Complete & Label: A Domain Adaptation Approach to Semantic Segmentation of LiDAR Point Clouds

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Abstract

We study an unsupervised domain adaptation problem for the semantic labeling of 3D point clouds, with a particular focus on domain discrepancies induced by different LiDAR sensors. Based on the observation that sparse 3D point clouds are sampled from 3D surfaces, we take a Complete and Label approach to recover the underlying surfaces before passing them to a segmentation network. Specifically, we design a Sparse Voxel Completion Network (SVCN) to complete the 3D surfaces of a sparse point cloud. Unlike semantic labels, to obtain training pairs for SVCN requires no manual labeling. We also introduce local adversarial learning to model the surface prior. The recovered 3D surfaces serve as a canonical domain, from which semantic labels can transfer across different LiDAR sensors. Experiments and ablation studies with our new benchmark for cross-domain semantic labeling of LiDAR data show that the proposed approach provides 8.2-36.6% better performance than previous domain adaptation methods.

1 Introduction

Semantic segmentation of LiDAR point clouds is important for many applications, including autonomous driving, semantic mapping, and construction site monitoring to name a few. Given a LiDAR sweep (frame), the goal is to produce a semantic label for each point.

Although there is great potential for deep neural networks on this semantic segmentation task, their performance is limited by the availability of labeled training data. Acquiring manual labels for 3D points is very expensive, and thus few large training sets are available with dense semantic segmentations for LiDAR (e.g., [23]). Several datasets have recently been released by autonomous driving companies [1, 4, 5, 14, 15, 28, 30, 51]. However, each has a different configuration of LiDAR sensors, which produce different 3D sampling patterns (Figure 1), and each covers distinct geographic regions with distinct distributions of scene contents. As a result, deep networks trained on one dataset do not perform well on others.

There is a domain adaptation problem. While the mismatch of scene contents is similar to those studied in 2D visual domain adaptation [37, 9], the sampling mismatch is unique to 3D point clouds. Each time a new LiDAR sensor configuration is selected, data is acquired with a different 3D sampling pattern, so models trained on the old data are no longer effective, and new labeled data must be acquired for supervised training in the conventional machine learning paradigm. In contrast, domain adaptation aims to take a better advantage of the old labeled data by revealing some unlabeled data of the new LiDAR configuration to a machine learner so that it can account for the new scenarios while learning a segmentation function from the old labeled point clouds.

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To address the sampling caused domain gap, we observe that LiDAR samples have an underlying geometric structure, and domain adaptation can be performed more effectively with a 3D model leveraging that structure. Specifically, assuming the physical world is composed of 3D surfaces, and that LiDAR sensor samples come from those surfaces, we address the domain adaption problem by transforming it into a 3D surface completion task. That is, if we can recover the underlying complete 3D surfaces from sparse LiDAR point samples, and train networks that operate on the completed surfaces, then we can leverage labeled data from any LiDAR scanner to work on data from any other.

The motivation for this approach is that surface completion is an easier task than semantic segmentation. First, there are strong priors on the shapes of 3D surfaces encountered in the real world, and thus a network trained to densify a point cloud can learn and leverage those priors with relatively little training data. Second, surface completion can be learned from self-supervision (e.g., from multi-view observations) and/or from synthetic datasets (e.g., from sampled computer graphics models). Unlike semantic segmentation, no manual labels are required. We train our completion network with supervision from complete surfaces reconstructed from multiple frames of LiDAR data.

Our network architecture is composed of two phases: surface completion and semantic labeling. In the first phase, we use a sparse voxel completion network (SVCN) to recover the 3D surface from a LiDAR point cloud. In the second phase, we use a sparse convolutional U-Net to predict a semantic label for each voxel on the completed surface.

Extensive experiments with different autonomous vehicle driving datasets verify the effectiveness of our domain adaptation approach to the semantic segmentation of 3D point clouds. For example, using a network trained on the Waymo open dataset [51] to perform semantic segmentation on the nuScenes dataset [4] provides 10.4% better mIoU with our proposed method than without, and 8.5% better than 2D domain adaptation methods. Similarly, training on NuScenes and testing on Waymo provides 10.9% better mIoU than state-of-the-art domain adaptation methods.

Our contributions are three-fold. First and foremost, we identify the cross-sensor domain gap for LiDAR point clouds caused by sampling differences, and we propose to recover complete 3D surfaces from the point clouds to eliminate the discrepancies in sampling patterns. Second, we present a novel sparse voxel completion network, which efficiently processes sparse and incomplete LiDAR point clouds and completes the underlying 3D surfaces with high resolution. Third, we provide thorough quantitative evaluations to validate our design choices on three datasets.

2 Related Work

Unsupervised domain adaptation. Conventional machine learning relies on the assumption that training and test sets share the same underlying distribution, but the practice often violates the assumption. Unsupervised domain adaptation (UDA) [9, 37] handles the mismatch by revealing some test examples to the machine learner such that it can account for the test-time scenarios while learning from the training set. Early work on UDA mainly reweights [45, 66] or re-samples [16, 17] the source-domain examples to match the target distribution. Besides, there is a fruitful line of works on learning domain-invariant representations, such as subspace alignment [12] and interpolation [18, 20], adversarial training [13, 54, 2, 46, 26], maximum mean discrepancy [35], maximum classifier discrepancy [43], correlation alignment [50], etc. As noted in [40], these methods by design align two domains in a holistic view and fail to capture the idiosyncratic geometric properties in point clouds.

