Université Bretagne Sud ubs Valeo UMR IRISA

SALUDA: Surface-based Automotive LiDAR Unsupervised Domain Adaptation


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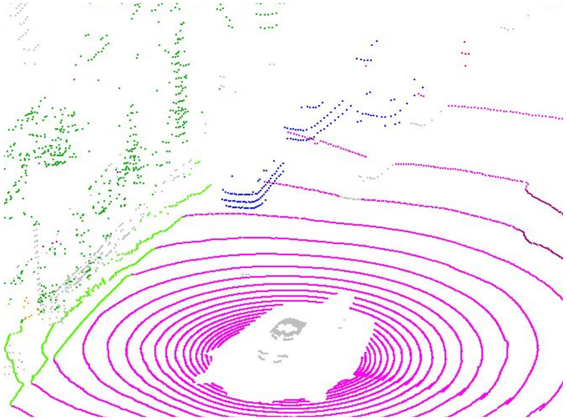
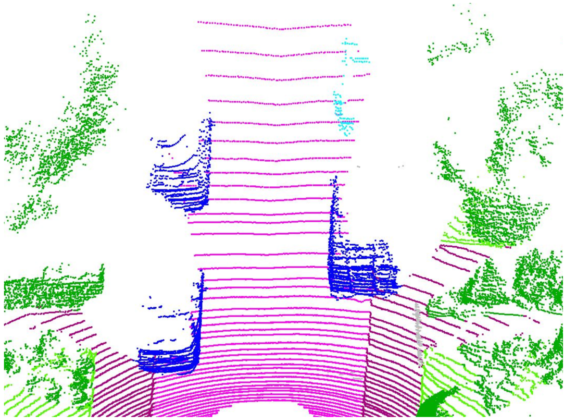
LiDAR data for autonomous driving

nuScenes



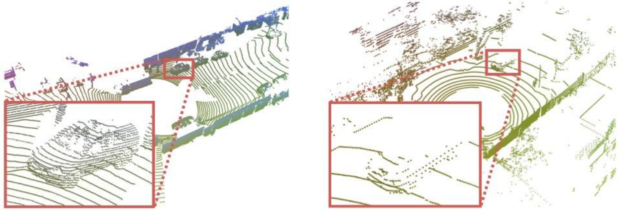
SemanticKITTI



Why Domain adaptation for LiDAR data ?

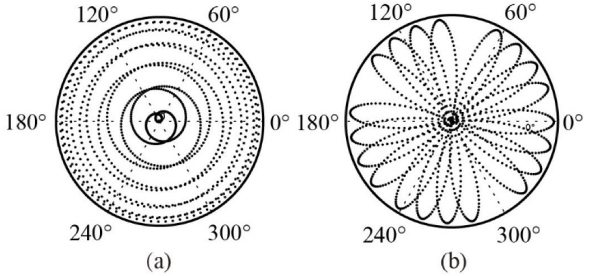
Very wide gaps:

- type of scenes: indoors vs outdoors, static vs dynamic, world location, weather...
- type of sensors: depth camera (struct. light or ToF), (ir)regular scanning patterns...
- number of sensors and scan fusion, if any
- sensor characteristics: no. beams, angular resolution, range, intensity calibration, orient.
- sensor location: bumper level, roof
- synthetic vs real: noise, outliers, intensity, etc.

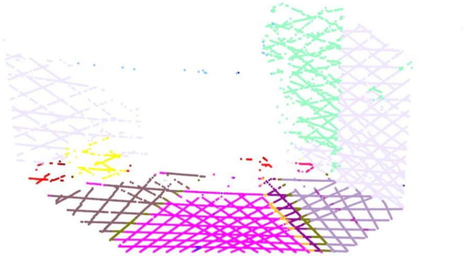


(a) captured by a 64-beam LiDAR (b) captured by a 32-beam LiDAR

(Yi et al. CVPR 2021)



(Liu et al. TMECH 2022)



