THEORY

Object Detection

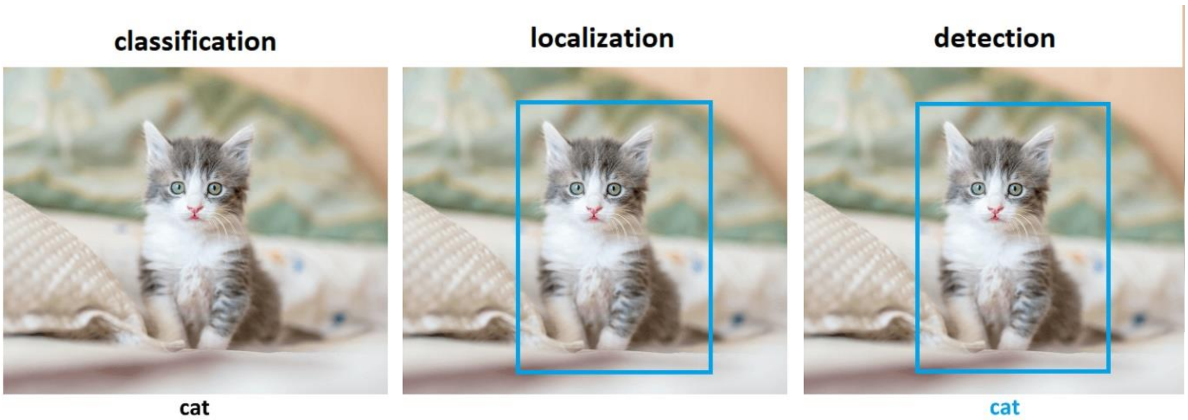
Object detection is the task of detecting instances of objects of a specific class within an image or video. Basically, it locates the existence of objects in an image using a bounding box and assigns the types or classes of the objects found. For instance, it takes an image as input and generates one or more bounding boxes, each with the class label attached. These algorithms are powerful enough to handle multi-class classification and localization and objects with multiple occurrences.

Object detection is a combination of two tasks:

- Image classification
- Object localization

Image classification algorithms predict the type or class of an object in an image among a predefined set of classes that the algorithm was trained for. Usually, input is an image with a single object, such as a cat. Output is a class or label representing a particular object, often with a probability of that prediction.

Object localization algorithms locate the presence of an object in the image and represent its location with a bounding box. They take an image with one or more objects as input and output the location of one or more bounding boxes using their position, height, and width.



2.1. Object Detection Methods

Generally, object detection methods can be classified as either neural network-based or non-neural approaches. Also, some of them are rule-based, where the rule is predefined to match specific objects. Non-neural approaches require defining features using some feature engineering techniques and then using a method such as a support vector machine (SVM) to do the classification.

Some of the non-neural methods are:

- Viola-Jones object detection method based on Haar features
- Scale-invariant feature transform (SIFT)
- Histogram of Oriented Gradients (HOG)
- Other methods based on template, shape, or color matching

On the other hand, neural network techniques can do end-to-end object detection without explicitly defining features. They are far more accurate than non-neural based and are typically built on convolutional neural networks (CNN).

Some of the neural network methods are:

- Region-Based Convolutional Neural Networks (R-CNN, Fast R-CNN, etc.)
- Single Shot Detector (SSD)
- Retina-Net
- You Only Look Once (YOLO)

2.2. Challenges in Object Detection

In object detection, the bounding boxes are always rectangular. As a result, if the object contains the curvature part, it does not help determine its shape. In order to find precisely the shape of the object, we should use some of the image segmentation techniques.

Some non-neural methods may not detect objects with high accuracy or may produce a large number of false-positive detections. Although neural network methods are more accurate, there are some drawbacks. For example, they require a large amount of annotated data for training. Training is often expensive in time and space and, as a result, prolonged on standard computers.

In order to solve these challenges, we used the YOLO algorithm. Thanks to the transfer learning capabilities, we were able to use already pre-trained models or spend some time fine-tuning models with our data. Furthermore, the YOLO algorithm is one of the most popular methods for performing object detection in real-time because it achieves high accuracy on most real-time processing tasks while maintaining a reasonable speed and frames per second, even on devices accessible to almost everyone.

