

Faster-RCNN论文阅读

前言

fast_rcnn还有一个缺点就是它的roi的提取还是采用的ss方法,需要在网络外独立提取,而Faster-RCNN提出了A Region Proposal Network (RPN) 解决region提取.

region proposal (SS)		region proposal (SS)		region proposal	
feature extraction (Deep Net)		feature extraction		feature extraction	
classification (SVM)	rect refine (regression)	classification + rect refine (Deep Net)		classification + rect refine (Deep Net)	
RCNN		fast RCNN		faster RCNN	

1.Region Proposal Network (RPN)原理

RPN网络用于生成region proposals。该层通过softmax判断anchors属于foreground或者background，再利用bounding box regression修正anchors获得精确的proposals。
网络的整体架构就是在fast的基础上在conv和ROI pooling层之间加了一条Region Proposal Network (RPN)支路.

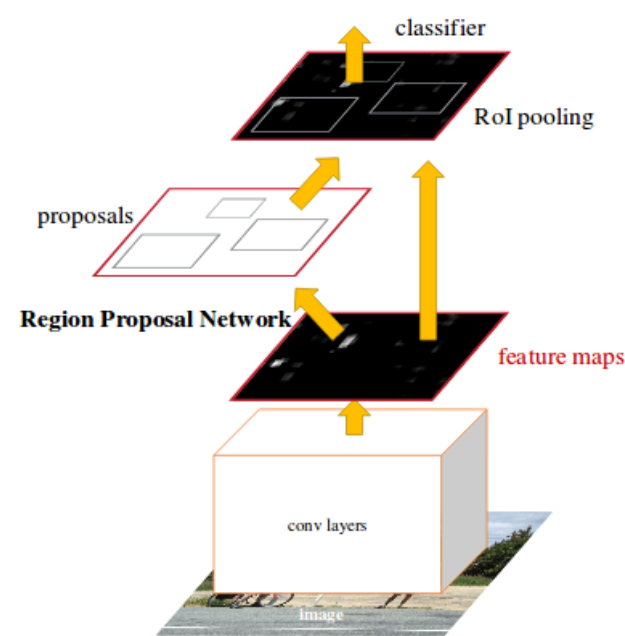


Figure 2: Faster R-CNN is a single, unified network for object detection. The RPN module serves as the 'attention' of this unified network.

rpn实际上也是一种fully convolutional network.

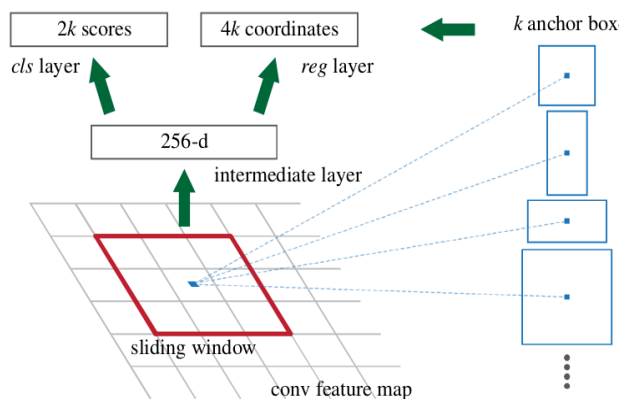
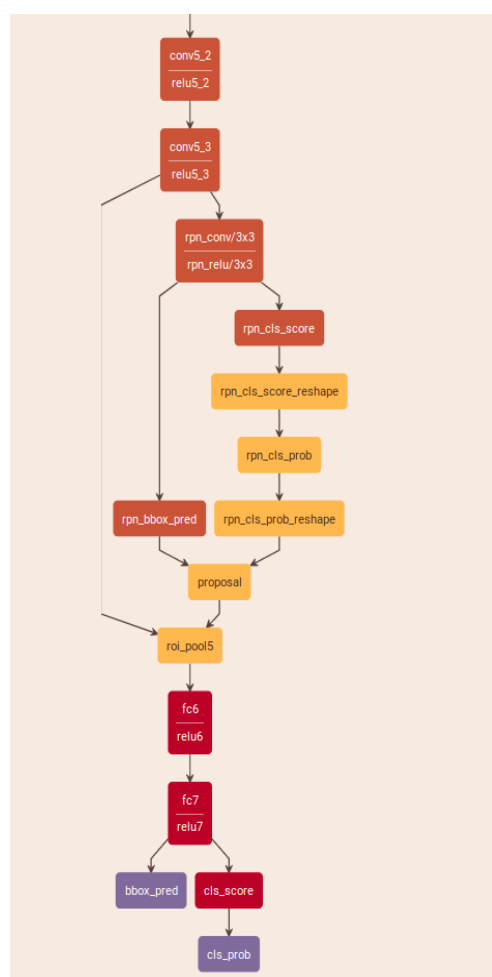


