

YOLOv5

Newest and Fastest One-Stage Objection Detection Model

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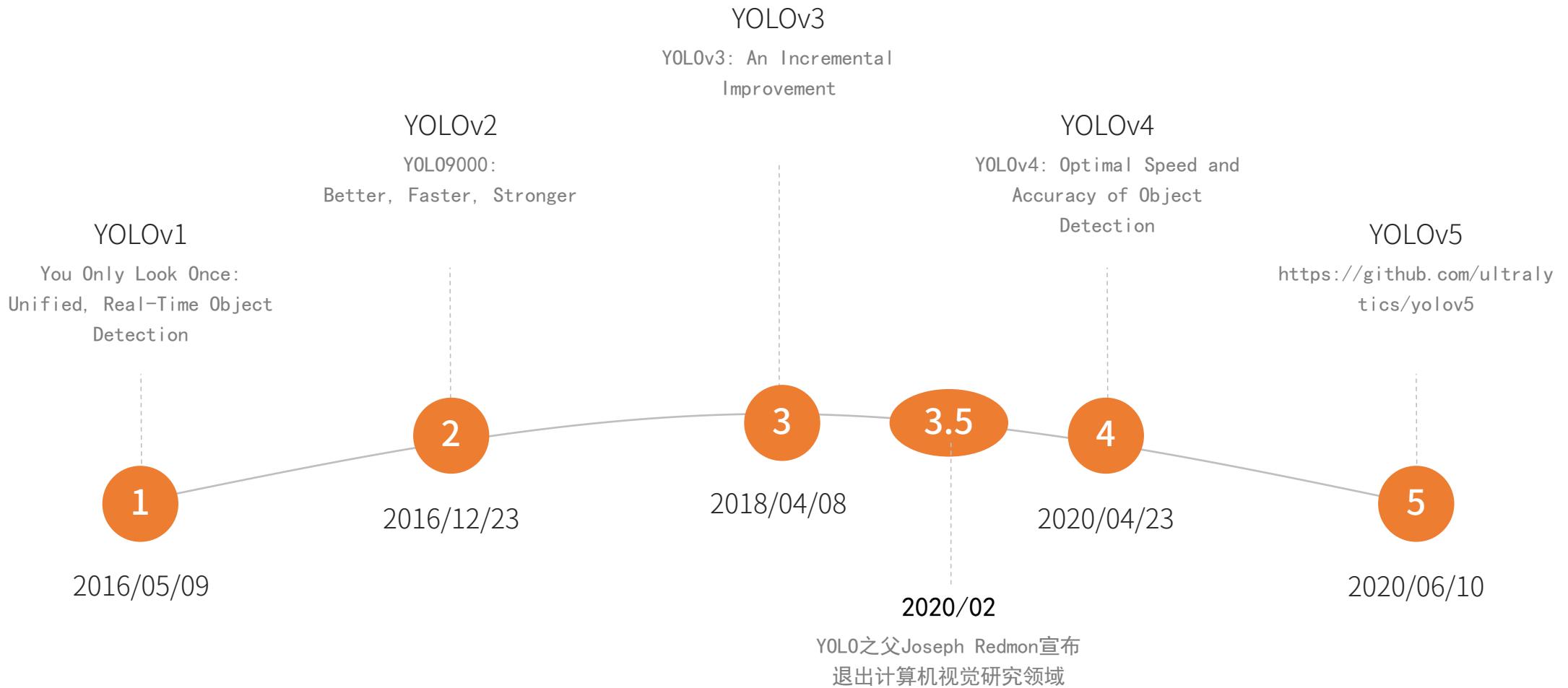
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01 v5之引入

The Introduction of YOLOv5

YOLO系列时间轴



YOLOv5介绍

项目地址: <https://github.com/ultralytics/yolov5>
暂无Paper

命名与争议: Is YOL0v5 the Correct Name?

反对者:

- (1) he is not an original YOL0 author,
- (2) he did not publish a paper, and/or
- (3) the implementation is not sufficiently novel.

认可者/中立者:

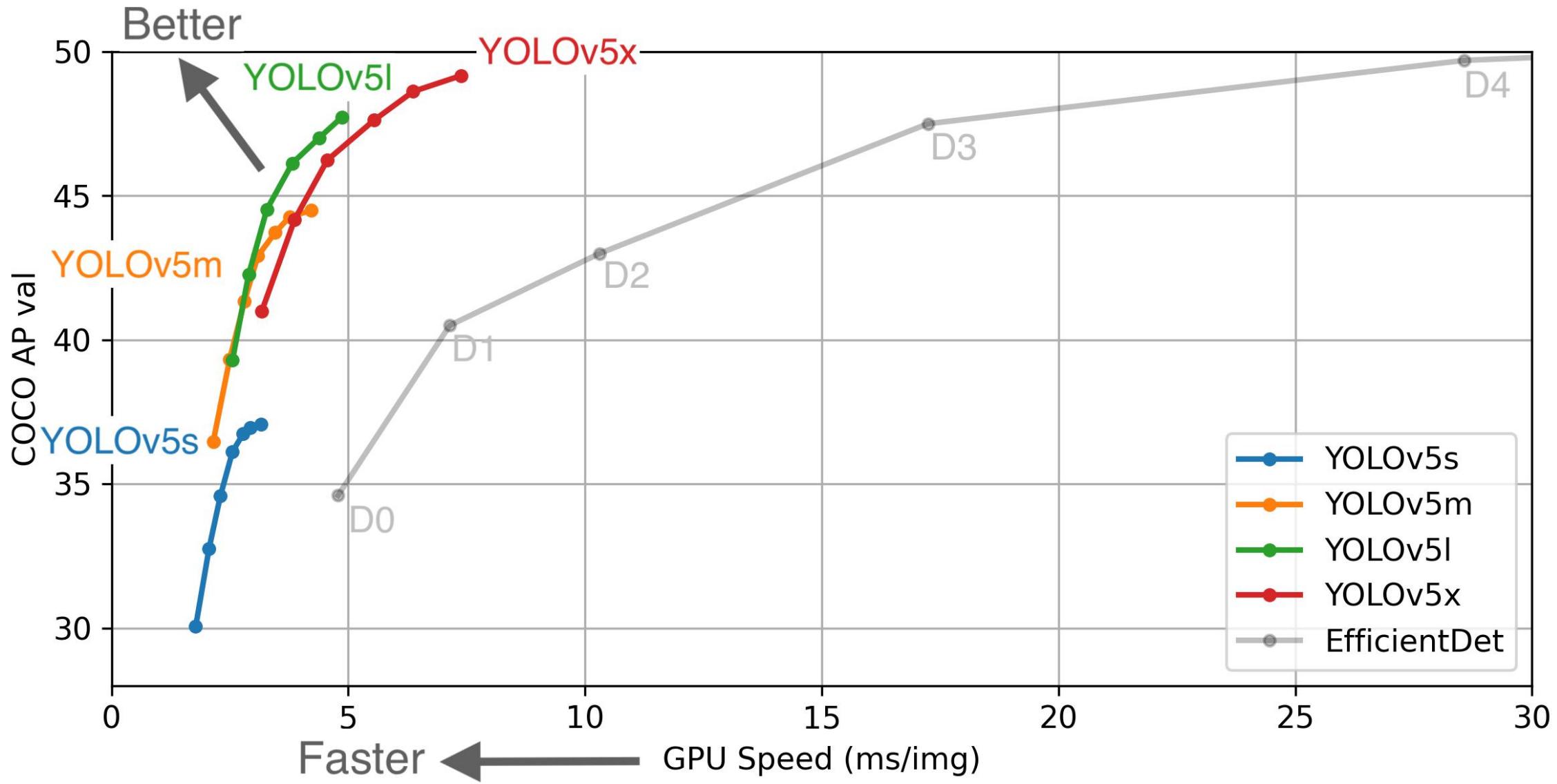
- (1) PyTorch版最强模型;
- (2) 动机认可: v4性能提升最多的Mosaic的发明者;
- (3) 命名无所谓, 有贡献就行。