3. You Only Look Once (YOLO)

You Only Look Once (YOLO) is one of the most popular model architectures and object detection algorithms. It uses one of the best neural network architectures to produce high accuracy and overall processing speed, which is the main reason for its popularity. If we search Google for object detection algorithms, the first result will be related to the YOLO model.

YOLO algorithm aims to predict a class of an object and the bounding box that defines the object location on the input image. It recognizes each bounding box using four numbers:

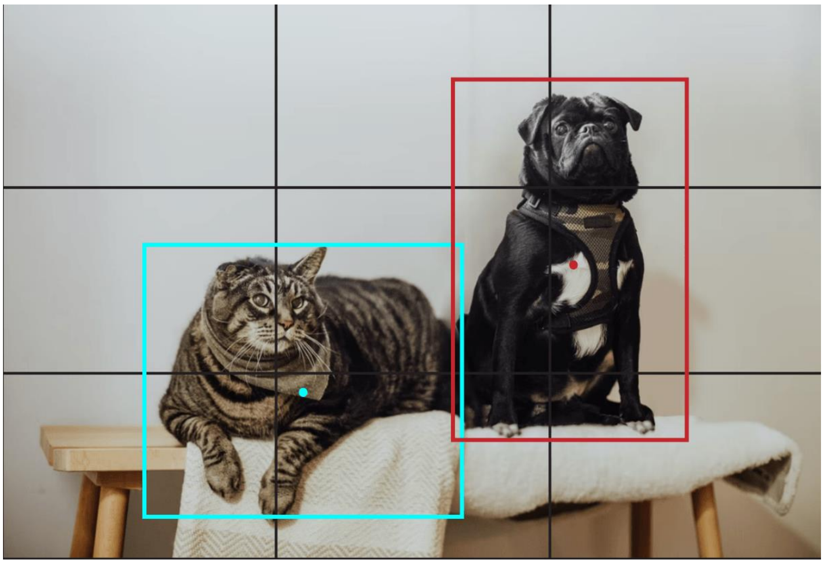
- Center of the bounding box ((b_x, by))
- Width of the box (b_w)

- Height of the box (b_h)

In addition to that, YOLO predicts the corresponding number c for the predicted class as well as the probability of the prediction P_c .

3.1. How does YOLO Work?

Let’s say that we have an image with two bounding boxes representing a cat and dog. The first step that YOLO does is dividing the image into a grid. For example, a 3×3 grid as below:



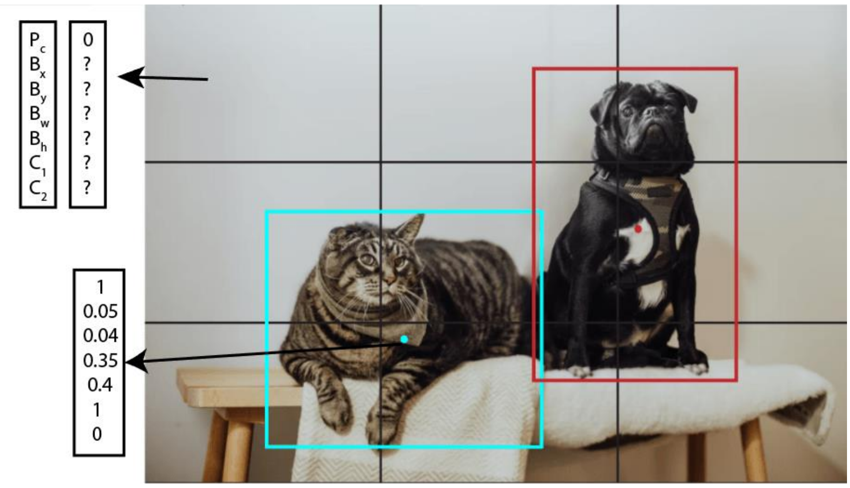
With the existence of a grid, it’s possible to detect one object per grid cell instead of one object per image. For each grid cell, we can encode a vector that will describe the cell. For instance, the first cell from the top-left doesn’t have any object, and we describe it as:

