Object detection with Deep Neural Networks

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Object detection with Deep Neural Networks

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- Introduction to object detection
- Required tools
- Multi Stage detectors
- Evaluation metrics for object detection
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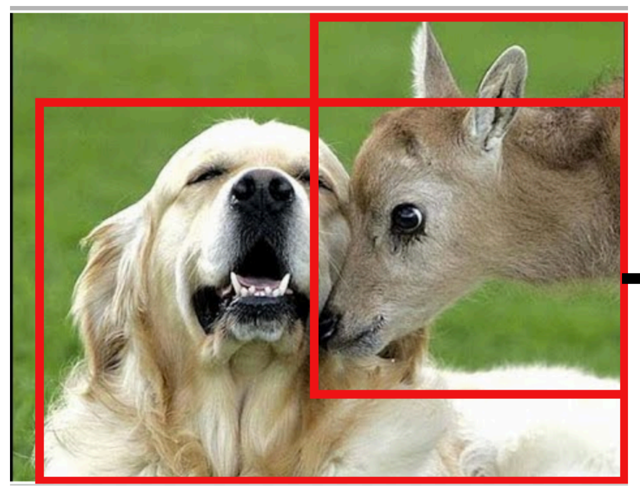
Introduction

- Object detection is an extension of image classification task
- Multi-Class classifiers: Focuses on only one object per image
- Multi-Label classifiers: Focuses on multiple objects per image
- Object detection: Focuses on multiple objects and their locations per image



Detection model(s) and/or mechanisms (Feature Extraction)

Bounding Box Coordinates and classes (Classifier and Regressor heads)

Highlevel overview of Object detection

Detection model acts as a feature extractor

Classification head performs class classification

Regression Head performs bounding box coordinate regression

Object detectors are a combination of classifiers and regressors

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Introduction

- Datasets in object detection:
  - Unlike in the classification case, a dataset for object detection requires the bounding box coordinates for each class
  - The bounding box coordinates can be defined with different formats
    - Pascal VOC Format: XML
    - COCO Format: JSON object
    - The bounding box coordinates can be in $[min, max]$ format or $[center, hight, width]$ format
  - Both these formats can represent labels for other tasks such as:
    - Image segmentation
    - Key Point detection

```xml
<annotation>
        <folder>Kangaroo</folder>
        <filename>00001.jpg</filename>
        <path>./Kangaroo/stock-12.jpg</path>
        <source>
                <database>Kangaroo</database>
        </source>
        <size>
                <width>450</width>
                <height>319</height>
                <depth>3</depth>
        </size>
        <segmented>0</segmented>
        <object>
                <name>kangaroo</name>
                <pose>Unspecified</pose>
                <truncated>0</truncated>
                <difficult>0</difficult>
                <bndbox>
                        <xmin>233</xmin>
                        <ymin>89</ymin>
                        <xmax>386</xmax>
                        <ymax>262</ymax>
                </bndbox>
        </object>
</annotation>
```

Ref.1: Pascal VOC format

```
{
    "info": {...},
    "licenses": [...],
    "images": [...],
    "annotations": [...],
    "categories": [...], <-- Not in Captions annotations
    "segment_info": [...] <-- Only in Panoptic annotations
}
```

Ref.2: COCO format

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Required tools

- Dataset annotator:
  - Performs the annotation of the bounding boxes
  - In most cases the bounding boxes are orthogonal
  - Rotates bounding boxes that encodes the rotation angle is possible
    - In this case one has to use a specific type of detection models
      - Check refs for some resources
  - Most data annotation tools can perform other tasks such as: Keypoint annotation, Image segmentation

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Required tools

- Object detection frameworks:
  - Since the object detection task is more complex than the image classification, the underline models can be complex
  - Therefore popular frameworks such as TensorFlow and PyTorch has object detection libraries which simplifies the training and model inference process
    - Model Inference: Once a model is trained, The model graph + trained parameters can be extracted to deploy in production.
    - The goal of graph extraction is to prune all the nodes that were used for training (optimiser ops, gradient ops) and keep only a forward model
    - Advance inference techniques: Model weight quantisations; Sacrifice the classification performance for resource saving

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Multi Stage detectors

- The multistage detectors:
  - object proposal stage
    - Selective search for potential object proposals, Region proposal networks (RPN) that learns to find proposals
    - Suggest the objectness of a proposal and predict the required coordinate shift from a reference position
  - Proposal classification and regression stage
    - This stage further fine tune the suggested proposals by:
      - classifying them in to the respective classes
      - regress the required coordinate shift from current coordinate position

