

Rethinking Atrous Convolution for Semantic Image Segmentation

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Liang-Chieh Chen George Papandreou Florian Schroff Hartwig Adam

Google Inc.

{lcchen, gpapan, fschroff, hadam}@google.com

➤ 引入了Multi-grid

➤ 改进ASPP结构

➤ 移除CRFs后处理

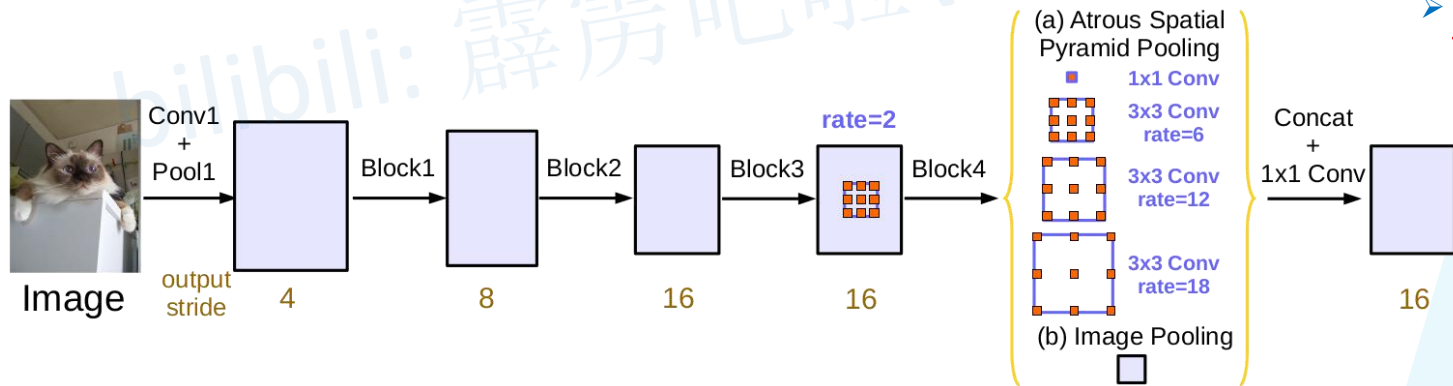
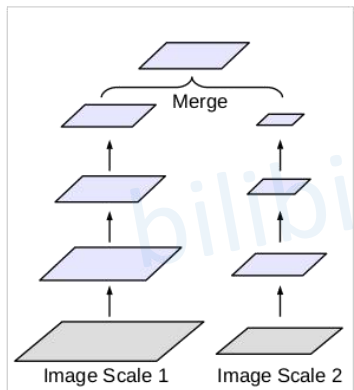


Figure 5. Parallel modules with atrous convolution (ASPP), augmented with image-level features.

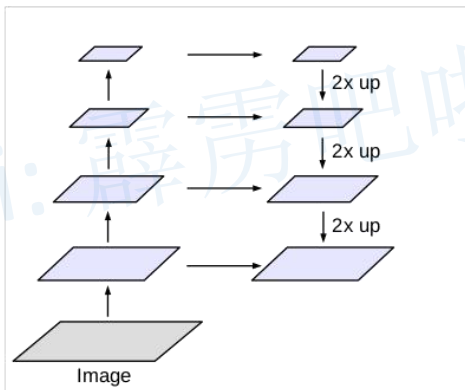
论文下载地址: <https://arxiv.org/abs/1706.05587>

