DeepLab: Semantic Image Segmentation with Deep Convolutional Nets, Atrous Convolution, and Fully Connected CRFs

Liang-Chieh Chen, George Papandreou, Senior Member, IEEE, Iasonas Kokkinos, Member, IEEE, Kevin Murphy, and Alan L. Yuille, Fellow, IEEE

Final Output

Fully Connected CRF

Bi-linear Interpolation

2016 CVPR

论文下载地址: https://arxiv.org/abs/1606.00915

博文推荐: https://blog.csdn.net/qq_37541097/article/details/121752679

DCNNs应用在语义分割任务中问题

In particular we consider three challenges in the application of DCNNs to semantic image segmentation: (1) reduced feature resolution, (2) existence of objects at multiple scales, and (3) reduced localization accuracy due to DCNN invariance.

- ▶ 分辨率被降低 (主要由于下采样stride>1的层导致)
- ▶ 目标的多尺度问题
- DCNNs的不变性(invariance)会降低定位精度

对应的解决方法

- ▶ **针对分辨率被降低的问题**,一般就是将最后的几个Maxpooling层的**stride设置成1**(如果是通过卷积下采样的,比如resnet,同样将stride设置成1即可),**配合使用膨胀卷积**。
- ▶ 针对目标多尺度的问题,最容易想到的就是将图像缩放到多个尺度分别通过网络进行推理,最后将多个结果进行融合即可。这样做虽然有用但是计算量太大了。为了解决这个问题, DeepLab V2 中提出了ASPP模块(atrous spatial pyramid pooling)。
- > 针对DCNNs不变性导致定位精度降低的问题,和DeepLab V1差不多还是通过CRFs解决,不过这里用的是fully connected pairwise CRF,相比V1里的fully connected CRF要更高效点。

网络优势

- > 速度更快
- ▶ 准确率更高 (当时的state-of-art)
- ▶ 模型结构简单,还是DCNNs和CRFs联级

ASPP(atrous spatial pyramid pooling)

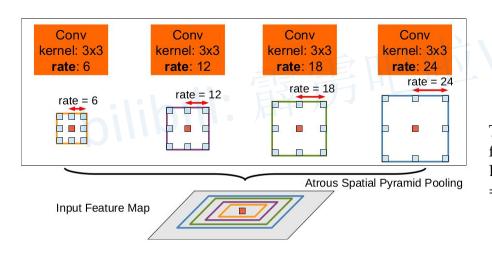


Fig. 4: Atrous Spatial Pyramid Pooling (ASPP). To classify the center pixel (orange), ASPP exploits multi-scale features by employing multiple parallel filters with different rates. The effective Field-Of-Views are shown in different colors.

Method	before CRF	after CRF
LargeFOV	65.76	69.84
ASPP-S	66.98	69.73
ASPP-L	68.96	71.57

TABLE 3: Effect of ASPP on PASCAL VOC 2012 val set performance (mean IOU) for VGG-16 based DeepLab model. **LargeFOV**: single branch, r=12. **ASPP-S**: four branches, $r=\{2,4,8,12\}$. **ASPP-L**: four branches, $r=\{6,12,18,24\}$.

ASPP(atrous spatial pyramid pooling)

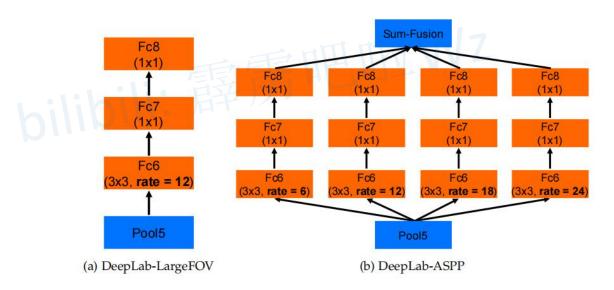


Fig. 7: DeepLab-ASPP employs multiple filters with different rates to capture objects and context at multiple scales.

消融实验

MSC	COCO	Aug	LargeFOV	ASPP	CRF	mIOU
			三	電影「	TH!	68.72
\checkmark						71.27
\checkmark	V					73.28
\checkmark	\checkmark	\checkmark				74.87
\checkmark	1	\checkmark	\checkmark			75.54
\checkmark	\checkmark	\checkmark		\checkmark		76.35
\checkmark	\checkmark	\checkmark		\checkmark	✓	77.69

TABLE 4: Employing ResNet-101 for DeepLab on PASCAL VOC 2012 *val* set. **MSC**: Employing mutli-scale inputs with max fusion. **COCO**: Models pretrained on MS-COCO. **Aug**: Data augmentation by randomly rescaling inputs.

of [17], [18], [39], [40], [58], [59], [62]: (1) Multi-scale inputs: We separately feed to the DCNN images at scale = $\{0.5, 0.75,$ 1}, fusing their score maps by taking the maximum response across scales for each position separately [17]. (2) Models pretrained on MS-COCO [87]. (3) Data augmentation by randomly scaling the input images (from 0.5 to 1.5) during training. In Tab. 4 we evaluate how each of these factors, along with LargeFOV and atrous spatial pyramid pooling (ASPP), affects val set performance. Adopting ResNet-101 instead of VGG-16 significantly improves DeepLab performance (e.g., our simplest ResNet-101 based model attains 68.72%, compared to 65.76% of our DeepLab-LargeFOV VGG-16 based variant, both before CRF). Multiscale fusion 17 brings extra 2.55% improvement, while pretraining the model on MS-COCO gives another 2.01% gain. Data augmentation during training is effective (about 1.6% improvement). Employing LargeFOV (adding an atrous convolutional layer on top of ResNet, with 3×3 kernel and rate = 12) is beneficial (about 0.6% improvement). Further 0.8% improvement is achieved by atrous spatial pyramid pooling (ASPP). Post-processing our best model by dense CRF yields

Learning rate policy

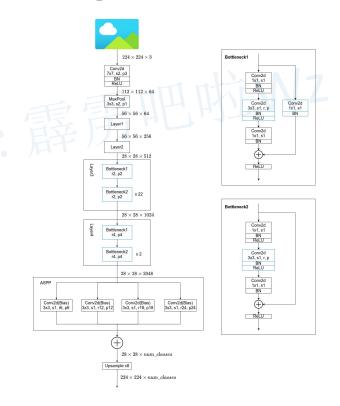
$$lr imes (1 - rac{iter}{max_iter})^{power}$$

Learning policy	Batch size	Iteration	mean IOU	
step	1 30 日	6K	62.25	
poly poly poly poly	30 30 10 10	6K 10K 10K 20K	63.42 64.90 64.71 65.88	

TABLE 2: PASCAL VOC 2012 *val* set results (%) (before CRF) as different learning hyper parameters vary. Employing "poly" learning policy is more effective than "step" when training DeepLab-LargeFOV.

power = 0.9

DeepLab V2网络结构



backbone: ResNet101

不考虑MSC的情况