

## Appendix

### A. Initial Superpoint Generation

In this section, we describe the detailed steps to generate initial superpoints on three datasets. For the two indoor datasets ScanNet and S3DIS, we adhere to the steps outlined in GrowSP [91], utilizing Voxel Cloud Connectivity Segmentation (VCCS) [50] and Region Growing [1] while maintaining the same parameters used in GrowSP. Figure 7 illustrates examples of ScanNet and S3DIS datasets.

For the outdoor dataset nuScenes, we adapt from GrowSP by employing RANSAC and Euclidean Clustering to generate superpoints. Initially, RANSAC is applied to identify a large planar surface, designated as the ground. Subsequently, the remaining 3D points are partitioned into clusters using Euclidean Clustering. In RANSAC, points within 0.2 meters of the fitted plane are classified as plane points and aggregated into a single superpoint. For the remaining points, those with an Euclidean distance of less than 0.2 meters are grouped into a single superpoint. Qualitative examples are shown in Figure 7.

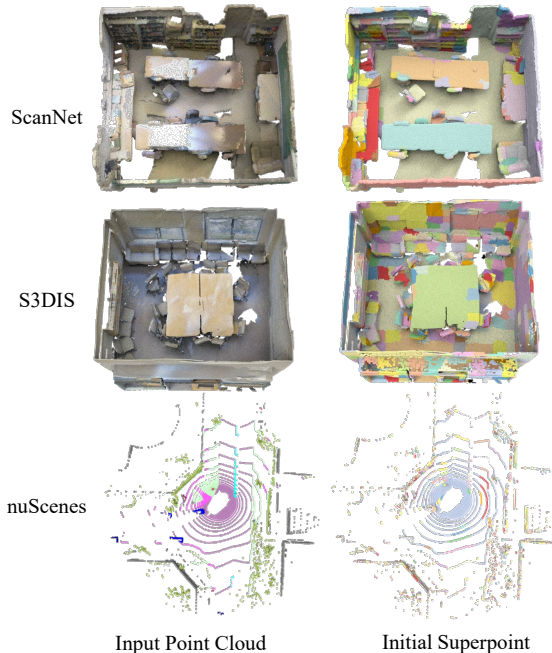


Figure 7. Examples of initial superpoints.

### B. Additional Ablation Study

We conduct additional ablation studies to examine the impact of the semantic category number, distillation process, and segmentation component.

**(1) K-means on distilled features:** The distilled point features appear to be aware of semantics, thus we apply K-

Table 9. The mIoU scores of all ablated networks on the validation set of ScanNet based on our full LogoSP.

	mIoU(%)
(1) K-means on distilled features	18.2
(2) GrowSP with distillation	27.4
(3) $C = 10$	32.8
(4) $C = 15$	33.7
<b>(5) <math>C = 20</math></b>	<b>35.8</b>
(6) $C = 30$	34.7
(7) $C = 50$	32.9
<b>(8) The full framework (LogoSP)</b>	<b>35.8</b>

means on the distilled point features of ScanNet val set to cluster into 20 classes.

**(2) GrowSP with distillation:** To demonstrate the effectiveness of our global grouping strategy, we apply the well-trained distillation model to GrowSP and complete its subsequent training.

**(3) ~ (7):** In our experiments,  $C$  is set as 20 for ScanNet, but it can be freely chosen in training. To verify it, we adopt different values:  $\{10, 15, 20, 30, 50\}$ .

**Analysis:** From Table 9, we can see that: 1) A simple K-means is not sufficient to discover semantics from the distilled features, so the top-down semantic pseudo-label generation is necessary. 2) GrowSP can be also benefited from the distillation, but the gap between 27.4 and 35.8 indicates our global patterns in the frequency domain is more aligned with semantics. 3)  $C$  can be flexible, though too large or too small is not preferred.

### C. Impacts of Initial Superpoint Purity

The initial superpoints are crucial in our LogoSP. If the initial superpoints extensively cover points from different categories, it can lead to a decline in segmentation performance. To measure this, we define the purity of superpoints as follows: we use ground truth semantic labels to assign a unique label to each superpoint through a voting process. Consequently, all points receive a label generated from this voting. We then compute the mIoU between these voting labels and the ground truth to assess the purity of initial superpoints.

The initial superpoints are constructed by VCCS and Region Growing, the smaller resolutions of VCCS yield purer superpoints, and the higher the mIoU against GT, the purer. As shown in Table 10, we obtain robust results even at rather low purity on ScanNet val.

Another interesting observation is the trend of purity over the growing process. From Table 11, when  $M^i$  is reduced to  $M^0 \rightarrow 80/70/60/50/40$ , the superpoint purity (mIoU) drops  $76.8 \rightarrow 74.6/73.8/72.6/71.4/69.4$  as expected.

