TensorFlow

PYTORCH

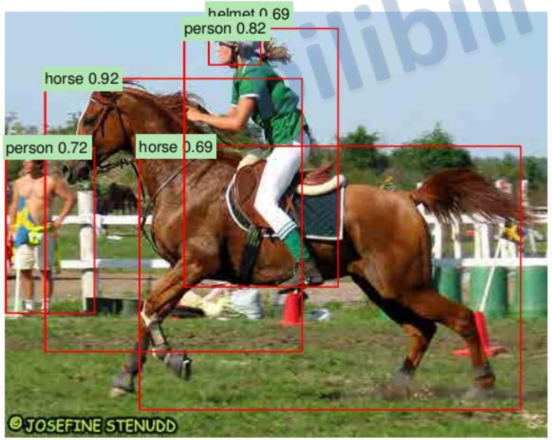
深度学习-目标检测篇

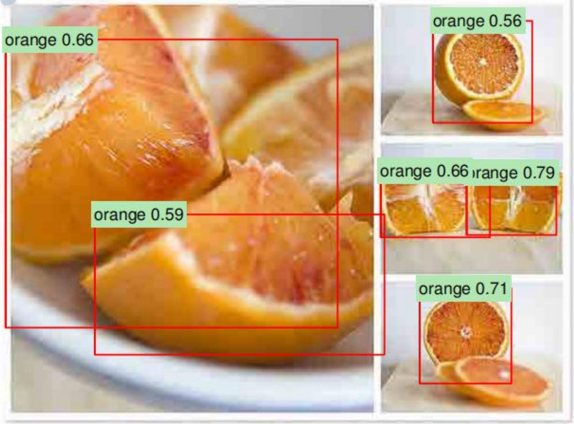
作者：神秘的wz

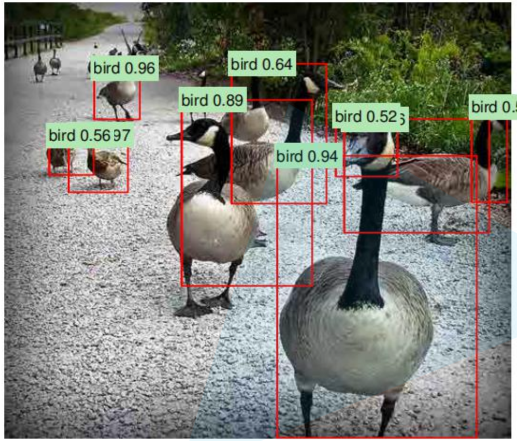
Fast R-CNN

原论文名称
Fast R-CNN

Fast R-CNN是作者Ross Girshick继R-CNN后的又一力作。同样使用VGG16作为网络的backbone，与R-CNN相比训练时间快9倍，测试推理时间快213倍，准确率从62%提升至66%(再Pascal VOC数据集上)。





