

GrowSP: Unsupervised Semantic Segmentation of 3D Point Clouds

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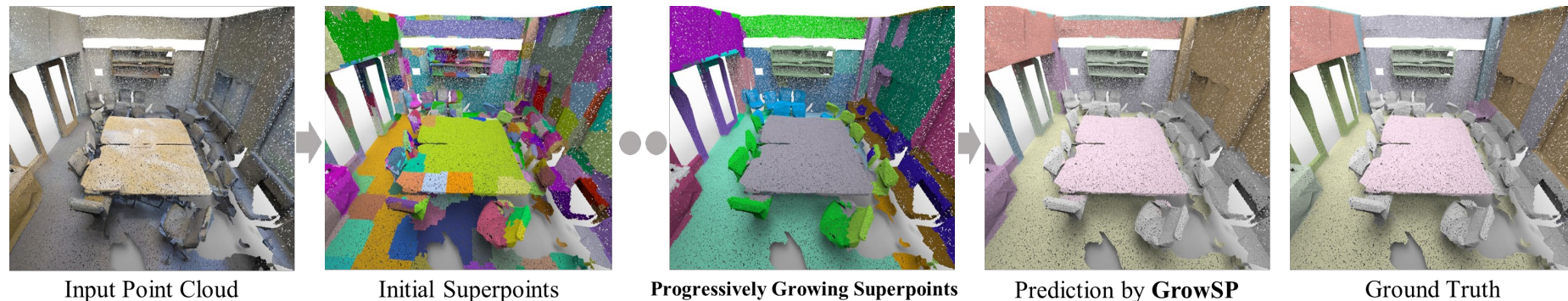
Paper Tag: THU-AM-109

Brief Introduction

Motivations: Annotation is costly

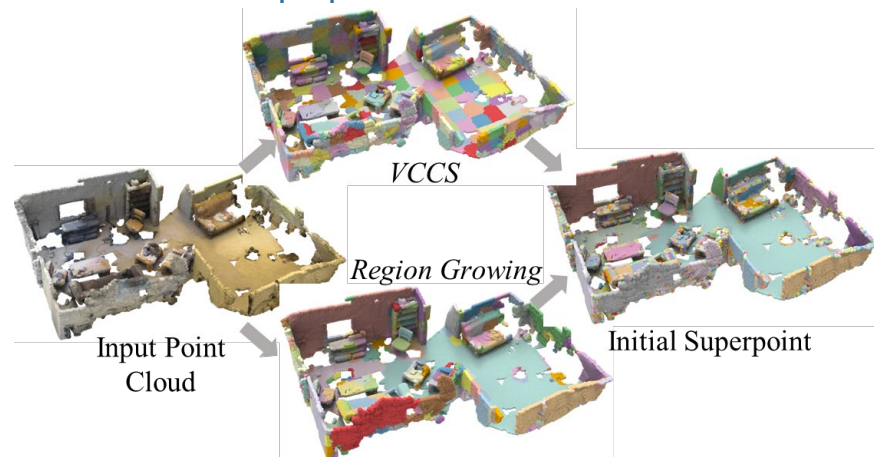


Overall Pipeline:

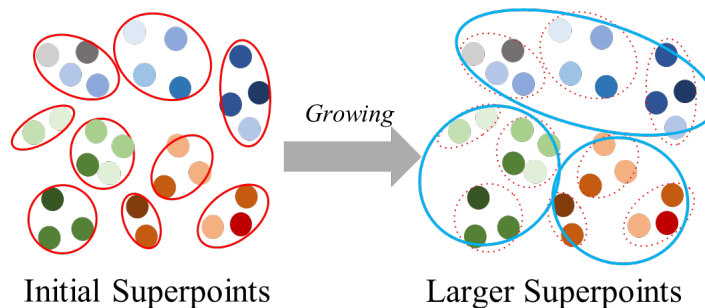


Superpoint Constructor → Superpoint Growing → Semantic Primitives

① Initial Superpoint Constructor:



② Superpoint Growing: Merge similar superpoints.