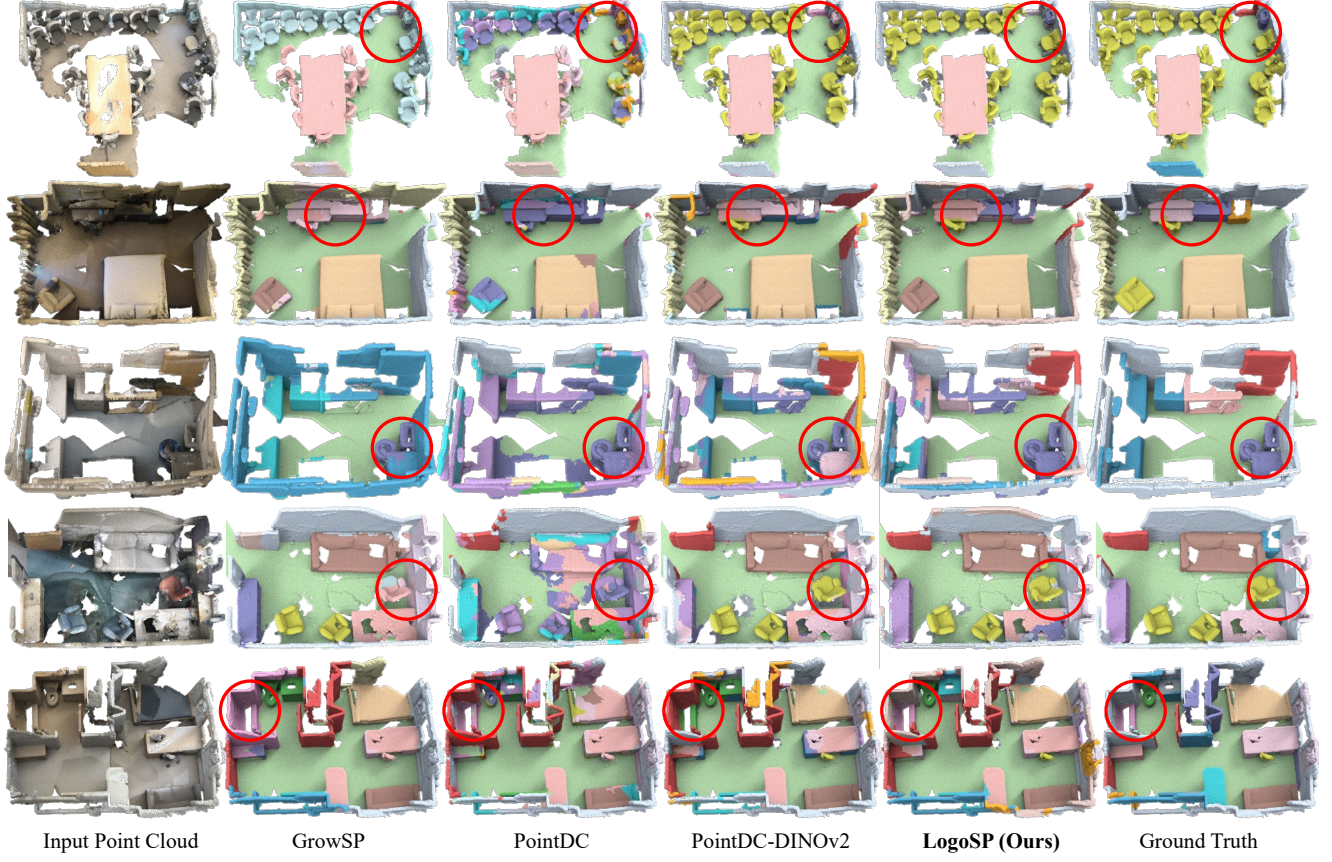


Figure 8. Qualitative results of our method and baselines on the validation set of ScanNet dataset.

Table 10. Impact of initial superpoint purity on ScanNet val.

resolution (m)	0.1	0.3	0.5	0.7	0.9
Initial superpoint purity (mIoU)	83.9	81.7	76.8	71.7	66.1
Segmentation results (mIoU)	34.7	35.9	35.8	34.8	31.3

Table 11. Trend of purity over growing.

Number of superpoints ( $M^i$ )	$M^0$	80	70	60	50	40
Superpoints purity (mIoU)	76.8	74.6	73.8	72.6	71.4	69.4

## D. Evaluation on ScanNet

When evaluating on the ScanNet dataset, we utilize SparseConv as our backbone which is the same as GrowSP[91]. A voxel size of 5cm is employed to convert point clouds into voxel grids for both distillation and segmentation tasks. For distillation, we select the ViT-S/14 version of DINOv2 as the 2D feature extractor for our method and the baseline PointDC-DINOv2. The distillation process is conducted over 200 epochs with a batch size of 8, a learning rate of  $1e-3$ , and the Adam optimizer. The Poly scheduler is used to progressively decrease the learning rate. For training our segmentation network, we employ cross-entropy as the loss

function, maintaining a batch size of 8 and a constant learning rate of  $1e-4$  with the Adam optimizer over 200 epochs. The superpoints growing parameters  $M^1$  and  $M^T$  are set as 80 and 40. The extraction of global patterns and generation of pseudo labels are conducted every 10 epochs.

The per-category results on both validation and hidden test sets are detailed in Tables 12&13. Our method significantly outperforms all unsupervised baselines, particularly on minor classes such as *books*, *curtain*, and *toilet*. Figure 8 provides further comparisons with baselines.

## E. Evaluation on S3DIS

Prior to training, we downsample input point clouds by applying grid sampling with a 0.01m grid size. Distillation and segmentation are then performed on the downsampled data. Same as ScanNet, we also choose ViT-S/14 of DINOv2 model in the configuration. For distillation, we choose the learning rate of  $1e-3$ , the Adam optimizer, and the Poly scheduler. When training the segmentation network, we employ a learning rate of  $1e-4$  over 200 epochs, with the parameter  $S'$  for grouping global patterns being 10.  $M^1$  and  $M^T$  are also set as 80 and 40 respectively.

