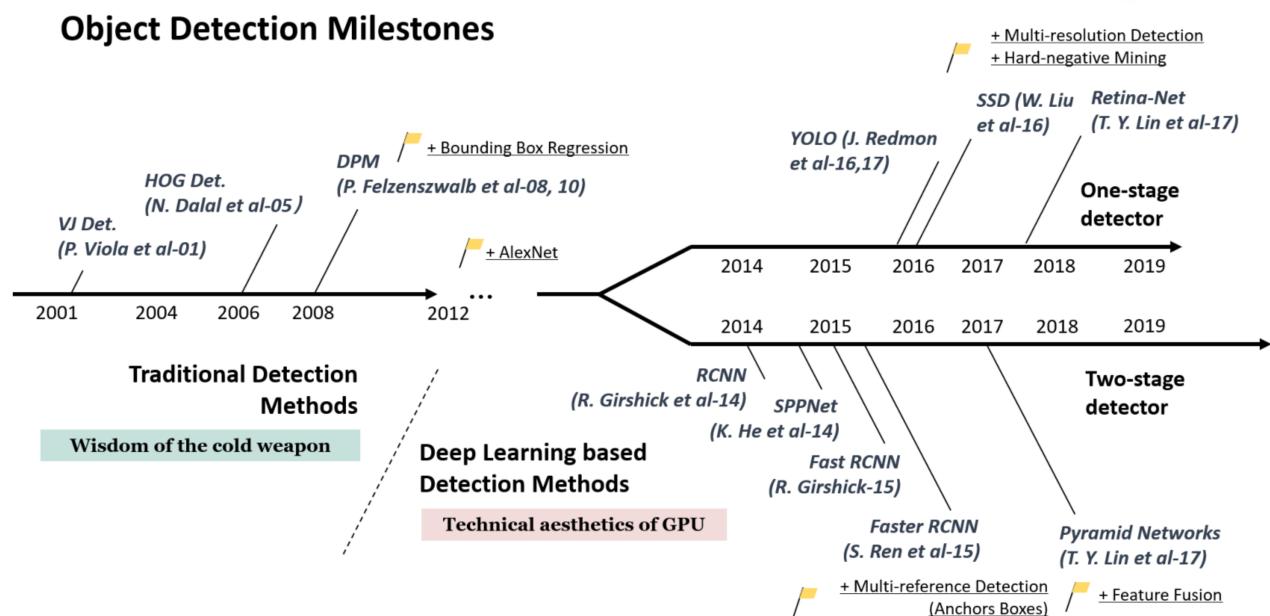
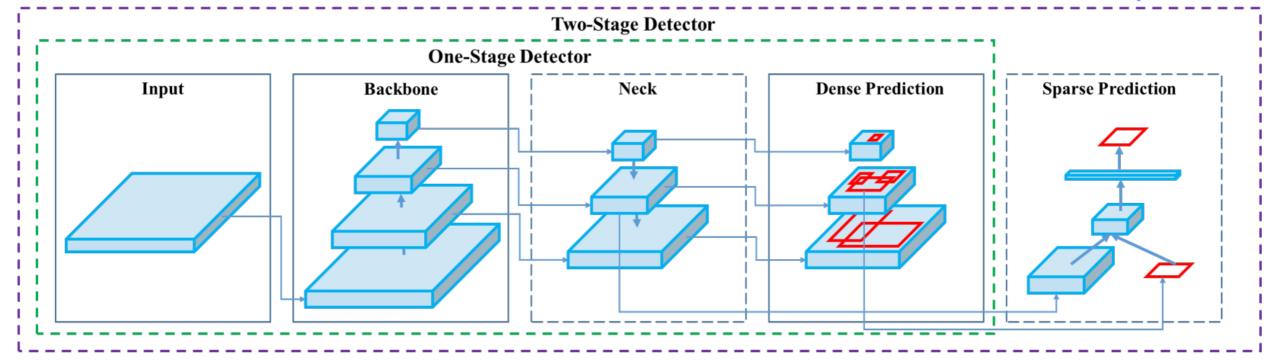