02

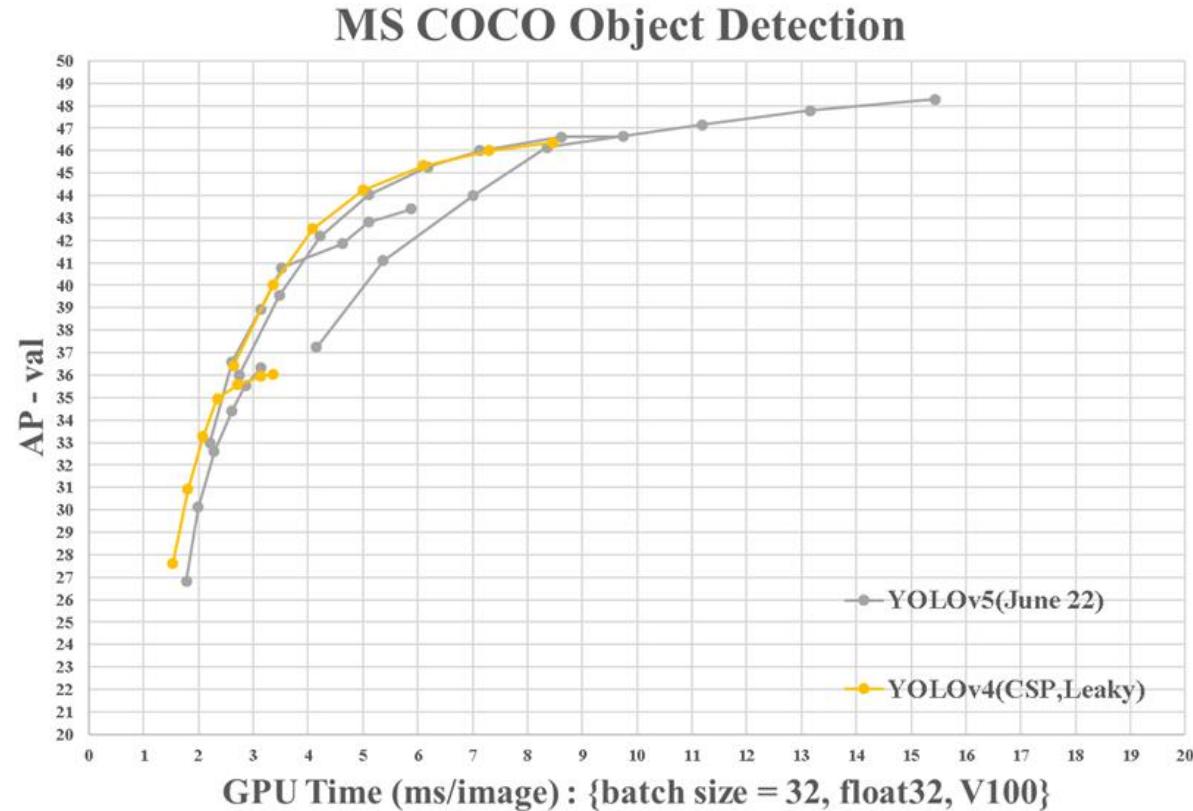
v5之性能

The Performance of YOLOv5

YOLOv5性能 (官方)

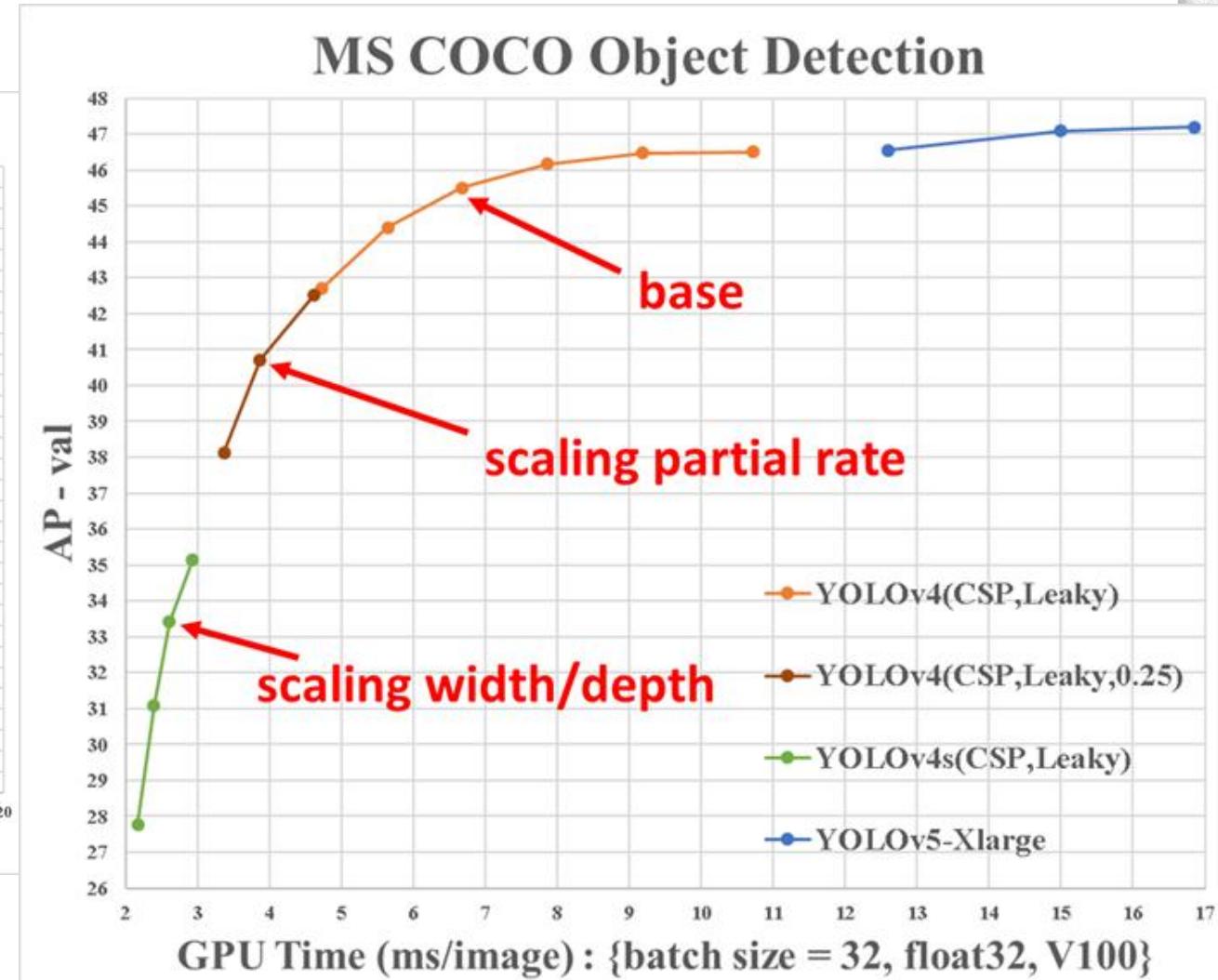


YOLOv5性能 (非官方)



