The simplest strategy for object detection is to classify local regions, at multiple scales and locations.

This “sliding window” approach evaluates a classifier multiple times, and its computational cost increases with the prediction accuracy.
This was mitigated in overfeat (Sermanet et al., 2013) by adding a regression part to predict the object’s bounding box.

In the single-object case, the convolutional layers are frozen, and the localization layers are trained with a $\ell^2$ loss.

Combining the multiple boxes is done with an ad hoc greedy algorithm.
This architecture can be applied directly to detection by adding a class “Background” to the object classes.

Negative samples are taken in each scene either at random or by selecting the ones with the worst miss-classification.

Surprisingly, using class-specific localization layers did not provide better results than having a single one shared across classes (Sermanet et al., 2013).

Other approaches evolved from AlexNet, relying on region proposals:

- Generate thousands of proposal bounding boxes with a non-CNN “objectness” approach such as Selective search (Uijlings et al., 2013),
- feed to an AlexNet-like network sub-images cropped and warped from the input image (“R-CNN”, Girshick et al., 2013), or from the convolutional feature maps to share computation (“Fast R-CNN”, Girshick, 2015).

These methods suffer from the cost of the region proposal computation, which is non-convolutional and not implementable on GPU.

They were improved by Ren et al. (2015) in “Faster R-CNN” by replacing the region proposal algorithm with a convolutional processing similar to Overfeat.
The most famous algorithm from this lineage is “You Only Look Once” (YOLO, Redmon et al. 2015).

It comes back to a classical architecture with a series of convolutional layers followed by a few fully connected layers. It is sometime described as “one shot” since a single information pathway suffices.

YOLO’s network is not a pre-existing one. It uses leaky ReLU, and its convolutional layers make use of the $1 \times 1$ bottleneck filters (Lin et al., 2013) to control the memory footprint and computational cost.
The output corresponds to splitting the image into a regular $S \times S$ grid, with $S = 7$, and for each cell, to predict a 30d vector:

- $B = 2$ bounding boxes coordinates and confidence,
- $C = 20$ class probabilities, corresponding to the classes of Pascal VOC.

So the network predicts class scores and bounding-box regressions, and although the output comes from fully connected layers, it has a 2D structure.

It allows in particular YOLO to leverage the absolute location in the image to improve performance (e.g. vehicles tend to be at the bottom, umbrella at the top), which may or may not be desirable.
During training, YOLO makes the assumption that any of the $S^2$ cells contains at most [the center of] a single object. We define for every image, cell index $i = 1, \ldots, S^2$, predicted box index $j = 1, \ldots, B$ and class index $c = 1, \ldots, C$

- $1_{i,j}^{\text{obj}}$ is 1 if there is an object in cell $i$ and 0 otherwise,
- $1_{i,j}^{\text{obj}}$ is 1 if there is an object in cell $i$ and predicted box $j$ is the most fitting one, 0 otherwise,
- $p_{i,c}$ is 1 if there is an object of class $c$ in cell $i$, and 0 otherwise,
- $x_i, y_i, w_i, h_i$ the annotated object bounding box (defined only if $1_{i,j}^{\text{obj}} = 1$, and relative in location and scale to the cell),
- $c_{i,j}$ IOU between the predicted box and the ground truth target.

The training procedure first computes on each image the value of the $1_{i,j}^{\text{obj}}$’s and $c_{i,j}$, and then does one step to minimize

$$
\lambda_{\text{coord}} \sum_{i=1}^{S^2} \sum_{j=1}^{B} 1_{i,j}^{\text{obj}} \left( (x_i - \hat{x}_{i,j})^2 + (y_i - \hat{y}_{i,j})^2 + (\sqrt{w_i} - \sqrt{\hat{w}_{i,j}})^2 + (\sqrt{h_i} - \sqrt{\hat{h}_{i,j}})^2 \right)
$$

$$
+ \lambda_{\text{obj}} \sum_{i=1}^{S^2} \sum_{j=1}^{B} 1_{i,j}^{\text{obj}} (c_{i,j} - \hat{c}_{i,j})^2 + \lambda_{\text{noobj}} \sum_{i=1}^{S^2} \sum_{j=1}^{B} \left(1 - 1_{i,j}^{\text{obj}}\right) \hat{c}_{i,j}^2
$$

$$
+ \lambda_{\text{classes}} \sum_{i=1}^{S^2} 1_{i,j}^{\text{obj}} \sum_{c=1}^{C} (p_{i,c} - \hat{p}_{i,c})^2.
$$

where $\hat{p}_{i,c}, \hat{x}_{i,j}, \hat{y}_{i,j}, \hat{w}_{i,j}, \hat{h}_{i,j}, \hat{c}_{i,j}$ are the network’s outputs.

(slightly re-written from Redmon et al. 2015)
Training YOLO relies on many engineering choices that illustrate well how involved is deep-learning “in practice”:

- Pre-train the 20 first convolutional layers on ImageNet classification,
- use 448 × 448 input for detection, instead of 224 × 224,
- use Leaky ReLU for all layers,
- dropout after the first fully connected layer,
- normalize bounding boxes parameters in [0, 1],
- use a quadratic loss not only for the bounding box coordinates, but also for the confidence and the class scores,
- reduce the weight of large bounding boxes by using the square roots of the size in the loss,
- reduce the importance of empty cells by weighting less the confidence-related loss on them,
- use momentum 0.9, decay 5e − 4,
- data augmentation with scaling, translation, and HSV transformation.

A critical technical point is the design of the loss function that articulates both a classification and a regression objectives.

The Single Shot Multi-box Detector (SSD, Liu et al., 2015) improves upon YOLO with a fully-convolutional architectures and multi-scale maps.

(Liu et al., 2015)
To summarize roughly how “one shot” deep detection can be achieved:

- networks trained on image classification capture localization information,
- regression layers can be attached to classification-trained networks,
- object localization does not have to be class-specific,
- multiple detection are estimated at each location to account for different aspect ratios and scales.
References


