Learning Transferable Features for Point Cloud Detection via 3D Contrastive Co-training –Supplementary Material–

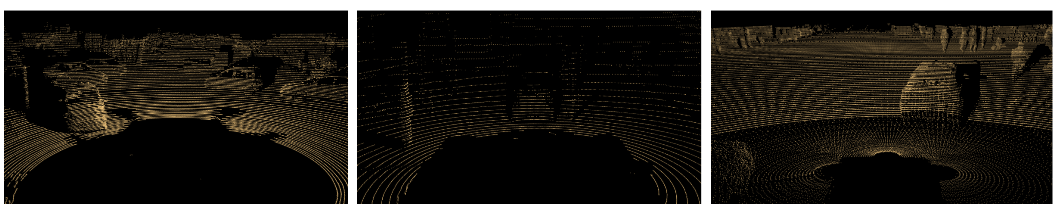
This supplementary material consists of four parts, including details about the dataset configurations (Sec. 1), technical details of hard sample mining (Sec. 2), implementation details of the proposed 3D-CoCo framework (Sec. 3) and additional experimental results (Sec. 4).

1 Datasets

Table 1 provides more details about the datasets used in the paper, including the number of point clouds, sensor configurations, and specific environments, which indicates the existence of the domain shift. Fig. 1 gives three showcases that are randomly selected from the above datasets. It is obvious that the distributions of the 3D patterns are very diverse.

Dataset	Size		Sensor		Environment		
	#Training	#Validation	LiDAR Type	Beam Angles	Location	Rainy	Night
Waymo	158081	39987	1×64+4×200-beam	[-24°, 4°]	USA	Yes	Yes
nuScenes	28130	6018	1×32-beam	[-16°,11°]	USA, Singapore	Yes	Yes
KITTI	3712	3769	1×64-beam	[-24°,4°]	Germany	No	No

Table 1: Details of the datasets that indicate the existence of the domain shift.



KITTI nuScenes Waymo

Figure 1: The visualization of LiDAR point clouds from the frontal view.

2 Hard Sample Mining

To construct hard samples for contrastive alignment, we transform the point clouds of the target domain from two aspects, *i.e.*, object density and object completeness.

Object density. For each point $p_n = (x_n, y_n, z_n, i_n)$ of a point cloud $P = (p_1, p_2, \dots, p_N)$, we first calculate its elevation angle θ_n and the perspective angle ϕ_n to the LiDAR sensor:

$$\theta_n = \arccos\left(\frac{\sqrt{x_n^2 + y_n^2}}{\sqrt{x_n^2 + y_n^2 + z_n^2}}\right), \quad \phi_n = \arctan\left(\frac{y_n}{x_n}\right). \tag{1}$$

We then arrange the points according to their elevation angles θ and use a sampling interval δ to slice them into L separate lines as virtual laser beams, where δ is set to 0.4 for KITTI and 1.3 for nuScenes. For Waymo data where point clouds are transferred from range images, we directly extract virtual laser beams according to the corresponding horizontal axis of range coordinate. At last, we uniformly sample the virtual beams by random step Δ_L to reserve L' beams, where

$$L' = \lceil L/\Delta_L \rceil, \ \Delta_L \in [1, L). \tag{2}$$

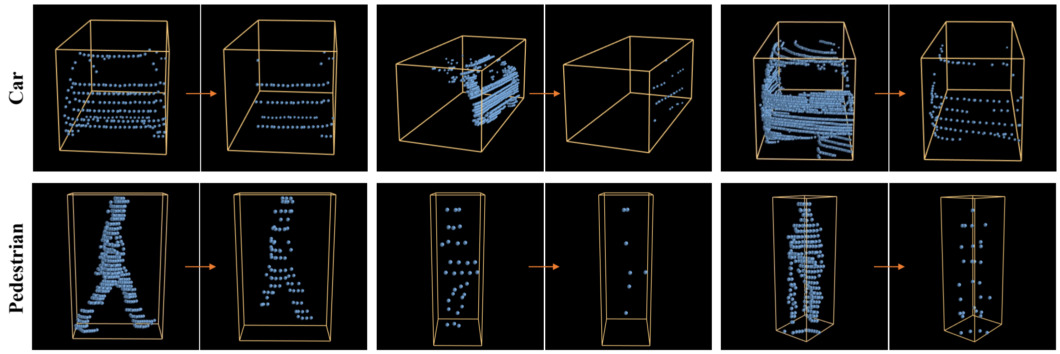


Figure 2: The visualization of mined hard examples for the categories of Car and Pedestrian.