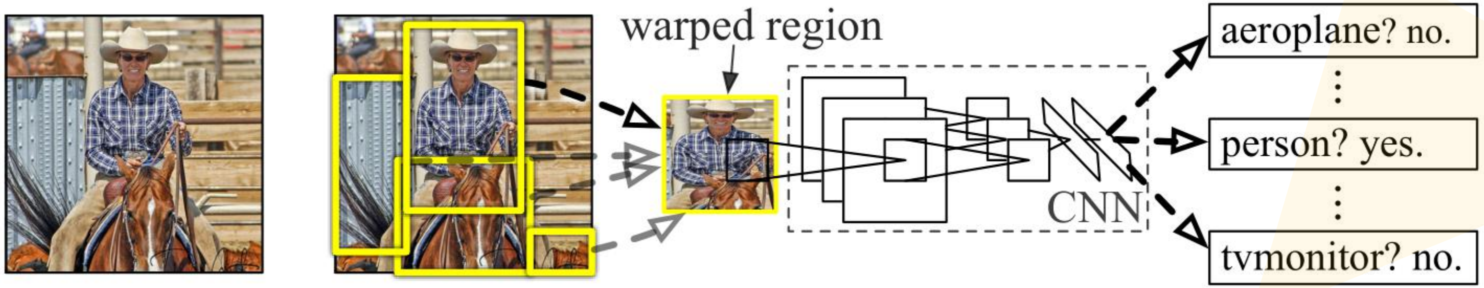


Fast R-CNN

RCNN算法流程可分为4个步骤

- 一张图像生成1K~2K个**候选区域**(使用Selective Search方法)
- 对每个候选区域，使用深度网络**提取特征**
- 特征送入每一类的**SVM 分类器**，判别是否属于该类
- 使用回归器**精细修正**候选框位置

R-CNN: ***Regions with CNN features***



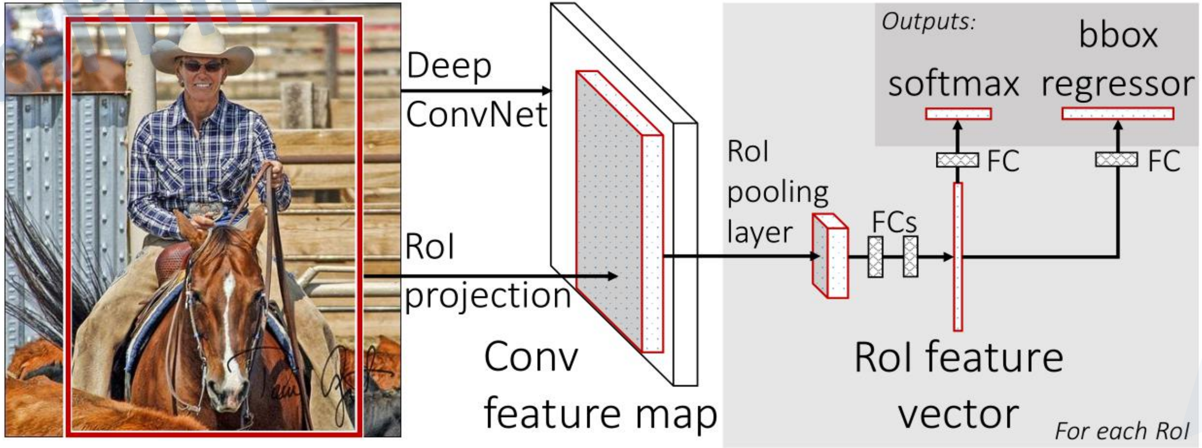
Fast R-CNN

Fast R-CNN算法流程可分为3个步骤

- 一张图像生成1K~2K个**候选区域**(使用Selective Search方法)
- 将图像输入网络得到相应的**特征图**，将SS算法生成的候选框投影到特征图上获得相应的**特征矩阵**
- 将每个特征矩阵通过ROI pooling层缩放到**7x7大小的特征图**，接着将特征图展平通过一系列全连接层得到预测结果

