# **Robust Semantic Segmentation with Ladder-DenseNet Models**

Ivan Krešo Marin Oršić Petra Bevandić Siniša Šegvić Faculty of Electrical Engineering and Computing University of Zagreb, Croatia

name.surname@fer.hr

### Abstract

We present semantic segmentation experiments with a model capable to perform predictions on four benchmark datasets: Cityscapes, ScanNet, WildDash and KITTI. We employ a ladder-style convolutional architecture featuring a modified DenseNet-169 model in the downsampling datapath, and only one convolution in each stage of the upsampling datapath. Due to limited computing resources, we perform the training only on Cityscapes Fine train+val, ScanNet train, WildDash val and KITTI train. We evaluate the trained model on the test subsets of the four benchmarks in concordance with the guidelines of the Robust Vision Challenge ROB 2018. The performed experiments reveal several interesting findings which we describe and discuss.

## 1. Introduction

Semantic image segmentation provides rich information on surrounding environment, which presents clear application potential in many domains. However, there are challenges which are still to be solved before this exciting technique becomes ready for the real world.

Firstly, assessing the prediction uncertainty is necessary if we wish to be able to warn downstream processing elements when model predictions are likely to be wrong. Half of the solution consists in detecting image regions which are completely different from the training images and therefore fall in the category of out-of-distribution examples [4]. The other half of the solution is to detect regions which are poorly learned or inherently hard to classify [6], that is to recognize parts of the scene where our models consistently fail to produce correct results.

Furthermore, there is little previous research on semantic segmentation models which are suitable for recognizing different kinds of environments in images with no photographer bias. Before performing experiments presented in this report we did not know whether such models could be trained without one domain knowledge interfering with another. We also did not know how much capacity is required in order to produce state of the art predictions in different scenarios.

The Robust Vision Challenge provides a good testbed to address these questions. Diversity of the included datasets poses challenges to models which may be biased towards a single dataset while not generalizing well on others. Simultaneous training on diverse datasets provides an opportunity to learn representations which produce good and robust results in a multitude of environments.

This report presents main findings gathered while participating in the ROB 2018 challenge. We describe the employed model [8], detail the training procedure and present main insights obtained during our experiments.

## 2. Datasets

We train our common model on the following four training subsets: Cityscapes Fine train+val, WildDash, KITTI train and ScanNet train. Due to limited computing resources and limited time we chose to leave other prospective datasets for future work. Thus, we did not train on Berkeley Deep Drive, Vistas and Cityscapes coarse, although we did initialize our training with parameters learned on ImageNet [11]. The rest of this section provides a brief overview of each of the four training datasets.

## 2.1. Cityscapes

The Cityscapes dataset [1] contains images from the driver's perspective acquired in cities from Germany and neighbouring countries. The dataset provides 2MPx images split into train, val and test subsets, where the semantic labels for the test subset are not publicly available. There are 19 label classes used for evaluation which we train upon. Train and val subsets consist of 2975 and 500 finely annotated images, respectively. The dataset also provides 20 000 coarsely annotated images which we do not use in any of our experiments.

## 2.2. WildDash

The WildDash dataset contains a small selection of worldwide driving images with a strong potential to present difficulties for recognition algorithms. The dataset contains 70 validation and 156 testing images which are grouped into ten specific hazardous scenarios such as blur, wind-screen interference, lens distortion etc. The image resolution is 1920x1080px while the semantic annotations follow the Cityscapes labeling policy. As in other datasets, the test labels are not publicly available.

This dataset is unique since the test subset contains a number of heavily distorted and out-of-distribution images whose correct pixel-level predictions may either be the exact class or the class "Void" (both cases are counted as true positives). The negative images must be treated in the same way as the rest of the dataset, which suggests that aspiring models should include a method for detecting out-ofdistribution patches in input images.

Due to some labeling inconsistencies (e.g. terrain vs vegetation and car vs truck) we follow the ROB practice and evaluate WildDash performance with the category iIoU metric.

## 2.3. KITTI

The KITTI dataset [3] has been collected in Karlsruhe, Germany while driving through the city itself and the surrounding area. It provides 200 images for training and 200 images for testing at 1242x370px. The dataset uses the Cityscapes labeling policy, same as the previous three driving datasets.

#### 2.4. ScanNet

The ScanNet dataset [2] is the only indoor dataset used. It is by far the largest dataset of the four, consisting of nearly 25 000 training and 962 test images. This introduces a large distribution disbalance between indoor and driving labels which needs to be suitably handled. There are 20 semantic classes common to indoor scenery. The image resolution varies, while most images have  $1296 \times 968$  px.

