Durham University

JUNE 18-22, 2023
CVPR
VANCOUVER, CANADA

Less is More
Reducing Task and Model Complexity for 3D Point Cloud Semantic Segmentation

Poster: June 21, 2023 @ WED-AM-108

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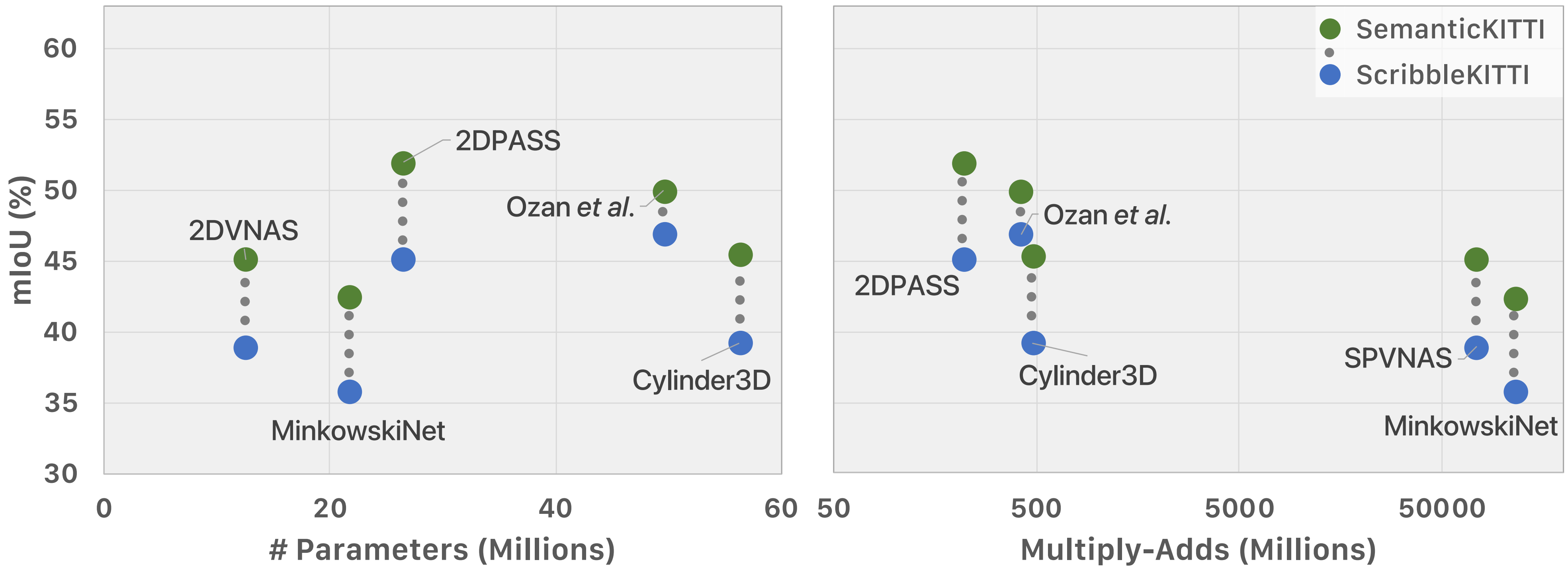
Department of {Computer Science[1] | Engineering[2]}
Durham University

LESS IS MORE



Previous methods

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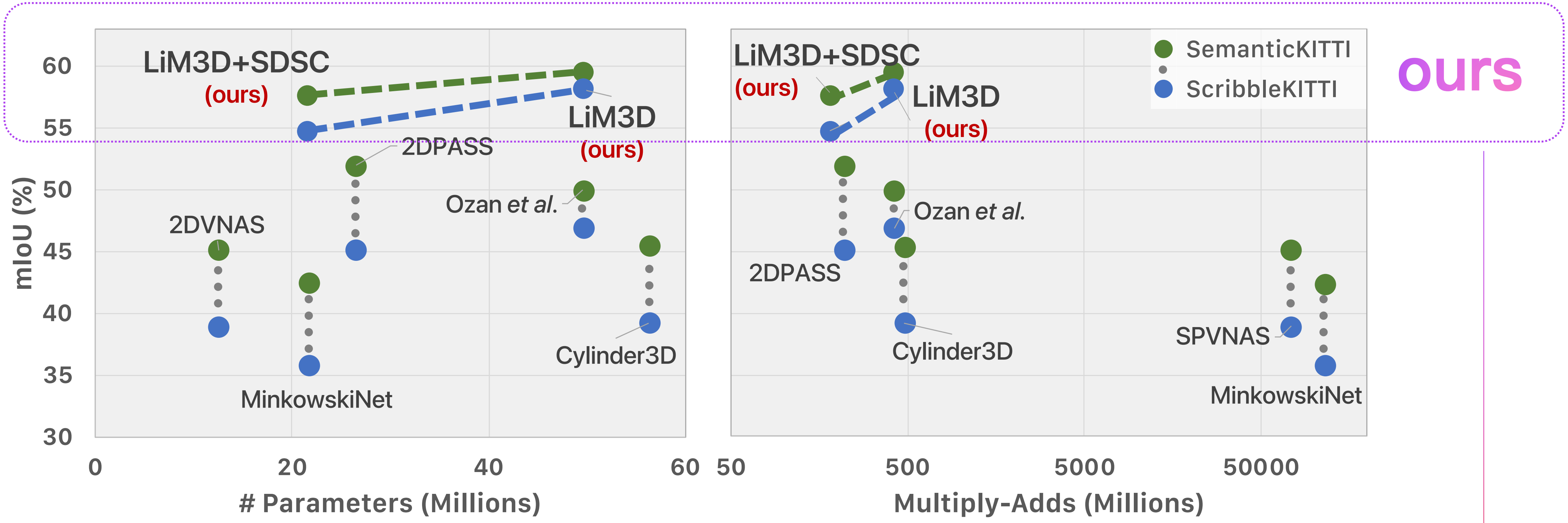
3D Point Cloud Semantic Segmentation, CVPR 2023, Li, Shum, Breckon

LESS IS MORE



2.3x model size reduction

641x fewer multiply–adds

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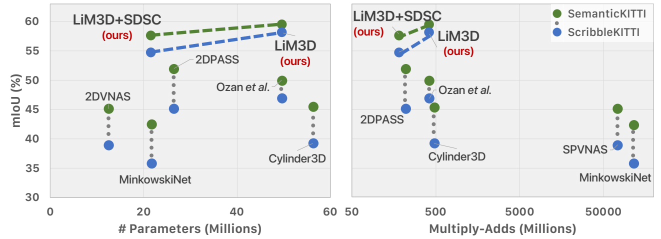
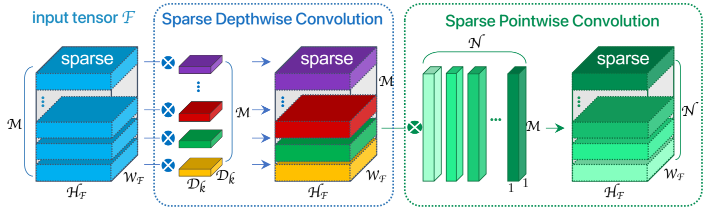
Contributions

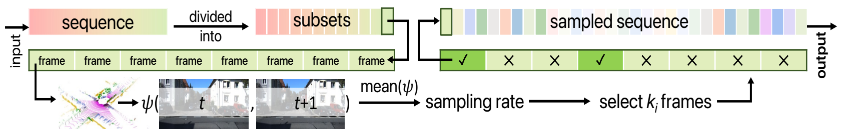
1. semantic segmentation: *less* **parameters** and **(*more*) superior accuracy**.



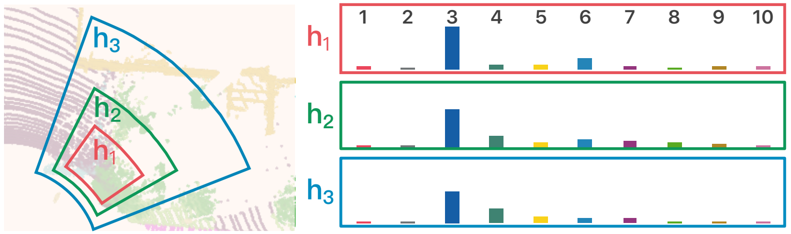
2. **Sparse Depthwise Separable Convolution**: to reduce trainable network without loss.



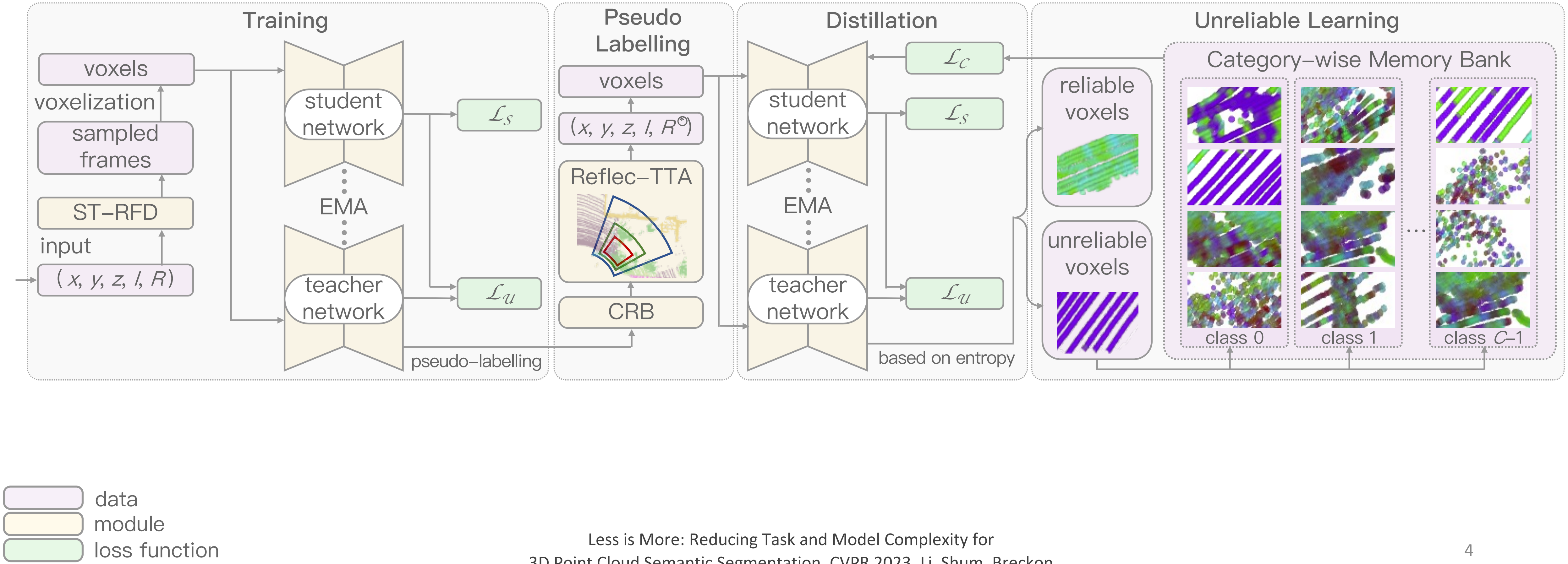
3. **Spatio-Temporal Redundant Frame Downsampling**: to remove temporal redundancy and annotation requirements.



4. Soft pseudo-labeling method informed by **LiDAR reflectivity**: to use limited data annotation effectively.

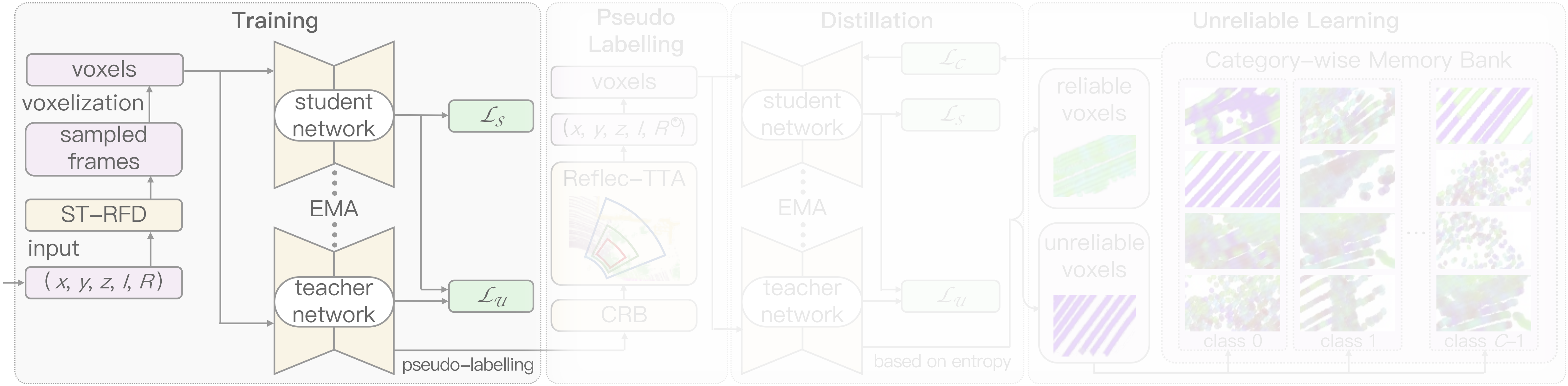


Our Proposed Architecture



Our Proposed Architecture

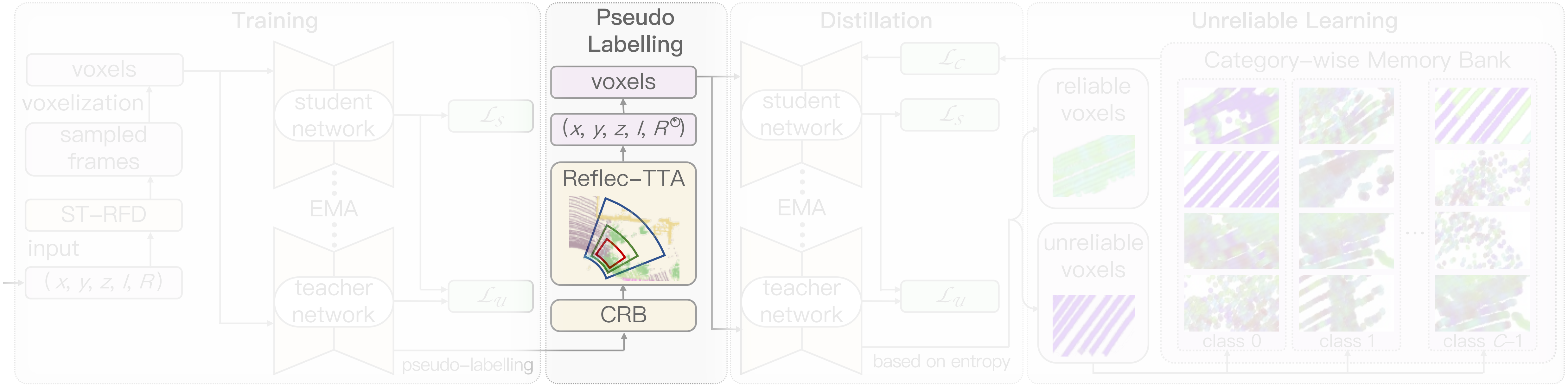
training > to utilize **reflectivity–prior descriptors** and adapt the **Mean Teacher** framework to generate high–quality pseudo–labels



