Custom Semantic Image Segmentation with DeepLabv3+

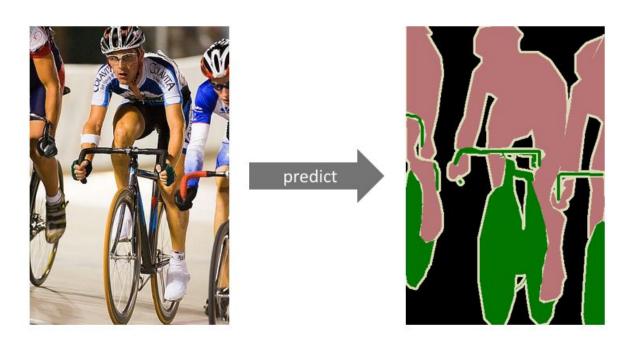
Computational Intelligence Lab in the Department of Computer Science at Cal Poly Pomona

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Resources

- Deeplabv3+ paper
 - https://arxiv.org/abs/1802.02611
- Tensorflow implementation of deeplab
 - https://github.com/tensorflow/models/tree/master/research/deeplab
- Github for custom training with Tensorflow's deeplab
 - https://github.com/David-Hughes3/deeplab_project

Semantic Image Segmentation



Person Bicycle Background

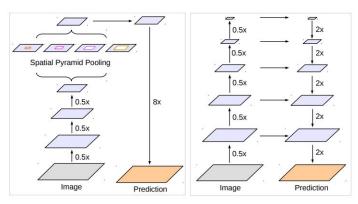
http://host.robots.ox.ac.uk/pascal/VOC/voc2012/#devkit

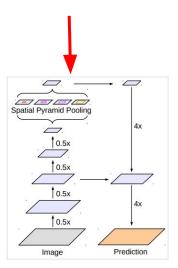
Deeplabv3+

Goal of Deeplabv3+

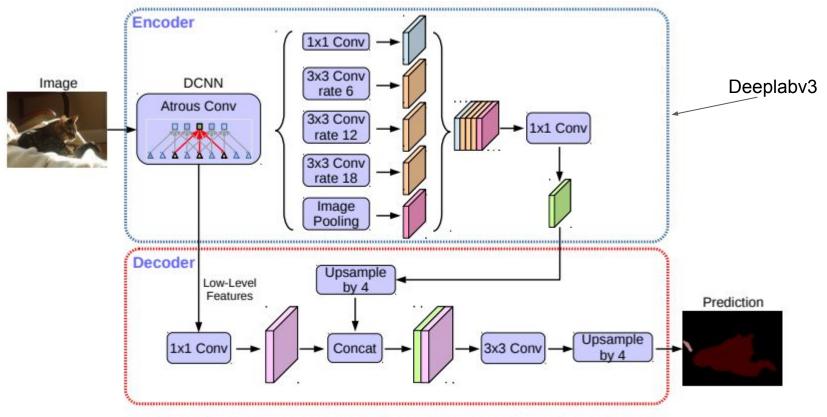
Combine the advantages of:

- Spatial pyramid pooling module
 - Encode multi-scale contextual information
 - By probing incoming features with filters or pooling ops at multiple rates and effective FOVs
- Encoder-decoder structure
 - Capture sharper object boundaries
 - By recovering spatial information





(c) Encoder-Decoder with Atrous Conv

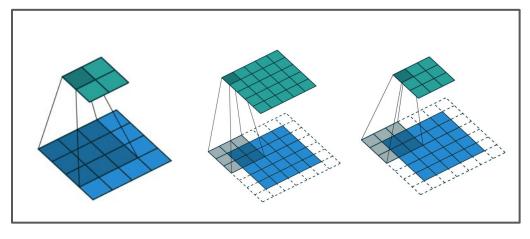


Deeplabv3+ Structure

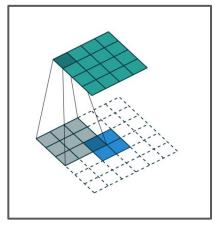
Encoder = DeepLabv3

Basic Types of Convolutions

Blue maps are inputs, and cyan maps are outputs.