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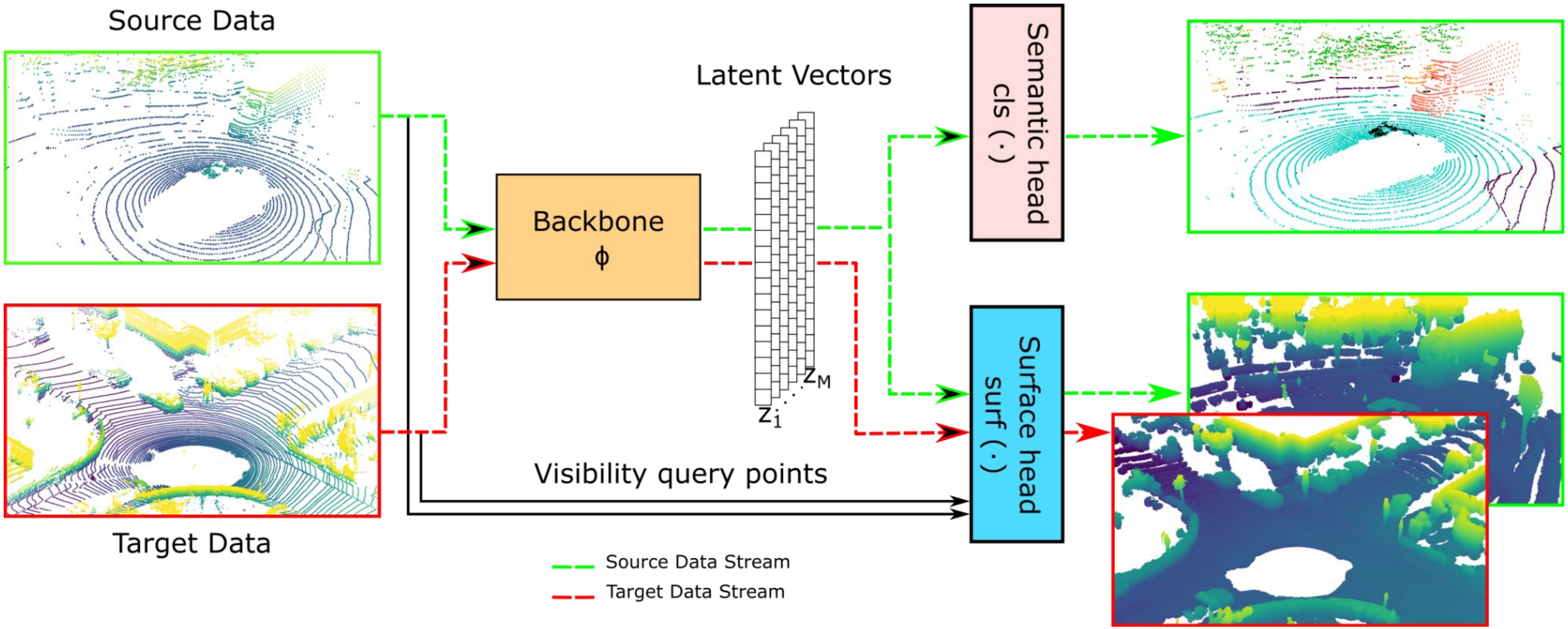
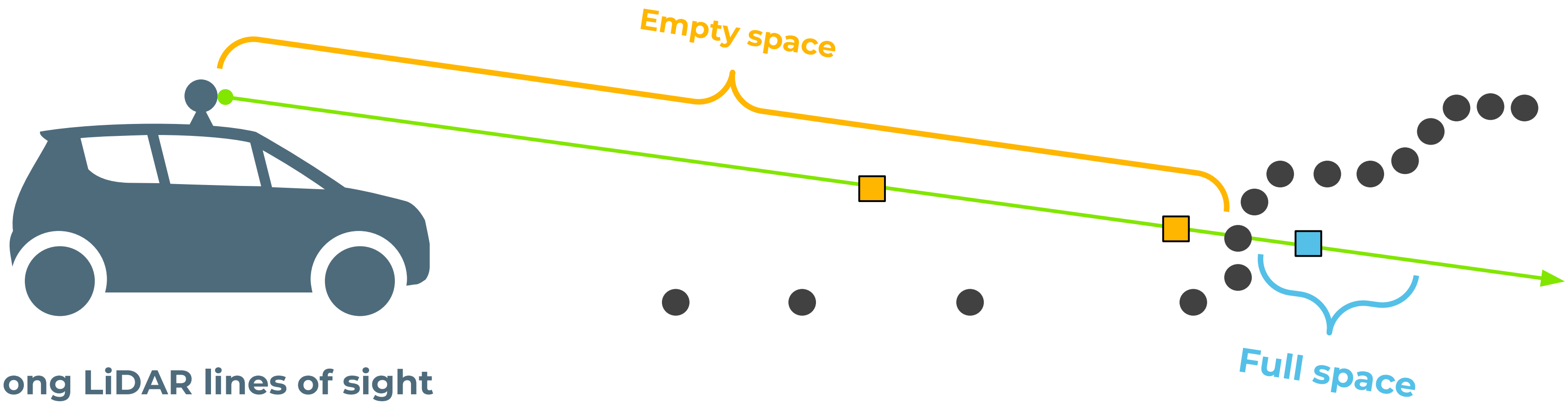
Implicit surface reconstruction as a self-supervised auxiliary task