Table 12. Per-category quantitative results on the validation split of ScanNet dataset.

	OA(%)	mAcc(%)	mIoU(%)	wall.	floor.	cab.	bed.	chair.	sofa.	table	door.	wind.	books.	pic.	counter.	desk.	curtain.	fridge.	shower.	toilet.	sink.	bathub.	otherf.
K-means	10.1	10.0	3.4	9.0	9.8	3.2	2.9	5.5	3.3	4.3	3.5	5.5	3.3	<b>2.6</b>	0.8	2.9	4.3	0.8	0.7	0.3	0.9	4.0	
IIC [27]	27.7	6.1	2.9	25.3	20.5	0.6	0.3	3.7	0.4	1.3	1.3	1.1	1.9	0.2	0.1	0.6	0.3	0.4	0	0	0	0.2	0.5
PICIE [10]	20.4	16.5	7.6	14.7	24.5	6.3	5.2	18.0	8.4	33.2	6.7	4.8	9.3	2.1	0.1	2.7	8.0	1.1	2.1	0	0	0.5	5.0
GrowSP [91]	57.3	44.2	25.4	40.7	89.8	<b>24.0</b>	47.2	45.5	43.0	39.4	14.1	20.0	53.5	0.1	5.4	13.3	8.4	<b>2.1</b>	<b>11.3</b>	20.6	<b>19.4</b>	0	9.8
PointDC [8]	62.4	38.8	26.0	<b>59.1</b>	<b>94.0</b>	22.0	43.2	30.4	35.9	38.3	14.3	37.4	44.4	1.2	2.4	2.3	<b>39.4</b>	2.0	0	38.6	0	2.2	12.7
PointDC-DINOv2 [8]	64.7	45.0	29.6	57.0	86.0	18.5	60.6	60.1	46.2	46.4	27.0	39.0	54.2	0.7	25.0	<b>18.1</b>	22.7	0.2	2.8	16.8	0	0	10.4
<b>LogoSP (Ours)</b>	<b>64.7</b>	<b>50.8</b>	<b>35.8</b>	46.3	86.6	20.7	<b>66.8</b>	<b>63.3</b>	<b>50.9</b>	<b>47.1</b>	<b>33.8</b>	<b>41.6</b>	<b>62.8</b>	1.0	<b>38.0</b>	10.5	28.6	0.5	0	<b>46.3</b>	0	<b>42.3</b>	<b>29.6</b>

Table 13. Per-category quantitative results on the hidden test split of ScanNet dataset.

		mIoU(%)	wall.	floor.	cab.	bed.	chair.	sofa.	table	door.	wind.	books.	pic.	counter.	desk.	curtain.	fridge.	shower.	toilet.	sink.	bathub.	otherf.
Supervised	PointNet++ [55]	33.9	52.3	67.7	25.6	47.8	36.0	34.6	23.2	26.1	25.2	45.8	11.7	25.0	27.8	24.7	18.3	14.5	54.8	36.4	58.4	18.3
	DGCNN [75]	44.6	72.3	93.7	36.6	62.3	65.1	57.7	44.5	33.0	39.4	46.3	12.6	31.0	34.9	38.9	28.5	22.4	62.5	35.0	47.4	27.1
	PointCNN [36]	45.8	70.9	94.4	32.1	61.1	71.5	54.5	45.6	31.9	47.5	35.6	16.4	29.9	32.8	37.6	21.6	22.9	75.5	48.4	57.7	28.5
	SparseConv [16]	72.5	86.5	95.5	72.1	82.1	86.9	82.3	62.8	61.4	68.3	84.6	32.5	53.3	60.3	75.4	71.0	87.0	93.4	72.4	64.7	57.2
Unsupervised	GrowSP [91]	26.9	32.8	<b>89.6</b>	15.2	62.9	55.3	38.9	32.0	14.4	23.0	<b>59.9</b>	0	12.5	<b>11.4</b>	6.1	<b>1.2</b>	<b>9.3</b>	43.9	<b>14.0</b>	0	16.5
	<b>LogoSP(Ours)</b>	<b>32.7</b>	<b>41.4</b>	87.1	<b>18.1</b>	<b>68.4</b>	<b>56.2</b>	<b>49.9</b>	<b>39.6</b>	<b>30.2</b>	<b>48.7</b>	49.2	<b>0.1</b>	<b>29.1</b>	7.3	<b>33.4</b>	0	0	<b>54.3</b>	0	<b>21.1</b>	<b>19.3</b>

