

LaserMix for Semi-Supervised LiDAR Semantic Segmentation

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TL;DR

LaserMix is a data-efficient learning framework designed for LiDAR segmentation that:

- Leverages the spatial prior in driving scenes for data-efficient learning;
- Constructs low-variational areas via laser beam mixing;
- Encourages the model to make confident and consistent predictions before and after mixing;
- Achieves competitive results over full supervision counterparts with 2x to 5x fewer annotations



TL;DR



Autonomous Driving Perception



From left to right:

- LiDAR semantic segmentation
- LiDAR panoptic segmentation
- 3D object detection
- 4D LiDAR panoptic segmentation

Why LiDAR sensors?

- Accurate depth sensing
- Robust at low-light conditions
- Dense perceptions
- •

LiDAR Semantic Segmentation



A. Milioto, et al. "RangeNet++: Fast and accurate LiDAR semantic segmentation," IROS, 2019.

LiDAR Semantic Segmentation



• SemanticKITTI

- Full labels (100%)
- 19 semantic classes
- 100 m x 100 m
- Up to 4.5 hours

• ScribbleKITTI

- Weak (scribble) labels (8.06%)
- 19 semantic classes
- 100 m x 100 m
- 10 25 min per scan
- 90% time saving

O. Unal, et al. "Scribble-supervised LiDAR semantic segmentation," CVPR, 2022.

Semi-Supervised LiDAR Segmentation



Objective

- We target on the less-explored semisupervised LiDAR semantic segmentation.
- Our goal is to leverage the abundant raw LiDAR scans for training accurate segmentation models.
- We propose LaserMix to make advantages of the spatial prior in LiDAR scenes for effective learning with semi supervisions.

Spatial Prior

Class	Туре	Proportion	Distribution	Heatmap
vegetation	static	24.825%		
road	static	22.545%		
sidewalk	static	16.353%		
car	dynamic	4.657%		
traffic-sign	static	0.061%		
motorcycle	dynamic	0.045%		
person	dynamic	0.036%		
bicycle	dynamic	0.018%		

Certain class tends to appear at certain areas around the ego-vehicle!

Overview



(a) Motivation. Semantic scene priors are overt for each category in LiDAR point clouds.
(b)Generalizability. LaserMix can be added into various popular LiDAR representations.
(c)Effectiveness. LaserMix helps to improve both semi- and fully-supervised settings.

Laser Partition & Mixing



Three-Step Procedure

- 1. Partitioning the captured LiDAR scan into low-variation areas.
- 2. Efficiently mixing every area in the LiDAR scan with foreign data.
- 3. Encouraging the LiDAR segmentation models to make confident and consistent predictions on the same area in different mixing.

Laser Partition & Mixing



• Inclination:

$$\phi_i = \arctan(\frac{p_i^z}{\sqrt{(p_i^x)^2 + (p_i^y)^2}})$$

• Depth: $\rho_i = \sqrt{(p_i^x)^2 + (p_i^y)^2}$

• Azimuth: $\alpha_i = \arctan \alpha_i$

$$tan(\frac{p_i^y}{p_i^x})$$

Laser Partition & Mixing



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Consistency Regularization



Derivation (See Our Paper)



LiDAR data and labels strongly correlate with the area A $H(X_{in}, Y_{in}|A)$ is low



Experimental Settings

3	nuScenes [15]	SemanticKITTI [16]	ScribbleKITTI [4]		
Vis.					
#Class	16	19	19		
#Train	29130	19130	19130		
#Val	6019	4071	4071		
Res. (RV)	32×1920	64×2048	64×2048		
Res. (voxel)	[240, 180, 20]	[240, 180, 20]	[240, 180, 20]		
#Beam	32	64	64		
$[\phi_{\rm up},\phi_{\rm low}]$	$[10^{\circ}, -30^{\circ}]$	$[3^{\circ}, -25^{\circ}]$	$[3^{\circ}, -25^{\circ}]$		
$[p_{\max}^x, p_{\min}^x]$	[50m, -50m]	[50m, -50m]	[50m, -50m]		
$[p_{\max}^y, p_{\min}^y]$	[50m, -50m]	[50m, -50m]	[50m, -50m]		
$[p_{\max}^{\boldsymbol{z}}, p_{\min}^{\boldsymbol{z}}]$	[3m, -5m]	[2m, -4m]	[2m, -4m]		
#Label	100%	100%	8.06%		
Intensity					
Range					
Semantics					

