Learning to Identify Out-of-Distribution Objects for 3D LiDAR Anomaly Segmentation

UNIVERSITÀ DI PADOVA
Dipartimento di Ingegneria dell'Informazione

Simone Mosco, Daniel Fusaro, Alberto Pretto
University of Padova

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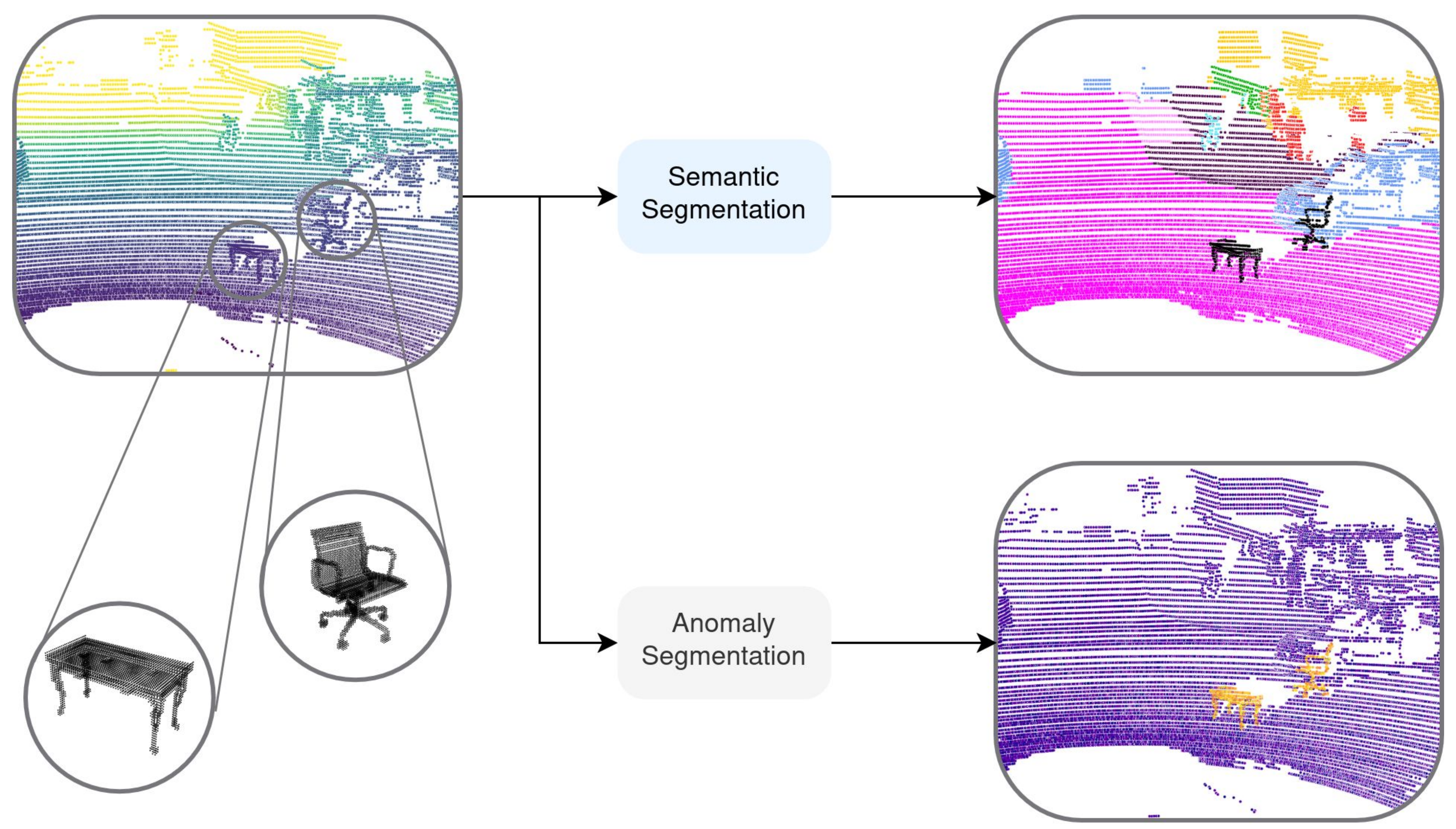
Motivation and Contribution

We present **LIDO**, a novel approach for **3D LiDAR Anomaly Segmentation** that directly works on the feature space with feature prototypes and contrastive learning to distinguish known and unknown classes and identify anomalous objects.