Domain adaptation for 3D point clouds. Relatively little work has been done to study domain adaptation for 3D point clouds. Rist et al. [42] propose that dense 3D voxels are preferable to point clouds for sensor-invariant processing of LiDAR point clouds. Salah et al. [44] propose a CycleGAN approach to the adaptation of 2D bird’s eye view images of LiDAR between synthetic and real domains. Wu et al. [58] compensate for differences in missing points and intensities between real and synthetic data using geodesic correlation alignment. Qin et al. [40] and Wang et al. [57] propose multi-scale feature matching methods for object detection from 3D point clouds. None of these methods explicitly account for differences in point sampling patterns in the 3D domain.

Deep 3D Semantic Segmentation. We target at deep 3D semantic segmentation in this paper, which associates semantic labels to 3D data via deep learning approaches. Different from 2D images, 3D data can be represented in various forms, introducing extra challenges for deep learning methods design. Early works use dense voxel grid to represent 3D objects and leverage dense 3D convolution to
predict semantic labels \([59, 39]\), with usually a limited resolution due to the heavy computation cost. To reduce the computation load, point cloud based methods are proposed which directly operate on point sets \([38, 38, 33, 48]\). To further leverage the relationship among 3D points, deep neural networks working on graphs \([61, 56]\) and meshes \([3, 27, 25]\) are used. Recently, sparse convolution based methods \([22, 21, 8]\) have been very popular, achieving superior performance on various indoor and outdoor semantic segmentation benchmarks. They treat 3D data as a set of sparse voxels and restrict 3D convolution to these voxels. Our segmentation backbone is based upon SparseConvNet \([21]\) but we focus on improving its domain transfer ability to 3D data with different sampling patterns.

**Deep 3D Shape Completion.** Deep 3D shape completion aims at complete missing geometry pieces of some partial 3D observation using deep learning methods. Dense voxel representation has been explored to complete single 3D objects \([10, 60, 24]\) and indoor scenes \([47]\). The heavy computation cost is a big issue for these methods, making them not scale well to large-scale LiDAR point clouds. To improve the computation efficiency, octree-based methods have been proposed \([41, 52, 65]\) which are able to produce high resolution 3D outputs. We present a sparse voxel completion network sharing similar flavors to \([41, 52, 65]\) with an improved network architecture and loss function. We demonstrate how we could complete sparse LiDAR point clouds with high resolution using sparse convolution when the output structure is unknown and also one main difference is that we consider the application of shape completion to 3D domain adaptation. Another relevant track of works study point cloud upsampling using deep learning methods \([63, 62, 32]\). They usually require an upsampling factor and have no control on the sampling patterns of the results.

### 3 Method

This paper proposes a method to overcome the domain gap caused by differences in 3D point sampling in LiDAR sensors. Observing that all the sensors acquire samples of 3D surfaces, we propose a two-stage approach, where a sensor-specific surface completion neural network first recovers the underlying 3D surfaces from the sparse LiDAR point samples, and then a sensor-agnostic semantic segmentation network assigns labels to the recovered 3D surfaces. This two-phase approach focuses on improving the domain transfer ability to 3D data with different sampling patterns.

#### 3.1 Overview and notations

Figure 2 illustrates the overall workflow of our approach. We consider an unsupervised domain adaptation (UDA) setting, but our approach is readily applicable to other settings such as multi-domain adaptation \([11]\) and open domain adaptation \([36, 34]\). In UDA, we have access to a set of labeled LiDAR point clouds, \((x_i^s, y_i^s)_{i=1}^{N_s}\) from the source domain and a set of unlabeled LiDAR point clouds \((x_j^t)_{j=1}^{N_t}\) in a target domain, where \(x_i^s \in \mathbb{R}^{T_i^s \times 3}\) and \(x_j^t \in \mathbb{R}^{T_j^t \times 3}\) represent two sets of \(T_i^s\) and \(T_j^t\) 3D points, respectively, and \(y_i^s \in \mathcal{Y} = \{1, ..., Y\}^{T_i^s}\) corresponds to a per-point semantic label ranging within \(Y\) different classes. The two sets of point clouds are captured with different LiDAR sensors, which have their unique sampling patterns. Our goal is to learn a segmentation model that achieves high performance on the target-domain LiDAR points.

To cope with the domain gap caused by different LiDAR sensors, we learn neural surface completion networks to recover the 3D surfaces underlying incomplete 3D point clouds. Denote by \(\psi_i^s(x_i^s) \in \mathbb{R}^{M_i^s \times 3}\) and \(\psi_j^t(x_j^t) \in \mathbb{R}^{M_j^t \times 3}\) the surface completion networks for the two domains, respectively,
Figure 3: The architecture of sparse voxel completion network. We use sparse convolution with a kernel size 3 and a stride 1, max pooling with a kernel size 2 and a stride 2. Both dense and sparse upsampling are done with a factor of 2.

where $M^s_i$ and $M^t_j$ are the numbers of dense points used to represent the completed surfaces. We say the 3D surfaces reside in a canonical domain.

We train a semantic segmentation network, $\phi(\psi^s(x^s_i))$, over this canonical domain by using the labeled training set of the source domain, and then apply it to the densified point clouds of the target domain, i.e., $\phi(\psi^t(x^t_i))$. The per-point labels of the original target-domain point cloud $x^t_i$ are obtained by projecting the segmentation results back to the target domain.

### 3.2 A Sparse Voxel Completion Network (SVCN) for Surface Completion

In this section, we describe the sparse voxel completion network (SVCN), which recovers the underlying 3D surfaces from a sparse, incomplete LiDAR point cloud and is the core of our approach.