③ Semantic Primitives:

Cluster superpoints to primitives

$$primitives \xleftarrow{\text{Kmeans}} (f_1^1 \dots f_m^H)$$

④ Semantic Classes:

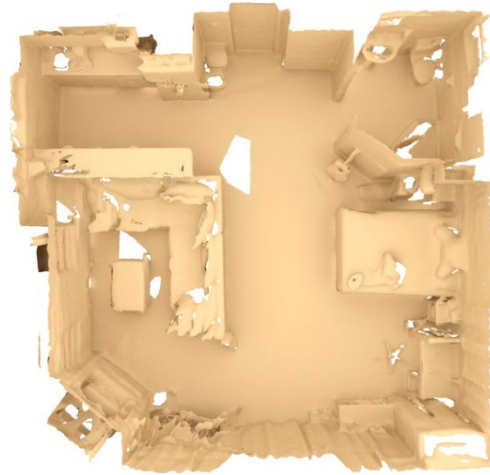
Cluster primitives to categories

$$categories \xleftarrow{\text{Kmeans}} (pri_1 \dots pri_s)$$

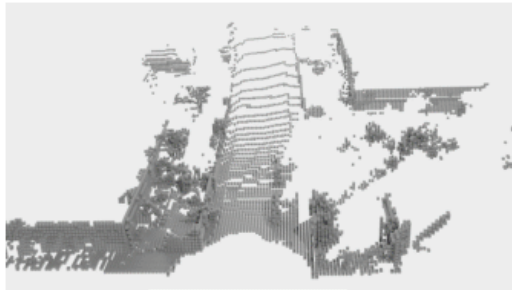
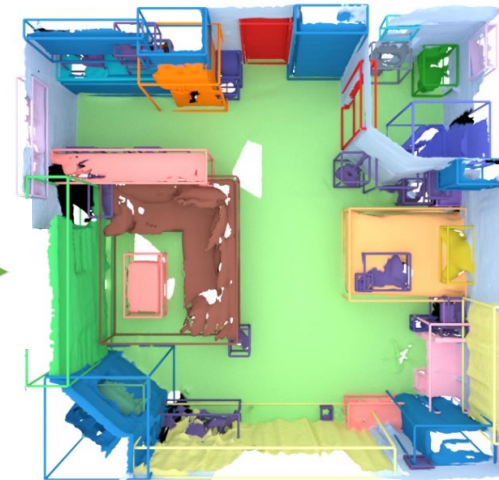
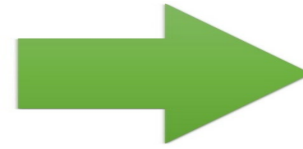


Background

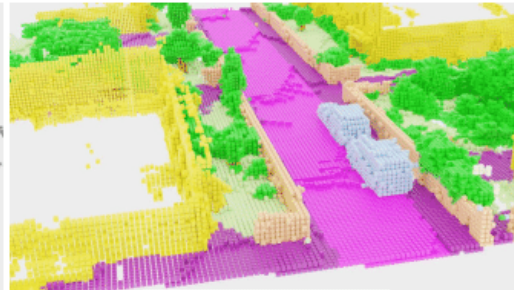
Assign semantic labels to each point



Semantic Segmentation



(a) Input Sparse Tensor



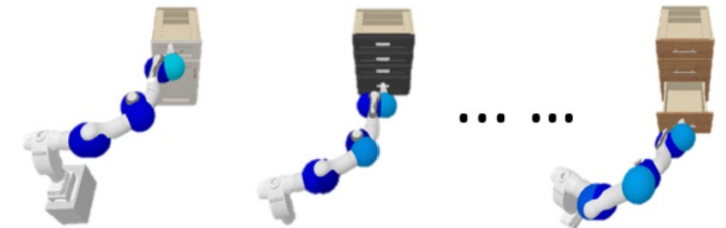
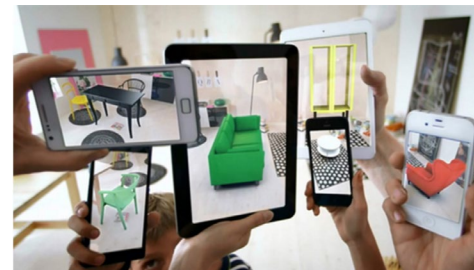
(b) Predicted Semantic Label



