

EE-559 – Deep learning

7.4. 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) use a pre-trained classification network (e.g. VGG 16 layers) from which the final fully connected layer is removed, and the other ones are converted to 1×1 convolutional filters.

They add a final 1×1 convolutional layers with 21 output channels (VOC 20 classes + “background”).

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This map is then up-scaled with a de-convolution layer with kernel 64×64 and stride 32×32 to get a final map of same size as the input image.

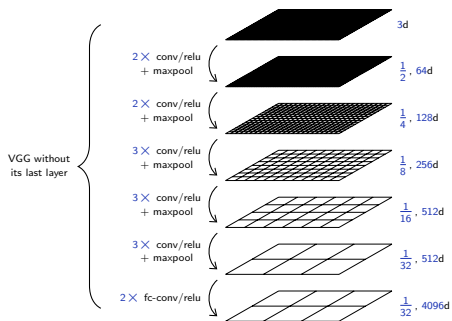
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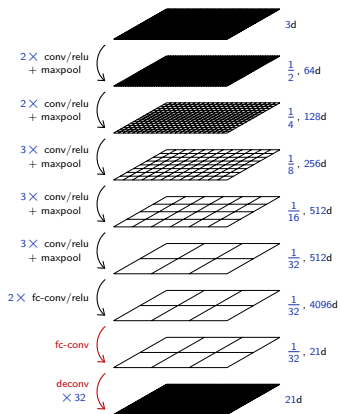
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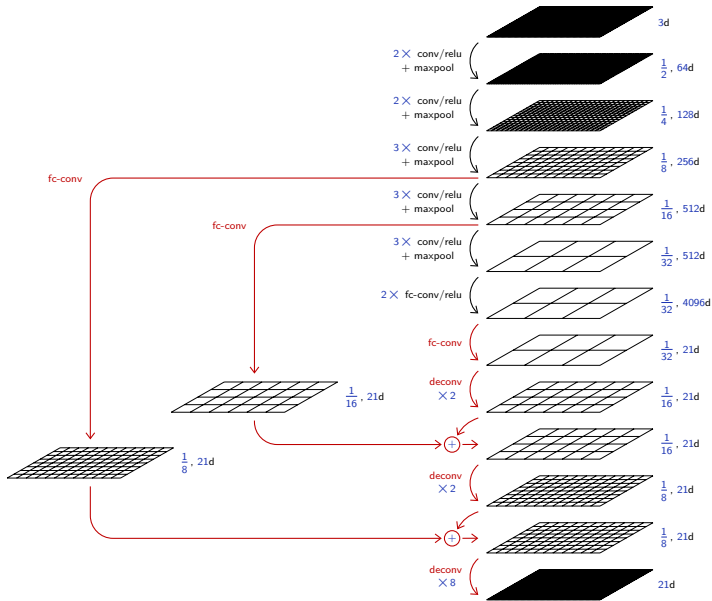
Training is achieved with full images and pixel-wise cross-entropy, starting with a pre-trained VGG16. All layers are fine-tuned, although fixing the up-scaling de-convolution to bilinear does as well.

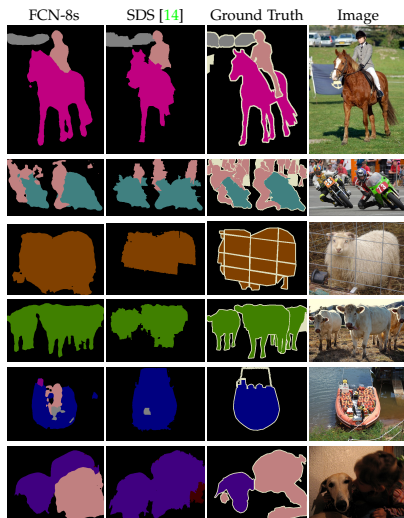




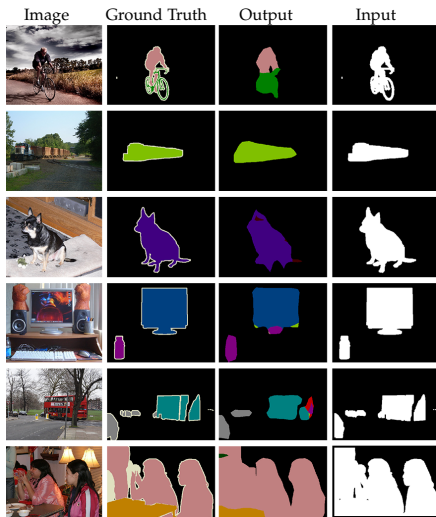
Although this Fully Connected Network (FCN) achieved almost state-of-the-art results when published, its main weakness is the coarseness of the signal from which the final output is produced ($1/32$ of the original resolution).

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





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



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

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

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