data
module
loss function

Our Proposed Architecture

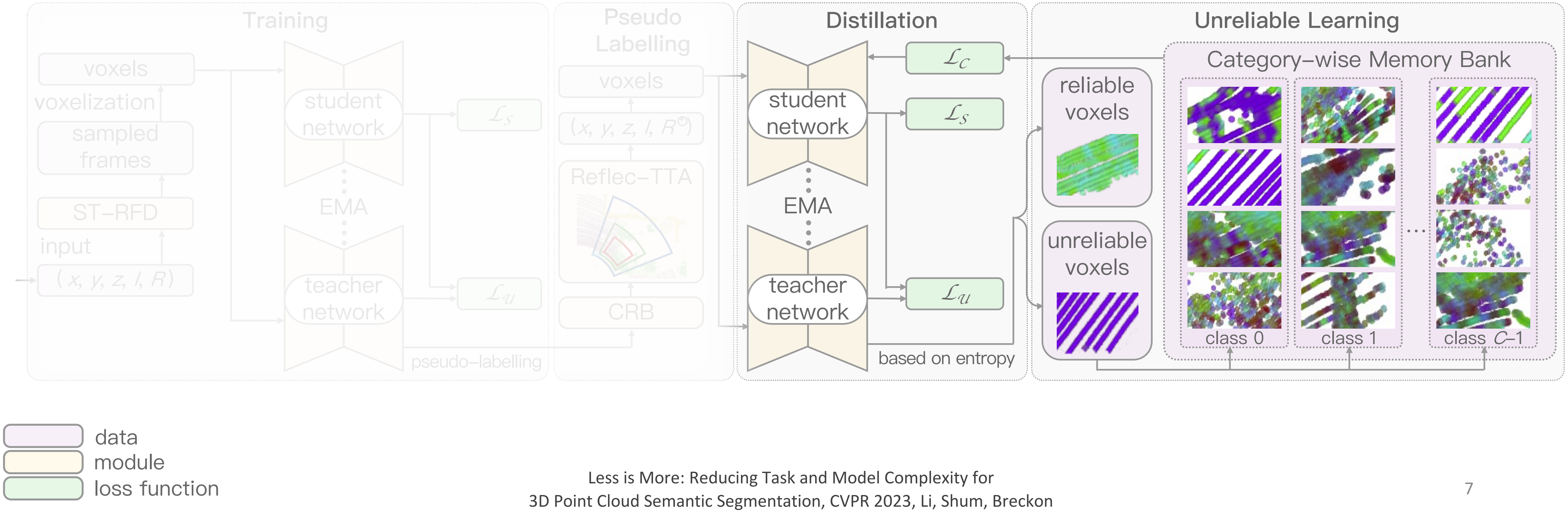
pseudo labelling > to fix the trained teacher model prediction in a **CRB** manner, expanding dataset with **Reflec−TTA** during test time



data
module
loss function

Our Proposed Architecture

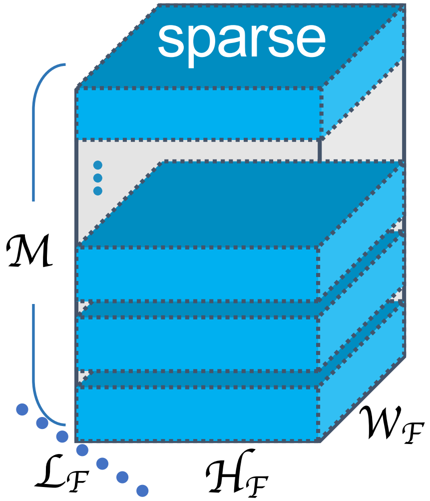
distillation & unreliable learning > to train on the generated pseudo–labels, and **utilize unreliable pseudo–labels** in a memory bank for improved discrimination



Sparse Depthwise Separable Convolution

to reduce trainable network without loss

Input tensor $\mathcal{F}$



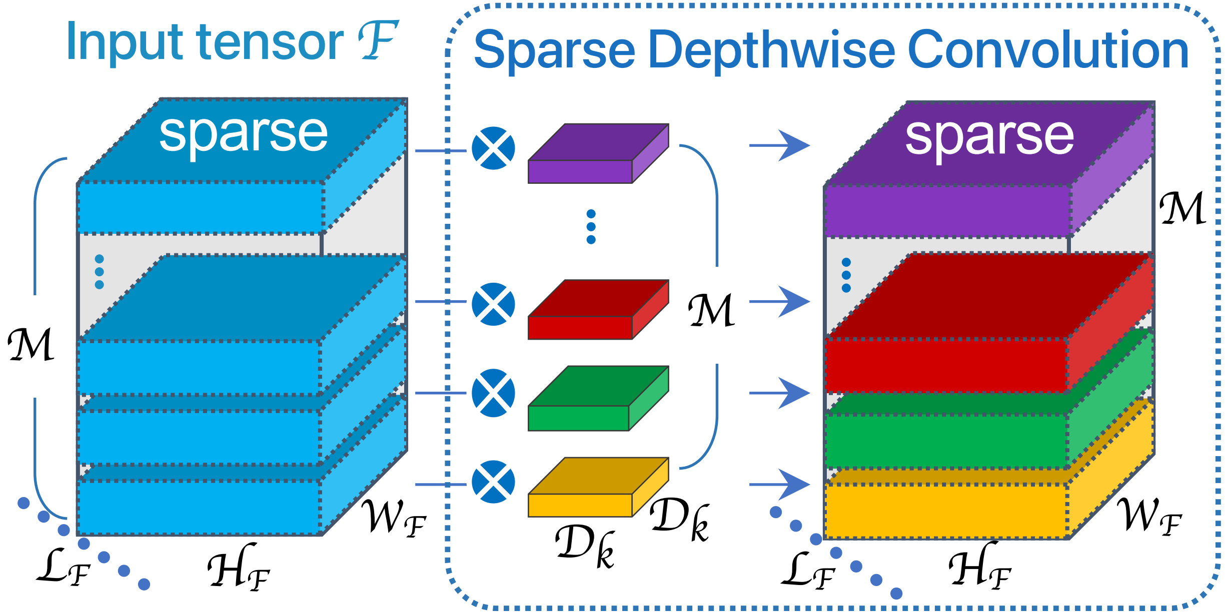
1 taking 3D voxels as input

submanifold sparse convolution

pointwise convolution

Sparse Depthwise Separable Convolution

to reduce trainable network without loss



2 going through the Sparse Depthwise Convolution

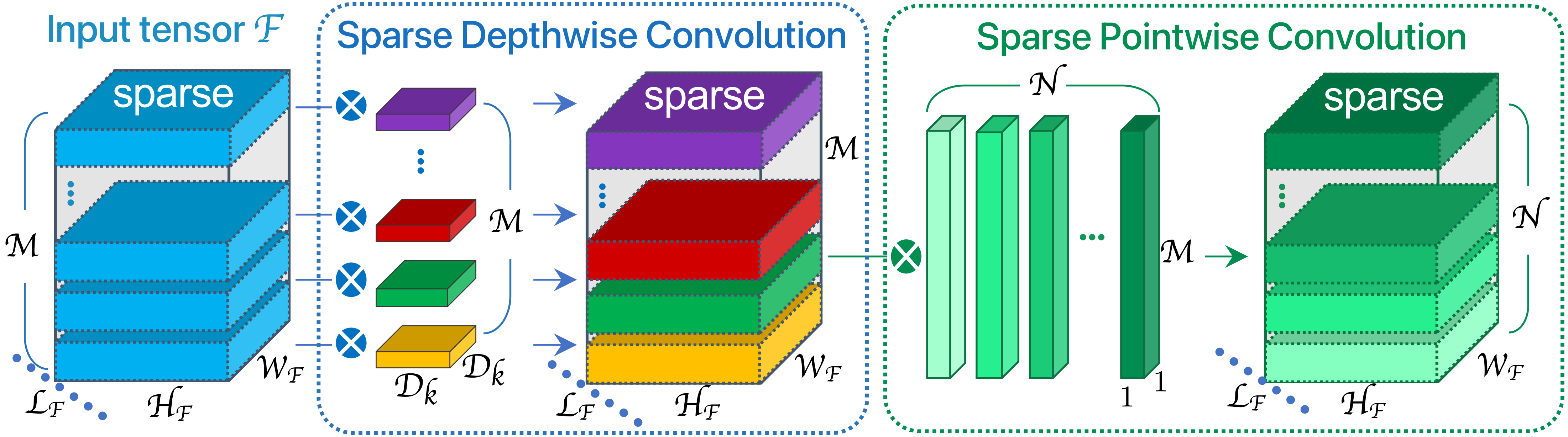
to perform convolution with the trainable parameter reduction

submanifold sparse convolution

pointwise convolution

Sparse Depthwise Separable Convolution

to reduce trainable network without loss



3 going through the Sparse Pointwise Convolution
to mix the information across different channels

submanifold sparse convolution
pointwise convolution

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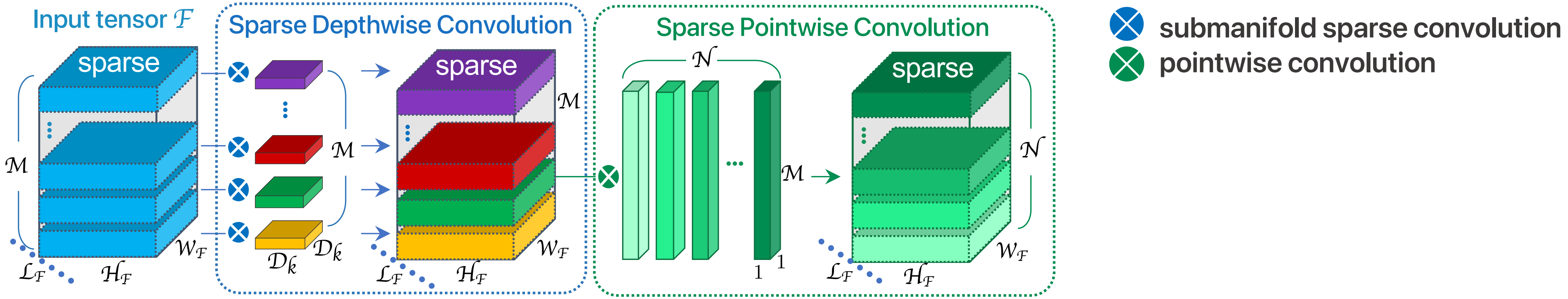
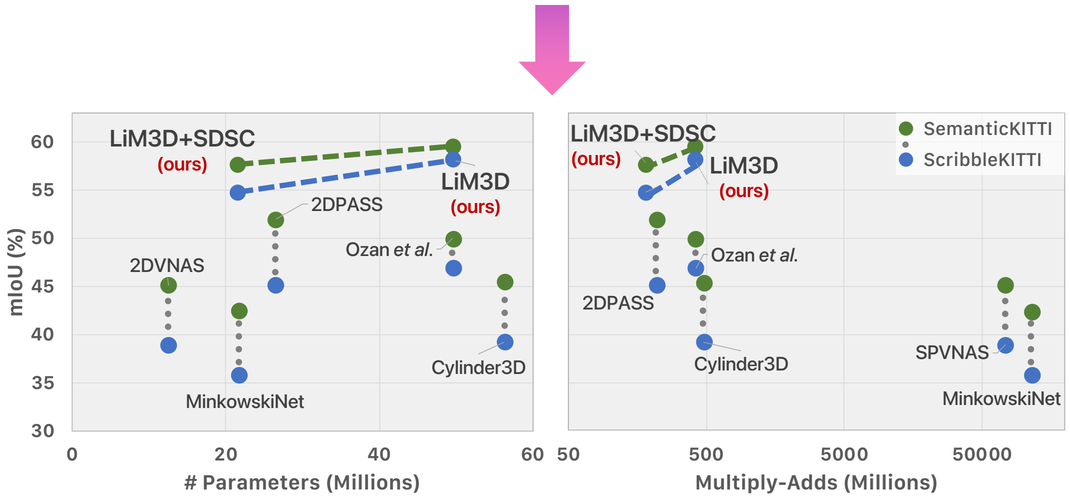
Sparse Depthwise Separable Convolution

to reduce trainable network without loss





with our Sparse Depthwise Separable Convolution we can achieve:

2.3x model size reduction

641x fewer multiply–adds

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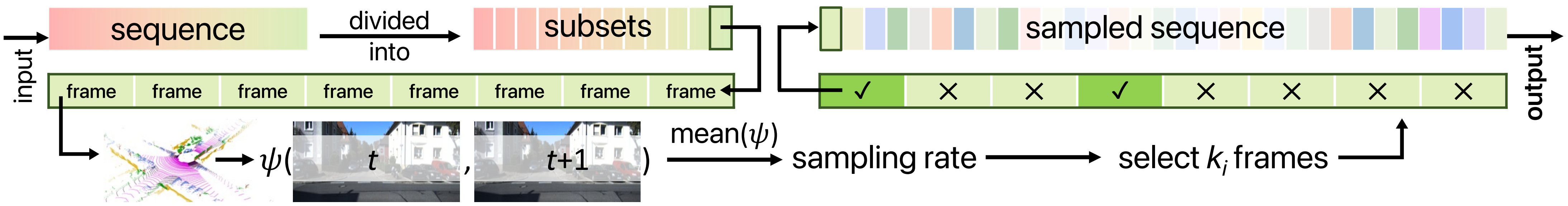
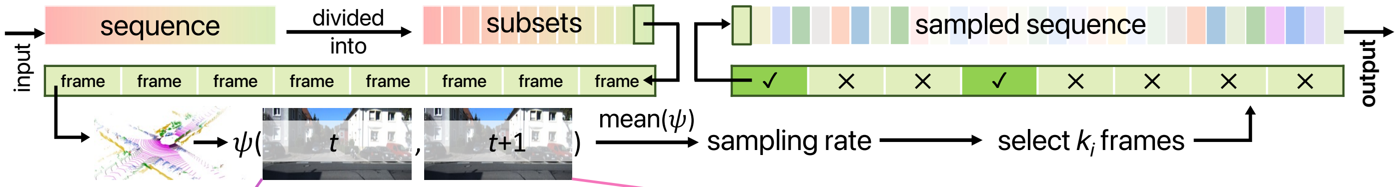
Spatio-Temporal Redundant Frame Downsampling (ST-RFD)

Using ST-RFD to extract a maximally diverse data subset for training by **removing temporal redundancy** and hence future **annotation requirements**



Spatio-Temporal Redundant Frame Downsampling (ST-RFD)



computing the similarity between temporally adjacent frames

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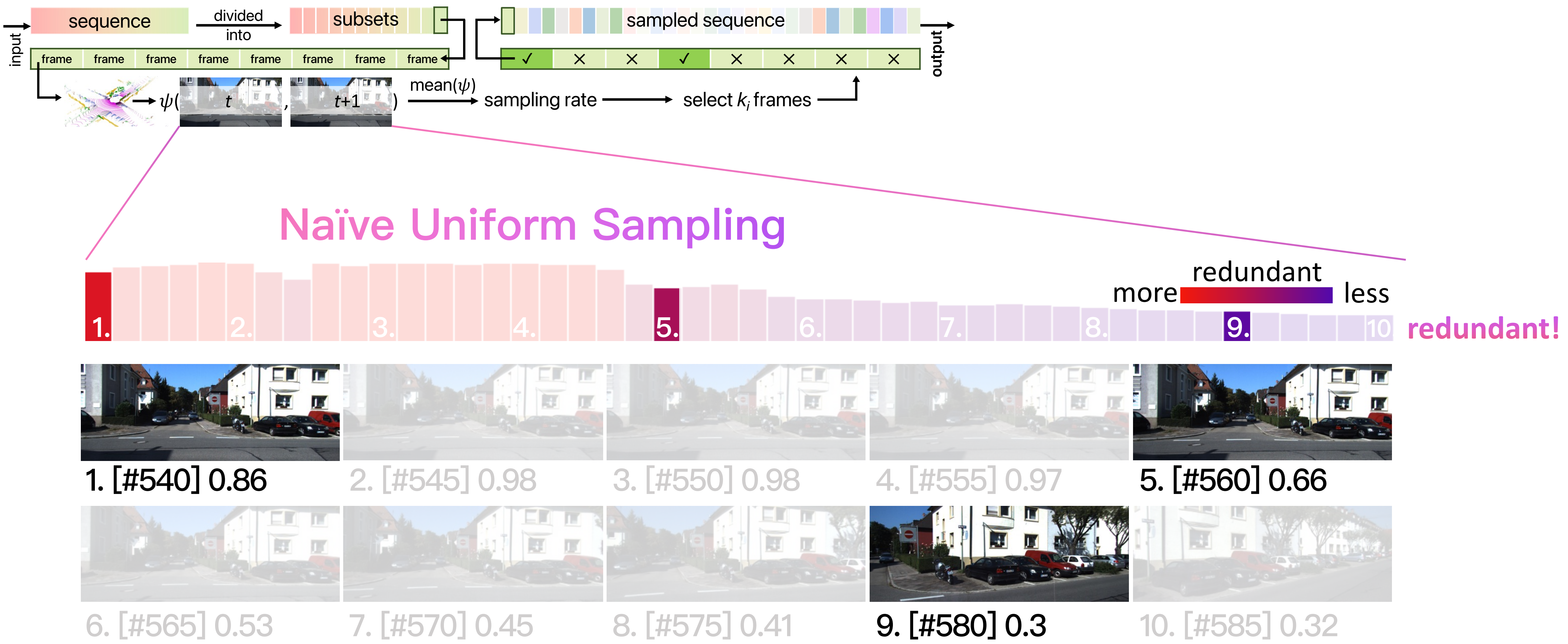
Spatio-Temporal Redundant Frame Downsampling (ST-RFD)



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Spatio–Temporal Redundant Frame Downsampling (ST–RFD)

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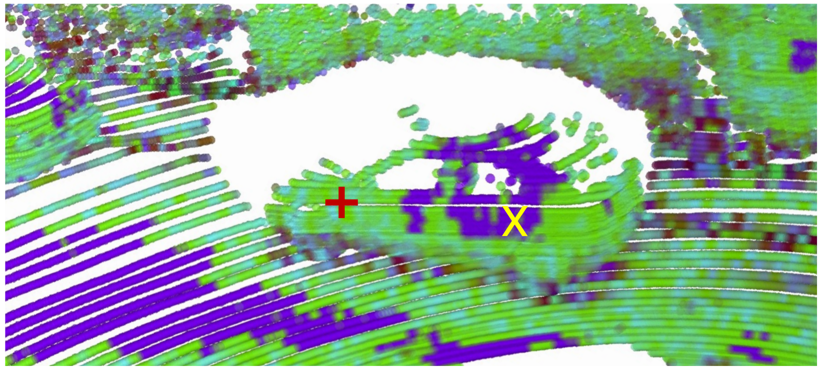
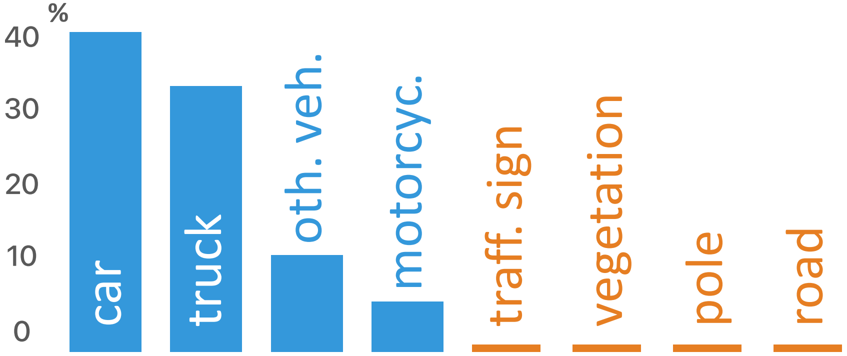
Using Unreliable Pseudo-labels
to Make Full Use of All Available Labels



$$\mathcal{L}_C = -\frac{1}{C}\sum_{c=0}^{C-1} \mathop{\mathbb{E}}_{\mathbf{E}_c}\left[\log \frac{f(\mathbf{e}_c, \mathbf{e}_c^{+}, \tau)}{\sum_{\mathbf{e}_{c,j}^{-}\in\mathbf{E}_c^{-}} f(\mathbf{e}_c, \mathbf{e}_{c,j}^{-}, \tau)}\right]$$

$$= -\frac{1}{C}\sum_{c=0}^{C-1} \mathop{\mathbb{E}}_{\mathbf{E}_c}\left[\log \frac{\exp(\langle \mathbf{e}_c, \mathbf{e}_c^{+}\rangle/\tau)}{\exp\left(\langle \mathbf{e}_c, \mathbf{e}_c^{+}\rangle/\tau\right) + \sum_{j=1}^{N-1} \exp\left(\langle \mathbf{e}_c, \mathbf{e}_{c,j}^{-}\rangle/\tau\right)}\right]$$



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Using Unreliable Pseudo-labels
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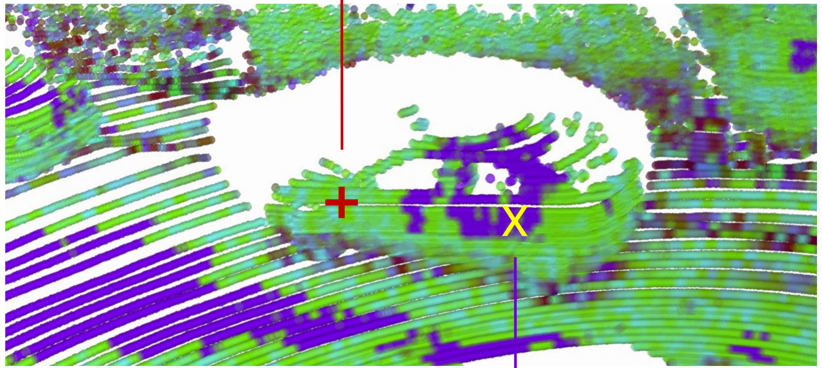
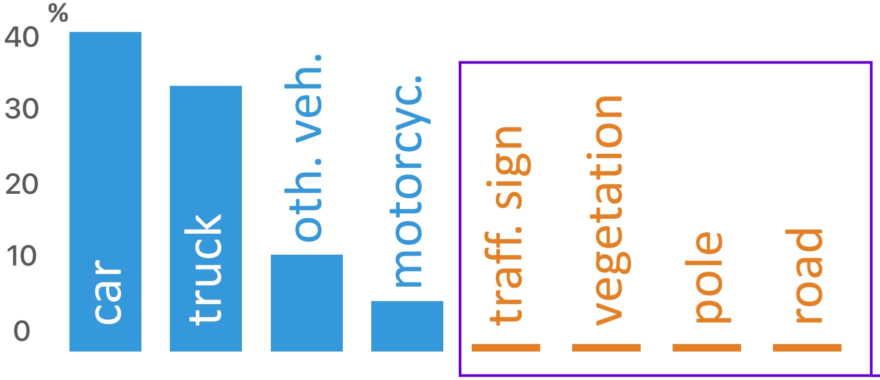


positive sample

$$\mathcal{L}_C = -\frac{1}{C}\sum_{c=0}^{C-1} \mathbb{E}_{\mathbf{E}_c}\left[\log \frac{f(\mathbf{e}_c, \boxed{\mathbf{e}_c^+}, \tau)}{\sum_{\mathbf{e}_{c,j}^- \in \mathbf{E}_c^-} f(\mathbf{e}_c, \mathbf{e}_{c,j}^-, \tau)}\right]$$

$$= -\frac{1}{C}\sum_{c=0}^{C-1} \mathbb{E}_{\mathbf{E}_c}\left[\log \frac{\exp(\langle \mathbf{e}_c, \mathbf{e}_c^+ \rangle / \tau)}{\exp\left(\langle \mathbf{e}_c, \mathbf{e}_c^+ \rangle / \tau\right) + \sum_{j=1}^{N-1} \exp\left(\langle \mathbf{e}_c, \boxed{\mathbf{e}_{c,j}^-} \rangle / \tau\right)}\right]$$



negatives sample

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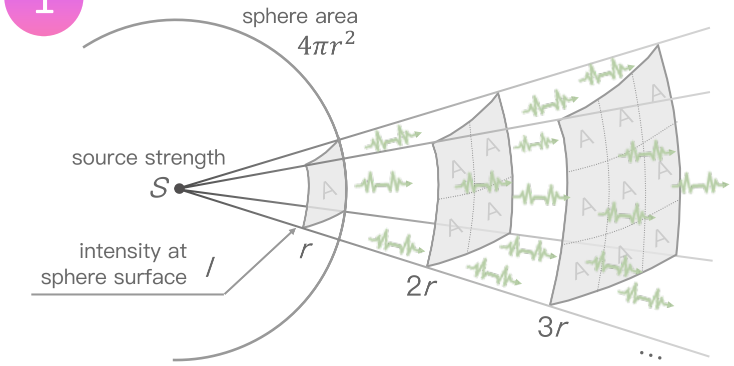
Using reflectivity-based Test Time Augmentation
to enhance performance of false or non-existent pseudo-labels

1



reflectivity

$$R = Ir^2 = \frac{S}{4\pi r^2} \cdot r^2 \propto S$$

Reflectivity is
a **distance-normalized intensity** feature

Using reflectivity-based Test Time Augmentation
to enhance performance of false or non-existent pseudo-labels