Figure 3: **Left:** Region Proposal Network (RPN). **Right:** E

强烈吐槽paper中的rpn结构图,上图云里雾里描述anchor和3*3卷积核.

直接看[py_faster_rcnn/model/pascal_voc/vgg16/faster_rcnn_alt_opt]网络,

下图是我截取rpn和后续的fc.输入的conv5_3就是vgg16 conv层的feature map.这里的map就是RPN和ROIpooling共享的.



上图中中间的三条支路的右边两条就是rpn网络.

1.1 rpn_conv层

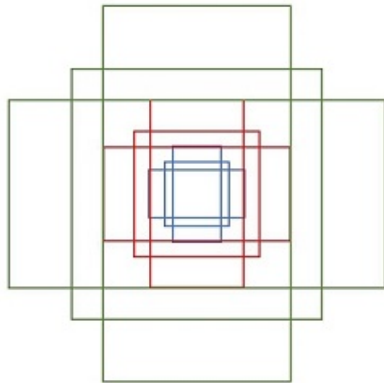
这一层是作者加上去的,采用的3*3的卷积核,固定输出512维的feature map.为了增加感受野,降维和鲁棒性.

```
layer {
  name: "conv5_3"
  type: "Convolution"
  bottom: "conv5_2"
  top: "conv5_3"
  convolution_param {
    num_output: 512
    pad: 1 kernel_size: 3
  }
}
```

```
}
}
```

1.2 rpn_bbox_pred层

这一层输出中map中的点对应anchor,anchor就是一些不同size和长宽比例的窗口,paper中用了三种size和三种长宽



(1:1,1:2,2:1),那么就有9种anchor如图:

```
layer {
  name: "rpn_bbox_pred"
  type: "Convolution"
  bottom: "rpn/output"
  top: "rpn_bbox_pred"
  convolution_param {
    num_output: 36 # 4 * 9(anchors)
    kernel_size: 1 pad: 0 stride: 1
  }
}
```

rpn_bbox_pred的输出是36维的,每个对应点的是9个anchor的[x,y,w,h], $4*9=36$,刚好是对应36维的向量.[x,y,w,h]分别是对应anchor的左上角坐标,和长宽.这一层就是学习9个anchor,定位比较粗糙,但是后面的fc层有Bbox回归,所以只需要大概在哪里就可以..mapx中每个点都有9个anchor似乎会很多anchor,其实有些边缘点的anchor大小已经超出了图像的大小的,是会被舍弃的.后面也不会把所有的anchor送入分类.会选取一部分的.

1.3rpn_cls层

分类支路是判断每个anchor是前景还是背景.

做了1x1卷积,num_output=18,对应9个anchors,每个anchors又有可能是foreground和background.

