# Classification with an edge: improving semantic image segmentation with boundary detection

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#### Abstract

We present an end-to-end trainable deep convolutional neural network (DCNN) for semantic segmentation with built-in awareness of semantically meaningful boundaries. Semantic segmentation is a fundamental remote sensing task, and most state-of-the-art methods rely on DCNNs as their workhorse. A major reason for their success is that deep networks learn to accumulate contextual information over very large windows (receptive fields). However, this success comes at a cost, since the associated loss of effective spatial resolution washes out high-frequency details and leads to blurry object boundaries. Here, we propose to counter this effect by combining semantic segmentation with semantically informed edge detection, thus making class boundaries explicit in the model, First, we construct a comparatively simple, memory-efficient model by adding boundary detection to the SEGNET encoder-decoder architecture. Second, we also include boundary detection in FCN-type models and set up a high-end classifier ensemble. We show that boundary detection significantly improves semantic segmentation with CNNs. Our high-end ensemble achhieves > 90\% overall accuracy on the ISPRS Vaihingen bechmark.

# 1. Introduction

Semantic image segmentation (a.k.a. landcover classification) is the process of turning an input image into raster map, by assigning every pixel to

an object class from a predefined class nomenclature. Automatic semantic segmentation has been a fundamental problem of remote sensing data analysis for many years (Fu et al., 1969; Richards, 2013). In recent years there is a growing interest to perform semantic segmentation also in urban areas, using conventional aerial images or even image data recorded from low-flying drones. Images at such high resolution (GSD 5-30 cm) have quite different properties. Intricate spatial details emerge such as road markings, roof tiles or individual branches of trees, increasing the spectral variability within an object class. On the other hand, the spectral resolution of sensors is limited to three or four broad bands<sup>1</sup>, so spectral material signatures are less distinctive. Hence, a large portion of the semantic information is encoded in the image texture rather than the individual pixel intensities, and much effort has gone into extracting features from the raw images that make the class information explicit (e.g. Franklin and McDermid, 1993; Barnsley and Barr, 1996; Dalla Mura et al., 2010; Tokarczyk et al., 2015).

At present the state-of-the-art tool for semantic image segmentation, in remote sensing as well as other fields of image analysis, are deep convolutional neural networks (DCNNs).<sup>2</sup> For semantic segmentation one uses so-called fully convolutional networks (FCNs), which output the class likelihoods for an entire image at once. FCNs have become a standard tool that is readily available in neural network software.

Why are DCNNs so successful (if given sufficient training data and computing resources)? Much has been said about their ability to learn the complete mapping from raw images to class labels ("end-to-end learning"), thus making heuristic feature design obsolete. Another strength is maybe even more important for their excellent performance: deep networks capture a lot of *context* in a tractable manner. Each convolution layer propagates information between nearby pixels, and each pooling layer enlarges the footprint of subsequent convolutions in the input image. Together, this means that the output at a given pixel is influenced by a large spatial neighborhood. When the task is pixel-wise semantic segmentation<sup>3</sup>, their unparalleled ability to

<sup>&</sup>lt;sup>1</sup>Note, aerial mapping campaigns are usually flown with overlapping images (or combined camera+LiDAR systems). Therefore, a digital elevation model is normally available, which can be regarded as an additional "height channel".

<sup>&</sup>lt;sup>2</sup>For example, the five best-performing participants in the *ISPRS Vaihingen* benchmark, not counting multiple entries from the same group / network design, all use DCNNs.

<sup>&</sup>lt;sup>3</sup>As opposed to, e.g., object recognition or speech recognition.

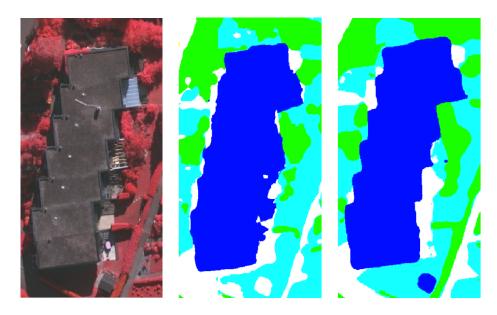


Table 1: Semantic segmentation. Left: input image. Middle: DCNN segmentation, object boundaries tend to be blurred. Right: We propose to mitigate this effect by including an explicit object boundary detector in the network.

represent context however comes at a price. There is a trade-off between strong downsampling, which allows the network to see a large context, but loses high-frequency detail; and accurate localization of the object boundaries, which requires just that local detail. We note that in generic computer vision with everyday images that effect is much less critical. In a typical photo, say a portrait or a street scene, there are few, big individual objects and only few object boundaries, whose precise location moreover is only defined up to a few pixels.

There has been some research that tries to mitigate the blurring of boundaries due to down-sampling and subsequent up-sampling, either by using the a-trous convolution (dilated convolution) (Yu and Koltun, 2016; Chen et al., 2016; Sherrah, 2016) or by adding skip connections from early to deep layers of the network, so as to reintroduce the high-frequency detail after upsampling (Dosovitskiy et al., 2015; Badrinarayanan et al., 2015; Marmanis et al., 2016). Still, we find that when applied to remote sensing data with small objects and many boundaries, FCNs tend to blur object boundaries and visually degrade the result (see Fig.1).

In this paper, we propose to explicitly represent class-boundaries in the

form of pixel-wise contour likelihoods, and to include them in the segmentation process. By class-boundaries we mean the boundaries between regions that have different semantic class, i.e., we aim for a "semantic edge-detection". Our hypothesis is that if those boundaries, which by definition correspond to the location of the label transitions, are made available to the network, then it should learn to align the segmentation to them. Importantly, recent work has shown that edge-detection can also be formulated as FCN, reaching excellent results (Xie and Tu, 2015; Kokkinos, 2016). We can therefore merge the two tasks into a single network, train them together and exploit synergies between them. The result is an end-to-end trainable model for semantic segmentation with a built-in awareness of semantically meaningful boundaries. We show experimentally that explicitly taking into account class boundaries significantly improves labeling accuracy, for our datasets up to 6%.

Overall, our boundary-aware ensemble segmentation network reaches state-of-the-art accuracy on the ISPRS Vaihingen semantic labeling benchmark. In particular, we find that adding boundary detection consistently improves the segmentation of man-made object classes with well-defined boundaries. On the contrary, we do not observe an improvement for vegetation classes, which have intrinsically fuzzy boundaries at our target resolution. Moreover, our experiments suggest that integrated boundary detection is especially beneficial for light DCNN architectures with few parameters. By themselves, lean encoder/decoder networks generally do not work quite as well as those with costly fully connected layers, which is in line with the literature (Badrinarayanan et al., 2015). On the contrary, the SEGNET encoder-decoder network in conjunction with a HED style boundary extractor matches an ensemble of VGG-style models, although the latter is a lot heavier in memory usage and training time.

A second, yet important message is that DCNNs perform optimally when merged into *ensemble models*. Combining multiple semantic segmentation networks seems beneficial to reduce the bias of individual models, both when using the same architecture with different initializations, and when using different model architectures with identical initializations.

In terms of practical relevance, a main message of this paper is that, with DCNNs, semantic segmentation is practically usable also for very high resolution urban remote sensing. It is typically thought that object extraction algorithms are good enough for (possibly semi-automatic) applications when their predictions are at least 80% correct (Mayer et al., 2006). In our experi-

ments, the  $F_1$ -score (harmonic mean between precision and recall) surpasses this threshold for all object classes, including small ones like cars. Frequent, well-defined man-made classes reach well above 90%.