不需要warp

Region of Interest



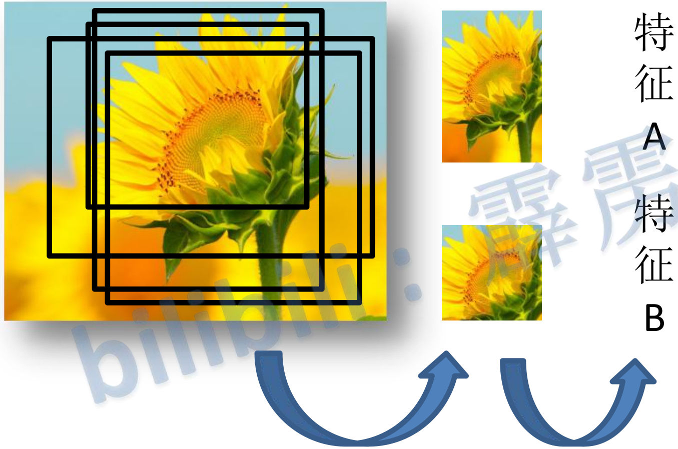
Fast R-CNN

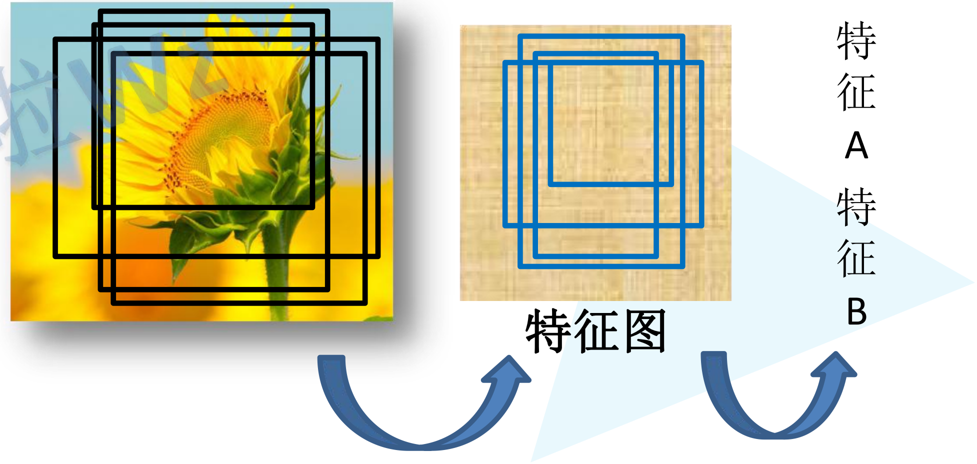
一次性计算整张图像特征

不限制输入图像的尺寸

R-CNN依次将候选框区域输入卷积神经网络得到特征。

Fast-RCNN将整张图像送入网络，紧接着从特征图像上提取相应的候选区域。这些候选区域的特征**不需要再重复计算**。

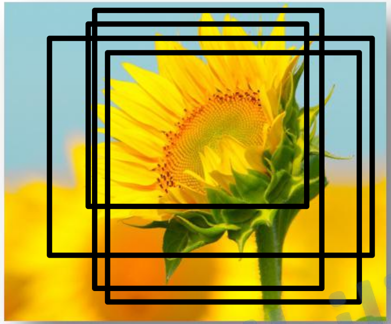


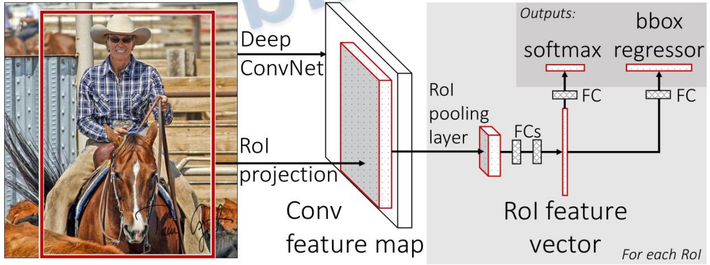


Fast R-CNN

正负样本构造；随机选取64个候选框

训练数据的采样
(正样本，负样本)





