

GLiDR: Topologically Regularized Graph Generative Network for Sparse LiDAR Point Clouds

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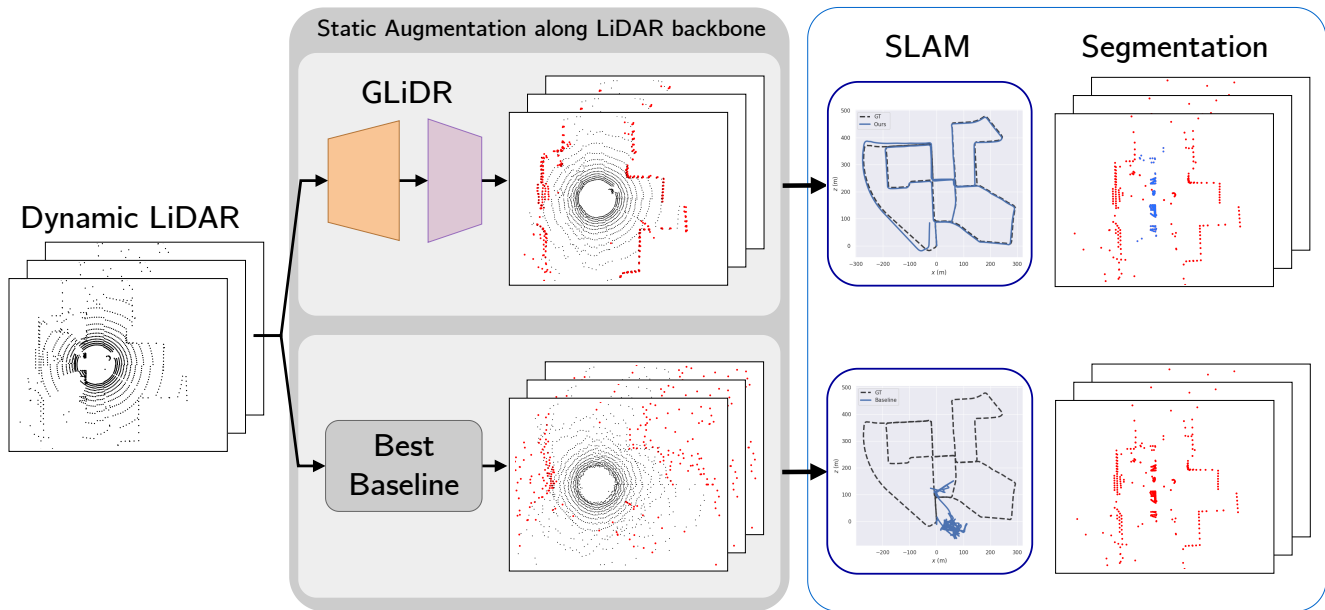


Figure 1. **GLiDR** outperforms the best baselines on SLAM results with sparse LiDAR scans. Binary segmentation masks of dynamic and static points (blue denotes dynamic and red denotes static points) obtained using **GLiDR** are also better.

Abstract

Sparse LiDAR point clouds cause severe loss of detail of static structures and reduce the density of static points available for navigation. Reduced density can be detrimental to navigation under several scenarios. We observe that despite high sparsity, in most cases, *the global topology of LiDAR outlining the static structures can be inferred*. We utilize this property to obtain a backbone skeleton of a LiDAR scan in the form of a single connected component that is a proxy to its global topology. We utilize the backbone to augment new points along static structures to overcome sparsity. Newly introduced points could correspond to existing static structures or to static points that were earlier obstructed by dynamic objects. To the best of our knowledge, we are the first to use such a strategy for sparse LiDAR point clouds. Existing solutions close to our

approach fail to identify and preserve the global static LiDAR topology and generate sub-optimal points. We propose **GLiDR**, a Graph Generative network that is topologically regularized using *0-dimensional Persistent Homology (PH) constraints*. This enables **GLiDR** to introduce newer static points *along a topologically consistent global static LiDAR backbone*. **GLiDR** generates precise static points using $32\times$ sparser dynamic scans and performs better than the baselines across three datasets. **GLiDR** generates a valuable byproduct - an accurate binary segmentation mask of static and dynamic objects that are helpful for navigation planning and safety in constrained environments. The newly introduced static points allow **GLiDR** to outperform LiDAR-based navigation using SLAM in several settings. Source code is available at <https://github.com/GLiDR-CVPR2024/GLiDR>.

1. Introduction

Sparse LiDAR scans have fewer laser beams. Fewer points fall on object structures, leading to sparse point density. The sparsity increases further for distant objects and in adverse weather conditions. Sparse scans lead to fewer static points available for SLAM. Additionally, low-cost and limited compute autonomous LiDAR systems drop LiDAR points (reducing points by several factors) to work in real-time. Under moderate to high *dynamic* environments, the loss of static points to dynamic obstructions increases sparsity further. Increasing the density of points along the LiDAR scan cross-section introduces a significant portion of redundant points that are not useful for SLAM (e.g., ground points). Further, compute-constrained systems deployed with sparse LiDAR cannot handle dense point clouds. Several works solve the scarcity of static points by completing dynamic LiDAR point clouds to obtain a precise view of obstructed static regions [19, 20]. They fail to identify and preserve the global shape and LiDAR topology, which is diluted due to sparsity. Sparsity also hinders the learning of accurate representation of the local geometry.