$$C_{1,1} = (P_c, B_x, B_y, B_w, B_h, C_1, C_2) = (0, ?, ?, ?, ?, ?, ?),$$

where P_c is the probability of the object class, B_x and B_y are coordinates of the center of the bounding box, relative to the cell, B_x and B_y are width and height of the bounding box relative to the whole image, C_1 and C_2 are 0 or 1 depending on which class represents the bounding box (C_1 for cat and C_2 for dog). Vector $C_{1,1}$ consists of symbols because if the first component P_c is equal to zero, then the rest of the components can have random numbers are they are not taken into consideration.

Next, if we take the cell that contains the center of the blue bounding box with the cat, we’ll have a vector

$$C_{3,2} = (1, 0.05, 0.04, 0.35, 0.4, 1, 0).$$



Following this procedure, if we define one vector for each grid cell, the whole image is represented with nine vectors with size 7 or 3x3x7 tensor. This means that in our data set, each image sample is labeled with one 3x3x7 tensor. Using that data set, we are able to create a training and test set and train the convolutional network, which is exactly how YOLO works.

Using CNN, YOLO is able to predict all objects in one forward pass and that is the reason for its full name “You Only Look Once”.

3.2. Non-Max Suppression

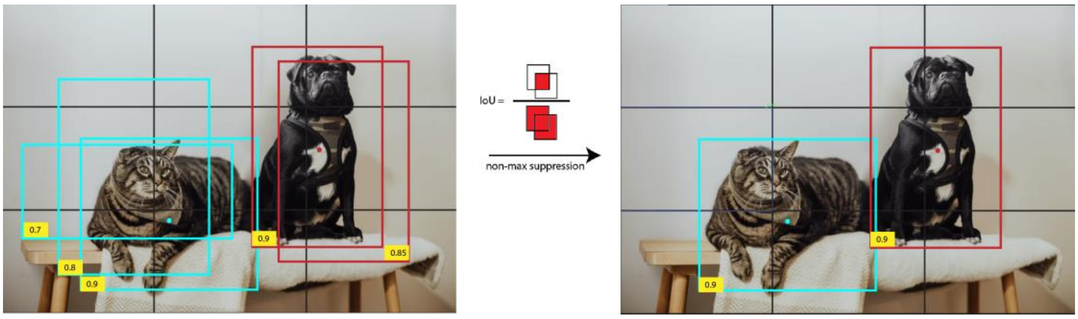
One issue that might happen is when the algorithm predicts several bounding boxes for one class. We could select only one box per class, that has the highest probability, but what if there are more objects of one class on the image (for example a few cats). Because of that, we’ll use a non-max suppression algorithm.

First, we take the box with the maximum probability. After that, we compare the box with all other boxes of that particular class using intersection over union (IoU). Generally, this metric is also known as the Jaccard index but in computer vision, the name IoU is used. The formula of IoU is

$$IoU = \frac{\text{area of the intersection between } B_1 \text{ and } B_2}{\text{area of the union between } B_1 \text{ and } B_2},$$

where B_1 and B_2 are two bounding boxes.

If the IoU is higher than the predefined threshold (for example 0.5), then the box with a smaller probability is suppressed or excluded. It means that two boxes with high IoU values probably indicate the same object on the image, so we exclude the box with a lower probability. This process is repeated until all boxes are taken as object prediction or excluded.



3.3. Vector Generalization

In this article, we mentioned that one object can be predicted per one grid cell. Generally, it doesn't need to be only one object. The authors used two boxes per cell in the original paper that can only have one class. Basically, the vector that defines the cell will have two times more components that define the probability of the object and the dimension of the boxes. For example

$$C_{1,1} = (P_c^1, B_x^1, B_y^1, B_w^1, B_h^1, P_c^2, B_x^2, B_y^2, B_w^2, B_h^2, C_1, C_2),$$

where the notation is already explained except the superscript number that indicates the bounding box index.