#### 3.2.1 Architecture

Figure 3 shows the architecture of SVCN, which comprises a structure generation sub-net and a structure refinement sub-net. The former consumes a set of sparse voxels obtained by voxelizing an input point cloud, and it outputs denser voxels representing the underlying 3D surfaces from which the input points are sampled. The structure refinement network then prunes out redundant voxels.

Both sub-nets are highly relevant to the sparse convolutional U-Net [21], which is an encoder-decoder architecture involving a series of sparse conv/deconv operations. Multi-scale features can be integrated, and skip connections provide additional information pathways in the network. However, the sparse convolutional U-Net is not directly applicable to our setting since it applies all convolutional operations only to active sites without changing the voxel structure, while we need extrapolation.

**Structure generation network.** In order to generate new structures for completion purposes, we replace sparse deconvolutions with dense upsampling and voxel pruning operations. Specifically, in the decoder, each voxel in the lower resolution level $l$ will generate $2^3$ voxels in the higher resolution level $l-1$ after a dense upsampling operation. Low-resolution voxel features are also duplicated to the corresponding positions of high-resolution voxels.

The above procedure allows generating new structures, but it could easily break the inherent sparsity of voxelized 3D surfaces. Similar to [41][52][65], we introduce a voxel pruning module to trim voxels and avoid expanding too many voxels in the decoder. Given a set of voxels equipped with features, the voxel pruning module applies a linear layer together with a sigmoid function on each voxel, and outputs a probability score indicating the existence of each voxel. At training time, only the ground truth voxels are kept. At test time, we prune voxels with an existence probability lower than 0.5.

To guarantee the faithfulness of the generated shape to input voxels, for each resolution level $l$, we single out intersections between the densely upsampld voxels in the decoder and the sparse voxels in the corresponding encoder level and avoid pruning these voxels. The skip connections need some special care. Through them, we pass encoder features to the upsampled voxels. For newly generated voxels, we pass zeros because there are no counterparts in the encoder.

**Structure refinement network.** The structure generation network is able to generate new structures for shape completion purposes. However, since we prune voxels using the ground truth existence probabilities on each level during training, the network could be sensitive to noisy outlier points (e.g., an outlier input voxel could possibly add a big chunk of wrong voxels to the final prediction). To cope with this issue, we introduce a structure refinement network, which is essentially a sparse
convolutional U-Net adding no new voxels any more. Instead, it predicts an existence confidence score for each voxel. This is achieved by replacing the dense upsampling and voxel pruning modules in the structure generation network with sparse upsampling operations, which unpool voxel features only to the voxels that exist in the higher encoder level.

For more details of the SVCN network architecture, please refer to the supplementary materials.

### 3.2.2 Training Data

We need to prepare training data, \( \{(z^s_i, z^c_i)\} \) and \( \{(z^t_i, z^c_i)\} \), for the surface completion networks \( \psi^s \) and \( \psi^t \) of the source and target domains, respectively, where \( z^c_i \) stands for a dense surface point cloud in the canonical domain from which we can sample both a source-domain point cloud \( z^s_i \) and a target-domain point clouds \( z^t_i \). It is important to note that the training data for the surface completion network SVCN could be different from that for semantic segmentation, so we use different notations here. Indeed, one advantage of surface completion is that it can be learned from self-supervision which does not require manual labels. Exemplar supervisions include dense surface points via simulation, multi-view registration, and high-resolution LiDAR point clouds, to name a few. We first describe how we obtain the dense surface point clouds \( \{z^c_i\} \), followed by how to sample domain-specific incomplete point clouds \( \{z^s_i\} \) or \( \{z^t_i\} \) for constructing the training pairs for SVCN.

**Dense surface point clouds.** To obtain the dense point clouds of complete 3D surfaces, we leverage the LiDAR sequences in existing autonomous driving datasets, for example [51]. Specifically, we aggregate multiple LiDAR frames within a sequence to generate a denser and more complete point cloud. Poisson surface reconstruction [29] is then applied to recover the underlying mesh surfaces. We discretize a surface by uniformly sampling points on it, ensuring the point resolution is higher than the resolutions in the source or target domain. An example is shown in Figure 4(a). The complete scene point clouds act as a canonical domain with uniform sampling patterns.

**Domain-specific incomplete point clouds.** Given the dense, complete surface point clouds \( \{z^c_i\} \), we simulate a “virtual LiDAR” to generate incomplete point clouds for the source (target) domain such that the virtual LiDAR point clouds \( \{z^s_i\} \) \( \{z^t_i\} \) share the same distribution as the real point clouds in that domain. In particular, we propose a polar sampling scheme to implement the “virtual LiDAR”. First, we randomly pick up a reference point cloud from a domain and compute the polar coordinate \( (r, \theta, \phi) \) for each point \( (x, y, z) \), where \( r = \sqrt{x^2 + y^2 + z^2}, \theta = \text{atan2}(\sqrt{x^2 + y^2}, z), \phi = \text{atan2}(y, x) \). We argue that \( (\theta, \phi) \) reveals the sampling pattern in this point cloud without containing much scene-specific information and can be used to re-sample a different complete scene point cloud to simulate the corresponding sampling pattern. Second, we select a sensor location in the complete scene point cloud, remove occluded points, and convert the rest points into their polar coordinates. Finally, we search for the nearest neighbor point in the complete scene point cloud for each point in a reference frame and sample these points to imitate the reference sampling pattern. Notice this is done in the \( (\theta, \phi) \) space to transfer the sampling pattern only. In Figure 4(b) and (c), we shown simulated incomplete point clouds with sampling patterns transferred from reference point clouds in Waymo open dataset [51] and nuScenes dataset [4], respectively.

