Supplementary Material for
Unsupervised Adaptation from Repeated Traversals for Autonomous Driving

S1 Implementation Details

The parameters that we used in this work were $\beta = 0.333$, and N_c^S values are 14357, 2207, and 734 for Cars, Pedestrians, and Cyclists, respectively. We include an ablation table for different values of β in Table S1. For the focal loss, we set $\alpha = 0.25$ and $\gamma = 2.0$ which are the default values. For the Posterior Filtering, we set $\alpha_{\text{FB-F}} = 20$ and $\gamma_{\text{FB-F}} = 0.5$. We selected the best hyperparameters based on the performance on KITTI → Lyft and used the same hyperparameters for the rest of the settings.

Table S1: **β-Value Experiment Results.** Evaluated under AP_{BEV} with IoU 0.7 for Car, 0.5 for Pedestrian and Cyclists. We show results experiementing with different β parameters.

	Car				Pedestrian				Cyclist			
β-Values	0-30	30-50	50-80	0-80	0-30	30-50	50-80	0-80	0-30	30-50	50-80	0-80
0.333	69.0	58.8	22.6	52.1	48.1	40.8	2.6	28.7	64.7	26.4	0.0	40.0
0.500	65.5	61.4	26.4	53.4	39.2	31.3	1.2	20.4	52.0	20.3	0.0	33.0
0.666	61.9	51.9	19.1	48.3	40.8	29.0	1.0	20.4	46.5	14.6	0.0	28.3

S2 Additional Detection Evaluation on the Lyft dataset

S2.1 On different metrics.

We include additional evaluations on the Lyft dataset. In Tables S2, S3, and S4 we show the results with metrics AP_{3D} at IoU 0.7 (cars) / 0.5 (pedestrian and cyclists), AP_{BEV} at IoU 0.7 / 0.5, and AP_{3D} at IoU 0.5 / 0.25, respectively. This corresponds to Table 1 in the main paper.

Table S2: **Detection performance of KITTI → Lyft adaptation.** Evaluated under AP_{3D} with IoU 0.7 for Car, 0.5 for Pedestrian and Cyclist. Please refer to Table 1 for naming.

	Car				Pedestrian				Cyclist			
Method	0-30	30-50	50-80	0-80	0-30	30-50	50-80	0-80	0-30	30-50	50-80	0-80
No Adaptation	22.3	6.9	1.2	10.8	29.9	16.5	0.5	15.2	35.4	5.6	0.0	19.0
ST3D (R10)*	37.6	23.2	6.0	23.3	27.1	23.1	0.0	15.6	48.6	12.4	0.0	27.0
ST3D (R30)	**44.1**	**26.8**	5.0	26.5	0.0	0.0	0.0	0.0	10.7	2.5	0.0	6.3
Rote-DA (Ours)	43.5	25.9	**7.8**	**27.4**	**36.3**	**35.2**	**2.6**	**23.0**	**57.7**	**22.1**	0.0	**35.0**
SN	57.1	30.7	6.5	33.3	31.4	25.8	1.5	18.6	31.1	6.3	0.0	17.2
In Domain	63.5	43.1	15.9	43.1	34.6	30.1	8.3	24.6	59.4	25.2	0.4	36.2

Table S3: **Detection performance of KITTI → Lyft adaptation.** Evaluated under AP_{BEV} with IoU 0.5 for Car, 0.25 for Pedestrian and Cyclist. Please refer to Table 1 for naming.

	Car				Pedestrian				Cyclist			
Method	0-30	30-50	50-80	0-80	0-30	30-50	50-80	0-80	0-30	30-50	50-80	0-80
No Adaptation	81.0	**68.8**	27.9	60.2	55.4	26.8	0.7	26.5	**70.3**	19.7	0.0	41.3
ST3D (R10)	**82.2**	68.3	36.3	**64.0**	48.1	27.3	0.0	24.0	69.2	23.6	0.0	41.6
ST3D (R30)	80.3	65.5	**37.1**	62.7	0.0	0.0	0.0	0.0	15.0	2.5	0.0	7.5
Rote-DA (Ours)	78.8	66.4	28.3	59.4	**62.7**	**44.6**	**2.8**	**34.8**	69.6	**34.4**	0.2	**44.7**
SN	81.3	65.5	30.7	60.1	53.9	38.5	2.0	30.2	67.3	26.9	2.5	42.6
In Domain	85.7	76.5	58.1	74.7	59.2	44.8	15.1	40.2	67.7	35.1	1.3	44.2

Table S4: **Detection performance of KITTI → Lyft adaptation.** Evaluated under AP_{3D} with IoU 0.5 for Car, 0.25 for Pedestrian and Cyclist. Please refer to Table 1 for naming.

