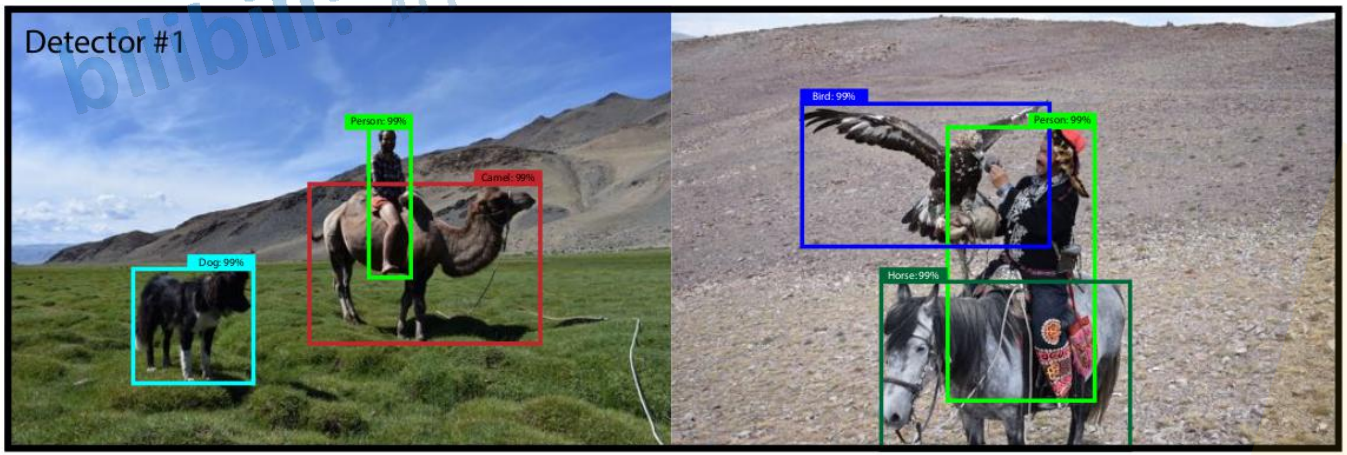
YOLO v3

YOLOv3: An Incremental Improvement

做大做强，再创辉煌

Joseph Redmon Ali Farhadi
University of Washington

2018 CVPR



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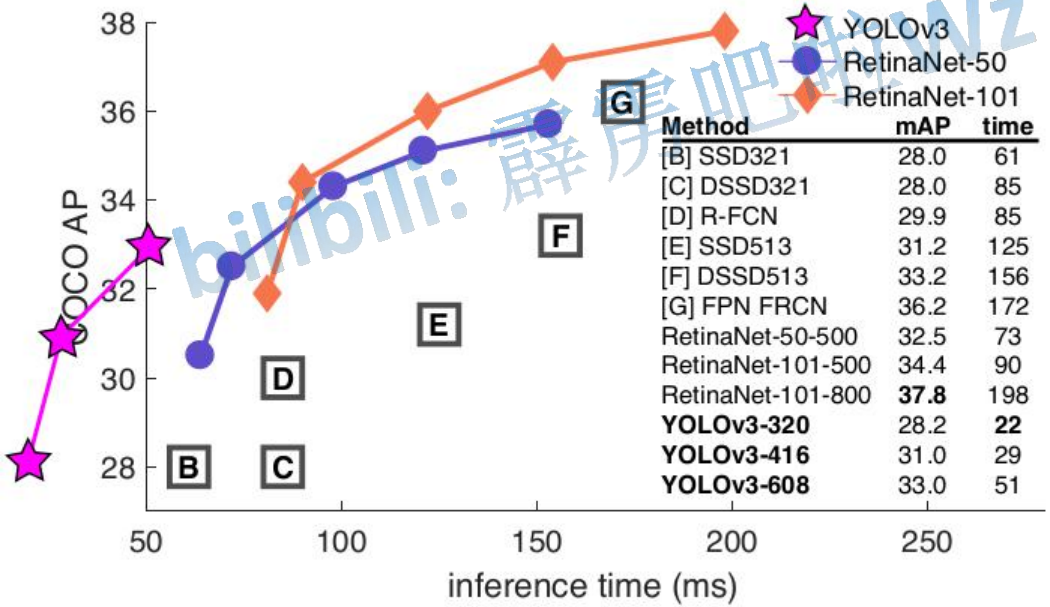
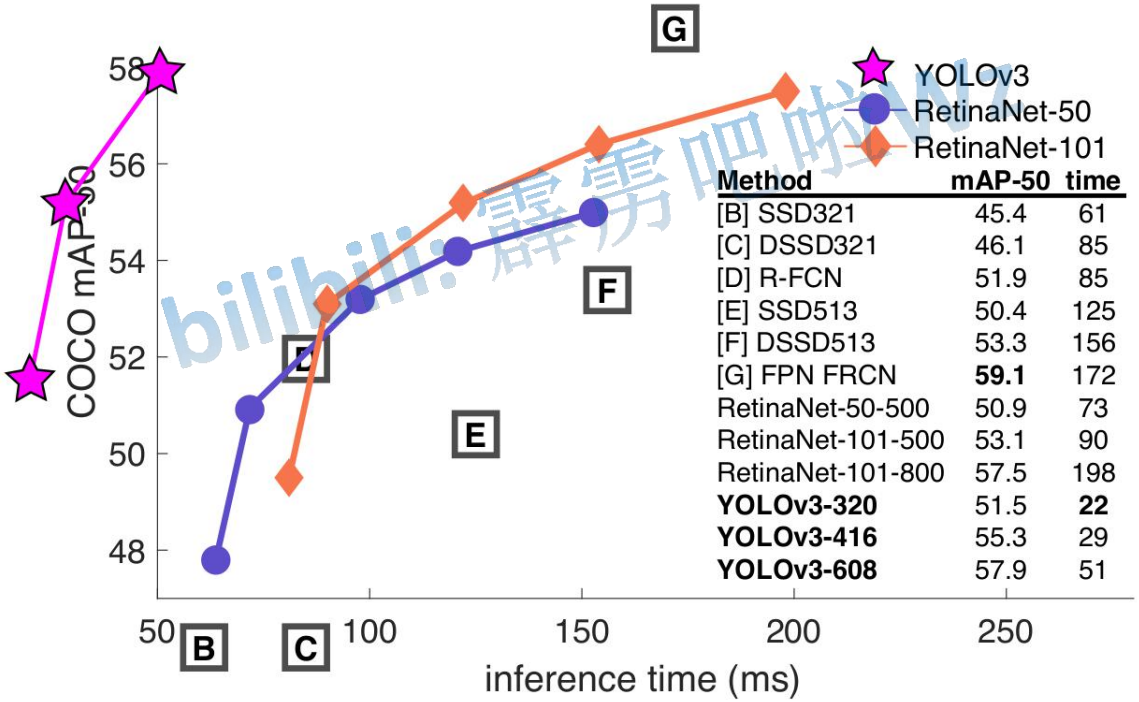


Method	mAP	time
[B] SSD321	28.0	61
[C] DSSD321	28.0	85
[D] R-FCN	29.9	85
[E] SSD513	31.2	125
[F] DSSD513	33.2	156
[G] FPN FRCN	36.2	172
RetinaNet-50-500	32.5	73
RetinaNet-101-500	34.4	90
RetinaNet-101-800	**37.8**	198
YOLOv3-320	28.2	**22**
YOLOv3-416	31.0	29
YOLOv3-608	33.0	51

COCO AP

YOLO v3



Method	mAP-50	time
[B] SSD321	45.4	61
[C] DSSD321	46.1	85
[D] R-FCN	51.9	85
[E] SSD513	50.4	125
[F] DSSD513	53.3	156
[G] FPN FRCN	**59.1**	172
RetinaNet-50-500	50.9	73
RetinaNet-101-500	53.1	90
RetinaNet-101-800	57.5	198
YOLOv3-320	51.5	**22**
YOLOv3-416	55.3	29
YOLOv3-608	57.9	51

COCO AP IOU=0.5

YOLO v3

Darknet-53

	Type	Filters	Size	Output
	Convolutional	32	3 × 3	256 × 256
	Convolutional	64	3 × 3 / 2	128 × 128
1×	Convolutional	32	1 × 1	
	Convolutional	64	3 × 3	
	Residual			128 × 128
	Convolutional	128	3 × 3 / 2	64 × 64
2×	Convolutional	64	1 × 1	
	Convolutional	128	3 × 3	
	Residual			64 × 64
	Convolutional	256	3 × 3 / 2	32 × 32
8×	Convolutional	128	1 × 1	
	Convolutional	256	3 × 3	
	Residual			32 × 32
	Convolutional	512	3 × 3 / 2	16 × 16
8×	Convolutional	256	1 × 1	
	Convolutional	512	3 × 3	
	Residual			16 × 16
	Convolutional	1024	3 × 3 / 2	8 × 8
4×	Convolutional	512	1 × 1	
	Convolutional	1024	3 × 3	
	Residual			8 × 8
	Avgpool		Global	
	Connected		1000	
	Softmax			