### 3.2.3 Training Algorithm

Given the paired training data, we convert them to voxels and employ a voxel-wise binary cross-entropy loss to first pre-train the structure generation sub-net. We then fix it and switch it to the
inference mode, using the predicted voxel existence probability to train the structure refinement
sub-net with another voxel-wise binary cross-entropy loss.

Local Adversarial Learning. Since we have a strong prior on the scene completed by SVCN,
namely, the densified voxels should lie on 3D surfaces, we propose an adversarial loss to capture this
prior, in a similar spirit to [31][55][32]. This loss can be added to the training of either the structure
generation sub-net or the refinement sub-net. A notable property of our adversarial loss is that it is
imposed over local surface patches, as opposed to the global output of SVCN. Please refer to the
supplementary materials for more details.

3.3 A Semantic Segmentation Network Over the Canonical Domain

We train a semantic segmentation network \( \phi(\cdot) \) over the canonical domain using the labeled data
\( \{(x_s^i, y_s^i)\} \) in the source domain. Given a test point cloud \( x_t^i \) in the target domain, we first map it to the
canonical domain by the surface completion network SVCN \( \psi^i(x_t^i) \), apply the segmentation network
over it \( \phi(\psi^i(x_t^i)) \), and finally project the segmentation results back to the original target-domain
point cloud \( x_t^i \). We postpone to the supplementary materials how to propagate the source-domain
labels to the dense, complete point clouds in the canonical domain and how to project segmentation
results to the target domain. Both depend on nearest neighbor search and majority voting.

4 Experiments

We experiment with three autonomous driving datasets captured by different LiDAR configurations.

- Waymo open dataset [51]: It contains LiDAR point cloud sequences from 1K scenes, and
each sequence contains about 200 frames. There are five LiDAR sensors. We use the top
64-beam LiDAR in all our experiments. The LiDAR frames are annotated with 3D object
bounding boxes, from which we obtain the per-point labels. The data is officially split into
798 training scenes and 202 validation scenes. Following this split, we have ~160K training
frames and ~40K validation frames.

- nuScenes dataset [4]: It contains ~40K annotated LiDAR frames from 1K scenes. Different
from the Waymo open dataset, it adopts a 32-beam LiDAR sensor and different configu-
rations, causing a sampling gap from the Waymo point clouds. Following the dataset’s
recommendation, we train our models using ~28K frames from 700 scenes and evaluate on
~6K frames from 150 validation scenes.

- KITTI dataset [14]: It adopts a Velodyne 64-beam LiDAR similar to Waymo but with a
different sensor configuration. Following [6], we split the official training set into 3712
training samples and 3769 test samples, respectively. Unlike nuScenes and Waymo, KITTI
only annotates objects that are visible within the front camera images, therefore we only
process the point clouds within the field of view of the images.

We consider the semantic segmentation of vehicles and pedestrians, two classes that are both common
and safety-critical in self-driving scenes. The three datasets provide an organic, large-scale testbed
to study domain adaptation methods for 3D point clouds. By design, our approach copes with the
domain discrepancy among the three datasets caused by different configurations of LiDAR sensors.

4.1 Sparse LiDAR Point Cloud Completion

We first evaluate our sparse voxel completion network (SVCN) in this section.

Training data. SVCN takes as input an incomplete point cloud and predicts its underlying complete
3D surfaces in a dense volumetric form. To generate data pairs for training and evaluation, we
aggregate multiple frames within each sequence from the Waymo open dataset, resulting in 2400
complete scene point clouds for training and 200 for test. We then sample incomplete point clouds
via the “virtual LiDAR” described in Section [3.2] We voxelize the complete point clouds using a
voxel size of 20cm to provide ground truth supervision for various learning methods.

Evaluation. We use two evaluation metrics. One is voxel-level intersection over union (IoU). The
other is the Chamfer Distance (CD) between the predicted voxel set and the ground truth voxel set.
Figure 5: Visualizations of the surface completion results from different datasets. Black points indicate the original sparse incomplete LiDAR points, and we use colored points to represent the output of our sparse voxel completion network.

To compute the CD between two voxel sets, we convert each voxel set into a point cloud by keeping the center of each voxel and then compute CD between the two point clouds.

**SVCN vs. Baselines.** There is not much prior work on using sparse convolution to complete sparse LiDAR inputs. The closest baseline is a variant of ESSCNet [65] that uses only one group in the spatial group convolution, which achieves state-of-the-art results for semantic indoor scene completion in [65]. That network is similar to our structure generation network (the first half of SVCN), so it also provides an ablation of our SVCN without the structure refinement. A second ablation baseline is our full SVCN network trained without the local adversarial loss.

| Test domain | Metric | ESSCNet [65] | SVCN w/o adv. | SVCN |
|-------------|--------|--------------|---------------|------|
| Waymo       | IoU(%)↑ | 44.1         | 46.3          | 47.5 |
|             | CD↓     | 1.070        | 1.013         | 0.968|
| nuScenes    | IoU(%)↑ | 24.9         | 26.7          | 28.8 |
|             | CD↓     | 1.745        | 1.730         | 1.610|
| KITTI       | IoU(%)↑ | 40.9         | 42.9          | 44.3 |
|             | CD↓     | 1.147        | 1.122         | 1.052|

**Results.** Table 1 shows the comparison results. Our full network with local adversarial learning outperforms all competing methods for inputs with the sampling patterns of all three datasets. Comparing ESSCNet and SVCN without the local adversarial loss, we can see that the structure refinement network does improve the scene completion quality. Finally, the local adversarial loss, which accounts for surface priors, results in better completions than SVCN without it. Notice that the LiDAR point clouds from nuScenes hold a much sparser sampling pattern compared with those from Waymo or KITTI, and are thus more challenging for the completion task. This is revealed by the relatively low IoU and high CD scores when the inputs hold nuScenes sampling patterns.
To better understand how our surface completion network SVCN could canonicalize different sampling patterns and therefore mitigate the corresponding domain gap, we visualize the surface completion results from different datasets in Figure 5. We use black points to represent the sparse incomplete LiDAR inputs and the outputs of our SVCN are shown in colored points. It is clear that SVCN is able to recover the underlying surfaces regardless of the input sampling patterns. SVCN is also able to fill small holes to make the geometry more complete. Comparing vehicles from Waymo and nuScenes datasets, we can observe a clear domain gap in the inputs while after surface completion they share more similar sampling patterns and geometry, leading to a better domain transfer result.