High-res LiDAR:

- SemanticKITTI
- Denser scenes

Low-res LiDAR:

- nuScenes
- Sparser scenes

Weak supervision:

- ScribbleKITTI
- Sparse labels

Experimental Settings

- Range View
 - Backbone: FIDNet [IROS'21]
 - # Param: 6.05M
 - 6 x 32 x 1920 (nuScenes)
 - 6 x 64 x 2048 (SemanticKITTI/ScribbleKITTI)
- Voxel
 - Backbone: Cylinder3D [CVPR'21]
 - # Param: 28.13M
 - [240, 180, 20]
- Data Split
 - 1%, 10%, 20%, 50% (labeled)
 - Random sampling
 - Assume the remaining ones are unlabeled



Y. Zhao, et al. "FIDNet: LiDAR point cloud semantic segmentation with fully interpolation decoding," IROS, 2021. X. Zhu, et al. "Cylindrical and asymmetrical 3D convolution networks for LiDAR segmentation," CVPR, 2021.

Experimental Results

Dopr	Mathad	nuScenes [15]			SemanticKITTI [16]			ScribbleKITTI [4]					
кері.	Method	1%	10%	20%	50%	1%	10%	20%	50%	1%	10%	20%	50%
Range View	Suponly	38.3	57.5	62.7	67.6	36.2	52.2	55.9	57.2	33.1	47.7	49.9	52.5
	MeanTeacher [26] CBST [30] CutMix-Seg [29] CPS [13]	42.1 40.9 43.8 40.7	60.4 60.5 63.9 60.8	65.4 64.3 64.8 64.9	69.4 69.3 69.8 68.0	37.5 39.9 37.4 36.5	53.1 53.4 54.3 52.3	56.1 56.1 56.6 56.3	57.4 56.9 57.6 57.4	34.2 35.7 36.7 33.7	49.8 50.7 50.7 50.0	51.6 52.7 52.9 52.8	53.3 54.6 54.3 54.6
	Laser Mix (Ours) $\Delta \uparrow$	$\begin{array}{c c} 49.5 \\ +11.2 \end{array}$	08.2 + 10.7	70.6 +7.9	73.0 + 5.4	43.4 + 7.2	58.8 + 6.6	59.4 + 3.5	61.4 + 4.2	38.3 + 5.2	54.4 + 6.7	55.0 + 5.7	58.7 +6.2
	Suponly	50.9	65.9	66.6	71.2	45.4	56.1	57.8	58.7	39.2	48.0	52.1	53.8
Voxel	MeanTeacher [26] CBST [30] CPS [13]	$51.6 \\ 53.0 \\ 52.9$	$\begin{array}{c} 66.0 \\ 66.5 \\ 66.3 \end{array}$	$67.1 \\ 69.6 \\ 70.0$	71.7 71.6 72.5	$\begin{array}{c} 45.4 \\ 48.8 \\ 46.7 \end{array}$	$57.1 \\ 58.3 \\ 58.7$	$59.2 \\ 59.4 \\ 59.6$	$ \begin{array}{r} 60.0 \\ 59.7 \\ 60.5 \end{array} $	$\begin{array}{c c} 41.0 \\ 41.5 \\ 41.4 \end{array}$	$50.1 \\ 50.6 \\ 51.8$	$52.8 \\ 53.3 \\ 53.9$	$53.9 \\ 54.5 \\ 54.8$
	LaserMix (Ours) $\Delta \uparrow$	$\begin{vmatrix} 55.3 \\ +4.4 \end{vmatrix}$	69.9 + 4.0	71.8 + 5.2	73.2 + 2.0	$50.6 \\ +5.2$	60.0 + 3.9	$\begin{array}{c} 61.9 \\ \mathbf{+4.1} \end{array}$	62.3 + 3.6	$\begin{array}{c} \textbf{44.2} \\ \textbf{+5.0} \end{array}$	$\begin{array}{c} 53.7 \\ \mathbf{+5.7} \end{array}$	$\begin{array}{c} 55.1 \\ \mathbf{+3.0} \end{array}$	56.8 +3.0

A. Tarvainen and H. Valpola. "Mean teachers are better role models: Weight-averaged consistency targets improve semisupervised deep learning results," NeurIPS, 2017.