Table 1. **Darknet-53.**

Backbone	Top-1	Top-5	Bn Ops	BFLOP/s	FPS
Darknet-19 [15]	74.1	91.8	7.29	1246	**171**
ResNet-101[5]	77.1	93.7	19.7	1039	53
ResNet-152 [5]	**77.6**	**93.8**	29.4	1090	37
Darknet-53	77.2	**93.8**	18.7	**1457**	78

Table 2. **Comparison of backbones.** Accuracy, billions of operations, billion floating point operations per second, and FPS for various networks.

2+
(1x2)+1+
(2x2)+1+
(8x2)+1+
(8x2)+1+
(4x2)+1=53

https://blog.csdn.net/qq_37541097/article/details/81214953

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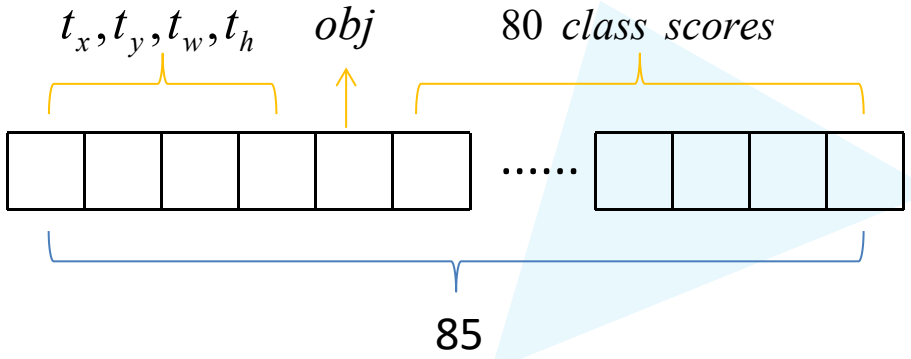
YOLO V3 model structure

Next we take the feature map from 2 layers previous and upsample it by 2×. We also take a feature map from earlier in the network and merge it with our upsampled features using concatenation. This method allows us to get more meaningful semantic information from the upsampled features and finer-grained information from the earlier feature map. We then add a few more convolutional layers to process this combined feature map, and eventually predict a similar tensor, although now twice the size.

We perform the same design one more time to predict boxes for the final scale. Thus our predictions for the 3rd scale benefit from all the prior computation as well as fine-grained features from early on in the network.

We still use k-means clustering to determine our bounding box priors. We just sort of chose 9 clusters and 3 scales arbitrarily and then divide up the clusters evenly across scales. On the COCO dataset the 9 clusters were: $(10 \times 13), (16 \times 30), (33 \times 23), (30 \times 61), (62 \times 45), (59 \times 119), (116 \times 90), (156 \times 198), (373 \times 326)$.

YOLOv3 predicts boxes at 3 different scales. Our system extracts features from those scales using a similar concept to feature pyramid networks [8]. From our base feature extractor we add several convolutional layers. The last of these predicts a 3-d tensor encoding bounding box, objectness, and class predictions. In our experiments with COCO [10] we predict 3 boxes at each scale so the tensor is $N \times N \times [3 * (4 + 1 + 80)]$ for the 4 bounding box offsets, 1 objectness prediction, and 80 class predictions.



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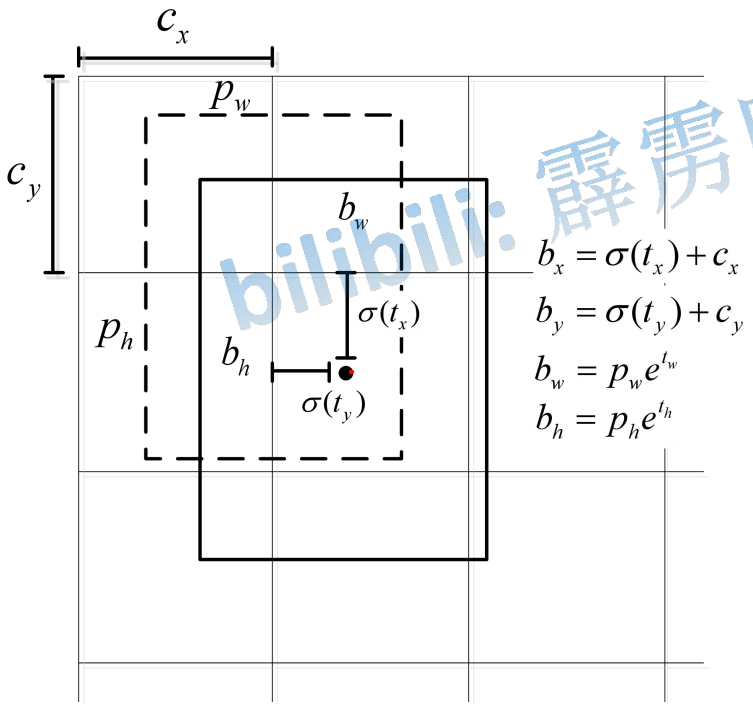
目标边界框的预测