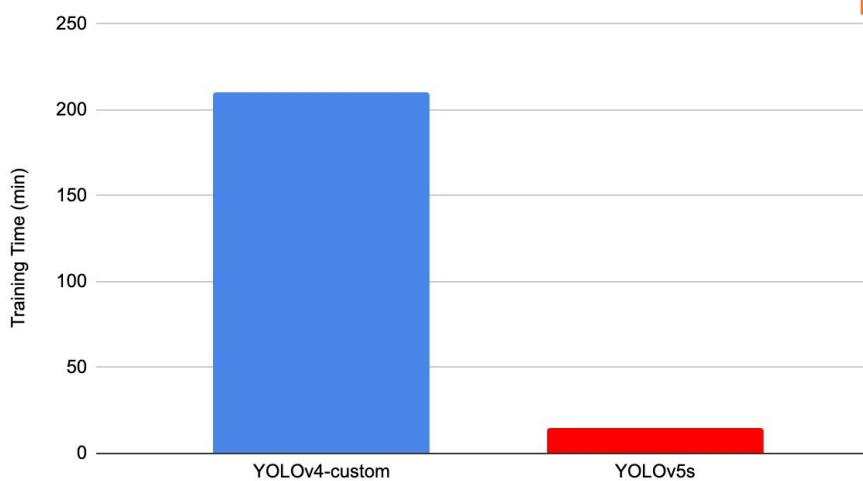
两者性能其实很接近，但是从数据上看YOLO V4仍然是最佳对象检测框架。

<https://github.com/ultralytics/yoloV5/issues/6>



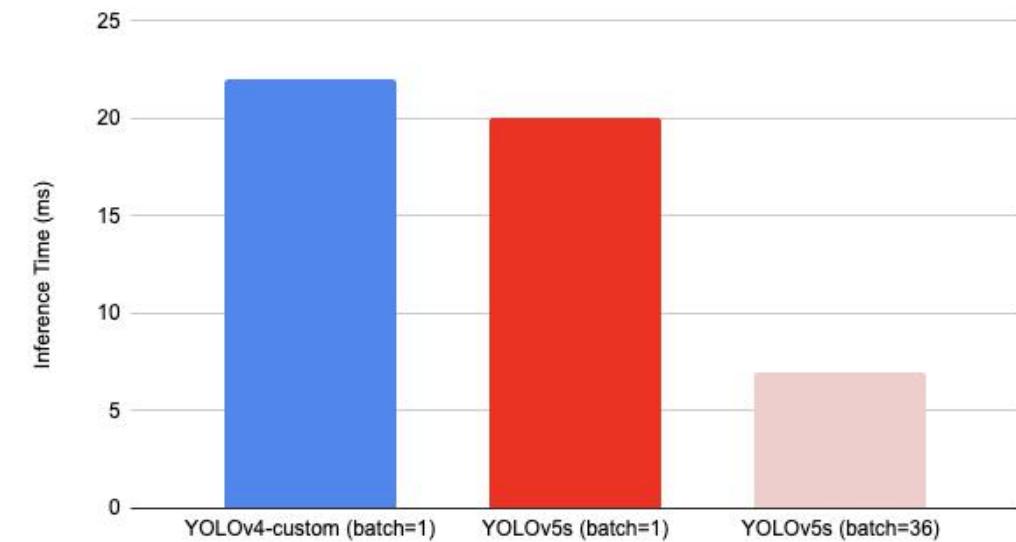
only keep Pareto optimality curve

Training Time Comparison



YOLOv5vsYOLOv4

Inference Time (ms)



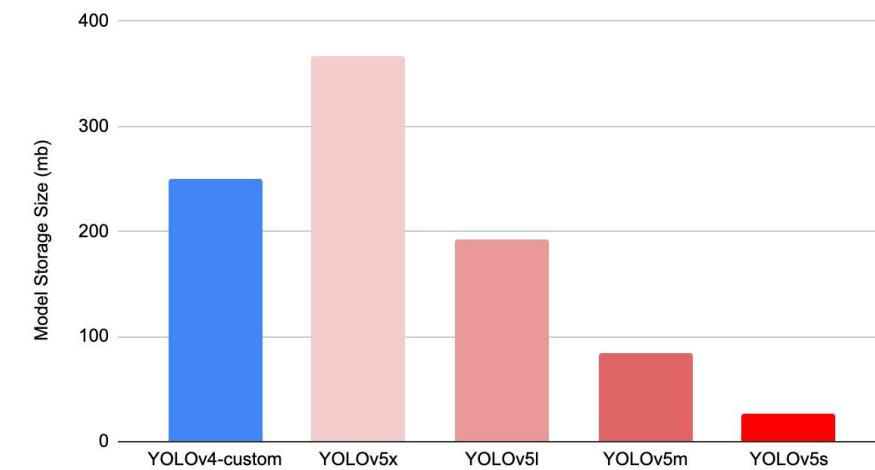
max validation evaluation: 3.5 hrs(1300) vs 14.46 minutes(200)

Max Val mAP @0.5



mAP was similar, both models achieved their max.

Model Storage Size (mb)

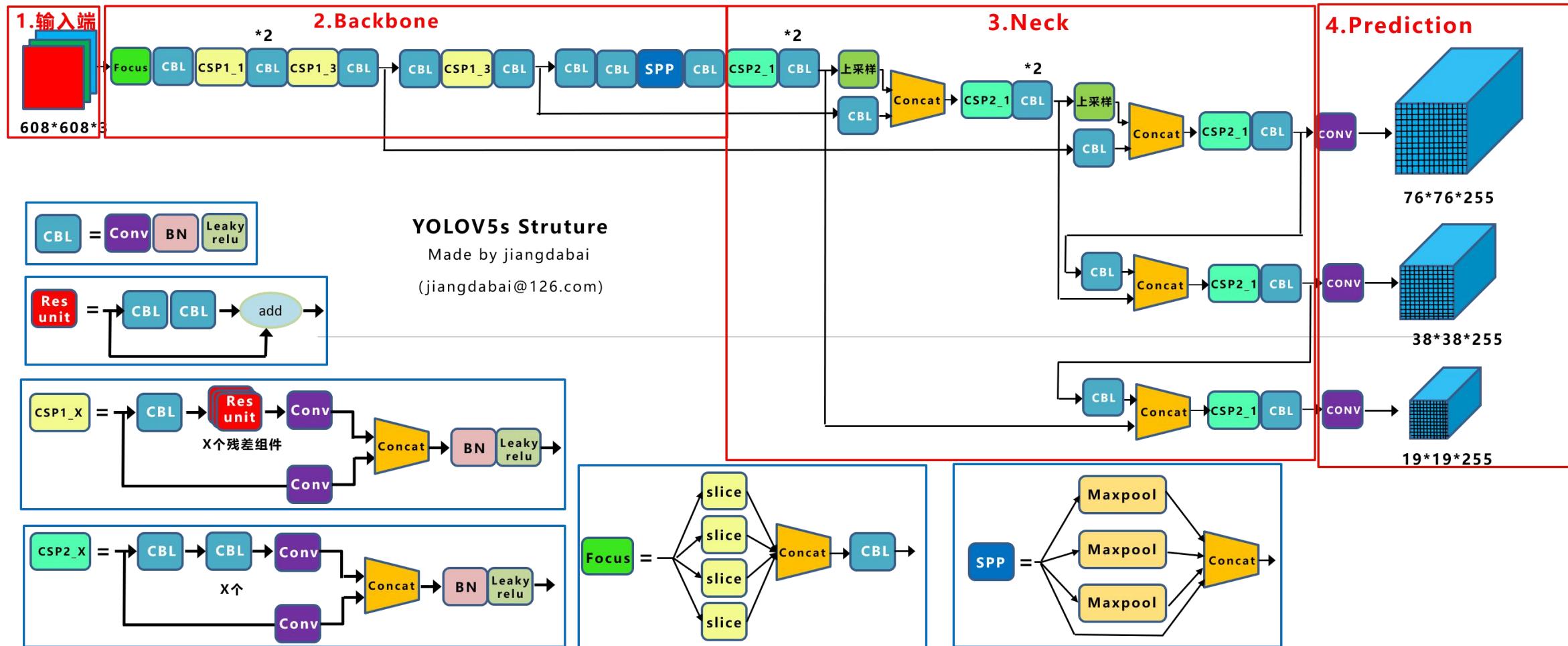


03

v5之框图

The Architecture of YOLOv5

YOLOv5框架



Yolov5的四种网络结构

Yolov5代码中的四种网络，和之前的Yolov3, Yolov4中的cfg文件不同，都是以yaml的形式来呈现。

而且四个文件的内容基本上都是一样的，只有最上方的depth_multiple和width_multiple两个参数不同。

yolov5s.yaml

```
3  depth_multiple: 0.33 # model depth multiple  
4  width_multiple: 0.50 # layer channel multiple
```

