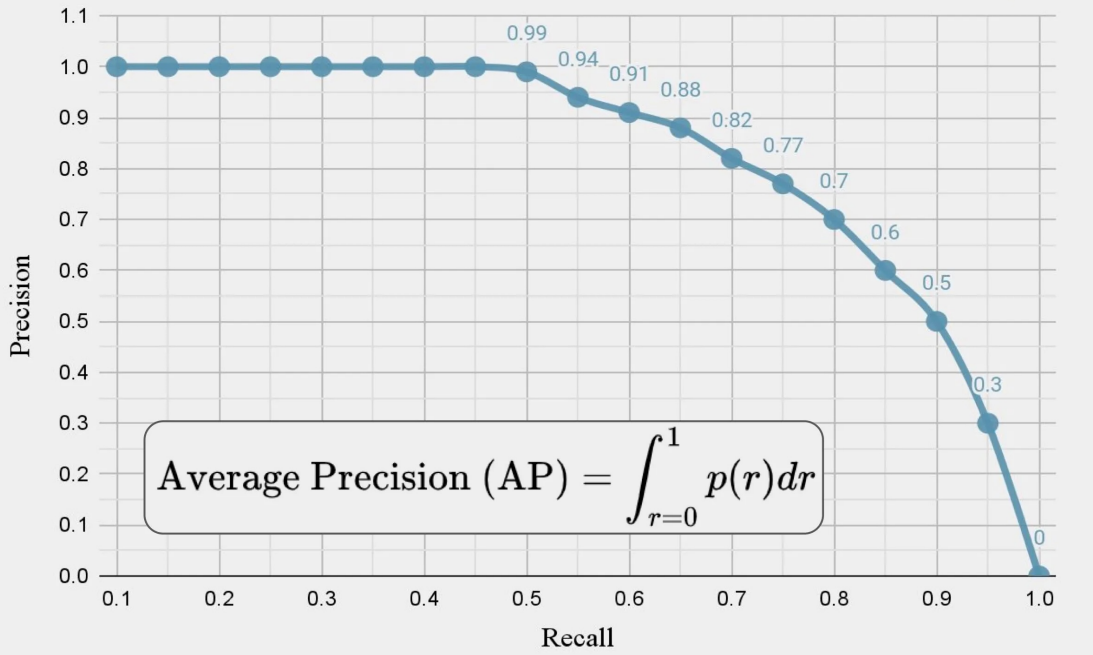
Different thresholds w.r.t the importance to detect precisely an object

Average Precision: Varying Confidence to Create the PR Curve

Precision Recall Curve (PR Curve)

Conf. Thresh.	Recall	Precision	Effect
0.95	0.1	1	More FN
0.9	0.15	1	
0.85	0.2	1	
0.8	0.25	1	
0.75	0.3	1	
0.7	0.35	1	
0.65	0.4	1	
0.6	0.45	1	
0.55	0.5	0.99	
0.5	0.55	0.94	
0.45	0.6	0.91	
0.4	0.65	0.88	
0.35	0.7	0.82	
0.3	0.75	0.77	
0.25	0.8	0.7	
0.2	0.85	0.6	
0.15	0.9	0.5	
0.1	0.95	0.3	
0.05	1	0	More FP

The **smaller the probability confidence threshold**, the higher the number of detections made by the model, and the lower the chances that the ground-truth labels were missed and hence **higher the recall** *(Generally, but not always)*. On the other hand, **the higher the confidence threshold**, the more confident the model is in what it predicts and hence **higher the precision** *(Generally, but not always)*.



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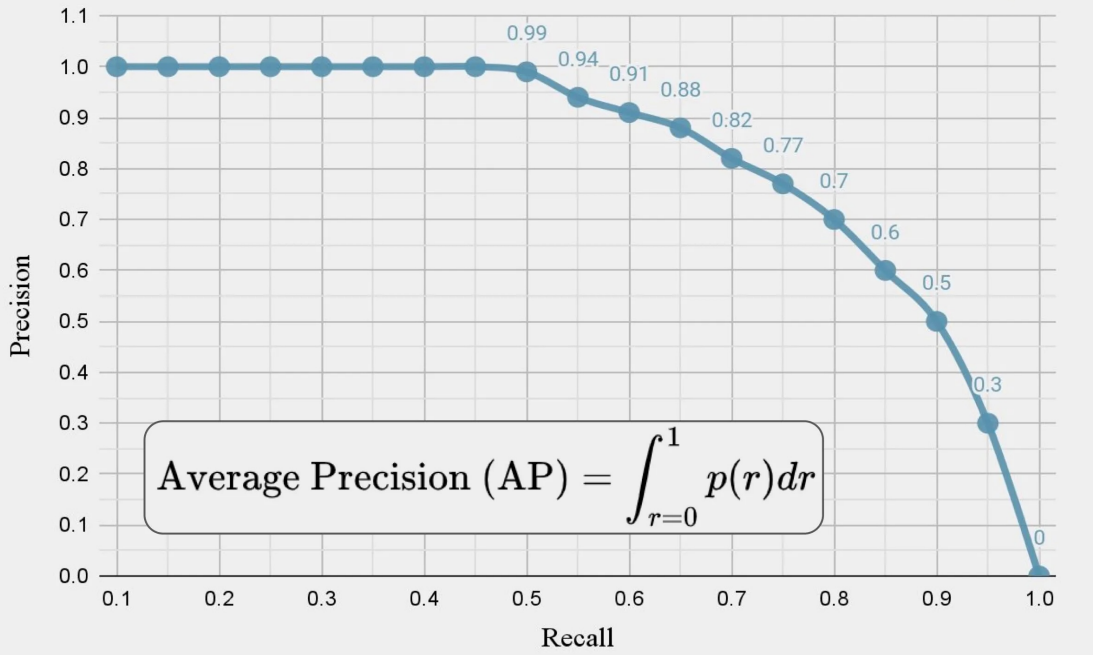
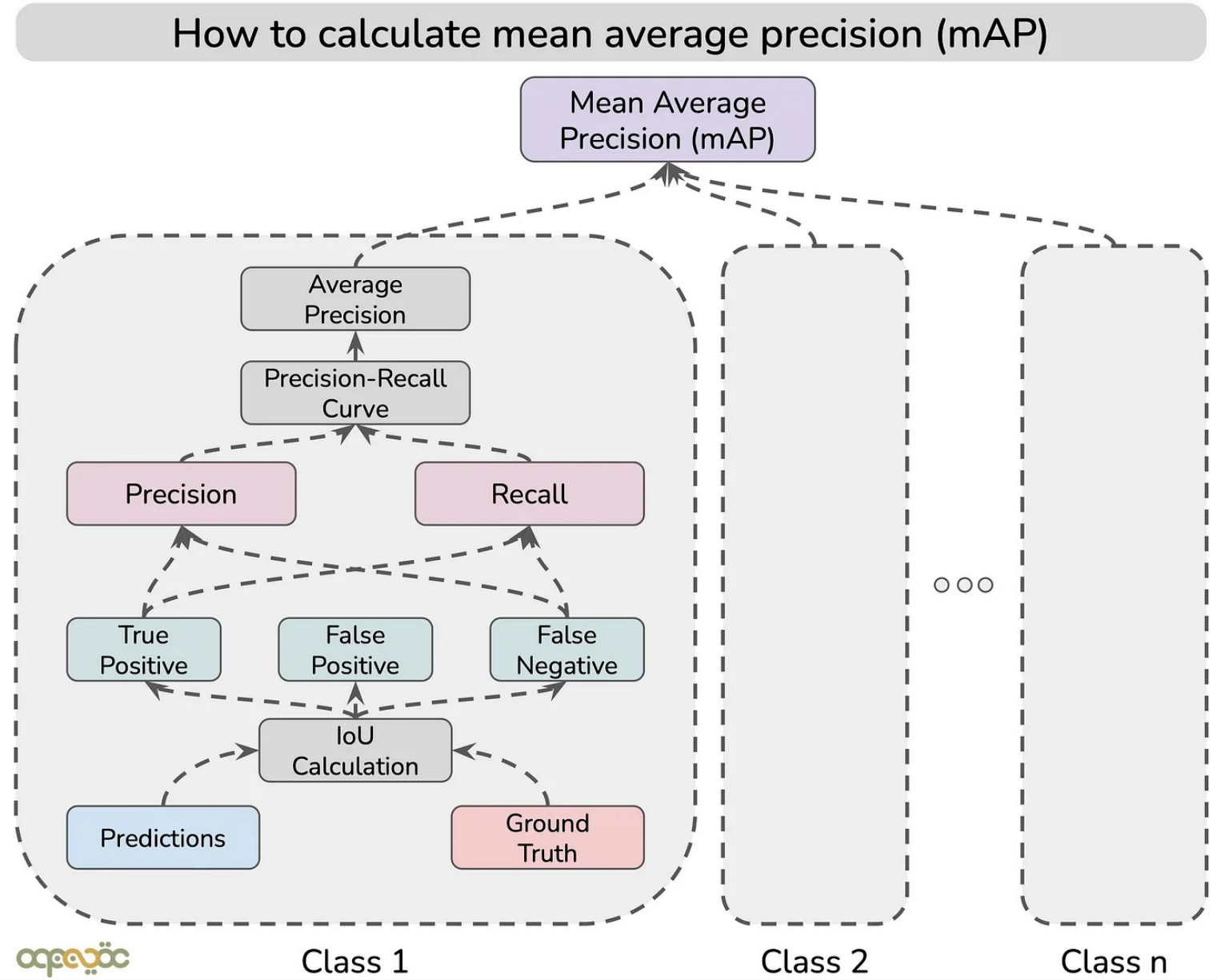