4.2 Unsupervised Domain Adaptation for 3D Point Cloud Semantic Segmentation

In this section, we study the domain transfer ability of our approach among the Waymo, nuScenes and KITTI datasets by treating one as the source domain and another as the target domain. Domain adaptation methods for 3D LiDAR point cloud segmentation has not been studied much previously, so we compare with state-of-the-art adaptation methods for 2D semantic segmentation, including feature space adversarial domain adaptation (FeaDA) [7] and output space adversarial domain adaptation (OutDA) [53]. We report the results in Table 2.

Table 2: Unsupervised domain adaptation for 3D semantic segmentation among Waymo, nuScenes and KITTI dataset. N denotes nuScenes dataset, W denotes Waymo dataset and K denotes KITTI dataset. The two numbers in each cell represent the IoU for vehicle and pedestrian respectively.

| Source → Target | Method | 0m-30m | 30m-50m | 50m-inf | Overall |
|-----------------|--------|--------|---------|---------|---------|
| N → N           | No Adaptation | 89.3 60.4 | 55.1 12.8 | 21.0 0.1 | 86.8 56.6 |
| W → N           | No Adaptation | 74.5 30.3 | 2.5 0.0 | 0.0 0.0 | 70.5 28.0 |
|                 | FeaDA | 79.2 29.6 | 4.4 0.0 | 0.0 0.0 | 75.0 27.3 |
|                 | OutDA | 73.3 26.1 | 8.5 0.0 | 0.8 0.0 | 68.8 23.9 |
|                 | Ours  | **82.2 44.3** | **20.6 0.2** | **2.6 0.0** | **78.3 41.0** |
| K → N           | No Adaptation | 55.5 14.7 | 0.4 0.0 | 0.0 0.0 | 52.5 13.6 |
|                 | FeaDA | 49.9 11.0 | 0.2 0.0 | 0.0 0.0 | 47.0 10.2 |
|                 | OutDA | 46.4 11.7 | 2.4 0.0 | 0.1 0.0 | 43.7 10.8 |
|                 | Ours  | **60.4 16.4** | **5.7 0.0** | **0.3 0.0** | **57.1 15.2** |
| W → W           | No Adaptation | 96.4 79.6 | 89.9 72.4 | 76.9 50.0 | 95.3 77.4 |
| N → W           | No Adaptation | 44.0 48.7 | 63.3 41.6 | 45.4 24.0 | 45.8 46.6 |
|                 | FeaDA | 49.9 48.1 | 60.3 45.3 | 45.7 23.3 | 50.7 46.7 |
|                 | OutDA | 39.1 47.5 | 61.6 42.6 | 46.7 22.8 | 41.5 45.8 |
|                 | Ours  | **73.2 49.3** | **68.2 42.3** | **47.6 24.5** | **71.9 47.2** |
| K → W           | No Adaptation | 61.7 30.7 | 43.5 14.7 | 13.9 1.5 | 58.8 27.6 |
|                 | FeaDA | 61.5 24.5 | 48.4 15.1 | 19.2 0.9 | 59.3 22.4 |
|                 | OutDA | 59.9 25.5 | 42.6 17.0 | 24.8 1.6 | 57.1 23.6 |
|                 | Ours  | **65.7 33.8** | **58.9 15.2** | **33.6 2.4** | **64.0 30.5** |
| K → K           | No Adaptation | 86.0 67.4 | 61.7 5.5 | 23.8 0.0 | 84.2 66.7 |
| W → K           | No Adaptation | 83.4 51.0 | 61.0 9.1 | 25.4 0.1 | 81.7 49.8 |
|                 | FeaDA | 84.1 54.1 | 58.9 7.4 | 28.9 0.0 | 82.2 53.1 |
|                 | OutDA | 83.2 49.2 | 54.2 7.3 | 25.5 0.0 | 81.4 48.3 |
|                 | Ours  | **84.5 66.3** | **61.5 7.6** | **33.8 2.4** | **82.8 63.6** |
| N → K           | No Adaptation | 41.9 29.4 | 32.7 7.1 | 15.1 3.9 | 41.2 28.4 |
|                 | FeaDA | 53.0 28.5 | 43.9 3.9 | 21.3 2.4 | 52.3 26.8 |
|                 | OutDA | 49.1 33.9 | 32.5 4.4 | 14.2 3.1 | 47.7 32.3 |
|                 | Ours  | **75.8 37.5** | **51.7 4.5** | **24.3 4.0** | **73.9 35.4** |

From Table 2 we can see an obvious performance drop when transferring segmentation networks from one domain to another. For example, compared with both training and testing on nuScenes (N → N), training on the Waymo dataset while evaluating on the nuScenes dataset (W → N) would cause the mean IoU (mIoU) to drop from 71.7% to 49.3%. This shows the importance of studying the domain adaptation problem. Our method successfully brings the mIoU to 59.7% and outperforms the prior arts. We draw the same observation on other pairs of domains tested. Besides, the results on KITTI (W → K and N → K) verify that the domain gap between Waymo and KITTI is smaller than that between other domain pairs, because they both adopt 64-beam LiDARs.
Figure 6: A comparison of different domain adaptation methods on an example Waymo frame. We consider the domain adaptation direction from nuScenes to Waymo dataset. Different colors indicate different semantic classes. FeaDA and OutDA represent feature space domain and output space domain adaptation respectively. We use green circles to highlight the prediction errors.

