You Only Look Once: Unified, Real-Time Object Detection

Research paper: https://arxiv.org/pdf/1506.02640v5.pdf

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Unified, Real-Time Object Detection

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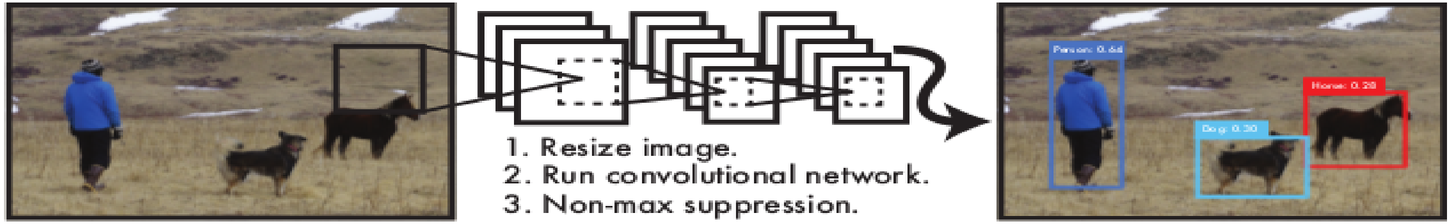

Base YOLO model runs at 45 FPS. A smaller version, Fast YOLO, runs astounding 155 FPS second, outperforms DPM (deformable parts models) and R-CNN.

Figure 1: The YOLO Detection System. (1) resizes image to 448 × 448, (2) runs a convolutional network, and (3) thresholds the result by the model's confidence.

YOLO github Code and readme

https://github.com/hualili/opencv/blob/master/deep-learning-2022s/2022F-106-YOLO4-README-Tiny-Yolo4-GPU-YY-2022-9-28.pdf

Tutorial: https://pjreddie.com/darknet/yolo/

GitHub, Inc. (US)

```
git clone https://github.com/pjreddie/darknet
```

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1x1 Convolution for Dimension Reduction and Pooling

The 1x1 convolution enables dimension reduction by reducing the number of channels in convolution layers

1. Suppose the input layers is C⋆H⋆W, where C is its channels. The 1x1 convolution generates one average result in shape H⋆W. The 1x1 kernel (filter) is a vector of length C.
2. Now if you have F 1x1 filters, you get F layers of output, the output shape is F⋆H⋆W. For input layer C⋆H⋆W with F 1x1 convolution (with each of its channel is C), you will get F⋆H⋆W layers.