Similarly, instead of predicting only two classes, it's possible to define as many classes as we need. Of course, it'll influence the algorithm's accuracy, so the authors used a maximum of 20 classes. Also, in order to detect more objects, we can increase the dimension of the grid.

Generally, we can describe each cell using a vector with dimension $B \times 5 + C$ where B is the number of bounding boxes, and C is the number of classes. If the image is divided into $S \times S$ grid then it can be represented using $S \times S \times (B \times 5 + C)$ tensor.

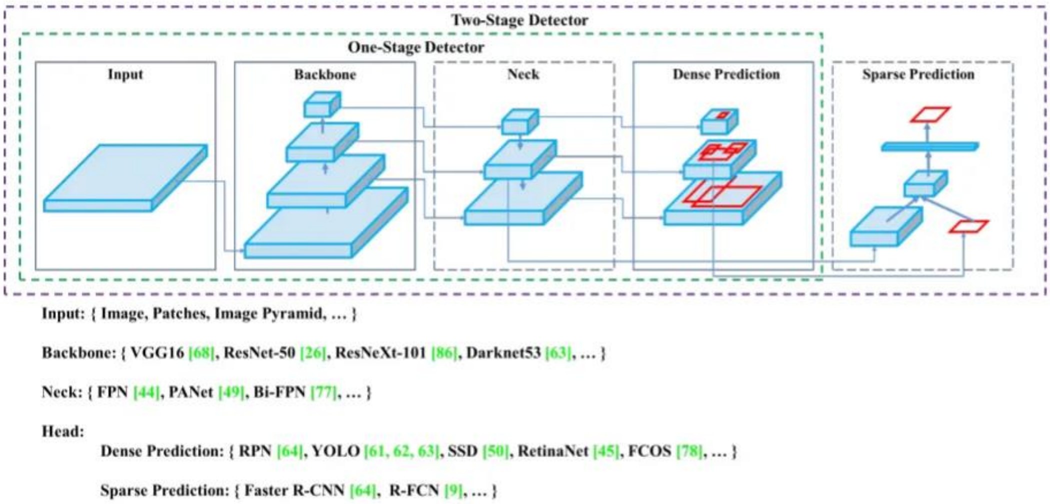
4. Improvements

So far described procedure for the YOLO algorithm refers to its first version v1. Version v2 could predict even 9000 different object classes and still run in real-time. YOLO v2 introduces the concept of anchor boxes.

4.1. Further Improvements

The subsequent versions of the YOLO algorithm brought some additional changes. Besides minor changes, YOLO v3 used a more complex CNN architecture with 53 convolutional layers instead of 19 in the last version. Next, version v4 introduced several new concepts such as weighted residual connections, cross-stage partial connections, CIoU loss, and other features.

4.2 What is YOLOv4?



Yolov4 Architecture

YOLOv4 is the 4th addition to the family of YOLO object detector models. It is a milestone model which solidified YOLO's name and position in the computer vision field. It was released with the concept of BoF (bag of freebies) and BoS (bag of specials) techniques to enhance model performance.