Specifically, considering that Waymo integrates points from 5 sensors, we process data of each sensor respectively and integrate the transformed points as results.

Object completeness. We denote the perspective range of P as $\Delta\phi$. To simulate the patterns of severe occlusions, we transform P by randomly removing the points that locate within a subinterval of $\Delta\phi$, where

$$\begin{aligned} \Delta\phi &= \phi_{\text{max}} - \phi_{\text{min}} \\ \phi_{\text{min}} &= \min(\{\phi_n\}_{n=1:N}) \\ \phi_{\text{max}} &= \max(\{\phi_n\}_{n=1:N}). \end{aligned} \tag{3}$$

Notably, in real scenes, hard samples tend to appear at a great distance, therefore we also move the transformed patterns to a remote location c' according to

$$c' = (\Delta_L \times c_x, \Delta_L \times c_y, c_z), \tag{4}$$

where $c = (c_x, c_y, c_z)$ is the original center of the point cloud P. Fig. 2 provides more showcases of the transformed point clouds.

3 Implementation Details

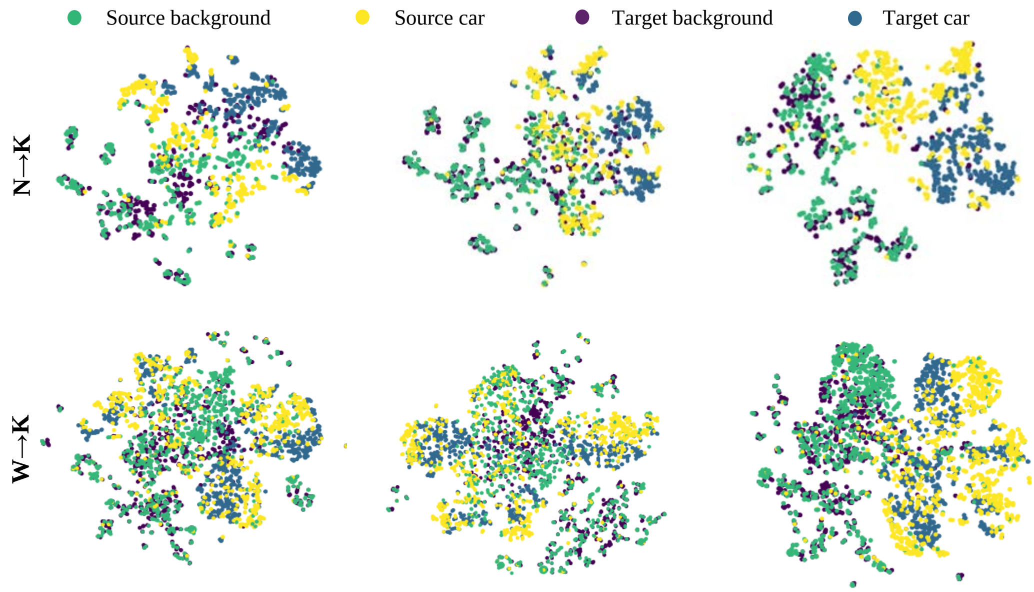
We use the complete training and validation sets of nuScenes and KITTI, and sample $1/5$ training scenes and $1/4$ validation scenes for Waymo. For all datasets, the coordinate origins are shifted to the ground plane and the detection range is set to $[-2m, 4m]$ for the Z axis. For the other two axes, the detection ranges are $\big([0m, 70.4m], [-40m, 40m]\big)$ for KITTI, $\big([-51.2m, 51.2m], [-51.2m, 51.2m]\big)$ for nuScenes, and $\big([-75.2m, 75.2m], [-75.2m, 75.2m]\big)$ for Waymo.

