DODA: Data-oriented Sim-to-Real Domain Adaptation for 3D Semantic Segmentation

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Abstract. Deep learning approaches achieve prominent success in 3D semantic segmentation. However, collecting densely annotated real-world 3D datasets is extremely time-consuming and expensive. Training models on synthetic data and generalizing on real-world scenarios becomes an appealing alternative, but unfortunately suffers from notorious domain shifts. In this work, we propose a Data-Oriented Domain Adaptation (DODA) framework to mitigate pattern and context gaps caused by different sensing mechanisms and layout placements across domains. Our DODA encompasses virtual scan simulation to imitate real-world point cloud patterns and tail-aware cuboid mixing to alleviate the interior context gap with a cuboid-based intermediate domain. The first unsupervised sim-to-real adaptation benchmark on 3D indoor semantic segmentation is also built on 3D-FRONT, ScanNet and S3DIS along with 8 popular Unsupervised Domain Adaptation (UDA) methods. Our DODA surpasses existing UDA approaches by over 13% on both 3D-FRONT \rightarrow ScanNet and 3D-FRONT \rightarrow S3DIS. Code is available at https://github.com/CVMI-Lab/DODA.

Keywords: Domain Adaptation, 3D Semantic Segmentation

1 Introduction

3D semantic segmentation is a fundamental perception task receiving incredible attention from both industry and academia due to its wide applications in robotics, augmented reality, and human-computer interaction, to name a few. Data hungry deep learning approaches have attained remarkable success for 3D semantic segmentation [47, 30, 56, 62, 22, 64]. Nevertheless, harvesting a large amount of annotated data is expensive and time-consuming [3, 7].

An appealing avenue to overcome such data scarcity is to leverage simulation data where both data and labels can be obtained for free. Simulated datasets can be arbitrarily large, easily adapted to different label spaces and customized for various usages [18, 54, 8, 34, 73, 26]. However, due to notorious domain gaps in point patterns and context (see Fig. 1), models trained on simulated scenes

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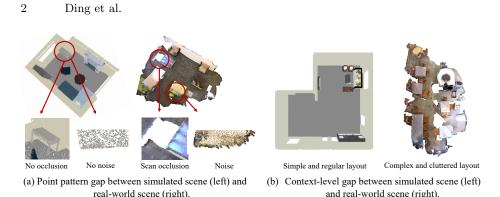


Fig. 1. The domain gaps between simulated scenes from 3D-FRONT [8] and realworld scenes from ScanNet [7]. (a): The point pattern gap. The simulated scene is perfect without occlusions or noise, while the real-world scene inevitably contains scan occlusion and noise patterns such as rough surfaces. (b): The context gap. While the simulated scene applies simple layout with regularly placed objects, the real scene is complex with cluttered interiors.

suffer drastic performance degradation when generalized to real-world scenarios. This motivates us to study sim-to-real unsupervised domain adaptation (UDA), leveraging labeled source data (simulation) and unlabeled target data (real) for effectively adapting knowledge across domains.

Recent efforts on 3D domain adaptation for outdoor scene parsing have obtained considerable progress [23, 61, 72, 29]. However, they often adopt LiDARspecific range image format, not applicable for indoor scenarios with scenes constructed by RGB-D sequences. Besides, such outdoor attempts could be suboptimal in addressing the indoor domain gaps raised from different scene construction processes. Further, indoor scenes have more sophisticated interior context than outdoor, which makes the context gap a more essential issue in indoor settings. Here, we explore sim-to-real UDA in the 3D indoor scenario which is challenging and largely under explored.

Challenges. Our empirical studies on sim-to-real adaptation demonstrate two unique challenges in this setting: the *point pattern gap* owing to different sensing mechanisms, and the *context gap* due to dissimilar semantic layouts. As shown in Fig. 1 (a), simulated scenes tend to contain complete objects as well as smooth surfaces, while real scenes include inevitable scan occlusions and noise patterns during reconstructing point clouds from RGB-D videos captured by depth cameras [7, 3]. Also, even professionally designed layouts in simulated scenes are much simpler and more regular than real layouts as illustrated in Fig. 1 (b).

To tackle the above domain gaps, we develop a holistic two stage pipeline DODA with a pretrain and a self-training stage, which is widely proved to be effective in UDA settings [50, 74, 65]. As the root of the challenges lies in "data", we thus design two data-oriented modules which are shown to dramatically reduce domain gaps without incurring any computational costs during inference. Specifically, we develop Virtual Scan Simulation (VSS) to mimic occlusion and noise patterns that occur during the construction of real scenes. Such pattern imitation

yields a more transferable model to real-world data. Afterwards, to adapt the model to target domain, we design Tail-aware Cuboid Mixing (TACM) for boosting self-training. While source supervision is utilized to stabilize gradients with clean labels in self-training, it unfortunately introduces context bias. Thus, we propose TACM to create an intermediate domain by splitting, permuting, mixing and re-sampling source and target cuboids, which explicitly mitigates the context gap through breaking and rectifying source bias with target pseudo-labeled data, and simultaneously eases long-tail issue by oversampling tail cuboids.

To the best of our knowledge, we are the first to explore unsupervised domain adaptation on 3D indoor semantic segmentation. To verify the effectiveness of our DODA, we construct the first 3D indoor sim-to-real UDA benchmark on a simulated dataset 3D-FRONT [8] and two widely used real-world scene understanding datasets ScanNet [7] and S3DIS [3] along with 8 popular UDA methods with task-specific modifications as our baselines. Experimental results show that DODA obtains 22% and 19% performance gains in terms of mIoU compared to source only model on 3D-FRONT \rightarrow ScanNet and 3D-FRONT \rightarrow S3DIS respectively. Even compared to existing UDA methods, over 13% improvement is still achieved. It is also noteworthy that the proposed VSS can lift previous UDA methods by a large margin (8% ~ 14%) as a plug-and-play data augmentation, and TACM further facilitates real-world cross-site adaptation tasks with 4% ~ 5% improvements.

2 Related Work

3D Indoor Semantic Segmentation focuses on obtaining point-wise category predictions from point clouds, which is a fundamental while challenging task due to the irregularity and sparsity of 3D point clouds. Some previous works [42, 54] feed 3D grids constructed from point clouds into 3D convolutional neural networks. Some approaches [16, 6] further employ sparse convolution [17] to leverage the sparsity of 3D voxel representation to accelerate computation. Another line of works [46, 47, 25, 62, 71] directly extract feature embeddings from raw point clouds with hierarchical feature aggregation schemes. Recent methods [56, 64] assign position-related kernel functions on local point areas to perform dynamic convolutions. Additionally, graph-based works [53, 31, 60] adopt graph convolutions to mimic point cloud structure for point representation learning. Although the above methods achieve prominent performance on various indoor scene datasets, they require large-scale human-annotated datasets which we aim to address using simulation data. Our experimental investigation is built upon the sparse-convolution-based U-Net [16, 6] due to its high performance.

Unsupervised Domain Adaptation aims at adapting models obtained from annotated source data towards unlabeled target samples. The annotation efficiency of UDA and existing data-hungry deep neural networks make it receive great attention from the computer vision community. Some previous works [39, 40] attempt to learn domain-invariant representations by minimizing maximum mean discrepancy [5]. Another line of research leverages adversarial training [14] to align distributions in feature [10, 51, 20], pixel [21, 20, 13] or output space [57] across domains. Adversarial attacks [15] have also been utilized in [36, 67] to train domain-invariant classifiers. Recently, Self-training has been investigated in addressing this problem [50] which formulate UDA as a supervised learning problem guided by pseudo-labeled target data and achieves state-of-the-art performance in semantic segmentation [74] and object detection [28, 49].