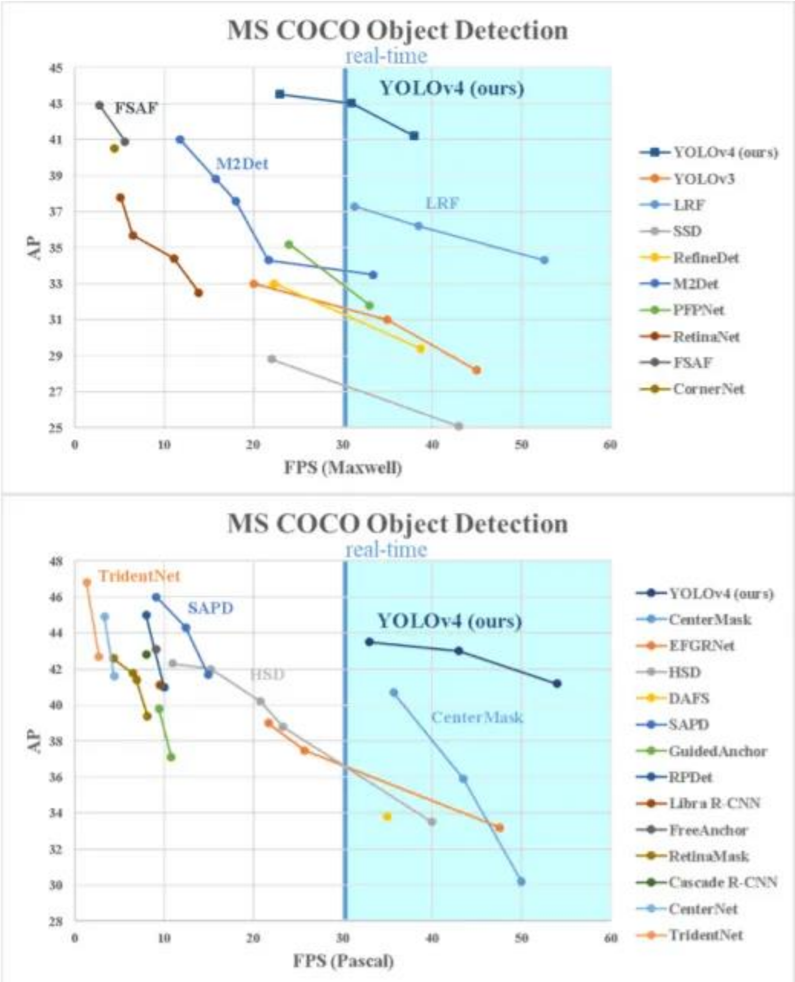
BoF: Techniques that enhance model accuracy without increasing the inference cost (computation or inference times). Examples: Data augmentation, regularization, Normalization.

BoS: Techniques that improve accuracy while slightly increasing the inference cost. These techniques are generally in the form of plugin modules i.e. One can add or remove these techniques from the model at any time. Examples: Spatial attention modules, Non-max suppression, Non-linear activations.

Other characteristics of YOLOv4 includes:

- Self adversarial training for data augmentation.
- Genetic algorithm to find optimal hyper-parameters.
- New normalization techniques.

In testing environments, the model obtained average precision of 43.5 percent on the MS COCO dataset along with an inference speed of 65 FPS.



4.3 Anchor Boxes

Instead of making arbitrary guesses on the boundary boxes, in YOLO v2 authors defined 5 anchor boxes with predefined width and height. To identify the most appropriate dimension of the boxes, [k-means clustering]() is used on the dimensions of bounding boxes from the data set, with distance metric based on IoU

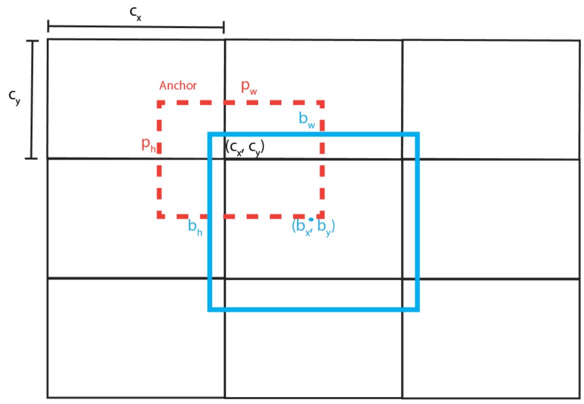
$$d(box, centroid) = 1 - IoU(box, centroid).$$

To make it clear, YOLO v2 doesn't use anchor boxes to slide over the image and compare them with objects. Instead of that, it makes predictions on the offsets to the anchors.

Basically, it predicts parameters , , and which are used to calculate real bounding box coordinates and dimension in a way

$$b_x = \sigma(t_x) + c_x$$
$$b_y = \sigma(t_y) + c_y$$
$$b_w = p_w e^{t_w}$$
$$b_h = p_h e^{t_h}$$

where p_w and p_h are the width and height of the anchor, c_x and c_y is the top left corner of the current grid cell and σ sigmoid function. These parameters are explained in the image below:



c_x
c_y
Anchor
p_w
b_w
p_h
(c_x, c_y)
b_h
(b_x, b_y)