

Supplementary material for: Learning Where to Drive by Watching Others

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1 Ablation Studies

We have presented a self-supervised approach for the prediction of drivable areas in images. Our strategy makes use of large collections of unlabeled dashcam videos to teach a FCN which areas are drivable by watching others drive. We now analyze the impact of our contributions on the overall performance of our method by means of ablations. We evaluate several ablation methods: *(I)* Self-supervision via a fixed drivable area. Instead of obtaining self-supervision by tracking patches we fix a drivable area in front of the car bumper and collect self-supervision (e.g. Fig. 2(a) vs. 2(c)). *(II)* Single patch-based training of a binary CNN classifier. As opposed to a spatial-pyramid approach [6], we train a CNN for binary classification of drivable patches obtained via our tracking approach. *(III)* Training of a binary CNN classifier on a spatial-pyramid encoding of drivable patches [6]. *(IV)* Utilizing a FCN with dense up-stream convolutions for predicting pixel-wise labels of drivability obtained by self-supervision. *(V)* Our approach. In Tab. 1 we show different evaluation measures for all the ablation methods. We can see that the biggest performance improvement is obtained when comparing our approach with the fixed area self-supervision strategy, which does not track patches the other cars have driven over. In addition, we show that simple binary classification of drivable patches, even with spatial-pyramid encoding is not as successful as a FCN. Finally, using dilated convolutions gives us a broader context, which further improves results.

	No tracking (I)			Single patch (II)			Context-pyramid (III)			FCN dense upconv. (IV)			Ours (V) Sect. 3		
	UM	UMM	UU	UM	UMM	UU	UM	UMM	UU	UM	UMM	UU	UM	UMM	UU
MaxF	62.4	57.5	68.2	78.4	78.8	72.4	85.3	81.1	84.6	83.4	86.0	80.2	90.9	87.5	88.2
AP	45.7	47.4	55.0	84.7	85.9	79.0	91.2	91.2	91.8	83.5	87.7	81.8	88.6	89.2	87.6
PRE	65.8	72.5	71.9	77.4	82.0	70.1	83.5	83.4	83.8	78.9	83.0	78.7	90.6	88.5	87.6
REC	59.3	47.7	64.8	79.4	75.8	74.8	87.2	78.9	85.4	88.5	89.3	81.8	91.3	86.6	88.7
FPR	6.9	5.5	4.0	4.5	5.1	5.0	3.3	4.8	2.6	4.6	5.6	3.5	1.8	3.4	2.0
FNR	40.7	52.3	35.2	20.6	24.2	25.2	12.8	21.1	14.6	11.5	10.7	18.2	8.7	13.4	11.3

Table 1: Ablation experiments performed on KITTI [3].

28 **2 Extended Quantitative Experimentation on KITTI** 28

29 In addition to the experiments reported in the main submission, we also tested our 29
 30 approach on the KITTI [3] benchmark suite. In order to do so, we disregard the 30
 31 training labels provided by the benchmark and only use the 60 unlabeled video 31
 32 sequences provided with KITTI, utilizing just monocular color images. We then 32
 33 play the sequences backwards in time and generate the self-supervised labeling 33
 34 of drivable surfaces, gathering 42000 frames labeled with our self-supervision 34
 35 strategy. 35

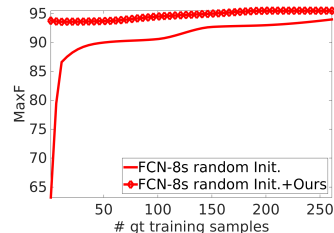
36 **2.1 Zero-shot Learning** 36

37 To assess the performance of our self-supervision method we tackle the problem of 37
 38 zero-shot learning of drivable areas on KITTI [3]. That is, methods are provided 38
 39 with 0 ground-truth labeled training images. We compare state-of-the-art fully 39
 40 convolutional architectures with and without our self-supervision method trained 40
 41 on the unlabeled sequences of KITTI. Tab. 1 summarizes the performance of 41
 42 two different architectures with and without our self-supervision method. We 42
 43 show results for our variant of FCN-8s [7] (with dilated upconvolutional layers), 43
 44 with and without Imagenet [2] pre-training. In addition, we also make use of 44
 45 the ResNet-101 model [4] pre-trained on Imagenet. In Tab. 1(a) we observe that 45
 46 our proposed approach for self-supervision drastically boosts the performance of 46
 47 zero-shot learning for all different architectures, with a performance improvement 47
 48 of at least 52%. 48

49 In addition to the zero-shot learning analysis we also show how our approach 49
 50 behaves when presented with few labeled samples, taking FCN-8s [7] as a partic- 50
 51 ular instance. Fig. 1(b) shows how performance increases as a function of 51
 52 the number of labeled training samples. We see how our self-supervision train- 52
 53 ing greatly amplifies the generalization capabilities of the network, consistently 53
 54 outperforming the same network without using our self-supervised pre-training 54

Model	UM	UMM	UU
FCN-8s Random Init.	25.5	36.8	22.4
FCN-8s Random Init. + Ours	90.7	85.8	87.0
FCN-8s Imagenet Init.	27.9	37.9	23.9
FCN-8s Imagenet Init + Ours	90.1	85.8	86.4
ResNet-101 Imagenet Init.	29.4	38.7	20.6
ResNet-101 Imagenet Init. + Ours	91.0	85.9	87.6

(a)



(b)

Fig. 1: (a) Zero-shot MaxF results for KITTI benchmark, where our model was trained on the unlabeled sequences of KITTI. (b) MaxF score as a function of the number of labeled ground-truth training samples. FCN-8s is trained from random weight initialization with and without our self-supervised pre-training.