# YOLO目标检测系列发展史









**Input:** { Image, Patches, Image Pyramid, ... }

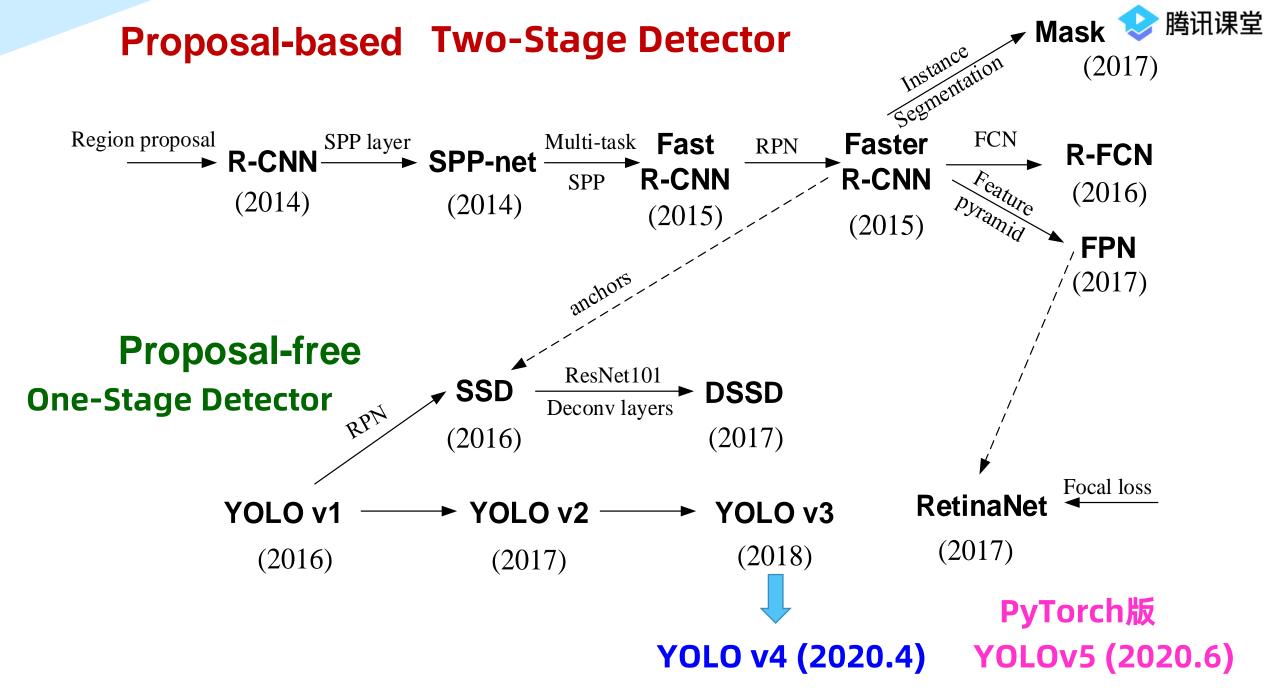
Backbone: { VGG16 [68], ResNet-50 [26], ResNeXt-101 [86], Darknet53 [63], ... }

Neck: { FPN [44], PANet [49], Bi-FPN [77], ... }

Head:

Dense Prediction: { RPN [64], YOLO [61, 62, 63], SSD [50], RetinaNet [45], FCOS [78], ... }

Sparse Prediction: { Faster R-CNN [64], R-FCN [9], ... }







## Darknet

Darknet is an open source neural network framework written in C and CUDA. It is fast, easy to install, and supports CPU and GPU computation.

Yolo v4 paper: https://arxiv.org/abs/2004.10934

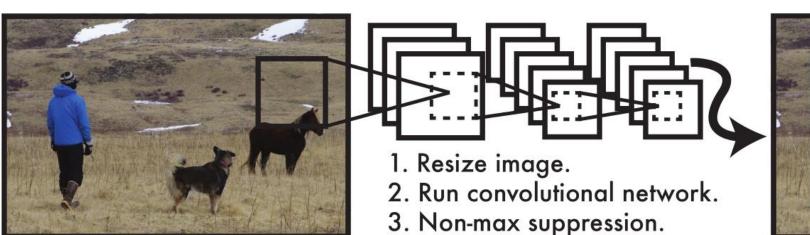
Yolo v4 source code: https://github.com/AlexeyAB/darknet

For more information see the Darknet project website.