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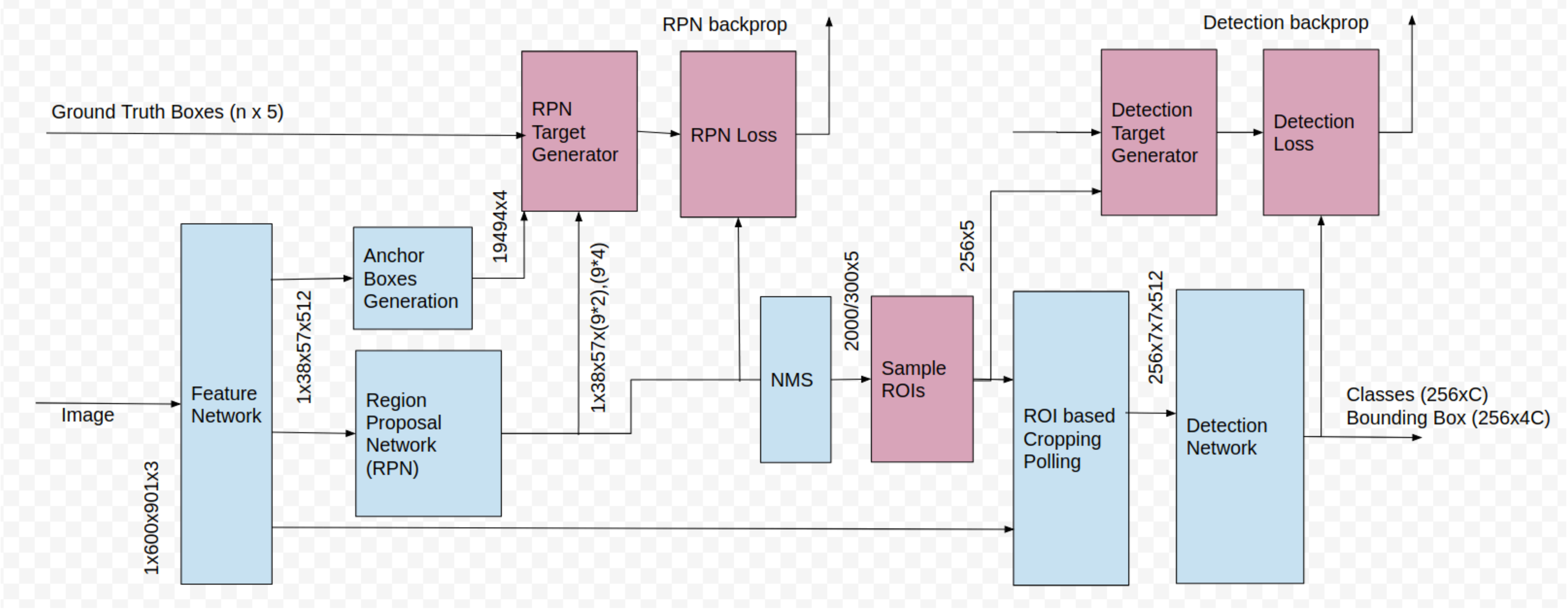
Multi Stage detectors (Faster RCNN)



Ref.3: Faster RCNN model

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Multi Stage detectors (Faster RCNN Stage-1)

- **Feature Network:**
  - A typical Convolutional Neural Network (CNN) such as VGG or ResNet can be used
  - For Fast model inference a MobileNet (Ref.4) can be used
  - Take VGG16 architecture: This model reduces the input by a ratio 32
    - Input (800x800) — VGG —> output (25x25)