	Car				Pedestrian				Cyclist			
Method	0-30	30-50	50-80	0-80	0-30	30-50	50-80	0-80	0-30	30-50	50-80	0-80
No Adaptation	78.2	62.9	19.8	55.1	55.4	26.7	0.7	26.4	**70.3**	19.3	0.0	41.2
ST3D (R10)*	**81.5**	**66.4**	33.3	**61.9**	48.1	27.3	0.0	24.0	69.2	23.6	0.0	41.6
ST3D (R30)	79.7	64.5	**33.5**	60.9	0.0	0.0	0.0	0.0	15.0	2.5	0.0	7.5
Rote-DA (Ours)	76.4	65.4	25.6	57.0	**62.2**	**44.5**	**2.8**	**34.6**	69.6	**34.4**	**0.2**	**44.1**
SN	81.2	64.4	26.8	59.2	53.9	38.5	2.0	30.2	67.2	26.5	2.5	42.4
In Domain	83.8	74.4	51.7	72.0	59.2	44.5	14.8	40.1	67.7	35.1	1.2	44.2

S2.2 On a different detection model.

In Tables S5, S6, S7 and S8, we include additional adaptation results on the PVRCNN [1] model. We use the same hyperparameters as those in the main paper. Since PVRCNN does not have the point-proposal module as in PointRCNN, we apply only PO-F and / or FB-F for adaptation. We observe our method is consistently better than baseline methods.

Table S5: **Detection performance of KITTI → Lyft adaptation with PVRCNN model.** Evaluated under AP_{BEV} with IoU 0.7 for Car, 0.5 for Pedestrian and Cyclist. Please refer to Table 1 for naming.

	Car				Pedestrian				Cyclist			
Method	0-30	30-50	50-80	0-80	0-30	30-50	50-80	0-80	0-30	30-50	50-80	0-80
No Adaptation	61.6	33.9	10.3	36.9	29.3	18.1	0.5	15.2	34.1	**4.5**	**0.1**	**18.2**
ST3D (R10)*	62.9	51.5	27.9	49.1	20.6	5.6	0.1	7.0	31.3	1.9	0.0	15.0
ST3D (R30)	57.8	47.1	19.1	43.2	1.5	0.9	0.2	0.7	18.7	0.5	0.0	8.7
PO-F (R10)	76.4	62.3	26.7	60.0	34.9	23.8	1.8	17.7	**52.4**	0.3	0.0	9.2
PO-F + FB-F (R10)	**79.7**	**67.3**	**31.9**	**64.7**	**40.4**	**30.7**	**3.7**	**23.2**	48.1	0.4	0.0	10.7
SN	79.8	55.5	20.6	54.7	33.6	18.9	0.5	17.1	40.9	6.2	0.0	21.5

Table S6: **Detection performance of KITTI → Lyft adaptation with PVRCNN model.** Evaluated under AP_{3D} with IoU 0.7 for Car, 0.5 for Pedestrian and Cyclist. Please refer to Table 1 for naming.

	Car				Pedestrian				Cyclist			
Method	0-30	30-50	50-80	0-80	0-30	30-50	50-80	0-80	0-30	30-50	50-80	0-80
No Adaptation	25.5	6.5	0.9	11.9	18.2	5.8	0.0	7.1	23.4	**2.8**	0.0	**12.0**
ST3D (R10)*	20.5	9.1	1.7	10.9	10.4	2.1	0.0	3.2	18.9	1.0	0.0	9.2
ST3D (R30)	17.3	9.5	1.7	9.8	0.6	0.2	0.0	0.2	14.9	0.5	0.0	7.7
PO-F (R10)	52.1	37.7	10.3	36.5	**23.1**	14.1	1.7	11.2	38.8	0.2	0.0	6.7
PO-F + FB-F (R10)	**56.3**	**40.3**	**11.2**	**40.7**	22.9	**17.9**	**3.2**	**13.2**	**39.4**	0.2	0.0	8.4
SN	58.1	21.1	3.5	28.7	21.6	9.8	0.2	9.9	29.5	3.4	0.0	15.0

Table S7: **Detection performance of KITTI → Lyft adaptation with PVRCNN model.** Evaluated under AP_{BEV} with IoU 0.5 for Car, 0.25 for Pedestrian and Cyclist. Please refer to Table 1 for naming.