Implicit surface reconstruction

Query generation

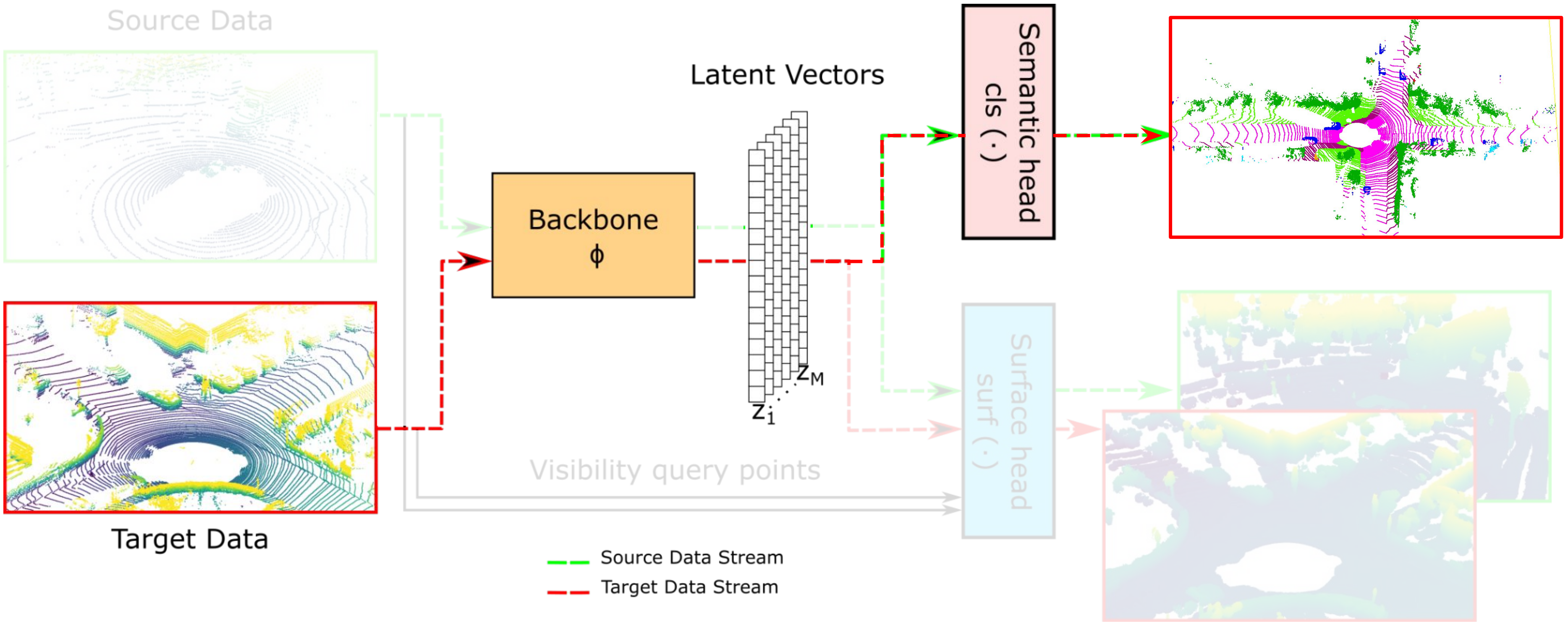


Along LiDAR lines of sight

- **Empty queries:** from sensor to observed point
- **Full queries:** just behind the point (max distance δ = 0.1 m)

Boulch, A., Sautier, C., Michele, B., Puy, G. and Marlet, R., 2023. ALSO: Automotive Lidar Self-supervision by Occupancy estimation. In CVPR.