The 2D domain adaptation methods do not work well on the 3D point clouds. The feature space adversarial adaptation method tries to bring close two domains in a global feature space, but it fails to model rich local cues in 3D point clouds, such as sampling patterns, surfaces, and contexts. Output space adversarial adaptation fails in most cases with no surprise because it assumes that the segmentation masks of two domains are indistinguishable. While this assumption works for 2D scenes, it breaks given different 3D sampling patterns in two domains.

**Qualitative Results.** Figure 6 shows some qualitative results of both surface completion and semantic segmentation when adapting from nuScenes to Waymo. We can see that the baseline methods mislabel objects that are both close to and distant from the sensor location. The sparsity of distant objects is a great challenge for all methods. Our approach completes the underlying 3D surfaces from only sparse observations, making it easier for the segmentation network to discover those distant objects.

**Ablation Studies.** We provide additional ablation studies about the correlation between the quality of scene completion and the performance of domain adaptation. We replace SVCN in our method with its variants described in Section 4.1 and report the resulting segmentation results in Table 3.

| Source→Target | Ours w/o refinement | Ours w/o adv. | Ours-full |
|---------------|---------------------|--------------|-----------|
| W→N           | 55.2                | 58.7         | 59.7      |
| N→W           | 58.2                | 59.0         | 59.6      |

It can be clearly seen that better scene completion qualities lead to better domain transfer performances, indicating the importance of high-quality surface completion in our method.

### 4.3 Domain Generalization without Accessing Target Domain Data

Getting rid of the need of accessing target domain data at training time has been argued to be an important feature in real applications [64], which allows domain generalization to multiple real-world target domains. In this section, we demonstrate our approach can also be used in a domain generalization manner and still achieves good performance on various target domains.

As an example, we choose the Waymo dataset as our source domain and aim at generalizing a segmentation neural network to the nuScenes and KITTI datasets without accessing to these target-domain data during training. We train a generic surface completion network by only accessing the source domain data. For this purpose, we introduce data augmentation while generating virtual LiDAR point clouds \{z^i_s\} from complete surface point clouds \{z^i_c\} based upon some reference point cloud from the source domain. As we mentioned, \((\theta, \phi)\) in the polar coordinates of the reference point cloud represents the corresponding sampling pattern. We normalize \(\theta\) into 0 to 1 and quantize \(\theta\) into 64 evenly distributed bins. We randomly select a subset of these bins (a random percentage from 30% to 70%) as well as the corresponding points to augment our reference sampling patterns. This simple strategy allows our SVCN to handle a broad range of sampling patterns, therefore generalizing to different target domains.

We demonstrate the domain generalization capability of our approach through experiments. We train our SVCN using only the reference point clouds from Waymo, with the data augmentation strategy mentioned above, and evaluate the surface completion quality on nuScenes and KITTI sampling patterns. We use the same evaluation metric as we used in Section 4.1 of the main text. Furthermore, we show how the surface completion quality contributes to the domain transfer performance on the
semantic segmentation task using mIoU as the evaluation metric. Table 4 shows both the surface completion results and the semantic segmentation results on nuScenes and KITTI, where we report both the domain generalization performance (i.e., by a generic SVCN trained without any target-domain data) and the domain adaptation results (i.e., by a domain-specific SVCN which learns from the target-domain sampling pattern).

Table 4: Domain generalization from Waymo to nuScenes and KITTI datasets. Our original domain adaptation setting trains a SVCN for each target domain separately. By training a generic SVCN with the source-domain data only, the surface completion quality as well as the semantic segmentation results on different target domains only degrade slightly.

| Source→Target | Method             | Surface Completion Metrics (IoU(%)/CD) | Semantic Segmentation Metrics (mIoU(%) ) |
|---------------|--------------------|---------------------------------------|----------------------------------------|
| W→N           | No Adaptation      | -/-                                   | 49.3                                   |
|               | Domain Specific SVCN | 28.8/1.610                            | 59.7                                   |
|               | Generic SVCN       | 25.7/1.800                            | 59.4                                   |
| W→K           | No Adaptation      | -/-                                   | 65.8                                   |
|               | Domain Specific SVCN | 44.3/1.052                            | 73.2                                   |
|               | Generic SVCN       | 42.8/1.115                            | 72.5                                   |

We can see the generic SVCN trained using Waymo data only results in slightly worse surface completion as well as semantic segmentation results on both nuScenes and KITTI datasets compared with the domain-specific SVCNs. However, the segmentation results still outperform the no adaptation baselines by a large margin, indicating the efficacy of our domain generalization method.

5 Conclusion

In this paper, we present “complete and label”, a novel domain adaptation approach designed to overcome the domain gap in 3D point clouds acquired with different LiDAR sensors. We show that by leveraging geometric priors, we can transform this domain adaptation problem into a 3D surface completion task, and then perform downstream tasks such as semantic segmentation on the completed 3D surfaces with sensor-agnostic networks. During experiments with multiple autonomous driving datasets, we find this approach provides double-digit improvements in semantic segmentation IoU in comparison to previous domain adaption methods.