#### 2. Related Work

Semantic segmentation has been a core topic of computer vision as well as remote sensing for many years. A full review is beyond the scope of this paper, we refer the reader to textbooks such as (Szeliski, 2010; Richards, 2013). Here, we concentrate on methods that employ neural networks.

Even in the early phase of the CNN revival, semantic segmentation was tackled by Grangier et al. (2009). The study investigates progressively deeper CNNs for predicting pixel labels from a local neighborhood, and already shows very promising results, albeit at coarse spatial resolution. Socher et al. (2012) start their semantic segmentation pipeline with a single convolution and pooling layer. On top of that "feature extractor" they stack recursive neural networks (RNN), which are employed on local blocks of the previous layer in a rather convolutional manner. The RNNs have random weights, there is no end-to-end training. Notably, that work uses RGB-D images as input and processes depth in a separate stream, as we do in the present work. Related to this is the approach of Pinheiro and Collobert (2014), who use "recurrent CNNs", meaning that they stack multiple shallow networks with tied convolution weights on top of each other, at each level using the predicted label maps from the previous level and an appropriately down-scaled version of the raw image as input. Farabet et al. (2013) train CNNs with 3 convolutional layers and a fully connected layer for semantic segmentation, then post-process the results with a CRF or by averaging over super-pixels to obtain a smooth segmentation. Like in our work, that paper generates an image pyramid and processes each scale separately with the CNN, but in contrast to our work the filter weights are tied across scales. An important milestone was the fully convolutional network (FCN) of Long et al. (2015). In that work it is shown that the final, fully connected layers of the network can be seen as a large stack of convolutions, which makes it possible to compute spatially explicit label maps efficiently. An important work in this context is also the Holistically-Nested Edge Detection (HED) of Xie and Tu (2015), who showed that an FCN trained to output edge maps instead of class labels is also an excellent edge detector. Their network was initialized with the VGG object detection network, so arguably the edge detection is supported by the semantic information captured in that network. Variants of HED have been explored by other authors, (Kokkinos, 2016) confirming that CNNs are at present also the state of the art for edge detection.

To undo the loss of spatial resolution due to the pooling layers of FCN, Noh et al. (2015) propose to add an unpooling and upsampling ("deconvolution") network (Zeiler and Fergus, 2014) on top of it. The result is a sort of encoder-decoder structure that upsamples the segmentation map back to the resolution of the input image. Yang et al. (2016) employ a similar strategy for the opposite purpose: their primary goal is not semantic labeling but rather a "semantically informed" edge detection which accentuates edges that lie on object contours. Also related is the work of Bertasius et al. (2015). They find candidate edge pixels with conventional edge detection, read out the activations at those pixels from the convolution layers of the (frozen) VGG object detection network, and separately train a classifier on the vector of activations to separate object boundaries from other edges. For semantic segmentation, it has also been proposed to additionally add skip connections from lower layers in the encoder part (before pooling) to corresponding decoder layers (after unpooling) so as to re-inject high-frequency image contours into the upsampling process (Dosovitskiy et al., 2015; Marmanis et al., 2016). This architecture has been simplified by the SEGNET model of Badrinarayanan et al. (2015): the fully connected layers are discarded, which drastically reduces the number of free parameters. Moreover, that architecture makes it possible to keep track of pixel indices during max-pooling and restore the values to the correct position during unpooling.

In the context of individual object detection it has also been proposed to train the encoder/detector part first, freeze it, and train the decoder part separately (Pinheiro et al., 2016). The DEEPLAB network of Chen et al. (2014) explores a different upsampling strategy: low-resolution output from the FCN is first upsampled bilinearly, then refined with a fully connected CRF (Krähenbühl and Koltun, 2011) whose pairwise potentials are modulated by colour differences in the original image. Later DEEPLAB was extended to simultaneously learn edge detection and semantic segmentation (Chen et al., 2015). This is perhaps the work most closely related to ours, motivated by the same intuition that there are synergies between the two tasks, because object boundaries often coincide with edges. Going even further, Dai et al. (2015) construct a joint network for detecting object instances, assigning them to a semantic class, and extracting a mask for each object – i.e., per-object class boundaries. The method is very efficient for

well-localized compact objects ("things"), since the object instances can be detected first so as to restrict subsequent processing to those regions of interest. On the other hand, it appears less applicable to remote sensing, where the scene is to a large extent composed of objects without a well-defined bounding box ("stuff").

Regarding applications in remote sensing, shallow neural networks were already used for semantic segmentation before the advent of deep learning, e.g. Bischof et al. (1992) use a classical multi-layer perceptron to predict the semantic class of a pixel from a small neighborhood window. Shallow architectures are still in use: Malmgren-Hansen et al. (2015) train a relatively shallow CNN with 3 convolution layer and 2 pooling layers to classify pixels in SAR images. Längkvist et al. (2016) make per-pixel predictions with shallow CNNs (where the convolution weights are found by clustering rather than end-to-end training) and smooth the results by averaging over independently generated super-pixels. The mentioned works predict individually for each pixel, on the contrary Mnih and Hinton (2010) have designed a shallow, fully connected network for patch-wise prediction of road pixels. An also relatively shallow FCN with 3 convolution layers and 1 pooling layer is used in (Saito et al., 2016).

In the last few years, different deep CNN variants have been proposed for semantic segmentation of remote sensing images. Paisitkriangkrai et al. (2015) learn three separate 6-layer CNNs that predict semantic labels for a single pixel from three different neighborhoods. The scores are averaged with those of a conventional random forest classifier trained on per-pixel features, and smoothed with a conditional random field. Marcu and Leordeanu (2016) design a network for patchwise 2-class prediction. It takes as input patches of two different sizes (to represent local and global context), passes them through separate deep convolutional architectures, and combines the results in three deep, fully connected layers to directly output 16×16 patches of pairwise labels.

More often, recent works adopt the FCN architecture. Overall, the results indicate that the empirical findings from computer vision largely translate to remote sensing images. Both our own work (Marmanis et al., 2016) and Sherrah (2016) advocate a two-stream architecture that learns separate convolution layers for the spectral information and the DSM channel, and recommend to start from pretrained networks for the spectral channels. Our work further supports the practice of training multiple copies of the same CNN architecture and averaging their results (Marmanis et al., 2016), and Sher-

rah (2016) reports that the a-trous convolution trick slightly mitigates the information loss due to pooling, at the cost of much larger  $(40\times)$  computation times. Mou and Zhu (2016) prefer to avoid upsampling altogether, and instead combine the coarser semantic segmentation with a super-pixel segmentation of the input image to restore accurate segmentation boundaries (but not small objects below the scale of the FCN output). Of course, such a strategy cannot be trained end-to-end and heavily depends on the success of the low-level super-pixel segmentation.

A formal comparison between per-pixel CNNs and FCNshas been carried out by Volpi and Tuia (2016). It shows advantages for FCN, but unfortunately both networks do not attain the state of the art, presumably because their encoder-decoder network lacks skip connections to support the upsampling steps, and has been trained from scratch, losing the benefit of large-scale pretraining. A similar comparison is reported in (Kampffmeyer et al., 2016), with a single upsampling layer, and also trained from scratch. Again the results stay below the state-of-the-art but favor FCN. Median-balancing of class frequencies is also tested, but seems to introduce a bias towards small classes. An interesting aspect of that paper is the quantification of the network's prediction uncertainty, based on the interpretation of drop-out as approximate Bayesian inference (Gal and Ghahramani, 2015). As expected, the uncertainty is highest near class-contours.