博文推荐: https://blog.csdn.net/qq_37541097/article/details/121797301

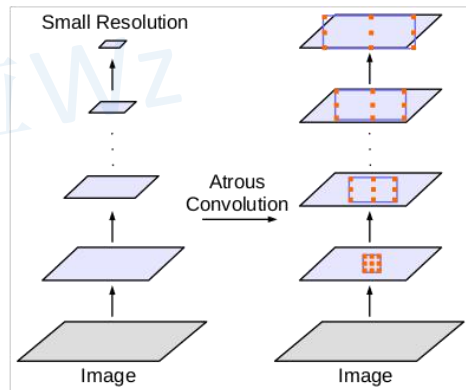
DeepLab V3



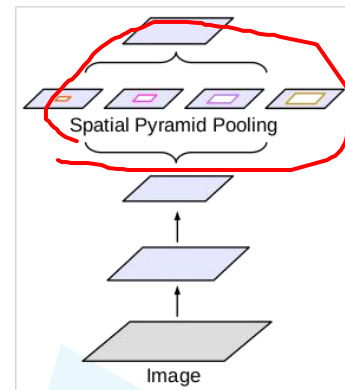
(a) Image Pyramid



(b) Encoder-Decoder



(c) Deeper w. Atrous Convolution



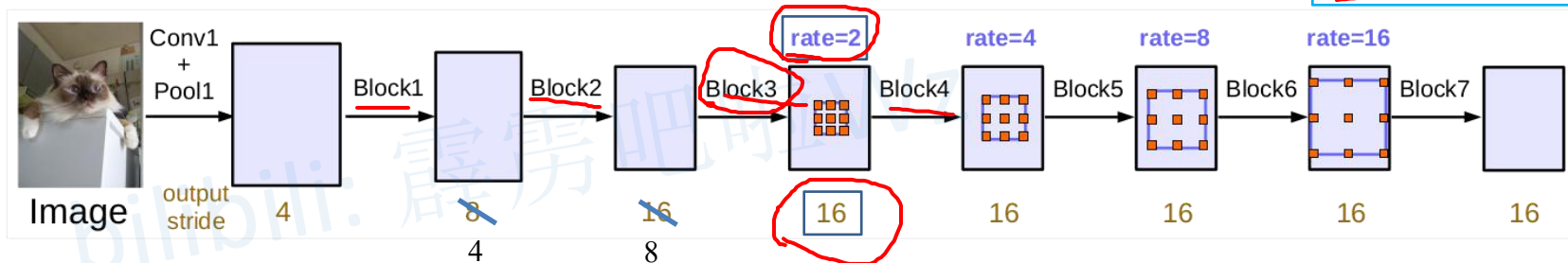
(d) Spatial Pyramid Pooling

Figure 2. Alternative architectures to capture multi-scale context.