### 3. Method

We use a custom fully convolutional model based on DenseNet-169 [5]. The model features a ladder-style upsampling path [12, 10, 9, 8] which blends high quality semantics of the deep layers with fine spatial detail of the early layers. The model produces logits at  $4 \times$  subsampled resolution which we upsample to the input resolution with bilinear interpolation, and feed to the usual cross-entropy loss with respect to one-hot groundtruth labels.

The main differences with respect to our previous work [8] are as follows. First, we have replaced all concatenations in the upsampling path with summations. This increased

the efficiency of our upsampling path without losing any IoU accuracy in validation experiments. Following that, we have increased the number of convolution filters in the upsampling path from 128 to 256 because we assumed that 128 feature maps could lead to underfitting while training on all four ROB 2018 datasets. Second, we replace the context layer at the end of the downsampling path with a spatial pyramid pooling block very similar to [13]. Third, we remove the auxiliary loss at the end of the downsampling path and replace it with a novel auxiliary loss which we call the pyramid loss. The components of the new loss are defined in terms of softmax predictions obtained from representations obtained right after feature blending units within the upsampling path at  $64 \times$ ,  $32 \times$ ,  $16 \times$  and  $8 \times$  subsampled resolution. We do not upsample these auxiliary predictions to the input resolution as in the main loss. Instead, we define the pyramid loss components as cross-entropy between softmax predictions and the groundtruth distribution over class labels in the N×N boxes where N denotes the corresponding subsampling factor.

During training we oversample Cityscapes, KITTI and WildDash images multiple times in order to achieve 2:1 example ratio with respect to ScanNet in each epoch. Mixing outdoor and indoor images into each batch was very important in order to get batchnorm moving population statistics that correctly approximates batch statistics on both tasks. For data augmentation, we apply random scale resize between 0.5 and 2, random crop with 768x768 window size and random horizontal flip with 0.5 probability. These hyperparameter values are shared for all datasets. We used the Adam optimizer [7] with the base learning rate of  $4e^{-4}$  and additionally divide the learning rate by a factor of 4 for the ImageNet pre-trained subset of parameters. The contribution weight of the pyramid auxiliary loss was set to 0.4. We set the batch size to 8 and train the common model for 200k iterations. The training took around 3 days on one Titan Xp GPU.

#### 4. Results

We apply the common model to the test subsets of all four datasets, collect the model predictions and map them to the required formats of the individual benchmarks where necessary (Cityscapes). We analyze the obtained results and present the most interesting findings.

#### 4.1. Mapping predictions to the dataset formats

A common model for the ROB semantic segmentation challenge has to predict at least 39 object classes: the 19 driving classes from Cityscapes and 20 indoor classes from ScanNet. The benchmark scripts for WildDash, KITI and ScanNet datasets automatically map foreign class indices to the negative classes "Void" (Cityscapes) or "Ignore" (Scan-Net). The Cityscapes benchmark is oblivious of ScanNet indices and therefore we had to manually remap ScanNet predictions to the class "Void" (we had very few such pixels as shown in Table 1).

Note that the negative classes ("Void" and "Ignore") are separate form the 39 object classes. Predictions of negative classes do not contribute to true positives on Cityscapes, KITTI and ScanNet, however they still may improve performance since they do not count as false positives. However, negative predictions constitute true positives in several WildDash images.

### 4.2. False-positive detections of foreign classes

This group of experiments explores incidence of false negative detections due to predictions of foreign classes. This can be easily evaluated on the test datasets because there is no overlap between indoor and driving classes. We look at the number of "driving" pixels in the ScanNet test dataset as well as at the number of "indoor" pixels in Cityscapes test, WildDash test and KITTI test. The results are summarized in Table 1. The results show that, perhaps surprisingly, cross-dataset training resulted in negligible increase of false positive detections due to sharing the model across different kinds of scenery.

	driving classes (%)	indoor classes (%)
Cityscapes	99.857	0.143
WildDash	97.649	2.351
KITTI	100	0
ScanNet	$\approx 0$	$\approx 100$

Table 1. Incidence of foreign pixels in the test subsets of the four datasets. The rows correspond to the four datasets while the columns correspond to the two groups of classes. We see that cross-dataset training causes very few false positive pixels and therefore results in a negligible performance hit.

Most foreign pixels in Cityscapes test images are located on the car hood which is ignored during training. Figure 1 shows the only Cityscapes test image with a relatively large group of predictions to foreign classes. There were zero detections of foreign classes on KITTI, and only 8 detections of foreign classes on ScanNet. Most of foreign pixels on WildDash test are located in negative images and are therefore treated as true positives (we explore this in more detail later).