Current generative models represent LiDAR data as range images and are locally robust and receptive to a local area of the input. LiDAR scans have a global topology that requires explicit focus and needs to be preserved. Apart from local structures, they have global long-range structures that require global receptivity. These structures are diluted in the presence of sparsity, leading to detail and precision loss. Existing solutions find it harder to capture the global topology in sparse scenarios, leading to a loss of detail and precision. We solve these challenges using two tools — a Graph Generative network and Persistent Homology (\mathcal{PH}).

Popularized by [31], several works explore graph representation to capture global dependencies between LiDAR points. Graph-based models are adept at learning global topology and long-range dependencies via message passing and ensuring global receptivity. They have been shown to perform well on several tasks, including 3D object detection [27, 30], point cloud up-sampling [22, 26], registration [5], and segmentation [36]. Inspired by these works, we represent LiDAR point clouds in the form of a graph to learn rich global and local shapes accurately.

As sparsity levels increase, the density of points falling on objects reduces sharply, but the global topological structure is preserved. We exploit this property to generate explicit attention on the global topology to preserve global structures while augmenting new points. Persistent Homology(\mathcal{PH}) has been shown to learn the global shape and topology of complex datasets. It captures topological invariants (connected components, circles, and holes) that capture the global structure and embeds geometric information in the learned LiDAR representations [25]. It ensures that new points are augmented along the existing and oc-

cluded static LiDAR structures by following the backbone generated using 0-dim \mathcal{PH} . Several works have used \mathcal{PH} to integrate topological priors as regularization constraints [8, 12]. \mathcal{PH} based techniques have been used to preserve topological properties of the input in generative models [23] and graph-based learning tasks [17].

We list the contributions of our work here:

- We present **GLiDR** that visualizes a sparse LiDAR scan as an undirected graph. It learns global node representations via recursive updates from k -nearest points. Despite sparsity, the updates allow the diffusion of global topology information from distant nodes into a given node. Multiple nodes belonging to the same LiDAR structure, though separated by large distances, learn coherent representations after successive updates.
- To ensure that **GLiDR** augments new points in line with the global topology of a static scan even in the presence of sparsity, we enforce topological priors on the latent representations and the augmented output using 0-dimensional (dim) \mathcal{PH} . We generate 0-dim Persistence Diagram using sub-level set filtrations. This generates a single connected component that acts as a backbone (proxy to the global topology of static LiDAR scan). It guides the model to generate static points along the LiDAR backbone.
- **GLiDR** demonstrates superior static points augmentation on $32\times$ sparse and dense scans with five baselines using three datasets. It also demonstrates better SLAM performance in sparse and dense settings. Current standards in SLAM use labelled information to remove dynamic points before navigation. We perform better than them, irrespective of the availability of labelled information.
- We qualitatively demonstrate **GLiDR**'s capacity to generate accurate segmentation masks of dynamic and static points for sparse LiDAR scans while the best baseline fails to distinguish between static and dynamic points.

2. Related Work

2.1. Static Point Augmentation and LiDAR Generative Modelling

Point augmentation has been experimented with across several modalities. Bescos et al. [1] use a segmentation network to augment static points on images from urban driving datasets with a conditional-GAN. Xu et al. [33] use a pretrain-prompt-predict paradigm inspired from NLP and use self-supervised pretraining and semantic-guided predicting for point cloud completion. Zhang et al. [34] utilize a model pre-trained on complete shapes to generate complete shapes for incomplete point clouds. Standard shape-based point cloud methods do not work well when extended to LiDAR scans [3, 19]. LiDAR-based point augmentation has been used to generate novel static points to assist navigation [19, 20].

LiDAR generative modelling was introduced by Caccia et al. [3]. They used range image-based polar coordinate systems and structure-aware loss functions. Zyrianov et al. [37] formulate generation as a stochastic denoising process and leverage the score-matching energy-based model. Their sampling rate of 20s/scan makes them unusable for real-time navigation. Zhang et al. [35] introduce NeRF-LiDAR that learns a NeRF representation for real-world LiDAR scenes. They require multi-view images along with segmentation labels for training. Xiong et al. [32] present UltraLiDAR that learns discrete representations of LiDAR scenes by aligning sparse and dense point cloud representations for LiDAR generation and densification. It relies on manual intervention to identify explicit codes for objects, which can be perturbed for LiDAR completion. This is unrealistic for end-to-end real-time navigation.