Convolution



Transposed Convolution

Atrous Convolution / Hole Algorithm/ Dilated Conv

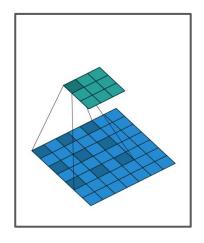
$$y[i] = \sum_{k} x[i + r \cdot k]w[k]$$

Atrous Convolution

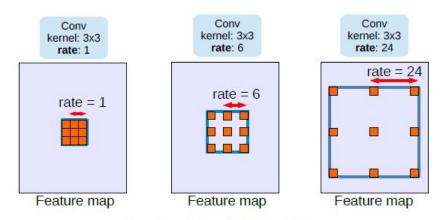
- Location i on output feature map y
- Conv filter w
- Applied over the input feature map x
- Atrous rate r is stride to sample input signal

- r=1, standard convolution
- Holes = introducing zeros between filter values
 - "convolving the input x with upsampled filters produced by inserting r-1 zeros between two consecutive filter values along each spatial dimension." source
- Filter's field-of-view can be changed by modifying rate
 - Small = accurate localization
 - Large = context assimilation

Atrous Convolution



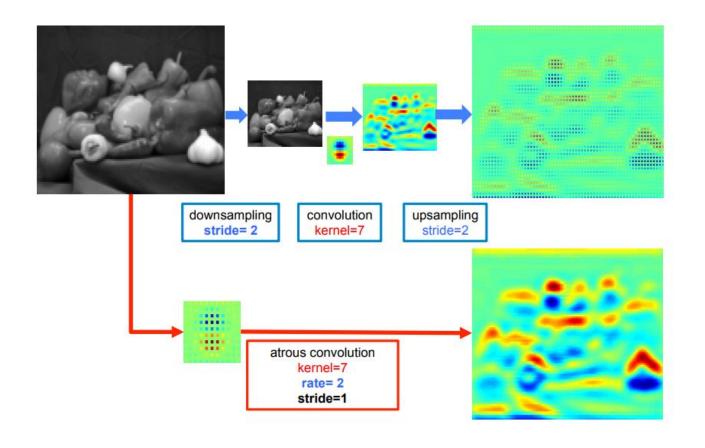
Dilated-Convolution



Atrous Convolution with Different Rates r

Reasoning

- repeated combination of max-pooling and striding at consecutive layers of these networks reduces significantly the spatial resolution of the resulting feature maps
- A partial remedy is to use 'deconvolutional'/transpose layers
 - However requires additional memory and time.
- Atrous convolution allows computing the responses of any layer at any desirable resolution

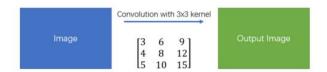


Depthwise separable convolution

First, spatial separable convolutions

- Instead of doing one conv with 9 multiplications
- Do two convolutions with 3 mults each (6 total)
- Less mults = less comp complexity

Simple Convolution



Spatial Separable Convolution



https://towardsdatascience.com/a-basic-introduction-to-separable-convolutions-b99ec3102728

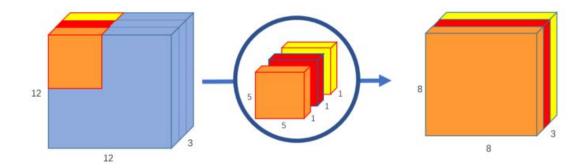
Depthwise separable convolution

- Not all kernels can be factored into two smaller kernels
 - Depthwise separable convolution work either way = more common
- Ex: keras.layers.SeparableConv2D or tf.layers.separable_conv2d

- Like spatial separable conv, depthwise splits a kernel into 2 separate kernels
 - Depthwise convolution kernel
 - Pointwise convolution kernel

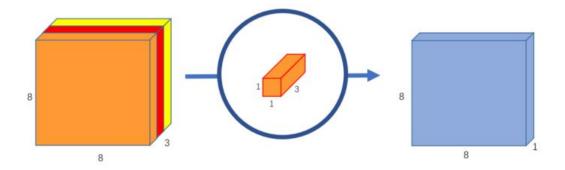
Depthwise Convolution Kernel

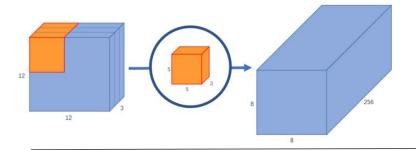
- Performs a spatial convolution independently for each channel
 - Apply a single filter for each input channel



Pointwise convolution kernel

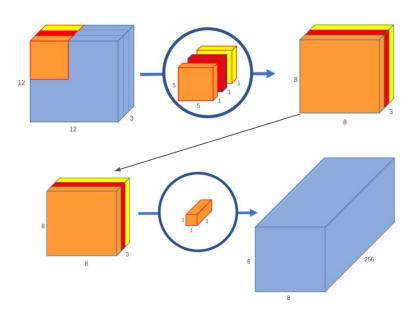
Combines the output from the depthwise convolution





Normal Convolution:

- 12x12x3 image with 256 (5x5x3) kernels -> 8x8x1 image
- 256 (5x5x3) kernels move 8x8 times
 - 256x3x5x5x8x8=1,228,800 multiplications.