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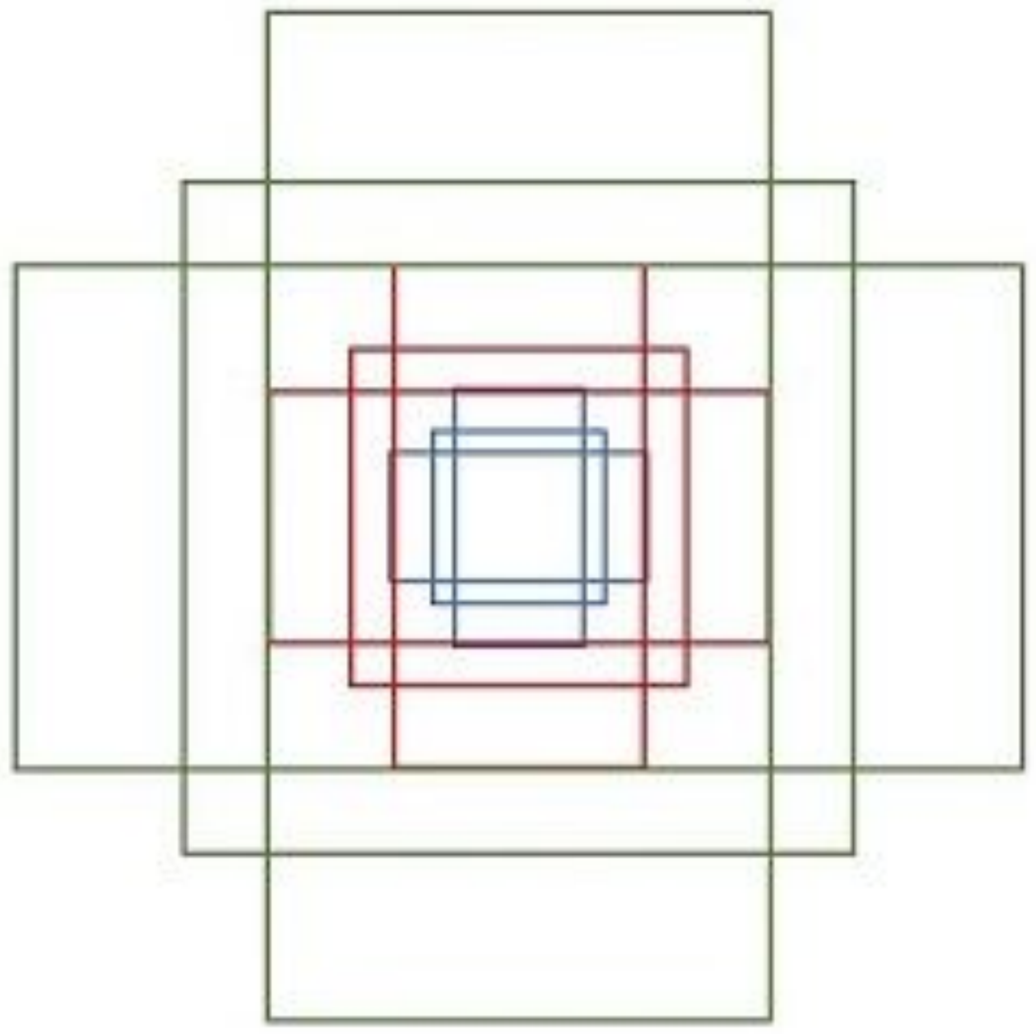
Multi Stage detectors (Faster RCNN Stage-1)

- **Anchor box generation:**
  - Anchors are used as the reference frames to find object proposals
  - It is an application specific hyper parameter
  - For each point in feature map:
    - Generate N number of anchors from different scales and aspect ratios (M)
  - So in the VGG16 case 25x25*9 = 5625 anchor boxes per feature map
  - Each anchor box is represented as 4 coordinates $[x_{min}, x_{max}, y_{min}, y_{max}]$
  - For 9 anchor boxes, $(M,4)$ matrix for each anchor location



Ref.5: 9 anchor boxes from 3 different scales and aspect ratios

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Multi Stage detectors (Faster RCNN Stage-1)

- **RPN Target generator**
    - Find target proposals by calculating the Intersection of Union (IoU) between an anchor and a ground truth (GT) object
    - One GT can have multiple anchors
    - $IoU = \frac{Area_{Overlap}}{Area_{Union}}$
    - If $IoU > 0.7$ label the anchor as positive (object)
    - If $0.0 < IoU < 0.3$ label the anchor as Negative (background)
    - Discard the anchors that are neither positive nor negative from training
    - So for each anchor box there will be $(N,2)$ classes and $(N,4)$ coordinates

