SQN: Weakly-Supervised Semantic Segmentation of Large-Scale 3D Point Clouds

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Motivation:

1D signal: KB 2D image: MB 3D point clouds: GB

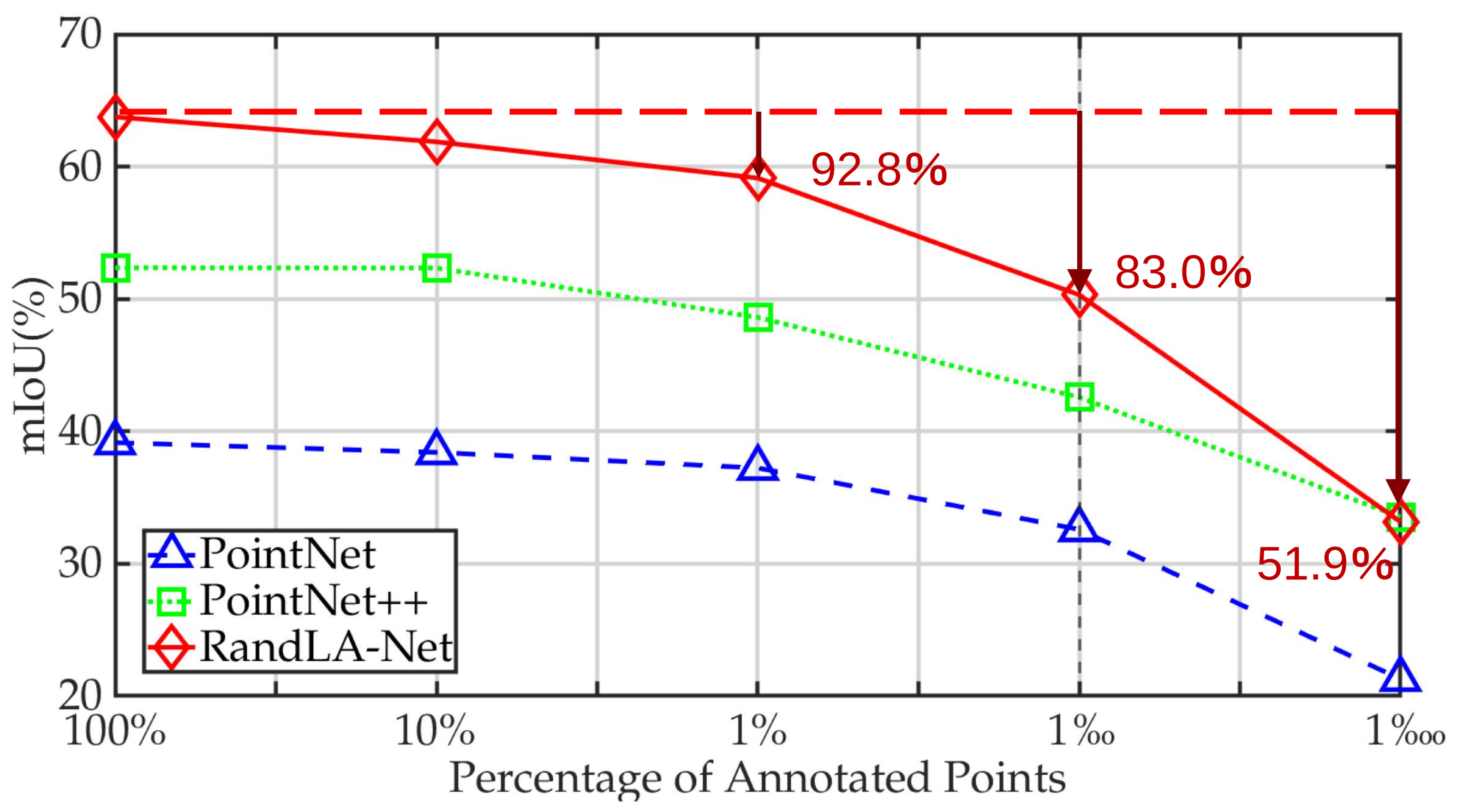
Velodyne HDL-64E
Up to 2.2M point/s

RealSense L515 LiDAR
Up to 23M point/s

ZED 2 Stereo camera