## 4.3. Detecting negative WildDash pixels

Closer inspection of WildDash test images revealed that almost all pixels classified as ScanNet occur in the negative WildDash images. We illustrate three such images in Figure 2. The figure shows that Cityscapes detections are often correct (people, building) or almost correct (indoor walls as building, lego pavement as road).

Table 2 shows the difference in category iIoU performance between our submissions M\_DN and LDN2\_ROB to



Figure 1. The only Cityscapes test image in which a large group of pixels was misclassified into indoor classes. The graffiti on the building (white pixels) were classified as the indoor class "wall".



Figure 2. Negative WildDash images (top), model predictions (middle) and out-of-distribution pixels for the WildDash dataset (bottom). In the bottom row we colored all pixels classified as Cityscapes classes in black. The remaining colored pixels are treated as the "Void" class during evaluation.

the WildDash benchmark. Both submissions correspond to instances of the model described in Section 3 trained with similar optimization settings. The submission M\_DN maps all indoor predictions to the class Cityscapes "Wall". The submission LDN2\_ROB leaves outdoor predictions as they were, which means that the benchmark script automatically maps them to class "Void". By treating ScanNet predictions as the WildDash negative class, LDN2\_ROB submission achieved 9.1 percentage points improvement in category iIoU. This improvement gives hope that we could estimate prediction uncertainty by simply assessing the likelihood of the foreign classes. In other words, we could train our future models in supervised or semi-supervised manner on diverse datasets and use the prediction of foreign classes (that is, classes that are not supposed to appear in this particular image) as a flag that the predictions are uncertain.

submission ID	ScanNet classes	negative iIoU	
	mapped to	category (%)	
M_DN	"Wall"	32.2	
LDN2_ROB	"Void"	42.8	

Table 2. Results of our two submissions to the WildDash benchmark (M\_DN and LDN2\_ROB). LDN2\_ROB improves the performance on negative WildDash test images by mapping ScanNet predictions to out-of-distribution pixels.

#### 4.4. Reduction of overfitting in the upsampling path

Early experiments showed very poor accuracy of the Ladder-DenseNet architecture on the WildDash test dataset. Further experiments with a simpler model based on bilinear upsampling resulted in better performance. Consequently, we hypothesized that the model with the ladder-style upsampling suffers from overfitting in the upsampling path. We attempt to alleviate this problem by regularizing the model with the pyramid loss described in Section 3 (i.e. by adding a classification head at each upsampling level), which resulted in significant improvement. We illustrate these effects in Table 3 which shows that the recognition accuracy significantly increases when we add pyramid loss. The table also shows that the benefits reproduce on the Berkeley Deep Drive dataset (note that we do not train on Berkeley Deep Drive in any of the experiments).

Dataset	WildDash		BDD	
Pyramid loss	No	Yes	No	Yes
Flat	67.2	66.5	70.9	74.6
Construction	18.1	16.8	51.9	52.4
Object	13.4	24.1	29.8	34.3
Nature	72.1	71.9	65.5	65.6
Sky	67.7	66.6	66.9	67.8
Human	30.4	36.0	45.4	46.2
Vehicle	44.1	54.5	75.6	76.3
mIoU	44.7	48.1	58.0	59.6

Table 3. Category IoU on WildDash val and Berkeley Deep Drive val for the model trained on Cityscapes only. We observe large improvements on objects, humans and vehicles. Both training and prediction was performed on half image resolution in this experiment.

Further inspection of semantic predictions along the upsampling path showed that some overfitting in the ladderupsampling remains despite the pyramid loss. We illustrate these effects in Figure 3. The image clearly shows that the prediction accuracy gradually decreases as we transition towards finer resolutions (top right). We believe that solving this issue might be an interesting direction for future work.

Finally, we show what happens on WildDash test when we include WildDash val to the training set. The effect is not easy to quantify since WildDash benchmarks allows only three submissions per researcher. We therefore perform qualitative analysis in several WildDash test images



Figure 3. Semantic segmentation predictions of a WildDash val image (top left) at different levels of the upsampling path by a model trained on Cityscapes only. The resolution increases from bottom to top and from right to left. We note that the accuracy gets worse as we transition from the coarsest resolution (bottom right) to the finest resolution (top right). Both training and prediction was performed on half image resolution in this experiment.

and show the results in Figure 4. We see that only 70 Wild-Dash val images succeeds to significantly impact the model despite being used along 3500 images from the Cityscapes dataset.