- High Confidence Threshold $\Rightarrow$ High Precision but Low Recall
- Low Confidence Threshold $\Rightarrow$ High Recall but Low Precision

mean Average Precision: AP mean over every classes



Concretely Calculating AP

Calculating Average Precision from PR Curve

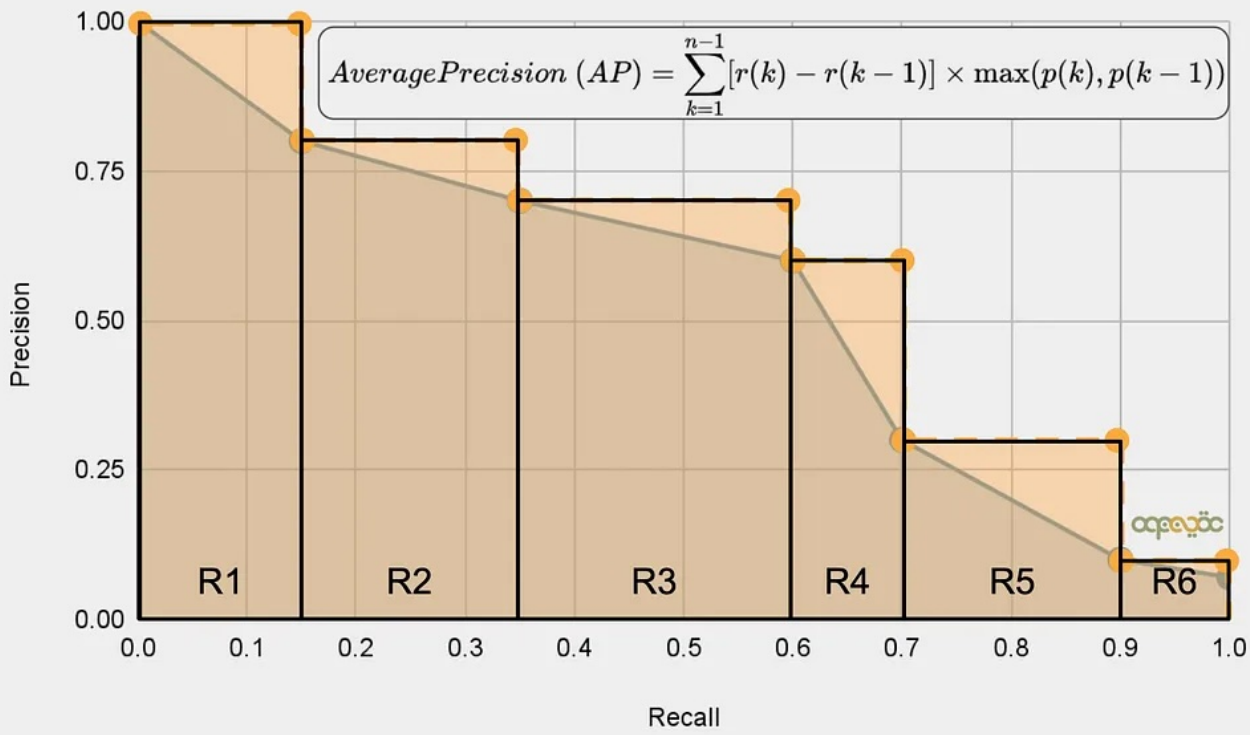
@_aqeelanwar aqeelanwarmalik

Approach 1: Sample-and-hold

- For each precision-recall pair (j=0, ..., n-1), the area under the PR curve can be found by approximating the curve using rectangles.
- The width of such rectangles can be found by taking the difference of two consecutive recall values (r(k), r(k-1)), and the height can be found by taking the maximum value of the precision for the selected recall values i.e.

  w = r(k)-r(k-1)
  h = max(p(k), p(k-1))

- AP can be calculated by the sum of the areas of these rectangles.



More info [here]

Concretely Calculating AP

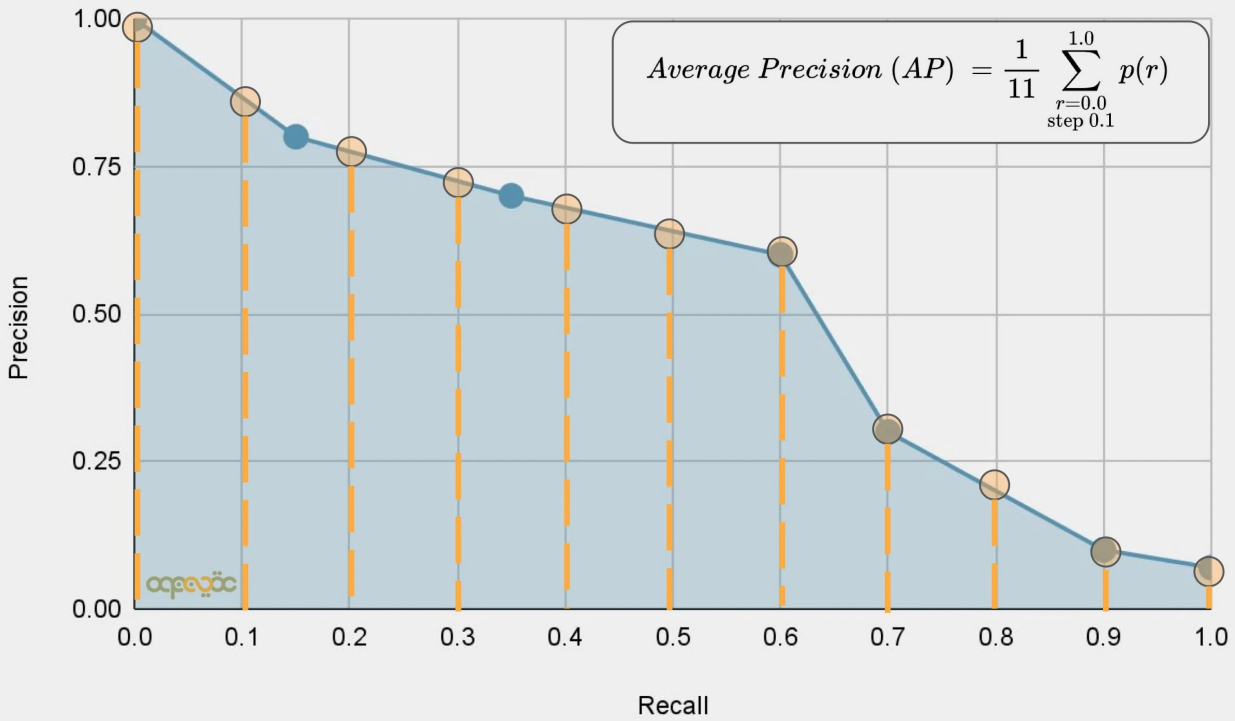
Calculating Average Precision from PR Curve

@_aqeelanwar aqeelanwarmalik

Approach 2: Interpolation and 11-point average

- The precision values for the 11 recall values from 0.0 to 1.0 with an increment of 0.1 is calculated
- These 11 points can be seen as orange samples in the figure on the right
- AP can be calculated by taking the mean of these 11 precision values i.e.

$$(AP) = \frac{1}{11} \sum_{\substack{r=0.0 \\ \text{step } 0.1}}^{1.0} p(r)$$



More info [here]

Datasets

Outline : Datasets

Datasets I

COCO (Common Objects in Context) [7]

- **Type**: Bounding Boxes, Segmentation Masks
- **Details**: The COCO dataset is one of the most widely used for object detection and segmentation. It includes over 330,000 images, with 80 object categories, and provides annotations for bounding boxes, segmentation masks, keypoints, and captions.
- **Applications**: Object detection, segmentation, human pose estimation.

Datasets II

Pascal VOC [1]

- **Type**: Bounding Boxes, Segmentation Masks
- **Details**: 20 object classes.
- **Applications**: detection, semantic segmentation, classification.

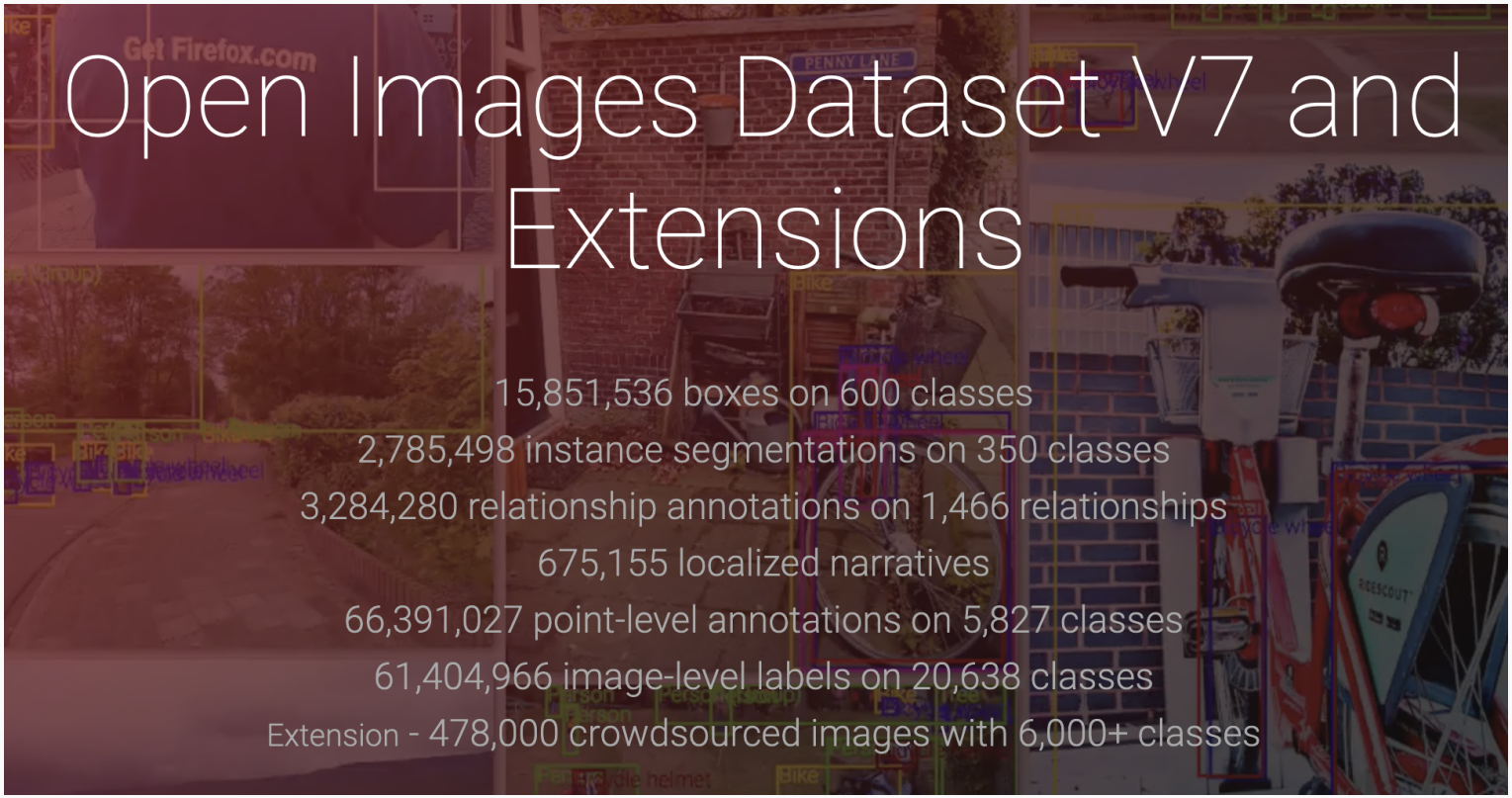


Figure 1: Open Images Dataset [6]