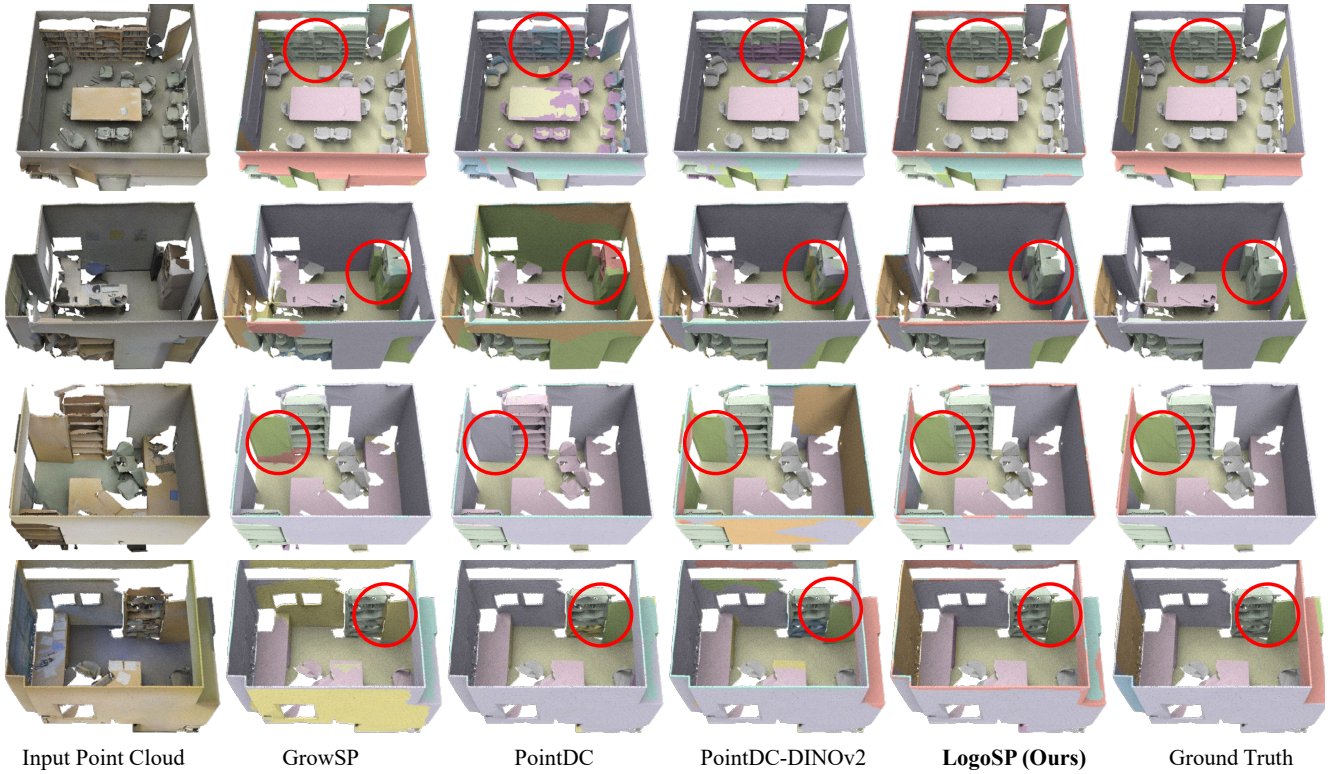


Figure 9. Qualitative results of our method and baselines on the S3DIS dataset.

The per-category results for each area and the 6-fold evaluation are presented in Tables 14 to 20. Our method demonstrates improvements across all areas. Figure 9 shows qualitative results. Since PointDC does not provide detailed results for each category, we reproduce results by training its own models.

## F. Evaluation on nuScenes

After obtaining initial superpoints using RANSAC and Euclidean Clustering, we employ a 15cm voxel grid to convert the point clouds into voxels for training the SparseC-

onv backbone. We also utilize the ViT-S/14 configuration of DINOv2 and maintain the same distillation and segmentation training hyperparameters as used on ScanNet. The training set of nuScenes contains an extremely large number of point clouds, which are challenging to store in memory. Therefore, in each epoch, we randomly select 5,000 point clouds for training; this approach is also applied to all baseline models.

Table 21 shows per-category results, where our model demonstrates superior performance on minor classes like *truck* and *car*. Qualitative results are shown in Figure 10.

Table 14. Quantitative results of our method and baselines on the Area-1 of S3DIS dataset.

		OA(%)	mAcc(%)	mIoU(%)	ceil.	floor	wall	beam	col.	wind.	door	table	chair	sofa	book.	board.
Supervised	PointNet [54]	75.4	74.8	55.0	88.3	93.2	69.2	49.5	37.8	74.5	65.6	41.2	42.5	22.3	35.4	40.9
	PointNet++ [55]	76.1	77.9	58.2	90.5	94.4	65.7	38.2	31.9	61.5	66.0	45.3	60.4	41.2	45.8	57.4
	SparseConv [16]	89.0	79.5	72.5	93.6	95.6	76.1	65.9	60.9	60.0	74.2	81.9	85.4	69.2	73.4	33.5
Unsupervised	Kmeans	20.9	24.1	10.1	15.4	17.8	10.5	16.8	1.9	16.0	12.1	9.9	8.1	0.1	6.2	6.7
	IIC [27]	29.2	14.3	8.0	17.0	31.4	25.6	4.3	11.1	0	2.6	1.4	0.7	0	0.2	1.4
	PICIE [10]	45.7	28.3	19.4	77.2	63.1	24.5	15.8	3.3	4.4	9.6	10.2	14.7	0	9.9	0
	GrowSP [91]	72.9	<b>60.4</b>	45.6	<b>94.2</b>	90.8	52.7	<b>36.7</b>	19.7	33.3	35.8	66.5	<b>72.6</b>	13.1	31.2	<b>16.7</b>
	PointDC [8]	58.0	41.5	28.8	88.7	89.5	31.9	1.5	7.1	17.6	12.4	46.4	17.0	0	32.7	0
	PointDC-DINOV2 [8]	73.8	55.4	44.0	85.7	<b>93.7</b>	58.9	10.1	<b>20.2</b>	0	<b>45.0</b>	<b>70.1</b>	61.5	<b>44.0</b>	39.4	0
	<b>LogoSP (Ours)</b>	<b>76.9</b>	60.0	<b>48.9</b>	89.0	93.2	<b>63.2</b>	27.5	19.2	<b>71.3</b>	39.7	69.7	69.2	0.7	<b>43.6</b>	0