At training time, we augment the datasets by applying point cloud flipping (along the X and Y axes), global scaling, global rotation, and random global translation (the entire point cloud scene is moved by a random distance) to the raw point clouds. We also adopt the GT-Sampling data augmentation strategy from [2], which pastes the ground-truth boxes and their inside points from other scenes to the same locations of current training scenes.

As mentioned in the main manuscript, the progressive training procedure is the key to improve the quality of pseudo-labels. Specifically, after the warm-up process, we update pseudo-labels every 3 epoches for KITTI. In order to save the computation time of generating pseudo-labels on large datasets, we update pseudo-labels every 5 epoches for nuScenes and Waymo.

4 Additional Experimental Results

t-SNE visualization. In Fig. 3, we use t-SNE [1] to visualize the distribution of features from the source and target domains, produced by three models (*i.e.*, the baseline model trained on the source domain, the self-training method, and 3D-CoCo). Due to the domain gap, as shown by the Source Only model, the features of different categories (*i.e.*, background or foreground car) in two domains



(a) Source Only (b) Self-Training (c) 3D-CoCo

Figure 3: The t-SNE visualization of sample features. **(a)** The source only model is trained without any adaptation technique. **(b)** The self-training method applies the pseudo-labels on target data for re-training, but it fails to align the distribution of features from the source and target domains without any access to the source data. **(c)** The proposed 3D-CoCo framework leverages both labeled source data and unlabeled target data for co-training, which obviously enhances the intra-class compactness and encourages inter-class separability in the feature space. **N:** nuScenes; **K:** KITTI; **W:** Waymo.

Task	Method	VoxelNet			
		AP_{BEV}	Closed Gap	AP_{3D}	Closed Gap
$N \to K$	Source Only	17.1	-	12.7	-
	3D-CoCo	27.2	+38.40%	24.9	+46.92%
	Oracle	43.4	-	38.7	-
$W \to K$	Source Only	48.3	-	45.3	-
	3D-CoCo	38.1	-	36.0	-
	Oracle	43.4	-	38.7	-
$W \to N$	Source Only	16.0	-	13.6	-
	3D-CoCo	19.5	+18.23%	15.9	+16.91%
	Oracle	35.2	-	27.2	-
$N \to W$	Source Only	9.1	-	9.1	-
	3D-CoCo	21.8	+21.38%	15.9	+12.93%
	Oracle	68.5	-	61.7	-

Table 2: Adaptation results on the Pedestrian category. **N:** nuScenes; **K:** KITTI; **W:** Waymo.

are heavily overlapped, which indicates poor generalization performance. After domain adaptation, we observe that the feature distribution of the self-training method is still irregular, while that of 3D-CoCo shows better clustering properties, in the sense that the features of the same category in the two domains are better aligned and those from different categories are separated more clearly.

The Pedestrian category. In addition to the *Car* category that is shown in the main manuscript, we here provide more experimental results on the *Pedestrian* category. Table 2 gives the adaptation results of 3D-CoCo with the VoxelNet encoder. It validates the effectiveness of 3D-CoCo with consistent improvements over the Source Only model on a variety of adaptation tasks, including nuScenes→KITTI, nuScenes→Waymo, and Waymo→nuScenes. The only exception on Waymo→KITTI, where the Source Only model outperforms 3D-CoCo and even the Oracle model, is largely caused by the limited number of training samples of Pedestrian on the target KITTI dataset.

Methods	AP_{BEV}	AP_{3D}
Pooling-based	75.8	62.9
Keypoint-based (ours)	77.1	65.6

Table 3: Comparison of extraction methods.

Methods	AP_{BEV}	AP_{3D}
$R = 3$	78.4	64.1
$R = 5$	75.9	62.4
$R = 7$	77.1	65.6

Table 4: Sensitivity analysis of R.

Methods	AP_{BEV}	AP_{3D}
$\tau = 0.01$	75.7	61.7
$\tau = 0.07$	77.1	65.6
$\tau = 0.2$	74.7	61.4

Table 5: Sensitivity analysis of τ.

Methods	AP_{BEV}	AP_{3D}
λ = 0.25	76.0	62.6
λ = 0.5	77.1	65.6
λ = 1.0	76.1	63.5

Table 6: Sensitivity analysis of λ.