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To train the structure refinement network, we first pre-train the structure generation network and then use a binary cross entropy loss $L_{\text{bce}}(c_{\text{gen}}^{l}, c_{\text{gen}}^{l})$ between the ground truth voxel existence probability $c_{\text{gen}}^{l}$ and the predicted voxel existence probability $\hat{c}_{\text{gen}}^{l}$, leading to a loss function $L_{\text{gen}} = \sum_{l} L_{\text{bce}}(c_{\text{gen}}^{l}, \hat{c}_{\text{gen}}^{l})$, where $l$ indexes the $l$-th level of the decoder.

To train the structure refinement network, we first pre-train the structure generation network and then fix it but switch to the inference mode where we use the predicted voxel existence probability to prune voxels. A binary cross entropy loss $L_{\text{refine}} = L_{\text{bce}}(c_{\text{refine}}^{0}, c_{\text{refine}}^{0})$ at level 0 between the ground truth voxel existence probability $c_{\text{refine}}^{0}$ and the predicted voxel existence probability $\hat{c}_{\text{refine}}^{0}$ is used to supervise the network.

Local adversarial loss to model the prior over surfaces. We have a strong prior on the completed scene, namely the recovered voxels should lie on 3D surfaces. Previously, researchers have investigated a lot about how to inject high level prior knowledge to get a better loss landscape and a higher

A Loss Function for Training SVCN

Figure 3 in the main text shows the architectures of the structure generation network and the structure refinement network, respectively. Both networks contain 7 resolution levels. For any input-output point clouds pairs, we have the ground truth voxel existence probability (0 or 1) at each of the 7 levels. In particular, we set the ground voxel existence probability for a voxel to be 1 if the voxel contains one or more 3D points of the output point cloud.

To train the structure generation network, we use a binary cross entropy loss $L_{\text{bce}}(c_{\text{gen}}^{l}, \hat{c}_{\text{gen}}^{l})$ between the ground truth voxel existence probability $c_{\text{gen}}^{l}$ and the predicted voxel existence probability $\hat{c}_{\text{gen}}^{l}$, leading to a loss function $L_{\text{gen}} = \sum_{l} L_{\text{bce}}(c_{\text{gen}}^{l}, \hat{c}_{\text{gen}}^{l})$, where $l$ indexes the $l$-th level of the decoder.

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model performance. Among them adversarial learning is a successful attempt\cite{41,55,32}. Inspired by this, we introduce local adversarial learning to further inject the 3D surface prior to our SVCN. In addition to the binary cross entropy loss we mentioned before, we add adversarial losses into $L_{\text{gen}}$ and $L_{\text{refine}}$, which we will detail below.

We treat SVCN as a generator which could estimate for a given incomplete LiDAR point cloud its corresponding complete counterpart and output a set of voxel existence predictions $\hat{c}^l_{\text{gen}}$ and $\hat{c}^l_{\text{refine}}$ on different resolution levels. We use $g_i$ to represent a set of voxels on resolution level $l$ from a real complete scene where each voxel is associated with an existence probability $1$. Following \cite{19}, we introduce discriminator networks $D^l_{\text{gen}}$ and $D^l_{\text{refine}}$ to differentiate $\hat{c}^l$ and $g_i$, and optimize SVCN together with the discriminators in an adversarial manner.

Instead of using a global discriminator encoding the whole scene which usually contains too much information besides the surface prior and could easily introduce complex noise for learning, we use local discriminators whose receptive field is restricted. This is achieved by using fully-convolutional architectures to retain the spatial information in the discriminator. We use the same fully-convolutional architecture for discriminators on all resolution levels. Specifically, we adopt 4 convolution layers with kernel size 3 and stride 2 followed by a linear layer in the end, where the output channel numbers $D$ we introduce discriminator networks $D^l_{\text{gen}}$ and $D^l_{\text{refine}}$ to differentiate $\hat{c}^l$ and $g_i$, and optimize SVCN together with the discriminators in an adversarial manner.

It is worth noticing that confidence-aware sparse convolution will not be able to differentiate it from realistic scenes. Seen that when SVCN generates perfect voxel existence probability in either 0 or 1, the discriminator predicts perfect existence scores, it is still very easy for a discriminator to tell its difference from real complete scenes where each voxel is associated with an existence probability $1$ on densely upsampled voxels. On the other hand, confident existence values are sharpened using confidence-aware sparse convolution. To further address this issue, we introduce confidence-aware sparse convolution to replace the normal sparse convolution operation becomes

$$f_i = \sum_{b \in N(a)} W_{ij} f_b.$$  

In confidence-aware sparse convolution, we have an additional confidence value $c_b$ associated with each voxel $b$ ranging from 0 to 1 and the output feature after each convolution operation becomes

$$f'_i = \sum_{b \in N(a)} c_b W_{ij} f_b.$$  

When applying such confidence-aware sparse convolution to $\hat{c}^l$ and $g_i$, $\hat{c}^l$ and $g_i$ will act as both input features and confidence values. It can be seen that when SVCN generates perfect voxel existence probability in either 0 or 1, the discriminator using confidence-aware sparse convolution will not be able to differentiate it from realistic scenes. Therefore confidence-aware sparse convolution is more suitable for our discriminators. To further reduce the difference between $\hat{c}^l$ and $g_i$ so that trivial solutions can be avoided and learning could start smoothly, we sharpen the predicted existence probability $\hat{c}^l$ from SVCN by replacing the sigmoid activation with a sharpened sigmoid activation $s(x) = \frac{1}{1+e^{-kx}}$ where $k \geq 1$ is a sharpening factor.

