EE-559 - Deep learning

7.4. Networks for semantic segmentation

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The historical approach to image segmentation was to define a measure of similarity between pixels, and to cluster groups of similar pixels. Such approaches account poorly for semantic content.

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").

Since VGG16 has 5 max-pooling with 2×2 kernels, with proper padding, the output is $1/2^5 = 1/32$ the size of the input.

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.

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.

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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.

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

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FCN-8s	SDS [14]	Ground Truth	Image
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Left column is the best network from Shelhamer et al. (2016).

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Image	Ground Truth	Output	Input
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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.

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References

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