Comparison of extraction methods. We use another feature extraction method based on average pooling as a compared method on the nuScenes→KITTI benchmark in Table 3. We believe that the average pooling method tends to result in more ambiguous features.

Sensitivity analysis. We conduct extra sensitivity analysis on other hyper-parameters, including the sample number of keypoints R, temperature parameter τ and the loss weight λ of adaptation loss. We show the results in Table 4, 5 and 6.

Analysis of error bars. We run 3D-CoCo and the self-training method for 5 times. As shown in Fig. 4, compared to the self-training method, 3D-CoCo achieves a higher median value of the accuracy and a more concentrated distribution of the results. It indicates that 3D-CoCo not only boosts accuracy but also performs more stably.

Qualitative results. We show the qualitative results in Fig. 5, which illustrates that 3D-CoCo improves the adaptive detection performance by greatly reducing the false positive predictions and increasing the localization accuracy. Specifically, when adapted from sparse source domain (*i.e.*, nuScenes) to dense target domain (*i.e.*, Waymo or KITTI), the Source Only model tends to easily produce false positives due to the increase of point cloud density, while 3D-CoCo can effectively avoid those erroneous predictions. Besides, due to changes in the physical environments and the size of objects, the domain shifts are also reflected in the inaccurate 3D bounding boxes produced by the Source Only model. We observe that our proposed 3D-CoCo achieves higher localization accuracy of the 3D bounding boxes.

References

[1] Laurens Van der Maaten and Geoffrey Hinton. Visualizing data using t-sne. *Journal of machine learning research*, 9(11), 2008.

[2] Yan Yan, Yuxing Mao, and Bo Li. Second: Sparsely embedded convolutional detection. *Sensors*, 18(10):3337, 2018.

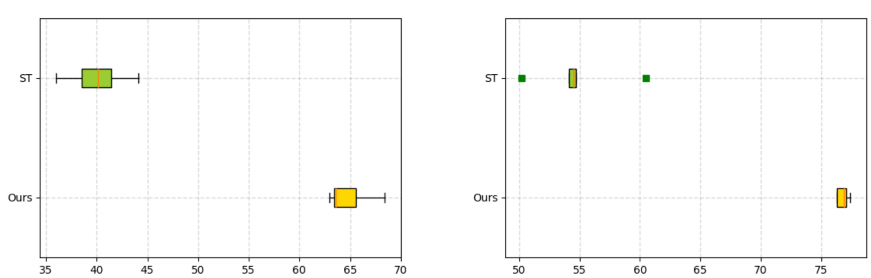


Figure 4: The box-plot on AP_{3D} (**Left**) and AP_{BEV} (**Right**) for 3D-CoCo and self-training (ST).