#### 3. The Model

In the following, we describe our network architecture for boundary-aware semantic segmentation in detail. Following our initial hypothesis, we include edge detection early in the process to support the subsequent semantic labeling. As further guiding principles, we stick to the deep learning paradigm and aim for models that can be learned end-to-end; we build on network designs, whose performance has been independently confirmed; and, where possible, we favor efficient, lean networks with comparatively few tunable weights as primary building blocks.

When designing image analysis pipelines there is invariably a trade-off between performance and usability, and DCNNs are no exception. One can get a respectable and useful result with a rather elegant and clean design, or push for maximum performance on the specific task, at the cost of a (often considerably) more complex and unwieldy model. In this work we explore both directions: on the one hand, our basic model is comparatively simple with  $8.8 \cdot 10^7$  free parameters (class boundaries & SEGNET single-scale), and can be trained with modest amounts of training data. On the other hand, we also explore the maximum performance our approach can achieve. Indeed, at the time of writing our high-end model, with multiscale processing and ensemble learning, achieves >90% overall accuracy on the ISPRS Vaihingen benchmark. But diminishing returns mean that this requires a more convoluted architecture with  $9 \times$  higher memory footprint and training time.

Since remote sensing images are too large to pass through a CNN, all described networks operate on tiles of  $256 \times 256$  pixels. We classify overlapping tiles with three different strides (150, 200, and 220 pixels) and average the results.

We start by introducing the blocks of our model, and then describe their integration and the associated technical details. Throughout, we refrain from repeating formal mathematical definitions for their own sake. Equation-level details can be found in the original publications. Moreover, we make our networks publicly available to ensure repeatability.

# 3.1. Building blocks

SEGNET encoder-decoder network

SEGNET (Badrinarayanan et al., 2015) is a crossbreed between a fully convolutional network (Long et al., 2015) and an encoder-decoder architecture. The input image is first passed through a sequence of convolutions, ReLU and max-pooling layers. During max-pooling, the network tracks the spatial location of the winning maximum value at every output pixel. The output of this encoding stage is a representation with reduced spatial resolution. That "bottleneck" forms the input to the decoding stage, which has the same layers as the encoder, but in reverse order. Max-pooling layers are replaced by unpooling, where the values are restored back to their original location, then convolution layes interpolate the higher-resolution image.

Since the network does not have any fully connected layers (which consume >90% of the parameters in a typical image processing CNN) it is much leaner. SEGNET is thus very memory-efficient and comparatively easy to train. We found, in agreement with its creators, that SEGNET on its own does not quite reach the performance of much heavier architectures with fully connected layers and learned upsampling. However, it turns out that in combination with learned class boundaries, SEGNET matches the more expensive competitors, see Section 4.

Our remote sensing variant consists of two segnet branches. One processes the colour channels and is initialised with the existing segnet. The other processes the height information (nDSM, DSM) and is initialised randomly. The outputs of the two streams are concatenated and transformed to class scores by a linear combination ( $1 \times 1$  convolution), followed by the usual softmax transformation.

Kokkinos (2016) reported significant quantitative improvements by an explicit multi-scale architecture, which passes down-scaled versions of the input image through identical copies of the network and fuses the results. Given the small size of SEGNET we have also experimented with that strategy, using three scales. We thus set up three copies of the described two-stream SEGNET with individual per-scale weights. Their final predictions, after fusing the image and height streams, are upsampled as needed with an fractional stride convolution layer and fused before the final prediction of the class scores. The multi-scale strategy only slightly improves the results by <0.5%, presumably because remote sensing images, taken in nadir direction from distant viewpoints, exhibit only little perspective effect and thus less scale variation (only due to actual scale variability in metric object coordinates). Still, the small improvement is consistent over all tiles of our validation set, hence we include the multi-scale option in the high-end variant of our system.

## HED boundary-detection network

We aim to include explicit boundary information in our processing, thus we require an edge detector that can be integrated into the labeling framework. In a nutshell, HED (Holistically-Nested Edge Detection) is an multiscale encoder-decoder CNN trained to output an image of edge likelihoods. An important feature of HED is that it uses multi-scale prediction in conjunction with deep-supervision (Lee et al., 2015). I.e., the (rectified) output of the last convolution before each pooling layer is read out of the network as prediction for that particular scale, and supervised during training by an additional (Euclidean distance) loss function. The multi-scale predictions are then combined into a final probability boundary map. Importantly, even though HED has no explicit mechanism to enforce closed contours, we find that by learning from global image context it does tend to generate closed contours, which is important to support our segmentation task.

For our purposes, we modify HED to better take into account the uncertainty of boundary annotations, by using a regression loss w.r.t. a continuous "boundary score" **y** rather than a hard classification loss. The intuition is

that the location of a class boundary has an inherent uncertainty. We therefore prefer to embrace and model the uncertainty, and predict the "likelihood" of the boundary being present at a certain pixel. The advantage is best explained by looking at pixels very close to the annotated boundary: using those pixels as negative (i.e., background) training samples will generate label noise; using them as positive samples contradicts the aim to predict precise boundary locations; and excluding them from the training altogether means depriving the network of training samples close to the boundary, where they matter most. For our task, the desired edges are the segment boundaries, i.e., the label transitions in the training data. To turn them into soft scores we dilate the binary boundary image with a diamond structuring element. The structuring element defines the width of the "uncertainty band" around an annotated boundary and depends on the ground sampling distance.

Then, we weight each class-boundary pixel according to its truncated Euclidean distance to the nearest background pixel, using the distance transform:  $Y = 5 \cdot \beta \cdot D_t^{\ell 2}(B_d)$ . The second factor  $\beta = \frac{|B_d=0|}{|B_d|}$  compensates the relative frequencies of boundary and background pixels, to avoid overfitting to the dominant background. The scaling is arbitrary. Importantly, the weights are normalized to the interval [0...1] to be consistent with the HED model. As above, we set up two separate streams for color images and for the height also during boundary detection. The image stream is initialized with the original HED weights, whereas the DEM stream is trained from scratch. For output (including side outputs) the two streams are fused by concatenation, convolution with a  $1 \times 1$  kernel and fractional convolution to the output resolution. A graphical overview of the boundary network is given in Figure 1, visual results of class-boundaries are shown in Figure 2.

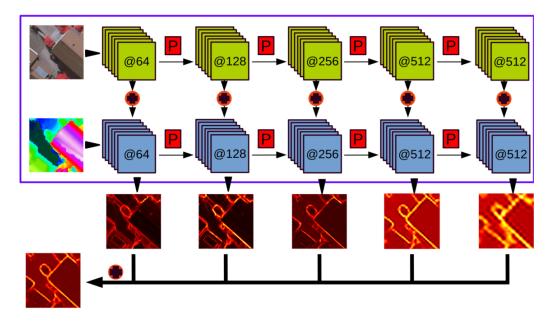


Figure 1: The Class-Boundary network. Color and height are processed in separate streams. Before each pooling level (red squares) the network outputs a set of scale-dependent class-boundaries, which are fused into the final multi-scale boundary prediction.

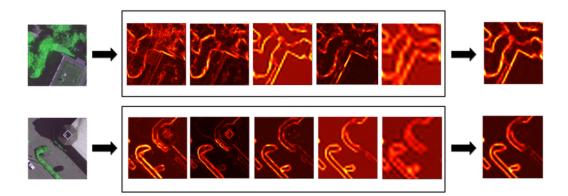


Figure 2: Examples of class boundary predictions. Left: input image. Middle: per-scale outputs. Right: estimated multi-scale boundary map.