G. French, et al. "Semi-supervised semantic segmentation needs strong, high-dimensional perturbations," BMVC, 2020. Y. Zou, et al. "Domain adaptation for semantic segmentation via class-balanced self-training," ECCV, 2018.

X. Chen, et al. "Semi-supervised semantic segmentation with cross pseudo supervision," CVPR, 2021.

Experimental Results

road	sidewalk	building	wall	fence
pole	traffic light	traffic sign	vegetation	terrain
sky	person	rider	car	truck
		Contraction of the local distance of the loc		
	Contraction of the local division of the loc	Contraction of the		
bus	train	motorcycle	bicycle	
				AISO NAS

Method	1/16	1/8	1/4	1/2
MeanTeacher [26]	66.1	71.2	74.4	76.3
w/ Ours ∧ ↑	68.7	72.3	75.7	76.8
	+ <u>2</u> .0	79.5	75.7	76.9
GCT [11]	$\begin{array}{c} 65.4 \\ 65.8 \end{array}$	$\begin{array}{c} 72.5 \\ 71.3 \end{array}$	75.7	70.8 77.1
CPS [13]	69.8	74.4	76.9	78.6
CPS-CutMix [13]	74.5	76.6	77.8	78.8
w/ Ours	75.5	77.1	78.3	79.1
$\Delta \uparrow$	+1.0	+0.5	+0.5	+0.3

Also has spatial priors in scenes!

Y. Ouali, et al. "Semi-supervised semantic segmentation with cross-consistency training," CVPR, 2020. Z. Ke, et al. "Guided collaborative training for pixel-wise semi-supervised learning," ECCV, 2020.

Ablation Study

#	\mathcal{L}_{mt}	$\mathcal{L}_{ ext{mix}}$	SS	TS	1%	10%	20%	50%
(1)	\checkmark				42.1	60.4	65.4	69.4
(2)	\checkmark	√ √	✓ ✓		$\begin{array}{c} 45.6\\ 47.0\end{array}$	$\begin{array}{c} 64.3 \\ 65.5 \end{array}$	$\begin{array}{c} 67.8 \\ 69.5 \end{array}$	$71.6 \\ 72.0$
(3)	\checkmark	√ √		✓ ✓	$\begin{array}{c} 46.0 \\ 49.5 \end{array}$	$\begin{array}{c} 64.1 \\ 68.2 \end{array}$	$\begin{array}{c} 69.5 \\ 70.6 \end{array}$	$72.3 \\ 73.0$



- (1) Results of MeanTeacher.
- (2) Results of LaserMix w/ student supervisions; much better than the counterpart.
- (3) Results of LaserMix w/ teacher supervisions; much better than the counterpart.

Ablation Study



(a) Comparisons among different mixing techniques. (b) EMA. (c) Confidence threshold.

A. Nekrasov, et al. "Mix3D: Out-of-context data augmentation for 3D scenes," 3DV, 2021.

S. Yun, et al. "Cutmix: Regularization strategy to train strong classifiers with localizable features," ICCV, 2019

T. DeVries and G. W. Taylor. "Improved regularization of convolutional neural networks with cutout," arXiv, 2017 H. Zhang, et al. "Mixup: Beyond empirical risk minimization," ICLR, 2018.

Ablation Study



• Inclination:

$$\phi_i = \arctan(\frac{p_i^z}{\sqrt{(p_i^x)^2 + (p_i^y)^2}})$$

• Depth:
$$\rho_i = \sqrt{(p_i^x)^2 + (p_i^y)^2}$$

• Azimuth: $\alpha_i = \arctan(\frac{p_i^y}{p_i^x})$

Public Resources



- Paper: https://arxiv.org/abs/2207.00026
- **Code:** <u>https://github.com/ldkong1205/LaserMix</u>
- **Tutorial:** <u>https://zhuanlan.zhihu.com/p/528689803</u>
- Project Page: https://ldkong.com/LaserMix