Visual Relationship

Figure 2: Open Image contains rich annotations, like visual relationships

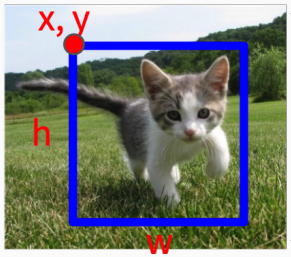
Models

Outline : Models

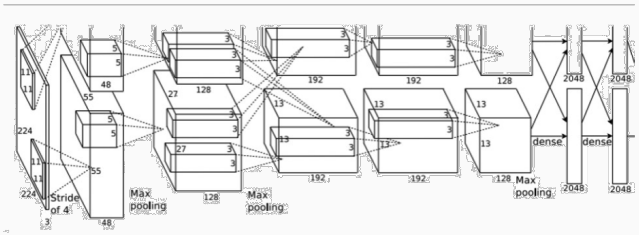
Outline : Object Detection

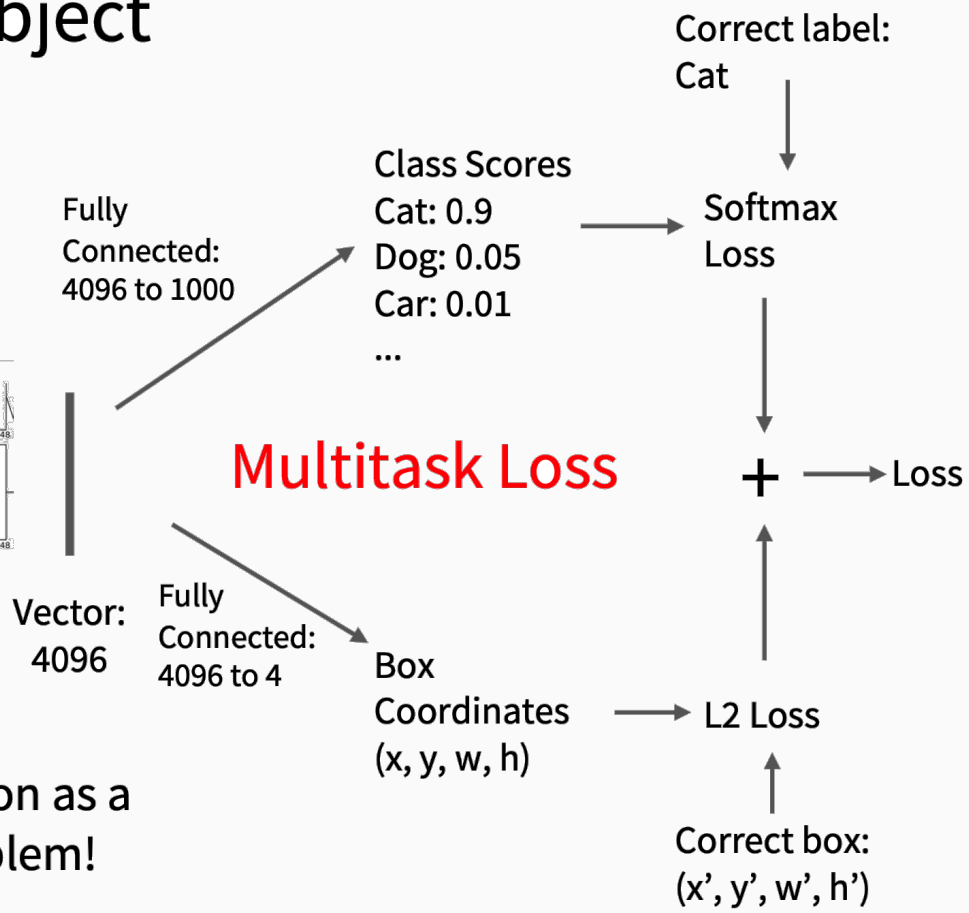
Object Detection: Single Object

(Classification + Localization)



This image is CC0 public domain



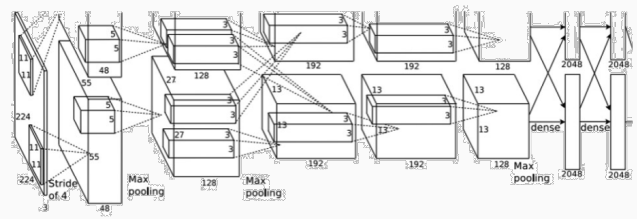


Treat localization as a regression problem!

Bounding boxes are represented by 4-uples with the starting point, height and width

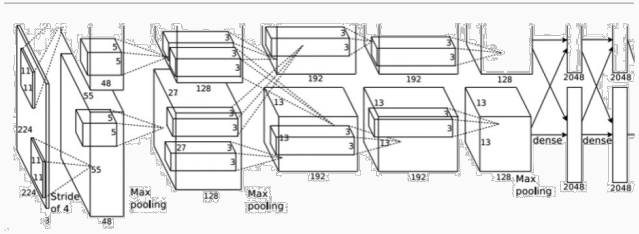
Object Detection: Multiple Objects

Each image needs a different number of outputs!



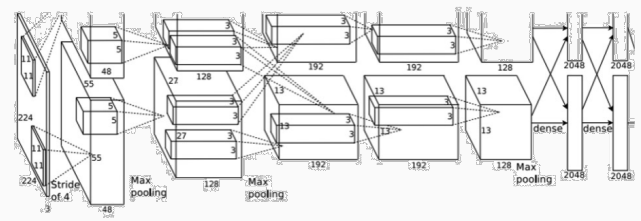
CAT: (x, y, w, h)

4 numbers



DOG: (x, y, w, h)
DOG: (x, y, w, h)
CAT: (x, y, w, h)

12 numbers



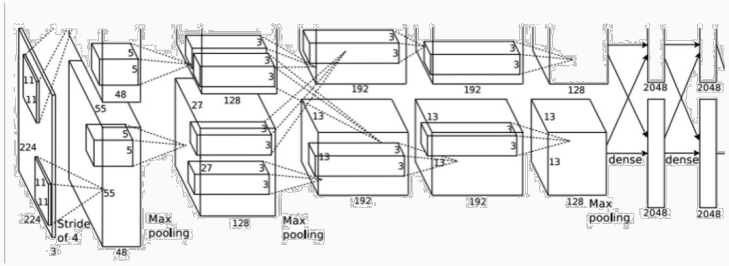
DUCK: (x, y, w, h)
DUCK: (x, y, w, h)
....

Many numbers!

Bounding boxes are represented by 4-uples with the starting point, height and width

Object Detection: Multiple Objects

Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Dog? NO
Cat? NO
Background? YES

Bounding boxes are represented by 4-uples with the starting point, height and width

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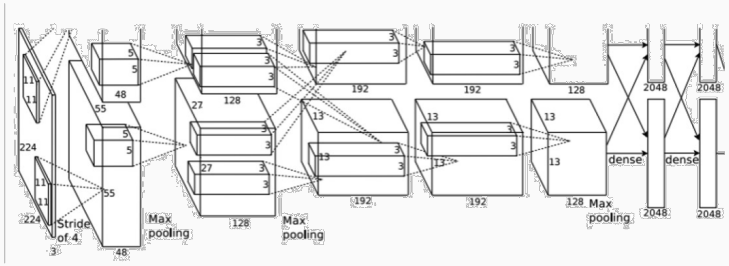

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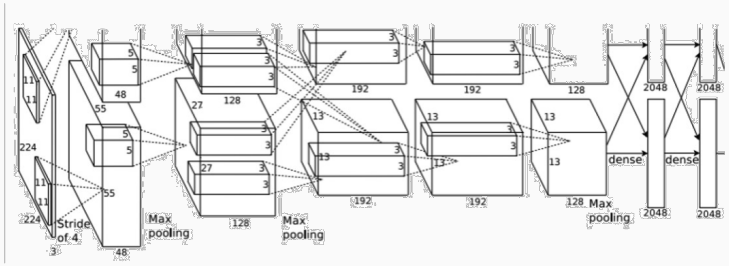

Dog? YES
Cat? NO
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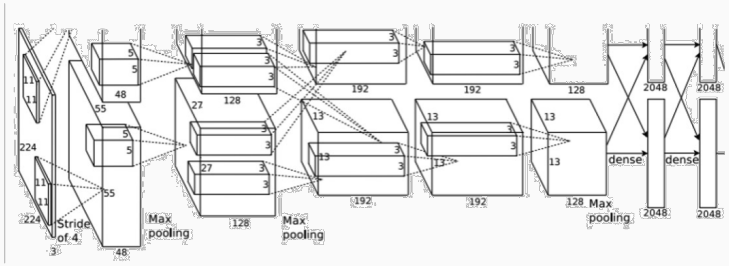
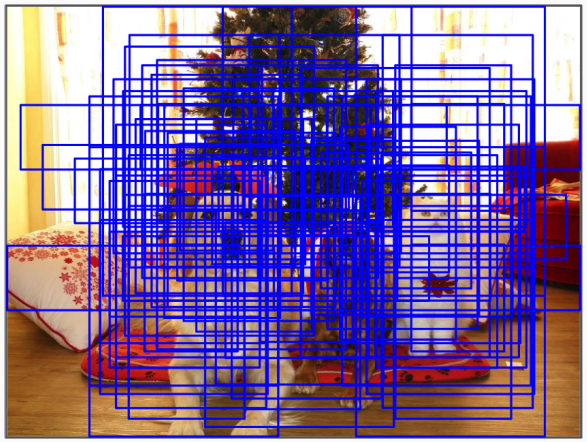


Dog? NO
Cat? YES
Background? NO

Q: What's the problem with this approach?