DLR/ETH semantic segmentation network

From the literature (Simonyan and Zisserman, 2014) it is known that, also for strong classifiers like CNNs, ensemble averaging tends to improve classification results. For highest classification accuracy we thus experiment with an ensemble of multiple CNNs. To that end we use our previous DLR/ETH semantic segmentation network, which has already shown competitive performance for remote sensing problems (Marmanis et al., 2016).

Contrary to SEGNET this model is derived from the standard FCN and has fully connected layers (reordered into convolutions). It is thus heavier in terms of memory and training, but empirically improves the predictions, presumably because the network can learn extensive high-level, global object information. Compared to the original FCN (Long et al., 2015), our variant has additional skip connections to minimize information loss from downsampling. As above, it has separate streams for image and DEM data.

# 3.2. Integrated class boundary detection and segmentation

Our strategy to combine class boundary detection with semantic segmentation is straight-forward: boundary likelihoods are treated as an additional "channel". In the image stream, the input is the raw colour image; in the DSM stream it is a 2-channel image consisting of the raw DSM and the nDSM (generated by automatically filtering above-ground objects and subtracting the result from the DSM). In both cases, the input is first passed through the HED network, producing a scalar image of boundary likelihoods. That image is concatenated to the raw input as an additional channel to form the input for the corresponding stream of the semantic segmentation network (note, in CNN language this can be seen as a skip connection that bypasses the boundary detection layers). For SEGNET, a further skip connection bypasses most of the segmentation network and reinjects the colour image boundaries as an extra channel after merging the image and DSM streams, before the final label prediction. See Figure 3.

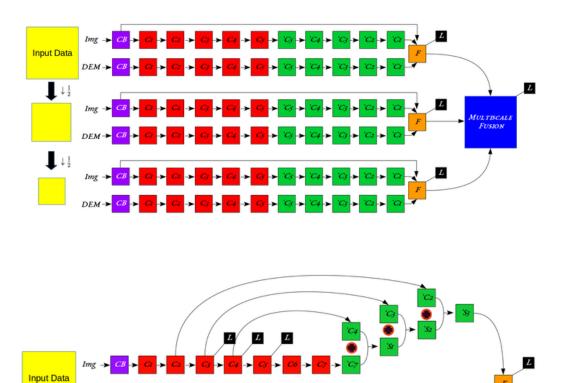


Figure 3: Semantic segmentation architectures tested in this work. Top: our multi-scale SEGNET architecture. Bottom: our FCN architecture (identical to our VGG except for initial weights). The boundary detection network is collapsed (violet box) for better readability. Encoder parts that reduce spatial resolution are marked in red, decoder parts that increase resolution are green. Orange denotes fusion by concatenation,  $(1 \times 1)$  convolution, and upsampling (as required).

The entire processing chain is trained end-to-end (see below for details), using boundaries as supervision signal for the HED layers and segmentations for the remaining network.

## 3.3. Ensemble learning

As discussed above, ensemble averaging typically improves DCNN predictions further. We thus also experiment with that strategy and combine the predictions of three different boundary-aware networks (given the effort to train deep networks, "ensembles" are typically small). In order to add two more high-quality models to the ensemble, we have trained two versions of the DLR/ETH network with integrated HED boundary detector, one initialised with the original FCN weights and the other initialised with VGG-16 weights.<sup>4</sup> In both cases, the DEM channel is again trained from random initialisations.

Ensemble predictions are made by simply averaging the outputs of the two DLR/ETH networks and SEGNET.<sup>5</sup> We note that the ensemble predictions give a significant performance boost, seemingly FCN and SEGNET are to some degree complementary. See Section 4. The two DLR/ETH models, each with >100 million parameters (see section 5), are memory-hungry and expensive to train, thus we do not generally recommend such a procedure, except when aiming for highest accuracy. Figure 4 depicts the complete ensemble.

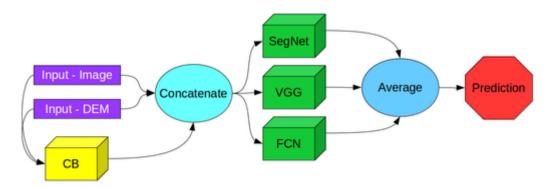


Figure 4: Ensemble prediction with SEGMENT, VGG and FCN. The CB component depicts the class-boundary network

# 3.4. Implementation details and training

The overall network with boundary detection is fairly deep, and the boundary and labelling parts use different target outputs and loss functions.

<sup>&</sup>lt;sup>4</sup>Their individual performance is comparable, with VGG-16 slightly better overall.

<sup>&</sup>lt;sup>5</sup>We did not experiment with trained fusion layers, since the complete ensemble is too large to fit into GPU memory.

We found that under these circumstances training must proceed in stages to achieve satisfactory performance, even if using pre-trained components. A conservative strategy gave the best results. First, we train the boundary detector separately, using HED weights to initialise the image stream and small random weights for the DSM stream. That step yields a single-scale DCNN boundary detector tailored to our aerial data. The actual segmentation network and loss is added only after this strong "initialisation" of the boundary detector. I.e., the boundary detector from the start delivers sensible results for training the semantic labeling component, and only needs to be fine-tuned to optimally interact with the subsequent layers. Moreover, the described two-stage training is carried out separately for each of the three scales. The separate single-scale segmentation networks are then combined into one multi-scale architecture and refined together. Empirically, separating the scales stabilizes the learning of the lower resolutions. When trained together immediately, they tend to converge to weak solutions and the overall result is dominated by the (still very competitive) highest resolution.

Normalization of gradients. Regarding the common problem of exploding or vanishing gradients during training, we stuck to the architectures recommended by the original authors, meaning that SEGNET does use batch normalization, while HED does not. A pragmatic solution is to use a large base learning rate appropriate for SEGNET and add layer-specific scale factors to decrease the learning rate in the HED layers. We also found that batch normalization in the final layers, after the SEGNET decoder phase, strongly sparsifies the feature maps. For our goal of dense per-pixel prediction this effect is detrimental, causing a  $\approx 1\%$  drop in labeling accuracy. We thus switch-off batch normalization for those layers.

Drop-out. The original SEGNET relies heavily on drop-out. The authors recommend to randomly drop 50% of the trainable decoder weights in each iteration. We found this drastic regularization to negatively affect our results, thus we decrease it to 20% for the highest resolution, respectively 10% for the two lower ones. Further research is needed to understand this big difference. We suspect that it might have to do with the different image statistics. In close-range images, each object normally covers a large image area, thus both image intensities and semantic labels are strongly correlated over fairly large regions. In remote sensing data, with its many small objects, nearby activations might not be able to "stand in" as easily for a dropped connection, especially in the early layers of the decoder.

Data Augmentation. DCNNs need large amounts of training data, which are not always available. It is standard practice to artificially increase the amount and variation of training data by randomly applying plausible transformations to the inputs. Synthetic data augmentation is particularly relevant for remote sensing data to avoid over-fitting: in a typical mapping project the training data comes in the form of a few spatially contiguous regions that have been annotated, not as individual pixels randomly scattered across the region of interest. This means that the network is prone to learn local biases like the size of houses or the orientation of the road network particular to the training region. Random transformations – in the example, scaling and rotation – will prevent such over-fitting.