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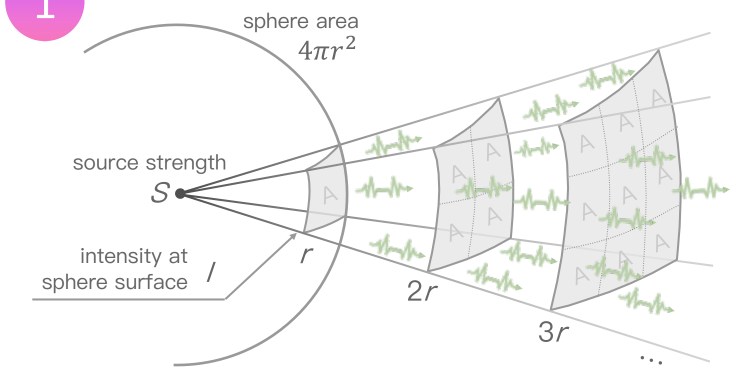

reflectivity

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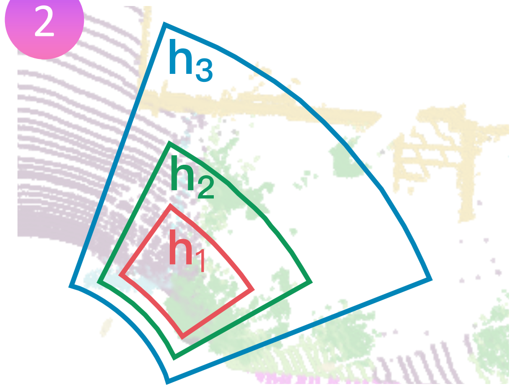
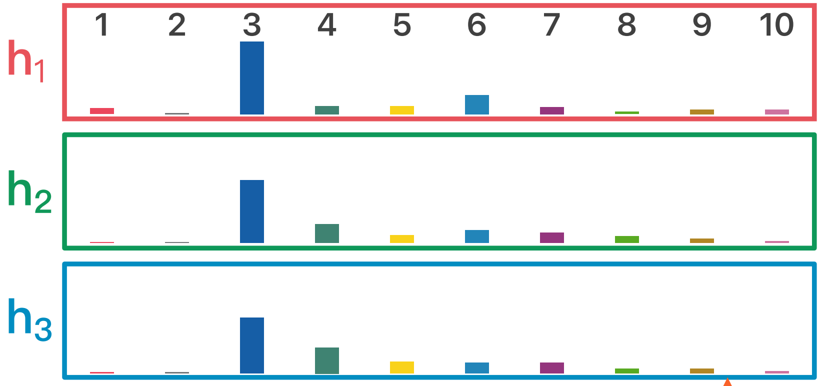
2





$$\mathbf{h}_i = \left\{h_i^{(k)} \mid k \in [1, N_b]\right\} \in \mathbb{R}^{N_b}, i \in [1, s],$$

$$h_i^{(k)} = \#\left\{\boxed{R_j} \in r_k, \forall j \mid p_j \in b_i\right\}$$

$$r_k = [(k-1)/N_b, k/N_b), k \in [1, N_b].$$

we apply various sizes of bins in cylindrical coordinates to analyze the intrinsic point distribution at varying resolutions (shown in h_1, h_2 and h_3).

Using reflectivity-based Test Time Augmentation

to enhance performance of false or non-existent pseudo-labels

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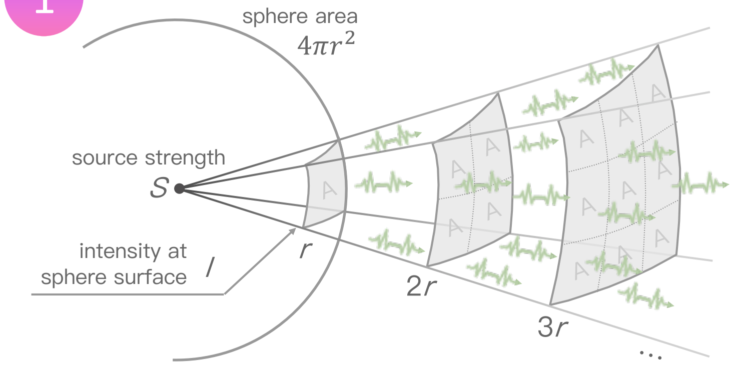

reflectivity

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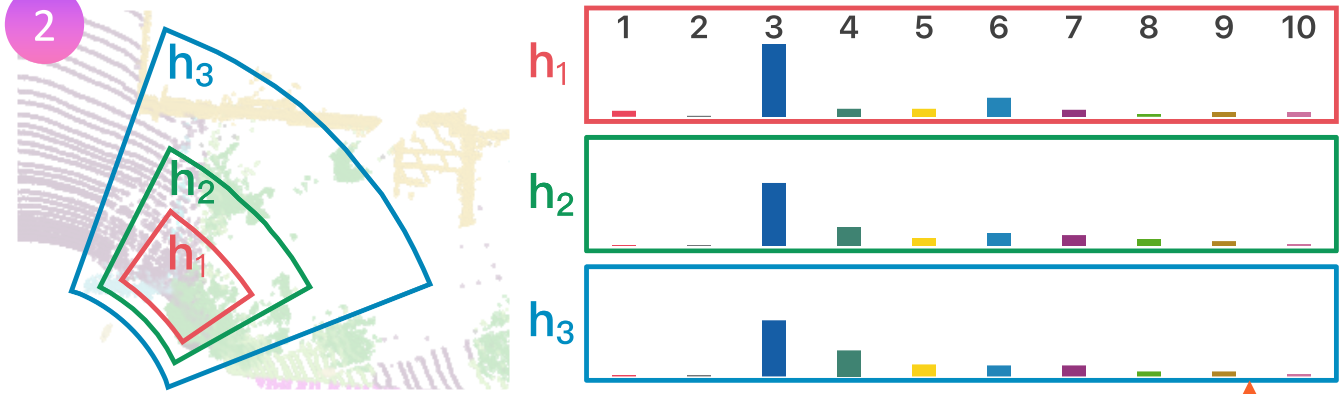

$$\mathbf{h}_i = \left\{ h_i^{(k)} \mid k \in [1, N_b] \right\} \in \mathbb{R}^{N_b}, i \in [1, s],$$

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$$r_k = [(k-1)/N_b, k/N_b), k \in [1, N_b].$$

3

normalize

augmentation

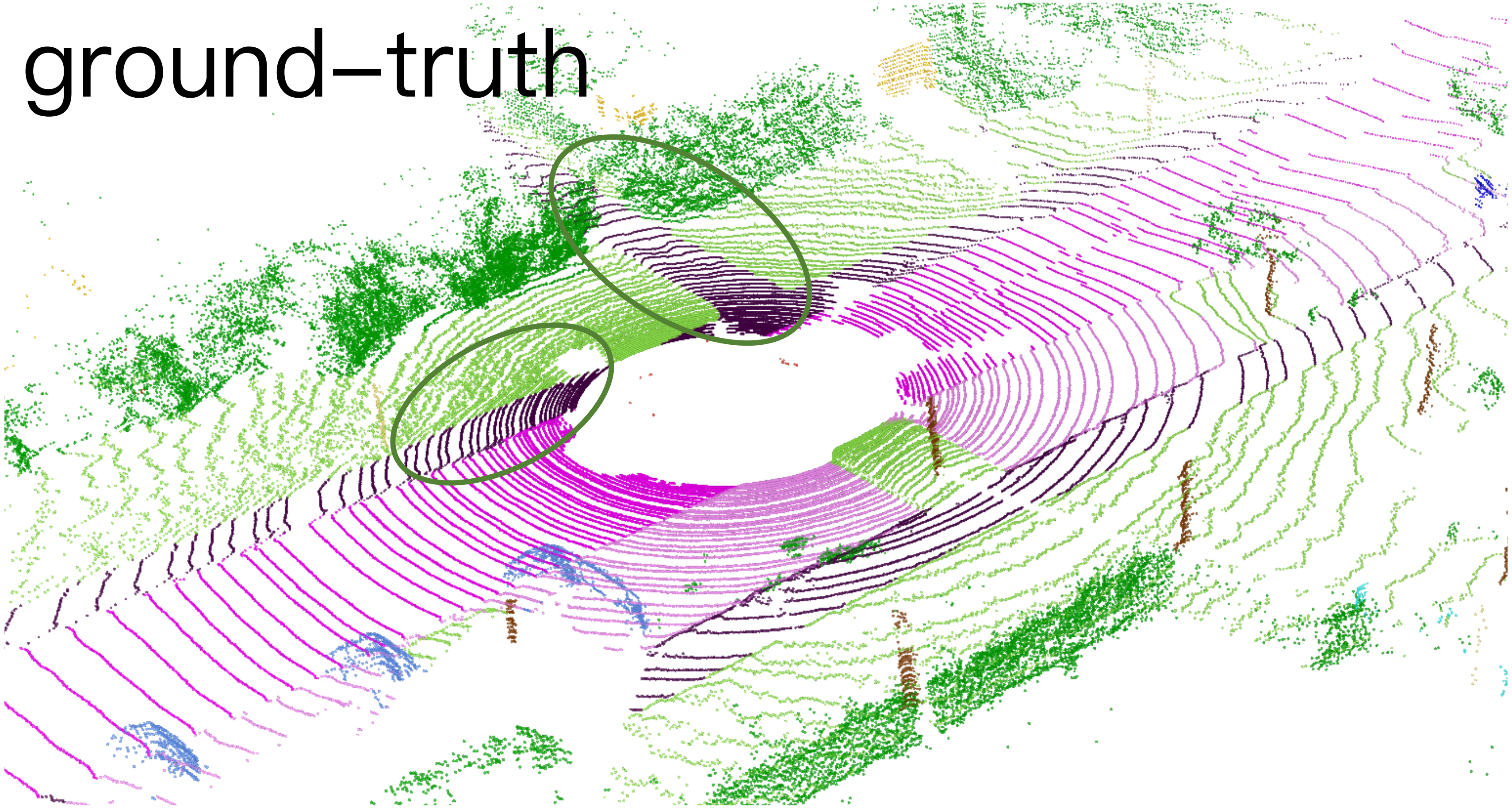
$$\begin{cases} R^{\circledast} = \{\mathbf{h}_i / \max(\mathbf{h}_i) \mid i \in [1, s]\} \in \mathbb{R}^{sN_b} \\ P^{\circledast} = \{p \mid (x, y, z, I, R^{\circledast}) \in \mathbb{R}^{sN_b+4}\} \end{cases}$$