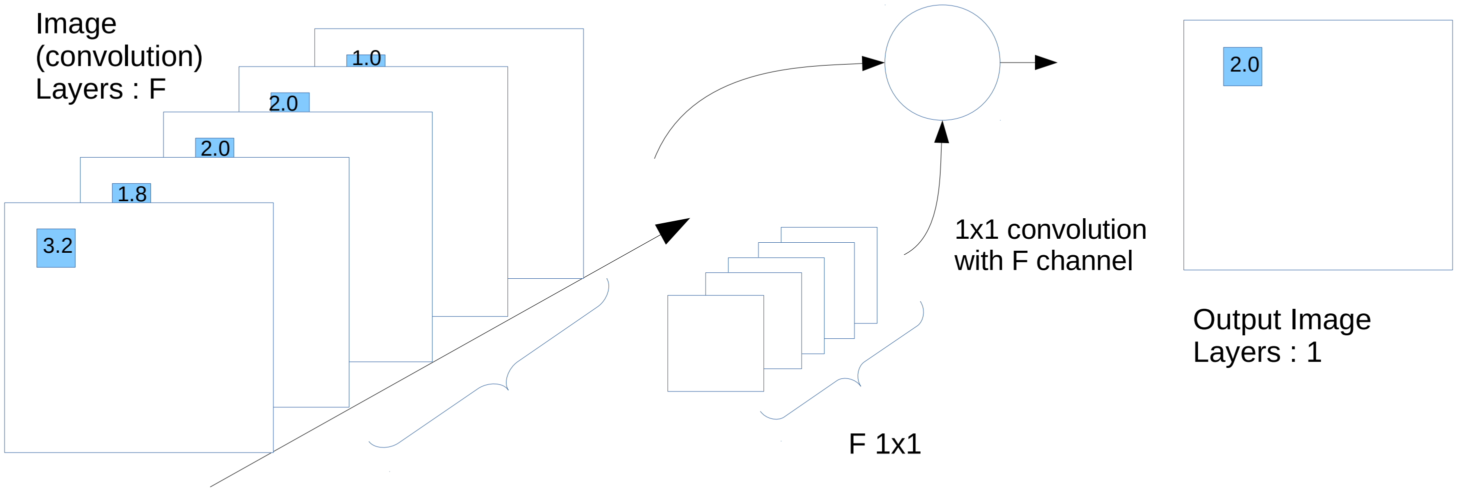

Image resolution
MxN

Average result:
(3.2 + 1.8 + 2.0 + 2.0 + 1.0) / 5 = 2.0

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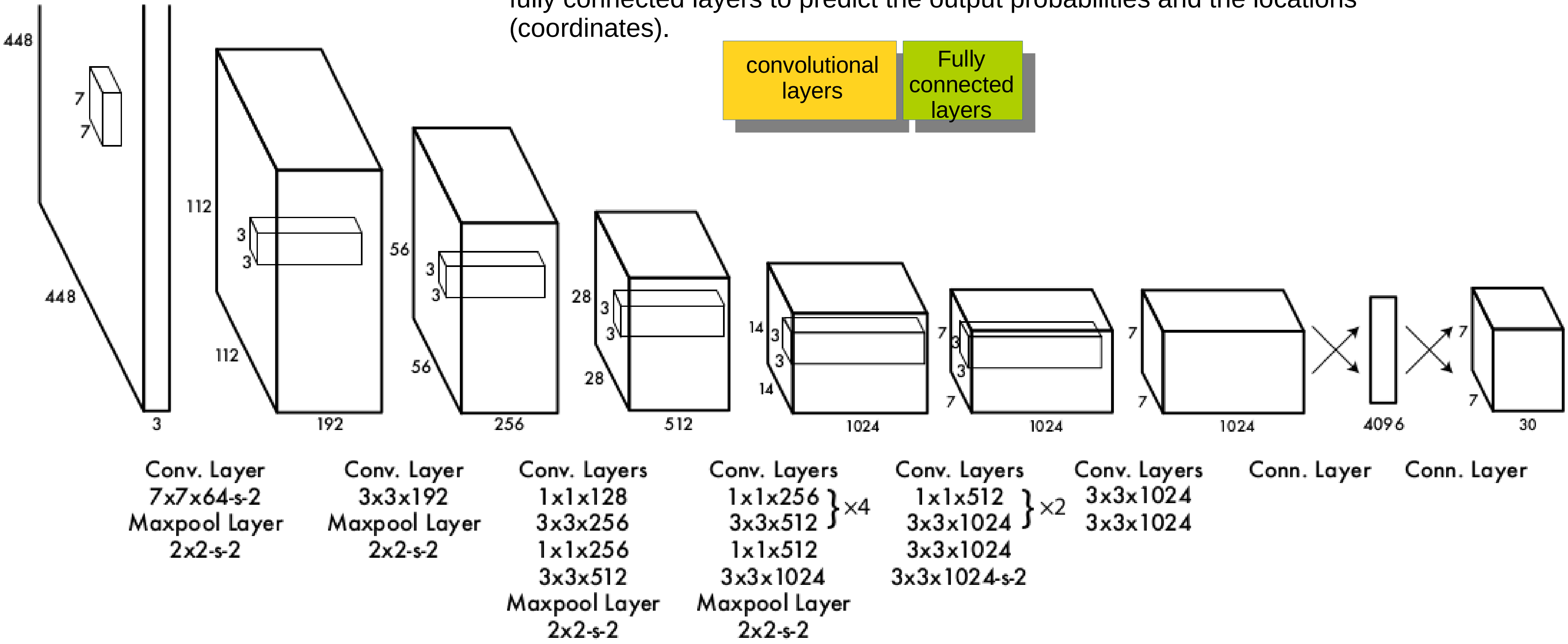
1. Input image size: 448x448x3; 2. Resolution reduction for feature extraction/abstraction Pooling and convolution with stride = 2;

Base Line Yolo Architecture

Design guideline: The block of convolutional layers to extract image features, the fully connected layers to predict the output probabilities and the locations (coordinates).