yolov5m.yaml

```
3  depth_multiple: 0.67 # model depth multiple  
4  width_multiple: 0.75 # layer channel multiple
```

yolov5l.yaml

```
3  depth_multiple: 1.0 # model depth multiple  
4  width_multiple: 1.0 # layer channel multiple
```

yolov5x.yaml

```
3  depth_multiple: 1.33 # model depth multiple  
4  width_multiple: 1.25 # layer channel multiple
```

四种结构就是通过上面的两个参数，来进行控制网络的深度和宽度。其中**depth_multiple**控制网络的深度，**width_multiple**控制网络的宽度。

Yolov5的四种网络结构

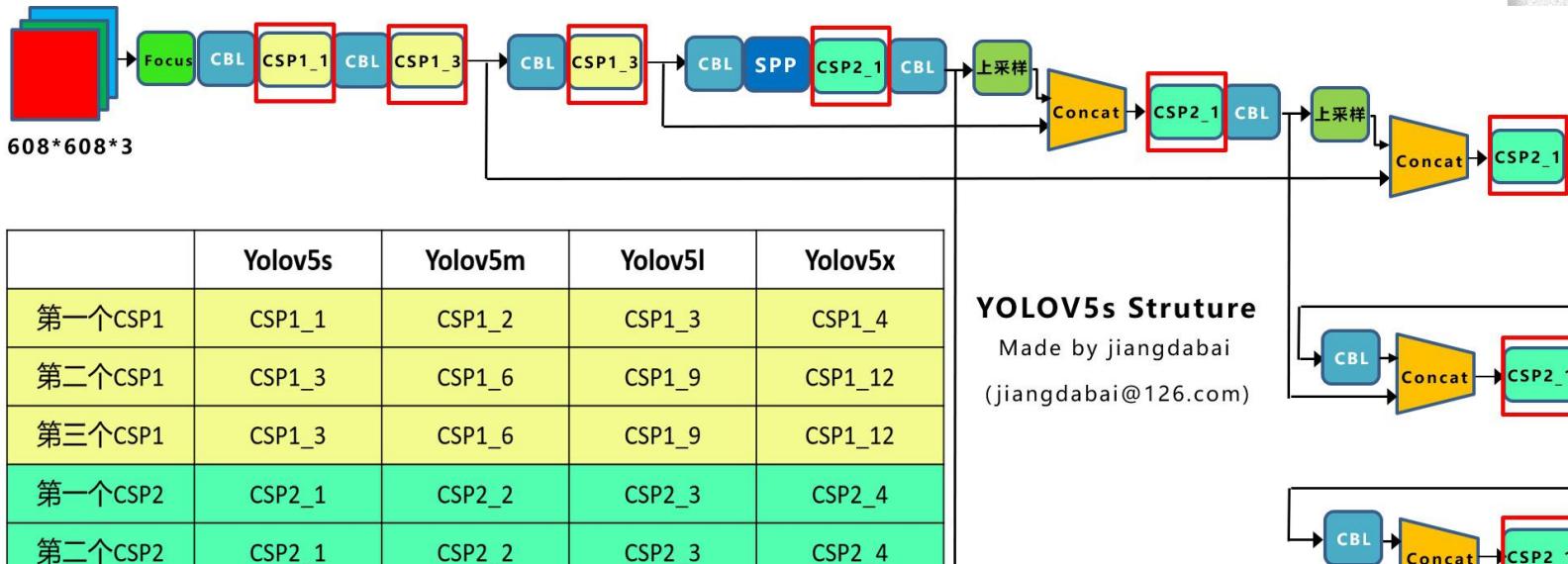
depth_multiple控制网络的深度

两种CSP结构，CSP1和CSP2，其中CSP1结构主要应用于Backbone中，CSP2结构主要用于Neck中。

```
12 # YOL0v5 backbone
13     backbone:
14         # [from, number, module, args]
15         [[-1, 1, Focus, [64, 3]], # 0-P1/2
16          [-1, 1, Conv, [128, 3, 2]], # 1-P2/4
17          [-1, 3, BottleneckCSP, [128]], 第一个CSP1
18          [-1, 1, Conv, [256, 3, 2]], # 3-P3/8
19          [-1, 9, BottleneckCSP, [256]], 第二个CSP1
20          [-1, 1, Conv, [512, 3, 2]], # 5-P4/16
21          [-1, 9, BottleneckCSP, [512]], 第三个CSP1
22          [-1, 1, Conv, [1024, 3, 2]], # 7-P5/32
23          [-1, 1, SPP, [1024, [5, 9, 13]]],
24          [-1, 3, BottleneckCSP, [1024, False]], # 9
25      ]
```

yolo.py

```
177     anchors, nc, gd, gw = d['anchors'], d['nc'], d['depth_multiple'], d['width_multiple']
182     for i, (f, n, m, args) in enumerate(d['backbone'] + d['head']): # from, number, module, args
190         n = max(round(n * gd), 1) if n > 1 else n # depth gain
```



	Yolov5s	Yolov5m	Yolov5l	Yolov5x
第一个CSP1	CSP1_1	CSP1_2	CSP1_3	CSP1_4
第二个CSP1	CSP1_3	CSP1_6	CSP1_9	CSP1_12
第三个CSP1	CSP1_3	CSP1_6	CSP1_9	CSP1_12
第一个CSP2	CSP2_1	CSP2_2	CSP2_3	CSP2_4
第二个CSP2	CSP2_1	CSP2_2	CSP2_3	CSP2_4
第三个CSP2	CSP2_1	CSP2_2	CSP2_3	CSP2_4
第四个CSP2	CSP2_1	CSP2_2	CSP2_3	CSP2_4
第五个CSP2	CSP2_1	CSP2_2	CSP2_3	CSP2_4