SALUDA
Inference



Experiments

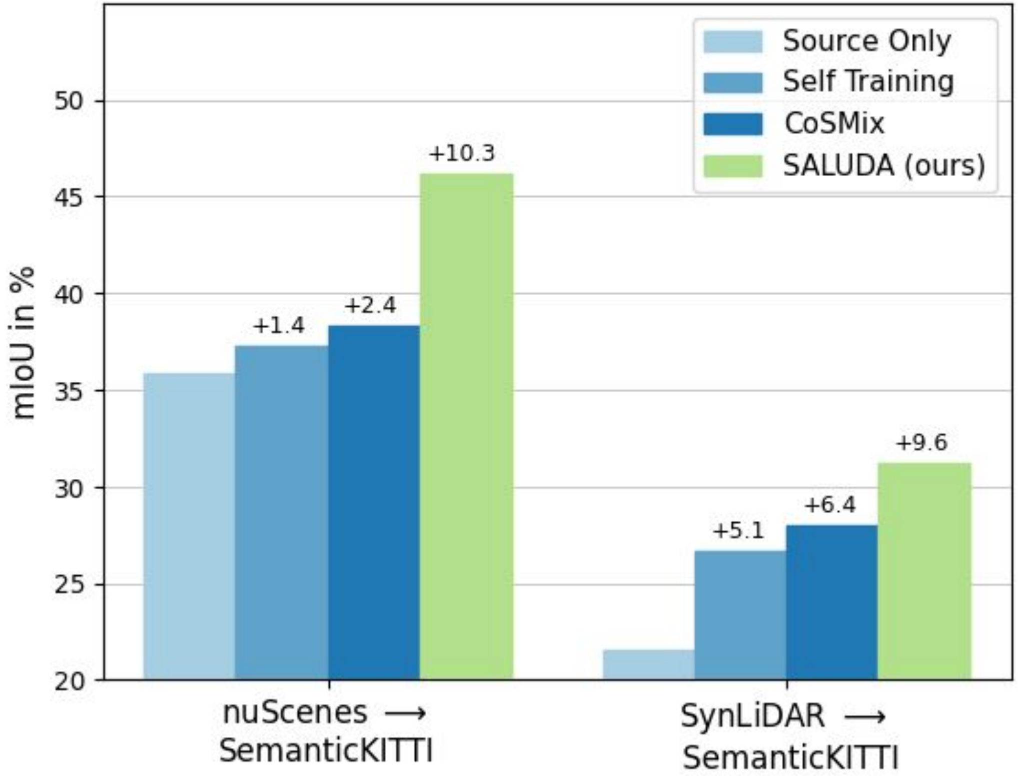
Settings

Real-to-Real, different sensor:
nuScenes to SemanticKITTI (32 Beams to 64 Beams)
nuScenes to SemanticPOSS (32 Beams to 40 Beams)

Synthetic-to-Real, same sensor:
SynLiDAR to SemanticKITTI (64 Beams to 64 Beams)

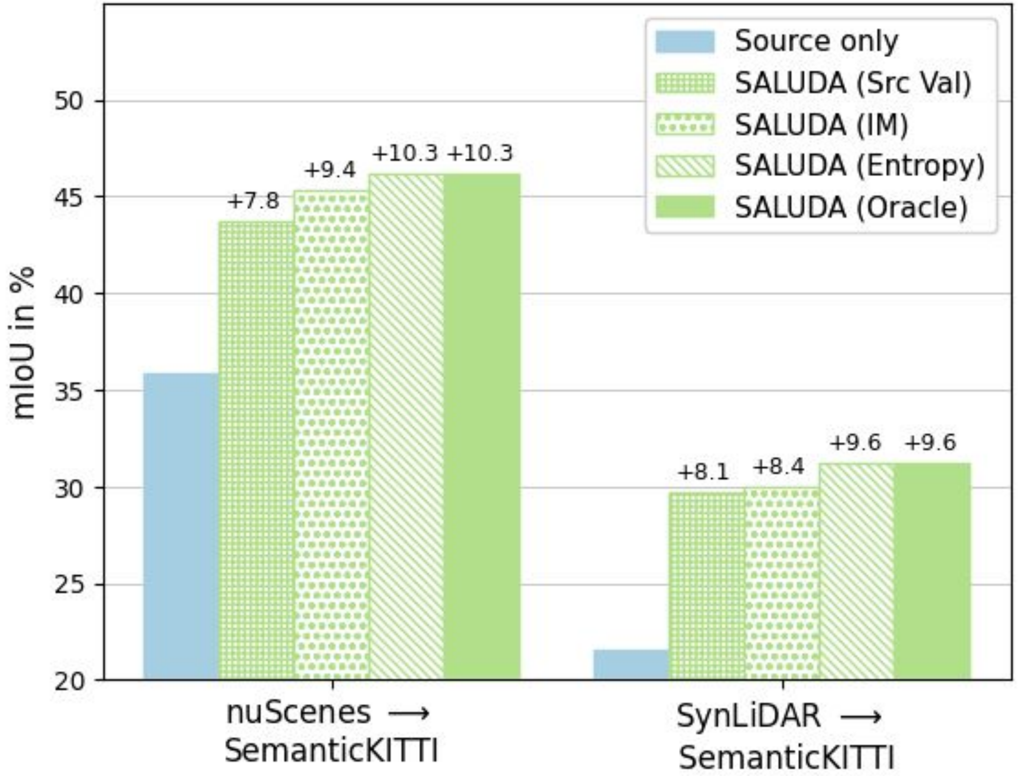
Synthetic-to-Real, different sensors:
SynLiDAR to SemanticPOSS (64 Beams to 40 Beams)