Following YOLO9000 our system predicts bounding boxes using dimension clusters as anchor boxes [15]. The network predicts 4 coordinates for each bounding box, t_x, t_y, t_w, t_h. If the cell is offset from the top left corner of the image by (c_x, c_y) and the bounding box prior has width and height p_w, p_h, then the predictions correspond to:

$$
\begin{aligned}
b_x &= \sigma(t_x) + c_x \\
b_y &= \sigma(t_y) + c_y \\
b_w &= p_w e^{t_w} \\
b_h &= p_h e^{t_h}
\end{aligned}
$$

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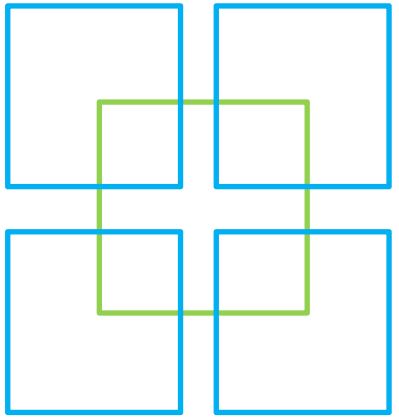
正负样本的匹配

YOLOv3 predicts an objectness score for each bounding box using logistic regression. This should be 1 if the bounding box prior overlaps a ground truth object by more than any other bounding box prior. If the bounding box prior is not the best but does overlap a ground truth object by more than some threshold we ignore the prediction, following [17]. We use the threshold of .5. Unlike [17] our system only assigns one bounding box prior for each ground truth object. If a bounding box prior is not assigned to a ground truth object it incurs no loss for coordinate or class predictions, only objectness.



YOLO v3

损失的计算

置信度损失　　分类损失　　定位损失

$$L(o,c,O,C,l,g)=\lambda_1 L_{conf}(o,c)+\lambda_2 L_{cla}(O,C)+\lambda_3 L_{loc}(l,g)$$

$\lambda_1,\lambda_2,\lambda_3$为平衡系数

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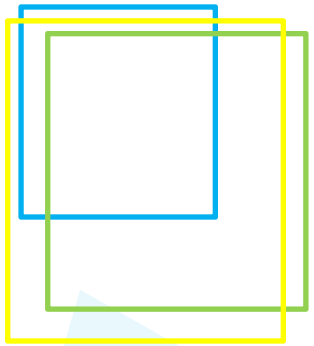
置信度损失

Binary Cross Entropy

$$L_{conf}(o,c) = -\frac{\sum_i (o_i \ln(\hat{c}_i) + (1-o_i)\ln(1-\hat{c}_i))}{N}$$

$$\hat{c}_i = Sigmoid(c_i)$$

可能和原文有出入



其中$o_i \in [0,1]$,表示预测目标边界框与真实目标边界框的IOU,

c为预测值,$\hat{c}_i$为c通过$Sigmoid$函数得到的预测置信度,

N为正负样本个数

YOLOv3 predicts an objectness score for each bounding box using logistic regression. This should be 1 if the bounding box prior overlaps a ground truth object by more than any other bounding box prior. If the bounding box prior

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类别损失

Binary Cross Entropy

$$L_{cla}(O,C) = -\frac{\sum_{i \in pos} \sum_{j \in cla} (O_{ij} \ln(\hat{C}_{ij}) + (1 - O_{ij}) \ln(1 - \hat{C}_{ij}))}{N_{pos}}$$

$$\hat{C}_{ij} = Sigmoid(C_{ij})$$

其中$O_{ij} \in \{0, 1\}$,表示预测目标边界框i中是否存在第j类目标，

C_{ij}为预测值,$\hat{C}_{ij}$为C_{ij}通过$Sigmoid$函数得到的目标概率

N_{pos}为正样本个数

Each box predicts the classes the bounding box may contain using multilabel classification. We do not use a softmax as we have found it is unnecessary for good performance, instead we simply use independent logistic classifiers. During training we use binary cross-entropy loss for the class predictions.