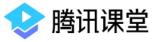
# You Only Look Once: Unified, Real-Time Object Detection

• YOLO将特征图划分为S×S的格子(grid cells),每个格子负责对落入其中的目标进行检测,一次性预测所有格子所含目标的边界框、定位置信度、以及所有类别概率向量。





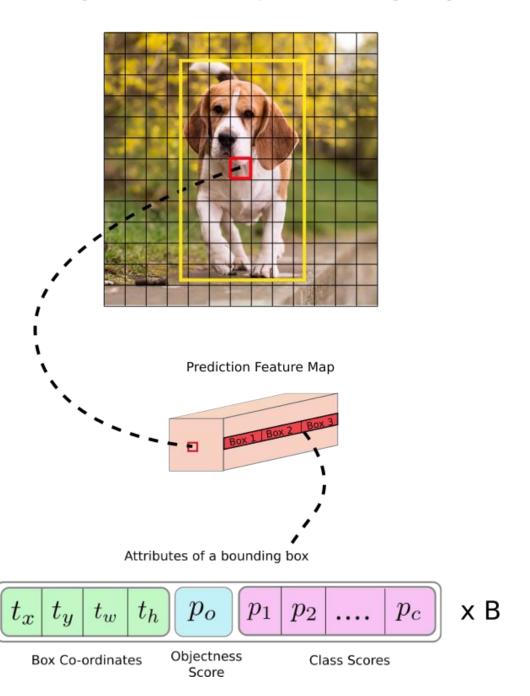
# YOLO算法的基本思想





Class probability map





# 多尺度融合



#### Prediction Feature Maps at different Scales



13 x 13

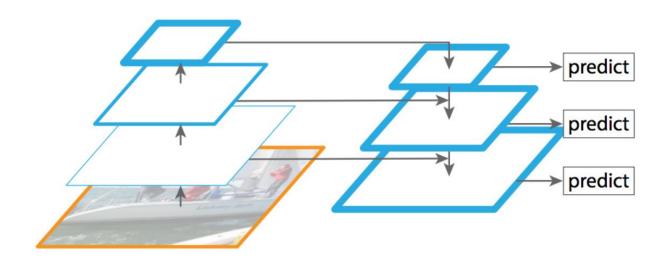


26 x 26



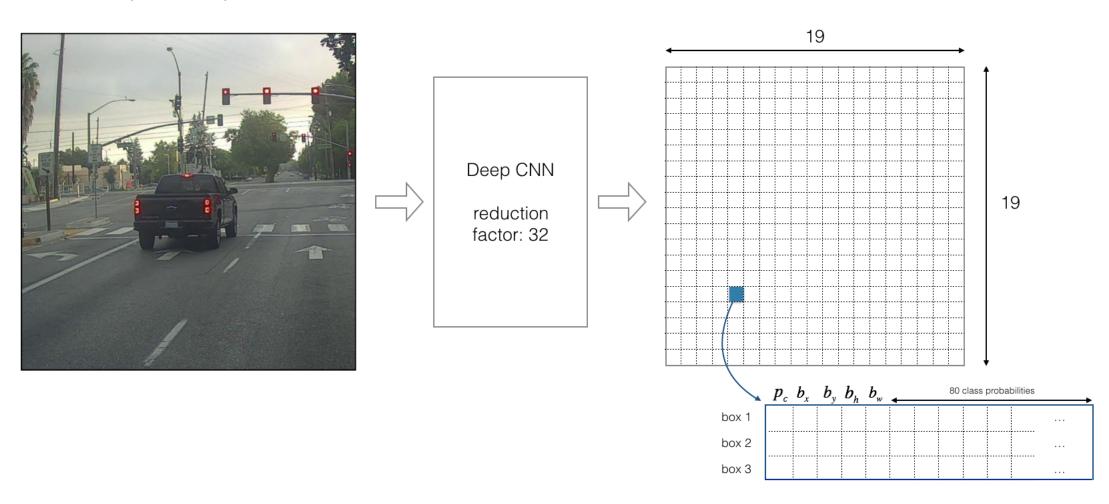
52 x 52

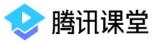
#### **Feature Pyramid Network (FPN)**



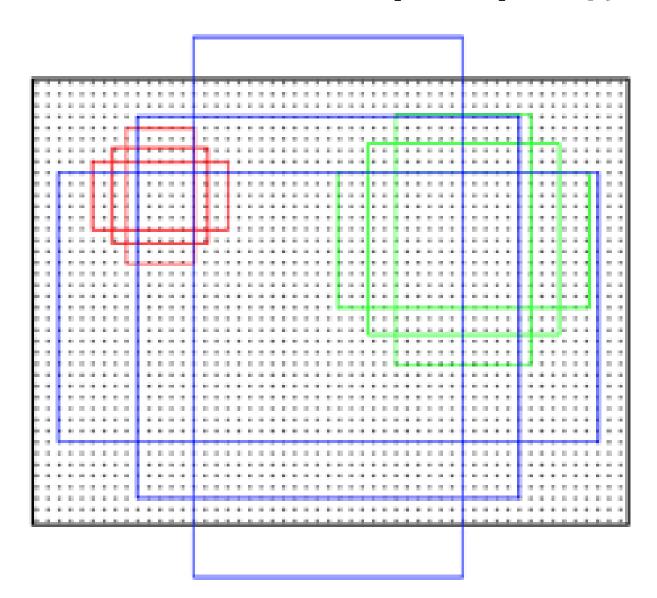