Table 15. Quantitative results of our method and baselines on the Area-2 of S3DIS dataset.

		OA(%)	mAcc(%)	mIoU(%)	ceil.	floor	wall	beam	col.	wind.	door	table	chair	sofa	book.	board.
Supervised	PointNet [54]	72.5	55.5	36.6	79.2	87.4	64.9	14.5	8.2	14.8	39.6	28.8	64.0	7.8	24.4	5.1
	PointNet++ [55]	72.1	62.3	39.9	85.8	69.6	71.2	24.9	27.5	32.5	43.6	27.4	51.3	6.0	26.8	12.4
	SparseConv [16]	87.9	69.5	57.3	89.5	93.8	77.0	29.1	32.5	65.5	45.7	67.9	88.8	34.9	54.5	8.2
Unsupervised	Kmeans	17.6	16.6	6.4	16.4	15.6	11.3	3.3	0.9	0.4	6.8	3.7	11.0	1.4	4.6	1.5
	IIC [27]	41.6	16.8	10.6	33.0	43.7	27.6	1.7	0	0	5.6	0.1	13.0	0	2.8	0
	PICIE [10]	48.3	27.2	17.4	72.4	44.2	39.6	6.2	1.7	0.5	7.7	4.1	20.1	0	7.7	3.6
	GrowSP [91]	<b>79.0</b>	51.8	39.1	85.7	88.2	67.0	<b>12.0</b>	<b>24.8</b>	0	24.2	51.2	77.1	<b>4.1</b>	24.5	0.2
	PointDC [8]	48.3	34.8	22.5	66.7	50.2	26.1	1.3	0.4	0	15.6	29.8	56.3	0.3	17.6	<b>5.6</b>
	PointDC-DINOV2 [8]	77.1	50.3	38.1	90.8	<b>92.0</b>	57.3	10.2	0.6	34.2	20.3	46.4	<b>85.6</b>	0	19.1	0.9
	<b>LogoSP (Ours)</b>	77.0	<b>52.2</b>	<b>39.4</b>	<b>92.3</b>	67.7	<b>72.0</b>	7.2	0.7	<b>44.8</b>	<b>32.4</b>	<b>58.0</b>	53.3	0.2	<b>44.1</b>	0.5

Table 16. Quantitative results of our method and baselines on the Area-3 of S3DIS dataset.

		OA(%)	mAcc(%)	mIoU(%)	ceil.	floor	wall	beam	col.	wind.	door	table	chair	sofa	book.	board.
Supervised	PointNet [54]	78.2	74.9	57.7	90.3	96.9	66.9	55.5	15.1	60.0	67.7	51.8	54.8	27.6	56.0	50.0
	PointNet++ [55]	79.8	85.9	65.8	91.4	98.0	68.5	50.1	15.2	74.8	74.7	63.2	70.1	53.6	54.0	76.5
	SparseConv [16]	91.3	86.8	78.6	93.1	96.2	80.4	74.7	63.3	77.2	69.5	80.1	85.5	89.5	80.1	52.5
Unsupervised	Kmeans	21.3	22.1	9.4	20.2	20.6	13.3	5.7	1.3	2.3	14.1	6.8	6.8	3.7	9.7	8.6
	IIC [27]	32.1	15.4	8.4	20.5	25.5	31.4	1.0	6.9	0.2	3.2	1.6	0.3	0	10.6	0
	PICIE [10]	40.4	29.2	16.2	50.5	49.6	33.7	13.2	3.0	1.8	6.5	8.9	7.5	3.5	16.2	0.4
	GrowSP [91]	74.2	<b>68.4</b>	47.7	<b>92.9</b>	91.7	48.3	<b>49.3</b>	15.8	21.1	38.7	60.6	<b>66.5</b>	<b>28.5</b>	59.2	0
	PointDC [8]	56.2	40.7	27.2	75.3	91.3	29.7	1.2	2.2	0	11.4	37.9	20.7	9.2	38.4	<b>8.9</b>
	PointDC-DINOV2 [8]	70.5	52.4	39.3	86.2	93.4	48.8	0	14.5	38.6	28.2	<b>68.7</b>	55.0	0	37.7	0
	<b>LogoSP (Ours)</b>	<b>79.8</b>	62.7	<b>48.9</b>	90.0	<b>94.3</b>	<b>65.9</b>	16.0	<b>18.6</b>	<b>67.8</b>	<b>45.5</b>	59.2	56.3	3.6	<b>69.4</b>	0

Table 17. Quantitative results of our method and baselines on the Area-4 of S3DIS dataset.