Bounding boxes are represented by 4-uples with the starting point, height and width

Object Detection: Multiple Objects



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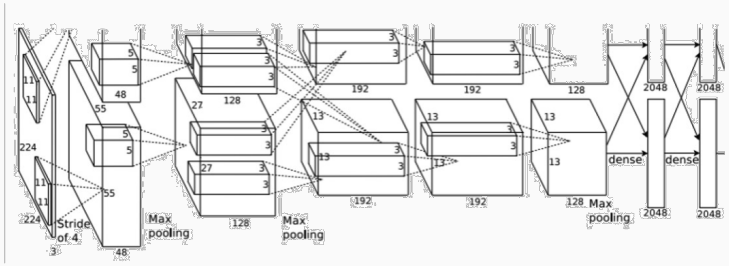

Dog? NO
Cat? YES
Background? NO

Problem: Need to apply CNN to huge number of locations, scales, and aspect ratios, very computationally expensive!

Bounding boxes are represented by 4-uples with the starting point, height and width

R-CNN [3]

Three-stage algorithm:

- Algorithm to generate candidate regions in images (Selective Search)
- Extract candidate region feature with CNN pre-trained
- Classification (object) + Regression (bounding box): SVM + least squares regressor. 25/75 training ratio on object/background

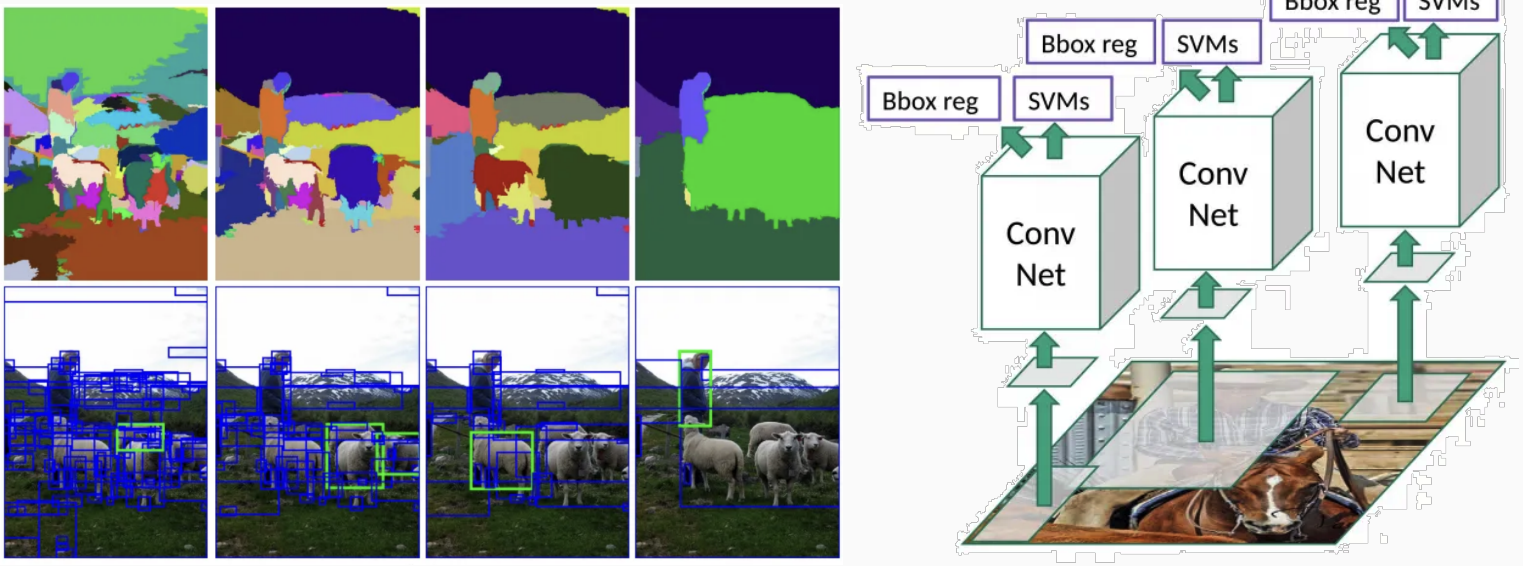

Figure 3: Train time: Selective Search + 2 Loss Functions

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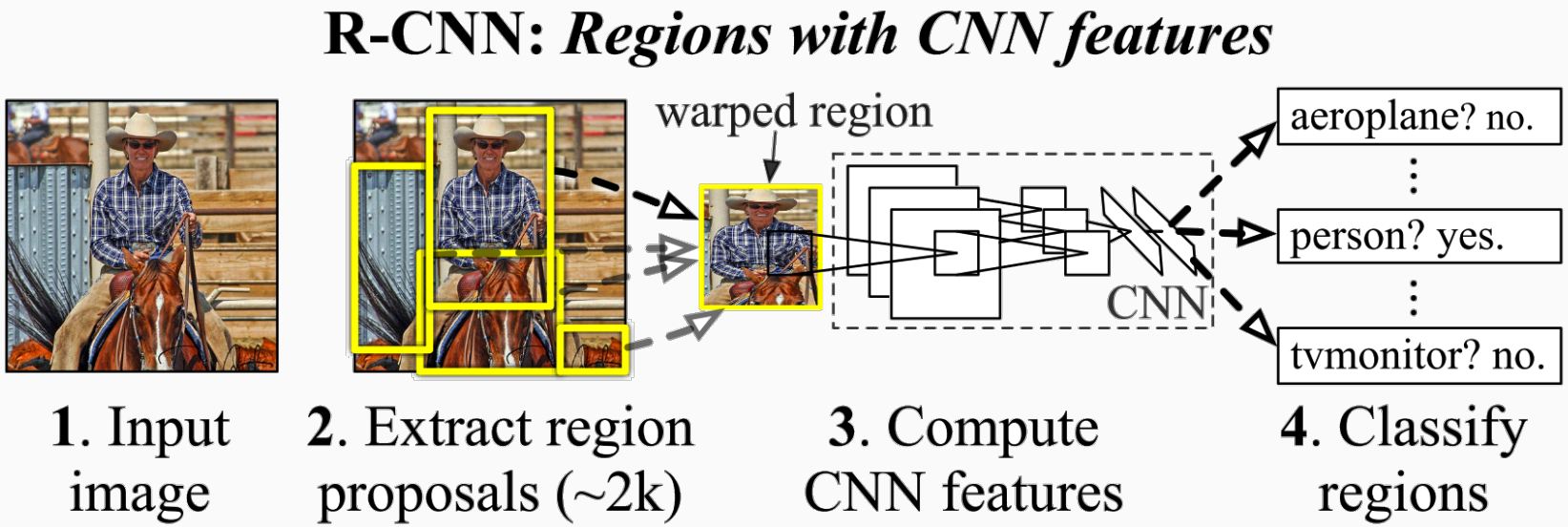
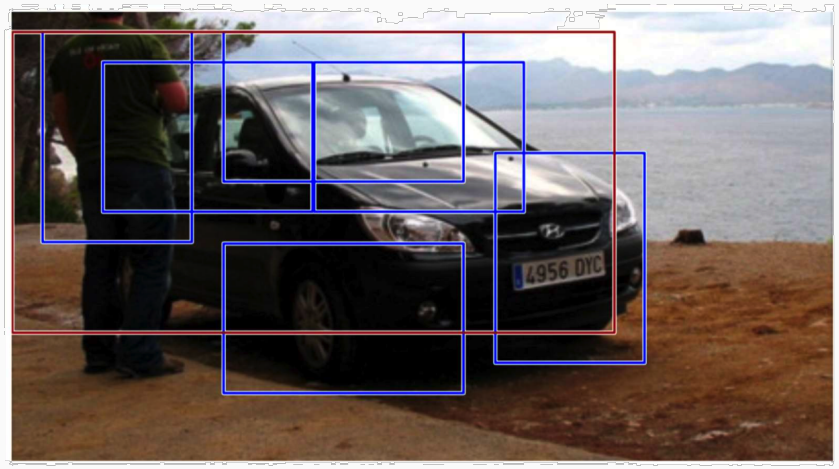


Figure 3: Test time: 2k region proposals, feature extraction + classification

R-CNN [3]: Select the best boxes

- Suppression of non-maximums: many bounding boxes associated with the same object could be generated.
- Sort bounding boxes by confidence value. Choose the one with the highest value.
- Remove all bounding boxes with IoU ≥ 0.5 and same class as the chosen one.
- Repeat until no more bounding boxes can be removed.