Up to 110M point/s

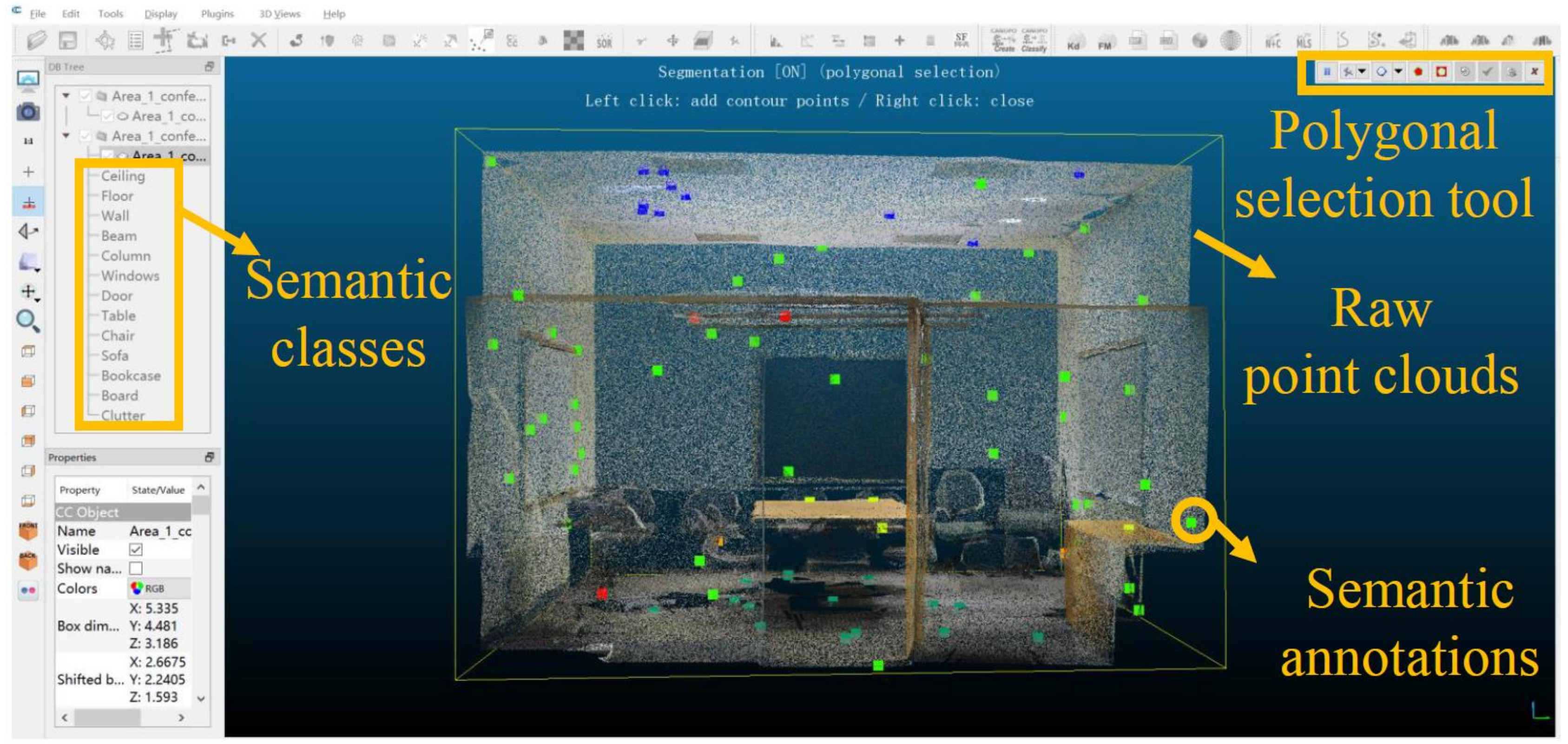
Reducing Labeling Efforts!

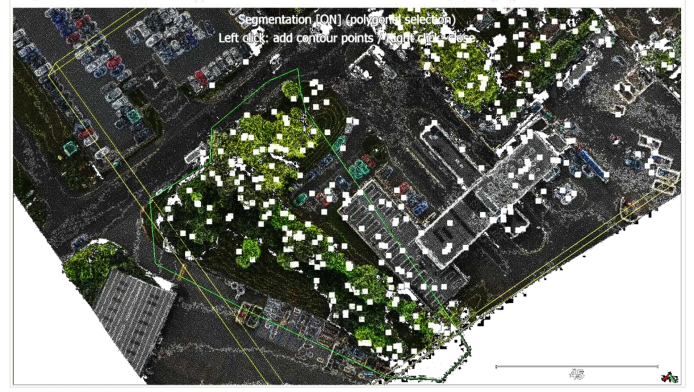
Exploring weak supervision:



- Reducing the annotated points from 100% to 1‱
- Dense annotations are unnecessary & redundant
- Indicate the critical point (1‰) for weak supervision

