SALUDA: Surface-based Automotive Lidar Unsupervised Domain Adaptation

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Code

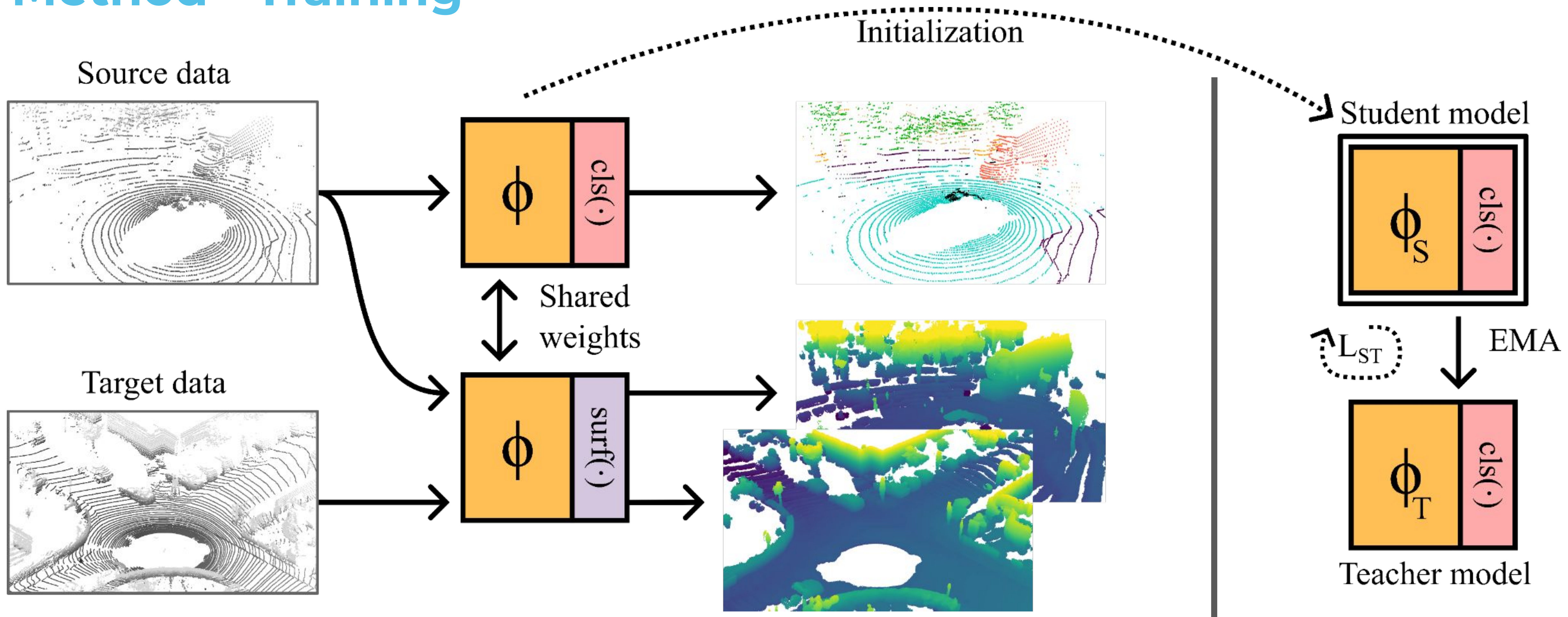
Challenge: Special Domain Gaps in Lidar Point Clouds

- Sensor characteristics: num. of beams, resolution, range, orient.
- Sensor location: bumper level, roof
- Synthetic vs real data: noise, outliers, intensity, etc.

Idea

Implicit surface reconstruction as a self-supervised auxiliary task helps aligning features from different domains.

Method - Training



Step 1: Training w/ surface reconstruction regularization

Backbone ϕ is trained to provide per-point latent vectors.

Source data (annotated) latent vectors are used in:

- the segmentation head cls(·) to classify each point;
- the surface reconstruction head surf(·) to estimate occupancy.

Target data (unannotated) latent vectors are fed to surf(·).

Step 2: Self-Training

True labels for source data.

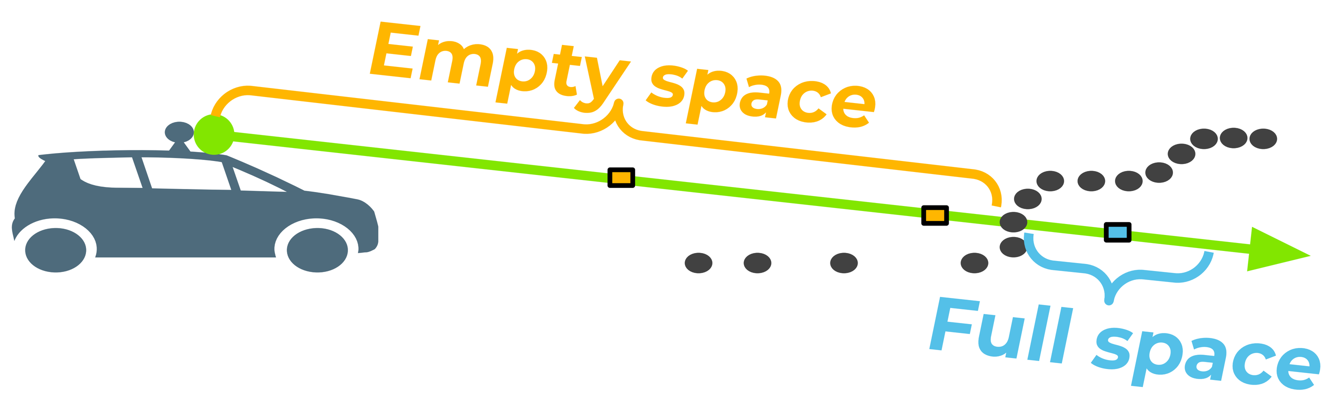
Pseudo-labels for target data.

