Navnit Kumar : YOLO object detection to detect car

Table of Contents

What is YOLO and Why is it Useful?

The YOLO framework (You Only Look Once) on the other hand, deals with object detection in a different way. It takes the entire image in a single instance and predicts the bounding box coordinates and class probabilities for these boxes. **The biggest advantage of using YOLO is its superb speed** – it's incredibly fast and can process 45 frames per second. YOLO also understands generalized object representation.

This is one of the best algorithms for object detection and has shown a comparatively similar performance to the R-CNN algorithms. In the upcoming sections, we will learn about different techniques used in YOLO algorithm. The following explanations are inspired by Andrew NG's course on Object Detection which helped me a lot in understanding the working of YOLO.

How does the YOLO Framework Function?

Now that we have grasp on why YOLO is such a useful framework, let's jump into how it actually works. In this section, I have mentioned the steps followed by YOLO for detecting objects in a given image.

- YOLO first takes an input image:
- The framework then divides the input image into grids (say a 3 X 3 grid):
- Image classification and localization are applied on each grid. YOLO then predicts the bounding boxes and their corresponding class probabilities for objects

We need to pass the labelled data to the model in order to train it. Suppose we have divided the image into a grid of size 3 X 3 and there are a total of 3 classes which we want the objects to be classified into. Let's say the classes are Pedestrian, Car, and Motorcycle respectively. So, for each grid cell, the label y will be an eight dimensional vector:

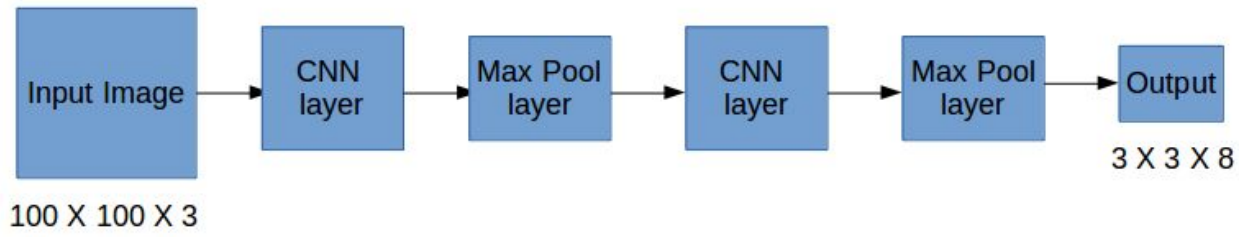
y =	pc
	bx
	by
	bh
	bw
	c1
	c2
	c3

Here,

- pc defines whether an object is present in the grid or not (it is the probability)
- bx, by, bh, bw specify the bounding box if there is an object
- c1, c2, c3 represent the classes. So, if the object is a car, c2 will be 1 and c1 & c3 will be 0, and so on

For each of the 9 grids, we will have an eight dimensional output vector. This output will have a shape of 3 X 3 X 8.

So now we have an input image and it's corresponding target vector. Using the above example (input image – 100 X 100 X 3, output – 3 X 3 X 8), our model will be trained as follows:



We will run both forward and backward propagation to train our model. During the testing phase, we pass an image to the model and run forward propagation until we get an output y. In order to keep things simple, I have explained this using a 3 X 3 grid here, but generally in real-world scenarios we take larger grids (perhaps 19 X 19).

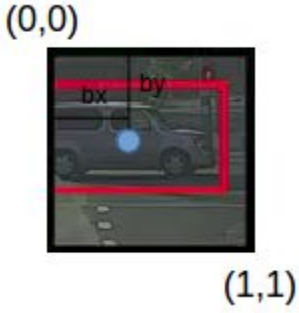
Even if an object spans out to more than one grid, it will only be assigned to a single grid in which its mid-point is located. We can reduce the chances of multiple objects appearing in the same grid cell by increasing the more number of grids (19 X 19, for example).

How to Encode Bounding Boxes?