2.2. Topological Machine Learning

Topological Machine Learning is an emerging field at the intersection of Topological Data Analysis and Machine Learning. It captures and quantifies the global shape and evolution of topological features - connected components, holes, voids, etc. in a dataset. An important computation tool in applied topology is Persistent Homology (\mathcal{PH}). Giansiracusa et al. [15], Hofer et al. [16], Pun et al. [25] use \mathcal{PH} to generate topological features for learning-based tasks. \mathcal{PH} has been used for geometric problems - shape matching [6], surface reconstruction [2], and pose-matching [10]. Gabrielsson et al. [12] introduce a general purpose topology layer to calculate \mathcal{PH} of datasets. Several works along the same line [8–10, 13, 21] use the differentiability of \mathcal{PH} for multiple deep learning applications. \mathcal{PH} has been integrated with deep learning across various domains - medical imaging [28], molecular biology [4], and social networks [24].

3. Background

3.1. Preliminaries

Given $k + 1$ affinely independent points, a k -simplex (or k -cell) is the convex hull of the k vertices. It is the simplest polytope in a given dimension — a line segment in one dimension, a triangle in two dimensions, a tetrahedron in three dimensions, and so on. A simplicial complex is a collection of simplices such that intersection of any two simplex is also a simplex. In topology, homology is used to count the number of k -dimensional holes in a simplicial complex — number of connected components in dimension 0, loops in dimension 1, voids in dimension 2, and so on.

3.2. Persistent Homology

A topological space can be encoded as a cell complex — a collection of k -dimensional simplices ($k = 0, 1, 2, \dots$). *Ho-*

mology, an algebraic invariant of a topological space, uses local computation to capture global shape information (k -dim holes) of a topological space. These holes, generalized to various dimensions form the basis of homology [11].

Persistent Homology (\mathcal{PH}) is an algebraic method to discover topological features of datasets. It converts a dataset (e.g. point cloud) to a simplicial complex and studies the change of homology across an increasing sequence of simplicial complexes $\phi \subseteq \mathcal{C}_1 \subseteq \mathcal{C}_2 \subseteq \mathcal{C}_3 \dots \mathcal{C}_i \dots \mathcal{C}_n = \mathcal{C}$, known as filtration [11]. Topological features are computed at different spatial resolutions across the subsequence. Examining the persistence of features over a range of scales reveals insights about the underlying patterns in datasets. For point clouds, filtration is defined on the edges of the complex. We define a sub-level filtration over \mathcal{C} . Every simplicial complex in the subsequence can be mapped to a number using a filtration function $f((v_0, v_1 \dots v_n)) = \max_{i < j; i, j \in \{0, 1, 2, 3 \dots n\}} f((v_i, v_j))$. This is known as a flag filtration and is based on pairwise distances between points. It is monotonic — every subsequent simplicial complex has a value higher than the previous one. For a detailed treatment of \mathcal{PH} , please refer to the Supplementary.

4. Problem Formulation

Given a sparse scan dy_i from a LiDAR sequence, we formulate **GLiDR** to augment dy_i with newer points along an existing static LiDAR topology-based backbone outlining the static structures. It augments existing sparse static structures as well as occluded static structures with newer points along the static topology-based backbone. To obtain the backbone, we need a static LiDAR scan (st_i) that corresponds to the original LiDAR dy_i , minus the dynamic objects and corresponding obstructions. It serves two purposes - (a) It enables the calculation of the static LiDAR backbone using 0-dim \mathcal{PH} , which serves as a prior over dy_i while augmenting new points. (b) It enables the introduction of points that were obstructed by dynamic objects along the static backbone.

4.1. LiDAR-based Graph Representation

We represent a sparse scan as an undirected graph to capture global dependencies and ensure global receptivity. A single LiDAR graph layer operates as follows:

- The scan points represent the nodes of the graph. Each node is associated with its unique embedding that represents its features. At the start, each node is initialized with initial features - the x, y, z coordinates. Edges are drawn from each node to its k -nearest neighbors. A node can have several neighbors outside its sparse immediate neighborhood.
- Each node aggregates information from its immediate and distant neighbors using message passing, followed by a max-pooling operation to update its features. This trans-

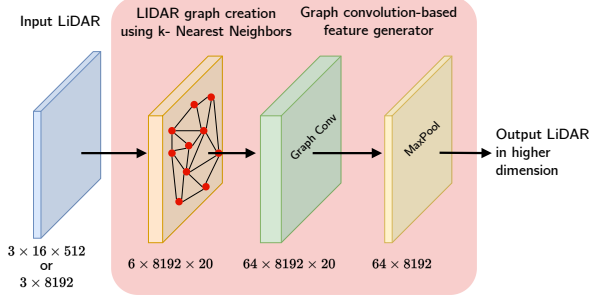


Figure 2. A sample LiDAR graph layer. The input LiDAR is transformed into a graph using k -nearest neighbors ($k=20$). Graph convolution extracts neighborhood features followed by max-pool transform the LiDAR embedding to a higher dimensional space.