In our experiments we used the following transformations for data augmentation, randomly sampled per mini-batch of the stochastic gradient descent (SGD) optimisation: scaling in the range  $[1 \dots 1.2]$ , rotation by  $[0^{\circ} \dots 15^{\circ}]$  degrees, linear shear with  $[0^{\circ} \dots 8^{\circ}]$ , translation by  $[-5 \dots 5]$  pixels, and random vertical as well as horizontal reflection.

# 4. Experiment Results

## 4.1. Dataset

We conduct experimental evaluations on the ISPRS Vaihingen 2D semantic labeling challenge. This is an open benchmark dataset provided online  $^6$ . The dataset consists of a color infrared orthophoto, a DSM generated by dense image matching, and manually annotated ground truth labels. Additionally, a nDSM has been released by one of the organizers (Gerke, 2014). It was generated by automatically filtering the DSM to a DTM and subtracting the two. Overall, there are 33 tiles of  $\approx 2500 \times 2000$  pixels at a GSD of  $\approx 9 \text{cm}$  GSD. 16 tiles are available for training and validation, the remaining 17 are withheld by the challenge organizers for testing. We thus remove 4 tiles (image numbers 5, 7, 23, 30) from the training set and use them as validation set for our experiments. All results refer to that validation set, unless noted otherwise.

 $<sup>^6 \</sup>rm{http://www2.isprs.org/commissions/comm3/wg4/2d-sem-label-vaihingen.html}$ 

Training details and parameters

As described above, each labeling and boundary detection network was first trained individually to convergence, then the pretrained pieces were assembled in a plug-and-play fashion and fine-tuned by further iterations of end-to-end training. For a tally of the unknown weights, see Table 2.

For the individual network parts, we always start from a quite high learning rate ( $lr=10^{-8}$ ) and decrease it by a factor  $\times 10$  every 12000 iterations. The total of number of iterations was 100000. The SEGNET part was trained with batch size 2, the HED boundary detector with batch size 5.

The complete, assembled boundary+segmentation model was trained for 30000 iterations, starting with a a smaller learning rate  $(lr=10^{-12})$ . Batch size had to be reduced to 1 to stay within the memory capacity of an Nvidia Titan-X GPU.

The remaining hyper-parameters were set to momentum = 0.9 and weight-decay = 0.00015, for all models.

Table 2: Sizes of model components in terms of trainable parameters. All models are dimensioned to fit on a single Nvidia Titan-X GPU (except for the ensemble, for which averaging is done on the CPU).

Class-Boundaries & SegNet-sc1	$88 \cdot 10^{6}$
Class-Boundaries & SegNet-Msc	$206 \cdot 10^6$
Class-Boundaries & FCN	$300 \cdot 10^6$
Class-Boundaries & VGG	$300 \cdot 10^6$
Class-Boundaries & Ensemble	$806 \cdot 10^{6}$

## 4.2. Results

We evaluate the different components of our model by gradually adding components. We start from the basic SEGNET, augment it with class boundaries, then with multi-scale processing. Finally, we include it in a DCNN ensemble. We will not separately discuss post-processing of the outputs with explicit smoothness or context models like CRFs. In our tests, post-processing with a fully connected CRF, as for example in (Chen et al., 2016; Marmanis et al., 2016), did not improve the results – if anything, it degraded the performance on small objects, especially the *car* class. For completeness, results of our networks with and without smoothing are available on the Vaihingen benchmark site. We conclude that our DCNNs already capture the

context in large context windows. Indeed, this is in our view a main reason for their excellent performance.

## Basic CNN Results

The basic single-scale SEGNET reaches 84.79% overall accuracy (SegNet-sc1) over the validation set. This is in line with other researchers' findings on the Vaihingen benchmark: straight-forward adaptations of state-of-the-art DCNN models from the computer vision literature typically reach around 85%. Our network performs particularly well on impervious ground and buildings, whereas it is challenged by low vegetation, which is frequently confused with the tree class. See Table 3.

For comparison, we also run our earlier DLR/ETH model Marmanis et al. (2016), which is a combination of the FCN and VGG models that we will later also use in our ensemble, without explicit class-boundary detection. That model performs comparably, with 85.5% overall accuracy. Interestingly, it is significantly better at classifying low vegetation, and also beats SEGNET on impervious surfaces and trees. On the contrary, it delivers clearly worse segmentations of buildings.

## Effect of Class-Boundaries

We now go on to evaluate the main claim of our paper, that explicit class boundary detection within the network improves segmentation performance. Adding the HED boundary network to SEGNET reaches 89.84% overall accuracy (*CB-SegNet-sc1*), a gain of more than 5 percent points, see Table 3.

The per-class results in Table 3 reveal that class boundaries significantly boost the performance of SEGNET for all target classes, including the vegetation classes that do not have sharp, unambiguous boundaries. We suspect that in vegetation areas, where matching-based DSMs are particularly inaccurate, even imprecise boundaries can play a noticeable role in delimiting high from low vegetation. Moreover, one might speculate that boundaries derived from semantic segmentation maps carry information about the extend and discontinuities at object level, and can to some degree mitigate a main limitation of SEGNET, namely the lack of fully connected layers that could extract long-range, global context. It is however an open, and rather far-reaching, question to what extent locally derived object boundary information can substitute more global semantic context.

For FCN-VGG ensemble, we observe a similar, albeit weaker effect. Overall accuracy increases by 3 percent points to 88.84% (CB-FCN-VGG). There

are however losses for the *car* and *low vegetation* classes, whereas the gains are due to better segmentation of buildings and trees.

As a side note, we found that the accuracy of the ground truth is noticeably lower for the vegetation classes as well as the cars. This can in part be explained by inherent definition uncertainty, especially in the case of vegetation boundaries. Still, we claim that the upper performance bound for automatic segmentation methods is probably well below 100% for Vaihingen, due to uncertainty and biases of the ground truth of both the training and test set. See also Section 4.4.

Table 3: Adding an explicit class-boundary model improves semantic segmentation, for both tested CNN architectures. The abbreviations CB and sc1 imply use of class-boundaries and single-scale model respectively. See text for details.

	Imp. Surf.	Building	Low Veg.	Tree	Car	OA
SegNet-sc1	87.50 %	93.75 %	59.00 %	79.00 %	63.00 %	84.79 %
CB-SegNet-sc1	91.25 %	95.50 %	70.75 %	92.25 %	69.00 %	89.84 %
FCN-VGG	89.25 %	87.50 %	77.25 %	88.75 %	68.25 %	85.80 %
CB-FCN-VGG	89.25 %	93.50 %	73.00 %	90.75 %	62.00 %	88.84 %

## Effect of Multi-scale CNN

Next, we test what can be gained by explicit multi-scale processing. This is inspired by Kokkinos (2016), who show significant improvements with multi-scale processing. Our implementation uses exactly the same architecture, with three streams that independently process inputs of different scale and fuse the results within the network.

We run this option only for SEGNET. The DLR/ETH network has multiple fully connected layers and should therefore be able to capture context globally over the entire input region, thus we do not expect an explicit multi-scale version to improve the results. Moreover, it is too large to fit multiple copies of the network into GPU memory.

Empirically, multi-scale processing did not improve the results to the same extent as in (Kokkinos, 2016). We only gain 0.2 percent points, see Table 4. Apparently, the single-scale network already captures the relevant information. We suspect that the gains from an explicit multi-scale architecture are largely achieved by better covering large scale variations due to different

perspective effects and camera viewpoints. In nadir-looking remote sensing images such effects are absent and scale variations occur only due to actual size variations in object space, which seem to be adequately captured by the simpler network. Nevertheless, since the gains are quite consistent across different validation images, we keep the multi-scale option included for the remaining tests. We note though, this triples the memory consumption and is therefore not generally recommended.