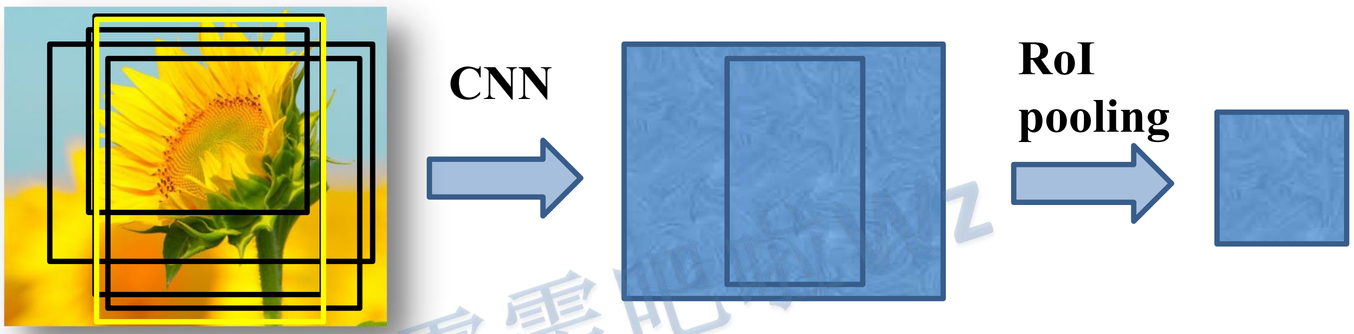
Mini-batch sampling. During fine-tuning, each SGD mini-batch is constructed from $N = 2$ images, chosen uniformly at random (as is common practice, we actually iterate over permutations of the dataset). We use mini-batches of size $R = 128$, sampling 64 RoIs from each image. As in [9], we take 25% of the RoIs from object proposals that have intersection over union (IoU) overlap with a ground-truth bounding box of at least 0.5. These RoIs comprise the examples labeled with a foreground object class, *i.e.* $u \geq 1$. The remaining RoIs are sampled from object proposals that have a maximum IoU with ground truth in the interval $[0.1, 0.5)$, following [11]. These are the background examples and are labeled with $u = 0$. The lower threshold of 0.1 appears to act as a heuristic for hard example mining [8]. During training, images are horizontally flipped with probability 0.5. No other data augmentation is used.

正负样本构造：随机选取64个候选框，与Ground Truth IOU高于0.5的设为正样本，反之设成负样本

Fast R-CNN

RoI Pooling Layer

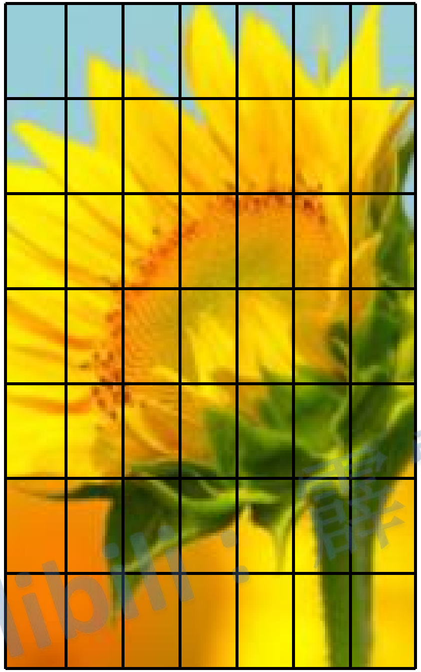
不限制输入
图像的尺寸



Fast R-CNN

RoI Pooling Layer

不限制输入图像的尺寸



0.1	0.1	0.2	0	0.3	0.2	0.3
0.3	0.4	0.5	0.2	0.1	0.1	0
0.4	0.5	0.2	0.1	0.1	0.2	0.1
0.2	0	0.3	0.2	0.3	0.2	0.1
0.2	0.1	0.4	0.5	0.2	0.1	0.1
0.3	0.2	0	0.3	0.2	0.2	0.1
0.3	0.4	0.5	0.2	0.1	0.1	0.1