		OA(%)	mAcc(%)	mIoU(%)	ceil.	floor	wall	beam	col.	wind.	door	table	chair	sofa	book.	board.
Supervised	PointNet [54]	73.0	58.6	41.6	81.3	95.7	68.4	1.3	22.4	29.0	44.8	39.3	42.5	17.6	36.6	20.1
	PointNet++ [55]	74.8	66.4	47.7	85.5	96.1	69.9	4.4	23.8	27.0	50.5	44.9	54.0	35.6	38.4	43.8
	SparseConv [16]	88.3	76.2	65.5	93.0	94.9	78.2	53.3	57.9	43.4	59.1	69.4	76.6	55.1	73.8	30.9
Unsupervised	Kmeans	17.9	19.9	7.8	18.6	18.2	10.6	0.9	3.8	5.2	11.7	5.8	7.4	2.4	8.7	0.4
	IIC [27]	33.0	13.5	8.2	14.9	25.9	35.1	0	1.1	1.4	3.7	4.1	0.9	0	10.8	0
	PICIE [10]	43.2	29.4	17.8	62.2	72.7	22.6	2.5	3.4	3.5	8.8	4.1	17.4	0	15.5	0.7
	GrowSP [91]	76.0	<b>59.8</b>	42.8	90.6	91.5	64.4	<b>15.9</b>	<b>7.6</b>	27.4	31.5	52.0	<b>67.4</b>	16.8	48.5	0
	PointDC [8]	54.0	35.3	25.2	87.9	86.8	24.7	0	4.2	12.2	18.7	32.6	17.6	1.9	15.6	0
	PointDC-DINOV2 [8]	73.0	46.5	39.8	89.4	91.9	58.2	0	0.7	25.3	19.0	52.4	53.8	0.7	59.0	0
	<b>LogoSP (Ours)</b>	<b>80.8</b>	54.4	<b>43.5</b>	<b>92.5</b>	<b>93.8</b>	<b>73.9</b>	4.1	0.1	<b>34.8</b>	<b>44.6</b>	<b>54.0</b>	64.9	<b>69.2</b>	<b>73.4</b>	<b>33.5</b>

In addition to the experiments conducted on the validation set of nuScenes, we present segmentation results on its online hidden test set. This test set comprises 6008 outdoor point clouds categorized into 16 classes. Since there is no other unsupervised baseline evaluated on the hidden test set, we include successful fully-supervised methods for comparison. All models listed in Table 22 are trained us-

ing the training set of nuScenes and then evaluated on the hidden test set. These results demonstrate the promising effectiveness of our unsupervised segmentation model.

Table 18. Quantitative results of our method and baselines on the Area-5 of S3DIS dataset.

		OA(%)	mAcc(%)	mIoU(%)	ceil.	floor	wall	beam	col.	wind.	door	table	chair	sofa	book.	board.
Supervised	PointNet [54]	77.5	59.1	44.6	85.2	97.4	72.3	0.1	10.6	54.9	18.5	48.4	39.5	12.4	55.5	40.2
	PointNet++ [55]	77.5	62.6	50.1	83.1	97.2	66.4	0	8.1	55.6	15.2	60.4	64.5	36.6	58.3	55.7
	SparseConv [16]	88.4	69.2	60.8	92.6	95.9	77.2	0.1	36.7	37.6	59.8	77.2	83.9	59.7	78.5	30.4
Unsupervised	Kmeans	21.4	21.2	8.7	18.7	18.0	16.7	<b>0.2</b>	2.5	12.0	5.7	8.7	5.6	0	13.6	<b>2.3</b>
	IIC [27]	28.5	12.5	6.4	6.1	19.8	27.9	0	2.1	0.1	3.4	7.9	0.4	0	8.6	0
	PICIE [10]	61.6	25.8	17.9	65.7	61.4	58.4	0	0.3	2.2	1.7	12.1	0	0	12.4	0
	GrowSP [91]	78.4	<b>57.2</b>	44.5	90.5	90.1	66.7	0	<b>14.8</b>	27.6	<b>45.6</b>	59.4	71.9	<b>10.7</b>	56.0	0.2
	PointDC [8]	55.5	35.1	23.9	84.4	84.3	30.2	0	1.8	12.2	7.1	24.6	6.9	5.4	29.7	0.7
	PointDC-DINOv2 [8]	75.7	48.7	40.2	87.7	89.5	59.2	0	0.8	25.8	26.3	<b>62.0</b>	68.3	1.5	61.0	0.5
	<b>LogoSP (Ours)</b>	<b>82.8</b>	55.9	<b>46.5</b>	<b>92.9</b>	<b>95.4</b>	<b>73.2</b>	0	3.3	<b>57.8</b>	35.9	55.5	<b>74.6</b>	1.9	<b>67.3</b>	0.3

Table 19. Quantitative results of our method and baselines on the Area-6 of S3DIS dataset.