Table 4: Multi-scale processing and ensemble learning. The results on the validation set confirm that gains are mostly due to the class contour detection, whereas multi-scale processing and ensemble prediction only slightly improve the results further. See text for details.

Scene	CB-Ensemble	CB-SegNet-Msc	CB-SegNet-sc1	SegNet-sc1	CB-VGG-FCN	$VGG ext{-}FCN$
Image 5	91.52 %	91.29 %	91.10 %	86.22 %	90.35 %	86.33~%
Image 7	89.23 %	89.61 %	89.64 %	84.17 %	89.05 %	87.10 %
Image 23	91.96 %	90.75 %	90.21 %	85.59 %	89.25 %	83.65 %
Image 30	88.66 %	88.47 %	88.42 %	83.19 %	86.71 %	86.12~%
OA	90.34 %	90.03 %	89.84 %	84.79 %	88.84 %	85.80 %

## Effect of the Ensemble

Several works have confirmed that also for DCNN models ensemble learning is beneficial to reduce individual model biases. We have also observed this effect in earlier work and thus test what can be gained by combining several *boundary-aware* segmentation networks.

We run the three introduced networks, SEGNET, FCN and VGG all with an integrated HED boundary detector, and average their predictions.

The ensemble beats both the stand-alone SEGNET model and the two-model ensemble of (boundary-enhanced) DLR/ETH, see Table 4. The advantage over SEGNET is marginal, whereas a clear improvement can be observed over DLR/ETH. In other words, SEGNET alone stays behind its VGG and FCN counterparts, but when augmented with class-boundaries it outperforms them, and reaches almost the performance of the full ensemble. It seems that for the lighter and less global SEGNET model the boundary information is particularly helpful.

We point out that, by-and-large, the quantitative behavior is consistent across the four individual tiles of the validation set. In all four cases, CB-VGG-FCN clearly beats plain VGG-FCN, and similarly CB-SegNet-sc1

comprehensively beats SegNet-sc1. Regarding multi-scale processing, CB-SegNet-Msc wins over CB-SegNet-sc1 except for one case (image 7), where the difference are a barely noticeable 0.03 percent points (ca. 1500 pixels /  $12 \text{ m}^2$ ). Ensemble averaging again help for the other three test tiles, with an average gain of 0.21 percent points, while for image 7 the ensemble prediction is better than CB-VGG-FCN but does not quite reach the SEGNET performance. A further analysis of the results is left for future work, but will probably require a larger test set.

# Effects of nDSM Errors

On the official Vaihingen test set the performance of our ensemble drops to 89.4%, see below. We visually checked the results and found a number of regions with large, uncharacteristic prediction errors. It turns out that there are gross errors in the test set that pose an additional, presumably unintended, difficulty. In the nDSM of Gerke (2014), a number of large industrial buildings are missing, since the "ground" surface follows their roofs, most likely due to incorrect filtering parameters. The affected buildings cover a significant area: 3.1% (154'752 pixels) of image 12, 9.3% (471'686 pixels) of image 31, and 10.0% (403'818 pixels) of image 33.

By itself this systematic error could be regarded as a recurring deficiency of automatically found nDTMs, which should be handled by the semantic segmentation. But unfortunately, they only occur in the test set, while in the training set no comparable situations exist. It is thus impossible for a machine learning model to learn how to handle them correctly.

To get an unbiased result we thus manually corrected the nDTMs of the four affected buildings. We then reran the testing, without altering the trained model in any way, and obtained an overall accuracy of 90.3%, almost perfectly in line with the one on our validation set, and 0.9 percent points up from the biased result.

In the following evaluation we thus quote both numbers. We regard the 90.3% as our "true" performance on a test set whose properties are adequately represented in the training data. Since competing methods did however, to our knowledge, not use the corrected test set, they should be compared to the 89.4% achieved with the biased nDSM. We note however that the discovered errors are significant in the context of the benchmark: the bias of almost 1 percent point is larger than the typical differences between recent competing methods.

# 4.3. Comparison to State-of-the-art

Our proposed class-contour ensemble model is among the top performers on the official benchmark test set, reaching 89.4% overall accuracy, respectively 90.3% with the correct nDSM. The strongest competitors are INRIA (89.5%, Maggiori et al., 2016), using a variant of FCN, and ONERA (89.8%, Audebert et al., 2016), with a variant of SEGNET. Importantly, we achieve above 90% accuracy over man-made classes, which are the most well-defined ones, where accurate segmentation boundaries matter most, see Table 5.

Detailed, results over the performance of the top-ranking models over the ISPRS benchmark are given in Table 6. Overall, the performance of different models is very similar, which may not be all that surprising, since the top performers are in fact all variants of FCN or SEGNET. We note our model and INRIA are the most "puristic" ones, in that they do not use any hand-engineered image features. ONERA uses the NDVI as additional input channel; DST seemingly includes a random forest in its ensemble, whose input features include the NDVI (Normalized Vegetation Index) as well as statistics over the DSM normals. It appears that the additional features enable a similar performance boost as our class boundaries, although it is at this point unclear whether they encode the same information. Interestingly, our model scores rather well on the car class, although we do not use any stratified sampling to boost rare classes. We believe that this is in part a consequence of not smoothing the label probabilities.

One can also see that after correcting the nDSM for large errors, our performance is 0.9 percent point above the closest competitor for impervious surfaces, while it is also 0.5 percent ahead for buildings. The bias in the test data thus seems to affect all models. Somewhat surprisingly, our scores on the vegetation classes are also on par with the competitors, although intuitively contours cannot contribute as much for those classes, because their boundaries are not well-defined. Still, they significantly improve the segmentation of vegetation classes, c.f. 3. Empirically, the multi-scale class-boundaries information boosts segmentation of the *tree* and *low vegetation* classes to a level reached by models that use a dedicated NDVI channel. A closer look at the underlying mechanisms is left for future work.

## 4.4. A word on data quality

In our experiments, we repeatedly noticed inaccuracies of the ground truth data (similar observations were made by Paisitkriangkrai et al. (2015)). Obviously, a certain degree of uncertainty is unavoidable when annotating

Table 5: Confusion matrix of our best result on the private Vaihingen test set.

	Impervious	Building	Low-Vegetation	Tree	Car
Impervious	93.2 %	2.2 %	3.6 %	0.9 %	0.1 %
Building	2.8 %	95.3~%	1.6 %	0.3 %	0.0 %
Low-Vegetation	3.7 %	1.4 %	82.5 %	12.5 %	0.0 %
Tree	0.7 %	0.2 %	6.9 %	92.3%	0.0 %
Car	19.5 %	7.0 %	0.5 %	0.4 %	72.60~%
Precision	91.6~%	95.0 %	85.5 %	87.5 %	92.1 %
Recall	93.2 %	95.3 %	82.5 %	92.3%	72.6 %
F1-score	92.4 %	95.2 %	83.9 %	89.9 %	81.2 %

Table 6: Per-class  $F_1$ -scores and overall accuracies of top performers on the Vaihingen benchmark (numbers copied from benchmark website). DLR\_7 is our ensemble model, DLR\_9 is our ensemble with corrected nDSM.