注意：这里忽略了深度channel

Fast R-CNN

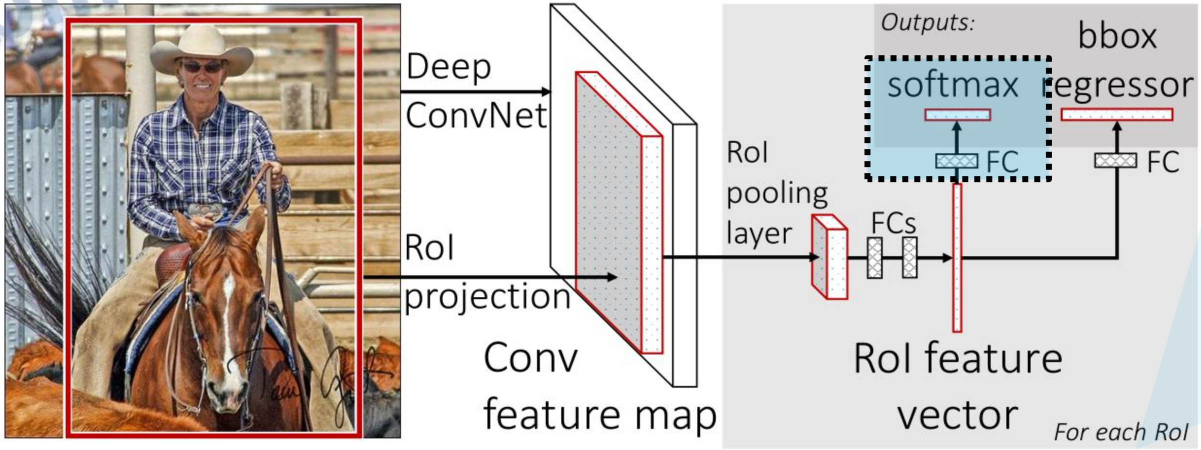
分类器

输出N+1个类别的概率（N为检测目标的种类, 1为背景）共N+1个节点

背景概率

20

0.0	0.1	0.0	0.0	0.3	0.2	0.0	0.1	0.0	0.1	0.0	0.1	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0

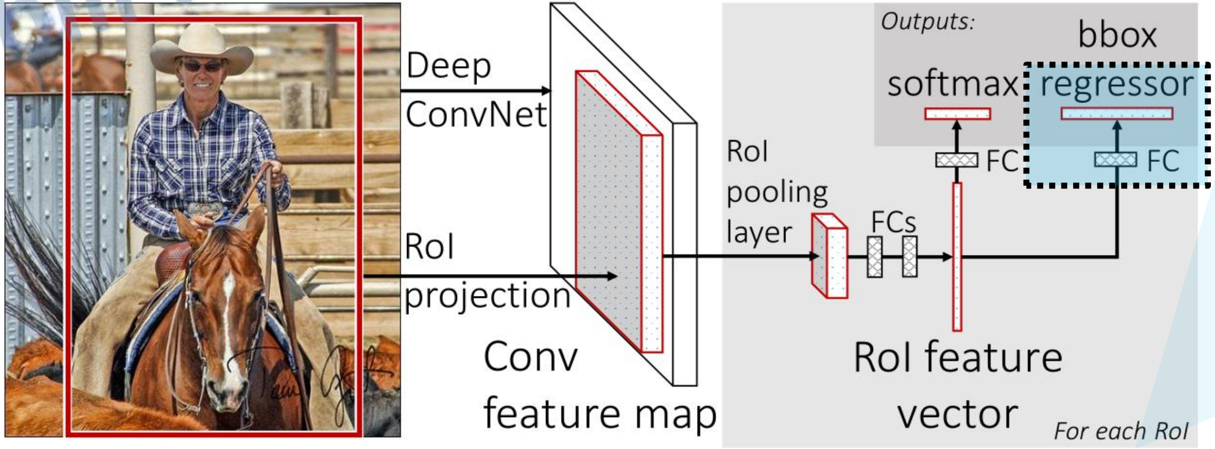


Fast R-CNN

边界框回归器

输出对应N+1个类别的候选边界框回归参数(d_x, d_y, d_w, d_h),共(N+1)x4个节点

d_x^0	d_y^0	d_w^0	d_h^0	d_x^1	d_y^1	d_w^1	d_h^1	……	d_x^{19}	d_y^{19}	d_w^{19}	d_h^{19}	d_x^{20}	d_y^{20}	d_w^{20}	d_h^{20}