Before non-max suppression

After non-max suppression

Fast R-CNN [2]

Idea

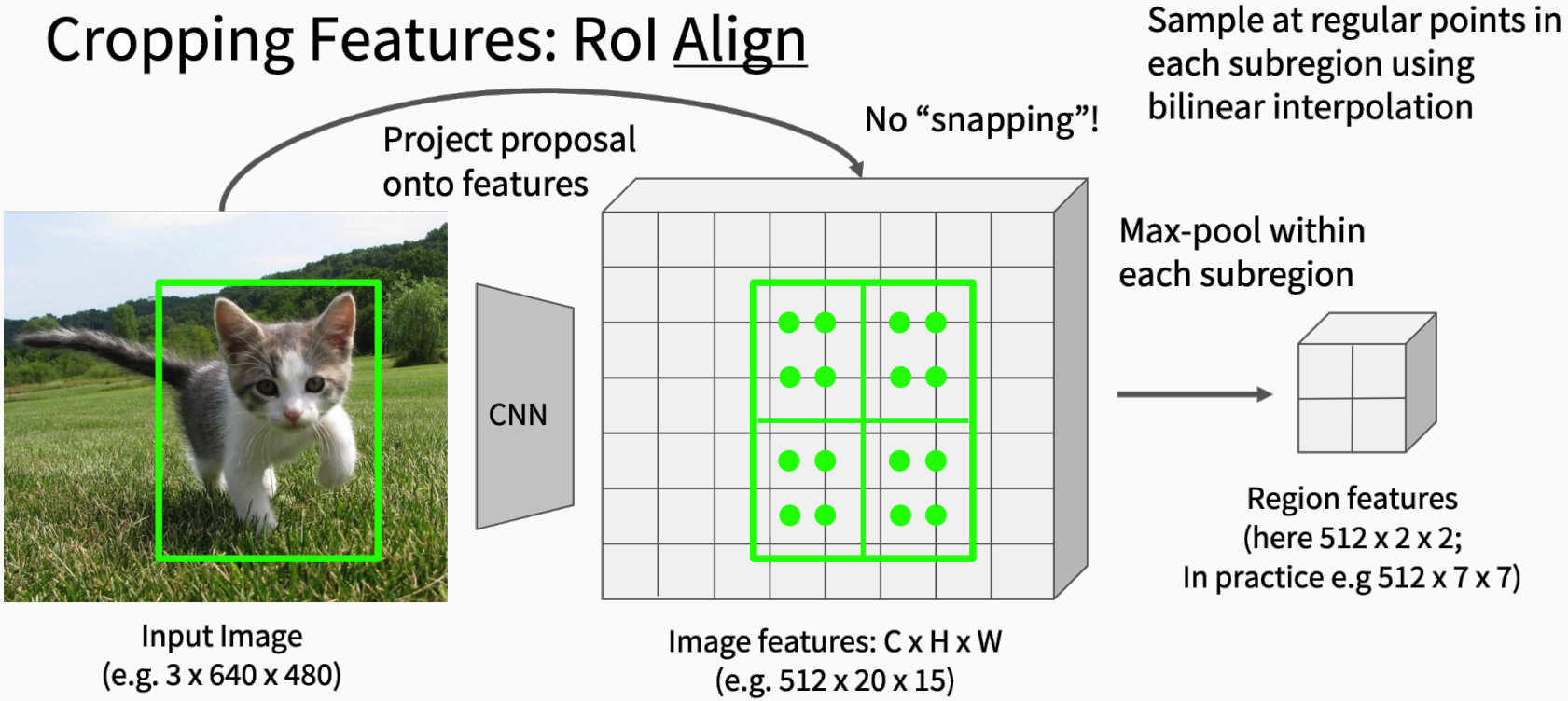
Why not run the CNN just once per image and then find a way to share that computation across the ≈ 2000 proposals?

Fast R-CNN [2]

Idea

Why not run the CNN just once per image and then find a way to share that computation across the ≈ 2000 proposals?

- Warp the RoIs directly on the activation maps
- Use a FC layers and then the 2 losses
- Convolution operation is done only once per image and a feature map is generated from it



Fast R-CNN [2]

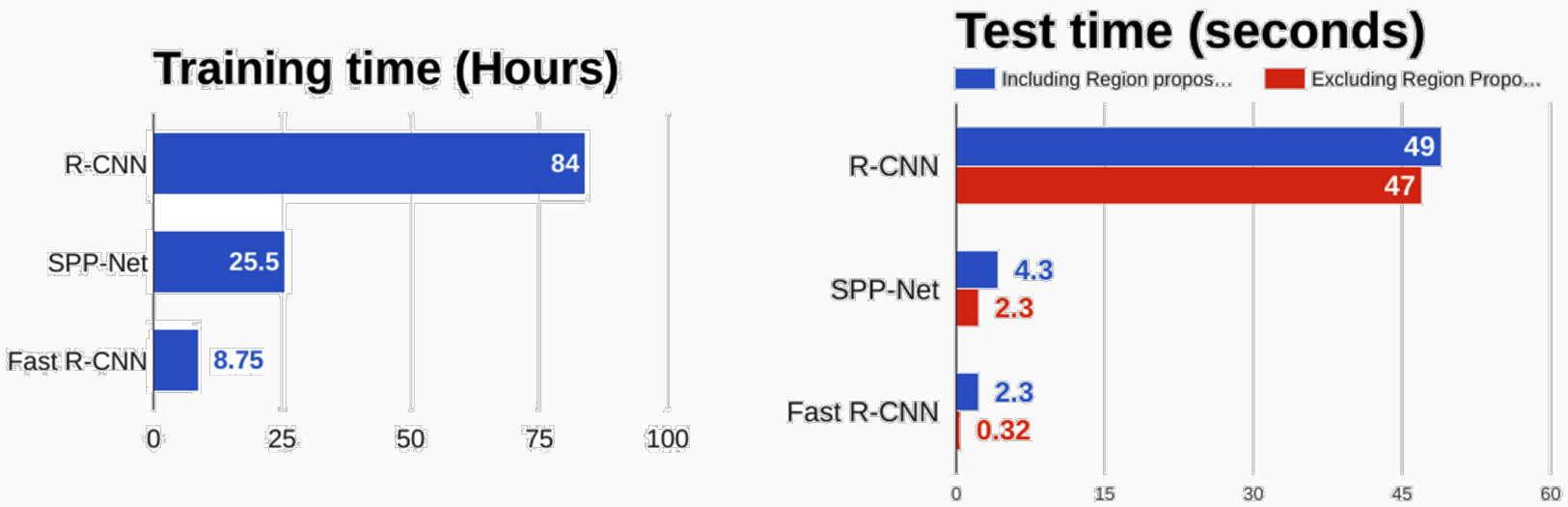


Figure 4: Way Faster than R-CNN

YOLO [8]

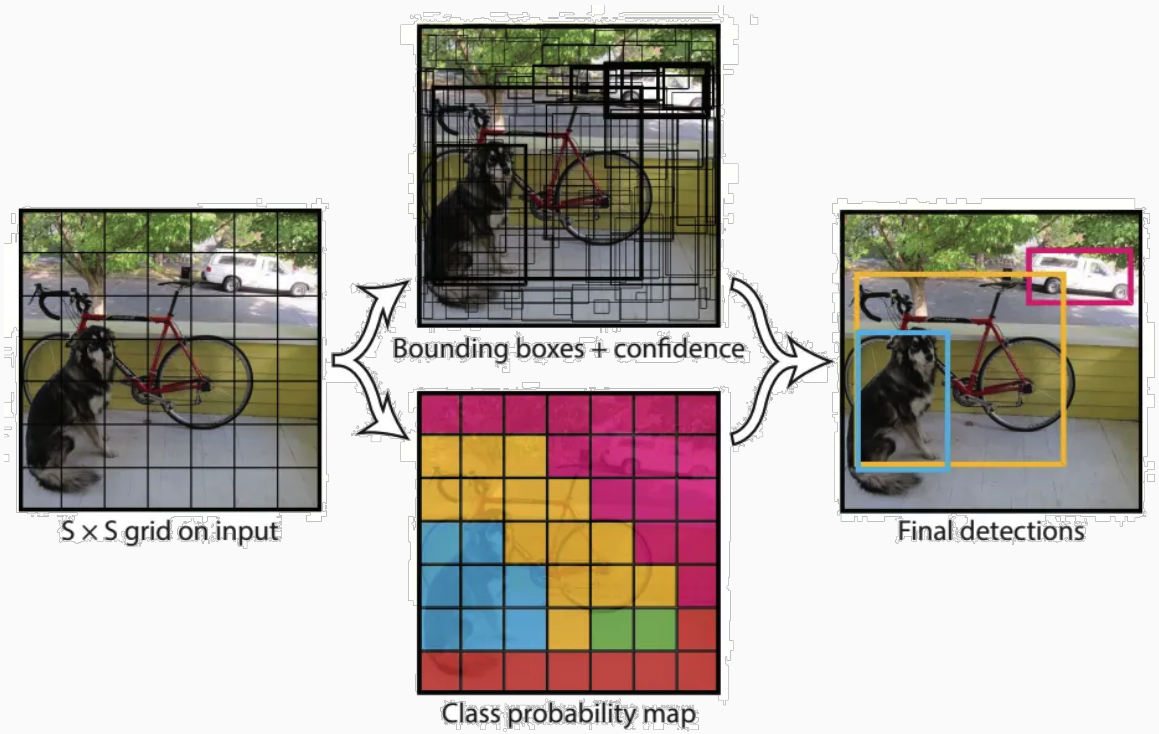
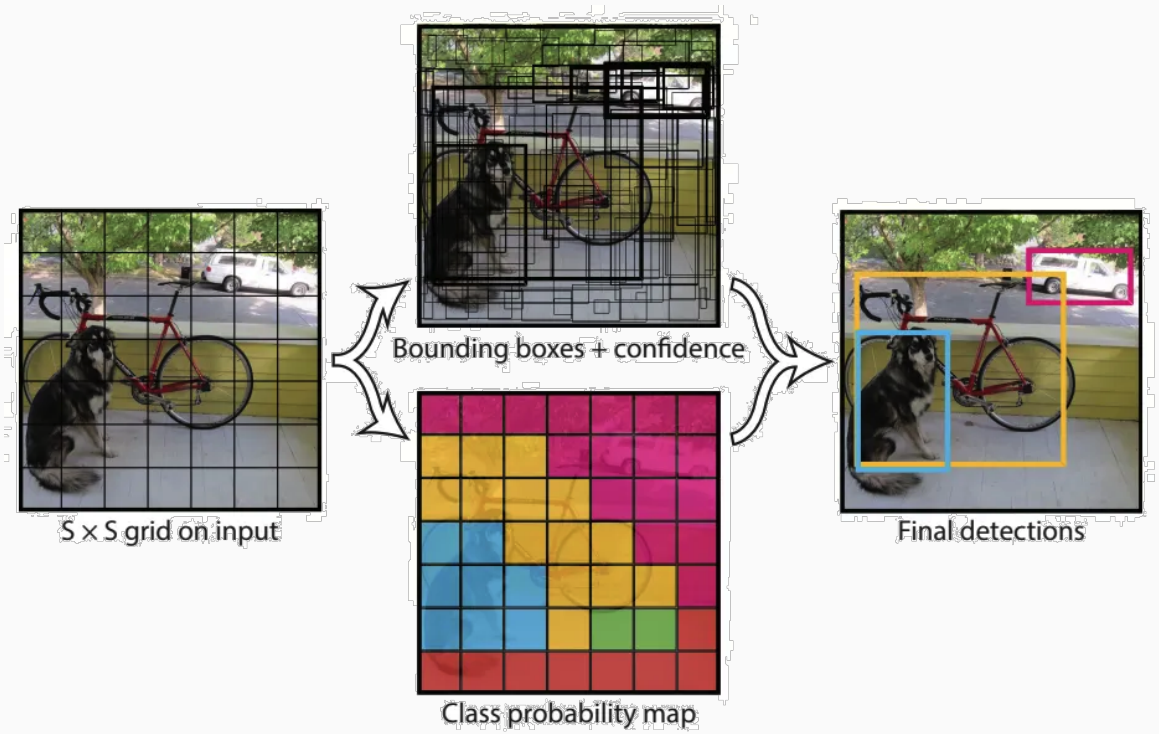