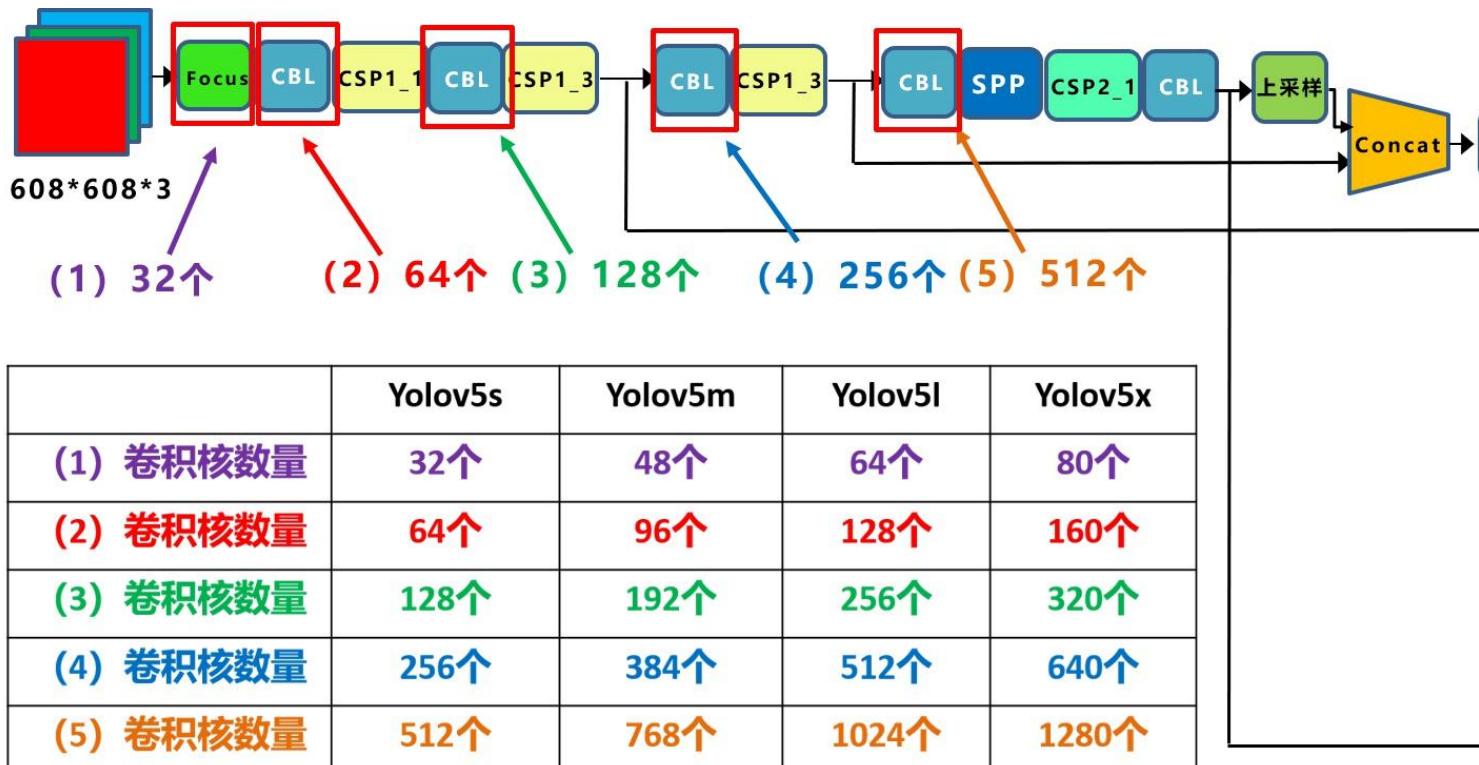
Yolov5中，网络的不断加深，也在不断增加网络特征提取和特征融合的能力。

Yolov5的四种网络结构

width_multiple控制网络的宽度

四种yolov5结构在不同阶段的卷积核的数量都是不一样的，即网络的宽度。

当然卷积核的数量越多，特征图的宽度越宽，网络提取特征的学习能力也越强。



yolo.py

```
177     anchors, nc, gd, gw = d['anchors'], d['nc'], d['depth_multiple'], d['width_multiple']
182     for i, (f, n, m, args) in enumerate(d['backbone'] + d['head']): # from, number, module, args
191         if m in [nn.Conv2d, Conv, Bottleneck, SPP, DWConv, MixConv2d, Focus, CrossConv, BottleneckCSP, C3]:
192             c1, c2 = ch[f], args[0]
193             c2 = make_divisible(c2 * gw, 8) if c2 != no else c2
```

04 v5之改进

Improvement in YOLOv5

YOLOv5改进

01

输入端

- (1) Mosaic数据增强
- (2) 自适应锚框计算
- (3) 自适应图片缩放

02

Backbone

- (1) Focus结构
- (2) CSP结构

03

Neck

- (1) FPN+PAN结构

04

Prediction

- (1) GIOU_Loss
- (2) 加权nms

输入端之一：Mosaic数据增强



优点：

(1) **丰富数据集：**

随机使用4张图片，随机缩放，再随机分布进行拼接，大大丰富了检测数据集，特别是随机缩放增加了很多小目标，让网络的鲁棒性更好。

(2) **减少GPU：**

Mosaic增强训练时，可以直接计算4张图片的数据，使得 Mini-batch大小并不需要很大，一个GPU就可以达到比较好的效果。

输入端之二：自适应锚框计算

yolo5l.yaml

```
6      # anchors
7  anchors:
8      - [10,13, 16,30, 33,23]  # P3/8
9      - [30,61, 62,45, 59,119] # P4/16
10     - [116,90, 156,198, 373,326] # P5/32
```

train.py

```
398     parser.add_argument('--noautoanchor', action='store_true', help='disable autoanchor check')
195
196         # Check anchors
197         if not opt.noautoanchor:
198             check_anchors(dataset, model=model, thr=hyp['anchor_t'], imgsz=imgsz)
```

在Yolov3、Yolov4中，训练不同的数据集时，计算初始锚框的值是通过单独的程序运行的。

但Yolov5中将此功能嵌入到代码中，每次训练时，自适应的计算不同训练集中的最佳锚框值。

控制的代码即train.py中上面一行代码，设置成True，每次训练时，不会自动计算。

输入端之二：自适应锚框计算

generate.py/check_anchors

```
83     def check_anchors(dataset, model, thr=4.0, imgsz=640):|
84         # Check anchor fit to data, recompute if necessary
85         print('\nAnalyzing anchors... ', end=' ')
86
87         def metric(k): # compute metric
88             r = wh[:, None] / k[None]
89             x = torch.min(r, 1. / r).min(2)[0] # ratio metric
90             best = x.max(1)[0] # best_x
91             aat = (x > 1. / thr).float().sum(1).mean() # anchors above threshold
92             bpr = (best > 1. / thr).float().mean() # best possible recall
93
94             return bpr, aat
95
96
97         bpr, aat = metric(m.anchor_grid.clone().cpu().view(-1, 2))
98         print('anchors/target = %.2f, Best Possible Recall (BPR) = %.4f' % (aat, bpr), end=' ')
99
100        if bpr < 0.98: # threshold to recompute
101            print('. Attempting to generate improved anchors, please wait...' % bpr)
102            na = m.anchor_grid.numel() // 2 # number of anchors
103            new_anchors = kmean_anchors(dataset, n=na, img_size=imgsz, thr=thr, gen=1000, verbose=False)
104            new_bpr = metric(new_anchors.reshape(-1, 2))[0]
105
106            if new_bpr > bpr: # replace anchors
107                new_anchors = torch.tensor(new_anchors, device=m.anchors.device).type_as(m.anchors)
108                m.anchor_grid[:] = new_anchors.clone().view_as(m.anchor_grid) # for inference
109                m.anchors[:] = new_anchors.clone().view_as(m.anchors) / m.stride.to(m.anchors.device).view(-1, 1, 1) # loss
110                check_anchor_order(m)
111                print('New anchors saved to model. Update model *.yaml to use these anchors in the future.')
112            else:
113                print('Original anchors better than new anchors. Proceeding with original anchors.')
114
115        print('') # newline
```

输入端之三：自适应图片缩放

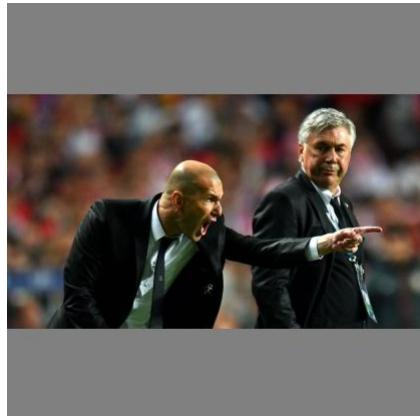
train.py

```
396     parser.add_argument('--rect', action='store_true', help='rectangular training')
```

datasets.py

```
294 class LoadImagesAndLabels(Dataset): # for training/testing  
  
325     self.image_weights = image_weights  
326     self.rect = False if image_weights else rect  
327     self.mosaic = self.augment and not self.rect # load 4 images at a time into a mosaic (only during training)
```