Lately, with the rising of 3D vision tasks, UDA has also attracted a lot of attention in such 3D tasks as 3D object classification [48, 1], 3D outdoor semantic segmentation [61, 23, 68, 45, 29] and 3D outdoor object detection [59, 66, 70, 41, 65]. Especially, Wu *et al.* [61] propose intensity rendering, geodesic alignment and domain calibration modules to align sim-to-real gaps of outdoor 3D semantic segmentation datasets. Jaritz *et al.* [23] explore multi-modality UDA by leveraging images and point clouds simultaneously. Nevertheless, no previous work studies UDA on 3D indoor scenes. The unique point pattern gap and the context gap also render 3D outdoor UDA approaches not readily applicable to indoor scenarios. Hence, in this work, we make the first attempt on UDA for 3D indoor semantic segmentation. Particularly, we focus on the most practical and challenging scenario – simulation to real adaptation.

Data Augmentation for UDA has also been investigated to remedy data-level gaps across domains. Data augmentation techniques have been widely employed to construct an intermediate domain [49, 29, 13] to benefit optimization and facilitate gradual domain adaptation. However, they mainly focus on image-like input formats, which is not suitable for sparse and irregular raw 3D point clouds. Different from existing works, we build a holistic pipeline with two data-oriented modules on two stages to manipulate raw point clouds for mimicking target point cloud patterns and creating a cuboid-based intermediate domain.

3 Method

3.1 Overview

In this work, we aim at adapting a 3D semantic scene parsing model trained on a source domain $\mathcal{D}_s = \{(P_i^s, Y_i^s)\}_{i=1}^{N_s}$ of N_s samples to an unlabeled target domain $\mathcal{D}_t = \{P_i^t\}_{i=1}^{N_t}$ of N_t samples. P and Y represent the point cloud and the point-wise semantic labels respectively.

In this section, we present DODA, a data-oriented domain adaptation framework to simultaneously close pattern and context gaps by imitating target patterns as well as breaking source bias with the generated intermediate domain. Specifically, as shown in Fig. 2, DODA begins with pretraining the 3D scene parsing model F on labeled source data with our proposed virtual scan simulation module for better generalization. VSS puts virtual cameras on the feasible regions in source scenes to simulate occlusion patterns, and jitters source points to imitate sensing and reconstruction noise in the real scenes. The pseudo labels are then generated with the pretrained model. In the self-training stage, we develop tail-aware cuboid mixing to build an intermediate domain between source

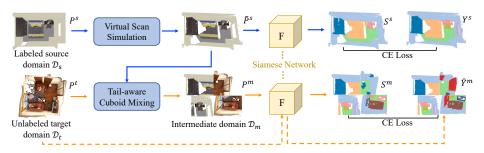


Fig. 2. Our DODA framework consists of two data-oriented modules: Virtual Scan Simulation (VSS) and Tail-aware Cuboid Mixing (TACM). VSS mimics real-world data patterns and TACM constructs an intermediate domain through mixing source and target cuboids. P denotes the point cloud; Y denotes the semantic labels and \hat{Y} denotes the pseudo labels. The superscripts s, t and m stand for source, target and intermediate domain, respectively. The blue line denotes source training flow; the orange line denotes target training flow and the orange dotted line denotes target pseudo label generation procedure. Best viewed in color.

and target, which is constructed by splitting and mixing cuboids from both domains. Besides, cuboids including high percentage tail classes are over-sampled to overcome the class imbalance issue during learning with pseudo labeled data. Elaborations of our tailored VSS and TACM are presented in the following parts.

3.2 Virtual Scan Simulation

DODA starts from training a 3D scene parsing network on labeled source data, to provide pseudo labels on the target domain in the next self-training stage. Hence, a model with a good generalization ability is highly desirable. As analyzed in Sec. 1, different scene construction procedures cause point pattern gaps across domains, significantly hindering the transferability of source-trained models. Specifically, we find that the missing of occlusion patterns and sensing or reconstruction noise in simulation scenes raises huge negative transfer during the adaptation, which cannot be readily addressed by previous UDA methods (see Sec. 5). This is potentially caused by the fact that models trained on clean source data are incapable of extracting useful features to handle real-world challenging scenarios with ubiquitous occlusions and noise. To this end, we propose a plug-and-play data augmentation technique, namely virtual scan simulation, to imitate camera scanning procedure for augmenting the simulation data.

VSS includes two parts: the occlusion simulation that puts virtual cameras in feasible regions of simulated scenes to imitate occlusions in the scanning process, and the noise simulation that randomly jitters point patterns to mimic sensing or reconstruction errors, through which the pattern gaps are largely bridged. **Occlusion Simulation.** Scenes in real-world datasets are reconstructed from RGB-D frame sequences suffering from inevitable occlusions, while simulated scenes contain complete objects without any hidden points. We attempt to mimic occlusion patterns on the simulation data by simulating the real-world data acquisition procedures. Specifically, we divide it into the following three steps:

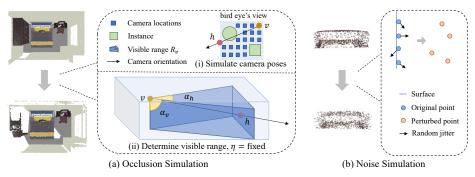


Fig. 3. Virtual scan simulation. (a): We simulate occlusion patterns by simulating camera poses and determining visible ranges. (b): We simulate noise by randomly jittering points to generate realistic irregular point patterns such as rough surfaces.

a) Simulate camera poses. To put virtual cameras in a given simulation scene, we need to determine camera poses including camera positions and camera orientations. First, feasible camera positions where a handheld camera can be placed are determined by checking free space in the simulated environment. We voxelize and project P^s to bird eye's view and remove voxels containing instance or room boundary. The centers of remaining free-space voxels are considered as feasible x-y coordinates for virtual cameras, as shown in Fig. 3 (a) (i). For the z axis, we randomly sample the camera height in the top half of the room.

Second, for each camera position v, we randomly generate a camera orientation using the direction from the camera position v to a corresponding randomly sampled point of interest h on the wall, as shown in Fig. 3 (a) (i). This ensures that simulated camera orientations are uniformly distributed among all potential directions without being influenced by scene-specific layout bias.

b) Determine visible range. Given a virtual camera pose and a simulated 3D scene, we are now able to determine the spatial range that the camera can cover, *i.e.*, R_v , which is determined by the camera field of view (FOV) (see Fig. 3 (a) (ii)). To ease the modeling difficulties, we decompose FOV into the horizontal viewing angle α_h , the vertical viewing angle α_v and the viewing mode η that determine horizontal range, vertical range and the shape of viewing frustum, respectively. For the viewing mode η , we approximate three versions from simple to sophisticated, namely fixed, parallel and perspective, with details presented in the supplementary materials. As illustrated in Fig. 3 (a) (ii), we show an example of the visible range R_v with random α_h and α_v and η in the fixed mode.

c) Determine visible points. After obtaining the visible range R_v , we then determine the visibility of each point within R_v . Specifically, we convert the point cloud to the camera coordinate and extend [27] with spherical projection to filter out occluded points and obtain visible points. By taking the union of visible points from all virtual cameras, we finally obtain the point set P_v^s with occluded points removed. Till now, we can generate occlusion patterns in simulation scenes by mimicking real-world scanning process and adjust the intensity of occlusion by changing the number of camera positions n_v and FOV configurations to ensure that enough semantic context is covered for model learning.

Noise Simulation. Besides occlusion patterns, sensing and reconstruction errors are unavoidable when generating 3D point clouds from sensor-captured RGB-D videos, which unfortunately results in non-uniform distributed points and rough surfaces in real-world datasets (See Fig. 1 (a)). To address this issue, we equip our VSS with another noise simulation module, which injects perturbations to each point as follows:

$$\tilde{P}^s = \{ p + \Delta p \mid p \in P_v^s \},\tag{1}$$

where Δ_p denotes the point perturbation following a uniform distribution ranging from $-\delta_p$ to δ_p , and \tilde{P}^s is the perturbed simulation point cloud. Though simple, we argue that this module efficiently imitates the noise in terms of nonuniform and irregular points patterns as illustrated in Fig. 3.