Ref.6: Overlap

Ref.6: Union

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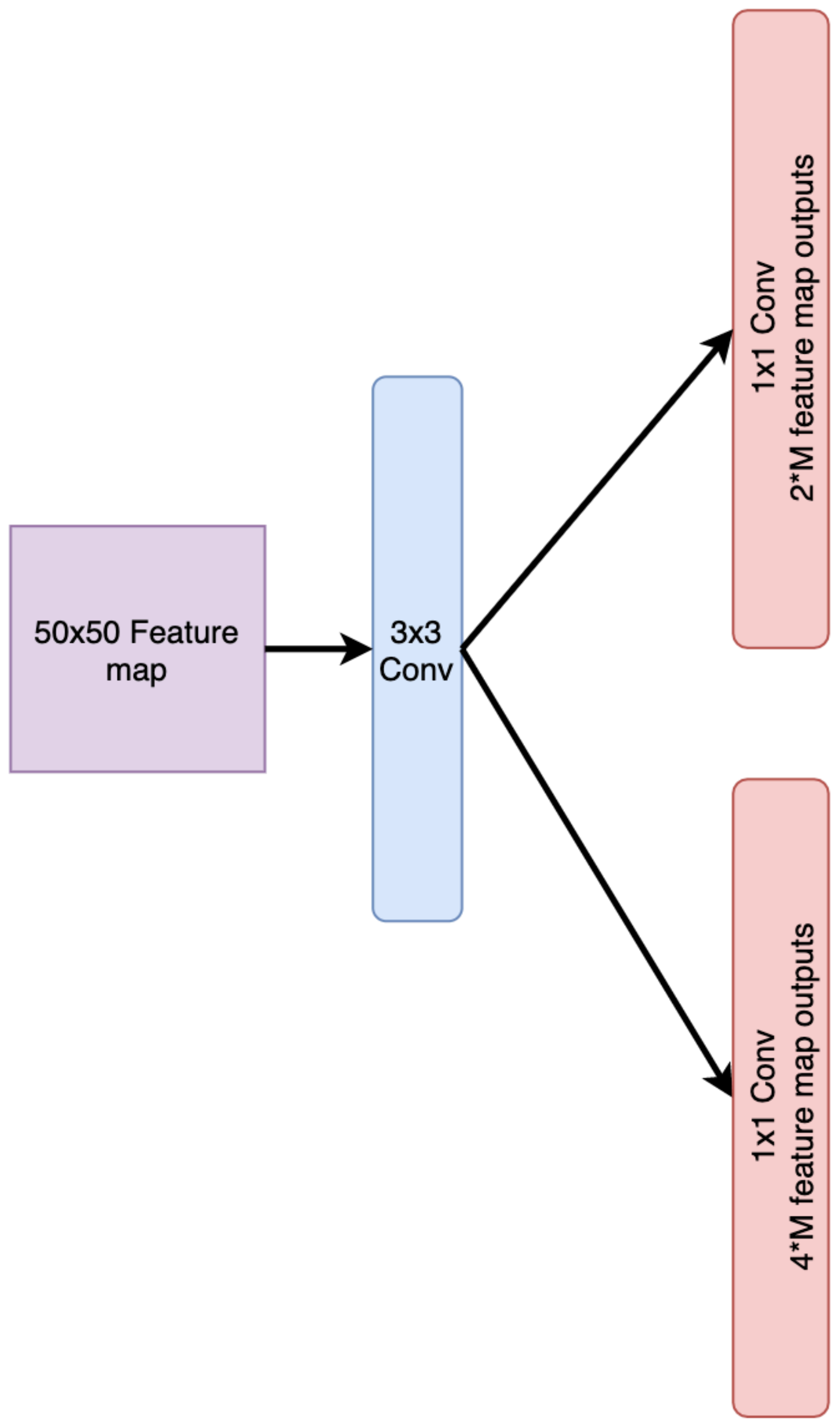
Multi Stage detectors (Faster RCNN Stage-1)

- **Region Proposal Network (RPN)**
  - Take the feature extractor output as the input
  - Classify for each anchor location:
    - Class logit (classification layer), 1 for object and 0 for background
    - Center shift (x, y) and scale variation (w, h)
  - These regressed values show how to shift the centre of the anchor and change the h, w
    - $t_x = \frac{x - x_a}{w_a}, t_y = \frac{y - y_a}{h_a}$; Scale invariant translation of the centre Eq.1
    - $t_w = log\frac{w}{w_a}, t_h = log\frac{h}{h_a}$; Log-space translation of the bounding box height width Eq.2
    - x, y predicted centers, x_a, y_a anchor centers, w, h predicted width height, w_a, h_a anchor width height
  - The Regression layer learns the $t_{x,y}, t_{w,h}$ functions and the predicted translation can be found from the equations
- **RPN Loss:**
  - $L(p_i, t_i) = \frac{1}{N_{cls}} \sum_i L_{cls}(p_i, p_i^*) + \lambda \frac{1}{N_{reg}} \sum_i p_i^* L_{reg}(t_i, t_i^*)$ (Ref.7)