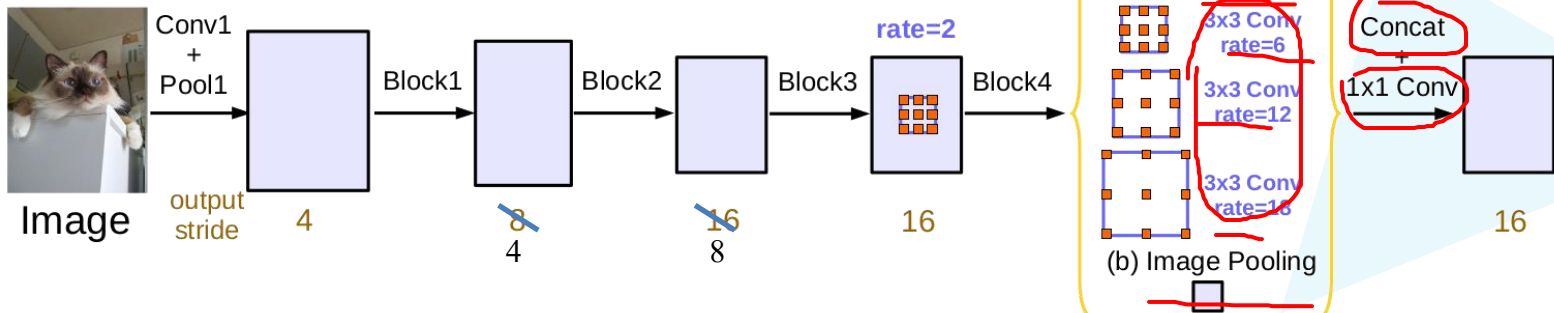
DeepLab V3

DeepLab V3两种模型结构

cascaded model

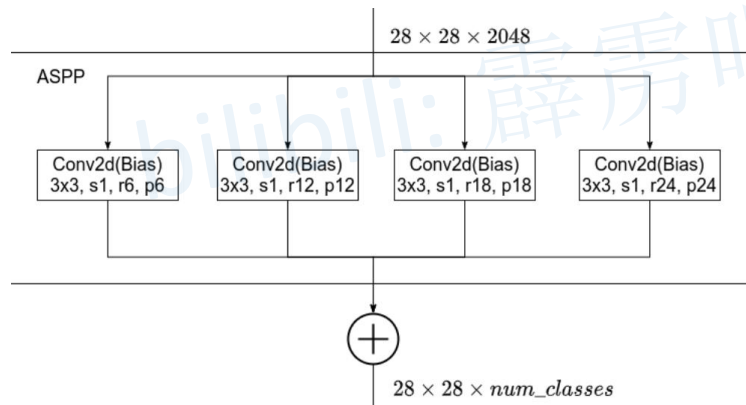


ASPP model

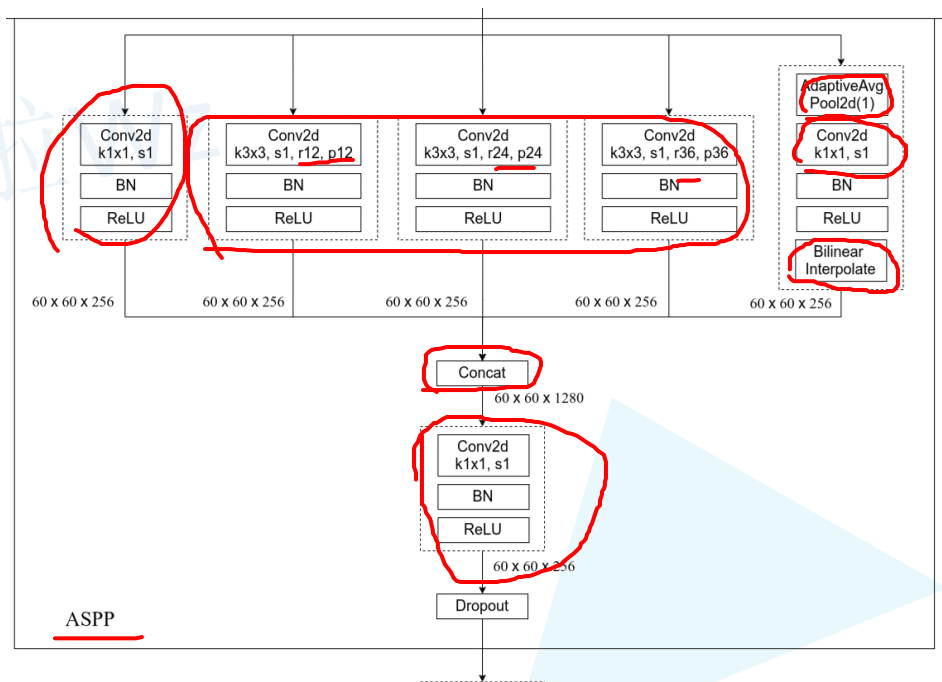


DeepLab V3

V2中的ASPP



V3中的ASPP



Multi-grid

| Multi-Grid | block4 | block5 | block6 | block7 |
|------------------|--------|--------|--------|---------------------|
| (1, 1, 1) | 68.39 | 73.21 | 75.34 | 75.76 |
| <u>(1, 2, 1)</u> | 70.23 | 75.67 | 76.09 | <u>76.66</u> |
| (1, 2, 3) | 73.14 | 75.78 | 75.96 | 76.11 |
| <u>(1, 2, 4)</u> | 73.45 | 75.74 | 75.85 | 76.02 |
| (2, 2, 2) | 71.45 | 74.30 | 74.70 | 74.62 |

Table 3. Employing multi-grid method for ResNet-101 with different number of cascaded blocks at *output_stride* = 16. The best model performance is shown in bold.

Multi-grid: We apply the multi-grid method to ResNet-101 with several cascadedly added blocks in Tab. 3. The unit rates, $Multi_Grid = (r_1, r_2, r_3)$, are applied to block4 and all the other added blocks. As shown in the table, we observe that (a) applying multi-grid method is generally better than the vanilla version where $(r_1, r_2, r_3) = (1, 1, 1)$, (b) simply doubling the unit rates (*i.e.*, $(r_1, r_2, r_3) = (2, 2, 2)$) is not effective, and (c) going deeper with multi-grid improves the performance. Our best model is the case where block7 and $(r_1, r_2, r_3) = (1, 2, 1)$ are employed.