Depthwise Convolution (conv without changing depth):

- 12x12x3 image with 3 (5x5x1) kernels
- 3 (5x5x1) kernels that move 8x8 times.
 - That's 3x5x5x8x8 = 4,800 multiplications

Pointwise Convolution:

- 256 (1x1x3) kernels that output a 8x8x1 image each to get a final image of shape 8x8x256.
- 256 (1x1x3) kernels that move 8x8 times.
 - That's 256x1x1x3x8x8=49,152 multiplications.

49,152 + 4,800 = 53,952 << 1,228,800

Atrous Separable Convolution

(a) Depthwise conv. (b) Pointwise conv. (c) Atrous depthwise conv.

DeepLabv3+: Encoder-Decoder with Atrous Separable Convolution

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Fig. 3. 3×3 Depthwise separable convolution decomposes a standard convolution into (a) a depthwise convolution (applying a single filter for each input channel) and (b) a pointwise convolution (combining the outputs from depthwise convolution across channels). In this work, we explore *atrous separable convolution* where atrous convolution is adopted in the depthwise convolution, as shown in (c) with rate = 2.

Atrous Spatial Pyramid Pooling (ASPP) module

probes convolutional features at multiple scales by applying atrous convolution with different rates

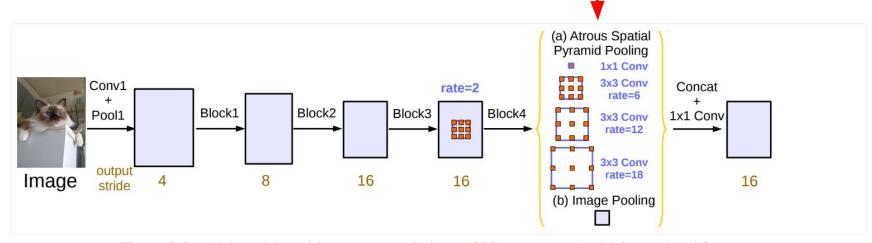
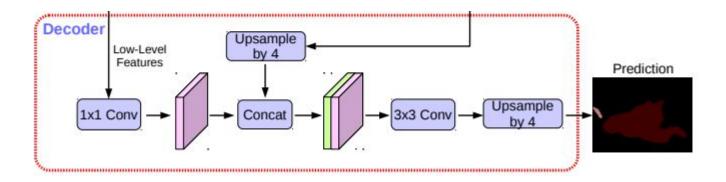


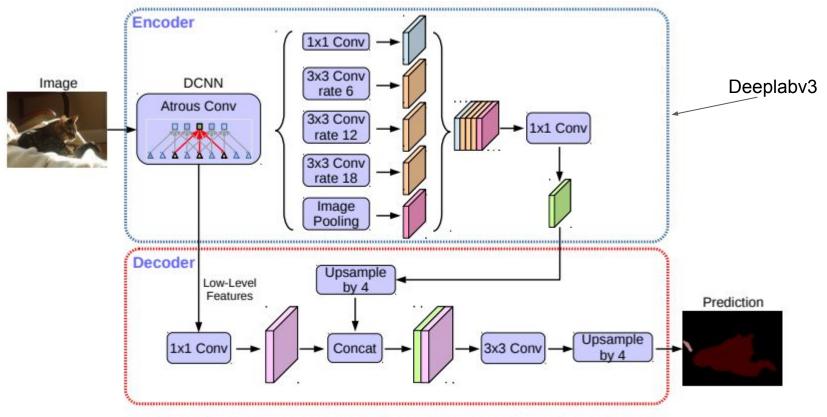
Figure 5. Parallel modules with atrous convolution (ASPP), augmented with image-level features.

Decoder

Simple Decoder

- very simple yet effective decoder module:
 - concatenation of
 - DeepLabv3 feature map
 - channel-reduced Conv2 feature map
 - o refined by two [3 × 3, 256] operations.