Region Proposal Network

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Multi Stage detectors (Faster RCNN Stage-1)

- Non-Max Suppression (NMS):
  - Since one GT box can have multiple anchors, we get multiple RoIs with similar overlap
  - NMS is used to remove all the RoIs except for the best RoI that represent the GT
  - Algorithm:
    1. Take the highest score for the objectiveness
    2. Remove all: IoU > Threshold (0.5 for e.g) boxes
    3. Move to the next highest objectiveness
    4. Repeat from 1
  - Refer to Ref.9 for more information on implementation

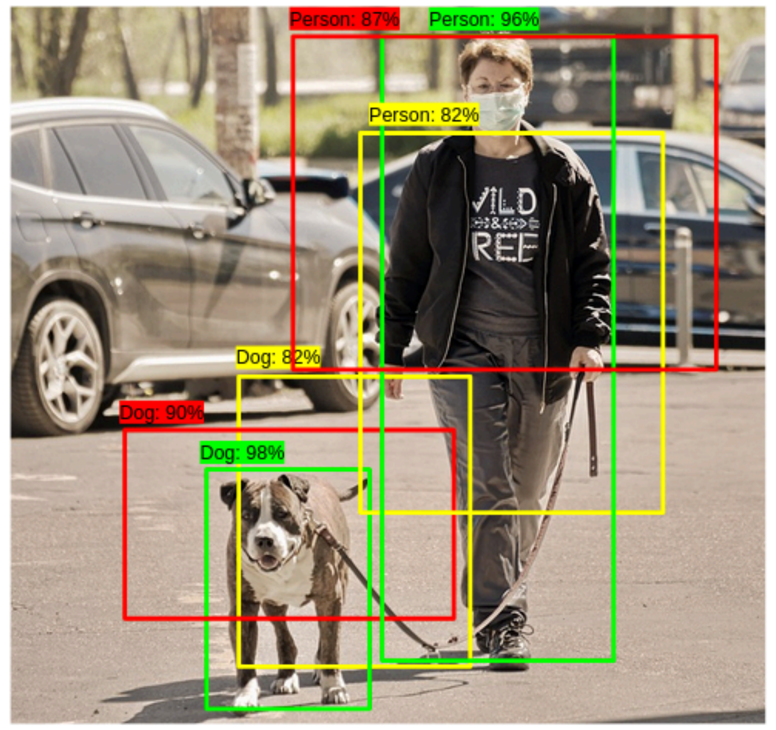

Fig.1

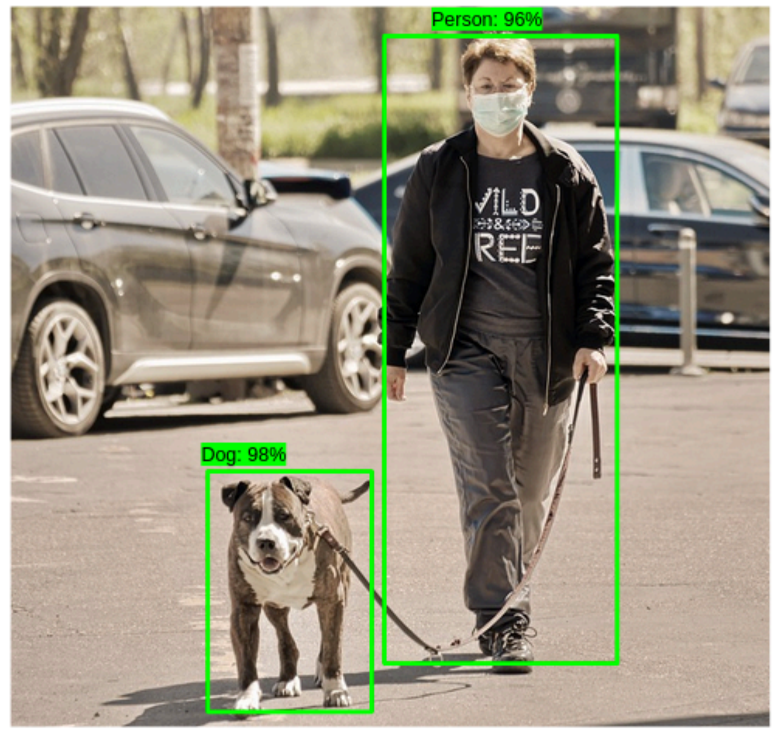

Fig.2

Ref.9: Fig.1 Two objects with multiple detections, Fig.2 Boxes after NSM

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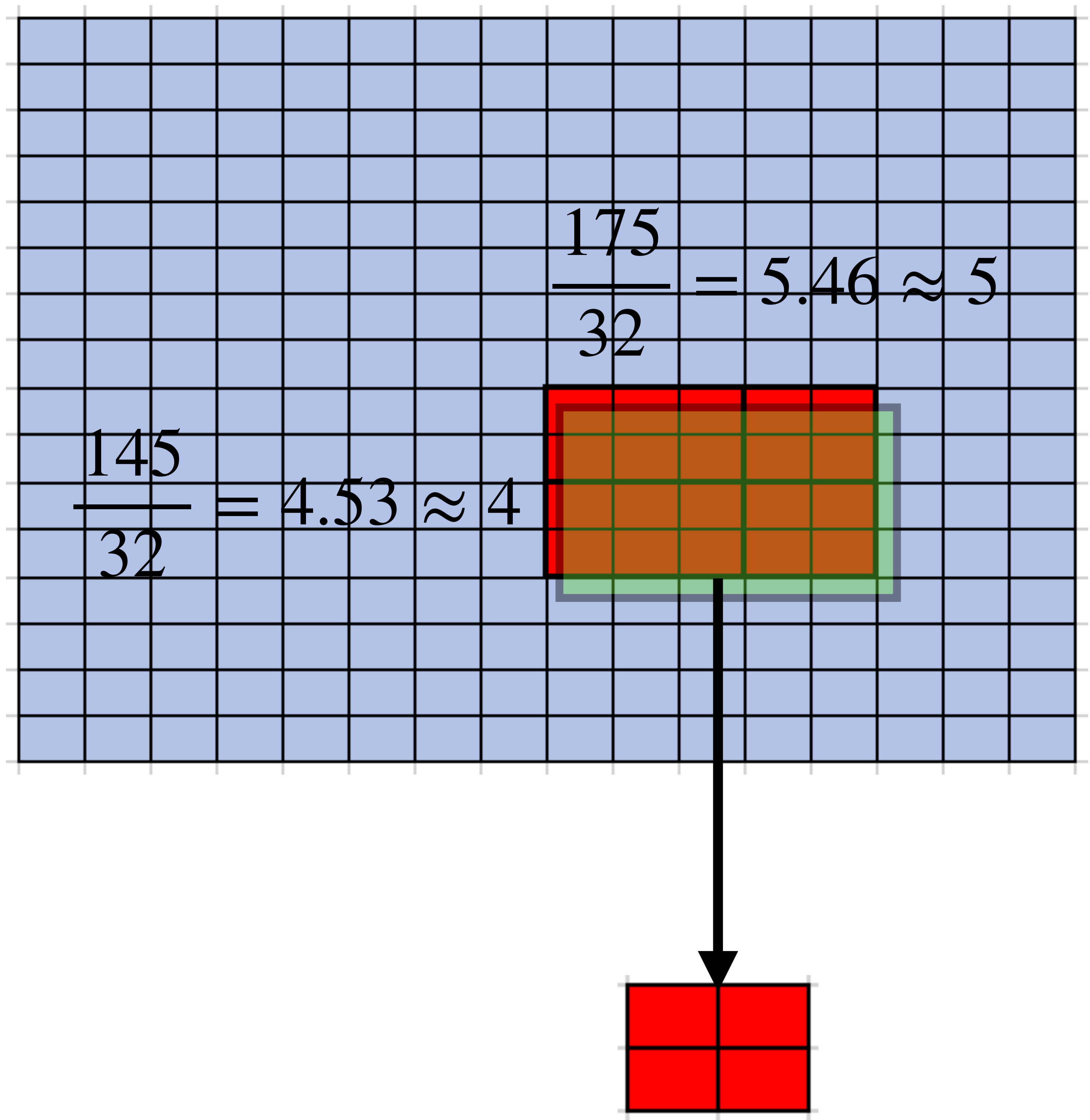
Multi Stage detectors (Faster RCNN Stage-2)