we then normalize it and append to the point set

Qualitative results

Comparing {5%, 10%, 20%, 40%} labeled splits

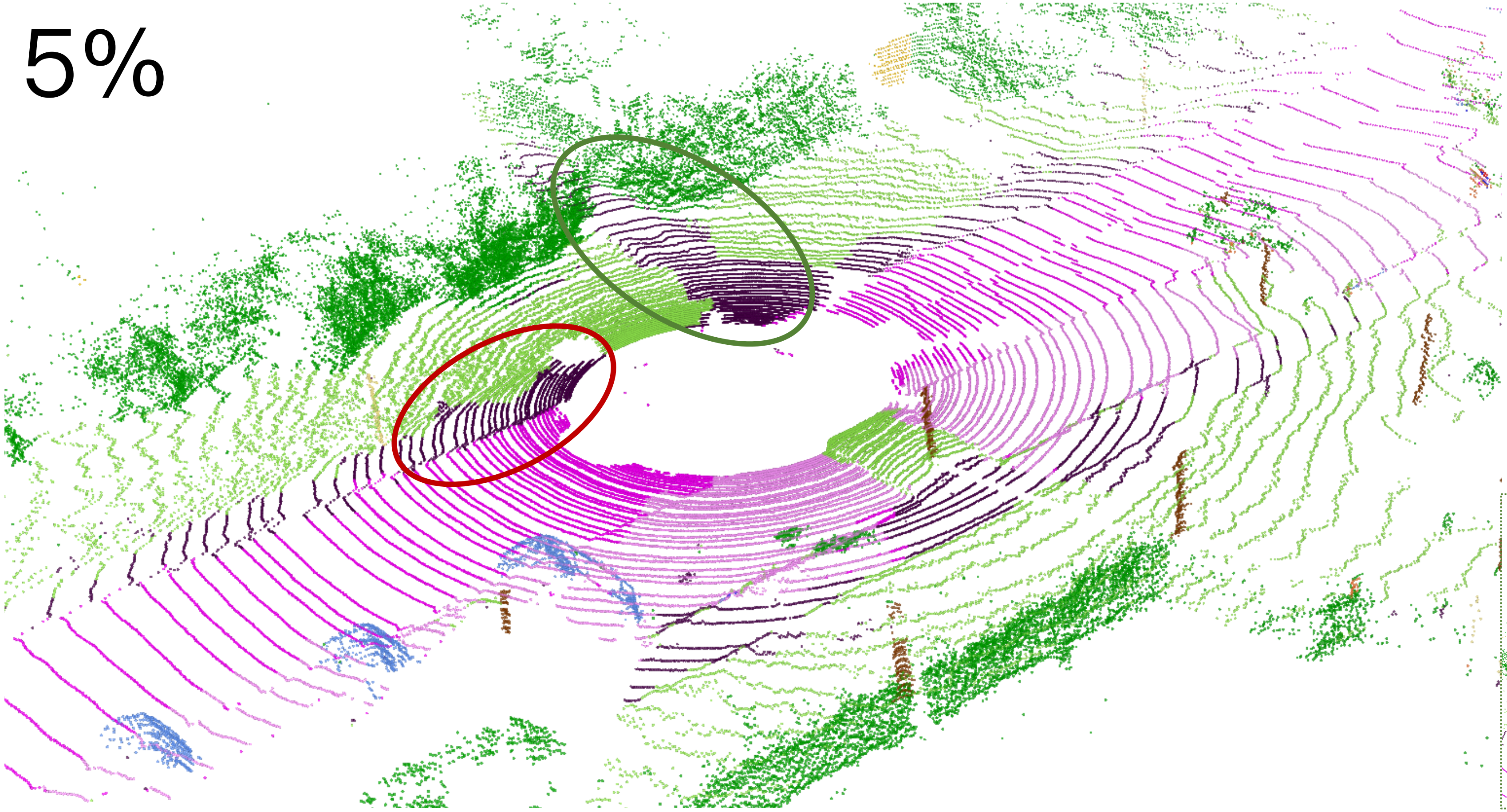
ground–truth

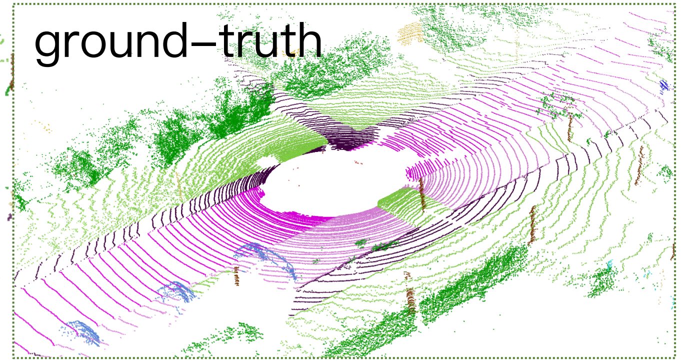


Qualitative results

Comparing {5%, 10%, 20%, 40%} labeled splits

5%





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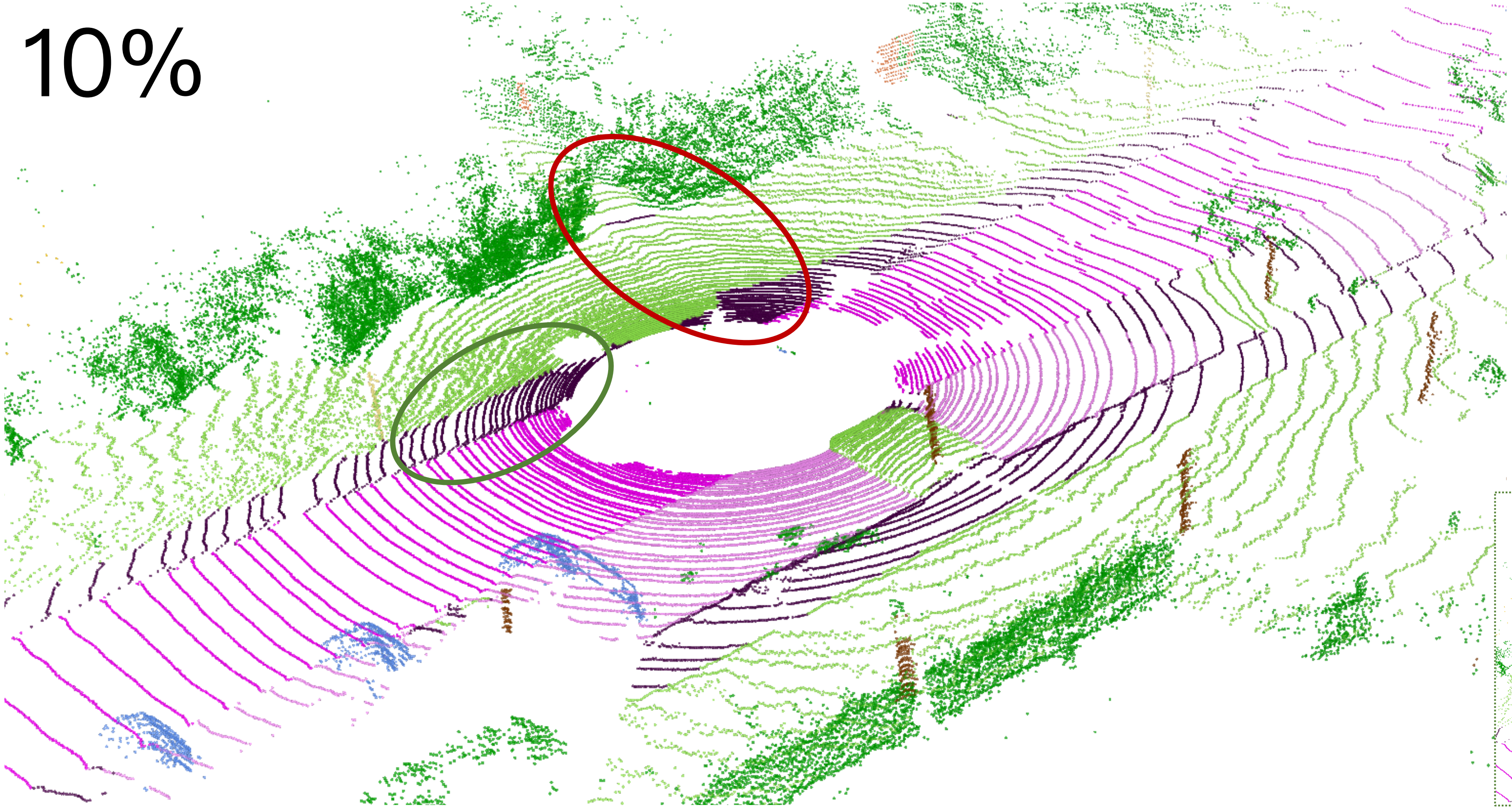
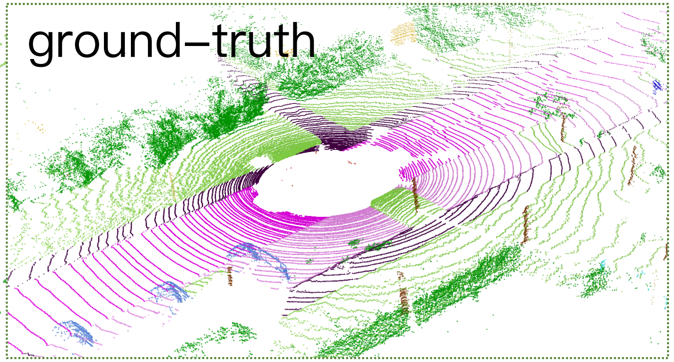
Qualitative results

Comparing {5%, 10%, 20%, 40%} labeled splits

10%





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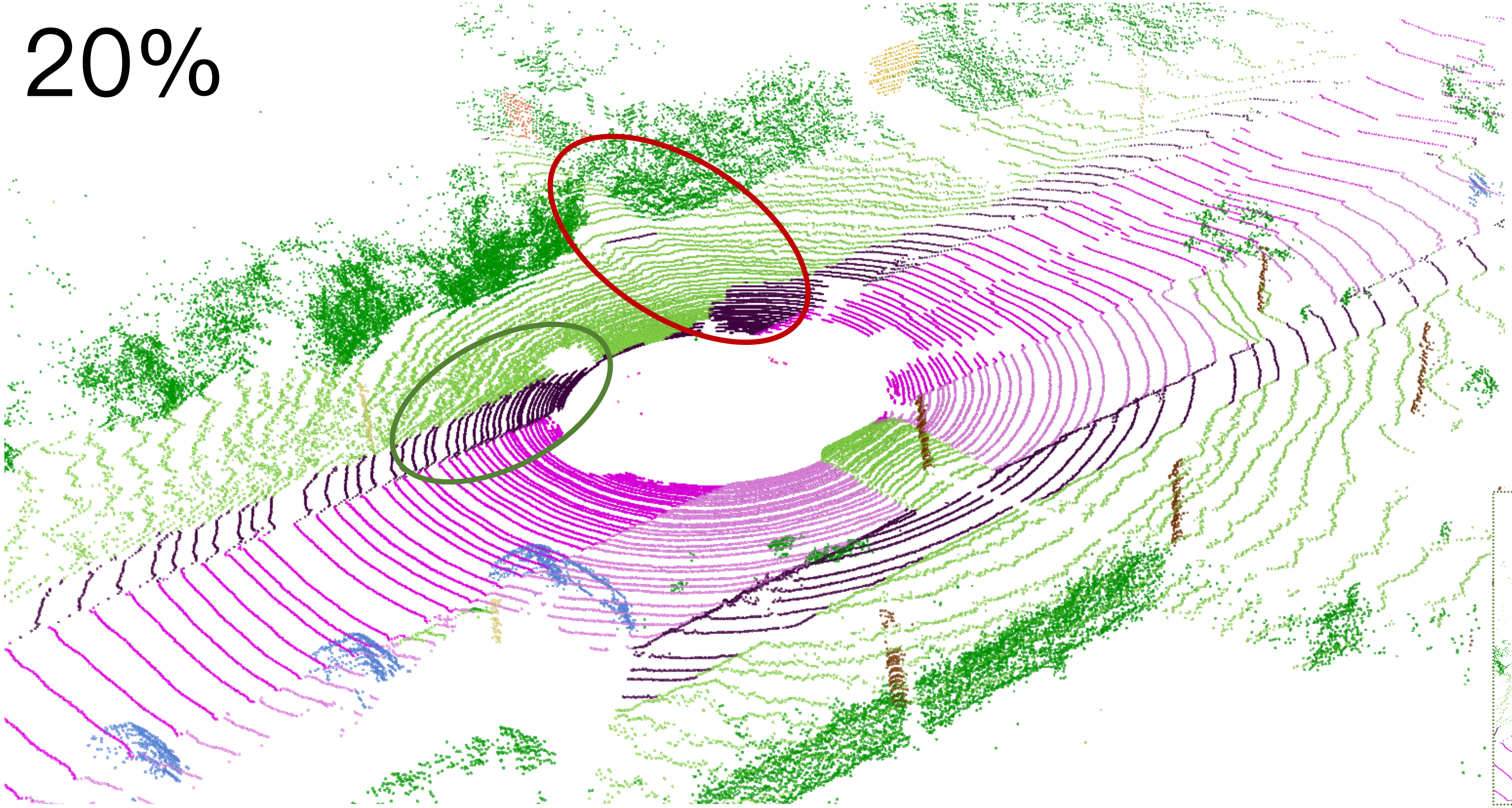
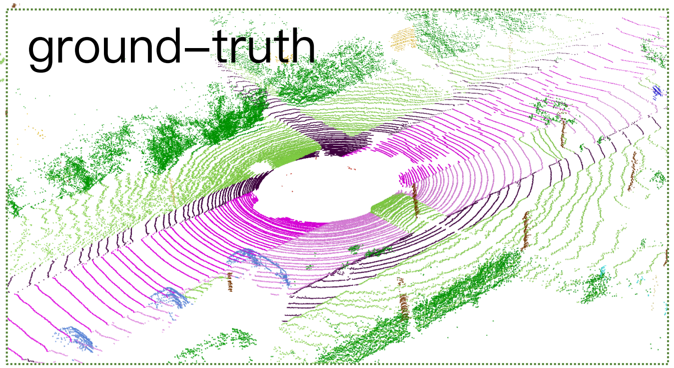
Qualitative results

Comparing {5%, 10%, 20%, 40%} labeled splits

20%





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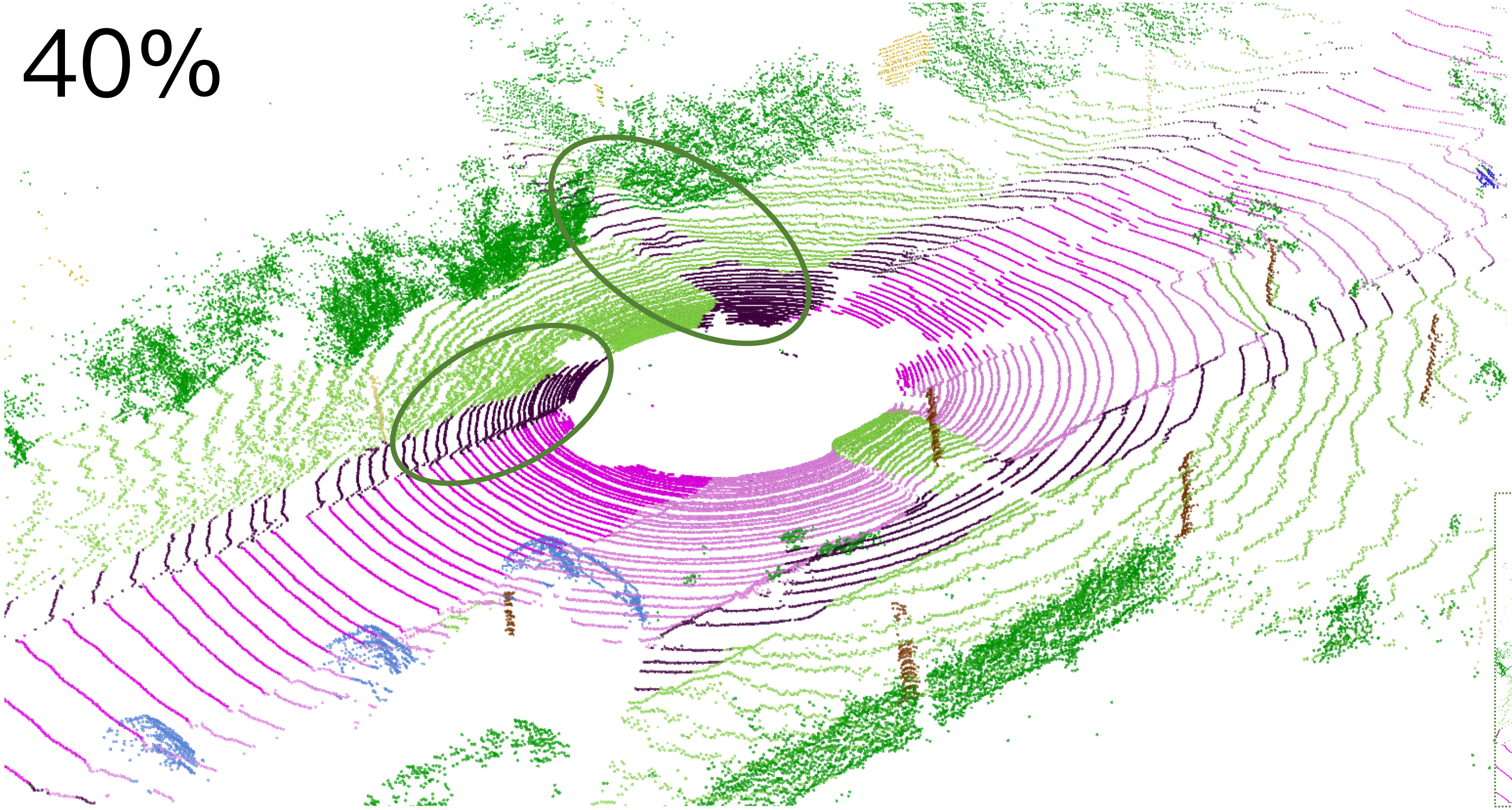
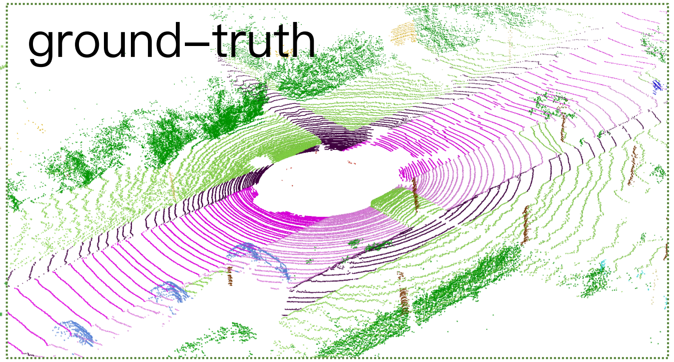
40%