		OA(%)	mAcc(%)	mIoU(%)	ceil.	floor	wall	beam	col.	wind.	door	table	chair	sofa	book.	board.
Supervised	PointNet [54]	79.0	79.6	60.9	85.7	96.5	71.8	59.4	47.4	67.4	74.3	56.2	48.9	20.9	50.0	52.5
	PointNet++ [55]	82.0	89.3	69.0	87.5	96.3	76.8	66.4	54.4	72.1	77.4	64.3	66.5	43.7	51.8	70.2
	SparseConv [16]	91.6	87.3	80.5	97.4	95.0	83.4	83.0	75.1	81.1	74.9	81.3	84.3	79.0	80.7	61.4
Unsupervised	Kmeans	21.0	25.0	10.4	18.6	17.6	8.9	11.3	0.6	14.8	17.6	12.0	8.7	0.3	7.8	<b>6.2</b>
	IIC [27]	32.5	15.9	9.2	21.9	33.8	29.1	3.1	15.2	0	2.7	0.7	0	0	1.5	1.8
	PICIE [10]	39.3	28.5	17.8	56.9	61.7	18.6	20.5	4.2	6.0	8.7	14.7	15.9	1.1	5.7	0
	GrowSP [91]	75.6	58.5	47.6	89.4	88.0	57.7	<b>70.6</b>	2.0	32.4	36.7	63.2	69.8	1.5	58.9	0.2
	PointDC [8]	62.4	38.7	28.6	85.8	85.6	43.8	5.0	16.5	8.8	10.7	41.7	12.5	0	33.0	0
	PointDC-DINOv2 [8]	76.4	55.5	46.4	<b>90.3</b>	91.4	61.7	0	19.7	63.1	33.6	67.9	65.7	1.4	62.5	0
	<b>LogoSP (Ours)</b>	<b>77.9</b>	<b>62.9</b>	<b>50.6</b>	84.6	<b>92.7</b>	<b>64.0</b>	25.7	<b>23.9</b>	<b>65.9</b>	<b>38.8</b>	<b>68.9</b>	<b>72.2</b>	<b>2.5</b>	<b>68.4</b>	0

Table 20. Quantitative results of our method and baselines on the 6-fold validation on S3DIS dataset.

		OA(%)	mAcc(%)	mIoU(%)	ceil.	floor	wall	beam	col.	wind.	door	table	chair	sofa	book.	board.
Supervised	PointNet [54]	75.9	67.1	49.4	85.0	94.5	68.9	30.0	23.6	50.1	51.8	44.3	48.7	18.1	43.0	34.8
	PointNet++ [55]	77.1	74.1	55.1	85.7	91.6	69.8	36.0	28.0	58.7	57.4	47.4	61.8	39.1	44.1	61.2
	SparseConv [16]	89.4	78.1	69.2	94.6	95.5	78.6	51.8	55.8	60.6	63.0	76.0	84.3	65.8	73.5	39.4
Unsupervised	Kmeans	20.0	21.5	8.8	17.9	17.9	11.6	6.5	1.8	8.2	11.1	7.9	7.9	1.5	8.4	4.8
	IIC [27]	32.8	14.7	8.5	18.9	30.0	29.3	1.7	7.2	0.4	3.4	2.8	2.5	0	5.5	0.6
	PICIE [10]	46.4	28.1	17.8	63.6	58.6	33.3	9.0	2.6	3.2	7.6	9.7	12.4	0.9	11.5	0.9
	GrowSP [91]	76.0	<b>59.4</b>	44.6	<b>90.7</b>	89.9	60.2	<b>30.6</b>	<b>14.9</b>	24.0	35.6	58.4	<b>70.6</b>	12.5	44.9	3.5
	PointDC [8]	55.7	37.7	26.0	81.5	81.5	31.4	1.5	6.4	8.8	12.2	35.8	20.8	2.6	27.5	2.4
	PointDC-DINOv2 [8]	74.4	51.5	41.3	88.8	<b>91.8</b>	57.9	3.4	10.4	27.5	28.3	<b>61.3</b>	64.8	<b>13.8</b>	43.9	0.3
	<b>LogoSP (Ours)</b>	<b>79.2</b>	58.0	<b>46.3</b>	90.2	89.5	<b>68.7</b>	13.4	10.9	<b>57.1</b>	<b>39.5</b>	60.9	65.1	13.0	<b>60.4</b>	<b>5.7</b>

Table 21. Per-category quantitative results on the validation split of nuScenes dataset.

	OA(%)	mAcc(%)	mIoU(%)	barrier.	bicycle.	bus.	car.	construction vehicle.	motorcycle.	pedestrian	traffic cone.	trailer.	truck.	drivable surface.	other flat.	sidewalk.	terrain.	manmade.	vegetation.
GrowSP [91]	39.2	17.5	10.2	7.5	0	0.4	42.9	0.1	0	0.6	0	0.7	1.4	48.4	<b>0.8</b>	6.5	13.1	21.4	19.7
PointDC [8]	<b>56.8</b>	<b>29.4</b>	17.7	11.6	0	0.5	63.1	<b>0.3</b>	0	4.4	0	1.2	26.4	70.1	0.1	7.1	19.3	21.1	<b>58.1</b>
PointDC-DINOv2 [8]	51.8	28.6	18.2	<b>17.0</b>	0	0.2	58.4	0.2	0	1.5	0	<b>1.6</b>	<b>43.3</b>	<b>71.8</b>	0	<b>8.3</b>	<b>19.5</b>	17.6	51.8
<b>LogoSP (Ours)</b>	54.8	29.2	<b>20.1</b>	16.6	0	<b>0.7</b>	<b>70.2</b>	0.2	<b>0.2</b>	<b>33.6</b>	0	0.3	38.4	59.4	0.4	8.0	10.7	<b>33.0</b>	49.3