Motivations

- In the real world the closed-set assumption fails to identify unknown objects, not seen in training (*anomalies*).
- Current approaches adapt post-processing techniques, rely on model ensemble or use OoD data in training.
- Lack of LiDAR OoD datasets introduces domain gaps, with only anomaly masks typically available.

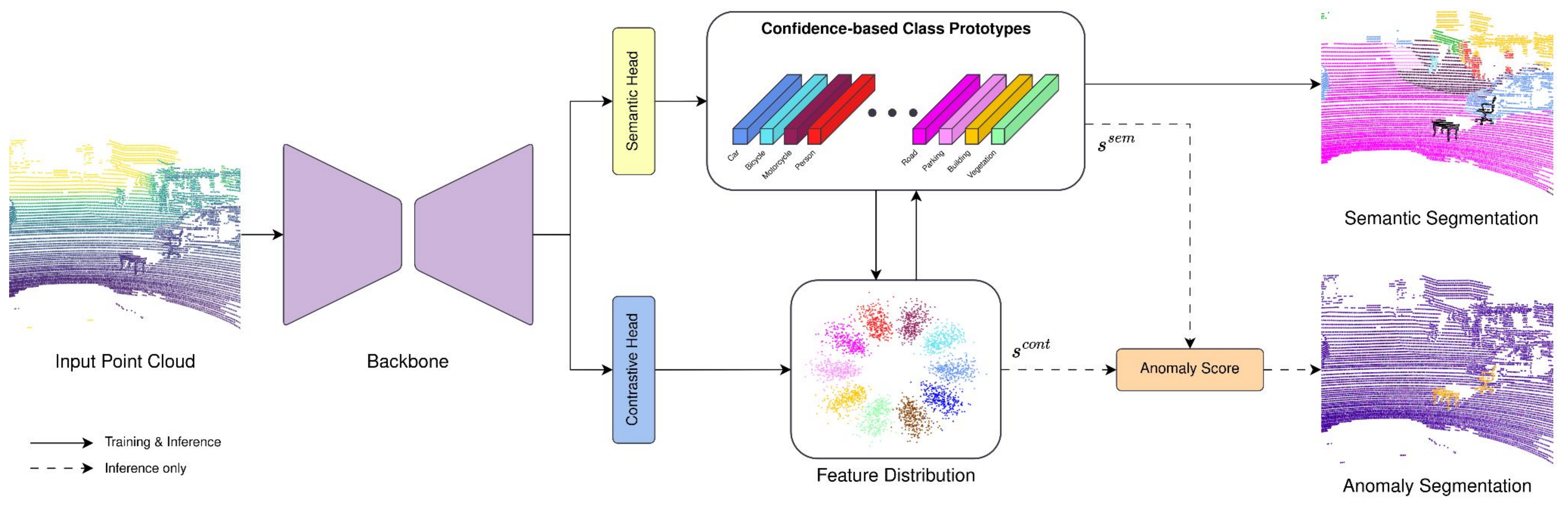


Contributions

- Novel method for **3D LiDAR Anomaly Segmentation** that directly models the **feature space** to identify anomalies.
- **New** set of mixed real-synthetic **LiDAR OoD datasets** with synthetic object insertion and geometric+intensity alignment.
- **Lightweight** and **real-time** approach with strong results.