The final atrous rate for the convolutional layer is equal to the multiplication of the unit rate and the corresponding rate. For example, when output stride = 16 and Multi Grid = (1, 2, 4), the three convolutions will have rates = 2 · (1, 2, 4) = (2, 4, 8) in the block4, respectively.

cascaded model消融实验

| Method | <u>OS=16</u> | <u>OS=8</u> | <u>MS</u> | <u>Flip</u> | mIOU |
|--------------------|--------------|-------------|-----------|-------------|--------------|
| <u>block7 +</u> | ✓ | | | | <u>76.66</u> |
| <u>MG(1, 2, 1)</u> | | ✓ | | | <u>78.05</u> |
| | | ✓ | ✓ | | 78.93 |
| | | ✓ | ✓ | ✓ | <u>79.35</u> |

Table 4. Inference strategy on the *val* set. **MG**: Multi-grid. **OS**: output_stride. **MS**: Multi-scale inputs during test. **Flip**: Adding left-right flipped inputs.

scales = {0.5, 0.75, 1.0, 1.25, 1.5, 1.75}

ASPP model消融实验

| Method | OS=16 | <u>OS=8</u> | <u>MS</u> | <u>Flip</u> | <u>COCO</u> | mIOU |
|--------------------------|-------|-------------|-----------|-------------|-------------|--------------|
| <u>MG(1, 2, 4) +</u> | ✓ | | | | | <u>77.21</u> |
| <u>ASPP(6, 12, 18) +</u> | | ✓ | | | | <u>78.51</u> |
| <u>Image Pooling</u> | | ✓ | ✓ | | | <u>79.45</u> |
| | | ✓ | ✓ | ✓ | | <u>79.77</u> |
| | | ✓ | ✓ | ✓ | ✓ | <u>82.70</u> |

Table 6. Inference strategy on the *val* set: **MG**: Multi-grid. **ASPP**: Atrous spatial pyramid pooling. **OS**: *output_stride*. **MS**: Multi-scale inputs during test. **Flip**: Adding left-right flipped inputs. **COCO**: Model pretrained on MS-COCO.

scales = {0.5, 0.75, 1.0, 1.25, 1.5, 1.75}

训练细节

A. Effect of hyper-parameters

As mentioned in the main paper, we change the training protocol in [10, 11] with three main differences:

- (1) larger crop size,
- (2) upsampling logits during training, and
- (3) fine-tuning batch normalization.

Here, we quantitatively measure the effect of the changes.

| Crop Size | UL | BN | mIOU |
|------------|----|----|--------------|
| 513 | ✓ | ✓ | 77.21 |
| 513 | ✓ | | 75.95 |
| <u>513</u> | | ✓ | <u>76.01</u> |
| <u>321</u> | | ✓ | <u>67.22</u> |

Table 8. Effect of hyper-parameters during training on PASCAL VOC 2012 *val* set at *output_stride*=16. UL: Upsampling Logits. BN: Fine-tuning batch normalization.

| Method | mIOU |
|--------------------------------|-------------|
| Adelaide_VeryDeep_FCN_VOC [85] | 79.1 |
| LRR_4x_ResNet-CRF [25] | 79.3 |
| <u>DeepLabv2-CRF [11]</u> | <u>79.7</u> |
| CentraleSupelec Deep G-CRF [8] | 80.2 |
| HikSeg_COCO [80] | 81.4 |
| SegModel [75] | 81.8 |
| Deep Layer Cascade (LC) [52] | 82.7 |
| TuSimple [84] | 83.1 |
| Large_Kernel_Matters [68] | 83.6 |
| Multipath-RefineNet [54] | 84.2 |
| ResNet-38_MS_COCO [86] | 84.9 |
| PSPNet [95] | 85.4 |
| IDW-CNN [83] | 86.3 |
| CASIA_IVA_SDN [23] | 86.6 |
| DIS [61] | 86.8 |
| <u>DeepLabv3</u> | <u>85.7</u> |
| <u>DeepLabv3-JFT</u> | <u>86.9</u> |

Table 7. Performance on PASCAL VOC 2012 *test* set.

DeepLab V3

Pytorch官方实现的DeepLabV3

- 没有使用Multi-Grid, 有兴趣的同学可以自己动手加上试试。
- 多了一个FCNHead辅助训练分支, 可以选择不使用。
- 无论是训练还是验证output_stride都使用的8。
- ASPP中三个膨胀卷积分支的膨胀系数是12, 24, 36