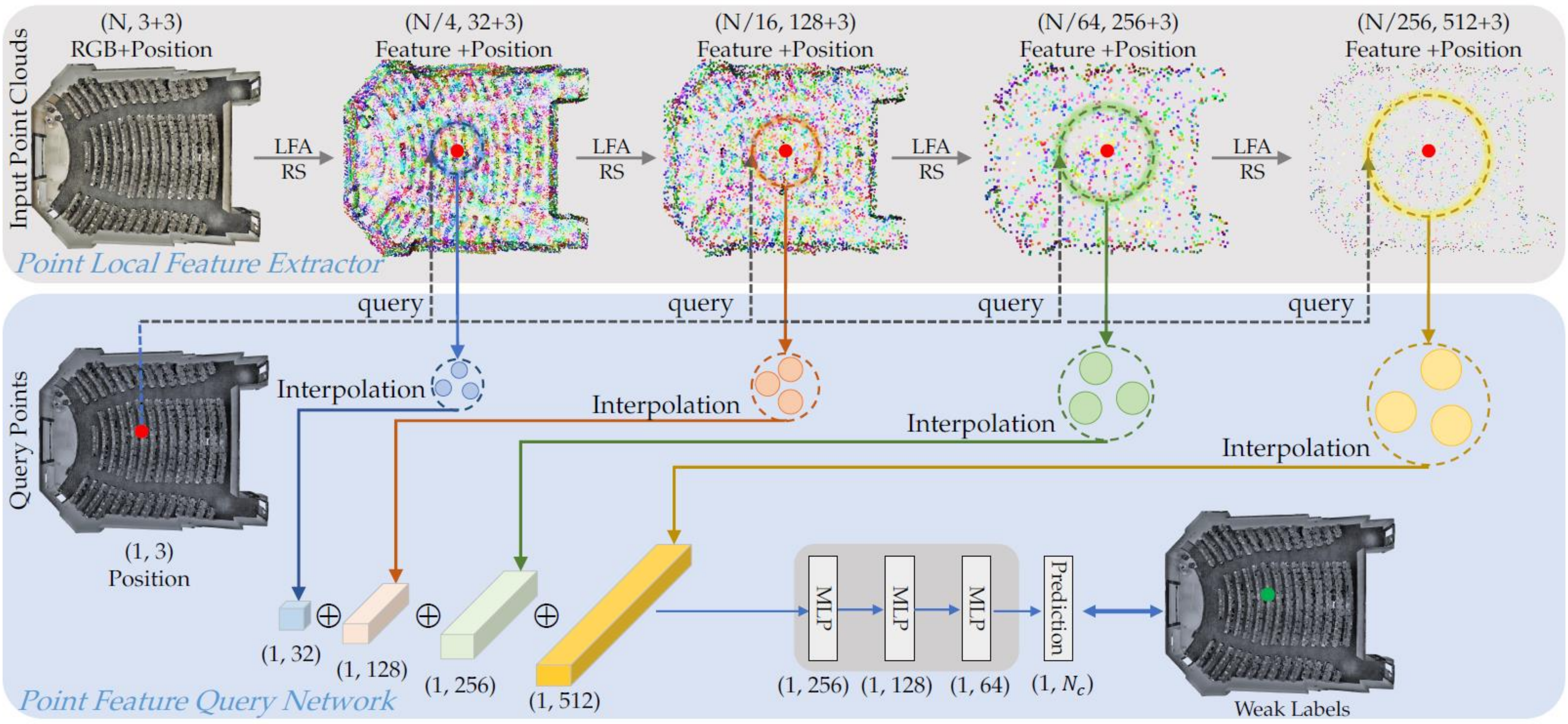
Random Sparse Annotation Tool





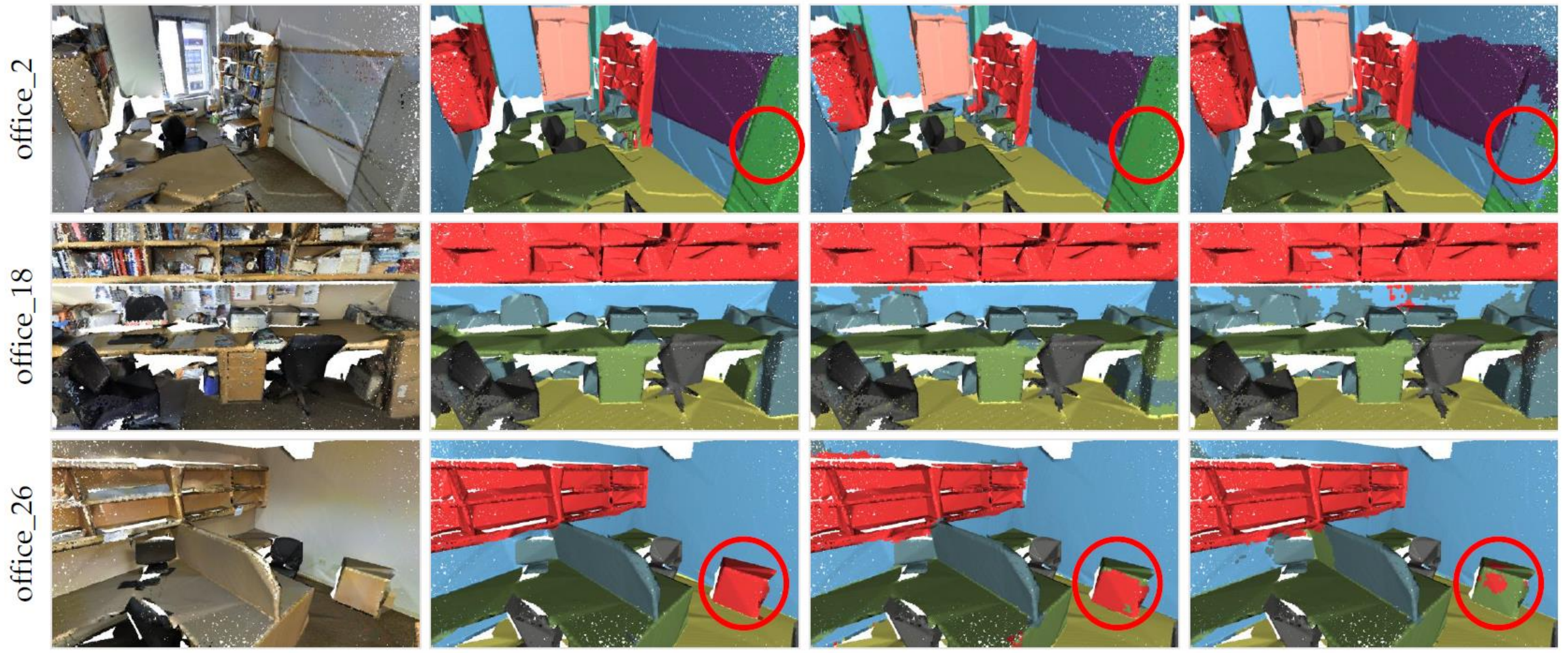
- ✓ Offers great error tolerance to avoid annotating boundary areas
- ✓ Save up to 98% annotation cost for large-scale 3D point clouds

SQN Architecture:



- ✓ Leverage the strong local semantic homogeneity of point neighbors
- ✓ Allow training signals shared and back-propagated to relevant points
- ✓ Query point can be arbitrary points in 3D space

Qualitative Comparison:



Input Point Clouds Ground Truth Ours with 0.1% labels RandLA with 100% labels

floor wall door chair board bookcase table clutter sofa

Quantitative Comparison:

Settings	Methods	DALES [57] OA(%)	DALES [57] mIoU(%)	SensatUrban [21] OA(%)	SensatUrban [21] mAcc (%)	SensatUrban [21] mIoU(%)	Toronto3D [48] OA(%)	Toronto3D [48] mIoU(%)	SemanticKITTI [3] mIoU(%)
Full supervision	PointNet [38]	-	-	80.8	30.3	23.7	-	-	14.6