Methodology

- A **Backbone** extracts initial per-point features, which are then processed by a **Semantic Head** and a **Contrastive Head** to build class prototypes for semantic segmentation and model the feature distribution to identify anomalous objects.

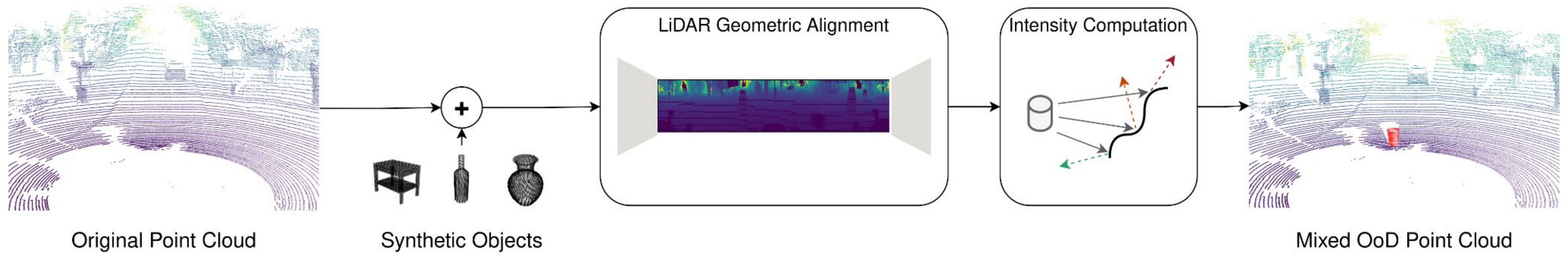


- **Semantic Head**: Cross Entropy, Lovasz and prototype-based losses.
- **Contrastive Head**: Contrastive loss and Objectosphere loss.
- **Anomaly Score**: prototype similarity + entropy + objectosphere score.

Out-of-Distribution Datasets

- New set of **mixed real-synthetic** Out-of-Distribution **datasets** built upon established benchmarks, with **realistic geometric alignment** of synthetic objects.