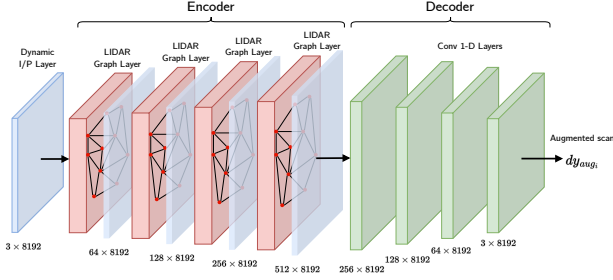


Figure 3. LiDAR Graph Generative Model using stacked LiDAR Graph layers

forms the sparse node features to higher dimensions. The current graph is then destroyed. Updated node embedding of the sparse LiDAR points represents the LiDAR graph in a higher-dimensional embedding space. This constitutes a single LiDAR graph layer (Figure 2).

For the next layers, the above steps are *repeated* with the new node embeddings. It projects the nodes to even higher embedding space. Similar LiDAR nodes that were not neighbors in the original graph get a chance to become neighbors in the updated embedding space. When applied recursively, it allows points belonging to long-range structures that are distant in the original LiDAR scan to come closer or become neighbors in the new embedding space, thereby aggregating global features. Embeddings of each node in successive layers encode more global information. We stack four LiDAR graph layers that constitute the encoder of our network. At the final layer, every node is in a 512-dimensional embedding space. The decoder uses four 1-D convolution layers. It projects the node features from the 512-dimensional embedding space down to the original three dimensions (x, y, z) input space.

We use range-image representation for LiDAR by converting LiDAR point clouds to range image. It allows the flexibility to represent LiDAR as a point cloud and an image. Loss in representation conversion only occurs while

preprocessing the raw LiDAR point cloud into range image using spherical projection, before feeding to **GLiDR**. This is standard across LiDAR AVs’ [7] and works well on navigation tasks in practice. After the range image is fed to **GLiDR**, conversion of the range image to point cloud for graph convolution and vice-versa for loss computation, is a simple reshape operation that preserves one-to-one mapping. The output of **GLiDR** — the augmented scan is compared against the ground-truth static scan. Range images allows us to use simple absolute error (AE) based augmentation loss instead of the costly Chamfer’s Distance (CD) and Earth Mover’s Distance (EMD) loss function. CD assumes the point cloud to have a uniform density, which is not the case with LiDAR. LiDAR point clouds are voluminous ($\approx 1,10,000$ points per scan for a 64-beam LiDAR scan), unlike standard shape-based point clouds (≈ 2600 points per scan). CD and EMD are memory and time-intensive for LiDAR scans, even on a powerful GPU.

4.2. Persistent Homology Constraints

Persistent Homology (\mathcal{PH}) integrates global topology into the learning problem. This is achieved either by integrating \mathcal{PH} based fixed predefined features extracted from the input, or by using certain topological loss functions. The latter compute \mathcal{PH} on the output or the latent representations and optimizes it to satisfy certain constraints and achieve a certain structure on the output and the latent representations.

GLiDR follows the second strategy. The fundamental idea is to ensure shape consistency of the augmented output along a global backbone by maintaining long structures accurately, apart from local consistency. We achieve this by constraining **GLiDR** to generate the static augmentation along a global prior that is estimated with the help of \mathcal{PH} .

Given a LiDAR point cloud, \mathcal{L} (also a simplicial complex with all 0-simplices), we create a sub-level filtration on it. We define a real-valued filtration function over the simplicial complex and sub-complexes ($f^{-1}(-\infty, \alpha]$). α has an initial value of 0 (corresponds to the initial simplicial complex — the original LiDAR point cloud). Let the simplicial complex being created be denoted by \mathcal{C} . As α increases, new k -dim simplices (k -cells) are added to \mathcal{C} . These additions create or destroy homology (k -dim holes — connected components, cycles, voids, and so on). As the filtration progresses with increasing α , newer k -dim simplices are added to the \mathcal{C} . Full information of the appearance and disappearance of homology of a certain dimension k in a filtration is captured in a k -dimensional persistence diagram, $PD_k = \{(b_i, d_i)\}$. It consists of a set of (*birth*, *death*) pairs representing the appearance and disappearance of homology. The difference ($b_i - d_i$) denotes the persistence of a homology that appears during the filtration.

Our focus is on PD_0 and the largest possible 0-dim hole — the *single largest connected component* that can be gen-