Teacher is an exponential moving average (EMA) of the student.

Surface reconstruction regularization

$$\mathcal{L} = \mathcal{L}_{\text{sem}} + \boxed{\lambda \mathcal{L}_{\text{occ}}}$$

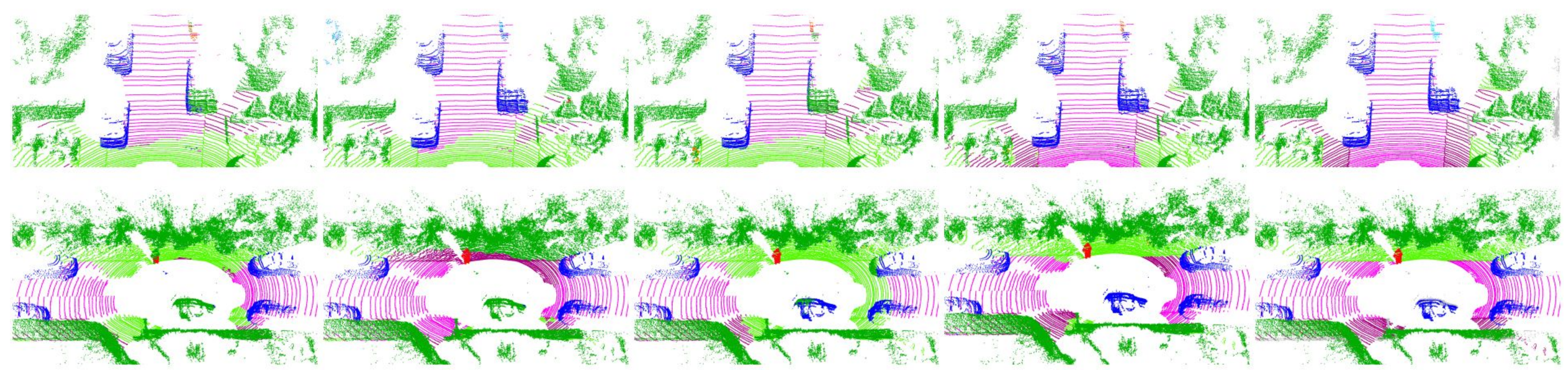
Query generation for implicit surface reconstruction



Following the lines of sight

- **Empty queries:** from sensor to point
- **Full queries:** just behind the point (max dist.=0.1)

Qualitative results



Source-only | Mixed BN | CoSMix [2] | SALUDA | Ground truth

Benchmarks

Method		$NS \rightarrow SK_{10}$	$SL \rightarrow SK_{19}$	$NS \rightarrow SP_{6}$
Source only		35.9 ±3.2	21.6 ±0.2	62.5 ±0.2
C&L	[1]	33.7	-	-
AdaBN		40.1 ±0.4	25.6 ±0.2	62.5 ±0.0
DUA		42.9 ±0.7	26.4 ±0.4	62.3 ±0.1
MixedBN	(ours)	43.3 ±0.6	27.0 ±0.6	62.4 ±0.1
MinEnt		*43.3 ±0.6*	*27.0 ±0.6*	62.6 ±0.1
Coral		*43.3 ±0.6*	27.3 ±0.3	63.0 ±0.2
LogCoral		*43.3 ±0.6*	*27.0 ±0.6*	62.5 ±0.1
Self-Training		37.3 ±2.9	26.7 ±0.4	65.5 ±0.2
CoSMix	[2]	38.3 ±2.8	28.0 ±1.4	65.2 ±0.2
SALUDA	(ours)	**46.2** ±0.6	**31.2** ±0.2	**65.8** ±0.3

Validators for hyperparam.

Validator	$NS \rightarrow SK_{10}$		$SL \rightarrow SK_{19}$	
	w/o ST	w/ ST	w/o ST	w/ ST
Oracle	44.9	46.2	27.6	31.2
Entropy	**44.8**	**46.2**	**27.6**	**31.2**
IM	44.0	45.3	26.6	30.0
SrcVal	43.3	43.7	27.0	29.7

Distance Ablations

	Distance (m)	0 →7.5	7.5 →15	15 →30	30 →50
	Proportion of points	45.3%	34.4%	15.7%	4.7%
$NS \rightarrow SK_{10}$	Supervised on SK_{10}	82.3	69.8	63.7	51.1
	Source-only	33.8	44.8	**47.1**	32.1
	SALUDA	**47.9**	**49.2**	47.0	**33.3**
	gain wrt src-only	+24.1	+4.4	-0.1	+1.2

[1] Yi et al.,Complete & Label: A domain adaptation approach to semantic segmentation of lidar point clouds. In CVPR, 2021
[2] Saltori et al., Cosmix: Compositional semantic mix for domain adaptation in 3d lidar segmentation. In ECCV, 2022