	Car				Pedestrian				Cyclist			
Method	0-30	30-50	50-80	0-80	0-30	30-50	50-80	0-80	0-30	30-50	50-80	0-80
No Adaptation	83.9	61.0	24.6	58.2	45.0	23.1	1.0	22.1	**68.6**	**9.6**	**0.2**	**36.7**
ST3D (R10)*	82.9	62.5	36.4	62.3	28.4	7.3	0.1	9.6	46.3	3.1	0.0	21.9
ST3D (R30)	71.3	54.8	22.7	51.3	2.5	1.5	0.5	1.3	21.8	0.8	0.0	9.1
PO-F (R10)	82.7	67.6	35.8	67.7	44.1	29.5	2.5	22.0	57.9	1.7	0.0	11.2
PO-F + FB-F (R10)	**85.3**	**72.2**	**39.6**	**70.4**	**48.0**	**36.4**	**4.6**	**27.5**	51.5	1.6	0.0	11.9
SN	83.0	61.1	27.3	59.8	48.0	24.4	0.8	23.8	64.5	10.0	0.2	35.0

Table S8: **Detection performance of KITTI → Lyft adaptation with PVRCNN model.** Evaluated under AP_{3D} with IoU 0.5 for Car, 0.25 for Pedestrian and Cyclist. Please refer to Table 1 for naming.

	Car				Pedestrian				Cyclist			
Method	0-30	30-50	50-80	0-80	0-30	30-50	50-80	0-80	0-30	30-50	50-80	0-80
No Adaptation	76.9	47.1	13.4	47.9	44.8	22.8	1.0	22.0	**68.4**	**8.8**	**0.2**	**36.3**
ST3D (R10)*	77.3	54.8	24.8	54.3	28.3	7.2	0.1	9.5	46.2	3.1	0.0	21.9
ST3D (R30)	67.7	49.3	17.1	46.2	2.5	1.4	0.4	1.1	21.8	0.8	0.0	9.1
PO-F (R10)	82.4	65.6	31.7	65.3	44.1	29.5	2.5	22.0	57.9	1.4	0.0	10.9
PO-F + FB-F (R10)	**85.0**	**70.2**	**36.5**	**69.4**	**48.0**	**36.3**	**4.6**	**27.4**	51.5	1.1	0.0	11.6
SN	80.8	56.2	20.2	55.3	48.0	24.2	0.8	23.8	64.4	9.8	0.1	34.9

Table S9: **Detection performance of WOD → Ithaca-365 adaptation.** We evaluate the mAP as described in section 4 by different depth ranges and object types. Please refer to Table 1 for namings.

	Car				Pedestrian			
Method	0-30	30-50	50-80	0-80	0-30	30-50	50-80	0-80
No Adaptation	55.7	38.1	11.7	37.0	53.0	33.6	2.1	32.9
ST3D (R10)	64.0	44.2	16.2	43.4	46.8	27.5	1.1	27.6
ST3D (R30)	**67.1**	**44.7**	17.4	**44.2**	39.1	22.1	1.8	22.3
Rote-DA (Ours)	62.5	44.4	**18.9**	43.2	**59.9**	**42.2**	**2.8**	**35.0**
In Domain	70.5	46.8	22.2	48.4	53.2	26.0	1.7	29.4

S2.3 Additional adaptation scenario.

In Table S9 we show adaptation results for different adaptation methods adapting a PointRCNN detector trained on the Waymo Open Dataset [2] to the Ithaca-365 dataset. We observe that our conclusion holds in this case as well, especially in the class of pedestrians with a marked improvement over direct adaptation of the source model.

S3 Additional Qualitative Visualization

Similar to Figure 4, in Figure S1 we show extra qualitative visualization of the adaptation results of various adaptation strategies in both Lyft and Ithaca-365 datasets.