preprocessed image (608, 608, 3)





# Anchor (锚框) 机制



# YOLO算法的基本思想

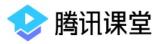
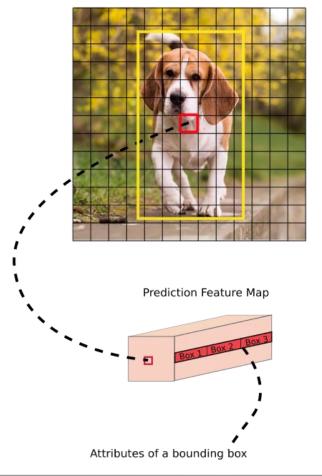


Image Grid. The Red Grid is responsible for detecting the dog

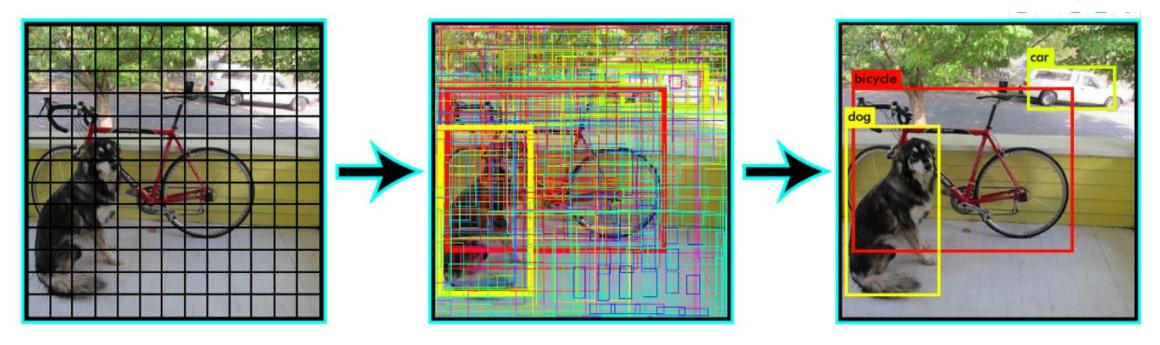


- 首先通过特征提取网络对输入图像提取特征,得到一定大小的特征图, 比如13×13(相当于416×416图片大小),然后将输入图像分成13 ×13个grid cells
- ➤ YOLOv3/v4: 如果GT中某个目标的中心坐标落在哪个grid cell中,那么就由该grid cell来预测该目标。每个grid cell都会预测3个不同尺度的边界框。
- ➤ YOLOv5: 不同于yolov3/v4, 其GT可以跨层预测,即有些bbox在多个预测层都算正样本; 匹配数范围可以是3-9个。
  - 预测得到的输出特征图有两个维度是提取到的特征的维度,比如13×13,还有一个维度(深度)是 B×(5+C)
- ➤ 注: B表示每个grid cell预测的边界框的数量(YOLO v3/v4中是3个);