Fast R-CNN

边界框回归器

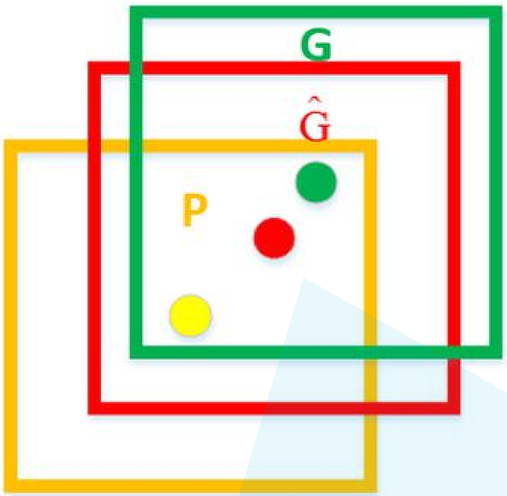
输出对应N+1个类别的候选边界框回归参数(d_x, d_y, d_w, d_h),共(N+1)x4个节点

$$\hat{G}_x = P_w d_x(P) + P_x$$

$$\hat{G}_y = P_h d_y(P) + P_y$$

$$\hat{G}_w = P_w \exp(d_w(P))$$

$$\hat{G}_h = P_h \exp(d_h(P))$$



P_x, P_y, P_w, P_h 分别为候选框的中心x，y坐标，以及宽高

$\hat{G}_x, \hat{G}_y, \hat{G}_w, \hat{G}_h$ 分别为最终预测的边界框中心x，y坐标，以及宽高

Fast R-CNN

Multi-task loss

分类损失　　边界框回归损失

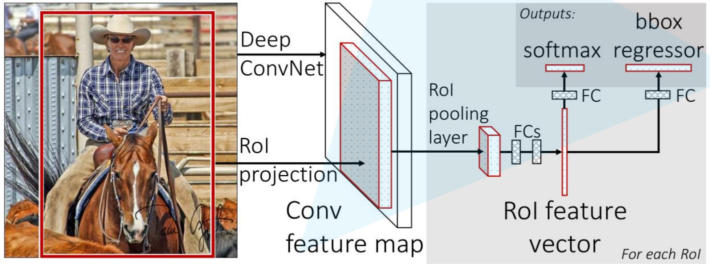
$$L(p,u,t^u,v)=\boxed{L_{cls}(p,u)}+\boxed{\lambda[u\geq 1]L_{loc}(t^u,v)}$$

p是分类器预测的softmax概率分布$p=(p_0,\ldots,p_k)$

u对应目标真实类别标签

t^u对应边界框回归器预测的对应类别u的回归参数$(t_x^u,t_y^u,t_w^u,t_h^u)$

v对应真实目标的边界框回归参数(v_x,v_y,v_w,v_h)



Fast R-CNN

Multi-task loss

分类损失

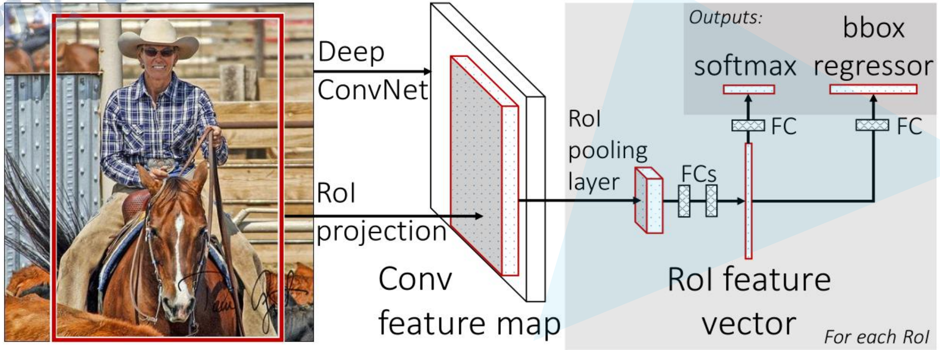
$$L(p,u,t^u,v) = \boxed{L_{cls}(p,u)} + \lambda[u \geq 1]L_{loc}(t^u,v)$$