SemanticKITTI-OoD - SemanticPOSS-OoD - nuScenes-OoD



Experiments

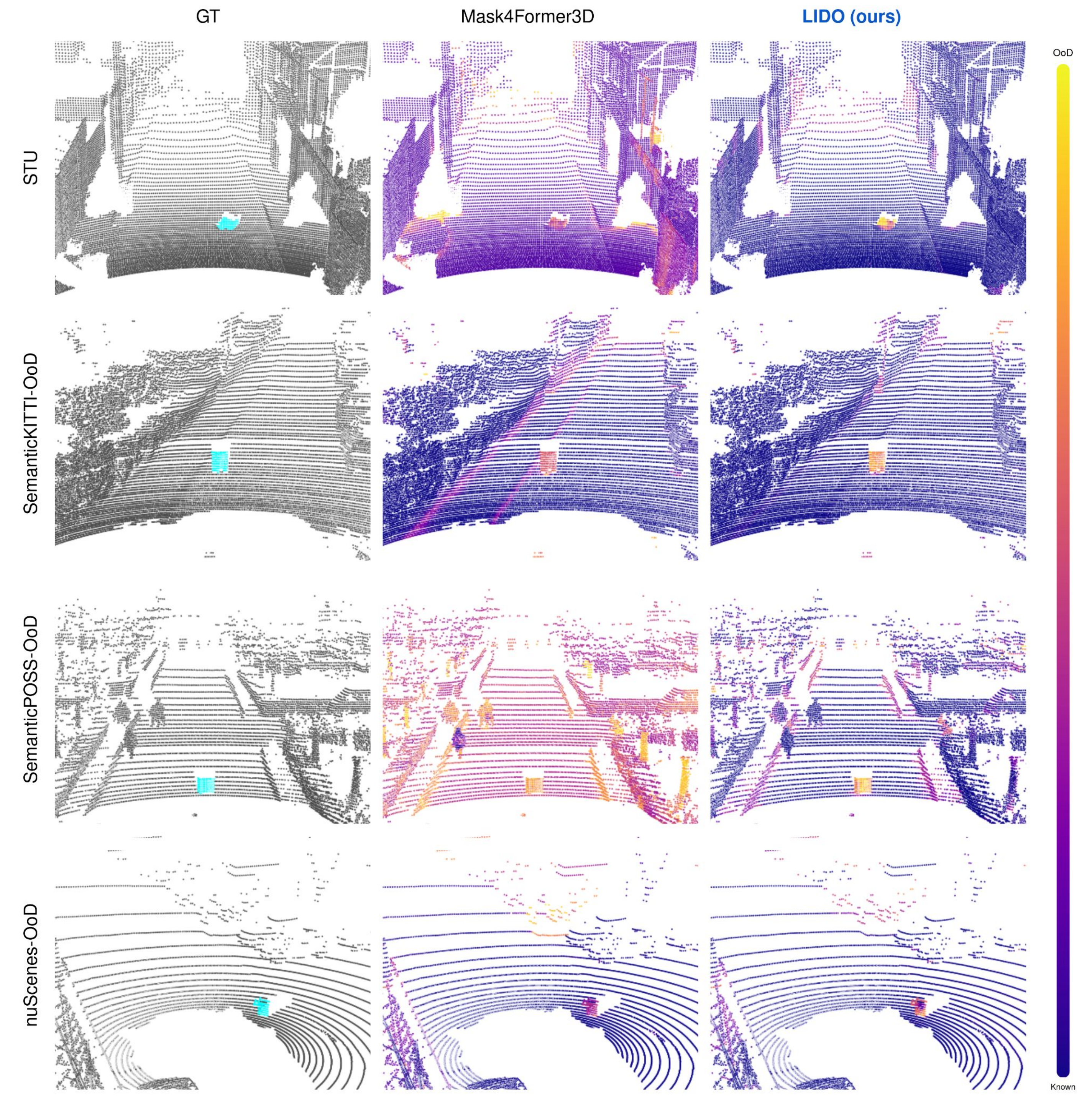
- **LIDO** achieves better results on STU and SemanticPOSS-OoD, competitive results on SemanticKITTI-OoD and nuScenes-OoD.

STU

Method	Validation Set AUROC [%] ↑	Validation Set FPR@95 [%] ↓	Validation Set AP [%] ↑	Test Set AUROC [%] ↑	Test Set FPR@95 [%] ↓	Test Set AP [%] ↑
Mask4Former3D + MC Dropout [56]	65.76	79.82	0.17	61.51	82.37	0.11
Mask4Former3D + RbA [41]	73.00	100.0	1.64	66.38	100.0	0.81
Mask4Former3D + Max Logit [24]	87.27	68.76	2.02	84.53	81.49	0.95
Mask4Former3D + Void Classifier [6]	89.77	79.50	2.62	85.99	78.60	3.92
Mask4Former3D + Deep Ensemble [30]	90.93	37.34	6.94	86.74	58.05	5.17
LIDO (ours)	**95.05**	**34.86**	**27.53**	**93.67**	**34.29**	**14.99**

POSS-OoD

Method	Single AUROC [%] ↑	Single FPR@95 [%] ↓	Single AP [%] ↑	Multi AUROC [%] ↑	Multi FPR@95 [%] ↓	Multi AP [%] ↑
Mask4Former3D + RbA [41]	49.09	100.0	0.13	50.42	100.0	0.26
Mask4Former3D + Max Logit [24]	61.05	91.85	0.19	63.77	88.74	0.40
Mask4Former3D + Deep Ensemble [30]	85.86	58.12	0.82	85.83	54.20	1.21
LIDO (ours)	**91.51**	**45.10**	**3.97**	**90.84**	**44.74**	**5.92**



- **LIDO** achieves strong results without using artifact anomalies in training; future work will investigate model uncertainty.