可以看到，Mosaic和Rectangular Training是互相对立的，不能同时实现。



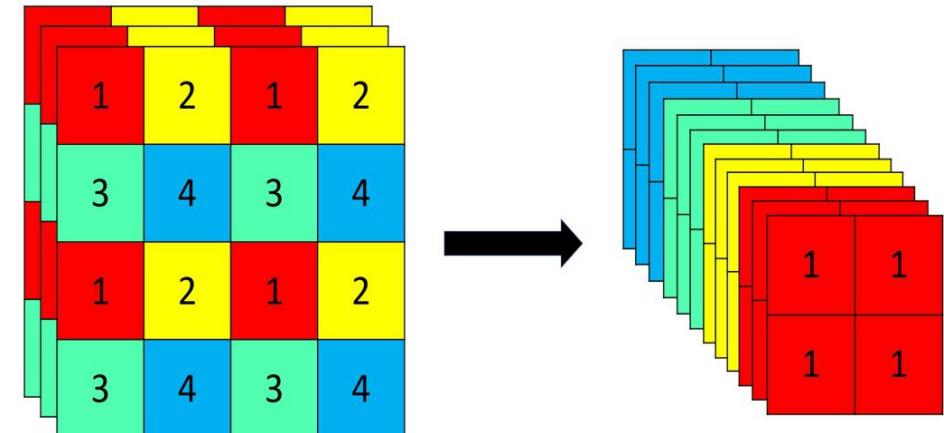
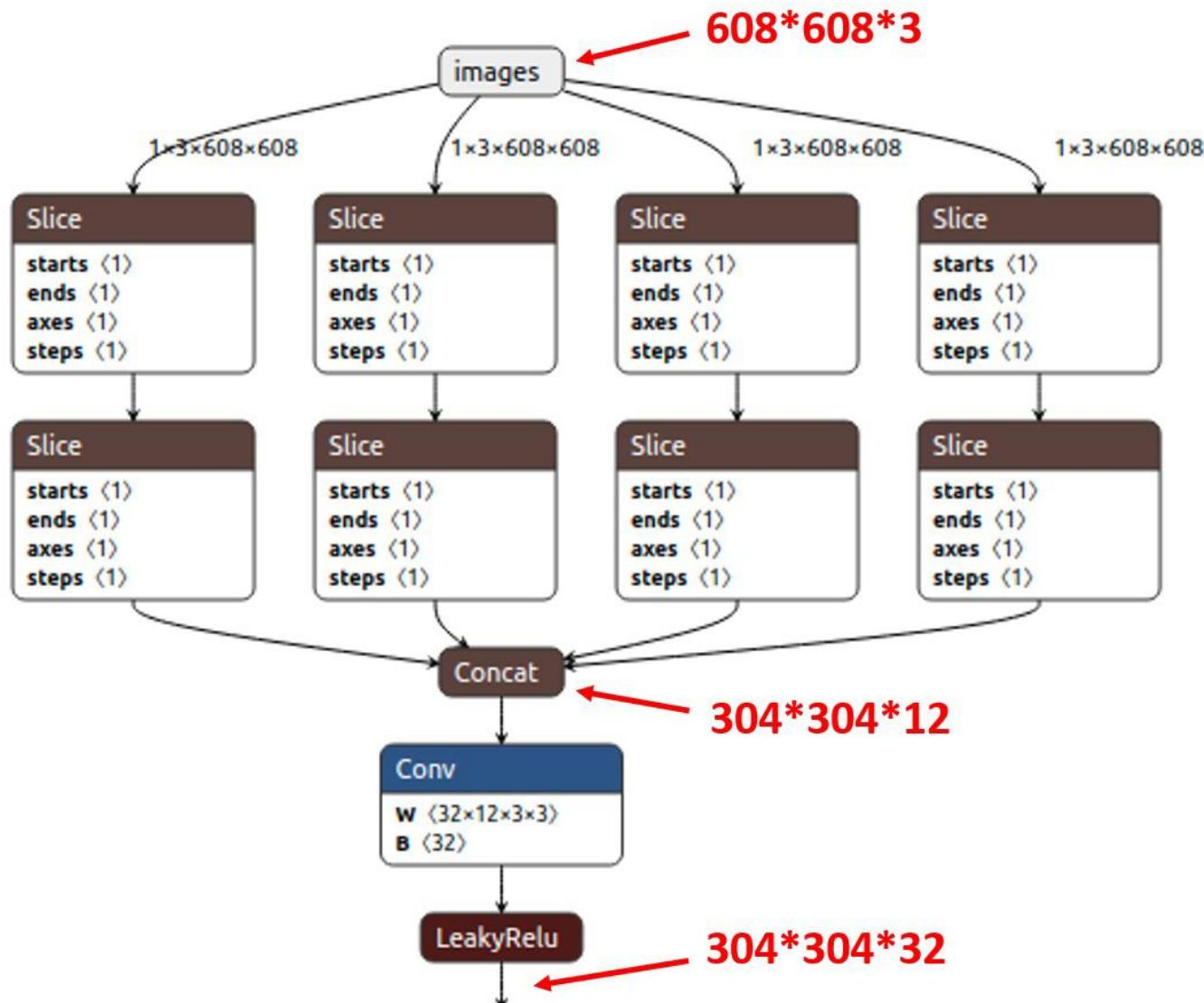
效果：About 1/3 faster on mixed aspect ratio datasets like COCO

输入端之三：自适应图片缩放

datasets.py

```
294     class LoadImagesAndLabels(Dataset): # for training/testing
295
296     def __getitem__(self, index):
297
298         if self.mosaic:
299             # Load mosaic
300
301         else:
302             # Load image
303             img, (h0, w0), (h, w) = load_image(self, index)
304
305             # Letterbox
306
307             shape = self.batch_shapes[self.batch[index]] if self.rect else self.img_size # final letterboxed shape
308             img, ratio, pad = letterbox(img, shape, auto=False, scaleup=self.augment)
309             shapes = (h0, w0), ((h / h0, w / w0), pad) # for COCO mAP rescaling
310
311
312             # Load labels
313             labels = []
314             x = self.labels[index]
315
316             if x.size > 0:
317                 # Normalized xywh to pixel xyxy format
318                 labels = x.copy()
319                 labels[:, 1] = ratio[0] * w * (x[:, 1] - x[:, 3] / 2) + pad[0] # pad width
320                 labels[:, 2] = ratio[1] * h * (x[:, 2] - x[:, 4] / 2) + pad[1] # pad height
321                 labels[:, 3] = ratio[0] * w * (x[:, 1] + x[:, 3] / 2) + pad[0]
322                 labels[:, 4] = ratio[1] * h * (x[:, 2] + x[:, 4] / 2) + pad[1]
```

Backbone之一：Focus结构



切片示意图（ $4 \times 4 \times 3$ 的图像切片后变成
 $2 \times 2 \times 12$ 的特征图）

以Yolov5s的结构为例，原始 $608 \times 608 \times 3$ 的图像输入Focus结构，采用切片操作，先变成 $304 \times 304 \times 12$ 的特征图；再经过一次32个卷积核的卷积操作，最终变成 $304 \times 304 \times 32$ 的特征图。