Deeplabv3+ Structure

Deeplabv3+ Paper results

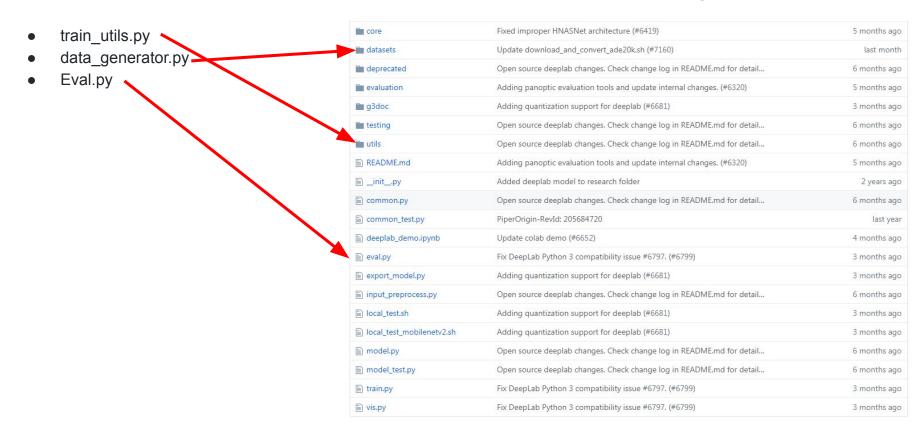
Method	mIOU
Deep Layer Cascade (LC) [82]	82.7
TuSimple [77]	83.1
Large_Kernel_Matters [60]	83.6
Multipath-RefineNet [58]	84.2
ResNet-38_MS_COCO [83]	84.9
PSPNet [24]	85.4
IDW-CNN [84]	86.3
CASIA_IVA_SDN [63]	86.6
DIS [85]	86.8
DeepLabv3 [23]	85.7
DeepLabv3-JFT [23]	86.9
DeepLabv3+ (Xception)	87.8
DeepLabv3+ (Xception-JFT)	89.0

Table 6. PASCAL VOC 2012 test set results with top-performing models.

Custom training

Custom Training

Tensorflow Files that must be modified for custom dataset training



Custom Training - Datasets

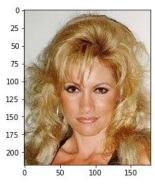
- Labeled Faces in the Wild Parts Dataset
- CelebA segmentation masks & CelebA

Preprocessing needs to be done to convert segmentation maps to color-indexed images.

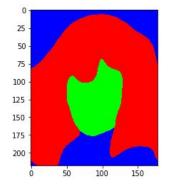
0 = background

1 = hair

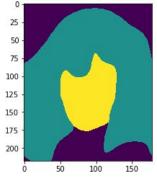
2 = skin



LFW image



LFW - parts mask



color-indexed mask

Custom Training Results

Weights for classes:

1, background 10, hair 5, face

10000 iterations: miou

class_0: 0.91722 class_1: 0.66235 class 2: 0.83431

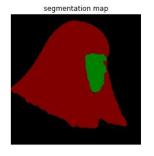
mean_iou: 0.8046266666666666

20000 iterations: miou

class_0: 0.92631 class_1: 0.67995 class_2: 0.85498

mean_iou: 0.82041333333333333

















Bibtex format References

```
[1] @inproceedings{deeplabv3plus2018,
title={Encoder-Decoder with Atrous Separable Convolution for Semantic Image Segmentation},
author={Liang-Chieh Chen and Yukun Zhu and George Papandreou and Florian Schroff and Hartwig Adam},
 booktitle={ECCV}.
 year={2018}
[2] @article{DBLP:journals/corr/ChenPSA17,
author = {Liang{-}Chieh Chen and George Papandreou and Florian Schroff and Hartwig Adam},
       = {Rethinking Atrous Convolution for Semantic Image Segmentation},
 journal = {CoRR},
volume = \{abs/1706.05587\},\
 vear
      = {2017},
       = {http://arxiv.org/abs/1706.05587},
 archivePrefix = {arXiv},
 eprint = \{1706.05587\},
 timestamp = {Mon, 13 Aug 2018 16:48:07 +0200},
 biburl = {https://dblp.org/rec/bib/journals/corr/ChenPSA17},
bibsource = {dblp computer science bibliography, https://dblp.org}
[3] @article{DBLP:journals/corr/ChenPK0Y16,
author = {Liang{-}Chieh Chen and George Papandreou and Iasonas Kokkinos and Kevin Murphy and Alan L. Yuille},
      = {DeepLab: Semantic Image Segmentation with Deep Convolutional Nets,
        Atrous Convolution, and Fully Connected CRFs},
 journal = \{CoRR\},\
 volume = \{abs/1606.00915\},\
        = \{2016\},\
       = {http://arxiv.org/abs/1606.00915},
 archivePrefix = {arXiv},
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 timestamp = {Mon, 13 Aug 2018 16:46:13 +0200},
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