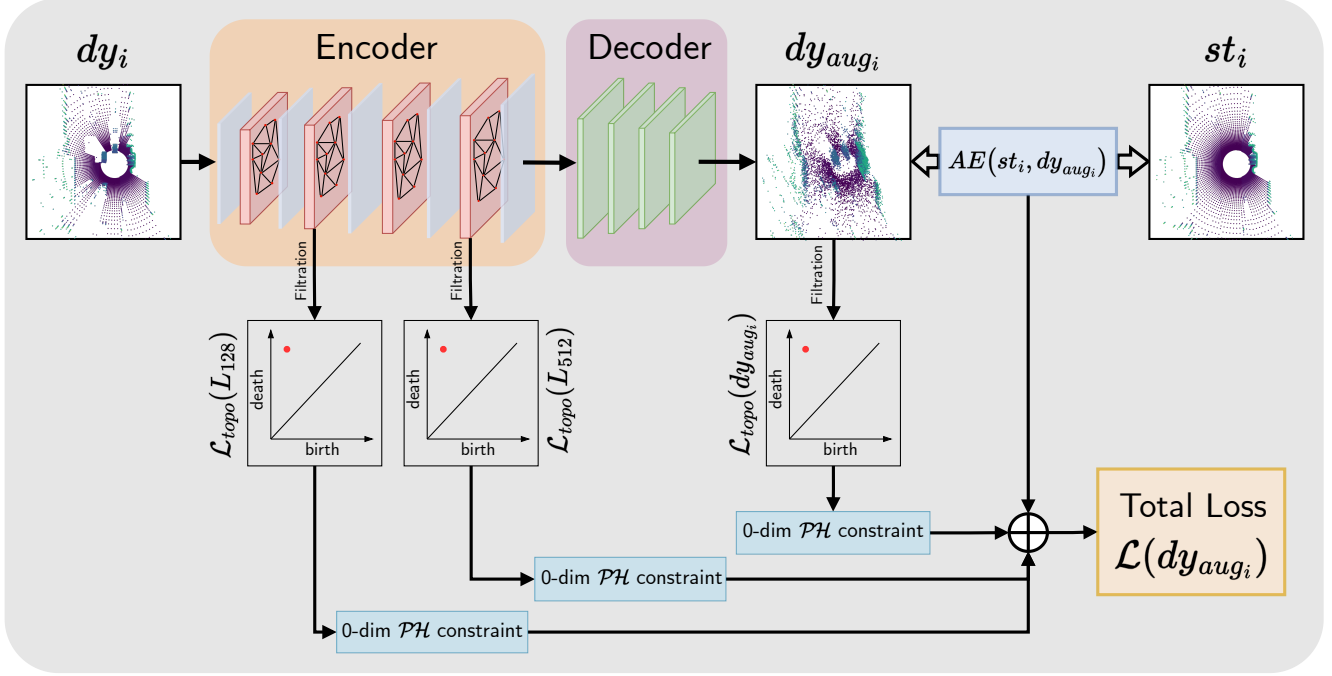


Figure 4. GLiDR network architecture with the generative LiDAR graph layers (upper branch). The lower branches constitute the 0-dim \mathcal{PH} constraints and generate the topological loss.

erated using filtration on the augmented LiDAR. Calculation \mathcal{PH} constraints while training is time-consuming as we increase the dimension of the Homology Group, even with very good compute. We show that sticking to 0-dim \mathcal{PH} features works very well for capturing long range dependencies and global topology details, especially when the size of each sample is large as in our case.

For 0-dim persistence, birth (b_i) of a homology (connected component) refers to the occurrence of the component in the PD_0 , while death (d_i) refers to the case when the component merges into another component. The connected component serves as a prior — a backbone along which the graph autoencoder can generate the augmented points. Given dy_i as input, our aim is to generate an augmented scan — dy_{aug_i} such that filtration over it generates a single-connected component (0-dim homology) by the end of the filtration. The creation of the component is facilitated by a LiDAR topology loss, along with a static LiDAR augmentation loss. The augmentation loss diffuses information about the static LiDAR into the filtration. It ensures that the connected component created over dy_{aug_i} at the end of the filtration for PD_0 follows the static LiDAR shape accurately.

Intuitively, for all the 0-dim homology (connected components) possible across the filtration — we would like the one with the earliest birth to persist (have very high values of $(b_i - d_i)$) and the rest to merge in it (have a minimal

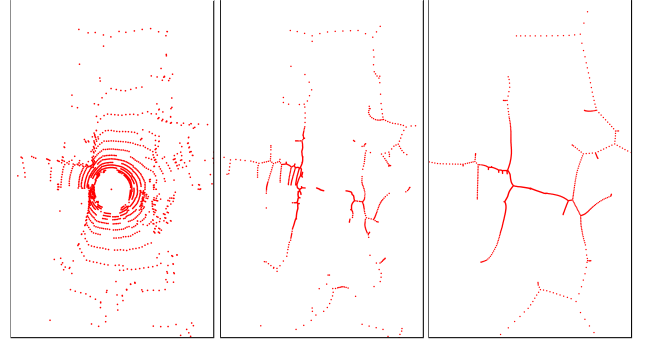


Figure 5. **Left:** Input Dynamic LiDAR **Middle:** Visualization of the 0-dim \mathcal{PH} based LiDAR backbone after some epochs. **Right:** LiDAR backbone at the end as a single connected component.