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Qualitative results
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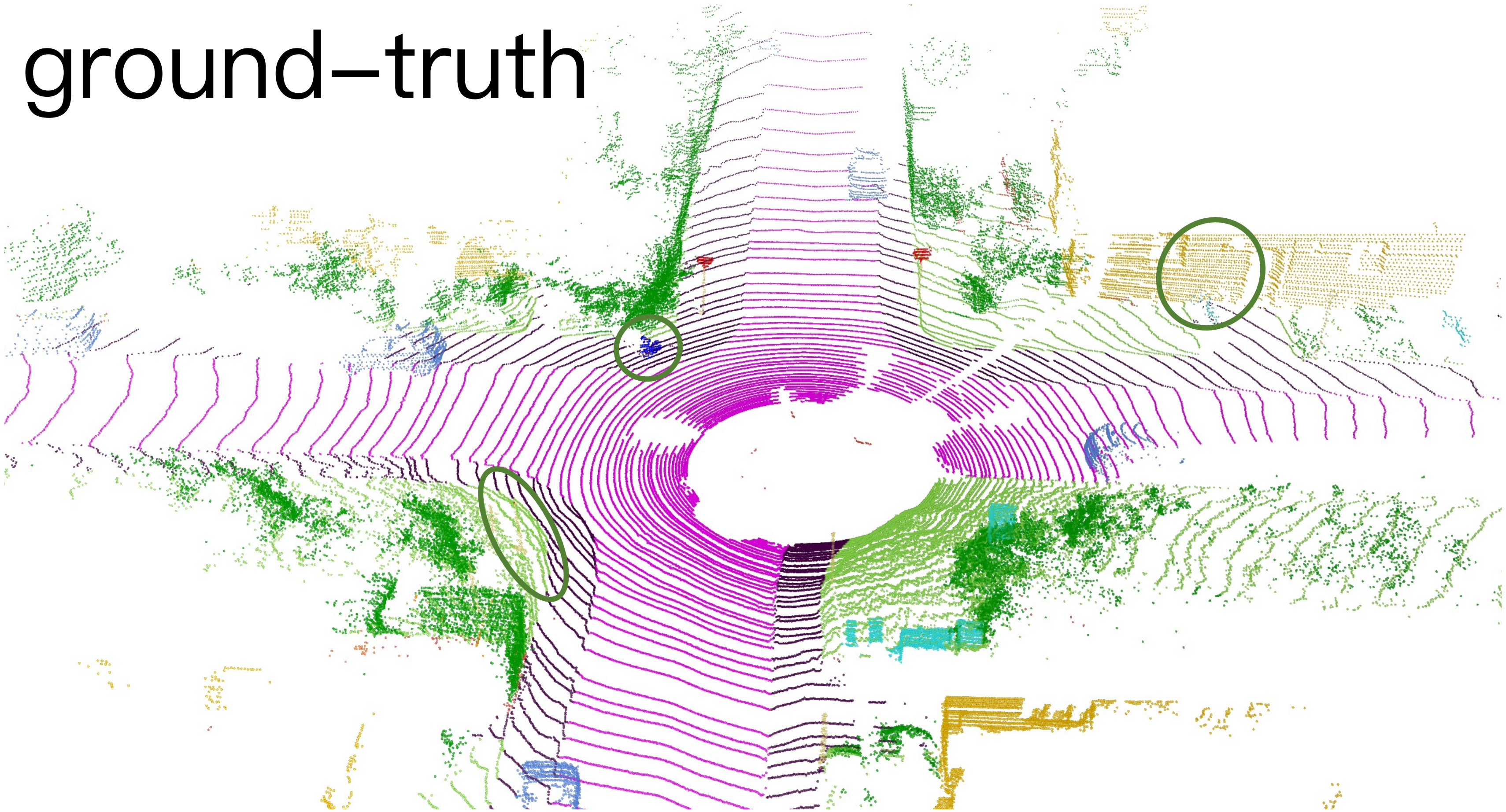
ground-truth



Qualitative results

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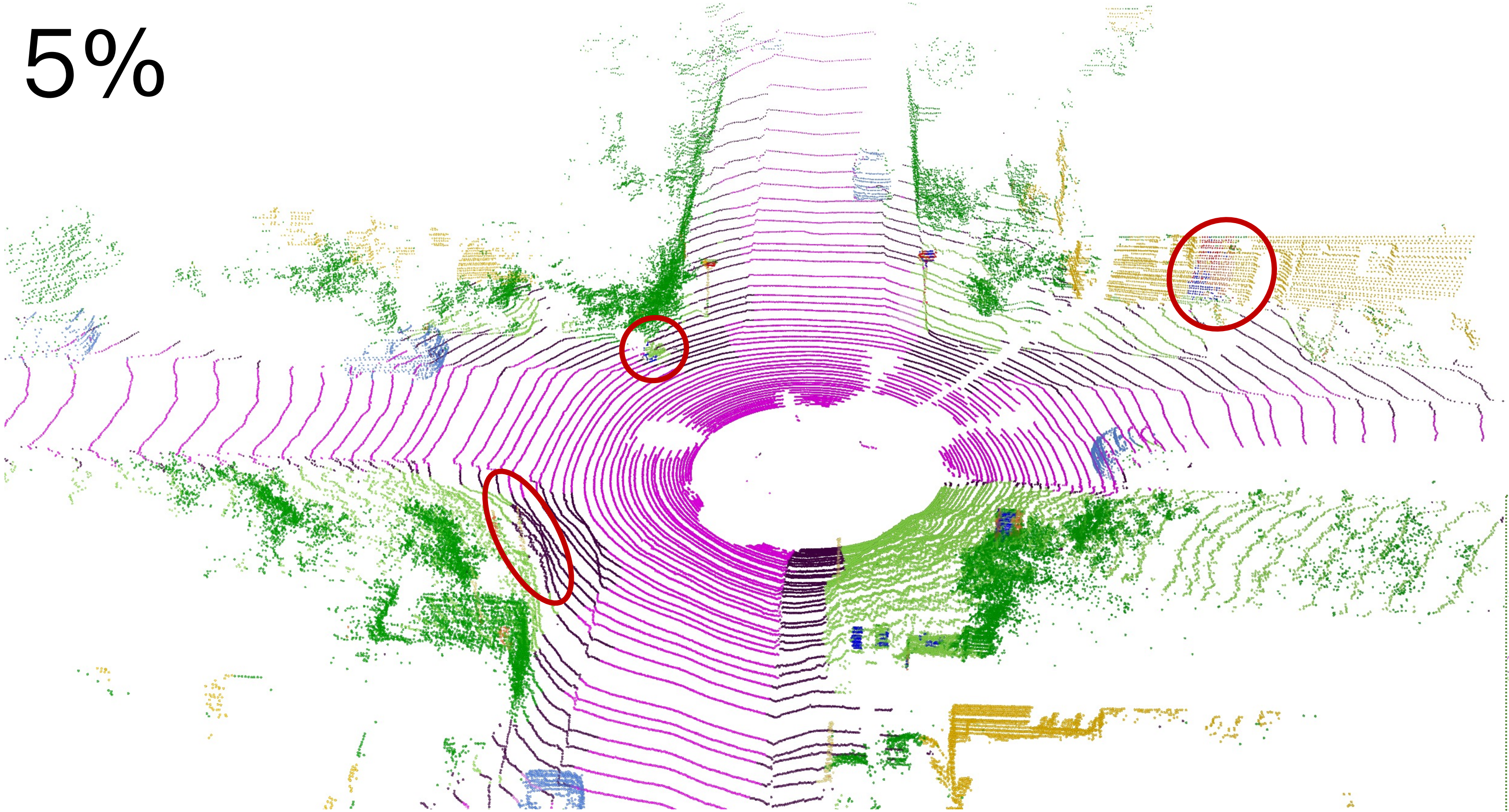
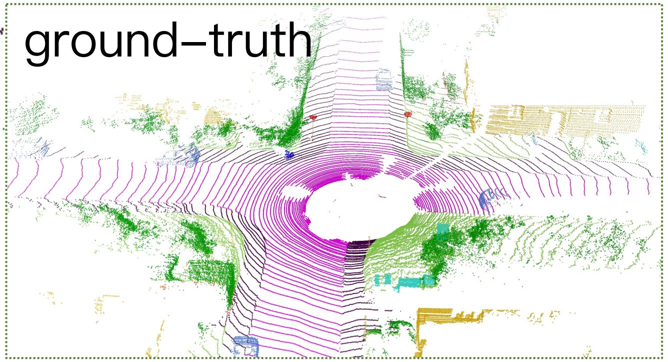
5%





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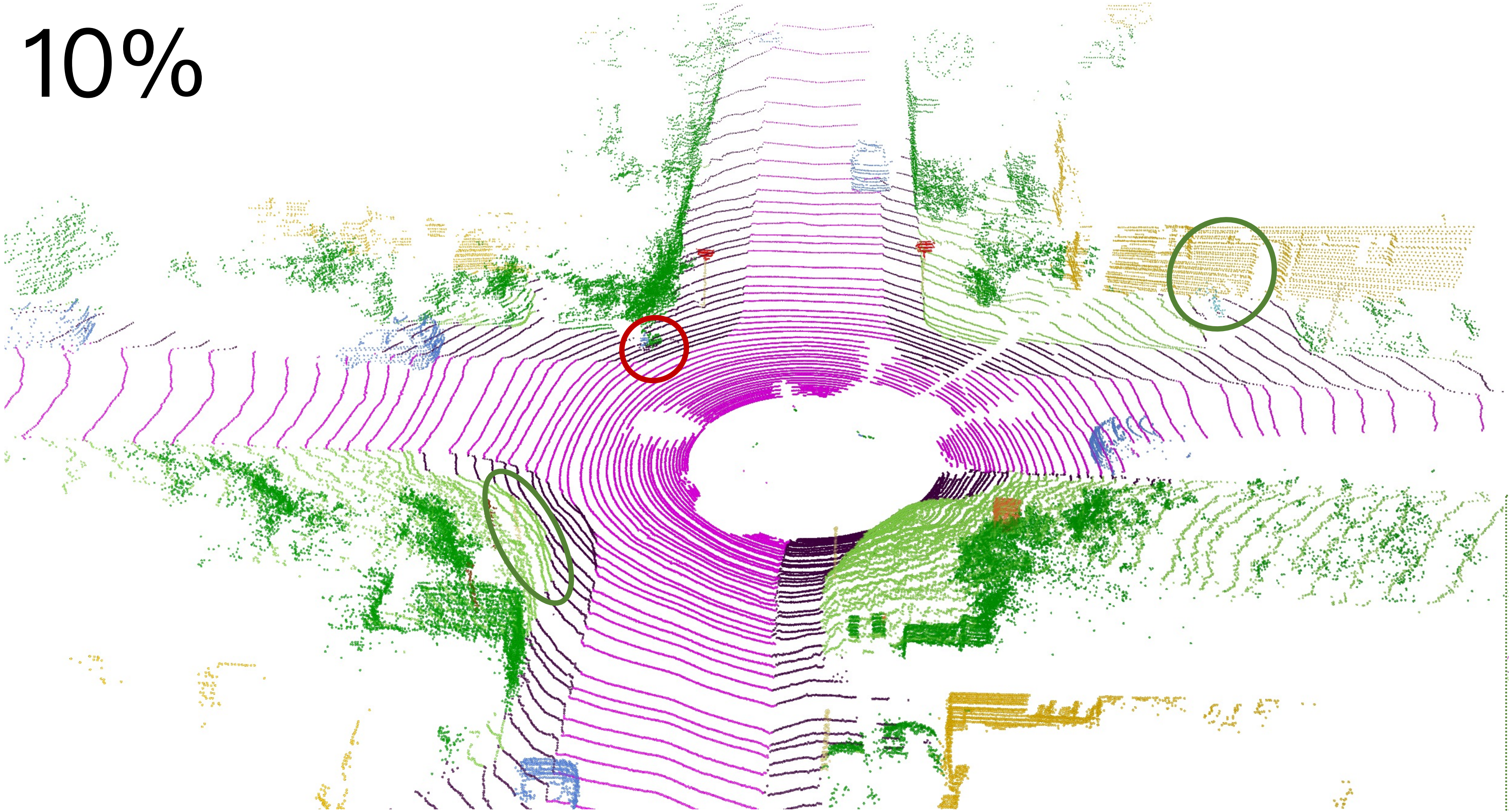