(c) RGB image

Autonomous Driving

VR



Robotic

3D scene semantic segmentation is crucial for practical application



Motivation

- Fully supervised:

ScanNet Benchmark

Method	Info	avg iou	bathtub	bed	bookshelf	cabinet	chair	counter	curtain
Mix3D		0.781 1	0.964 1	0.855 1	0.843 10	0.781 1	0.858 7	0.575 2	0.831 17
Alexey Nekrasov, Jonas Schult, Or Litany, Bastian Leibe, Francis Engelmann: Mix3D: Out-of-Context Data Augmentation for 3D Scenes. 3DV 2021 (Oral)									
OccuSeg+Semantic		0.764 2	0.758 42	0.796 16	0.839 11	0.746 8	0.907 1	0.562 3	0.850 12
O-CNN		0.762 3	0.924 2	0.823 4	0.844 9	0.770 2	0.852 9	0.577 1	0.847 13
Peng-Shuai Wang, Yang Liu, Yu-Xiao Guo, Chun-Yu Sun, Xin Tong: O-CNN: Octree-based Convolutional Neural Networks for 3D Shape Analysis. SIGGRAPH									
DMF-Net		0.752 4	0.906 4	0.793 19	0.802 25	0.689 22	0.825 25	0.556 4	0.867 8
PointTransformerV2		0.752 4	0.742 49	0.809 11	0.872 1	0.758 4	0.860 6	0.552 5	0.891 5

- Weakly supervised:

ScanNet Data Efficient

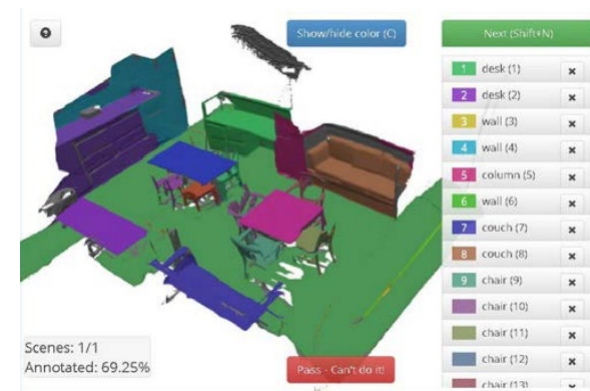
Limited Annotations Limited Rec

Trained points per scene: 20 points

Method	Info	avg iou	bathtub	bed	bookshelf	cabinet	chair	counter	curtain	de:
ActiveST		0.703 1	0.977 1	0.776 2	0.657 4	0.707 1	0.874 1	0.541 1	0.744 1	0.601 1
Gengxin Liu, Oliver van Kaick, Hui Huang, Ruizhen Hu: Active Self-Training for Weakly Supervised 3D Scene Semantic Segmentation.										
WeakLab-3D-Net(WS3D)		0.662 2	0.812 3	0.762 3	0.742 1	0.635 2	0.828 5	0.474 2	0.736 2	0.581 2
DE-3DLearner LA		0.639 3	0.839 2	0.723 5	0.681 2	0.629 3	0.839 4	0.424 3	0.728 3	0.531 3

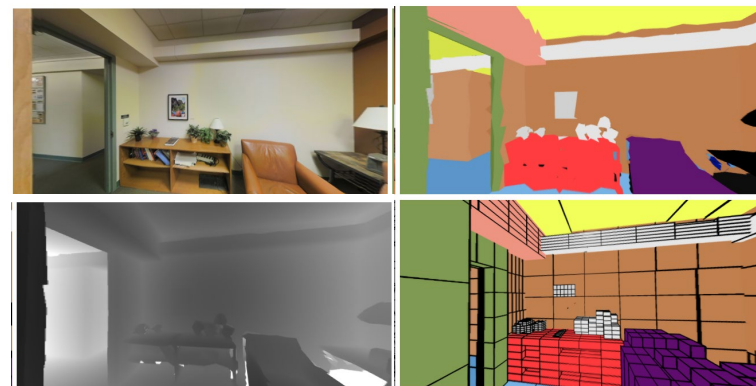
Manually annotating real-world 3D point cloud is costly

