



#### **Domain Adaptative LiDAR Segmentation**

#### TL;DR

> We propose ConDA, an unsupervised domain adaptation (UDA) framework for LiDAR segmentation in autonomous driving scenes that bridges two domains by establishing an intermediate domain consisting of intertwined source and targe range-view projections.



#### **Cross-City Benchmark**

> We establish the UDA benchmark upon Motional's nuScenes dataset, which contains large-scale LiDAR point clouds collected from different physical locations (Boston and Singapore).



Boston

Singapore

> The domain gap between two cities leads to severe performance degradation when a source-pretrained model is directly tested on the evaluation set of the annotation-void target domain.



# **ConDA: Unsupervised Domain Adaptation for LiDAR Segmentation** via Regularized Domain Concatenation

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# **Domain Concatenation & Regularization**

### **ConDA Framework**

 $\succ$  After the 3D-to-2D pre-processing, the LiDAR sample stripes from both the source domain and the target domain are mixed via range-view concatenation. The concatenated inputs are fed into the LiDAR segmentation network for feature extraction.



> We include anti-aliasing regularizers inside convolution operations to suppress the learning of high-frequency aliasing artifacts. The segmented range-view cells are then projected back to 3D.



 $\succ$  To mitigate the possible impediment caused by erroneous target predictions, we further design an entropy aggregator which splits samples into a confident set and an unsure set and disables the usage of samples from the latter set.

## **Scene Prior in Range-View**

> Spatial priors of representative classes in the range-view for the Boston split and Singapore split in nuScenes. Regions with lighter colors correspond to high-frequent occurrences and vice versa.



![](_page_0_Picture_31.jpeg)

![](_page_0_Picture_32.jpeg)

#### Experimental Result & Analysis

#### **UDA Performance**

Δ	mIoU	Configuration	0.50	42.4	45.6	44.7	44.0	43.1	0.50		46.9	46.9	46.0	45.5
-12.0	34.9	No adaptation (source-only) Baseline (vanilla self-training) += Anti-aliasing filters (Sec. III-C) += Domain concatenation (Sec. III-B) += Entropy aggregator (Sec. III-D)	0.40	42.4	45.6	44.9	44.5	43.5	0.40	45.0	46.8	46.9	46.2	45.1
-6.2	40.7		0.30	42.2	45.8	44.8	44.5	43.7	0.30	44.9	46.7	46.9	45.9	44.9
-1.6	45.3 45.9		0.25	42.2	45.9	45.1	44.1	43.5	0.25	45.4	46.8	46.1	45.8	45.0
0.0	46.9	Full ConDA framework	0.20	42.8	45.8	44.9	44.7	43.5	0.20	45.3	46.7	46.0	45.4	44.7
				0	0.25	0.50	0.75	1.0		0	0.25	0.50	0.75	1.0

most regions around the ego-vehicle.

![](_page_0_Picture_42.jpeg)

# **Summary & Conclusion**

- Code and benchmark suite are publicly accessible.

#### Acknowledgement

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![](_page_0_Picture_50.jpeg)

![](_page_0_Picture_51.jpeg)

 $\succ$  Our approach improves the domain adaptation performance in an effective manner. For example, for the established Boston -> Singapore setting, the LiDAR segmentation scores were boosted from 34.9 mIoU to 46.9 mIoU (34.4% better than the baseline).

 $\succ$  We observe that while the prior arts only give limited gains in certain areas, ConDA mitigates the false predictions holistically in

> A novel framework for cross-city UDA in LiDAR segmentation that leverages the scene priors for domain bridging and regularization. > A huge performance boost for the LiDAR segmentation network tested on the evaluation set of the annotation-void target domain. > We achieve better results than prior arts while still maintaining a relatively low training complexity for a scalable extension.

![](_page_0_Picture_56.jpeg)