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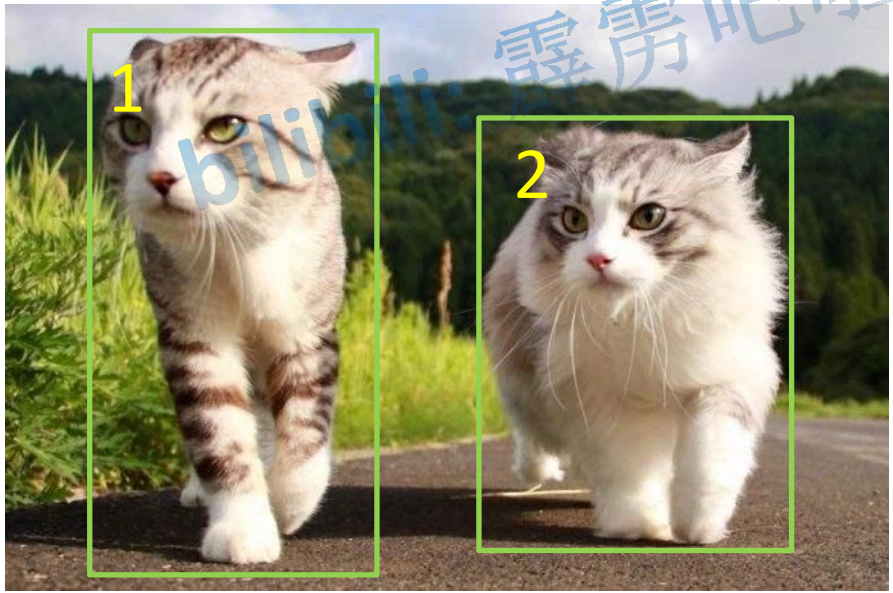
类别损失

[老虎，豹子，猫]



真实标签：
目标1：[0., 0., 1.]
目标2：[0., 0., 1.]

预测概率：
目标1：[0.1, 0.8, 0.9]
目标2：[0.2, 0.7, 0.8]

经过Sigmoid处理

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定位损失

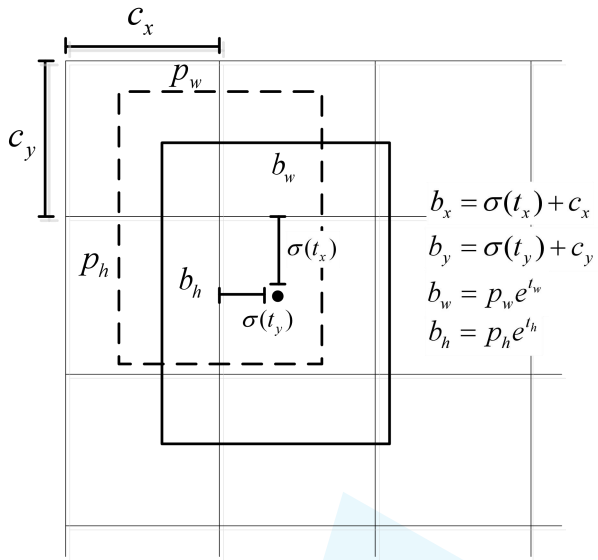
$$L_{loc}(l,g)=\frac{\sum_{i\in pos}\sum_{m\in\{x,y,w,h\}}(\hat{l}_i^m-\hat{g}_i^m)^2}{N_{pos}}$$

$$\hat{l}_i^x=Sigmoid(t_x),\quad \hat{l}_i^y=Sigmoid(t_y)$$

$$\hat{l}_i^w=t_w,\quad \hat{l}_i^h=t_h$$

$$\hat{g}_i^x=g_i^x-c_i^x,\quad \hat{g}_i^y=g_i^y-c_i^y$$

$$\hat{g}_i^w=\ln(g_i^w/p_i^w),\quad \hat{g}_i^h=\ln(g_i^h/p_i^h)$$



During training we use sum of squared error loss. If the ground truth for some coordinate prediction is $\hat{t}_*$ our gradient is the ground truth value (computed from the ground truth box) minus our prediction: $\hat{t}_*-t_*$. This ground truth value can be easily computed by inverting the equations above.

沟通方式

1.bilibili

https://space.bilibili.com/18161609/channel/index

2.CSDN

https://blog.csdn.net/qq_37541097/article/details/103482003

3.github

https://github.com/WZMIAOMIAO/deep-learning-for-image-processing

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