Figure 4. Segmentation results when training on Cityscapes + WildDash val (middle row) vs. training on Cityscapes only (bottom row). Both training and predictions was performed on half image resolution in this experiment.

## 4.5. Overall results

We have submitted the results of our common model to the ROB 2018 challenge under the identifier LDN2\_ROB. The obtained results on all four datasets are summarized in Table 4.

dataset	metric	our result	best result	our rank
KITTI	class IoU	63.5	69.6	3
ScanNet	class IoU	44.0	48.0	2
Cityscapes	class IoU	77.1	80.2	2
WildDash	category IoU	54.5	59.1	3

Table 4. Results of our common model LDN2\_ROB at the four semantic segmentation benchmarks.

## 5. Discussion

The presented experiments resulted in several interesting findings. Initial experiments with ladder-style models resulted in very poor cross-dataset performance. Closer inspection revealed that small errors had been multiplying along the upsampling datapath. This likely occured due to blending convolutions being overfit to the Cityscapes urban scenes with ideal weather conditions and a high-quality HDR camera. These effects might be even larger in models with more capacity in the upsampling datapaths. Experiments have showed that this problem can be successfully mitigated with suitable auxiliary losses and training on the WildDash val subset.

The second interesting result is that ScanNet training significantly improved recognition of out-of-distribution pixels on WildDash test. In fact, many such pixels were detected as some of the ScanNet classes and were therefore treated as true positive predictions. This raises hopes that future models will be able to detect unusual parts of the scene for free, only by virtue of being trained on a more diverse set of classes.

Further, we found that simultaneous training on multiple datasets resulted in virtually no performance hit with respect to training only on one dataset. In fact, less than 0.01 percent of valid in-distribution pixels in all three driving dataset test sets were recognized as one of the ScanNet indoor classes. Conversely, only 8 out of around billion pixels in ScanNet test were recognized as one of the Cityscapes driving classes.

Finally, we found that batch composition represents an important ingredient of cross-dataset training. The training convergence improved substantially when we switched from training on single-dataset batches to training on crossdataset batches. We hypothesize that the improvement occurred due to more stable training of batchnorm layers.

### Acknowledgements

This work has been supported by the European Regional Development Fund under the project "System for increased driving safety in public urban rail traffic (SafeTRAM)".

The Titan Xp used in experiments was donated by NVIDIA Corporation.

#### References

- M. Cordts, M. Omran, S. Ramos, T. Scharwächter, M. Enzweiler, R. Benenson, U. Franke, S. Roth, and B. Schiele. The cityscapes dataset. In *CVPRW*, 2015. 1
- [2] A. Dai, A. X. Chang, M. Savva, M. Halber, T. Funkhouser, and M. Nießner. Scannet: Richly-annotated 3d reconstructions of indoor scenes. In *CVPR*, 2017. 2
- [3] A. Geiger, P. Lenz, and R. Urtasun. Are we ready for autonomous driving? the kitti vision benchmark suite. In *CVPR*, 2012. 2
- [4] D. Hendrycks and K. Gimpel. A baseline for detecting misclassified and out-of-distribution examples in neural networks. In *ICLR*, 2017. 1
- [5] G. Huang, Z. Liu, and K. Q. Weinberger. Densely connected convolutional networks. In CVPR, 2016. 2
- [6] A. Kendall and Y. Gal. What uncertainties do we need in bayesian deep learning for computer vision? In *NIPS*, 2017.
- [7] D. P. Kingma and J. Ba. Adam: A method for stochastic optimization. *CoRR*, abs/1412.6980, 2014. 2
- [8] I. Kreso, J. Krapac, and S. Segvic. Ladder-style densenets for semantic segmentation of large natural images. In *ICCVW CVRSUAD*, pages 238–245, 2017. 1, 2
- [9] T. Lin, P. Dollár, R. B. Girshick, K. He, B. Hariharan, and S. J. Belongie. Feature pyramid networks for object detection. *CoRR*, abs/1612.03144, 2016. 2
- [10] O. Ronneberger, P. Fischer, and T. Brox. U-net: Convolutional networks for biomedical image segmentation. *CoRR*, abs/1505.04597, 2015. 2
- [11] O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein, A. C. Berg, and L. Fei-Fei. ImageNet Large Scale Visual Recognition Challenge. *International Journal of Computer Vision (IJCV)*, 115(3):211–252, 2015. 1
- [12] H. Valpola. From neural PCA to deep unsupervised learning. *CoRR*, abs/1411.7783, 2014. 2
- [13] H. Zhao, J. Shi, X. Qi, X. Wang, and J. Jia. Pyramid scene parsing network. In *ICCV*, 2017. 2