Experiments
Quantitative results



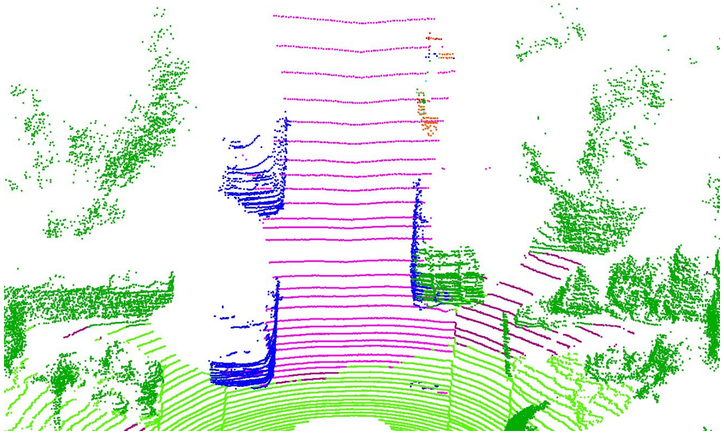
Experiments

Hyperparameter selection with validators

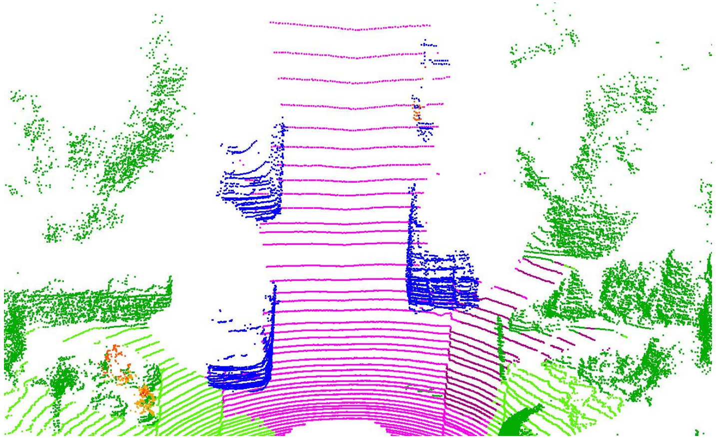


Experiments

Qualitative results - nuScenes to SemanticKITTI

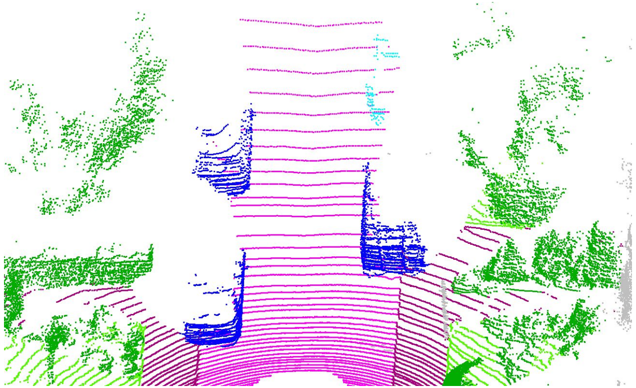


Source Only



SALUDA

GT



Conclusion

- ✔ Competitive results with geometric regularization
- ✔ Robust in unsupervised hyperparameter selection
- ✔ Can be combined with other SOTA methods

Code on Github