  C表示边界框的类别数(没有背景类,所以对于VOC数据集是20); 5表示

  4个坐标信息和一个目标性得分(objectness score)。





每个预测框的<u>类别置信度得分</u>(class confidence score ) 计算如下:

class confidence score = box confidence score  $\times$  conditional class probability

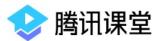
它测量分类和定位(目标对象所在的位置)的置信度。

$$\Pr(\text{Class}_i|\text{Object}) * \Pr(\text{Object}) * \text{IOU}_{\text{pred}}^{\text{truth}} = \Pr(\text{Class}_i) * \text{IOU}_{\text{pred}}^{\text{truth}}$$

box confidence score 
$$\equiv P_r(object) \cdot IoU$$
  
conditional class probability  $\equiv P_r(class_i|object)$   
class confidence score  $\equiv P_r(class_i) \cdot IoU$   
 $=$  box confidence score  $\times$  conditional class probability

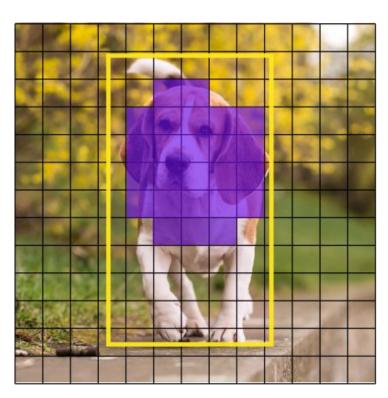
where

 $P_r(object)$  is the probability the box contains an object. IoU is the IoU (intersection over union) between the predicted box and the ground truth.  $P_r(class_i|object)$  is the probability the object belongs to  $class_i$  given an object is presence.  $P_r(class_i)$  is the probability the object belongs to  $class_i$ 



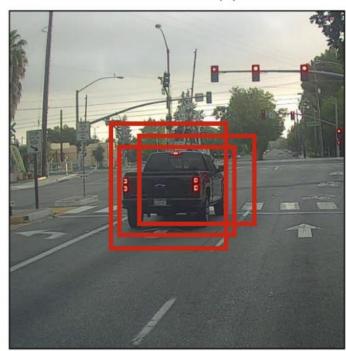
# NMS (Non-Maximum Suppression) 非极大抑制

### 测试时没有GT框,只能比较多个预测框,比较相互之间的IOU,做NMS



Multiple Grids may detect the same object NMS is used to remove multiple detections