其最大好处是可以最大程度的减少信息损失而进行下采样操作。

Backbone之一：Focus结构

common.py

```
81 class Focus(nn.Module):
82     # Focus wh information into c-space
83     def __init__(self, c1, c2, k=1, s=1, p=None, g=1, act=True): # ch_in, ch_out, kernel, stride, padding, groups
84         super(Focus, self).__init__()
85         self.conv = Conv(c1 * 4, c2, k, s, p, g, act)
86
87     def forward(self, x): # x(b,c,w,h) -> y(b,4c,w/2,h/2)
88         return self.conv(torch.cat([x[..., ::2, ::2], x[..., 1::2, ::2], x[..., ::2, 1::2], x[..., 1::2, 1::2]], 1))
```

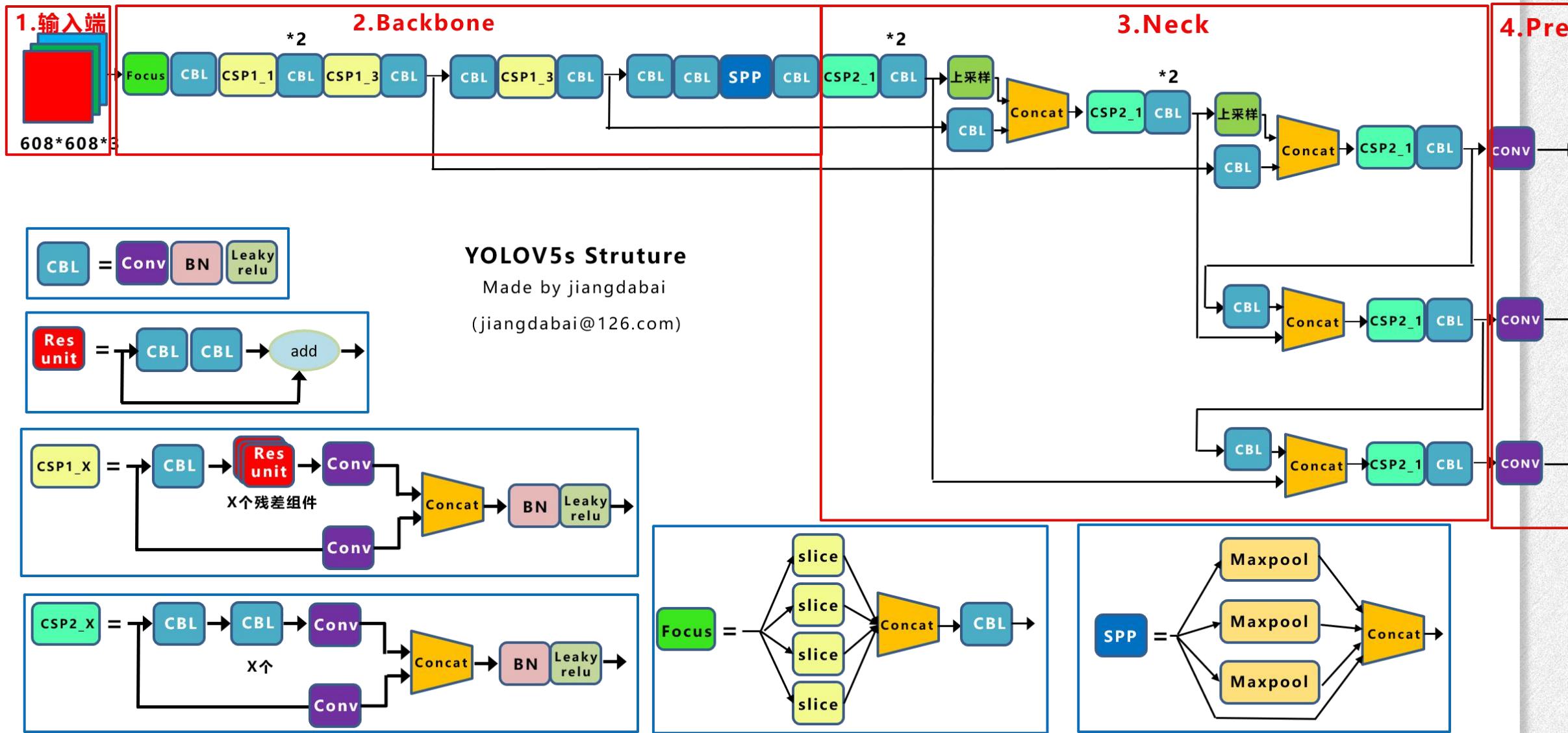
yolo5s.yaml

```
1 # parameters
2 nc: 80 # number of classes
3 depth_multiple: 0.33 # model depth multiple
4 width_multiple: 0.50 # layer channel multiple
12 # YOLOv5 backbone
13 backbone:
14     # [from, number, module, args]
15     [[-1, 1, Focus, [64, 3]], # 0-P1/2
```

train.py输出：

	from	n	params	module	arguments
0	-1	1	3520	models.common.Focus	[3, 32, 3]

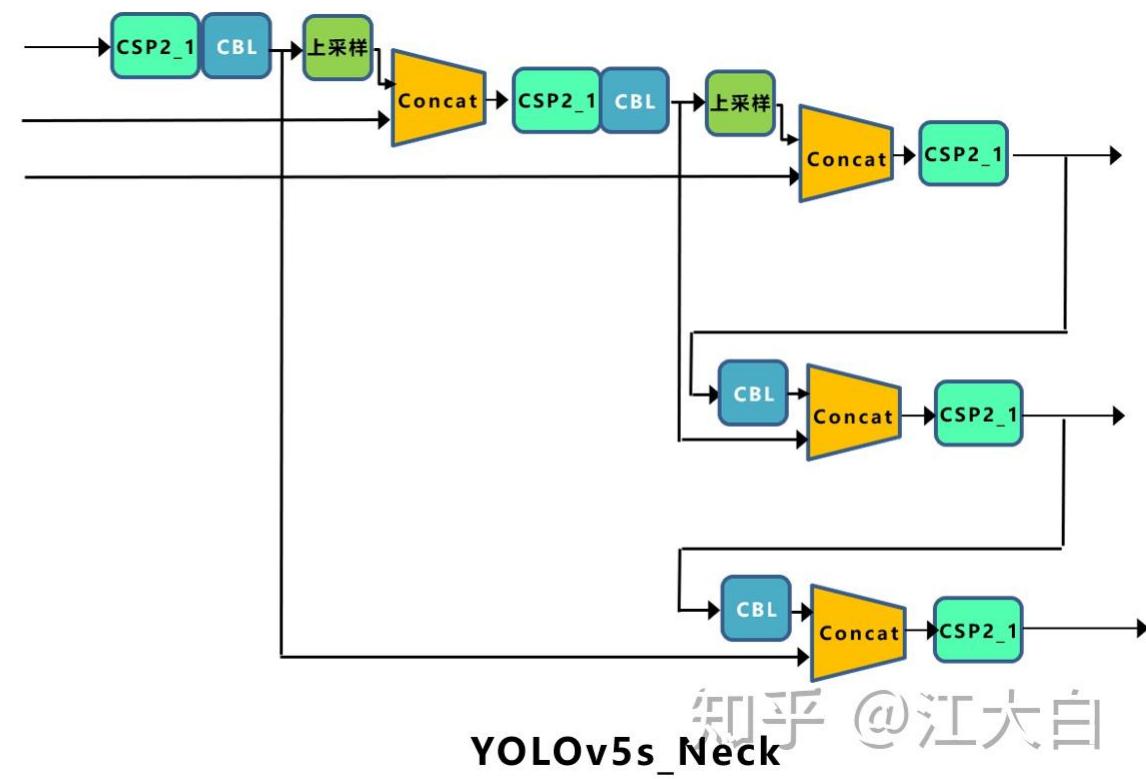
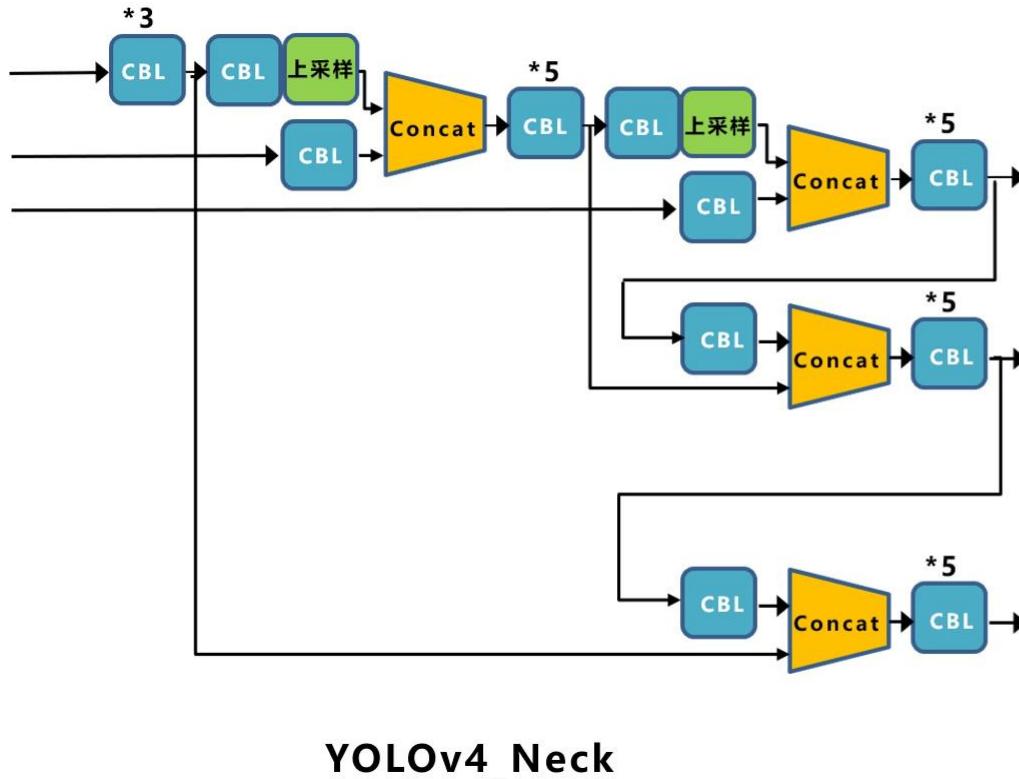
Backbone之二：CSP结构