value of persistence - 0) in the ideal case. In the ideal case, dy_{aug_i} is generated in a manner such that filtration over it leads to a *single 0-dim homology at the end of the filtration*. This single connected component serves two purposes: **(a)** It acts as a prior and ensures that generation of dy_{aug_i} progresses such that filtration over it results in only a single connected component in PD_0 . **(b)** The single connected component created along dy_{aug_i} helps to maintain long-range dependencies by connecting global structures via a single connected component (Figure 5). Due to the above, the dy_{aug_i} adheres to the global shape of the static LiDAR

point cloud, as expected. To this end, we add a simple and novel topology-based loss function on the augmented output scan (dy_{aug_i}). Let $\{(b_i, d_i)\}_{i=1}^n$ represent the (*birth*, *death*) pairs of the 0-dim homology in the filtration computed for dy_{aug_i} .

$$\mathcal{L}_{topo}(dy_{aug_i}) = - \sum_{i=1}^n \mathbb{1}\{i = 1\}(b_i - d_i) - \mathbb{1}\{i \neq 1\}(b_i - d_i) \quad (1)$$

PD_0 has two properties: **(a)** It has atleast one connected component for all values of α . **(b)** PD_0 starts at $\alpha = 0$ and continues for some finite value of α , after which increasing it does not add new simplices to the filtration. We conclude that the two loss terms in the Eq. (1) are complementary. Minimizing the persistence of 0-dim features from $i = 2$ to n ensures that the persistence of the first feature is maximized (due to point **(a)**) and leads to a single connected component. Therefore, the topology loss can be modified as follows -

$$\mathcal{L}_{topo}(dy_{aug_i}) = \sum_{i=2}^n \mathbb{1}\{i \neq 1\}(b_i - d_i) \quad (2)$$

Minimizing the above term ensures a single connected component at the end of the filtration of PD_0 .

We apply the filtration on the augmented output scan (dy_{aug_i}), the 128-dim and the 512-dim LiDAR scan generated at the output of the second and fourth LiDAR graph layer of the encoder. The single connected component constraint introduced by PD_0 at the output (along with the augmentation error) allows the position of the augmented LiDAR points (in dy_{aug_i}) to be perturbed in a manner that follows the global static LiDAR backbone. While the augmentation loss provides an estimate of the region where a generated static LiDAR point must be placed, the backbone constraint ensures that the position of the augmented point is in accordance with the global shape of the LiDAR scan. The 0-dim \mathcal{PH} based regularization on the second and fourth layer of the encoder ensures that the intermediate graph representation also follows the same homology constraints that outline the global LiDAR topology and are compliant with 0-dim \mathcal{PH} . The single connected component based global LiDAR backbone serves as a regularizer at the intermediate layers as well.

Given (dy_i, st_i) refers to the dynamic and static scan pair, dy_{aug_i} refers to the **GLiDR**'s augmented output, L_{128} and L_{512} refer to the updated LiDAR node embeddings in 128-dimensional and 512-dimensional space at the 2^{nd} and 4^{th} encoder layer, the loss function $\mathcal{L}(dy_{aug_i})$ of **GLiDR** is

$$= \mathcal{L}_{topo}(dy_{aug_i}) + \mathcal{L}_{topo}(L_{128}) + \mathcal{L}_{topo}(L_{512}) + AE(st_i, dy_{aug_i}) \quad (3)$$

4.3. Paired Scan Generation

Kumar et al. [19] demonstrate a pipeline to collect correspondence LiDAR pairs from scratch. Existing datasets in the literature (e.g. KITTI) may not have such data available. We devise a simple method to obtain such pairs in order to demonstrate **GLiDR**'s capabilities on such datasets.

Assume we have a sequence of scans $K = \{k_i: 1, 2, 3, \dots\}$. We require pairs K_D, K_S — K_D is the set of dynamic, and K_S denotes the static scans. We follow the following steps to transform K into K_S, K_D , by utilizing semantic segmentation information. **(a)** We create two copies of K : K_S and K_D . We use segmentation labels to remove all dynamic objects from K_S — these become our static scans. **(b)** For the dynamic part, we first remove existing dynamic objects from K_D using semantic labels. We divide the LiDAR scan (K_D) into eight equal sectors along the azimuth angle. We identify a source sector — that has the presence of the most number of dynamic objects. We also identify a target sector — devoid of any objects (and) is likely to have dynamic objects (e.g. an empty sector in the opposite driving lane that can be augmented with dynamic objects moving in the opposite direction). **(c)** We extract dynamic objects from the source using K (via seg. labels) and augment them in the target sector in K_D identified in the previous step. To ensure that the augmentation looks realistic across the whole LiDAR sequence, dynamic objects extracted from contiguous LiDAR scans (from the source sector) are inserted into the target sector contiguously across the same LiDAR scans. For more details, please refer to the Supplementary.

5. Experiments

We demonstrate the quantitative performance of **GLiDR** on static points augmentation along the static LiDAR backbone using six baselines on five metrics (Table 1) and on SLAM in segmentation-assisted and segmentation-devoid settings (results in Supplementary) on three datasets. We also qualitatively demonstrate the LiDAR binary mask (static and dynamic points) generation in Figure 1 and 6.