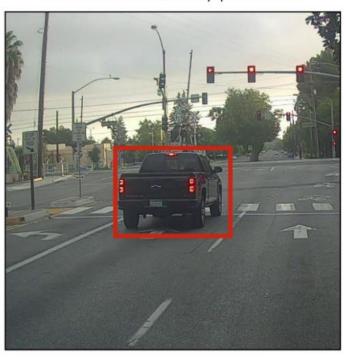




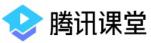
Non-Max Suppression

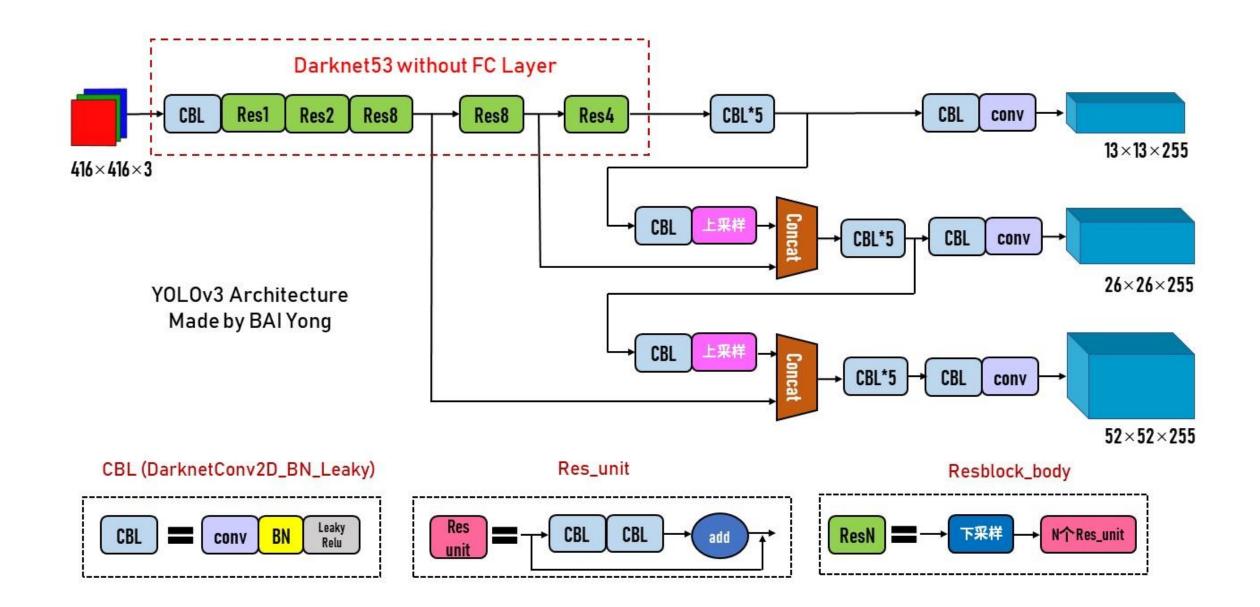


After non-max suppression



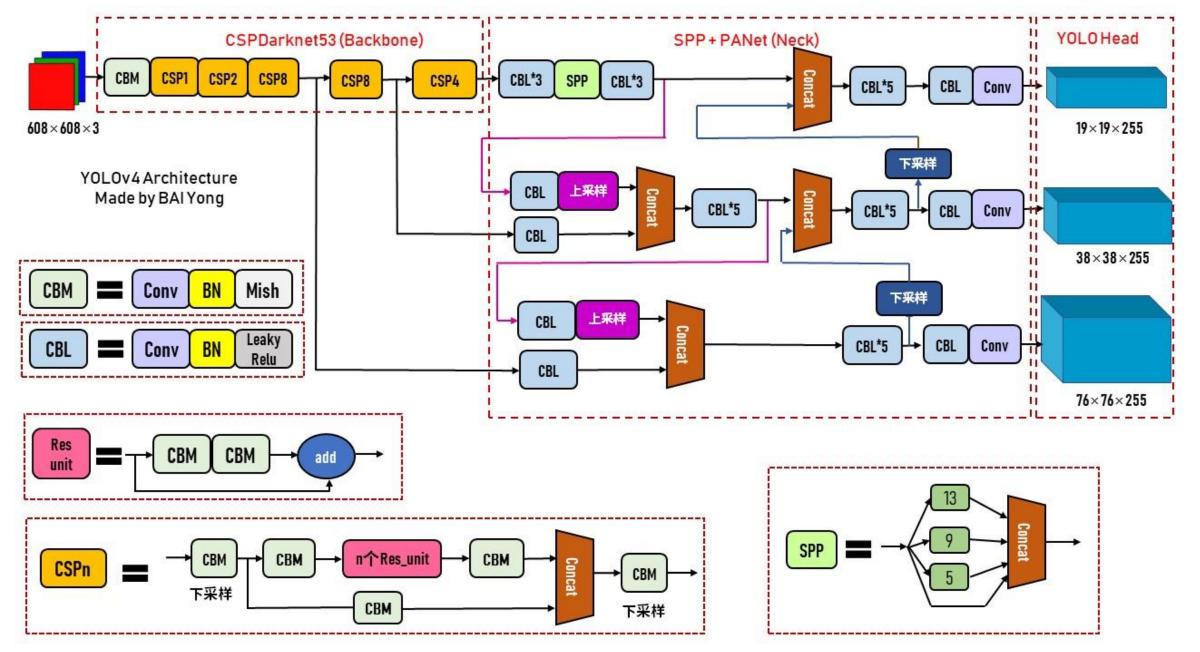
## YOLOv3 网络架构



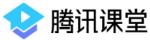


## YOLOv4 网络架构









## 损失函数包括:

- classification loss, 分类损失
- localization loss, 定位损失(预测边界框与GT之间的误差)
- confidence loss, 置信度损失(框的目标性; objectness of the box)

损失函数(Loss function)

### 总的损失函数:

classification loss + localization loss + confidence loss