As I mentioned earlier, bx, by, bh, and bw are calculated relative to the grid cell we are dealing with. Let's understand this concept with an example. Consider the center-right grid which contains a car. So, bx, by, bh, and bw will be calculated relative to this grid only. The y label for this grid will be:

y =	1
	bx
	by
	bh
	bw
	0
	1
	0

pc = 1 since there is an object in this grid and since it is a car, c2 = 1. Now, let's see how to decide bx, by, bh, and bw. In YOLO, the coordinates assigned to all the grids are:

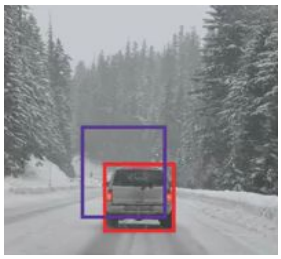


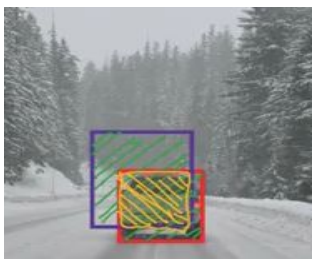
y =	1
	0.4
	0.3
	0.9
	0.5
	0
	1
	0

In the next section, we will look at more ideas that can potentially help us in making this algorithm's performance even better.

Intersection over Union and Non-Max Suppression

How can we decide whether the predicted bounding box is giving us a good outcome (or a bad one)? This is where Intersection over Union comes into the picture. It calculates the intersection over union of the actual bounding box and the predicted bonding box. Consider the actual and predicted bounding boxes for a car as shown below:

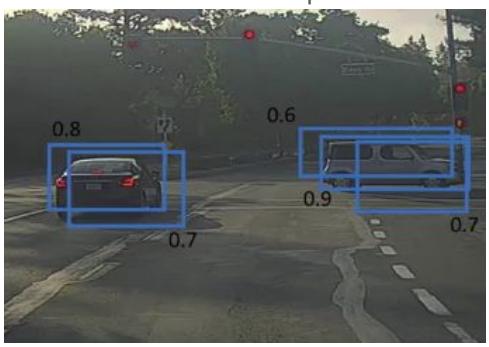




IoU = Area of the intersection / Area of the union

If IoU is greater than 0.5, we can say that the prediction is good enough.

There is one more technique that can improve the output of YOLO significantly – Non-Max Suppression. One of the most common problems with object detection algorithms : detect multiple times.



The Non-Max Suppression technique cleans up this up so that we get only a single detection per object. Let's see how this approach works.

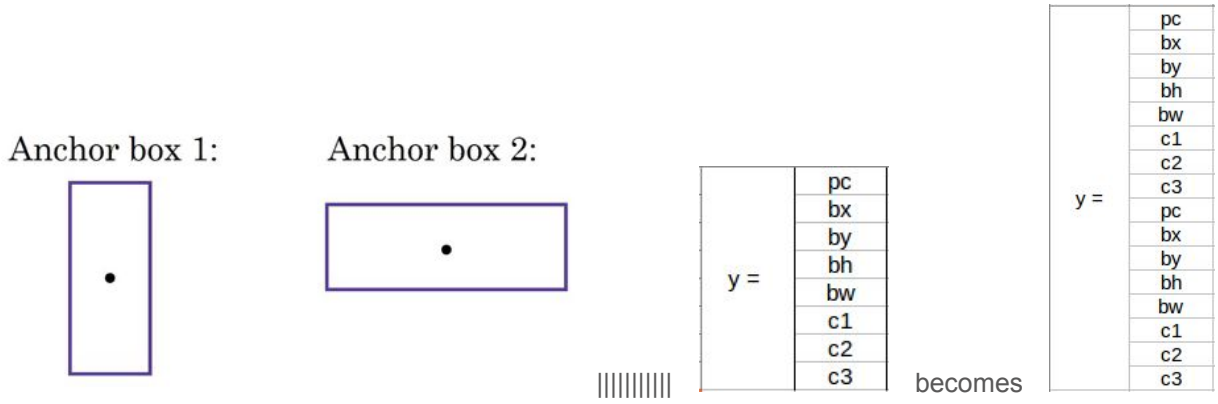
1. This is what Non-Max Suppression is all about. We are taking the boxes with maximum probability and suppressing the close-by boxes with non-max probabilities. Let's quickly summarize the points which we've seen in this section about the Non-Max suppression algorithm:
2. Discard all the boxes having probabilities less than or equal to a predefined threshold (say, 0.5)
3. For the remaining boxes:
    a. Pick the box with the highest probability and take that as the output prediction
    b. Discard any other box which has IoU greater than the threshold with the output box from the above step
4. Repeat step 2 until all the boxes are either taken as the output prediction or discarded
5. There is another method we can use to improve the perform of a YOLO algorithm – let's check it out!