	Impervious	Building	Low-Vegetation	Tree	Car	OA
DST_2	90.5 %	93.7 %	83.4 %	89.2 %	72.6~%	89.1 %
INR	91.1 %	94.7 %	83.4 %	89.3 %	71.2~%	89.5 %
ONE_6	91.5 %	94.3 %	82.7 %	89.3 %	85.7 %	89.4 %
ONE_7	91.0 %	94.5 %	84.4 %	89.9 %	77.8 %	89.8 %
DLR <sub>-</sub> 7	91.4 %	93.8 %	83.0 %	89.3 %	82.1 %	89.4 %
DLR_9	92.4 %	95.2 %	83.9 %	89.9 %	81.2 %	90.3 %

data, in particular in remote sensing images with their small objects and many boundaries. We thus decided to re-annotate one image (image-23) from our validation set with great care, to assess the "inherent" labeling accuracy. We did this only for the two easiest classes buildings and cars, since the remaining classes have significant definition uncertainty and we could not ensure to use exactly the same definitions as the original annotators.

We then evaluate the new annotation, the ground truth from the benchmark, and the output of our best model, against each other. Results are shown in Table 8. One can see significant differences, especially for the cars which are small and have a large fraction of pixels near the boundary. Considering the saturating progress on the benchmark – differences between recent submissions are generally < 2% – there is a very real danger that annotation errors influence the results and conclusions. It may be surprising, but the

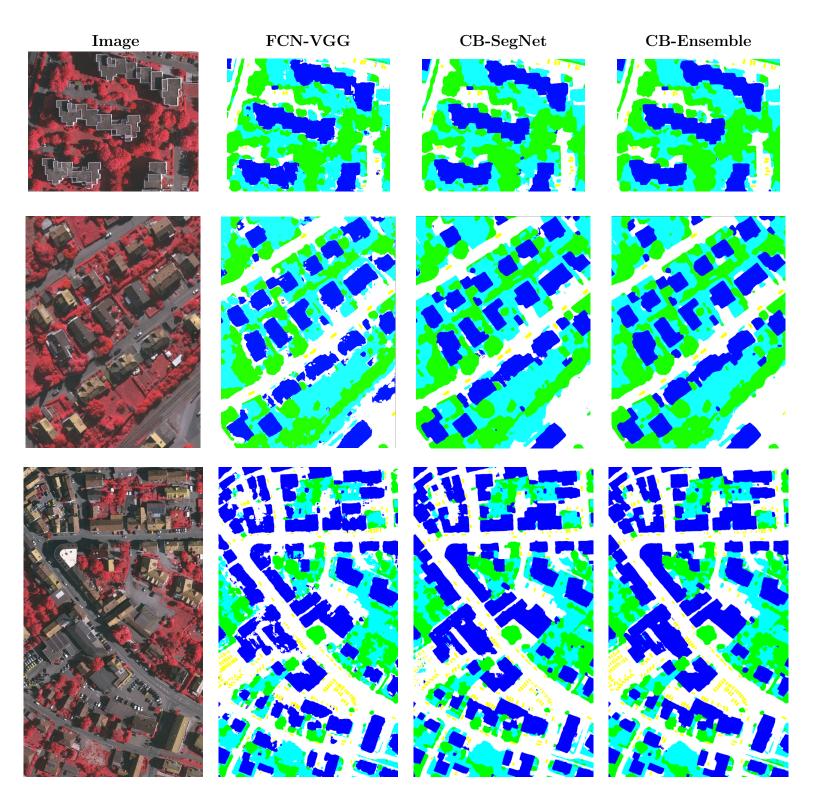


Table 7: Visual examples of predictions on the official ISPRS tes-set. The results of FCN-VGG, CB-SegNet, CB-Ensemble associate to our online official submissions, namely  $DLR_{-}1$ ,  $DLR_{-}5$  and  $DLR_{-}7$  respectively. Legend-colors, **White**: Impervious Surfaces, **Blue**: Buildings, **Cyan**: Low-Vegetation,

Green: Trees, Yellow: Cars

Vaihingen dataset appears to be reaching its limits after barely 3 years of activity. This is a very positive and tangible sign of progress and a strong argument in favor of public benchmarks. But it is also a message to the community: if we want to continue using benchmarks – which we should – then we have to make the effort and extend/renew them every few years. Ideally, it may be better to move to a new dataset altogether, to avoid overfitting and ensure state-of-the-art sensor quality.

	CB-SegNet-sc1-sc2-sc3		Full-l	ISPRS Label	
	IPSRS Label	Delineated Label	IPSRS Label	Delineated Label	Delineated Label
Building	97 %	98 %	98 %	98 %	98 %
Car	82 %	88 %	80 %	83 %	93 %

Table 8: Inter-comparison between ISPRS Vaihingen ground truth, our own annotation, and our best model. Significant differences occur, suggesting that the benchmark may have to be re-annotated or replaced. See text for details.

#### 5. Conclusion

We have developed DCNN models for semantic segmentation of highresolution aerial images, which explicitly represent and extract the boundaries between regions of different semantic classes. Empirically, including class boundaries significantly improves different DCNN architectures, and was the single most important performance boost in our final model, which achieves excellent performance on the ISPRS Vaihingen benchmark.

Moreover, we have presented an extensive study of semantic segmentation architectures, including presence or absence of fully connected layers, use of class boundaries, multi-scale processing, and multi-network ensembles.

One aspect that were have not yet investigated, but that might be needed to fully exploit the information in the segmentation boundaries, are class-specific boundaries. Our current boundaries are class-agnostic, they do not know which classes they actually separate. It appears that this information could be preserved and used. Pushing this idea to its extremes, it would in fact be enough to detect *only* the class boundaries, if one can ensure that they form closed regions.

Although DCNNs are the state-of-the-art tool for semantic segmentation, they have reached a certain degree of saturation, and further improvements of segmentation quality will probably be small, tedious, and increasingly problem-specific. Nevertheless, there are several promising directions for future research. We feel that model size is becoming an issue. Given the excessive size and complexity of all the best-performing DCNN models, an interesting option would be to develop methods for compressing large, deep models into smaller, more compact ones for further processing. First ideas in this direction have been brought up by Hinton et al. (2015).

## References

#### References

- Audebert, N., Saux, B. L., Lefèvre, S., 2016. Semantic segmentation of earth observation data using multimodal and multi-scale deep networks. arXiv preprint arXiv:1609.06846.
- Badrinarayanan, V., Kendall, A., Cipolla, R., 2015. Segnet: A deep convolutional encoder-decoder architecture for image segmentation. arXiv preprint arXiv:1511.00561.
- Barnsley, M. J., Barr, S. L., 1996. Inferring urban land use from satellite sensor images using kernel-based spatial reclassification. Photogrammetriv Engineering and Remote Sensing 62 (8), 949–958.
- Bertasius, G., Shi, J., Torresani, L., 2015. High-for-low and low-for-high: Efficient boundary detection from deep object features and its applications to high-level vision. In: Proceedings of the IEEE International Conference on Computer Vision. pp. 504–512.
- Bischof, H., Schneider, W., Pinz, A. J., 1992. Multispectral classification of landsat-images using neural networks. IEEE Transactions on Geoscience and Remote Sensing 30 (3), 482–490.
- Chen, L.-C., Barron, J. T., Papandreou, G., Murphy, K., Yuille, A. L., 2015. Semantic image segmentation with task-specific edge detection using cnns and a discriminatively trained domain transform. arXiv preprint arXiv:1511.03328.
- Chen, L.-C., Papandreou, G., Kokkinos, I., Murphy, K., Yuille, A. L., 2014. Semantic image segmentation with deep convolutional nets and fully connected crfs. arXiv preprint arXiv:1412.7062.