Model Pretraining on Source Data. By adopting VSS as a data augmentation for simulated data, we train a model with cross-entropy loss as Eq. (2) following settings in [24, 38].

$$\min \mathcal{L}_{pre} = \sum_{i=1}^{N_s} \operatorname{CE}(S_i^s, Y_i^s), \qquad (2)$$

where $CE(\cdot, \cdot)$ is the cross-entropy loss and S is the predicted semantic scores after performing *softmax* on logits.

3.3 Tail-aware Cuboid Mixing

After obtaining a more transferable scene parsing model with VSS augmentation, we further adopt self-training [32, 55,63, 74, 70], to adapt the model by directly utilizing target pseudo-labeled data for supervision. Since target pseudo label is rather noisy, containing incorrect pseudo labeled data and leading to erroneous supervisions [66], we also introduce source supervision to harvest its clean annotations and improve the percentage of correct labels. However, directly utilizing source data unfortunately brings source bias and large discrepancies in joint optimization. Even though point pattern gaps have already been alleviated with the pro-

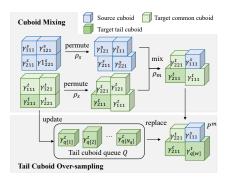


Fig. 4. An illustration of tail-aware cuboid mixing, which contains cuboid mixing and tail cuboid over-sampling. Notice that for clarity, we take $(n_x, n_y, n_z) = (2, 2, 1)$ as an example.

posed VSS, the model still suffers from the context gap due to different scene layouts. Fortunately, the availability of target domain data gives us the chance to rectify such context gaps. To this end, we design Tail-aware Cuboid Mixing

(TACM) to construct an intermediate domain \mathcal{D}_m that combines source and target cuboid-level patterns (see Fig 4), which augments and rectifies source layouts with target domain context. Besides, it also decreases the difficulty of simultaneously optimizing source and target domains with huge distribution discrepancies by providing a bridge for adaptation. TACM further moderates the pseudo label class imbalance issue by cuboid-level tail class oversampling. Details on pseudo labeling, cuboid mixing and tail cuboid oversampling are as follows.

Pseudo Label Generation. To employ self-training after pretraining, we first need to generate pseudo labels \hat{Y}^t for target scenes P^t . Similar to previous paradigms [74, 63, 66, 24], we obtain pseudo labels via the following equation:

$$\hat{Y}_{i,j}^t = \begin{cases} 1 , \text{ if } \max(S_i^t) > T, j = \arg\max S_i^t, \\ 0 , \text{ otherwise,} \end{cases}$$
(3)

where $\hat{Y}_i^t = [\hat{Y}_{i,1}^t, \cdots, \hat{Y}_{i,c}^t]$, *c* is the number of classes and *T* is the confidence threshold to filter out uncertain predictions.

Cuboid Mixing. Here, given labeled source data and pseudo-labeled target data, we carry out the cuboid mixing to construct a new intermediate domain \mathcal{D}_m as shown in Fig. 2 and Fig. 4. For each target scene, we randomly sample a source scene to perform cuboid mixing. We first partition two scenes into several cuboids with varying sizes as the smallest units to mix cuboid as Eq. (4):

$$P = \{\gamma_{ijk}\}, i \in \{1, ..., n_x\}, j \in \{1, ..., n_y\}, k \in \{1, ..., n_z\}, \gamma_{ijk} = \{p \mid p \text{ in } [x_{i-1}, y_{j-1}, z_{k-1}, x_i, y_j, z_k]\},$$
(4)

where γ_{ijk} denotes a single cuboid; n_x , n_y and n_z stand for the number of partitions in x, y and z axis, respectively; and each cuboid γ_{ijk} is constrained in a six-tuple bounding box $[x_{i-1}, y_{j-1}, z_{k-1}, x_i, y_j, z_k]$ defined by the partition positions x_i, y_j, z_k for corresponding dimensions, respectively. These partition positions are first initialized as equal-divisions and then injected with randomness to enhance diversities as below:

$$x_i = \begin{cases} \frac{i}{n_x} \max p_x + (1 - \frac{i}{n_x}) \min p_x, & \text{if } i \in \{0, n_x\}, \\ \frac{i}{n_x} \max p_x + (1 - \frac{i}{n_x}) \min p_x + \Delta \phi, & \text{otherwise,} \end{cases}$$
(5)

where $\Delta \phi$ is the random perturbation following uniform distribution ranging from $-\delta_{\phi}$ to δ_{ϕ} . The same formulation is also adopted for y_j and z_k . After partitioning, the source and target cuboids are first spatially permuted with a probability ρ_s and then randomly mixed with another probability ρ_m , as depicted in Fig. 4 and Fig. 2.

Though ConDA [29] shares some similarities with our cuboid mixing by mixing source and target, it aims to preserve cross-domain context consistency while ours attempts to mitigate context gaps. Besides, ConDA operates on 2D range images, inapplicable to reconstructed indoor scenes obtained by fusing depth images. Our cuboid mixing leverages the freedom of the raw 3D representation, *i.e.* point cloud, and thus is generalizable to arbitrary 3D scenarios.

Tail Cuboid Over-sampling. Besides embedding target context to source data, our cuboid mixing technique also allows adjusting the category distributions by designing cuboid sampling strategies. Here, as an add-on advantage, we leverage this nice property to alleviate the biased pseudo label problem [74, 19, 2, 37] in self-training: tail categories only occupy a small percentage of pseudo labeled data. Specifically, we sample cuboids with tail categories more frequently, namely tail cuboid over-sampling, detailed as follows.

We calculate per-class pseudo label ratio $r \in [0,1]^c$ and define n_r least common categories as tail categories. We then define tail cuboid whose pseudo label ratio is higher than the average value r on at least one of n_r tail categories. We construct a tail cuboid queue Q with size N_q to store tail cuboids. Formally, $\gamma_{q[w]}^{t}$ denotes the w^{th} tail cuboid in Q, as shown in Fig. 4. Notice that through training, Q is dynamically updated with First In, First Out (FIFO) rule since cuboids are randomly split in each iteration as Eq. (4). In each training iteration, we ensure that at least u tail cuboids are in each mixed scene by sampling cuboids from Q and replacing existing cuboids if needed. With such a simple over-sampling strategy, we make the cuboid mixing process tail-aware, and relieve the class imbalance issue in the self-training. Experimental results in Sec. 6 further demonstrate the effectiveness of our tail cuboid over-sampling strategy. Self-training with Target and Source data. In the self-training stage, for data augmentation, VSS is first adopted to augment the source domain data to reduce the pattern gap and then TACM mixes source and target scenes to construct a tail-aware intermediate domain $\mathcal{D}_m = \{P^m\}$ with labels \hat{Y}^m mixed by source ground-truth and target pseudo labels. To alleviate the noisy supervisions from incorrect target pseudo labels, we minimize dense cross-entropy loss on source data P^s and intermediate domain data P^m as below:

$$\min \mathcal{L}_{st} = \sum_{i=1}^{N_t} \operatorname{CE}(S_i^m, \hat{Y}_i^m) + \lambda \sum_{i=1}^{N_s} \operatorname{CE}(S_i^s, Y_i^s),$$
(6)

where λ denotes the trade-off factor between losses.

4 Benchmark Setup

4.1 Datasets

3D-FRONT [8] is a large-scale dataset of synthetic 3D indoor scenes, which contains 18,968 rooms with 13,151 CAD 3D furniture objects from 3D-FUTURE [9]. The layouts of rooms are created by professional designers and distinctively span 31 scene categories and 34 object semantic super-classes. We randomly select 4995 rooms as training samples and 500 rooms as validation samples after filtering out noisy rooms. Notice that we obtain source point clouds by uniformly sampling points from original mesh with CloudCompare [12] at 1250 surface density (number of points per square units). Comparison between 3D-FRONT and other simulation datasets are detailed in the nsupplemental materials.

ScanNet [7] is a popular real-world indoor 3D scene understanding dataset, consisting 1,613 real 3D scans with dense semantic annotations (*i.e.*, 1,201 scans for training, 3,12 scans for validation and 100 scans for testing). It provides semantic annotations for 20 categories.