Figure 5: Segments the image into a grid to predict a vector on each cell

For every cell in the grid predict B times (number maximum of Boxes):

- Bounding box size and center coordinate (4 dims)
- Probability of bounding box (1 dim)
- Classes probabilities (C dims)

YOLO [8]



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- Bounding box size and center coordinate (4 dims)
- Probability of bounding box (1 dim)
- Classes probabilities (C dims)

$\Rightarrow$ **Vector of size** $B * (1 + 4 + C)$ as label on every cell of the grid

Outline : Segmentation

From faster RCNN [9] to Mask-RCNN [4]

Object Detection: Faster R-CNN

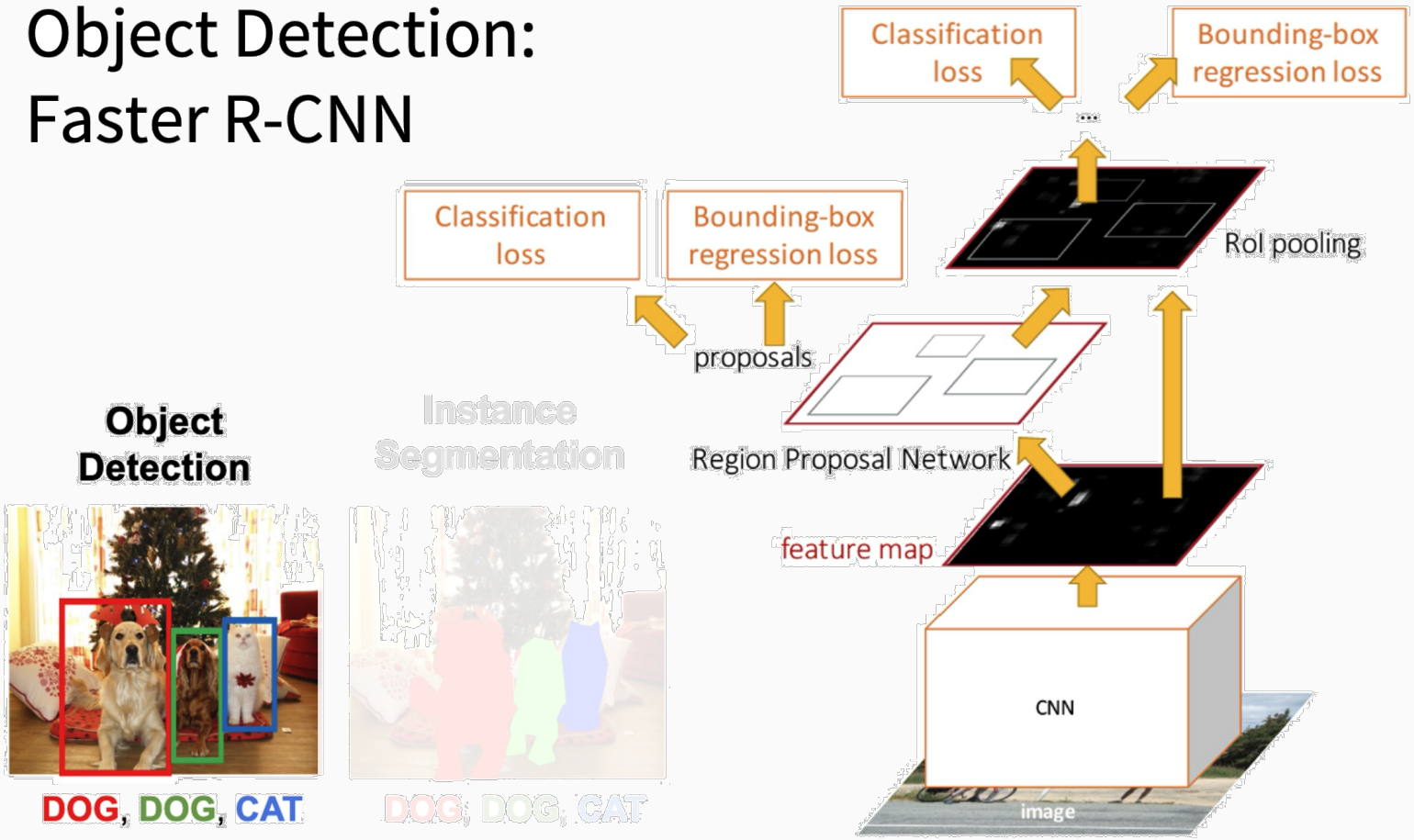
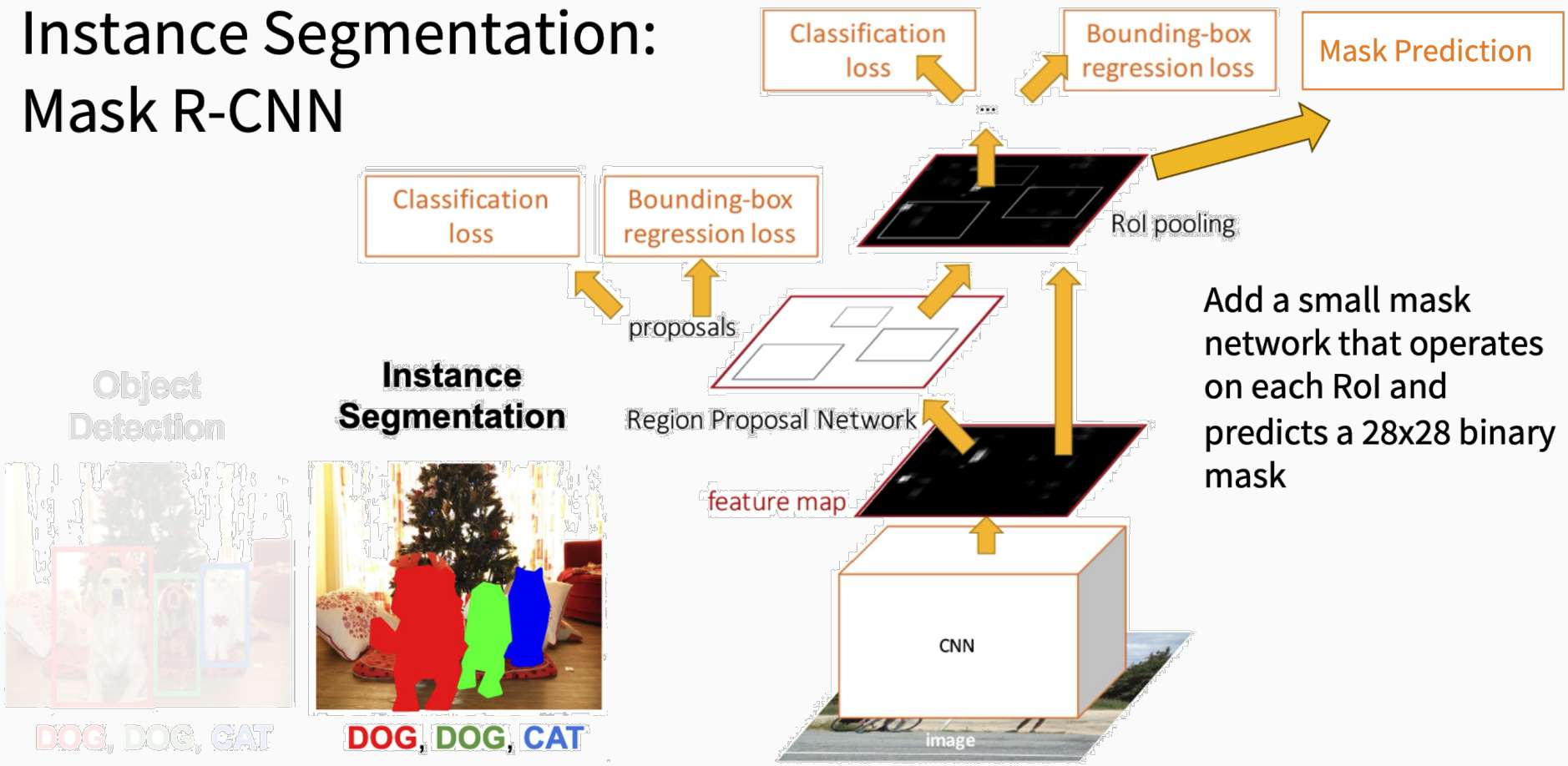