Neck端：FPN+PAN

参考yolov4

Yolov4的Neck结构中，采用的都是普通的卷积操作。而Yolov5的Neck结构中，采用借鉴CSPnet设计的CSP2结构，加强网络特征融合的能力。



知乎 @江大白

输出端之一：Bounding box损失函数

整体loss: 分类loss (BCE) + conf loss (BCE) + bbox loss (GIoU)

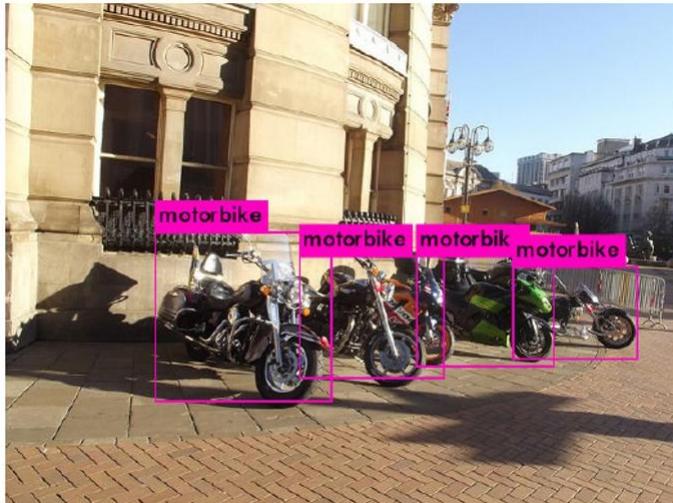
Yolov4: CIoU_Loss

Yolov5: GIoU_Loss

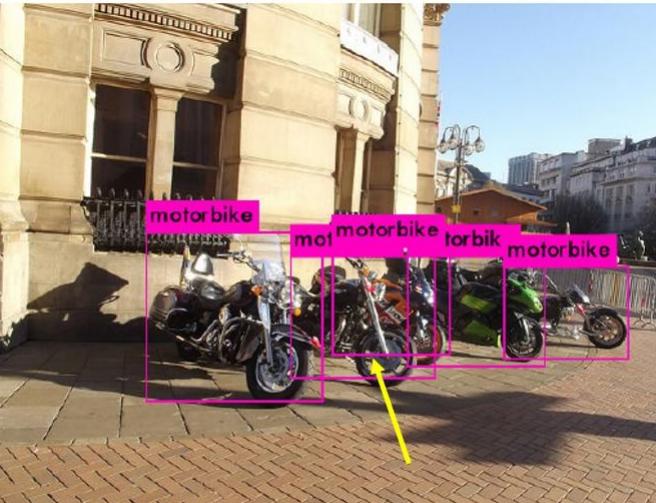
在v4中都有介绍，此处略。

输出端之二：nms非极大值抑制

在目标检测的后处理过程中，针对很多目标框的筛选，通常需要nms操作。



CIOU_Loss+NMS



CIOU_Loss+DIOU_nms

Yolov4: CIOU_Loss + DIOU_nms；在同样的参数情况下，将nms中IOU修改成 DIOU_nms，改进了目标遮挡重叠的问题。

在参数和普通的IOU_nms一致的情况下，修改成 DIOU_nms，可以将两个目标检出。（左图黄色箭头）

为什么不用CIOU_nms？
在测试推理时，没有groundtruth，则不考虑影响因子v，CIOU_nms退化为 DIOU_nms。

Yolov5中采用加权nms的方式。

虽然大多数状态下效果差不多，但在不增加计算成本的情况下，有稍微的改进也是好的。

参考资料

1. 深入浅出Yolo系列之Yolov5核心基础知识完整讲解: <https://zhuanlan.zhihu.com/p/172121380>
2. 如何评价YOLOv5? : <https://www.zhihu.com/question/399884529>
3. Responding to the Controversy about YOLOv5: <https://blog.roboflow.com/yolov4-versus-yolov5/>
4. 一文读懂YOLO V5 与 YOLO V4: <https://zhuanlan.zhihu.com/p/161083602>
5. About reproduced results #6: <https://github.com/ultralytics/yolov5/issues/6>
6. How to Train YOLOv5 On a Custom Dataset: <https://blog.roboflow.com/how-to-train-yolov5-on-a-custom-dataset/>
7. Train Custom Data: <https://github.com/ultralytics/yolov3/wiki/Train-Custom-Data>
8. 进击的后浪yolov5深度可视化解析: <https://zhuanlan.zhihu.com/p/183838757>
9. PPYOL0: 2020不容错过的目标检测调参Tricks:
<https://mp.weixin.qq.com/s/pH0FqFihkkrVTYbkSTIG4w>
10. YOL0系列: YOL0v1, YOL0v2, YOL0v3, YOL0v4, YOL0v5简介: <https://zhuanlan.zhihu.com/p/136382095>
11. 深入浅出Yolo系列之Yolov3&Yolov4&Yolov5核心基础知识完整讲解:
<https://zhuanlan.zhihu.com/p/143747206>

提问时间

QUESTION TIME