Semantic labeling on 3D points:



RGB image

Semantics in 2D



Depth

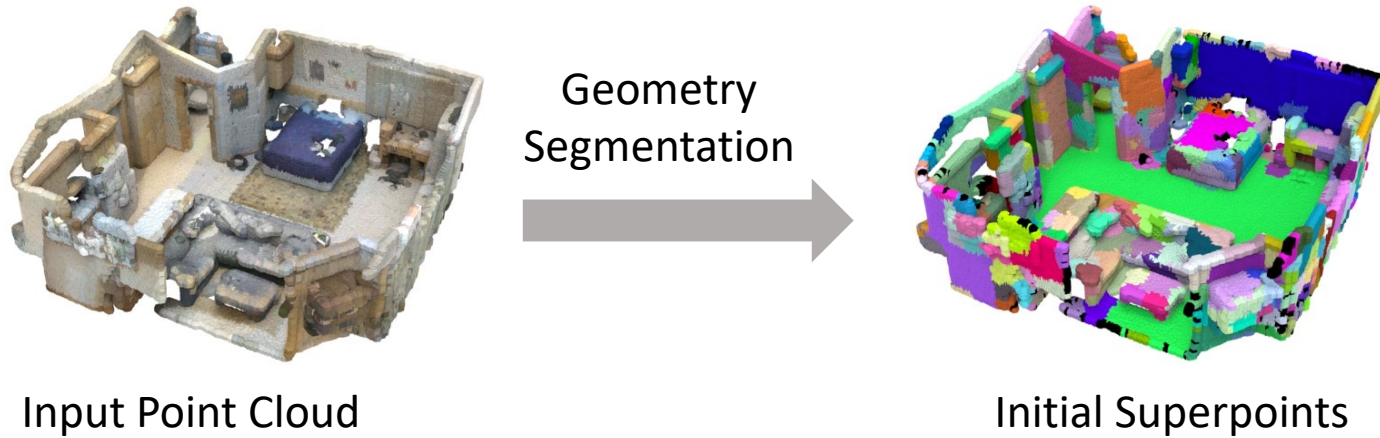
Semantics in 3D

Semantic labeling on RGBD



GrowSP:

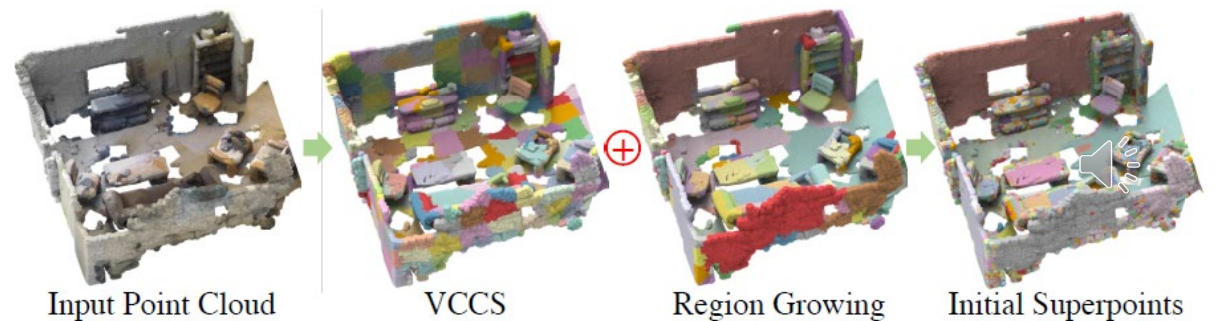
- Semantic Significance of Point Regions vs Individual Points



Superpoints Constructors:
Region Growing: normal similarity and connectivity

VCCS:

$$D = \sqrt{w_c D_c^2 + \frac{w_s D_s}{3R_{seed}^2} + w_n D_n}$$



GrowSP:

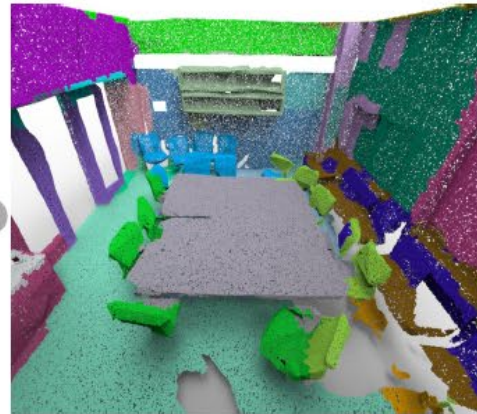
- Growing Superpoints to contain more semantics:



Input Point Cloud



Initial Superpoints



Progressively Growing Superpoints

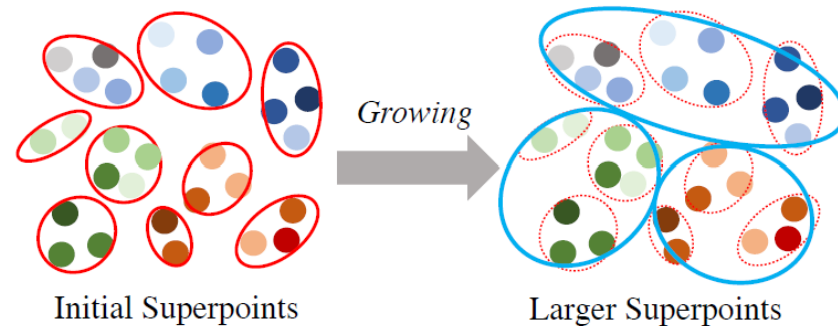


Prediction by **GrowSP**

In feature space:

$$\tilde{\mathbf{f}}_{m^0}^h = \frac{1}{Q} \sum_{q=1}^Q \mathbf{f}_q^h,$$

$$\{\tilde{\mathbf{p}}_1^h \cdots \tilde{\mathbf{p}}_{m^1}^h \cdots \tilde{\mathbf{p}}_{M^1}^h\} \xleftarrow{\text{Kmeans}} \{\tilde{\mathbf{f}}_1^h \cdots \tilde{\mathbf{f}}_{m^0}^h \cdots \tilde{\mathbf{f}}_{M^0}^h\}$$



GrowSP:

- Semantic Primitives(sub-class) and Auxiliary features:

1). Cluster superpoints into semantic categories is aggressive.

- We choose to constantly group superpoints into semantic primitives rather than semantic categories.

$$S \text{ primitives} \xleftarrow{\text{Kmeans}} (\{\hat{\mathbf{f}}_1^1 \cdots \hat{\mathbf{f}}_{m^0}^1 \cdots\} \cdots \{\hat{\mathbf{f}}_1^H \cdots \hat{\mathbf{f}}_{m^0}^H \cdots\})$$

2). Auxiliary features.

- The network output features are semantically meaningless, especially at the early training stages.