S3DIS [3] is also a well-known real-world indoor 3D point cloud dataset for semantic segmentation. It contains 271 scenes across six areas along with 13 categories with point-wise annotations. Similar to previous works [33, 47], we use the fifth area as the validation split and other areas as the training split. **Label Mapping.** Due to different category taxonomy of datasets, we condense

11 categories for 3D-FRONT \rightarrow ScanNet and 3D-FRONT \rightarrow S3DIS settings, individually. Besides, we condense 8 categories for cross-site settings between S3DIS and ScanNet. Please refer to the Suppl. for the detailed taxonomy.

4.2 UDA Baselines

As shown in Table 1 and 2, we reproduce 7 popular 2D UDA methods and 1 3D outdoor method as UDA baselines, encompassing MCD [52], AdaptSegNet [57], CBST [74], MinEnt [58], AdvEnt [58], Noisy Student [63], APO-DA [67] and SqueezeSegV2 [61]. These UDA baselines cover most existing streams such as adversarial alignment, discrepancy minimization, self-training and entropy guided adaptation. To perform these image-based methods on our setting, we carry out some task-specific modifications, which are detailed in supplemental materials.

5 Experiments

To validate our method, we benchmark DODA and other popular UDA methods with extensive experiments on 3D-FRONT [8], ScanNet [7] and S3DIS [3]. Moreover, we explore a more challenging setting, from simulated 3D-FRONT [8] to RGBD realistic dataset NYU-V2 [43], presented in the supplementary materials. To verify the generalizability of VSS and TACM, we further integrate VSS to previous UDA methods and adopt TACM in the real-world cross-site UDA setting. Note that since textures for some background classes are not provided in 3D-FRONT dataset, we only focus on adaptation using 3D point positions. The implementation details including network and training details are provided in the Suppl.

Comparison to Other UDA Methods. As shown in Table 1 and Table 2, compared to source only, DODA largely lifts the adaptation performance in terms of mIoU by around 21% and 19% on 3D-FRONT \rightarrow ScanNet and 3D-FRONT \rightarrow S3DIS, respectively. DODA also shows its superiority over other popular UDA methods, obtaining 14% ~ 22% performance gain on 3D-FRONT \rightarrow ScanNet and 13% ~ 19% gain on 3D-FRONT \rightarrow S3DIS. Even only equipping source only with VSS module, our DODA (only VSS) still outperforms UDA baselines by around 4% ~ 10%, indicating that the pattern gap caused by different sensing mechanisms significantly harms adaptation results while previous methods have not readily addressed it. Comparing DODA with DODA (w/o TACM), we observe that TACM mainly contributes to the performance of instances such as bed and bookshelf on ScanNet, since cuboid mixing forces model to focus more on local semantic clues and object shapes itself inside cuboids. It is noteworthy that though DODA yields general improvement around almost

all categories adaptation in both pretrain stage and self-training stage, challenging classes such as bed on ScanNet and sofa on S3DIS attain more conspicuous performance lift, demonstrating the predominance of DODA in tackling troublesome categories. However, the effectiveness of all UDA methods for column and beam on S3DIS are not obvious due to their large disparities in data patterns across domains and low appearing frequencies in source domain. To illustrate the reproducibility of our DODA, all results are repeated three times and reported as average performance along with standard variance.

Table 1. Adaptation results of 3D-FRONT \rightarrow ScanNet in terms of mIoU. We indicate the best adaptation result in **bold**. † denotes pretrain generalization results with VSS

Method	mIoU	wall	floor	cab.	bed	chair	sofa	table	door	wind.	bksf.	desk
Source Only	29.60	60.72	82.42	04.44	12.02	61.76	22.31	38.52	05.72	05.12	19.72	12.84
MCD [52]	32.27	62.86	88.70	03.81	38.50	57.51	21.48	41.67	05.78	01.29	18.81	15.69
AdaptSegNet [57]	34.51	61.81	83.90	03.64	36.06	55.05	34.26	44.21	06.59	05.54	31.87	16.64
CBST [74]	37.42	60.37	81.39	12.18	30.00	68.86	36.22	49.93	07.05	05.82	43.59	16.25
MinEnt [58]	34.61	63.35	85.54	04.66	26.05	61.98	33.05	48.38	05.20	03.15	35.84	13.49
AdvEnt [58]	32.81	64.31	79.21	04.39	35.01	61.05	24.36	41.64	05.97	01.60	29.07	14.32
Noisy student [63]	34.67	62.63	86.27	01.45	17.13	69.98	37.58	47.87	06.01	01.66	35.79	15.06
APO-DA [67]	31.73	62.84	85.43	02.77	15.08	64.24	34.41	46.41	03.94	03.59	18.88	11.41
SqueezeSegV2 [61]	29.77	61.85	72.74	02.50	16.89	58.79	16.81	38.19	05.08	03.24	35.68	15.72
DODA (only VSS) [†]	40.52 ± 0.80	67.36	90.24	15.98	39.98	63.11	46.38	48.05	07.63	13.98	33.17	19.86
DODA (w/o TACM)	48.13 ± 0.25	72.22	93.43	24.46	56.30	70.40	53.33	56.57	09.44	19.97	47.05	26.25
DODA	$51.42{\pm}0.90$	72.71	93.86	27.61	64.31	71.64	55.30	58.43	08.21	24.95	56.49	32.06
Oracle	75.19	83.39	95.11	69.62	81.15	88.95	85.11	71.63	47.67	62.74	82.63	59.05

Table 2. Adaptation results of 3D-FRONT \rightarrow S3DIS in terms of mIoU. We indicate the best adaptation result in **bold**. † denotes pretrain generalization results with VSS

Method	mIoU	wall	floor	chair	sofa	table	door	wind.	bkcase.	ceil.	beam	col.
Source Only	36.72	67.95	88.68	57.69	04.15	38.96	06.99	00.14	44.90	94.42	00.00	00.00
MCD [52]	36.62	64.53	92.16	54.76	13.31	46.67	8.54	00.08	28.86	93.89	00.00	00.00
AdaptSegNet [57]	38.14	68.14	93.17	55.14	05.31	43.14	14.67	00.33	45.75	93.88	00.00	00.00
CBST [74]	42.47	71.60	92.07	68.09	03.28	60.45	17.13	00.18	58.45	95.87	00.00	00.00
MinEnt [58]	37.08	66.15	87.92	52.30	06.27	25.79	15.70	04.44	55.72	93.58	00.00	00.00
AdvEnt [58]	37.98	66.94	91.84	57.96	02.39	46.18	15.14	00.54	44.31	92.50	00.00	00.00
Noisy student [63]	39.44	68.84	91.78	65.53	06.65	48.67	02.27	00.00	53.67	96.46	00.00	00.00
APO-DA [67]	38.23	68.63	89.66	58.84	03.51	40.66	13.73	02.61	47.88	94.97	00.04	00.00
SqueezeSegV2 [61]	36.50	65.01	89.95	54.29	06.79	45.75	10.23	01.70	32.93	94.81	00.00	00.00
DODA (only VSS) [†]	46.85 ± 0.78	70.96	96.12	68.70	25.47	58.47	17.87	27.65	54.39	95.66	00.00	00.00
DODA (w/o TACM)	53.86 ± 0.49	75.75	95.14	76.12	60.11	64.07	25.24	31.75	68.49	95.82	00.00	00.00
DODA	$55.54{\pm}0.91$	76.23	97.17	76.89	63.55	69.04	25.76	38.22	68.18	95.85	00.00	00.00
Oracle	62.29	82.82	96.95	78.16	40.37	78.56	56.91	47.90	77.10	96.29	00.41	29.69

VSS Plug-and-play Results to Other UDA Methods. Since VSS works as a data augmentation in our DODA, we argue that it can serve as a plug-and-play module to mimic occlusion and noise patterns on simulation data, and is orthogonal to existing UDA strategies. As demonstrated in Table 3, equipped with VSS, current popular UDA approaches consistently surpass their original performance by around $8\% \sim 13\%$. It also verifies that previous 2D-based methods fail to close the point pattern gap in 3D indoor scene adaptations, while our VSS can be incorporated into various pipelines to boost performance.