5.1. Experimental Setup

The architecture of **GLiDR** is explained in Section 4.1 and Figure 4. Our models are trained using an NVIDIA A100 GPU for a maximum of 100 epochs. We use Adam optimizer with a weight decay of 0.0001 and a cosine annealing scheduler with a minimum learning rate of 0.001.

5.2. Datasets

(a) KITTI Odometry dataset [14] is a 64-beam LiDAR dataset. It has 11 sequences with ground truth poses. Sequences 00-02, 04-07, 09-11 are used for training, 03 for validation, and 08 for testing **GLiDR**. We test our paired scan generation (Section 4.3) pipeline on KITTI.

Methods		CD		JSD (10^{-3})		MMD		RMSE (10^{-3})		EMD (10^{-3})	
		Dense	Sparse	Dense	Sparse	Dense	Sparse	Dense	Sparse	Dense	Sparse
KITTI	CP3	73.78	13.98	21.20	25.60	0.58	0.14	119.20	117.10	23.00	19.00
	Topo-AE	50.60	26.27	0.79	1.14	1.13	1.13	56.18	67.40	4.42	6.80
	C-Net	12.63	2.82	0.04	0.23	0.13	0.13	38.50	31.70	30.16	16.14
	DSLR	17.10	4.94	0.36	0.51	0.016	0.05	49.20	56.80	1.25	1.97
	MOVES	7.10	3.57	0.43	0.62	0.02	0.02	39.50	48.00	1.40	1.95
	GLiDR	3.57	1.60	0.05	0.20	0.06	0.03	13.71	23.50	0.05	1.32
CARLA-64	CP3	614.19	17.13	604.90	5.50	1.52	0.28	220.80	173.50	138.40	37.50
	Topo-AE	57.45	74.71	0.93	2.71	1.61	1.752	67.90	110.45	16.80	45.30
	C-Net	14.17	7.96	0.66	1.34	0.87	1.05	53.96	76.98	20.66	35.33
	DSLR	13.69	16.42	0.55	1.27	0.92	0.87	65.40	84.74	7.48	16.54
	MOVES	8.26	15.67	0.43	1.62	0.75	0.77	44.20	92.46	6.73	18.85
	GLiDR	2.08	0.91	0.21	0.22	0.81	0.72	29.23	29.30	2.60	2.57
ARD-16	CP3	12.27	8.40	10.10	1.50	0.14	0.09	98.88	122.5	15.70	41.60
	Topo-AE	12.15	2.96	0.39	0.24	1.27	1.38	44.33	35.02	4.70	2.30
	C-Net	2.78	1.19	0.23	0.19	0.34	0.65	34.88	31.34	14.17	16.83
	DSLR	0.40	0.27	324.37	166.99	0.02	0.02	34.07	34.39	1.58	1.69
	MOVES	0.34	0.33	436.30	159.31	0.02	0.02	14.69	33.40	2.30	0.70
	GLiDR	0.29	0.22	0.061	0.02	0.02	0.02	18.80	18.06	0.04	0.05

Table 1. Static Augmentation Comparison of **GLiDR** against five baselines using five metrics for sparse and dense LiDAR. For all metrics, lower is better.

(b) ARD-16 is a 16-beam industrial dataset collected using an UGV. It is distinct from urban road-based datasets in terms of structure and the type of objects. It is 4× sparser than other datasets. It has correspondence information available. We follow the train, test, and protocol mentioned at Kumar et al. [18].

(c) CARLA-64 is an extensive simulated 64-beam urban dataset with correspondence information. We follow the train, test protocol from Kumar et al. [18].

We use LiDAR range image representations. The original dimensions for KITTI and CARLA are $3 \times 64 \times 1024$, while it is $3 \times 16 \times 1024$ for ARD-16. The second and third dimensions represent the height and width of the range image. For all experiments, we *sparsify the outermost dimension* by $8\times$ by selecting every 8^{th} column in the range image. The outermost dimension is reduced to 128 for all experiments. For KITTI and CARLA-64, we use two versions - sparse (16-beam) and dense (64-beam). For the former, we extract LiDAR points generated by every fourth beam. The final shape is $3 \times 16 \times 128$ ($32\times$ sparser). The dense version has a shape of $3 \times 64 \times 128$. ARD-16 is already a 16-beam dataset. We use the original version and a sparser 8-beam version for ARD-16 with shapes $3 \times 16 \times 128$ and $3 \times 8 \times 128$, respectively.

5.3. Baselines

5.3.1 Static Points Augmentation

We compare **GLiDR** against baselines that demonstrate strong performance on new static points augmentation and point cloud completion across several modalities. We do

not use LiDARGen [37], NeRF-LiDAR [35], Ultra-LiDAR [32] for reasons explained in Section 2.1. We use the following methods as baselines for our work (a) CP3 [33] (b) Topo-AE [23] (c) CoarseNet (C-Net) [29] (d) DSLR [19] (e) MOVES [20]. We give details of the baselines in the Supplementary.