	PointNet++ [39]	95.7	68.3	84.3	40.0	32.9	84.9	41.8	20.1
	PointCNN [30]	97.2	58.4	-	-	-	-	-	-
	TangentConv [52]	-	-	77.0	43.7	33.3	-	-	40.9
	ShellNet [82]	96.4	57.4	-	-	-	-	-	-
	DGCNN [65]	-	-	-	-	-	94.2	61.8	-
	SPG [28]	95.5	60.6	85.3	44.4	37.3	-	-	17.4
	SparseConv [15]	-	-	88.7	63.3	42.7	-	-	-
	KPConv [55]	97.8	81.1	93.2	63.8	57.6	95.4	69.1	58.1
	ConvPoint [5]	97.2	67.4	-	-	-	-	-	-
	RandLA-Net [22]	97.1	80.0	89.8	69.6	52.7	92.9	77.7	53.9
Weak supervision	**Ours (0.1%)**	97.0	72.0	**91.0**	**70.9**	**54.0**	96.7	**77.7**	50.8
	Ours (0.01%)	95.9	60.4	85.6	49.4	37.2	94.2	68.2	39.1

Highlights

- ➢ We propose a new weakly supervised method that leverages a point neighbourhood query to fully utilize the sparse training signals.
- ➢ We observe that existing fully-supervised methods degrade slowly until 1% point annotations, showing that dense labelling is redundant and unnecessary.
- ➢ Random sparse annotation tool & annotation cost for reference

Code

Demo