Deep learning

8.4. Networks for semantic segmentation

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The deep-learning approach re-casts semantic segmentation as pixel classification, and re-uses networks trained for image classification by making them fully convolutional.

Shelhamer et al. (2016) proposed the FCN ("Fully Convolutional Network") that uses a pre-trained classification network (e.g. VGG 16 layers).

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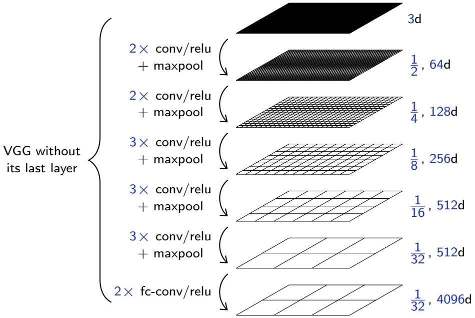
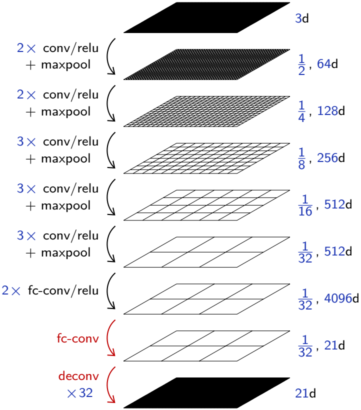
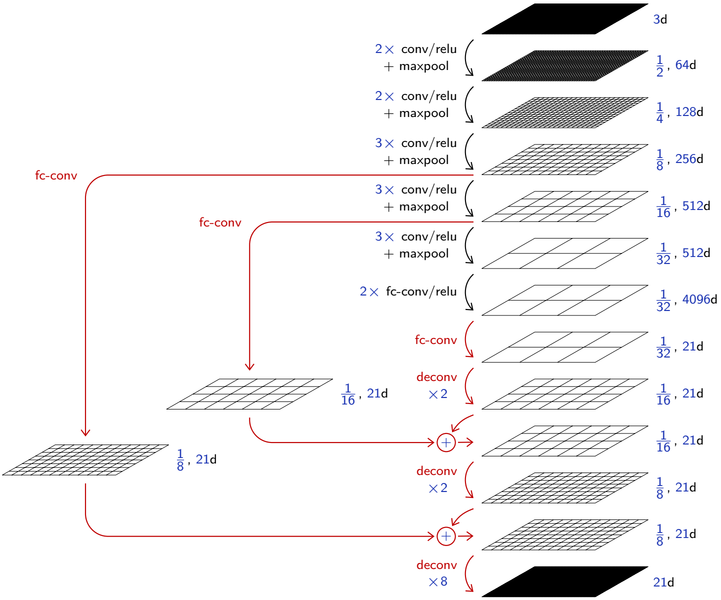
Training is achieved with full images and pixel-wise cross-entropy, starting with a pre-trained VGG16. All layers are fine-tuned, although fixing the up-scaling transposed convolution to bilinear does as well.


3d
2× conv/relu
+ maxpool
1/2, 64d
2× conv/relu
+ maxpool
1/4, 128d
VGG without
its last layer
3× conv/relu
+ maxpool
1/8, 256d
3× conv/relu
+ maxpool
1/16, 512d
3× conv/relu
+ maxpool
1/32, 512d
2× fc-conv/relu
1/32, 4096d

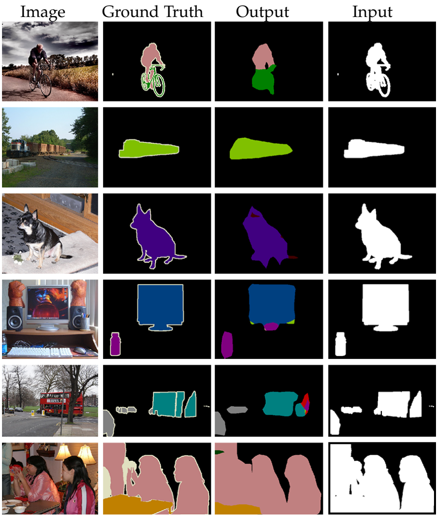

3d
2× conv/relu
+ maxpool
$\frac{1}{2}$, 64d
2× conv/relu
+ maxpool
$\frac{1}{4}$, 128d
3× conv/relu
+ maxpool
$\frac{1}{8}$, 256d
3× conv/relu
+ maxpool
$\frac{1}{16}$, 512d
3× conv/relu
+ maxpool
$\frac{1}{32}$, 512d
2× fc-conv/relu
$\frac{1}{32}$, 4096d
fc-conv
$\frac{1}{32}$, 21d
deconv
×32
21d

Although the FCN achieved almost state-of-the-art results when published, its main weakness is the coarseness of the signal from which the final output is produced ($1/32$ of the original resolution).

Shelhamer et al. proposed an additional element, that consists of using the same prediction/up-scaling from intermediate layers of the VGG network.


3d
2× conv/relu + maxpool
1/2, 64d
2× conv/relu + maxpool
1/4, 128d
3× conv/relu + maxpool
1/8, 256d
3× conv/relu + maxpool
1/16, 512d
3× conv/relu + maxpool
1/32, 512d
2× fc-conv/relu
1/32, 4096d
fc-conv
1/32, 21d
deconv ×2
1/16, 21d
1/16, 21d
deconv ×2
1/8, 21d
1/8, 21d
deconv ×8
21d
fc-conv
fc-conv
1/16, 21d
1/8, 21d

Left column is the best network from Shelhamer et al. (2016).



Results with a network trained from mask only (Shelhamer et al., 2016).

The most sophisticated object detection methods achieve **instance segmentation** and estimate a segmentation mask per detected object.

Mask R-CNN (He et al., 2017) adds a branch to the Faster R-CNN model to estimate a mask for each detected region of interest.

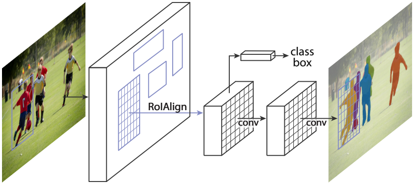


Figure 1. The **Mask R-CNN** framework for instance segmentation.

(He et al., 2017)

Figure 5. More results of **Mask R-CNN** on COCO test images, using ResNet-101-FPN and running at 5 fps, with 35.7 mask AP (Table 1).

(He et al., 2017)

It is noteworthy that for detection and semantic segmentation, there is an heavy re-use of large networks trained for classification.

The models themselves, as much as the source code of the algorithm that produced them, or the training data, are generic and re-usable assets.

The end

References

K. He, G. Gkioxari, P. Dollár, and R. Girshick. **Mask R-CNN**. In International Conference on Computer Vision, pages 2980–2988, 2017.

E. Shelhamer, J. Long, and T. Darrell. **Fully convolutional networks for semantic segmentation**. CoRR, abs/1605.06211, 2016.