Figure 6: Faster R-CNN

From faster RCNN [9] to Mask-RCNN [4]

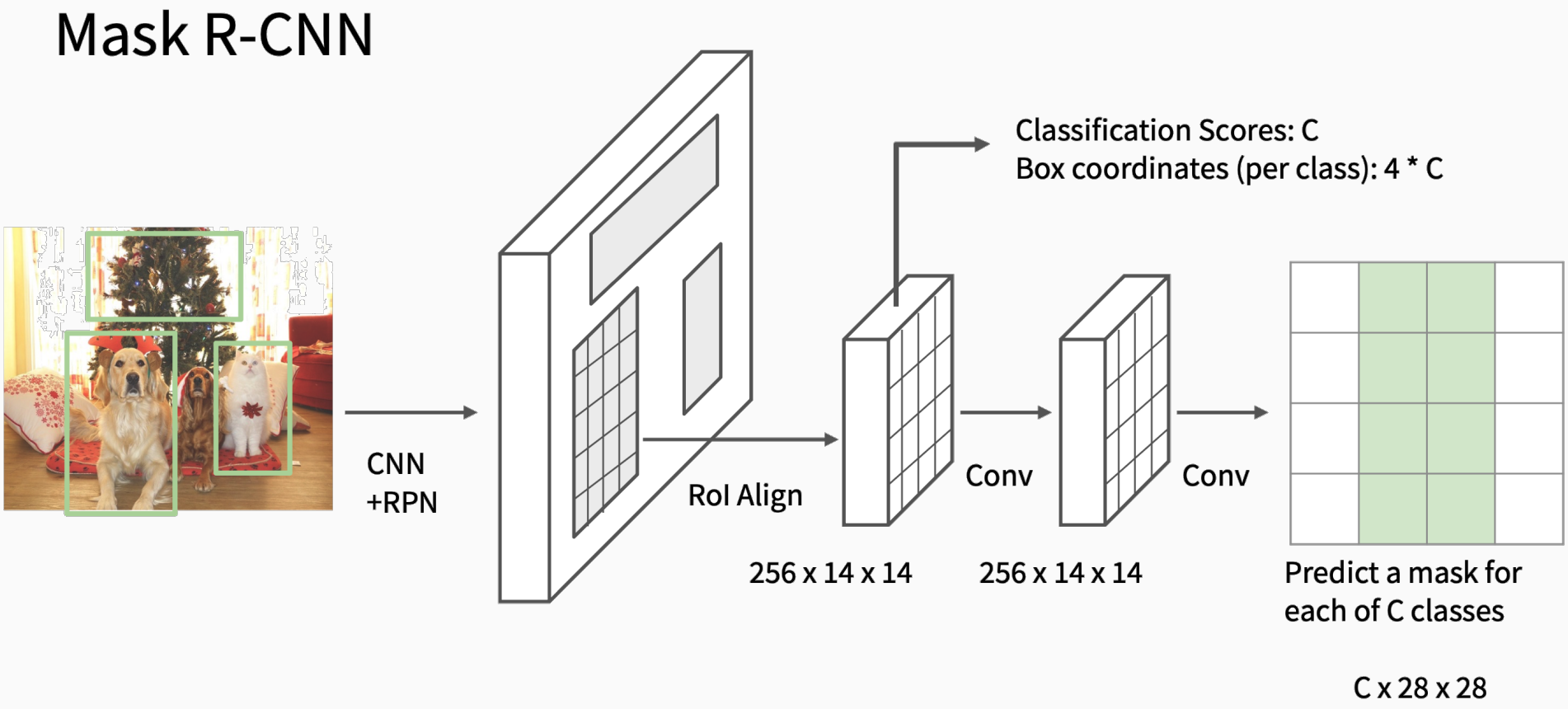
Instance Segmentation: Mask R-CNN



He et al, "Mask R-CNN", ICCV 2017

Figure 6: Mask R-CNN

Mask-RCNN [4]



He et al, "Mask R-CNN", arXiv 2017

Figure 7: Mask R-CNN

Mask-RCNN [4]

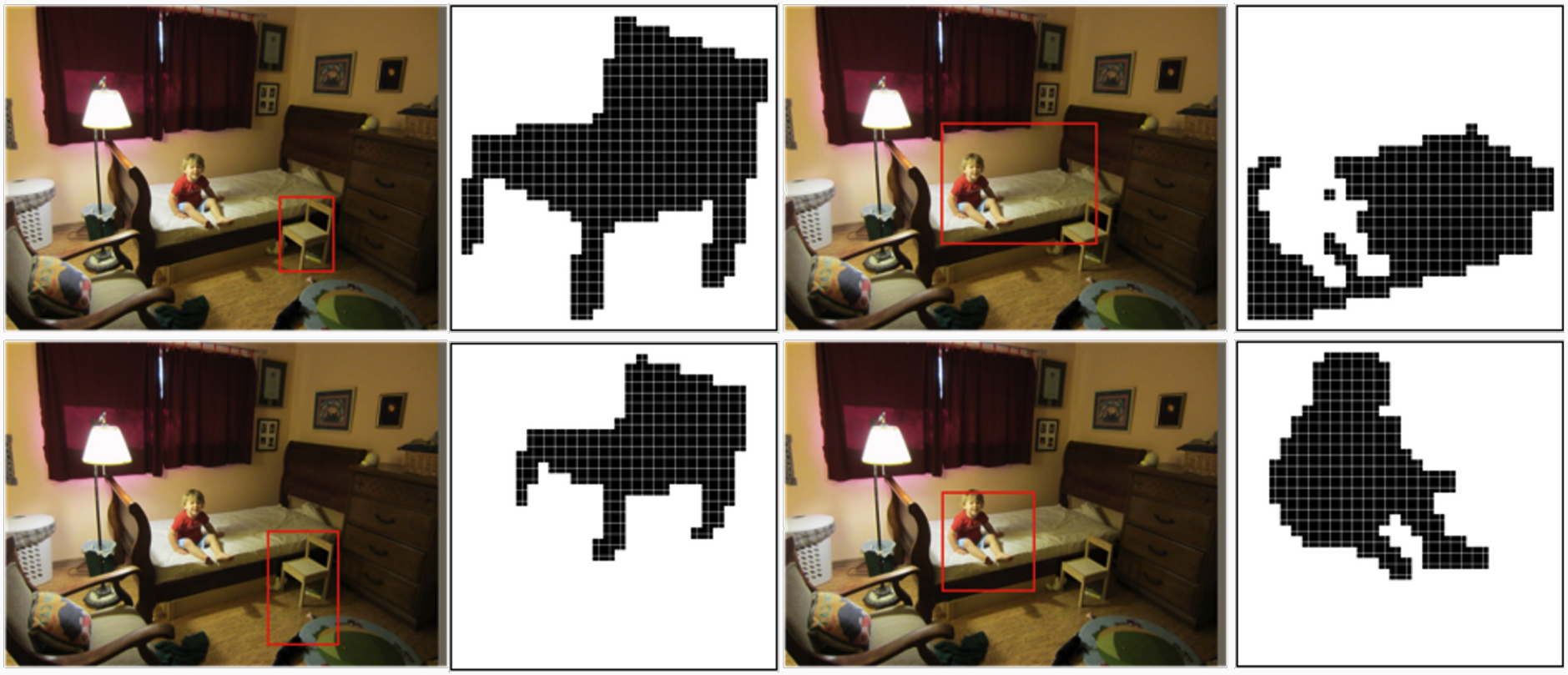
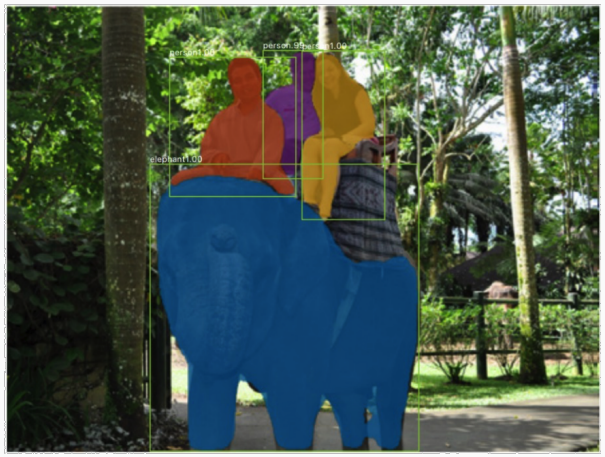
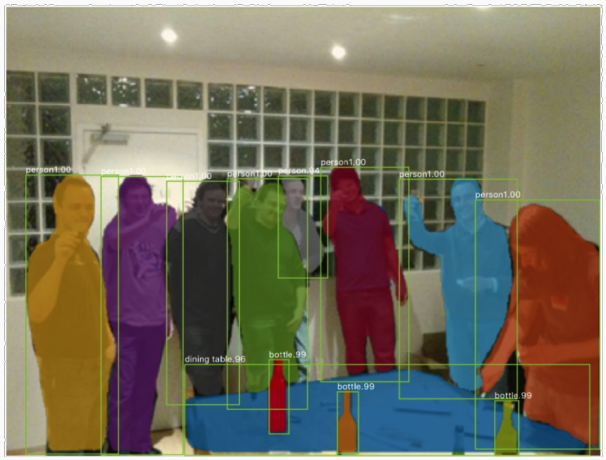