TACM Results in Cross-site Adaptation. Serving as a general module to alleviate domain shifts across domains, we show that TACM can consistently mitigate domain discrepancies on even real-to-real adaptation settings. For crosssite adaptation, scenes collected from different sites or room types also suffer a considerable data distribution gap. As shown in Table 4, the domain gaps in

real-to-real adaptation tasks are also large when comparing the source only and oracle results. When adopting TACM in the self-training pipelines, they obtain 5.64% and 3.66% relative performance boost separately in ScanNet \rightarrow S3DIS and S3DIS \rightarrow ScanNet. These results verify that TACM is general in relieving data gaps, especially the context gap on various 3D scene UDA tasks. We provide the cross-site benchmark with more UDA methods in the Suppl.

Table 3. UDA results equipped with 7VSS on 3D-FRONT \rightarrow ScanNet

Method	V	VSS		
	w/o	w/	Improv.	
MCD [52]	32.37	40.32	+7.95	
AdaptSegNet [57]	34.51	45.75	+11.24	
CBST [74]	36.30	47.70	+11.40	
MinEnt [58]	34.61	43.26	+8.65	
AdvEnt [58]	32.81	42.94	+10.13	
Noisy Student [63]	34.67	48.30	+13.63	
APO-DA [67]	31.73	43.98	+12.25	
SqueezeSegV2 [61]	29.77	40.60	+10.83	

Table 4.	${\rm Cross-site}$	adaptation	$\operatorname{results}$	with
ТАСМ				

Task	Method	mIoU
	Source Only	54.09
$ScanNet \rightarrow S3DIS$	CBST [74]	60.13
ScanNet→ 53D15	CBST+TACM	65.52
	Oracle	72.51
	Source Only	33.48
$S3DIS \rightarrow ScanNet$	Noisy Student [63]	44.81
$S3D1S \rightarrow Scannet$	Noisy Student+TACM	48.47
	Oracle	80.06

6 Ablation Study

In this section, we conduct extensive ablation experiments to investigate the individual components of our DODA. All experiments are conducted on 3D-FRONT \rightarrow ScanNet for simplicity. Default settings are marked in **bold**.

Component Analysis. Here, we investigate the effectiveness of each component and module in our DODA. As shown in Table 5, occlusion simulation brings the largest performance gain (around 9.7%), indicating that model trained on complete scenes is hard to adapt to scenes with occluded patterns. Noise simulation further supplements VSS to imitate sensing and reconstruction noise, obtaining about 1.3% boosts. Two sub-modules jointly mimic realistic scenes, largely alleviating the point distribution gap and leading to a more generalizable source only model. In the self-training stage, VSS also surpasses the baseline by around 13% due to its efficacy in reducing the point pattern gap and facilitating generating high-quality pseudo labels. Cuboid mixing combines cuboid patterns from source and target domains for moderating context-level bias, further boosting the performance by around 2.4%. Moreover, cuboid-level tail-class over-sampling yields 0.9% improvement with greater gains on tail classes. For instance, desk on ScanNet achieves 6% gain (see Suppl.).

VSS: Visible Range. Here, we study the effect of visible range of VSS, which is jointly determined by the horizontal angle α_h , vertical angle α_v , viewing mode η and the number of cameras n_v . As shown in Table 6, fewer cameras $n_v = 2$ and smaller viewing angle $\alpha_v = 45^\circ$ draw around 2% performance degradation with a smaller visible range. And decreasing α_h to 90° can also achieve similar performance with $\alpha_h = 180^\circ$ with more cameras $n_v = 8$, demonstrating that enough semantic coverage is a vital factor. Besides, as for the three viewing modes η , the simplest fixed mode achieves the highest performance in comparison to parallel

Baseline	Virtual scan simulation		Tail-aware cu	mIoU	
Dasenne	Occlusion sim.	Noise sim.	Cuboid mix.	Tail samp.	milliou
Source Only					29.60
Source Only	\checkmark				39.25 (+9.65)
Source Only	\checkmark	\checkmark			40.52 (+1.27)
Noisy Student					34.67
Noisy Student	\checkmark	\checkmark			48.13(+13.46)
Noisy Student	\checkmark	\checkmark	\checkmark		50.55 (+2.42)
Noisy Student	\checkmark	\checkmark	\checkmark	\checkmark	51.42 (+0.87)

Table 5. Component Analysis for DODA on 3D-FRONT \rightarrow ScanNet

and perspective modes. Even though parallel and perspective are more similar to reality practice, they cannot cover sufficient range with limited cameras, since real-world scenes are reconstructed through hundreds or thousands of view frames. This again demonstrates that large spatial coverage is essential. To trade off between the effectiveness and efficiency of on-the-fly VSS, we use fixed mode with 4 camera positions by default here.

Table 6. Ablation study of visible range design on 3D-FRONT \rightarrow ScanNet

Table	7.	Ablation	study	of	cuboid
partitic	ns	on 3D-FR	ONT -	\rightarrow S	canNet

α_h	α_v	η	n_v	mIoU
180°	90°	fixed	2	38.80
180°	90°	fixed	4	40.52
90°	90°	fixed	8	40.30
180°	90°	parallel	4	39.08
180°	90°	perspective	4	39.04
180°	45°	perspective	4	36.64

(n_x, n_y, n_z)	# cuboid	mIoU
(1, 1, 1)	1	48.10
(2, 1, 1)	2	50.00
(2, 2, 1)	4	50.55
(3, 2, 1)	6	50.57
(3, 3, 1)	9	50.02
(1, 1, 2)	2	49.49
(2, 1, 2)	4	49.48

TACM: Cuboid Partition. We study various cuboid partition manners in Table 7. Notice that random rotation along z axis is performed before cuboid partition, so the partition on x or y axes can be treated as identical. While horizontal partitioning yields consistent performance beyond 50% mIoU, vertical partitioning does not show robust improvements, suggesting the mixing of vertical spatial context is not necessary. Simultaneous partitioning on x and y axes also improves performance (*i.e.* (2,2,1) and (2,3,1)), while too small cuboid size (*i.e.* (3,3,1)) results in insufficient context cues in each cuboid with a slight decrease in mIoU.

TACM: Data-mixing Method. We compare TACM with other popular datamixing methods in Table 8. Experimental results show the superiority of TACM since it outperforms Mix3D [44], CutMix [69] and Copy-Paste [11] by around 2.2% to 2.9%. TACM effectively alleviates the context gap while preserving local context clues. Mix3D, however, results in large overlapping areas, which is unnatural and causes semantic confusions. CutMix and Copy-Paste only disrupt local areas without enough perturbations of the broader context (see Suppl.). **TACM:** Tail Cuboid Over-sampling with Class-balanced Loss. Tail cuboid over-sampling brings significant gains on tail classes as discussed in Sec. 6. As demonstrated in Table 9, the class-balanced lovasz loss [4] also boosts performance by considering each category more equally. We highlight that our TACM can also incorporate with other class-balancing methods during optimization since it eases long tail issue on the data-level.

Table 8. Ablation study of data-mixing methods on 3D-FRONT \rightarrow ScanNet

Table 9. Investigation of pseudo label class
imbalance issue on 3D-FRONT \rightarrow ScanNet

Method	mIoU	Method	mIoU
Mix3D [44]	48.62	Noisy Student	48.13
CutMix [69]	49.19	TACM	51.42
Copy-Paste [11]	48.51	CM + lovasz loss [4]	51.68
TACM	51.42	TACM + lovasz loss [4]	52.50

7 Limitations and Open Problems

Although our model largely closes the domain gaps across simulation and realworld datasets, we still suffer from the inherent limitations of the simulation data. For some categories such as beam and column, the simulator fails to generate realistic shape patterns, resulting in huge negative transfer. Besides, room layouts need to be developed by experts, which may limit the diversity and complexity of the created scenes. Therefore, in order to make simulation data benefit real-world applications, there are still several open problems: how to handle the failure modes of the simulator, how to unify the adaptation and simulation stage in one pipeline, and how to automate the simulation process, to name a few.

