



### The Goal

Segment and classify any object



## The Pseudo-Label Engine

**2D** foundation models to **3D** labels



# Better Call SAL: Towards Learning To Segment Anything in Lidar

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### How To Build Zero-Shot Panoptic Segmentation Models For Lidar?





Class-agnostic instance segmentation



Text prompts: {car, building, ...}

→ The SAL model performs class-agnostic instance segmentation and zero-shot classification via text prompting. → Our training pipeline does not utilize any Lidar or image ground truth labels.  $\rightarrow$  The pseudo-label engine generates 3D pseudo-labels via 2D foundation models.



Text prompts: {trash bin}



Text prompts: {streetcar}



### The Zero-Shot Model

**Class-agnostic** segmentation

Method	Frust. Eval	Image Feat.	PQ	Def SQ	${}^{ m fault~c}_{ m PQ^{Th}}$	$\frac{1}{PQ^{St}}$	mIoU	PQ	Su SQ	${}^{\mathrm{per \ cl}}_{\mathrm{PQ}^{\mathrm{Th}}}$	$^{ m asses}_{ m PQ}^{ m St}$	mIoU
Class-agnostic Segmentation (Semantic Oracle)												
$_{ m SAM}^{ m SAM}$	<b>\$</b> \$	√ ✓	$\begin{vmatrix} 46.0 \\ 42.2 \end{vmatrix}$	$\begin{array}{c} 72.1 \\ 69.4 \end{array}$	$\begin{array}{c} 49.7\\ 45.6\end{array}$	$\begin{array}{c} 43.4\\ 39.6\end{array}$	-	_	_	-	-	
SAM+DBS (filter) SAM+DBS (replace)	✓ ✓	\$ \$	$\begin{vmatrix} 46.7 \\ 48.7 \end{vmatrix}$	$\begin{array}{c} 70.3 \\ 73.7 \end{array}$	$\begin{array}{c} 76.8 \\ 53.1 \end{array}$	$\begin{array}{c} 24.8\\ 45.4\end{array}$	-	_	_	_	-	-
SAL	$\checkmark$	X	70.7	81.9	75.4	67.3		-	-	-		-
Zero-Shot Lidar Panoptic Segmentation												
SAM+DBS+CLIP SAL	<b>\$</b>	×	$\begin{vmatrix} 27.5 \\ 33.1 \end{vmatrix}$	71.5 71.4	$\begin{array}{c} 31.7\\22.8\end{array}$	$24.5 \\ 40.5$	30.6 33.5	51.1  63.9	$\begin{array}{c} 77.5 \\ 84.2 \end{array}$	$\begin{array}{c} 71.2 \\ 88.3 \end{array}$	$\begin{array}{c} 41.0\\51.7\end{array}$	54.3 66.4
SAM+DBS+CLIP SAL	×	×	8.2	56.4 66.8	$\begin{array}{c} 18.6 \\ 17.4 \end{array}$	0.6 30.2	7.5 28.7	11.5  $ 48.5 $	47.6 78.8	0.0 80.4	$\begin{array}{c} 17.3\\ 32.6\end{array}$	11.2 52.8

### Lidar panoptic segmentation benchmarks

	Method	Supervision	Default classes							Super classes			
			PQ	RQ	$\mathbf{SQ}$	$\left  \mathrm{PQ}^{\mathrm{Th}} \right $	$\mathrm{PQ}^{\mathrm{St}}$	mIoU	PQ	RQ	$\mathbf{SQ}$	mIoU	
SemanticKITTI	DS-Net [26]	Full	57.7	68.0	77.6	61.8	54.8	63.5	-	<u></u>	-	-	
	PolarSeg [98]	Full	59.1	70.2	78.3	65.7	54.3	64.5	-		-	1,000	
	EfficientLPS [74]	Full	59.2	69.8	75.0	58.0	60.9	64.9	-		—	—	
	GP-S3Net [70]	Full	63.3	75.9	81.4	70.2	58.3	73.0	-	<u></u>	—	—	
	MaskPLS [45]	Full	59.8	69.0	76.3	-	99 <del>- 11</del> 2	-	78.4	87.1	88.2	84.5	
	SAL	Full	59.5	69.2	75.7	62.3	57.4	63.8	81.7	90.0	89.2	85.9	
	SAL	Zero-shot	24.8	32.3	66.8	17.4	30.2	28.7	48.5	59.4	78.8	52.8	
nuScenes	PHNet [36]	Full	74.7	84.2	88.2	74.0	75.9	79.7	-	<u>1000</u>	-	_	
	DS-Net [26]	Full	51.2	59.0	86.1	38.4	72.3	73.5	-		—	—	
	GP-S3Net [70]	Full	61.0	72.0	84.1	56.0	66.0	75.8	-		—		
	EfficientLPS [74]	Full	62.0	73.9	83.4	56.8	70.6	65.6	_	<u></u>	_	_	
	PolarSeg [98]	Full	63.4	75.3	83.9	59.2	70.4	66.9	-		-	_	
	MaskPLS [45]	Full	57.7	66.0	71.8	64.4	52.2	62.5	71.5	81.0	86.2	80.6	
	SAL	Full	70.5	80.8	85.9	79.4	61.7	72.8	74.2	82.7	87.1	84.0	
	SAL	Zero-shot	38.4	47.8	77.2	47.5	29.2	33.9	52.6	63.5	77.3	52.6	