Figure 8: Training Examples

Output Examples

Output Examples





Outline : Others and SOTA

Transformers-based: Detectron2

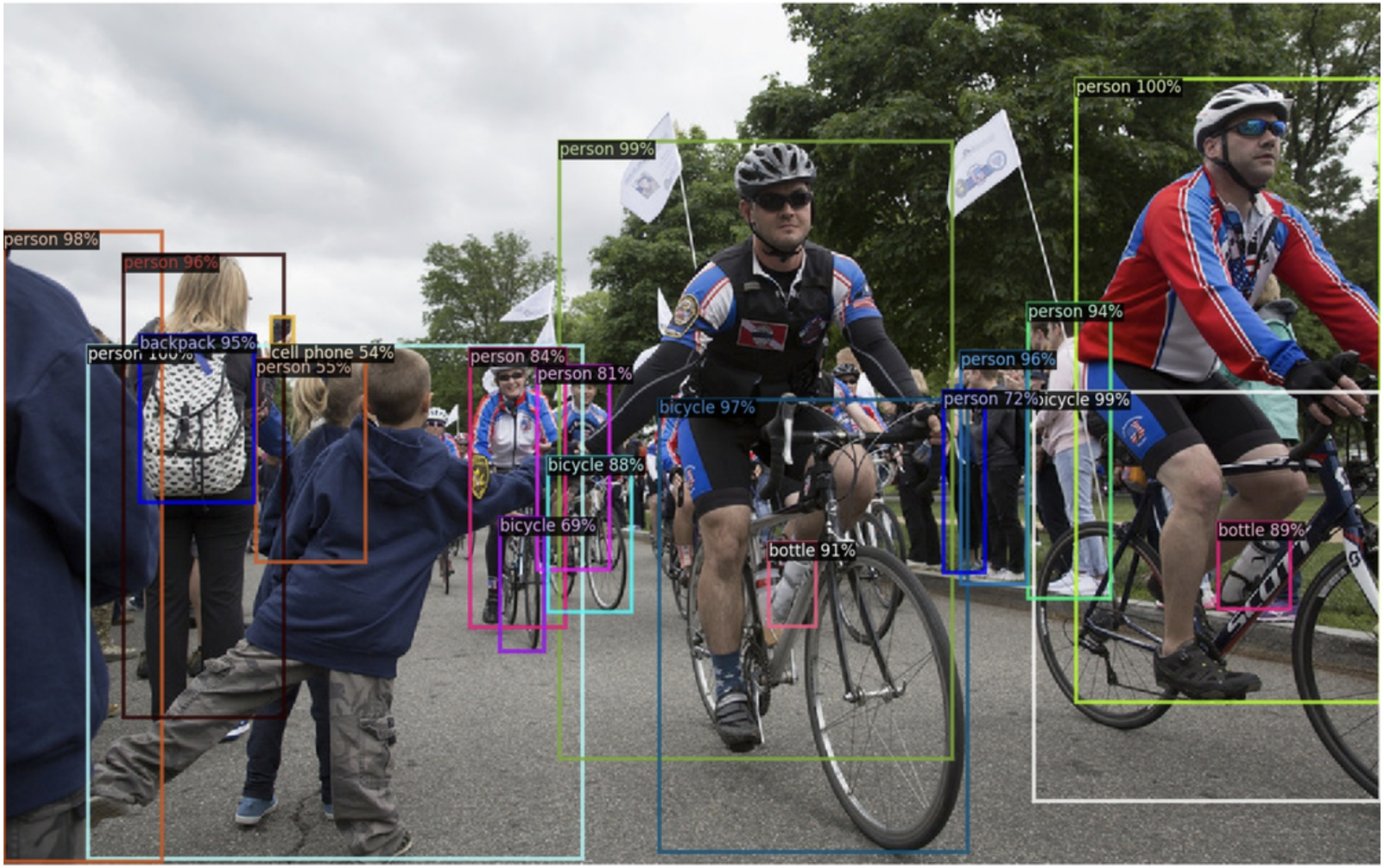


Figure 9: Detectron2 available [online]

Transformers-based: Detectron2

Figure 9: Detectron2 available [online]

Transformers-based: Detectron2

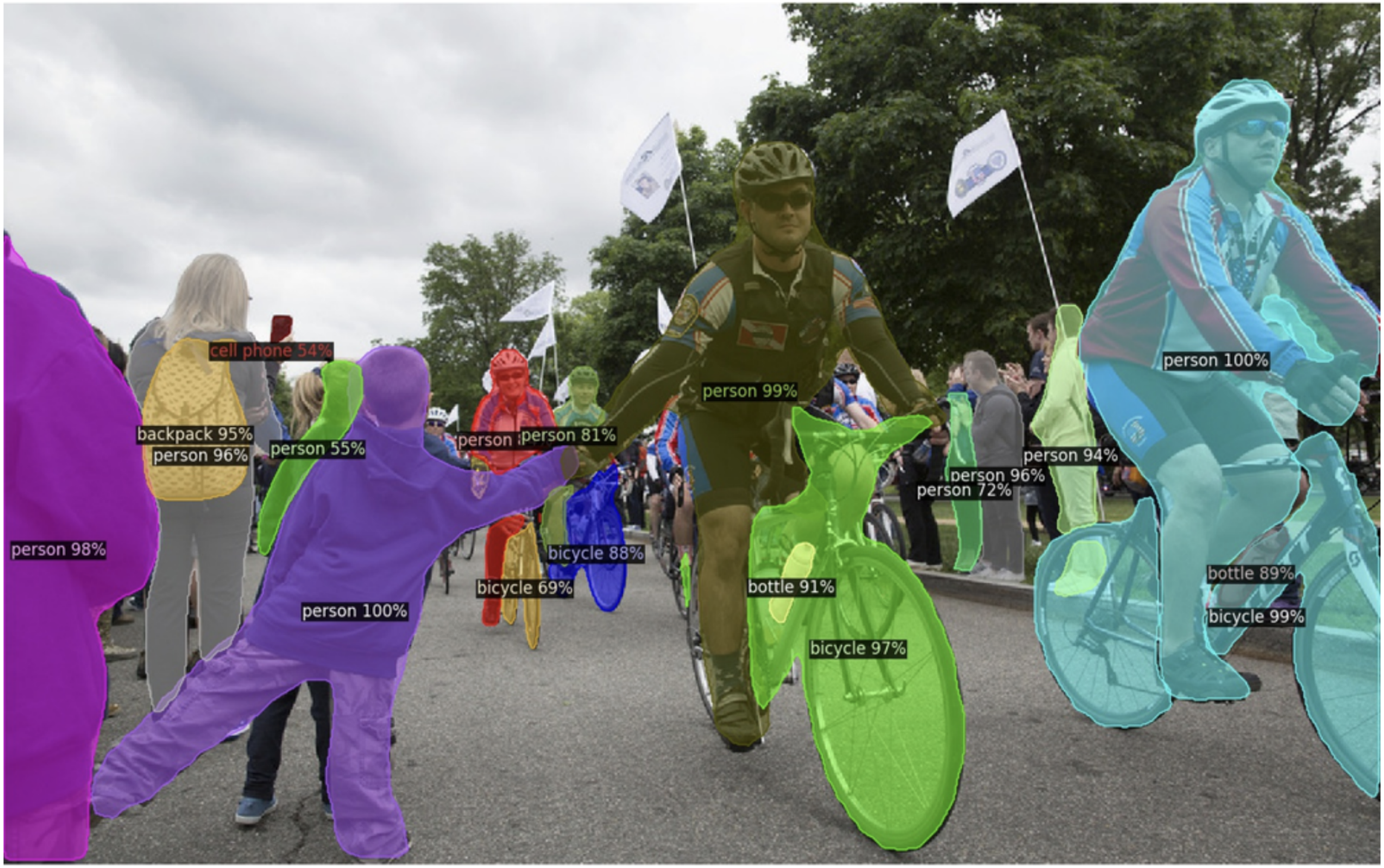


Figure 9: Detectron2 available [online]

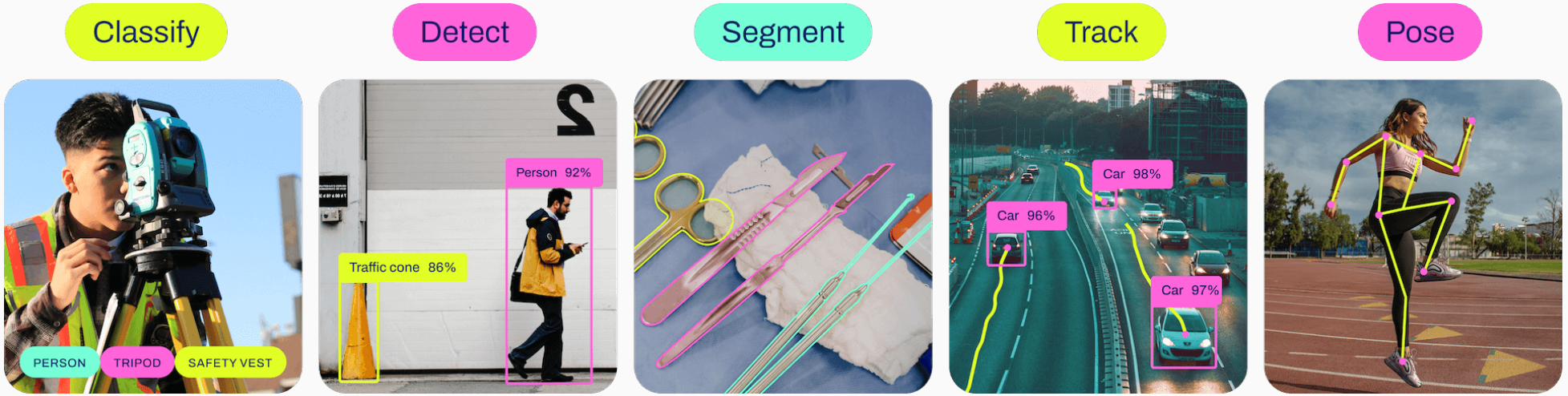
Transformers-based: Detectron2

Figure 9: Detectron2 available online

Transformers-based: Detectron2

Figure 9: Detectron2 available online

Yolov11



Many more tasks are now possible using the new off-the-shelf models, such as Yolov11.

Segment Anything Model [5]

- SAM can segment automatically

SAM2 github and demo

Segment Anything Model [5]

- SAM can segment automatically
- SAM can **interacts with the user** to find the right object

SAM2 [github](#) and [demo](#)

Segment Anything Model [5]

- SAM can segment automatically
- SAM can **interacts with the user** to find the right object
- Other similar models exists such as SEEM [10]

SAM2 github and demo

Questions?

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