5.4. Evaluation Metrics

5.4.1 Static Points Augmentation

We rigorously test **GLiDR** using 5 metrics - (1) Chamfer’s Distance (2) Earth Mover’s Distance (3) Jensen Shannon Divergence (4) Root Mean Square (5) Maximum Mean Discrepancy. We provide details on these in the Supplementary.

6. Results

6.1. Static Points Augmentation

We compare the static point augmentation results of **GLiDR** against the baselines in Table 1. **GLiDR** performs better than the baselines across most metrics. It retains the global topology of sparse LiDAR and generates points along the global static backbone accurately (Figure 1). This is due to the explicit attention on the global topology induced by the 0-dim \mathcal{PH} prior and the graph layers. Stacked graph layers learn global shape properties in the high-dimensional embedding space. Closeness in this space represents semantic similarity over long distances in the original LiDAR. Similar nodes (e.g. belonging to a long-range structure) far in the input space gain proximity in the high-dimensional space. 0-dim \mathcal{PH} constraints capture the global static Li-

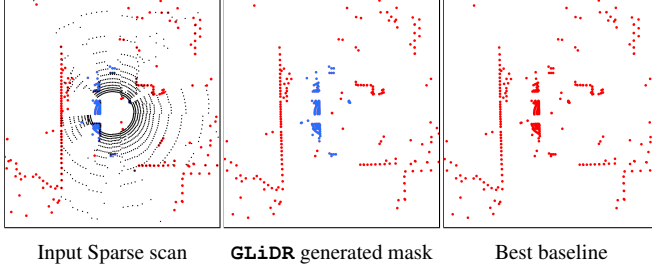


Figure 6. **Middle:** Seg. mask generated by **GLiDR** **Right:** Seg. mask generated by the best baseline. Blue denotes dynamic points. Red denotes the static non-ground points used for SLAM. The best baseline fails to segregate the static and dynamic points.

DAR structure in a single connected component (Figure 5) and enforce **GLiDR** to generate points along this backbone.

The 0-dim \mathcal{PH} prior, and the stacked graph layers work well despite reduced LiDAR point density. Both look over a LiDAR on a global scale. It enables **GLiDR** to capture global dependencies even if manifested through a sparse set of points over a long sequence. These characteristics allow **GLiDR** to identify accurate static structures and backbone and align the augmentation process accurately along them.

6.1.1 Segmentation of Dynamic Objects

GLiDR generates accurate segmentation masks of dynamic objects in the absence of segmentation and object information by subtracting the dynamic input from the augmented output of **GLiDR**. The rest of the points belong to static objects. The accuracy of these masks against those generated using the best baseline for sparse scans is shown in Figure 1 and 6. The baseline fails to separate dynamic and static points. It does not capture the global topology (Figure 1), resulting in leakage of all LiDAR points in the dynamic object mask during scan subtraction. We demonstrate the segmentation results for ARD-16 in the Supplementary material.

6.2. Ablation Studies

GLiDR has two parts - the LiDAR Graph network module that forms the main part of the network and the 0-dim \mathcal{PH} based LiDAR backbone regularizer. We perform ablation studies to study the impact of these modules on **GLiDR** in Table 2. We demonstrate the ablation results on the CARLA test set. We observe a positive impact of both on **GLiDR**'s performance.

We provide another ablation to where we replace the graph layers with standard convolutional layers - *GNN* vs *CNN ablation study* using the sparse and dense version with CARLA dataset in Table 3. ConvNets are not good at generating accurate long range structures due to only local re-

	Graph		Topology + Graph	
	Sparse	Dense	Sparse	Dense
CARLA	1.18	2.36	1.04	2.08

Table 2. Ablation studies to study the effect of the LiDAR graph layers and the 0-dim \mathcal{PH} constraint on **GLiDR**.

ceptivity, while graphs along with 0-dim \mathcal{PH} learn them effectively.

	ConvNets	GNN
Sparse	16.91	1.18
Dense	11.3	2.36

Table 3. Ablation Result for ConvNets and **GLiDR**

6.3. Performance

The inference rate of **GLiDR** is 4ms/scan on an NVIDIA A100 GPU, and the time for preprocessing is 30ms/scan on an Intel Xeon Silver 4208 CPU@2.10 GHz processor.

7. Limitations

GLiDR undergoes training on the respective training splits for different datasets. The model trained on an outdoor/ industrial/ indoor setting will find it hard to generalize to other environments. This is an important and fundamental problem of domain adaptation, which is not the goal of this work. Our premise is - **GLiDR** works extremely well in sparse environments when trained with scans captured in similar environments without the use of any form of labeled information.

8. Conclusion

Sparse LiDAR in restricted and constrained settings can pose numerous challenges to navigation. We address these challenges by augmenting them with points along static structures. We present **GLiDR** that utilizes a graph representation for LiDAR. We regularize the model using 0-dimensional \mathcal{PH} constraint that provides a static LiDAR backbone along which points can be accurately generated. The new points allow **GLiDR** to achieve superior navigation performance against current standards that may or may not use labeled information. We are hopeful that our approach for **GLiDR** will be very useful for future research on standard shape-based point cloud research and applications.

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