8 Conclusions

We have presented DODA, a data-oriented domain adaptation method with virtual scan simulation and tail-aware cuboid mixing for 3D indoor sim-to-real unsupervised domain adaptation. Virtual scan simulation generates a more transferable model by mitigating the real-and-simulation point pattern gap. Tailaware cuboid mixing rectifies context biases through creating a tail-aware intermediate domain and facilitating self-training to effectively leverage pseudo labeled target data, further reducing domain gaps. Our extensive experiments not only show the prominent performance of our DODA in two sim-to-real UDA tasks, but also illustrate the potential ability of TACM to solve general 3D UDA scene parsing tasks. More importantly, we have built the first benchmark for 3D indoor scene unsupervised domain adaptation, including sim to real adaptation and cross-site real-world adaptation. The benchmark suit will be publicly available. We hope our work could inspire further investigations on this problem.

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Outline

This supplementary document is arranged as follows:

- Sec. S1 elaborates the visible range design in occlusion simulation of VSS;
- Sec. S2 illustrates visualization and analysis of TACM and other data-mixing methods;
- Sec. S3 presents the implementation details of benchmark setup for sim-toreal settings and cross-site settings;
- Sec. S4 presents the per-class results of tail cuboid over-sampling in TACM;
- Sec. S5 benchmarks DODA with other popular UDA methods on cross-site settings;
- Sec. S6 investigates DODA performance on 3D-FRONT \rightarrow NYU-Depth V2, which focuses on the adaptation from simulation 3D to real RGBD;
- Sec. S7 analyzes the pseudo-label quality with VSS and TACM.
- Sec. S8 presents the qualitative results of S3DIS and ScanNet on sim-to-real settings.

S1 Visible Range Design

In this section, we elaborate the visible range design. Given the camera position v and the point of interest h, the maximum visible range R_v is determined by FOV configurations encompassing the horizontal viewing angle α_h , the vertical viewing angle α_v and the viewing mode η . Specifically, the horizontal visible range $R_v[xy]$ is determined by α_h as Eq. (7):

$$R_{v}[xy] = \left\{ p \mid \frac{(p_{xy} - v_{xy})^{T}(h_{xy} - v_{xy})}{||p_{xy} - v_{xy}||_{2}||h_{xy} - v_{xy}||_{2}} > \cos\frac{\alpha_{h}}{2} \right\},\tag{7}$$

where the subscript xy stands for the coordinate vector projected onto the X-Y plane. As for the vertical visible range $R_v[z]$, it depends on α_v and η as shown in

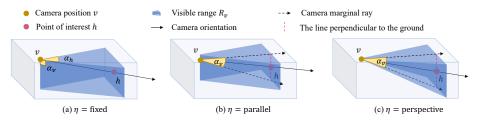


Fig. S5. An illustration of visible range with different viewing modes η . Note that for three modes, the definition of α_h is the same thus we only show it in the fixed mode.

Fig. S5. Specifically, for the simplest fixed mode ($\eta = \text{fixed}$), it selects the visible range lower than the horizontal plane passing through camera v if the camera look downwards (see Fig. S5 (a)); otherwise range above the horizontal plane through v will be selected. In this regard, α_v is fixed at 90°. More flexibly, the

parallel mode (η =parallel) decides the upper and lower bound of vertical visible range as the intersections of marginal rays and the line through h perpendicular to the ground (See Fig. S5 (b)). The perspective mode (η =perspective) further constrains the visible range into a rectangular pyramid bounded by the camera marginal rays (see Fig. S5 (c)), which is the most sophisticated and realistic camera projection process. Formally, the vertical range R[v] with different viewing modes can be expressed as Eq. (8).

$$R_{v}[z] = \begin{cases} \{p \mid p_{z} > v_{z}\} \text{ if } h_{z} > v_{z}, \text{ otherwise } \{p \mid p_{z} < v_{z}\}, & \eta = \text{fixed}, \\ \{p \mid ||v_{xy} - h_{xy}|| \tan\left(\theta - \frac{\alpha_{v}}{2}\right) < (p_{z} - v_{z}) < ||v_{xy} - h_{xy}|| \tan\left(\theta + \frac{\alpha_{v}}{2}\right)\}, & \eta = \text{parallel}, \\ \{p \mid ||v_{xy} - p_{xy}|| \tan\left(\theta - \frac{\alpha_{v}}{2}\right) < (p_{z} - v_{z}) < ||v_{xy} - p_{xy}|| \tan\left(\theta + \frac{\alpha_{v}}{2}\right)\}, & \eta = \text{perspective}, \end{cases}$$

$$\tag{8}$$

where θ is the camera pitch angle defined as $\arcsin\left(\frac{v_z - h_z}{||v - h||_2}\right)$ and $||\cdot||$ denotes the L_2 distance. Finally we obtain the visible range R_v as the intersection of $R_v[xy]$ and $R_v[z]$.

S2 Visualization Comparison and Analysis between TACM and Other Data-mixing Methods

Even though we already present experimental results in Table 8 in the main paper, to better demonstrate the priority of our TACM among other data-mixing methods, we also show some visualization examples here. As shown in Fig S6, when scenes are mixed in Mix3D [44], it leads to ambiguity and loss of semantic cues since the neighboring relationship in local areas has been disrupted by mixed points from two domains. As for Copy-paste [11] and CutMix [69], they perturb a local area with randomly sampled patches or instances, which break the local context while introducing no disruptions of the broader context. In contrast, our TACM mixes scenes with the cuboid as the smallest unit, which preserves the local context while also bringing diversity to the global context by different cuboid combinations.

S3 Benchmark Setup

S3.1 Comparison of Large-scale Simulation Datasets.

In our sim-to-real adaptation benchmark, we select 3D-FRONT [8] as the source domain which contains 18,968 professionally designed rooms with 13,151 CAD 3D furniture objects from 3D-FUTURE [9]. Regarding other large-scale synthetic datasets, SUNCG [54] is not publicly available. Structured3D [73] does not provide interior 3D furniture objects that populate the scenes, which cannot be used as a source dataset without instance classes and layouts. OpenRoom [35] only contains 2.5K CAD models as the objects, which constrains its diversity. Hence, 3D-FRONT is a favorable choice with adequate scenes as well as professional layouts.

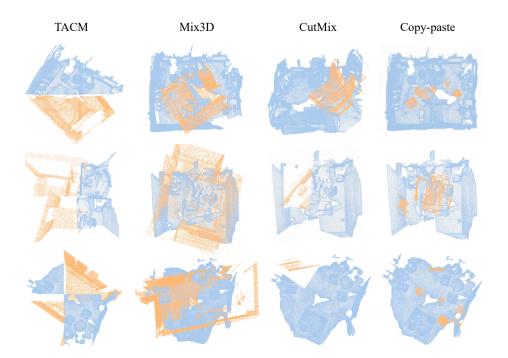


Fig. S6. An illustration of TACM examples along with other data-mixing methods. The yellow points are from source scenes and the blue points are from target scenes.

S3.2 Label Mapping.

Due to the different label spaces of datasets, we need to condense common categories for each adaptation task. We manually determine the category mapping relations according to the class names and representative shapes for each class in different datasets. The selected common classes and mapping relations for 3D-FRONT \rightarrow ScanNet, 3D-FRONT \rightarrow S3DIS, 3D-FRONT \rightarrow NYU-Depth V2 and ScanNet \leftrightarrows S3DIS are shown in Table S10, S11, S12 and S13, respectively.

S3.3 Implementation Details

Network Details. We validate DODA on the sparse-convolution-based U-Net backbone [16, 6], which is a popular and high-performance network on 3D segmentation tasks. The voxel size for point cloud voxelization is set to 2cm.