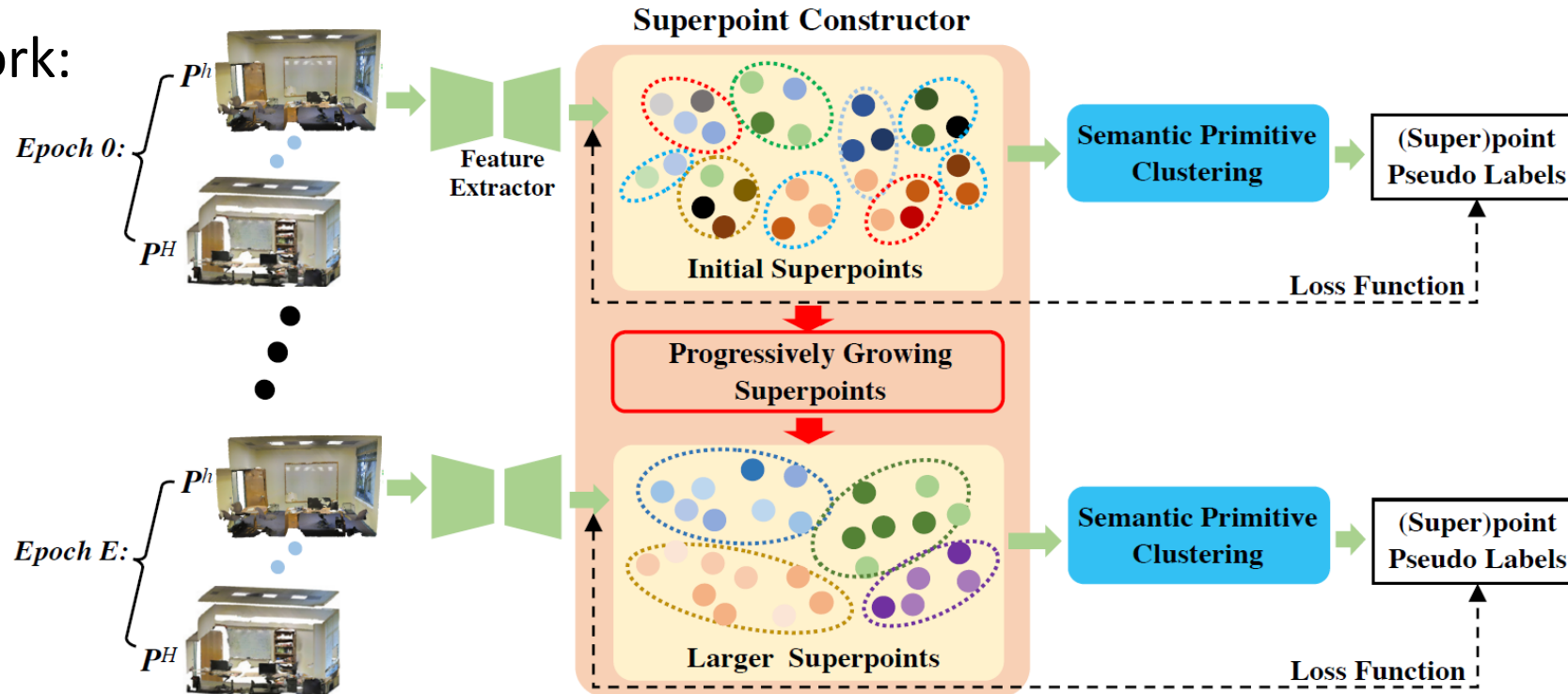
For each superpoints having k points:

- Compute k normal vectors and their cosine distance of any two points.
- Count the distribution of cosine distance to form a histogram within the range [-1, 1]



GrowSP:

- Framework:



1. Get per-point features.
2. Get superpoint-wise features.
3. Do clustering on superpoint-wise features.
4. Training backbone by pseudo labels.



Experiments:

- Compare with other unsup methods:

S3DIS:

		OA(%)	mAcc(%)	mIoU(%)
Unsupervised Methods	RandCNN	23.1	18.4	9.3
	van Kmeans	20.0	21.5	8.8
	van Kmeans-S	20.0	22.3	8.8
	van Kmeans-PFH	23.9	24.7	10.9
	van Kmeans-S-PFH	23.4	20.8	9.5
	IIC [24]	32.8	14.7	8.5
	IIC-S [24]	29.4	15.1	7.7
	IIC-PFH [24]	29.5	13.2	6.7
	IIC-S-PFH [24]	26.3	13.6	7.2
	PICIE [7]	46.4	28.1	17.8
	PICIE-S [7]	50.7	30.8	21.6
	PICIE-PFH [7]	55.0	38.8	26.6
PICIE-S-PFH [7]	49.1	40.5	26.7	
GrowSP (Ours)	76.0	59.4	44.6	

ScanNet:

		OA(%)	mAcc(%)	mIoU(%)
Unsupervised Methods	RandCNN	11.9±0.4	8.4±0.1	3.2±0
	van Kmeans	10.1±0.1	10.0±0.1	3.4±0
	van Kmeans-S	10.2±0.1	9.8±0.3	3.4±0.1
	van Kmeans-PFH	10.4±0.2	10.3±0.7	3.5±0.2
	van Kmeans-S-PFH	12.2±0.6	9.3±0.5	3.6±0.1
	IIC [24]	27.7±2.7	6.1±1.2	2.9±0.8
	IIC-S [24]	18.3±2.6	6.7±0.6	3.4±0.1
	IIC-PFH [24]	25.4±0.1	6.3±0	3.4±0
	IIC-S-PFH [24]	18.9±0.3	6.3±0.2	3.0±0.1
	PICIE [7]	20.4±0.5	16.5±0.3	7.6±0
	PICIE-S [7]	35.6±1.1	13.7±1.5	8.1±0.5
	PICIE-PFH [7]	23.1±1.4	14.0±0.1	8.1±0.3
PICIE-S-PFH [7]	23.6±0.4	15.1±0.6	7.4±0.2	
GrowSP (Ours)	57.3±2.3	44.2±3.1	25.4±2.3	