p是分类器预测的softmax概率分布$p=(p_0,\ldots,p_k)$

u对应目标真实类别标签

分类损失

$$L_{cls}(p,u) = -\log p_u$$



误差的计算

Cross Entropy Loss 交叉熵损失

1. 针对多分类问题（softmax输出，所有输出概率和为1）

$$H = -\sum_i o_i^* \log(o_i)$$

2. 针对二分类问题（sigmoid输出，每个输出节点之间互不相干）

$$H = -\frac{1}{N}\sum_{i=1}^{N}[o_i^* \log o_i + (1-o_i^*)\log(1-o_i)]$$

其中o_i^*为真实标签值，o_i为预测值，默认log以e为底等于ln

Fast R-CNN

Multi-task loss

边界框回归损失

$$L(p,u,t^u,v) = L_{cls}(p,u) + \boxed{\lambda[u \geq 1]L_{loc}(t^u,v)}$$

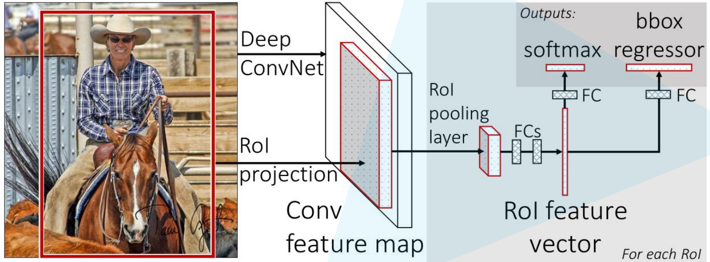
$[u \geq 1]$是艾弗森括号

t^u对应边界框回归器预测的对应类别u的回归参数$(t_x^u, t_y^u, t_w^u, t_h^u)$

v对应真实目标的边界框回归参数(v_x, v_y, v_w, v_h)

$$L_{loc}(t^u,v) = \sum_{i \in \{x,y,w,h\}} smooth_{L_1}(t_i^u - v_i)$$

$$smooth_{L_1}(x) = \begin{cases} 0.5x^2 & \text{if } |x| < 1 \\ |x| - 0.5 & \text{otherwise} \end{cases}$$



https://www.cnblogs.com/wangguchangqing/p/12021638.html

Fast R-CNN

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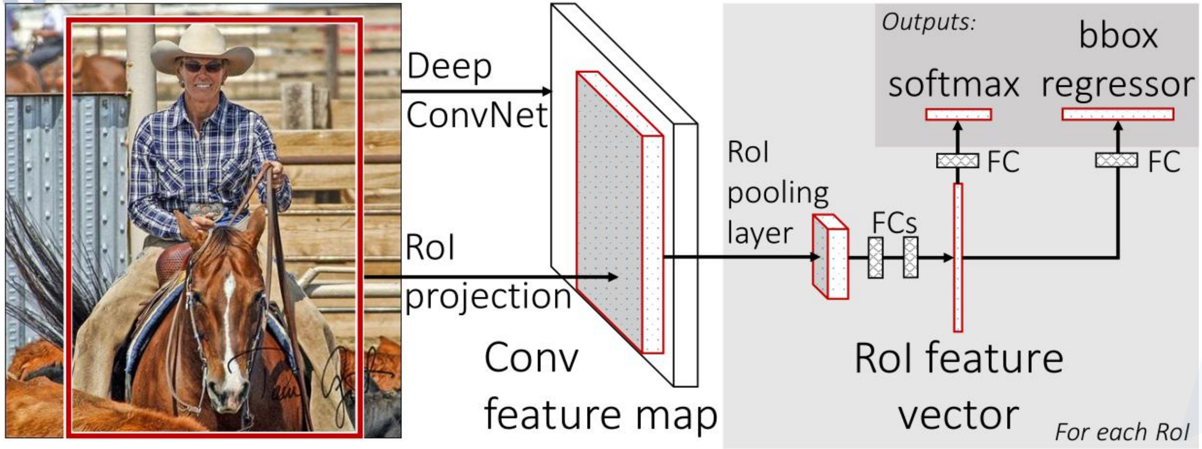

Fast R-CNN

Fast R-CNN框架

Region proposal(Selective Search)
Feature extraction Classification Bounding-box regression (CNN)

Fast R-CNN

R-CNN框架

Region proposal(Selective Search)	
Feature extraction(CNN)	
Classification (SVM)	Bounding-box regression (regression)

沟通方式

1.github

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

2.CSDN

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

3.bilibili

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

尽可能每周更新