卷积完成后来了一个reshape layer,之后softmax分类,然后有reshape layer

reshape layer其实只是为了便于softmax分类,至于具体原因这就要从caffe的实现形式说起了.在caffe基本数据结构blob中以如下形式保存数据:

blob=[batch_size, channel, height, width]

对应至上面的保存bg/fg anchors的矩阵,其在caffe blob中的存储形式为[1, 2*9, H, W]。而在softmax分类时需要进行fg/bg二分类,所以reshape layer会将其变为[1, 2, 9*H, W]大小,即单独“腾空”出来一个维度以便softmax分类,之后再reshape回复原状。

1.4Proposal layer

Proposal Layer负责综合所有[dx(A), dy(A), dw(A), dh(A)]变换量和foreground anchors,计算出精准的proposal,送入后续RoI Pooling Layer

```
layer {
  name: 'proposal'
  type: 'Python'
  bottom: 'rpn_cls_prob_reshape'
  bottom: 'rpn_bbox_pred'
  bottom: 'im_info'
  top: 'rois'
  python_param {
    module: 'rpn.proposal_layer'
    layer: 'ProposalLayer'
    param_str: "'feat_stride': 16"
  }
}
```

```
}
```

1.5 loss 函数

$$L(\{p_i, t_i\}) = \frac{1}{N_{cls}} \sum_i L_{cls}(p_i, p_i^*) + \frac{1}{N_{reg}} \sum_i P_i^* L_{reg}(t_i, t_i^*)$$

Here, i is the index of an anchor in a mini-batch and p_i is the predicted probability of anchor i being an object. The ground-truth label p_i^* is 1 if the anchor is positive, and is 0 if the anchor is negative. t_i is a vector representing the 4 parameterized coordinates of the predicted bounding box, and t_i^* is that of the ground-truth box associated with a positive anchor. The classification loss L_{cls} is log loss over two classes (object vs. not object). For the regression loss, we use $L_{reg}(t_i, t_i^*) = R(t_i - t_i^*)$ where R is the robust loss function (smooth L1) defined in [2]. The term $p_i^* L_{reg}$ means the regression loss is activated only for positive anchors ($p_i^* = 1$) and is disabled otherwise ($p_i^* = 0$). The outputs of the cls and reg layers consist of $\{p_i\}$ and $\{t_i\}$ respectively.

2 后续fc层

后面的fc层就是fast_rcnn中的bbox回归和softmax分类。

3 训练

Faster CNN的训练，是在已经训练好的model（如VGG_CNN_M_1024，VGG，ZF）的基础上继续进行训练。实际中训练过程分为6个步骤：

- 在已经训练好的model上，训练RPN网络，对应stage1_rpn_train.pt
 - 利用步骤1中训练好的RPN网络，收集proposals，对应rpn_test.pt
 - 第一次训练Fast RCNN网络，对应stage1_fast_rcnn_train.pt
 - 第二次训练RPN网络，对应stage2_rpn_train.pt
 - 再次利用步骤4中训练好的RPN网络，收集proposals，对应rpn_test.pt
 - 第二次训练Fast RCNN网络，对应stage2_fast_rcnn_train.pt

paper中是训练两遍,再增加次数好像也没有效果。

4 结果

Detection results on PASCAL VOC 2007 test set (trained on VOC 2007 trainval)

train-time region proposals		test-time region proposals		mAP (%)
method	# boxes	method	# proposals	
SS	2000	SS	2000	58.7
EB	2000	EB	2000	58.6
RPN+ZF, shared	2000	RPN+ZF, shared	300	59.9
<i>ablation experiments follow below</i>				
RPN+ZF, unshared	2000	RPN+ZF, unshared	300	58.7
SS	2000	RPN+ZF	100	55.1
SS	2000	RPN+ZF	300	56.8
SS	2000	RPN+ZF	1000	56.3
SS	2000	RPN+ZF (no NMS)	6000	55.2
SS	2000	RPN+ZF (no cls)	100	44.6
SS	2000	RPN+ZF (no cls)	300	51.4
SS	2000	RPN+ZF (no cls)	1000	55.8
SS	2000	RPN+ZF (no reg)	300	52.1
SS	2000	RPN+ZF (no reg)	1000	51.3
SS	2000	RPN+VGG	300	59.2