Anchor Boxes

We have seen that each grid can only identify one object. But what if there are multiple objects in a single grid? That can so often be the case in reality. And that leads us to the concept of anchor boxes. Consider the following image, divided into a 3 X 3 grid:

Remember how we assigned an object to a grid? We took the midpoint of the object and based on its location, assigned the object to the corresponding grid. In the above example, the midpoint of both the objects lies in the same grid. This is how the actual bounding boxes for the objects will be:

We will only be getting one of the two boxes, either for the car or for the person. But if we use anchor boxes, we might be able to output both boxes! How do we go about doing this? First, we pre-define two different shapes called anchor boxes or anchor box shapes. Now, for each grid, instead of having one output, we will have two outputs. We can always increase the number of anchor boxes as well. I have taken two here to make the concept easy to understand:



This is how the y label for YOLO without anchor boxes looks like:

The first 8 rows belong to anchor box 1 and the remaining 8 belongs to anchor box 2. The objects are assigned to the anchor boxes based on the similarity of the bounding boxes and the anchor box shape. Since the shape of anchor box 1 is similar to the bounding box for the person, the latter will be assigned to anchor box 1 and the car will be assigned to anchor box 2. The output in this case, instead of 3 X 3 X 8 (using a 3 X 3 grid and 3 classes), will be 3 X 3 X 16 (since we are using 2 anchors).

So, for each grid, we can detect two or more objects based on the number of anchors. Let's combine all the ideas we have covered so far and integrate them into the YOLO framework.

Combining the Ideas

In this section, we will first see how a YOLO model is trained and then how the predictions can be made for a new and previously unseen image.

Training

The input for training our model will obviously be images and their corresponding y labels. Let's see an image and make its y label:

Consider the scenario where we are using a 3 X 3 grid with two anchors per grid, and there are 3 different object classes. So the corresponding y labels will have a shape of 3 X 3 X 16. Now, suppose if we use 5 anchor boxes per grid and the number of classes has been increased to 5. So the target will be 3 X 3 X 10 X 5 = 3 X 3 X 50. This is how the training process is done – taking an image of a particular shape and mapping it with a 3 X 3 X 16 target (this may change as per the grid size, number of anchor boxes and the number of classes).

Testing

The new image will be divided into the same number of grids which we have chosen during the training period. For each grid, the model will predict an output of shape 3 X 3 X 16 (assuming this is the shape of the target during training time). The 16 values in this prediction will be in the same format as that of the training label. The first 8 values will correspond to anchor box 1, where the first value will be the probability of an object in that grid. Values 2-5 will be the bounding box coordinates for that object, and the last three values will tell us which class the object belongs to. The next 8 values will be for anchor box 2 and in the same format, i.e., first the probability, then the bounding box coordinates, and finally the classes.

Finally, the Non-Max Suppression technique will be applied on the predicted boxes to obtain a single prediction per object.

That brings us to the end of the theoretical aspect of understanding how the YOLO algorithm works, starting from training the model and then generating prediction boxes for the objects. Below are the exact dimensions and steps that the YOLO algorithm follows:

- Takes an input image of shape (608, 608, 3)
- Passes this image to a convolutional neural network (CNN), which returns a (19, 19, 5, 85) dimensional output
- The last two dimensions of the above output are flattened to get an output volume of (19, 19, 425):
    - Here, each cell of a 19 X 19 grid returns 425 numbers
    - 425 = 5 * 85, where 5 is the number of anchor boxes per grid
    - 85 = 5 + 80, where 5 is (pc, bx, by, bh, bw) and 80 is the number of classes we want to detect
- Finally, we do the IoU and Non-Max Suppression to avoid selecting overlapping boxes