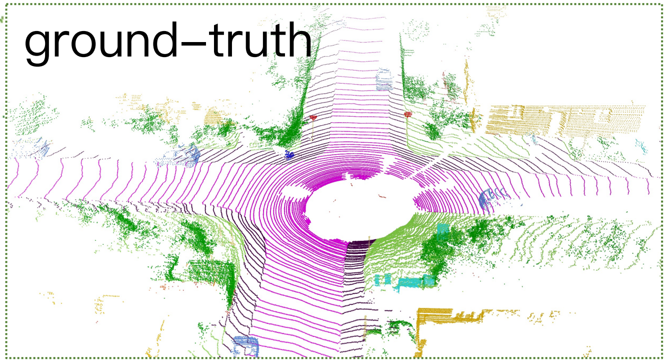

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Qualitative results

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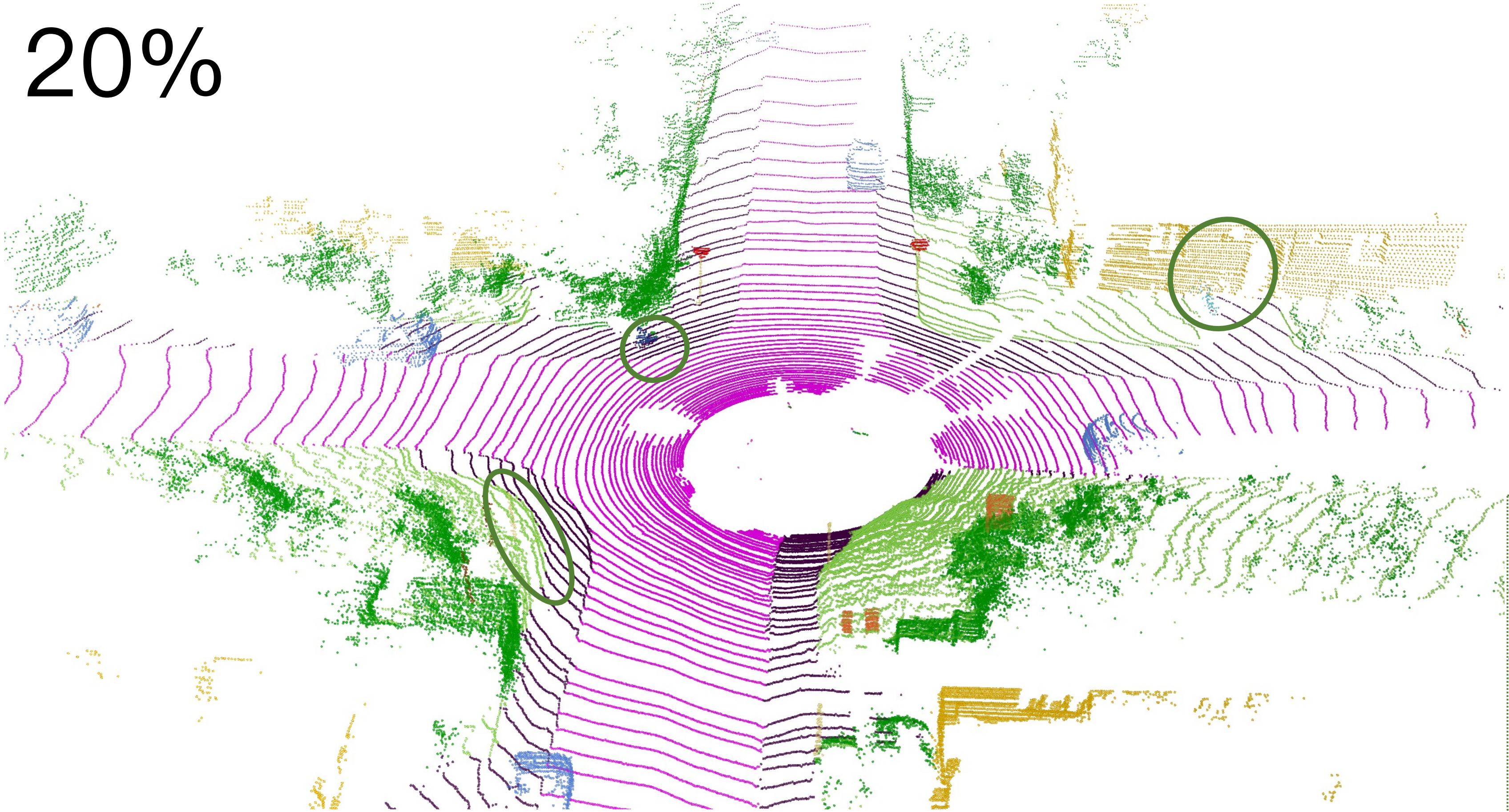

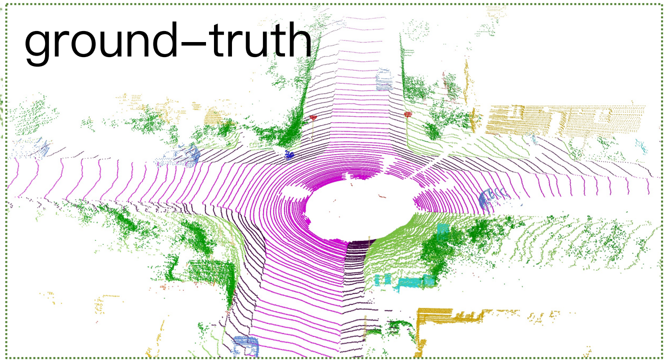

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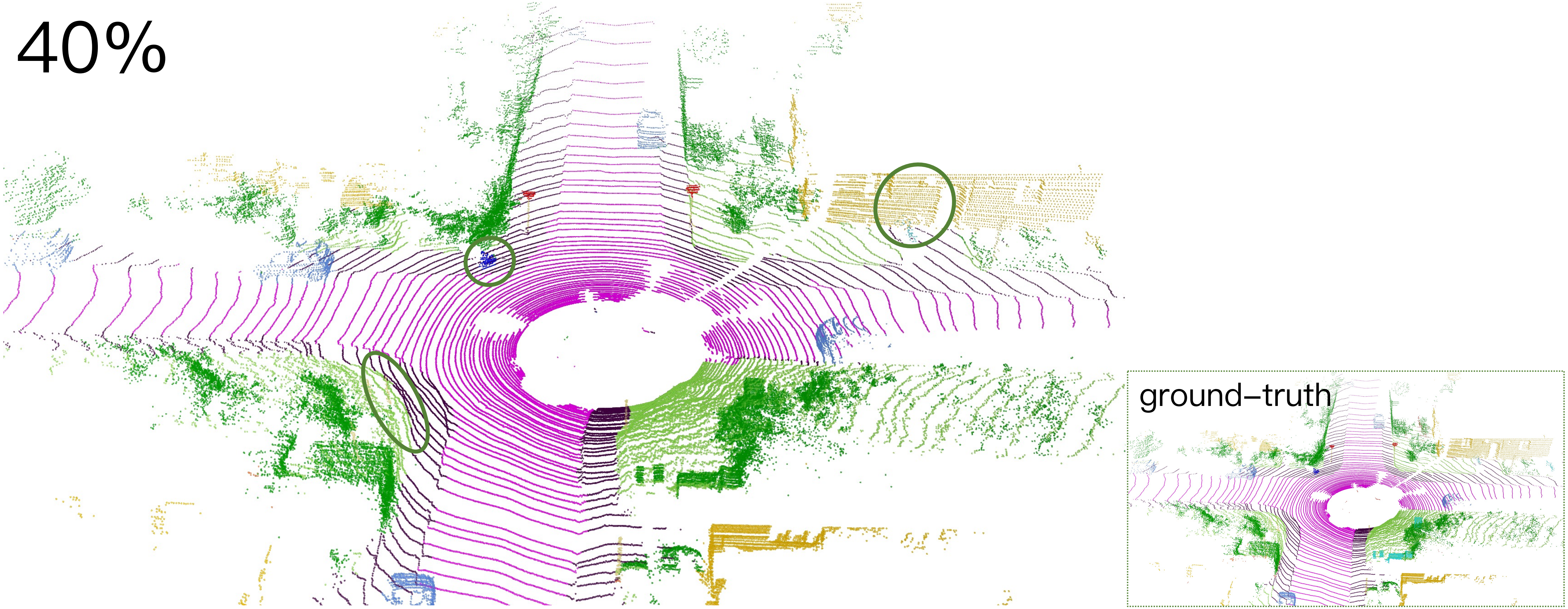

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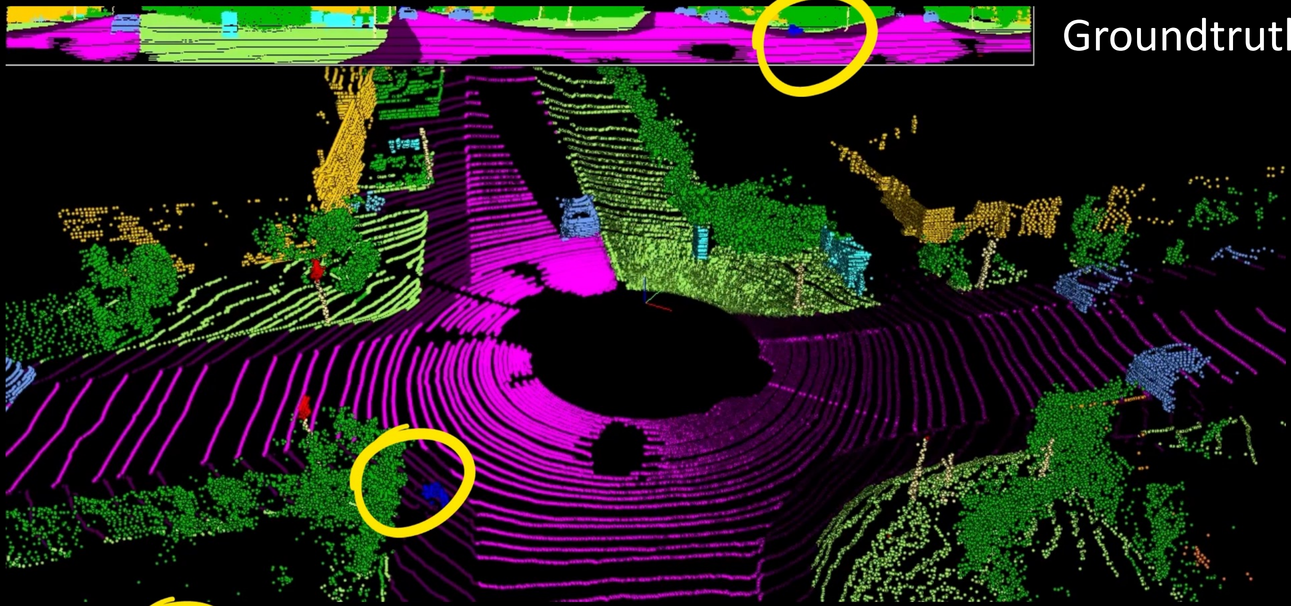
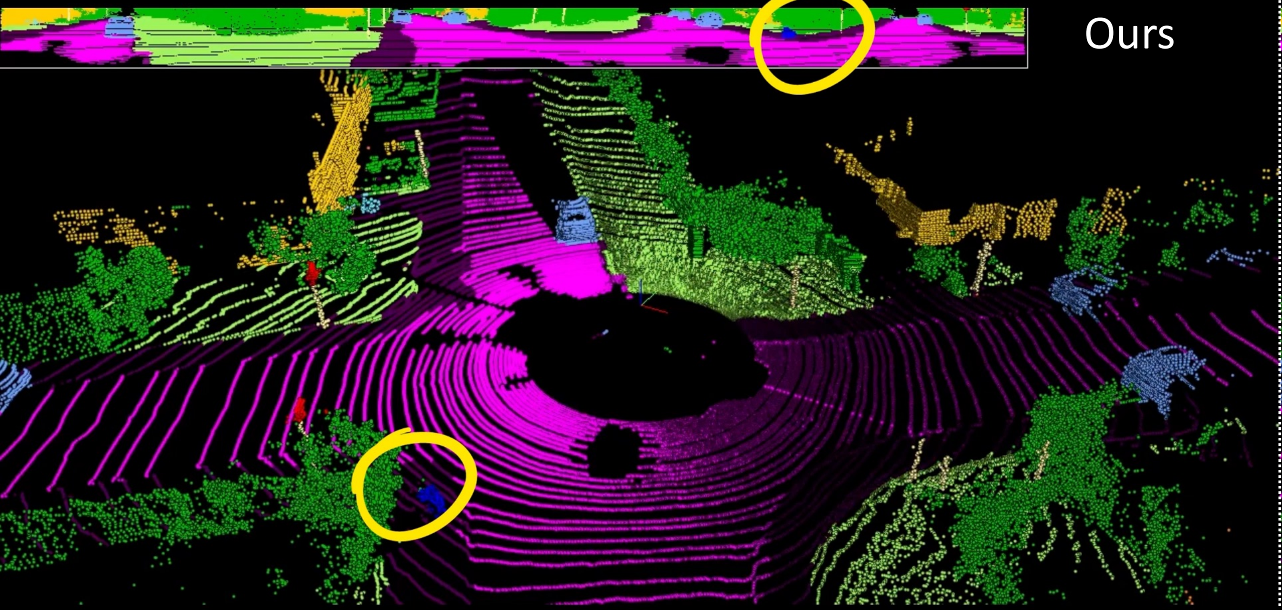
Qualitative results