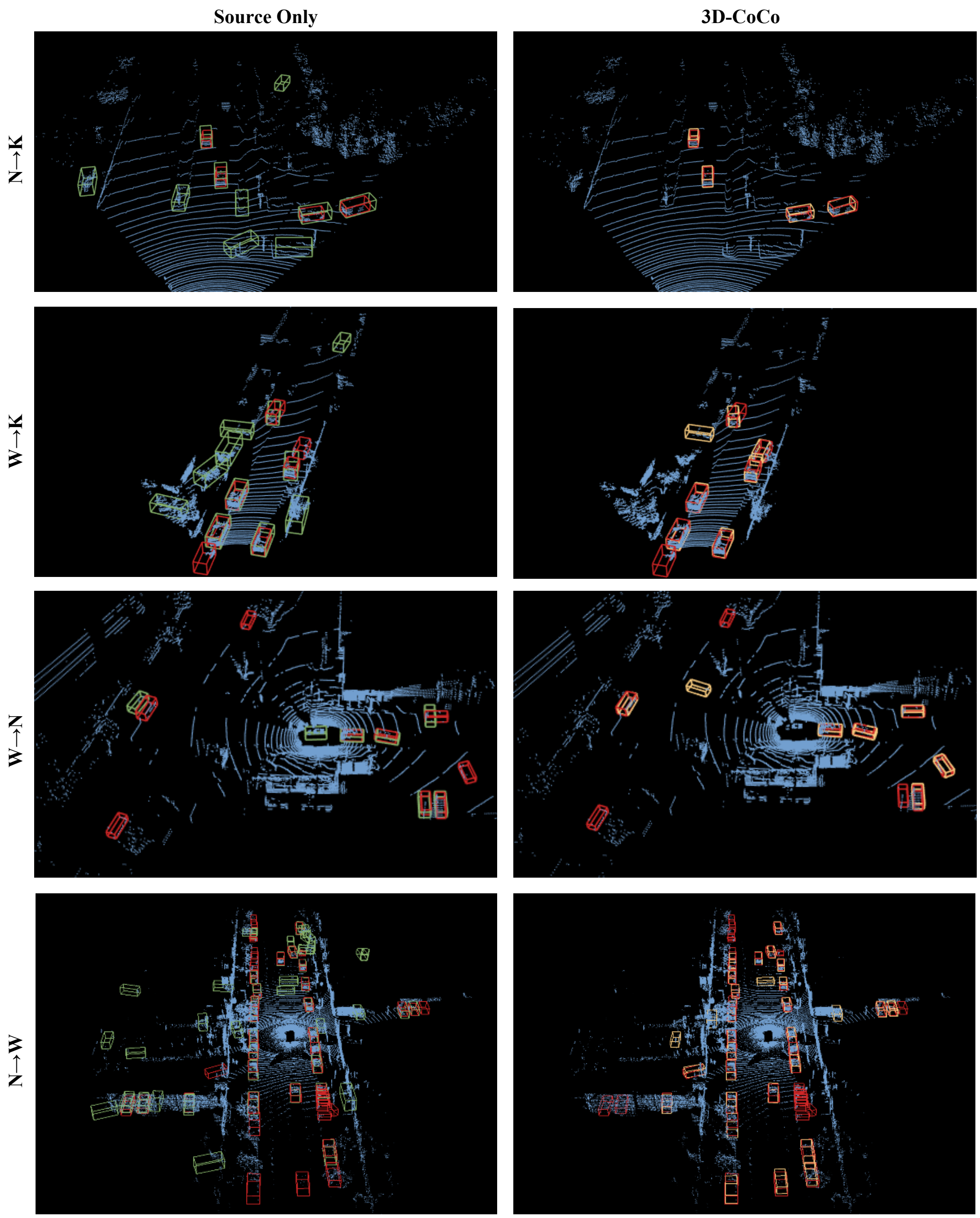


Figure 5: Qualitative results on four adaptation tasks. **N:** nuScenes; **K:** KITTI; **W:** Waymo. **Red:** Ground-truth; **Green:** Predictions by the Source Only model; **Yellow:** Predictions by 3D-CoCo. Obviously, the predictions of 3D-CoCo align better with the ground-truth bounding boxes.

Checklist

1. For all authors...

    (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes] See Section *Abstract* and *Introduction*

    (b) Did you describe the limitations of your work? [Yes] As discussed in Section 6, our approach follows the typical unsupervised domain adaptation setup in 2D vision, and thus takes more memory footprint than existing 3D self-training methods at training time.

(c) Did you discuss any potential negative societal impacts of your work? [N/A] Our work is only for academic research purpose.

(d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]

2. If you are including theoretical results...

   (a) Did you state the full set of assumptions of all theoretical results? [N/A] We report the experimental results in comparison with most related works to verify the effectiveness of our method.

   (b) Did you include complete proofs of all theoretical results? [N/A]

3. If you ran experiments...

   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [No] Our code is proprietary, but we will release the code once the paper is accepted.

   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] See Section *Experiments* and Supplementary materials.

   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [Yes] See Supplementary Materials. We provide the error bars of both our method and baselines.

   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes] Our model is trained on Ubuntu system, 8 V100 GPUs with 32G.

4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...

   (a) If your work uses existing assets, did you cite the creators? [Yes] See the *Reference* part.

   (b) Did you mention the license of the assets? [No] The data and models used in our work are publicly released.

   (c) Did you include any new assets either in the supplemental material or as a URL? [No]

   (d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? [Yes] The data and models used in our work are publicly released.

   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [Yes] The data used in our work does not contain personally identifiable information or offensive content.

5. If you used crowdsourcing or conducted research with human subjects...

   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A] Our work does not involve human subjects. And the following items are the same.

   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]

   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]