- Region of interest pooling:
  - The second stage of the model (Fully connected layers) requires equal size samples
  - Therefore the RoI proposals must be pooled to a fix size
  - The pooling window size is a hyper parameter and pooled output is independent of the input size
  - E.g: take a RoI at an input with w:175, h:145.
    - The feature extractor scale this RoI to 5.46, 4.53
    - By rounding, some information are lost and some are gained
    - The new scaled region is again divided by the pool window size
    - This involves ceiling and flooring the numbers (np.ceil, np.floor)
    - Finally the max values within the divided region are taken
  - More advanced pooling technique such as RoIAlign exists to address the issues of vanilla RoI method (check Ref 8)



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Multi Stage detectors (Faster RCNN Stage-2)

- Detection Target Generator:
  - Similar to the target generation in the RPN model;
    - For the labels:
      - Compute the IoU between a sampled RoI proposal and GTs,
      - If IoU $>$ 0.5 assign a positive label (the class label)
      - If 0.1 $<$ IoU $<$ 0.5 assign a negative sample (background)
      - Discard all the other RoIs since they do not contribute to training
    - For the box coordinates:
      - Use equations 1 and 2 to find the box regression GTs
      - $t_x = \frac{x - x_{GT}}{w_{GT}}; t_y = \frac{y - y_{GT}}{h_{GT}}; t_w = log\frac{w}{w_{GT}}; t_h = log\frac{h}{h_{GT}}$

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Multi Stage detectors (Faster RCNN Stage-2)

- **Detection Network:**
  - Refine the selected Region of Interest (RoI) coordinates and classify them into the respective classes
  - The network is a fully connected model with one hidden layer and one output layer
  - Inputs are K x $len_{Pool_{flatten}}$ feature matrix from the RoI pooling layer
    - K is the number of RoIs (both positive and negative) after the NMS
  - The classification layer outputs K x N_{cls} (class for each RoI)
  - The regression layer outputs a K x N_{reg} coordinate shifts
- **Detection Loss:**
  - For classifier, the cross entropy loss and regressor Smooth L1 loss

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Evaluation metrics for object detection

- Several object detection competitions (e.g Pascal VOC and COCO) defines different evaluation metrics to evaluate the performance of an object detector
- The detection metric for object detection is Average Precision (AP) and mean AP (mAP)
- The AP is the sum of weighted precision at different recalls in a precision recall curve for a given class or IoU Threshold
- mAP is calculated by either averaging over only the classes or classes and/or different IoU thresholds

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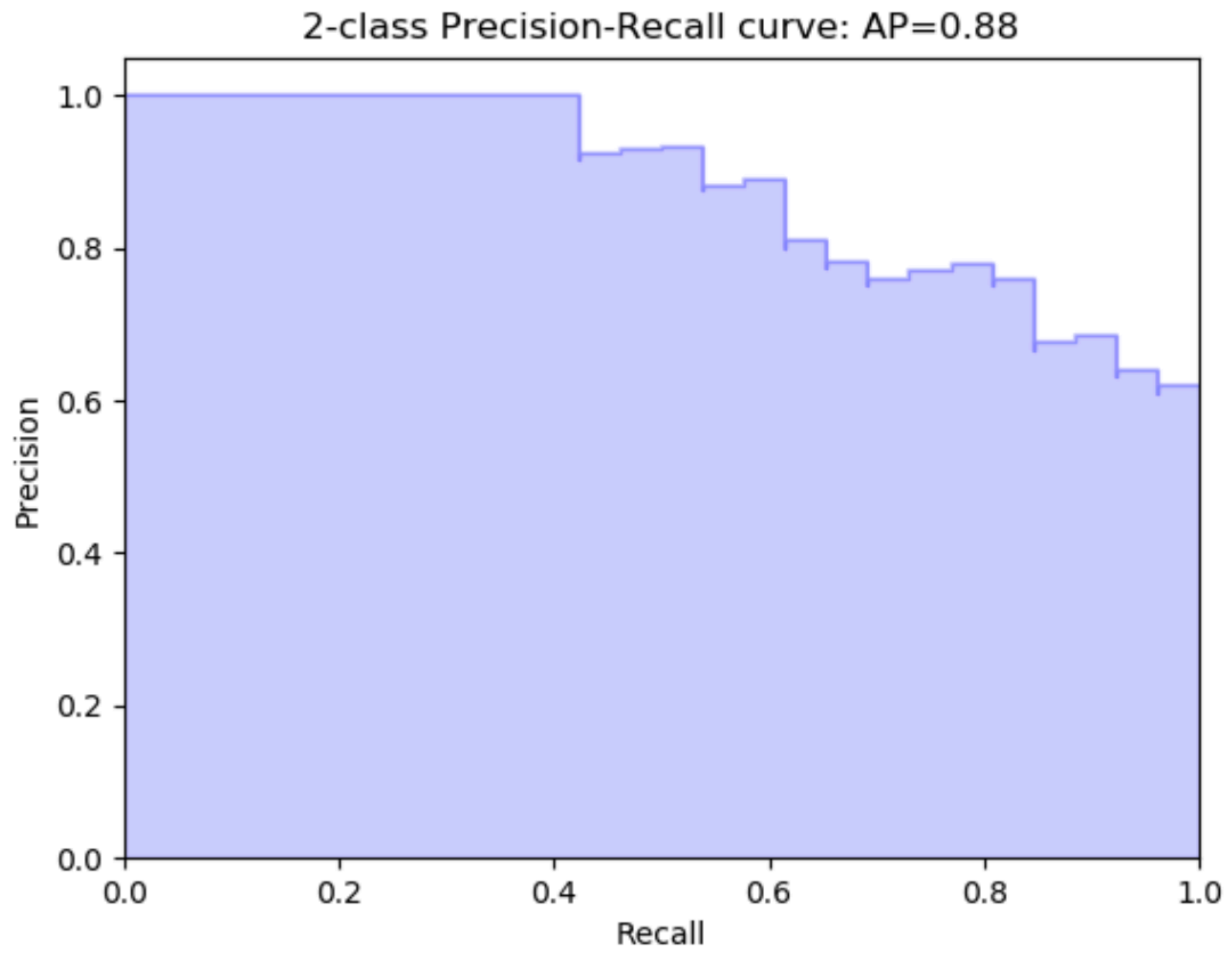
Evaluation metrics for object detection