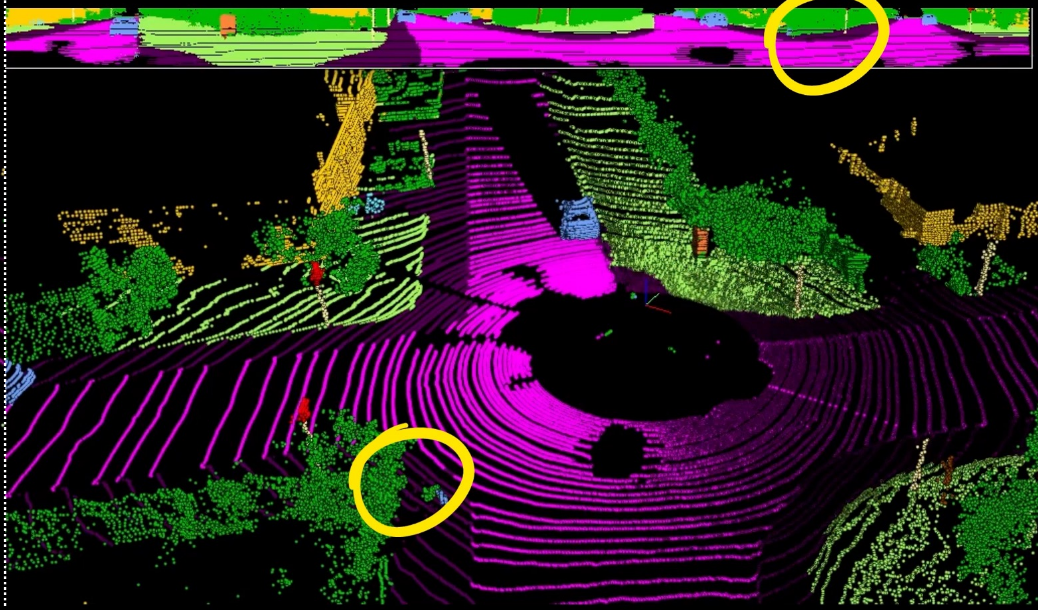
5%–Labeled Frames



Groundtruth



Ours



(Ozan et al)

Comparative mIoU for Semi-supervised Methods

Repr.	Samp.	Method		SemanticKITTI [7] 1%	5%	10%	20%	40%	50%	100%	ScribbleKITTI [46] 1%	5%	10%	20%	40%	50%	100%
Range	U	LaserMix [32]	(2022)	43.4	–	58.8	59.4	–	61.4	–	38.3	–	54.4	55.6	–	58.7	–
Voxel	U	Cylinder3D [63]	(CVPR'21)	–	45.4	56.1	57.8	58.7	–	67.8	–	39.2	48.0	52.1	53.8	–	56.3
	U	LaserMix [32]	(2022)	50.6	–	60.0	61.9	–	62.3	–	44.2	–	53.7	55.1	–	56.8	–
	P	Jiang *et al.* [29]	(ICCV'21)	–	41.8	49.9	58.8	59.9	–	65.8	–	–	–	–	–	–	–
	U	Unal *et al.* [46]	(CVPR'22)	–	49.9*	58.7*	59.1*	60.9	–	68.2*	–	46.9*	54.2*	56.5*	58.6*	–	61.3
	S	LiM3D+SDSC	(ours)	57.2	57.6	61.0	61.7	62.1	62.7	67.5	55.8	56.1	56.9	57.2	58.9	59.3	60.7
	S	LiM3D	(ours)	**58.4**	**59.5**	**62.2**	**63.1**	**63.3**	**63.6**	**69.5**	**57.0**	**58.1**	**61.0**	**61.2**	**62.0**	**62.1**	**62.4**

Comparative mIoU for Semi-supervised Methods

Repr.	Samp.	Method		SemanticKITTI [7] 1%	5%	10%	20%	40%	50%	100%	ScribbleKITTI [46] 1%	5%	10%	20%	40%	50%	100%
Range	U	LaserMix [32]	(2022)	43.4	–	58.8	59.4	–	61.4	–	38.3	–	54.4	55.6	–	58.7	–
Voxel	U	Cylinder3D [63]	(CVPR'21)	–	45.4	56.1	57.8	58.7	–	67.8	–	39.2	48.0	52.1	53.8	–	56.3
	U	LaserMix [32]	(2022)	50.6	–	60.0	61.9	–	62.3	–	44.2	–	53.7	55.1	–	56.8	–
	P	Jiang *et al.* [29]	(ICCV'21)	–	41.8	49.9	58.8	59.9	–	65.8	–	–	–	–	–	–	–
	U	Unal *et al.* [46]	(CVPR'22)	–	49.9*	58.7*	59.1*	60.9	–	68.2*	–	46.9*	54.2*	56.5*	58.6*	–	61.3
	S	LiM3D+SDSC	(ours)	57.2	57.6	61.0	61.7	62.1	62.7	67.5	55.8	56.1	56.9	57.2	58.9	59.3	60.7
	S	LiM3D	(ours)	**58.4**	**59.5**	**62.2**	**63.1**	**63.3**	**63.6**	**69.5**	**57.0**	**58.1**	**61.0**	**61.2**	**62.0**	**62.1**	**62.4**

Component-wise Ablation (Ours)

	UP	RF	RT	ST	SD	Training mIoU (%) 5%	10%	20%	40%	Validation mIoU (%) 5%	10%	20%	40%	#Params (M)
						82.8	87.5	87.8	88.2	54.8	58.1	59.3	60.8	49.6
	✓					–	–	–	–	55.9	58.8	59.9	61.2	49.6
	✓	✓				83.6	88.3	88.7	89.1	56.8	59.6	60.5	61.4	49.6
	✓		✓			–	–	–	–	57.5	59.8	61.2	62.6	49.6
	✓	✓	✓			–	–	–	–	58.7	61.3	62.4	62.8	49.6
LiM3D	✓	✓	✓	✓		**85.2**	**89.1**	**89.5**	**89.7**	**59.5**	**62.2**	**63.1**	**63.3**	49.6
LiM3D+SDSC	✓	✓	✓	✓	✓	83.8	88.6	89.0	89.2	57.6	61.0	61.7	62.1	**21.5**

UP Unreliable Pseudo labeling

RF Reflectivity Feature

RT Reflec-TTA

ST ST-RFD

SD SDSC module

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3D Point Cloud Semantic Segmentation, CVPR 2023, Li, Shum, Breckon

Component-wise Ablation (Ours)

	UP	RF	RT	ST	SD	Training mIoU (%) 5%	10%	20%	40%	Validation mIoU (%) 5%	10%	20%	40%	#Params (M)
						82.8	87.5	87.8	88.2	54.8	58.1	59.3	60.8	49.6
	✓					–	–	–	–	55.9	58.8	59.9	61.2	49.6
	✓	✓				83.6	88.3	88.7	89.1	56.8	59.6	60.5	61.4	49.6
	✓		✓			–	–	–	–	57.5	59.8	61.2	62.6	49.6
	✓	✓	✓			–	–	–	–	58.7	61.3	62.4	62.8	49.6
LiM3D	✓	✓	✓	✓		**85.2**	**89.1**	**89.5**	**89.7**	**59.5**	**62.2**	**63.1**	**63.3**	49.6
LiM3D+SDSC	✓	✓	✓	✓	✓	83.8	88.6	89.0	89.2	57.6	61.0	61.7	62.1	**21.5**

UP Unreliable Pseudo labeling

RF Reflectivity Feature

RT Reflec-TTA

ST ST-RFD

SD SDSC module

The Computation Cost and mIoU

Under 5%-labeled Training Results

Method	# Parameters	# Mult-Adds	SeK [7]	ScK [45]
Cylider3D [61]	56.3	476.9M	45.4	39.2
Ozan *et al.* [45]	49.6	420.2M	49.9	46.9
2DPASS [56]	26.5	217.4M	51.7	45.1
MinkowskiNet [13]	21.7	114.0G	42.4	35.8
SPVNAS [43]	**12.5**	73.8G	45.1	38.9
LiM3D+SDSC (ours)	21.5	**182.0M**	57.6	54.7
LiM3D (ours)	49.6	420.2M	**59.5**	**58.1**

The Computation Cost and mIoU

Under 5%-labeled Training Results

Method	# Parameters	# Mult-Adds	SeK [7]	ScK [45]
Cylider3D [61]	56.3	476.9M	45.4	39.2
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LiM3D+SDSC (ours)	21.5	**182.0M**	57.6	54.7
LiM3D (ours)	49.6	420.2M	**59.5**	**58.1**

2.3x model size reduction

641x fewer multiply-adds

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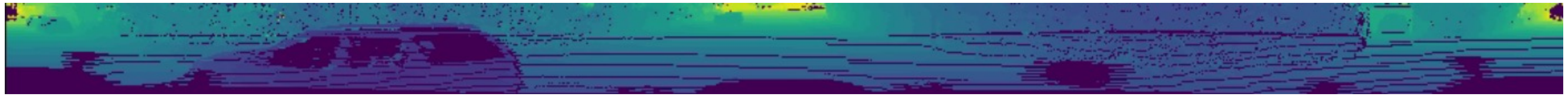
Effects of ST–RFD Sampling

Sampling	SemanticKITTI [7] 5%	SemanticKITTI [7] 10%	SemanticKITTI [7] 20%	SemanticKITTI [7] 40%	ScribbleKITTI [45] 5%	ScribbleKITTI [45] 10%	ScribbleKITTI [45] 20%	ScribbleKITTI [45] 40%
Random	58.5	61.6	62.6	62.7	57.1	60.3	60.5	60.9
Uniform	58.7	61.3	62.4	62.8	56.9	60.6	60.3	61.0
ours ST-RFD-R	59.1	**62.4**	62.9	**63.4**	58.0	60.7	**61.2**	61.8
ours ST-RFD	**59.5**	62.2	**63.1**	63.3	**58.1**	**61.0**	**61.2**	**62.0**

ST–RFD–R
Range Image:



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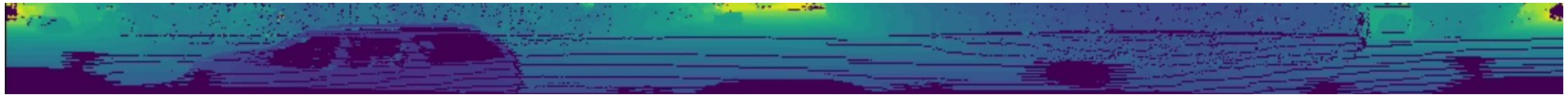
Effects of ST-RFD Sampling

	Sampling	SemanticKITTI [7]				ScribbleKITTI [45]			
		5%	10%	20%	40%	5%	10%	20%	40%
	Random	58.5	61.6	62.6	62.7	57.1	60.3	60.5	60.9
	Uniform	58.7	61.3	62.4	62.8	56.9	60.6	60.3	61.0
ours	ST-RFD-R	59.1	**62.4**	62.9	**63.4**	58.0	60.7	**61.2**	61.8
ours	ST-RFD	**59.5**	62.2	**63.1**	63.3	**58.1**	**61.0**	**61.2**	**62.0**

ST–RFD–R
Range Image:



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Effects of Differing Reliability Using Pseudo Voxels

Ratio	Unreliable		Reliable		Random	
	mIoU	SS/FF	mIoU	SS/FF	mIoU	SS/FF
5%	**59.5**	**85.6**	57.2	82.3	56.4	81.2
10%	**62.2**	**89.5**	60.8	87.5	59.7	85.9
20%	**63.1**	**90.8**	61.4	88.3	60.5	87.1
40%	**63.3**	**91.1**	62.8	90.4	61.3	88.2

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	mIoU	SS/FF	mIoU	SS/FF	mIoU	SS/FF
5%	**59.5**	**85.6**	57.2	82.3	56.4	81.2
10%	**62.2**	**89.5**	60.8	87.5	59.7	85.9
20%	**63.1**	**90.8**	61.4	88.3	60.5	87.1
40%	**63.3**	**91.1**	62.8	90.4	61.3	88.2

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Reflectivity (Reflec–TTA) vs. Intensity (Intensity–based TTA)

TTA	SemanticKITTI [7]				ScribbleKITTI [45]			
	5%	10%	20%	40%	5%	10%	20%	40%
Intensity	56.2	59.1	59.8	60.9	55.7	57.5	57.9	59.2
Reflectivity	**59.5**	**62.2**	**63.1**	**63.3**	**58.1**	**61.0**	**61.2**	**62.0**

Reflectivity (Reflec–TTA) vs. Intensity (Intensity–based TTA)

TTA	SemanticKITTI [7]				ScribbleKITTI [45]			
	5%	10%	20%	40%	5%	10%	20%	40%
Intensity	56.2	59.1	59.8	60.9	55.7	57.5	57.9	59.2
Reflectivity	**59.5**	**62.2**	**63.1**	**63.3**	**58.1**	**61.0**	**61.2**	**62.0**

Durham University

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