- Chen, L.-C., Papandreou, G., Kokkinos, I., Murphy, K., Yuille, A. L., 2016. DeepLab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected CRFs. CoRR abs/1606.00915. URL http://arxiv.org/abs/1606.00915
- Dai, J., He, K., Sun, J., 2015. Instance-aware semantic segmentation via multi-task network cascades. arXiv preprint arXiv:1512.04412.
- Dalla Mura, M., Benediktsson, J. A., Waske, B., Bruzzone, L., 2010. Morphological attribute profiles for the analysis of very high resolution images. IEEE Transactions on Geoscience and Remote Sensing 48 (10), 3747–3762.
- Dosovitskiy, A., Fischer, P., Ilg, E., Häusser, P., Hazırbaş, C., Golkov, V., v.d. Smagt, P., Cremers, D., Brox, T., 2015. FlowNet: Learning optical flow with convolutional networks. In: IEEE International Conference on Computer Vision (ICCV).
- Farabet, C., Couprie, C., Najman, L., LeCun, Y., 2013. Learning hierarchical features for scene labeling. IEEE transactions on pattern analysis and machine intelligence 35 (8), 1915–1929.
- Franklin, S. E., McDermid, G. J., 1993. Empirical relations between digital SPOT HRV and CASI spectral resonse and lodgepole pine (pinus contorta) forest stand parameters. International Journal of Remote Sensing 14 (12), 2331–2348.
- Fu, K. S., Landgrebe, D. A., Phillips, T. L., 1969. Information processing of remotely sensed agricultural data. Proceedings of the IEEE 57 (4), 639–653.
- Gal, Y., Ghahramani, Z., 2015. Dropout as a bayesian approximation: Representing model uncertainty in deep learning. arXiv preprint arXiv:1506.02142.
- Gerke, M., 2014. Use of the stair vision library within the isprs 2d semantic labeling benchmark (vaihingen). Tech. rep., ITC, University of Twente.
- Grangier, D., Bottou, L., Collobert, R., 2009. Deep convolutional networks for scene parsing. In: ICML 2009 Deep Learning Workshop. Vol. 3. Citeseer.

- Hinton, G., Vinyals, O., Dean, J., 2015. Distilling the knowledge in a neural network. arXiv preprint arXiv:1503.02531.
- Kampffmeyer, M., Salberg, A.-B., Jenssen, R., 2016. Semantic segmentation of small objects and modeling of uncertainty in urban remote sensing images using deep convolutional neural networks. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops. pp. 1–9.
- Kokkinos, I., 2016. Pushing the boundaries of boundary detection using deep learning. In: International Conference on Learning Representations (ICLR).
- Krähenbühl, P., Koltun, V., 2011. Efficient inference in fully connected crfs with gaussian edge potentials. In: Advances in Neural Information Processing Systems.
- Längkvist, M., Kiselev, A., Alirezaie, M., Loutfi, A., 2016. Classification and segmentation of satellite orthoimagery using convolutional neural networks. Remote Sensing 8 (4), 329.
- Lee, C.-Y., Xie, S., Gallagher, P., Zhang, Z., Tu, Z., 2015. Deeply-supervised nets. In: AISTATS.
- Long, J., Shelhamer, E., Darrell, T., 2015. Fully convolutional networks for semantic segmentation. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. pp. 3431–3440.
- Maggiori, E., Tarabalka, Y., Charpiat, G., Alliez, P., 2016. High-resolution semantic labeling with convolutional neural networks. arXiv preprint arXiv:1611.01962.
- Malmgren-Hansen, D., Nobel-J, M., et al., 2015. Convolutional neural networks for sar image segmentation. In: 2015 IEEE International Symposium on Signal Processing and Information Technology (ISSPIT). IEEE, pp. 231–236.
- Marcu, A., Leordeanu, M., 2016. Dual local-global contextual pathways for recognition in aerial imagery. arXiv preprint arXiv:1605.05462.

- Marmanis, D., Wegner, J., Galliani, S., Schindler, K., Datcu, M., Stilla, U., 2016. Semantic segmentation of aerial images with an ensemble of cnns. IS-PRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences, 473–480.
- Mayer, H., Hinz, S., Bacher, U., Baltsavias, E., 2006. A test of automatic road extraction approaches. ISPRS Annals 36 (3), 209–214.
- Mnih, V., Hinton, G. E., 2010. Learning to detect roads in high-resolution aerial images. In: European Conference on Computer Vision. Springer, pp. 210–223.
- Mou, L., Zhu, X., 2016. Spatiotemporal scene interpretation of space videos via deep neural network and tracklet analysis. In: 2016 IEEE International Geoscience and Remote Sensing Symposium (IGARSS). IEEE, pp. 4959–4962.
- Noh, H., Hong, S., Han, B., 2015. Learning deconvolution network for semantic segmentation. In: Proceedings of the IEEE International Conference on Computer Vision. pp. 1520–1528.
- Paisitkriangkrai, S., Sherrah, J., Janney, P., Hengel, V.-D., et al., 2015. Effective semantic pixel labelling with convolutional networks and conditional random fields. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops. pp. 36–43.
- Pinheiro, P. H., Collobert, R., 2014. Recurrent convolutional neural networks for scene labeling. In: ICML. pp. 82–90.
- Pinheiro, P. O., Lin, T.-Y., Collobert, R., Dollár, P., 2016. Learning to refine object segments. arXiv preprint arXiv:1603.08695.
- Richards, J. A., 2013. Remote sensing digital image analysis. Springer.
- Saito, S., Yamashita, T., Aoki, Y., 2016. Multiple object extraction from aerial imagery with convolutional neural networks. Electronic Imaging 2016 (10), 1–9.
- Sherrah, J., 2016. Fully convolutional networks for dense semantic labelling of high-resolution aerial imagery. arXiv preprint arXiv:1606.02585.

- Simonyan, K., Zisserman, A., 2014. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556.
- Socher, R., Huval, B., Bhat, B., Manning, C. D., Ng, A. Y., 2012. Convolutional-recursive deep learning for 3d object classification. In: Advances in Neural Information Processing Systems 25.
- Szeliski, R., 2010. Computer vision: algorithms and applications. Springer.
- Tokarczyk, P., Wegner, J. D., Walk, S., Schindler, K., 2015. Features, color spaces, and boosting: New insights on semantic classification of remote sensing images. IEEE Transactions on Geoscience and Remote Sensing 53 (1), 280–295.
- Volpi, M., Tuia, D., 2016. Dense semantic labeling of sub-decimeter resolution images with convolutional neural networks. arXiv preprint arXiv:1608.00775.
- Xie, S., Tu, Z., 2015. Holistically-nested edge detection. In: Proceedings of the IEEE International Conference on Computer Vision. pp. 1395–1403.
- Yang, J., Price, B., Cohen, S., Lee, H., Yang, M.-H., 2016. Object contour detection with a fully convolutional encoder-decoder network. arXiv preprint arXiv:1603.04530.
- Yu, F., Koltun, V., 2016. Multi-scale context aggregation by dilated convolutions. In: International Conference on Learning Representations (ICLR).
- Zeiler, M. D., Fergus, R., 2014. Visualizing and understanding convolutional networks. In: European Conference on Computer Vision. Springer, pp. 818–833.