Deep learning

8.3. Networks for object detection

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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.
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In the single-object case, the convolutional layers are frozen, and the localization layers are trained with a $\ell_2$ loss.

![Figure 7: Examples of bounding boxes produced by the regression network, before being combined into final predictions. The examples shown here are at a single scale. Predictions may be more optimal at other scales depending on the objects. Here, most of the bounding boxes which are initially organized as a grid, converge to a single location and scale. This indicates that the network is very confident in the location of the object, as opposed to being spread out randomly. The top left image shows that it can also correctly identify multiple location if several objects are present. The various aspect ratios of the predicted bounding boxes shows that the network is able to cope with various object poses.](image)

(Sermanet et al., 2013)

Combining the multiple boxes is done with an *ad hoc* greedy algorithm.
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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).
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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.
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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.
Making predictions. Unlike sliding window and region proposal-based techniques, YOLO sees the entire image during... 

Other than the size of the network, all training and testing parameters are the same between YOLO and Fast YOLO.

Our system models detection as a regression problem. It divides the image into an $S \times S$ grid, and for each grid cell, regardless of the number of boxes $B$, one set of class probabilities per grid cell, irrespective of the individual box confidence predictions.

For evaluating YOLO on PASCAL VOC, we use 20 labeled classes so $C = 20$. The model is trained on a large number of images. At test time, we multiply the conditional class probability $P(class|object)$ by the confidence score $P(\text{confidence} | \text{object})$ to estimate the total probability $P(class, \text{confidence} | \text{object})$.

If the center of an object falls into a grid cell, that grid cell is responsible for detecting that object.

We also train a fast version of YOLO designed to push speed while maintaining high average precision.

The YOLO design enables end-to-end training and real-time speeds while maintaining high average precision. This means our network reasons globally, producing a single output per image for all objects.

We unify the separate components of object detection: classification, regression, and the ground truth. Intersection over union (IOU) between the predicted box and the ground truth.

The confidence prediction represents the IOU between the predicted box and any ground truth box.

We only predict the output probabilities and coordinates. These probabilities are conditioned on the grid cell containing an object. We only predict bounding boxes and confidence. The class probability map.

Our network architecture is inspired by the GoogLeNet and the DarkNet architectures.

The input image is divided into an $S \times S$ grid. Each grid cell contains a single convolutional layer. There are two fully connected layers that take as input the output of a convolutional layer and predict the output probabilities and coordinates.

We implement this model as a convolutional neural network with fewer convolutional layers (9 instead of 24). The full network is comprised of 47 convolutional layers, similar to Lin et al [22]. The full network is comprised of 47 convolutional layers with 3 reduction layers followed by 2 fully connected layers.

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If no object is detected, the model simply uses $P(\text{confidence} | \text{object}) = 0$. Otherwise, we want the confidence score to equal the probability that the box contains an object and how confident the model is that the box contains an object and how accurate it thinks the box is that it predicts. For example, $P(\text{confidence} | \text{object})$.

Class probability map

Bounding boxes + confidence

Final detections

(Redmon et al., 2015)
The output corresponds to splitting the image into a regular $S \times S$ grid, with $S = 7$. 

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

(Redmon et al., 2015)
So the network predicts class scores and bounding-box regressions, and although the output comes from fully connected layers, it has a 2D structure.
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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 $c = 1, \ldots, C$

- $\mathbf{1}_i^{obj}$ is 1 if there is an object in cell $i$ and 0 otherwise,
- $\mathbf{1}_{i,j}^{obj}$ 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 $\mathbf{1}_i^{obj} = 1$, 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 $1_{i,j}^{obj}$'s and $c_{i,j}$, and then does one step to minimize

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

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

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

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 $448 \times 448$ input for detection, instead of $224 \times 224$,
- use Leaky ReLU for all layers,
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- 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,
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- 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.
Object detection networks

- **AlexNet** (Krizhevsky et al., 2012)
  - Box regression

- **Overfeat** (Sermanet et al., 2013)
  - Region proposal + crop in image

- **R-CNN** (Girshick et al., 2013)
  - Crop in feature maps

- **Fast R-CNN** (Girshick, 2015)
  - Convolutional region proposal

- **Faster R-CNN** (Ren et al., 2015)
  - No crop

- **YOLO** (Redmon et al., 2015)
  - Fully convolutional + multi-scale maps

- **SSD** (Liu et al., 2015)
  - Multi-scale convolutions + multi boxes
The end
References