References

[1] Shaoshuai Shi, Chaoxu Guo, Li Jiang, Zhe Wang, Jianping Shi, Xiaogang Wang, and Hongsheng Li. Pv-rcnn: Point-voxel feature set abstraction for 3d object detection. In *CVPR*, pages 10529–10538, 2020. 2

[2] Pei Sun, Henrik Kretzschmar, Xerxes Dotiwalla, Aurelien Chouard, Vijaysai Patnaik, Paul Tsui, James Guo, Yin Zhou, Yuning Chai, Benjamin Caine, Vijay Vasudevan, Wei Han, Jiquan Ngiam, Hang Zhao, Aleksei Timofeev, Scott Ettinger, Maxim Krivokon, Amy Gao, Aditya Joshi, Yu Zhang, Jonathon Shlens, Zhifeng Chen, and Dragomir Anguelov. Scalability in perception for autonomous driving: Waymo open dataset. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2020. 3

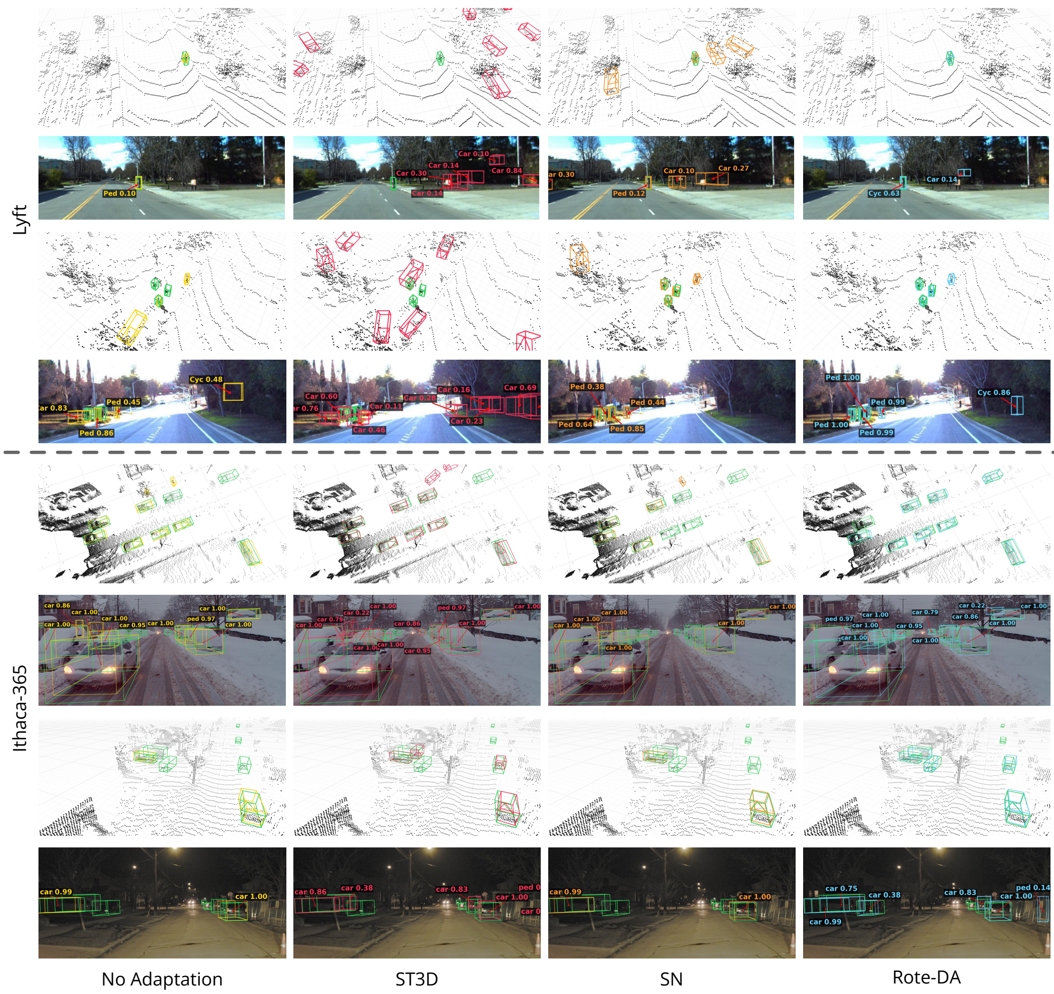

Figure S1: **Qualitative visualization of adaptation results.** We visualize two more example scenes in the Lyft and Ithaca-365 test split. Please refer to Figure 4 for more details.