Fig. 2: Sample score maps of drivable areas for zero-shot learning on KITTI.

Method	#gt labeled samples	UM	UMM	UU	ALL
MultiNet [10]	289	93.99	96.15	93.69	94.88
DDN [8]	289	93.65	94.17	91.76	93.43
Up-Conv-Poly [9]	289	92.20	95.52	92.65	93.83
FTP [5]	289	91.20	92.98	89.62	91.61
FCN-8s Random Init. + GT	289	89.50	92.81	84.50	89.83
FCN-8s Random Init. + Ours	0	87.39	86.14	84.96	85.74
Alvarez et. al [1]	1	73.69	86.21	72.25	79.02

Table 2: MaxF score for different method on the KITTI test server.

55 training. Finally, we show few score maps of drivable area yielded by our self- 55
 56 supervised approach on KITTI [3] in Fig. 2. Note that our method does not use 56
 57 any ground-truth labeled image during training. 57

58 To put our approach into context with state-of-the-art methods we report 58
 59 the results obtained by our self-supervised strategy on the test server of KITTI 59
 60 [3]. Since source code for top performing methods of KITTI is not available we 60
 61 take the widely used FCN-8s architecture as a study case. We then see that 61
 62 training FCN-8s using the KITTI ground-truth yields 5% worse performance than 62
 63 the top method. This situation is understandable since [10] is a more complex 63
 64 model than FCN-8s. To asses the quality of our approach we now train FCN-8s 64
 65 using self-supervision on the unlabeled KITTI video sequences, and compare 65
 66 it to FCN-8s trained on ground truth. We then see that the performance gap 66
 67 between using the KITTI training set and our self-supervised approach is 4%, 67
 68 despite using no labeled samples at all. In addition, we compare our approach 68
 69 with the one-shot method of Alvarez et. al [1] (which requires similar quantities 69
 70 of supervision as our approach) obtaining a performance improvement of 14% 70
 71 over it. 71

72 2.2 Transfer Learning 72

73 Conversely to Sect. 4.3 of the main submission in which we evaluate the potential 73
 74 of transferring a model trained on KITTI to Cityscapes, we now evaluate how a 74
 75 model trained on CityScapes transfers to KITTI. 75

76 The underlying rationale is that if a model is performing well on CityScapes 76
 77 it should also perform equivalently on KITTI. Therefore, we utilize the unlabeled 77
 78 sequences of KITTI for pre-training the FCNs using our self-supervised strategy, 78
 79 before using the CityScapes ground-truth labels to perform supervised learning. 79
 80 We evaluate transfer learning based on two separate network architectures, FCN- 80
 81 8s [7] and ResNet-101 [4]. In Tab. 3 we show the MaxF and IoU scores of the 81
 82 different models with and without our self-supervised pre-training. We can see 82
 83 that our self-supervised pre-training is extremely useful when transferring models 83
 84 between datasets, boosting performance by at least 10%. This performance 84
 85 improvement is due to the regularization properties of our self-supervision, which 85
 86 prevents the model from over-fitting to CityScapes-like scenarios, thus improving 86
 87 the capability to generalize to previously unseen scenarios. 87

88 3 Qualitative Results 88

89 In addition to the previous quantitative evaluation we also report qualitative 89
 90 results in the form of video sequences for different tasks. 90

91 3.1 Self-supervision 91

92 We now show how our training data is collected. We therefore take the unlabelled 92
 93 video sequences from KITTI and Cityscapes and apply our self-supervision 93
 94 strategy. To clearly illustrate our self-supervision approach we include few video 94
 95 sequences showing qualitative results in the folder `./self_supervision`. In 95
 96 these sequences, blue patches denote regions that have been driven over by the 96
 97 car equipped with the daschcam, while green patches are the ones driven over by 97
 98 other cars. Not drivable areas of the image are marked with red patches. Note 98
 99 how by playing videos back in time and tracking the patches that different cars 99
 100 have driven over, rich supervision can be obtained to learn which regions of an 100
 101 image are drivable. 101

102 3.2 Zero-shot learning 102

103 In addition, we also show how our FCN-8s performs when trained using our 103
 104 self-supervision strategy, without requiring tedious pixel-wise annotations of 104
 105 drivable areas. We collect few test sequences, which were not used for extracting 105

Model	MaxF	IoU
FCN-8s Random Init.	43.4	27.7
FCN-8s Random Init. + Ours	55.1	38.0
FCN-8s Imagenet Init.	50.1	33.4
FCN-8s Imagenet Init. + Ours	74.2	59.0
ResNet-101 Imagenet Init.	72.5	56.8
ResNet-101 Imagenet Init. + Ours	82.0	69.5

Table 3: Transfer Learning results from KITTI to Cityscapes benchmark.

106 self-supervision on neither KITTI or Cityscapes and let the network predict 106
 107 pixel-wise estimations of drivability. These zero-shot learning predictions can be 107
 108 found in ./zero_shot_pred. 108

109 3.3 Difficult scenarios: Snow and Sand 109

110 Finally, we include two sample sequences where our classifier was trained to 110
 111 predict drivable areas on both on a road completely covered in snow and on a 111
 112 dessert trail. In order to do this we had two different instances of our network 112
 113 trained on several YouTube dashcam sequences with roads covered in snow, and 113
 114 in different sandy desert videos. We then show our results in two video sequences 114
 115 which were not used during the training process. Our goal is to illustrate that 115
 116 our method is not bounded to predict drivability on asphalt regions, but can 116
 117 learn a general notion of drivability when trained with suitable data. 117

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