Training Details. In the pretrain stage, we train source data for 11k iterations with 32 batch size on 8 GPUs. SGD optimizer is employed with 0.9 momentum and 0.0001 weight decay. The learning rate is initialized as 0.005 without decay. For pseudo label generation, we set the pseudo label confidence threshold T to 0.7 for ScanNet and to per-class 30% for S3DIS, to achieve the highest performance. In the self-training stage, we fine-tune the pertrain model for 3.8k iterations on ScanNet and 0.6k iterations on S3DIS. The initial learning rate is set as 0.005 and decayed following the polynomial policy with 0.9 power. The same batch size and optimizer are utilized as in the pretrain stage. The loss trade-off factor λ is set as 0.5. During the two stages, commonly used augmentations are applied, in terms of rotation along vertical axis, flip, elastic distortion, jittering and point shuffling. All experiments are conducted on 8 NVIDIA GTX 2080 Ti GPUs.

For the hyper-parameters of VSS, the number of cameras n_v is set to 4 by default. We set the α_h as 180°, α_v as 90° and η as fixed for FOV configuration. The point jittering intensity δ_p is set as 0.01. For cuboid mixing in TACM, the permutation probability ρ_s and domain mixing probability ρ_m are both set as 0.5. The number of partitions (n_x, n_y, n_z) is set to (2,2,1) with partition perturbations δ_{ϕ} as 0.1. Thus a total of 4 cuboids are partitioned for each scene. As for tail cuboid over-sampling, we typically set the tail cuboid queue size N_q as 256 and the number of tail classes n_r as 2. The least number of tail cuboids per scene u is set as 2.

S3.4 UDA Baselines.

We reproduce 7 popular 2D UDA methods and 1 3D outdoor UDA method as our baselines, encompassing MCD [52], AdaptSegNet [57], CBST [74], MinEnt [58], AdvEnt [58], Noisy Student [63] APO-DA [67] and SqueezeSegV2 [61]. Similar to DODA, for each baseline, we adopt a sparse-convolution-based U-Net backbone [16, 6] and a linear fully-connected point-wise classification head as the overall segmentation network. Besides, some modifications are made for adapting to the 3D vision task as below. For MCD, the U-Net is used as the generator and the point-wise classification head is used as two-branch classifiers. For

Class	ScanNet	3D-FRONT
		wallInner; wallOuter; baseboard; wallTop;
11		customizedBackgroundModel; wallbottom;
wall	wall	customizedFeatureWall;
		extrusion Customized Background Model
floor	floor	floor
		children cabinet; wardrobe; sideboard/side cabinet/
$\operatorname{cabinet}$	cabinet	console table; wine cabinet; wardrobe; TV stand;
		drawer chest/corner cabinet
bed	bed king-size bed; bunk bed; bed frame; single bed; l	
chair	chair	dining chair; lounge chair/cafe chair/office chair;
chair	chair	dressing chair; classic Chinese chair; barstool
sofa	sofa	three-seat/multi-seat sofa; armchair; loveseat sofa;
sola	sola	L-shapped sofa; lazy sofa; chaise longue sofa
table	table	coffee table; round end table; dressing table;
table	table	dining table
door	door	door; pocket
window	window	window; baywindow
bookshelf	bookshelf	bookcase/jewelry armoire
desk	desk	desk

Table S10. Label mapping for 3D-FRONT \rightarrow ScanNet.

Table S11. Label mapping for 3D-FRONT \rightarrow S3DIS.

Class	S3DIS	3D-FRONT
wall	wall	wallInner; wallOuter; baseboard; wallTop; customizedBackgroundModel; wallBottom; customizedFeatureWall; extrusionCustomizedBackgroundModel
floor	floor	floor
chair	chair	dining chair; lounge chair/cafe chair/office chair; dressing chair; classic Chinese chair; barstool
sofa	sofa	three-seat/multi-seat sofa; armchair; loveseat sofa; L-shapped sofa; lazy sofa; chaise longue sofa
table	table	coffee table; round end table; dressing table; dining table; desk
door	door	door; pocket
window	window	window; baywindow
bookcase	bookshelf	bookcase/jewelry armoire
ceiling	ceiling	customizedCeiling; smartCustomizedCeiling; ceiling; extrusionCustomizedCeilingModel
beam	beam	beam
column	column	column

Class	NYU-Depth V2	3D-FRONT
wall	wall	wallInner; wallOuter; baseboard; wallTop; customizedBackgroundModel; wallBottom; customizedFeatureWall; extrusionCustomizedBackgroundModel
floor	floor	floor
cabinet	cabinet	children cabinet; wardrobe; sideboard/side cabinet/ console table; wine cabinet; wardrobe; TV stand; drawer chest/corner cabinet
bed	bed	king-size bed; bunk bed; bed frame; single bed; kids bed
chair	chair	dining chair; lounge chair/cafe chair/office chair; dressing chair; classic Chinese chair; barstool
sofa	sofa	three-seat/multi-seat sofa; armchair; loveseat sofa; L-shapped sofa; lazy sofa; chaise longue sofa
table	table	coffee table; round end table; dressing table; dining table
door	door	door; pocket
window	window	window; baywindow
bookshelf	bookshelf	bookcase/jewelry armoire
desk	desk	desk
ceiling	ceiling	customizedCeiling; smartCustomizedCeiling; ceiling; extrusionCustomizedCeilingModel

Table S12. Label mapping for 3D-FRONT \rightarrow NYU-Depth V2.

Table S13. Label mapping for ScanNet \rightarrow S3DIS and S3DIS \rightarrow ScanNet.

Class	ScanNet	S3DIS
wall	wall	wall
floor	floor	floor
chair	chair	chair
sofa	sofa	sofa
table	table	table
door	door	door
window	window	window
bookshelf	bookshelf	bookcase

AdaptSegNet, we employ its single-level adversarial training performed on the output space. Since the output of the segmentation network is the point-wise predictions, we implement the discriminator as a PointNet-like neural network with 3-layer shared MLP and point random downsampling. For MinEnt, we perform point-wise entropy minimization on target data. For AdvEnt, the same discriminator is utilized as in AdaptSegNet to discriminate outputs from different domains. For APO-DA, we also use the UNet as the generator and only attack the linear classification head to generate point-wise adversarial features. As for the self-training pipeline including CBST and Noisy Student, no other modifications are needed. For the 3D baseline SqueezeSegV2, without official implementations, we self-implement the geodesic alignment and domain calibration modules for our indoor UDA task. The intensity rendering module is discarded since it is specified for outdoor data.

S4 Per-class Results of Tail Cuboid Over-sampling

We present per-class results of Tail Cuboid Over-Sampling (TCOS) on 3D-FRONT \rightarrow ScanNet in Table S14 to demonstrate that the performance gain mainly comes from boosting tail categories. From target pseudo label statistics, the tail classes for this setting are bookshelf and desk with sampling ratios around 25% and 75%, respectively. For desk, the significant improvements around 6% verifies the effectiveness of our method in addressing the long-tail issue in pseudo labels.

Table S14. Supplementary adaptation results of 3D-FRONT \rightarrow ScanNet in terms of mIoU (%). We indicate the best adaptation results in **bold**. \dagger denotes DODA results without tail cuboid over-sampling.

Method	mIoU	wall	floor	cab.	bed	chair	sofa	table	door	wind.	bksf.	desk
DODA w/o TCOS [†]	50.55	72.63	93.98	28.11	65.88	71.43	53.17	57.40	08.53	21.76	57.10	26.09
DODA	51.42	72.71	93.86	27.61	64.31	71.64	55.30	58.43	08.21	24.95	56.49	32.06

S5 Experimental Results on Cross-site Adaptation Tasks

In real-to-real cross-site adaptation tasks, scenes collected from different sites or room types suffer considerable domain discrepancies. To verify the effectiveness of TACM in bridging the real-world domain gaps, we compare DODA (only TACM) with other popular UDA methods on ScanNet \rightarrow S3DIS and S3DIS \rightarrow ScanNet in Table S15 and Table S16, respectively. Results show that DODA (only TACM) outperforms other methods by a large margin around 6% \sim 16% on ScanNet \rightarrow S3DIS and 4% \sim 18% on S3DIS \rightarrow ScanNet. It verifies that our TACM can serve as a general module to eliminate source context bias through target cuboid-level contextual patterns complement.