Table 22. Per-category quantitative results on the **hidden test split** of nuScenes dataset.

		mIoU(%)	barrier.	bicycle.	bus.	car.	construction vehicle.	motorcycle.	pedestrian.	traffic cone.	trailer.	truck.	driveable.	other flat.	sidewalk.	terrain.	manmade.	vegetation.
Supervised	Cylinder3D [95]	77.2	82.8	29.8	84.3	89.4	63.0	79.3	77.2	73.4	84.6	69.1	97.7	70.2	80.3	75.5	90.4	87.6
	SPVNAS [68]	77.4	80.0	30.0	91.9	90.8	64.7	79.0	75.6	70.9	81.0	74.6	97.4	69.2	80.0	76.1	89.3	87.1
	Cylinder3D++ [95]	77.9	82.8	33.9	84.3	89.4	69.6	79.4	77.3	73.4	84.6	69.4	97.7	70.2	80.3	75.5	90.4	87.6
Unsupervised	<b>LogoSP(Ours)</b>	17.5	12.4	0	1.9	68.7	0	0.2	22.5	0	0.1	23.2	62.8	0.2	1.4	13.9	30.1	41.6

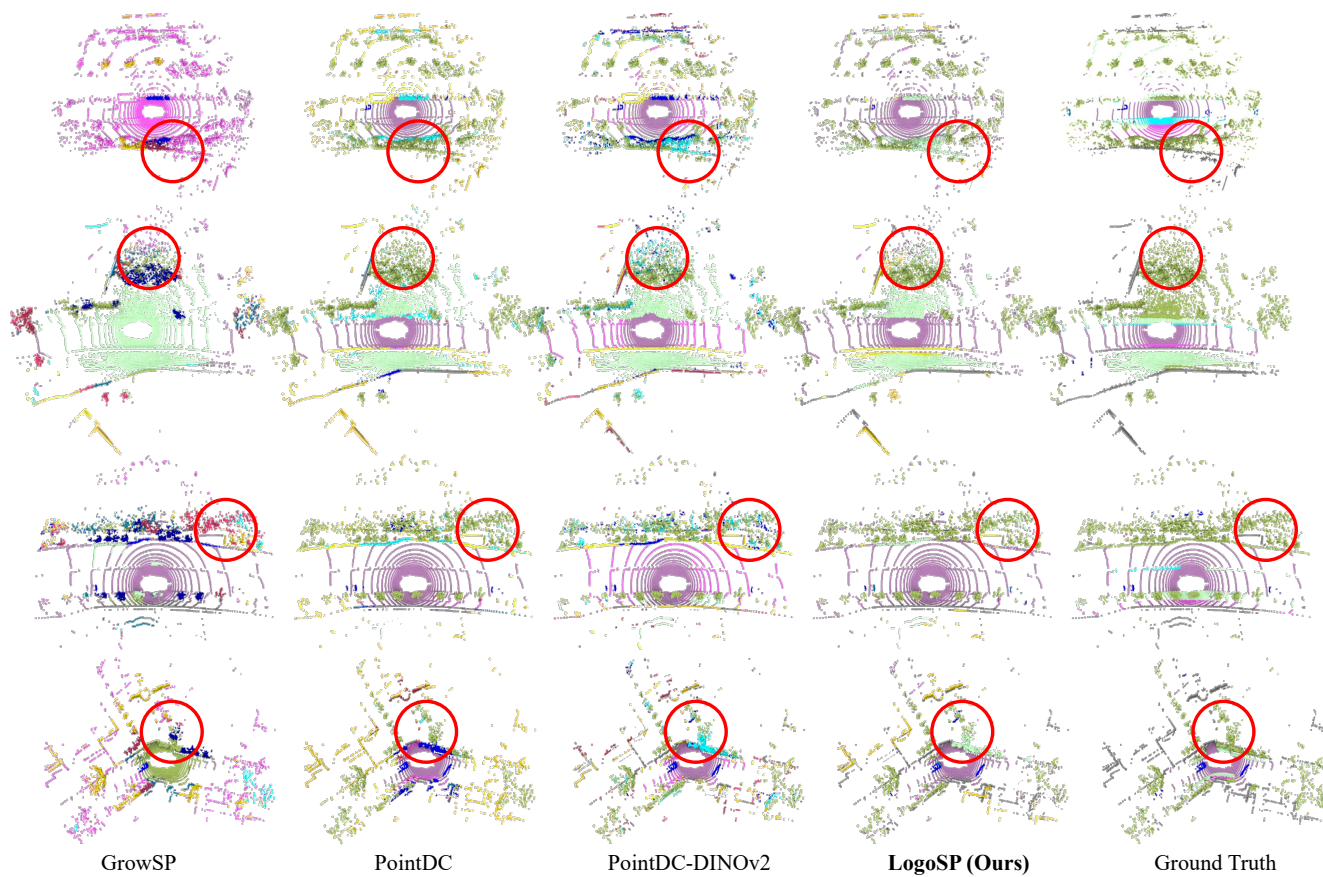


Figure 10. Qualitative results of our method and baselines on the nuScenes dataset.