对比

Table 6: Results on PASCAL VOC 2007 test set with Fast R-CNN detectors and VGG-16. For RPN, the train-time proposals for Fast R-CNN are 2000. RPN* denotes the unsharing feature version.

method	# box	data	mAP	areo	bike	bird	boat	bottle	bus	car	cat	chair	cow	table	dog	horse	mbike	person	plant	sheep	sofa	train	tv
SS	2000	07	66.9	74.5	78.3	69.2	53.2	36.6	77.3	78.2	82.0	40.7	72.7	67.9	79.6	79.2	73.0	69.0	30.1	65.4	70.2	75.8	65.8
SS	2000	07+12	70.0	77.0	78.1	69.3	59.4	38.3	81.6	78.6	86.7	42.8	78.8	68.9	84.7	82.0	76.6	69.9	31.8	70.1	74.8	80.4	70.4
RPN*	300	07	68.5	74.1	77.2	67.7	53.9	51.0	75.1	79.2	78.9	50.7	78.0	61.1	79.1	81.9	72.2	75.9	37.2	71.4	62.5	77.4	66.4
RPN	300	07	69.9	70.0	80.6	70.1	57.3	49.9	78.2	80.4	82.0	52.2	75.3	67.2	80.3	79.8	75.0	76.3	39.1	68.3	67.3	81.1	67.6
RPN	300	07+12	73.2	76.5	79.0	70.9	65.5	52.1	83.1	84.7	86.4	52.0	81.9	65.7	84.8	84.6	77.5	76.7	38.8	73.6	73.9	83.0	72.6
RPN	300	COCO+07+12	78.8	84.3	82.0	77.7	68.9	65.7	88.1	88.4	88.9	63.6	86.3	70.8	85.9	87.6	80.1	82.3	53.6	80.4	75.8	86.6	78.9

Table 7: Results on PASCAL VOC 2012 test set with Fast R-CNN detectors and VGG-16. For RPN, the train-time proposals for Fast R-CNN are 2000.

method	# box	data	mAP	areo	bike	bird	boat	bottle	bus	car	cat	chair	cow	table	dog	horse	mbike	person	plant	sheep	sofa	train	tv
SS	2000	12	65.7	80.3	74.7	66.9	46.9	37.7	73.9	68.6	87.7	41.7	71.1	51.1	86.0	77.8	79.8	69.8	32.1	65.5	63.8	76.4	61.7
SS	2000	07++12	68.4	82.3	78.4	70.8	52.3	38.7	77.8	71.6	89.3	44.2	73.0	55.0	87.5	80.5	80.8	72.0	35.1	68.3	65.7	80.4	64.2
RPN	300	12	67.0	82.3	76.4	71.0	48.4	45.2	72.1	72.3	87.3	42.2	73.7	50.0	86.8	78.7	78.4	77.4	34.5	70.1	57.1	77.1	58.9
RPN	300	07++12	70.4	84.9	79.8	74.3	53.9	49.8	77.5	75.9	88.5	45.6	77.1	55.3	86.9	81.7	80.9	79.6	40.1	72.6	60.9	81.2	61.5
RPN	300	COCO+07++12	75.9	87.4	83.6	76.8	62.9	59.6	81.9	82.0	91.3	54.9	82.6	59.0	89.0	85.5	84.7	84.1	52.2	78.9	65.5	85.4	70.2

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参考资料:

1.Faster-RCNN论文.:<https://arxiv.org/abs/1506.01497>

2.Faster-RCNN代码:<https://github.com/rbgirshick/py-faster-rcnn>

2.fasterrcnn详解:<http://blog.csdn.net/zy1034092330/article/details/62044941>