convolutional layers

Fully connected layers



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Loss Function for YOLO

$$\lambda_{\mathbf{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left[(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 \right]$$

$$+ \lambda_{\mathbf{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left[\left(\sqrt{w_i} - \sqrt{\hat{w}_i} \right)^2 + \left(\sqrt{h_i} - \sqrt{\hat{h}_i} \right)^2 \right]$$

$$+ \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left(C_i - \hat{C}_i \right)^2$$

$$+ \lambda_{\text{noobj}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{noobj}} \left(C_i - \hat{C}_i \right)^2$$

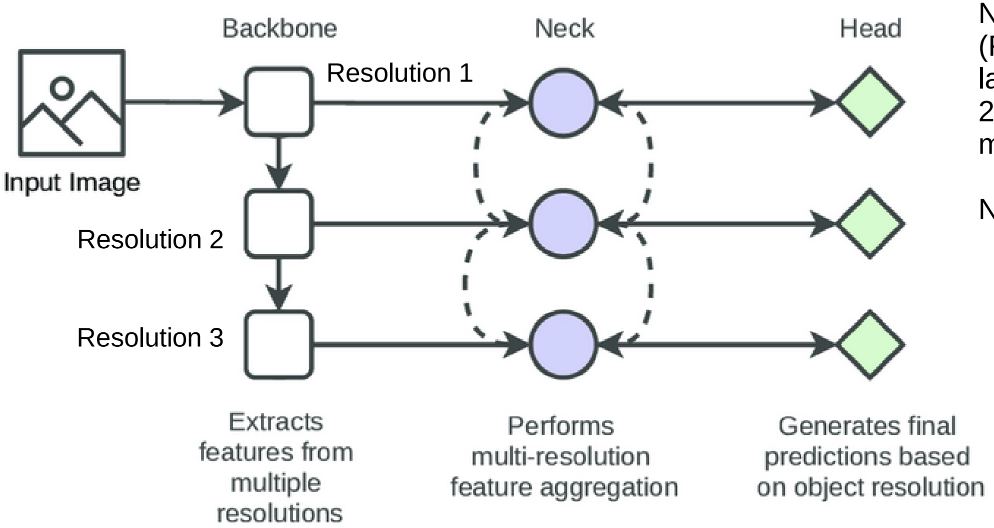
$$+ \sum_{i=0}^{S^2} \mathbb{1}_{i}^{\text{obj}} \sum_{c \in \text{classes}} (p_i(c) - \hat{p}_i(c))^2$$

Backbone, Neck, Head Module of CNN Architecture

1. A backbone module is the module that extract image features, usually at different resolutions as shown below;

2. A neck module fuses the features of different resolutions.

3. Finally, multiple head modules perform the detection of objects in different resolutions.



https://www.researchgate.net/figure/A-detection-model-contains-a-backbone-neck-head-module-The-backbone-module-exploits_fig1_356638292

Note: Object detection by YOLO, SSD, Mask RCNN and RetinaNet.

Implement a YOLO (v3) object detector from scratch in PyTorch

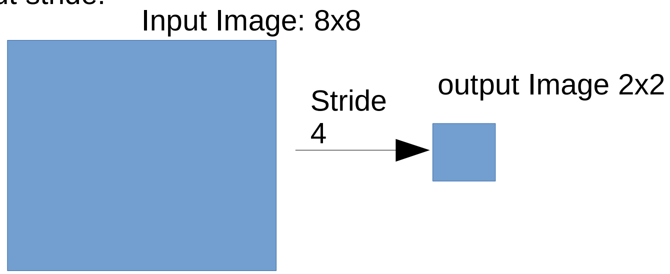
https://blog.paperspace.com/how-to-implement-a-yolo-object-detector-in-pytorch/

https://github.com/ayooshkathuria/YOLO_v3_tutorial_from_scratch

/ **YOLO_v3_tutorial_from_scratch**

Note: 1. YOLO only uses convolutional layers, e.g., fully convolutional network (FCN). It has 75 convolutional layers, with skip connections and upsampling layers.
2. No pooling, a convolutional layer with stride 2 for downsampling the feature map.

Note about stride:



Note 1. Images in batches can be processed in parallel by the GPU for speed gain. All images must have the same resolution to be concatenate multiple into a large batch (concatenating many PyTorch tensors into one);
Note 2. YOLO prediction is done by using a convolutional layer which uses 1 x 1 convolutions.

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