Besides, to evaluate unsupervised domain adaptation methods, we argue that S3DIS is unsuitable as a source dataset since the per-class results of DODA on real-to-real S3DIS \rightarrow ScanNet are even worse than its counterpart on the sim-to-real 3D-FRONT \rightarrow ScanNet setting (see Table 1 of the main paper). Although real-to-real adaptation theoretically shows smaller domain gaps than sim-to-real settings, S3DIS is rather simple with a small sample size and limited diversity as its scenes are collected only in three buildings of mainly office and educational use, thus resulting in poor performance of adaptation. It illustrates the importance of carefully selecting real-world datasets as the source domain. Simulated datasets, on the other hand, can be a consistently appealing choice as a source domain with arbitrarily large size, diverse samples and free annotations.

Table S15. Adaptation results of ScanNet \rightarrow S3DIS in terms of mIoU (%). We indicate the best adaptation result in **bold**. \dagger denotes the self-training results with TACM based on CBST.

Method	mIoU	wall	floor	chair	sofa	table	door	wind.	bkcase.
Source Only	54.09	64.38	94.39	76.15	25.46	70.55	28.98	28.52	44.31
MCD [52]	49.83	61.38	95.47	73.51	32.04	75.24	36.95	08.01	16.02
AdaptSegNet [57]	50.28	67.75	94.47	69.13	24.77	67.71	36.32	13.54	28.57
CBST [74]	60.13	68.66	96.02	84.61	55.04	63.80	33.47	35.61	43.84
MinEnt [58]	55.31	71.31	94.70	68.10	39.86	68.23	35.98	22.03	42.24
AdvEnt [58]	49.86	68.83	93.87	67.37	20.77	68.11	32.67	13.74	33.50
Noisy student [63]	58.82	66.76	95.84	83.56	52.05	64.39	36.36	37.51	34.08
APO-DA [67]	53.47	68.70	95.62	76.69	43.01	70.53	26.22	11.63	35.37
DODA (only TACM) ^{\dagger}	66.52	73.81	95.94	85.82	70.71	64.64	42.93	48.25	42.09
Oracle	72.51	84.89	97.63	83.72	55.26	81.47	53.94	44.61	78.55

Table S16. Adaptation results of S3DIS \rightarrow ScanNet in terms of mIoU (%). We indicate the best adaptation result in **bold**. \dagger denotes the self-training results with TACM based on Noisy Student.

Method	mIoU	wall	floor	chair	sofa	table	door	wind.	bksf.
Source Only	33.43	37.87	84.01	55.26	18.32	36.15	11.43	08.58	15.81
MCD [52]	30.65	39.50	92.76	43.74	00.00	40.57	09.67	06.03	12.88
AdaptSegNet [57]	36.14	58.48	91.61	35.47	21.35	44.23	07.18	09.17	21.62
CBST [74]	43.08	45.43	90.11	67.53	35.48	56.51	16.94	09.65	22.97
MinEnt [58]	39.40	58.11	90.31	51.18	24.86	44.20	08.10	10.27	28.19
AdvEnt [58]	38.09	58.83	90.24	41.73	28.96	40.68	10.58	08.11	25.59
Noisy student $+$ [63]	44.81	55.61	92.75	65.72	37.77	57.77	12.54	15.25	21.09
APO-DA [67]	38.67	63.85	90.18	49.86	22.34	41.89	06.44	04.64	30.15
DODA (only TACM)	48.47	65.03	94.25	69.23	43.13	58.79	03.58	13.86	29.91
Oracle	80.06	86.78	96.02	89.98	84.24	82.15	51.19	64.99	85.16

S6 Experimental Results on Sim $3D \rightarrow \text{Real RGBD task}$

S6.1 Datasets.

NYU-Depth V2 [43] is a popular RGBD dataset for semantic segmentation. It contains 1,449 densely annotated RGBD images, *i.e.* 795 training samples and 654 validation samples. Each image has a resolution of 640×480 , which can be back-projected to a 3D point cloud containing 3077,200 points. It provides 40 semantic categories.

S6.2 Main Results.

In the main paper, our experiments focus on the sim-to-real adaptation with target scenes reconstructed by RGBD sequences. However, in real-world scenarios, the real scene can be a single RGBD image captured by the depth camera without reconstructions. Therefore, we also investigate the performance of DODA in such a more challenging setting, *i.e.* sim 3D \rightarrow real RGBD. As demonstrated in Table S12, DODA significantly outperforms source only by around 14.3% and improves CBST by around 8.5%, largely reducing the cross-modal gaps between 3D-FRONT and NYU-Depth V2. Even only equipping source only with VSS, our DODA (only VSS) also shows its superiority, obtaining 6.3% and 0.6% gains compared to source only and CBST separately, which demonstrates the effectiveness of VSS in alleviating the point pattern gaps between simulation 3D and real RGBD. Compared to DODA w/o TACM, TACM further enhances the performance by around 3.4%, largely bridging the context gaps.

Table S17. Adaptation results of 3D-FRONT [8] \rightarrow NYU-Depth V2 in terms of mIoU (%). We indicate the best adaptation result in **bold**. \dagger denotes our pretrain generalization results only with VSS.

Method	mIoU
Source Only	17.80
CBST [74]	23.58
DODA (only VSS) ^{\dagger}	24.14
DODA w/o TACM	28.74
DODA	32.12
Oracle	52.88

S7 Analysis of Pseudo label quality

Self-training relies on both pseudo label accuracy and covering ratio (Eq. (9)) for diversity. As shown in Table S18, DODA (only VSS) generates pseudo labels with around 15.6% higher mIoU and 7.7% larger label covering ratio compared to source only, which benefits the follow-up self-training stage. Besides, TACM also improves the pseudo label quality after the first self-training round by about 3.6% mIoU and 0.5% covering ratio, which is supposed to further boost the iterative self-training if applied.

covering ratio =
$$\frac{\# \text{ pseudo-labeled points}}{\# \text{ all points}} \times 100\%$$
 (9)

S8 Visualization

We provide some qualitative results of DODA on sim-to-real adaptation tasks of 3D-FRONT \rightarrow ScanNet and 3D-FRONT \rightarrow S3DIS as illustrated in Fig. S7. Compared to self-training baselines, our DODA can segment instances better and generate more accurate and smooth predictions.

Method	pseudo label				
Method	mIoU	covering ratio (%)			
Source Only	35.16	59.85			
DODA (only VSS)	50.73	67.54			
DODA (w/o TACM)	53.24	81.51			
DODA	56.85	82.05			

Table S18. Results of pseudo label quality with threshold T = 0.7.

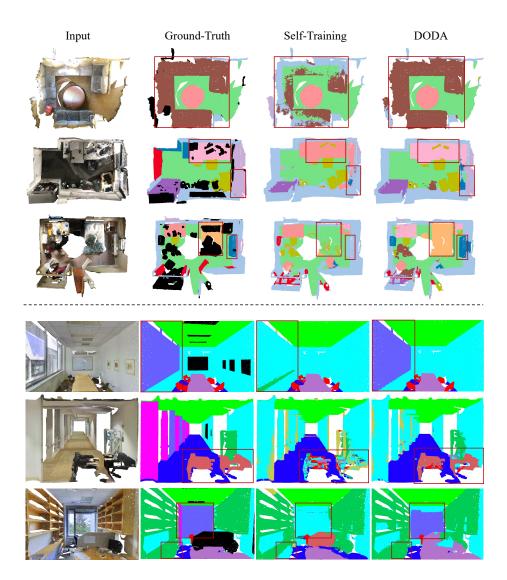


Fig. S7. Qualitative results of 3D-FRONT \rightarrow ScanNet (top) and 3D-FRONT \rightarrow S3DIS (bottom). Note that the third column is the prediction of self-training baselines, *i.e.* Noisy Student for ScanNet and CBST for S3DIS. The red bounding boxes indicate the specific areas where our DODA significantly outperforms self-training baselines.