- In detection the TP, FP, FN and TN are as follows:
    - For every detection, calculate the IoU between detected box and GT box:
        - If IoU > Threshold & predicted class = GT class for class threshold; TP
        - If IoU < Threshold; FP
        - If a GT not detected count a FN
        - No TN since everything that is not a TP is a TN and there are a large number of TN in a given input, so this metric is not considered
    - Vary the detection confidence threshold (like in classification) to Precision-Recall curve
- So the mAP at a given IoU threshold reflects the performance of the detector (higher the better) in respect to the class classification
- However finding mAP by averaging across the thresholds (eg 0.5:0.05:0.95) indicates the quality of the localisation



Ref.10: Precision recall curve and its AP

- Ref.1: https://towardsdatascience.com/coco-data-format-for-object-detection-a4c5eaf518c5
- Ref.2: https://www.immersivelimit.com/tutorials/create-coco-annotations-from-scratch#:~:text=The%20COCO%20bounding%20box%20format,other%20annotations%20in%20the%20dataset).
- Ref.3: https://whatdhack.medium.com/a-deeper-look-at-how-faster-rcnn-works-84081284e1cd
- Ref.4: https://arxiv.org/pdf/1704.04861.pdf
- Ref.5: https://www.programmersought.com/article/336611383/
- Ref.6: https://www.pyimagesearch.com/2016/11/07/intersection-over-union-iou-for-object-detection/
- Ref.7: https://arxiv.org/pdf/1506.01497.pdf, https://arxiv.org/pdf/1311.2524.pdf
- Ref.8: https://deepsense.io/region-of-interest-pooling-explained/, https://erdem.pl/2020/02/understanding-region-of-interest-ro-i-pooling, https://erdem.pl/2020/02/understanding-region-of-interest-part-2-ro-i-align
- Ref.9: https://www.analyticsvidhya.com/blog/2020/08/selecting-the-right-bounding-box-using-non-max-suppression-with-implementation/, https://www.pyimagesearch.com/2014/11/17/non-maximum-suppression-object-detection-python/, https://www.pyimagesearch.com/2015/02/16/faster-non-maximum-suppression-python/, https://www.coursera.org/lecture/convolutional-neural-networks/non-max-suppression-dvrjH
- Ref.10: http://cs230.stanford.edu/section/7/,
- Rotated bounding box detection: https://developer.nvidia.com/blog/detecting-rotated-objects-using-the-odtk/, https://github.com/NVIDIA/retinanet-examples