$$L'_d = -\sum_i \log(1 - D(\hat{c}^l)_i) - \sum_j \log D(g^l)_j$$  

The adversarial loss for SVCN encourages the generator to generate voxel existence predictions fooling the discriminator and can be written as $L_{\text{adv}}(\hat{c}^l) = -\sum_i \log D(\hat{c}^l)_i$, on resolution level $l$. After adding the adversarial loss into $L_{gen}$ and $L_{refine}$, our final loss functional for SVCN is:

$$L_{\text{gen}} = \sum_i L_{\text{bce}}(\hat{c}^l_{\text{gen}}, \hat{c}^l_{\text{gen}}) + \lambda L_{\text{adv}}(\hat{c}^l_{\text{gen}})$$  

$$L_{\text{refine}} = L_{\text{bce}}(\hat{c}^l_{\text{refine}}, \hat{c}^l_{\text{refine}}) + \lambda L_{\text{adv}}(\hat{c}^l_{\text{refine}})$$  

Confidence-aware convolution in the discriminators. It is worth noticing that $\hat{c}^l$ contains continuous probability values lying on densely upsampled voxels. On the other hand, $g^l$ lies on voxels from real complete scenes where each voxel is associated with an existence probability $1$. Even if SVCN predicts perfect existence scores, it is still very easy for a discriminator to tell its difference from realistic scenes using sparse convolution operations. This is to say, the gradients from discriminator will not necessarily push SVCN toward better predictions, which is against our hope. To cope with this issue, we introduce confidence-aware sparse convolution operation to replace the normal sparse convolution in all the discriminators. Recall that the sparse convolution operation proposed in \cite{22} resembles normal convolution operation but restricts the computation to only active sites. To be specific, assuming $a$ represents an active voxel site, $N(a)$ represents its neighboring active sites. For each $b \in N(a)$, $f_b$ represents the corresponding input voxel features, and $W_b$ represents the corresponding convolution kernel matrix. The output feature $f'_a$ on site $a$ after sparse convolution is $f'_a = \sum_{b \in N(a)} W_{ab} f_b$. In confidence-aware sparse convolution, we have an additional confidence value $c_b$ associated with each voxel $b$ ranging from 0 to 1 and the output feature after each convolution operation becomes $f'_a = \sum_{b \in N(a)} c_b W_{ab} f_b$. When applying such confidence-aware sparse convolution to $\hat{c}^l$ and $g^l$, $\hat{c}^l$ and $g^l$ will act as both input features and confidence values. It can be seen that when SVCN generates perfect voxel existence probability in either 0 or 1, the discriminator using confidence-aware sparse convolution will not be able to differentiate it from realistic scenes. Therefore confidence-aware sparse convolution is more suitable for our discriminators. To further reduce the difference between $\hat{c}^l$ and $g^l$ so that trivial solutions can be avoided and learning could start smoothly, we sharpen the predicted existence probability $\hat{c}^l$ from SVCN by replacing the sigmoid activation with a sharpened sigmoid activation $s(x) = \frac{1}{1+e^{-kx}}$ where $k \geq 1$ is a sharpening factor.
B Label Transfer to and from the Canonical Domain

In order to learn a segmentation network in the canonical domain using source domain labels while being able to infer the target domain point labels, we need two operations Prop(·) and Proj(·). Prop(·) propagates labels $y^s_i$ in the source domain to the canonical domain and Proj(·) projects predicted labels in the canonical domain back to the target domain, resulting in predicted labels $\hat{y}^t_j$. In this work, we simply adopt nearest neighbor based Prop(·) and Proj(·) operations. To be specific, we first voxelize input source domain point clouds $x^s_i$ and conduct majority-voting within each voxel to determine the voxel labels, and then for each voxel we propagate its label to its nearest neighbor voxel in the SVCN output $\psi^s(x^s_i)$. In the loss function, we mask out voxels without any propagated labels in $\psi^s(x^s_i)$ during training. At inference time, we voxelize input target domain point clouds $x^t_j$, fetch the voxel labels from the segmentation network predictions $\phi(\psi^t(x^t_j))$ through nearest neighbor search, and assign the fetched label to all the points from $x^t_j$ within each voxel.

C Implementation Details

The structure generation network, structure refinement network and the semantic segmentation network all contain 7 levels in their encoder-decoder architecture and adopt the same number of convolution filters on different levels. The numbers of filters from level 0 to level 6 of the encoder are $(24, 24), (24, 32), (32, 48), (48, 64), (64, 80), (80, 96), (96, 112)$ where each (·) corresponds to one level. The numbers of filters from level 5 to level 0 of the decoder are $(112, 96), (80, 80), (64, 64), (48, 48), (32, 32), (16, 16)$. In all our experiments, we use a voxel size of $d = 20$cm. To obtain the ground truth voxel existence probability $c_{\text{gen}}^l$ on level $l$ for structure generation network training, we voxelize the ground truth complete point cloud with a voxel size of $2^l d$ and the voxel existence probability is set to be 1 for a voxel as long as there is one point falls into it. We use only LiDAR point positions as inputs without considering the color or intensity information. While training the segmentation network, we augment the input point clouds through randomly rotating them around z-axis and randomly flipping them with respect to the x-axis and y-axis. For both SVCN and semantic segmentation network training, we use a batch size of 2. We use Adam optimizer where the momentum is set as 0.9 and 0.99. And we use an initial learning rate of $10^{-3}$, which is decayed with a factor of 0.7 after every 200k training steps. The learning rate of the discriminator for adversarial learning is set to be $10^{-4}$ initially and also decays with a factor of 0.7 after every 200k training steps.