SemanticKITTI:

	OA(%)	mAcc(%)	mIoU(%)	car.	bike.	mbike.	truck.	vehicle.	person.	cyclist.	mcyclist.	road.	parking.	sidewalk.	other-gr.	building.	fence.	veget.	trunk.	terrain.	pole.	sign.
RandCNN	25.4±3.3	6.0±0.2	3.3±0.1	2.5±0.4	0±0	0±0	0±0	0.2±0.1	0±0	0±0	0±0	8.5±2.1	0.8±0.5	4.9±1.8	0.3±0.3	6.2±1.3	1.3±0.3	29.0±3.1	1.0±0.2	8.1±1.6	0.4±0.1	0.1±0
van Kmeans	8.1±0	8.2±0.1	2.4±0	5.6±0.2	0.1±0	0.1±0	0.2±0	0.5±0.1	0.1±0	0±0	0±0	12.3±0.1	1.1±0.1	4.4±0.1	0.3±0	5.8±0.2	2.0±0	5.7±0.1	1.4±0	5.0±0.1	0.5±0	0.1±0
van Kmeans-S	10.3±0.3	7.7±0.1	2.6±0	5.6±0.4	0.1±0.1	0.1±0.1	0.1±0.1	0.3±0	0.1±0	0±0	0±0	13.5±0.6	1.0±0.4	5.0±0.2	0.3±0	7.1±0.6	1.5±0.2	7.5±0.7	1.5±0.1	6.0±0.1	3.4±0.1	0.1±0
IIC [23]	26.2±1.5	5.8±0.4	3.1±0.3	1.6±0.9	0±0	0±0	0±0	0±0	0±0	0±0	0±0	8.9±2.0	0.1±0.1	2.6±1.8	0±0	7.1±4.2	0.2±0.1	26.5±2.5	0.3±0.4	11.5±1.5	6.1±0.1	0.1±0.1
IIC-S [23]	23.9±1.1	6.1±0.3	3.2±0.2	1.6±0.8	0±0	0±0	0.1±0.1	0.1±0.1	0±0	0.1±0.1	9.7±1.9	0.6±0.5	4.3±2.8	0.1±0.1	8.8±3.2	0.5±0.6	24.3±2.3	0.6±0.5	9.7±2.6	0.3±0.3	0.1±0.1	0±0.1
PICIE [7]	22.3±0.4	14.6±0.3	5.9±0.1	7.4±0.2	0.3±0.2	0±0	0.1±0	0.6±0.1	0.3±0.1	0.1±0.1	0±0	4.826.5±0.3	1.6±0.1	14.8±1.4	0.6±0.3	20.5±0.4	4.8±0.1	16.3±1.0	2.1±0.9	14.2±0.9	1.4±0.3	0.4±0.2
PICIE-S [7]	18.4±0.5	13.2±0.2	5.1±0.1	6.1±1.4	0.1±0	0±0	0.1±0.1	0.4±0.1	0.3±0.1	0.1±0.1	0±0	21.3±1.4	1.7±0.1	12.9±2.3	0.4±0.2	21.2±0.9	2.6±0.3	13.4±0.4	2.4±0.3	11.5±2.9	2.6±0.2	0.4±0
GrowSP(Ours)	38.3±1.0	19.7±0.6	13.2±0.1	76.0±0.4	0±0	0.4±0.2	0.9±0.7	1.0±0.1	0.1±0.2	0.1±0.2	0±0	26.8±3.5	1.0±0.4	13.8±4.5	0.4±0.3	39.2±2.1	1.3±0.4	26.7±1.5	25.1±0.7	35.5±1.9	0.2±0.1	2.1±0.1

Experiments:

- Cross-datasets(Novel class discovery):

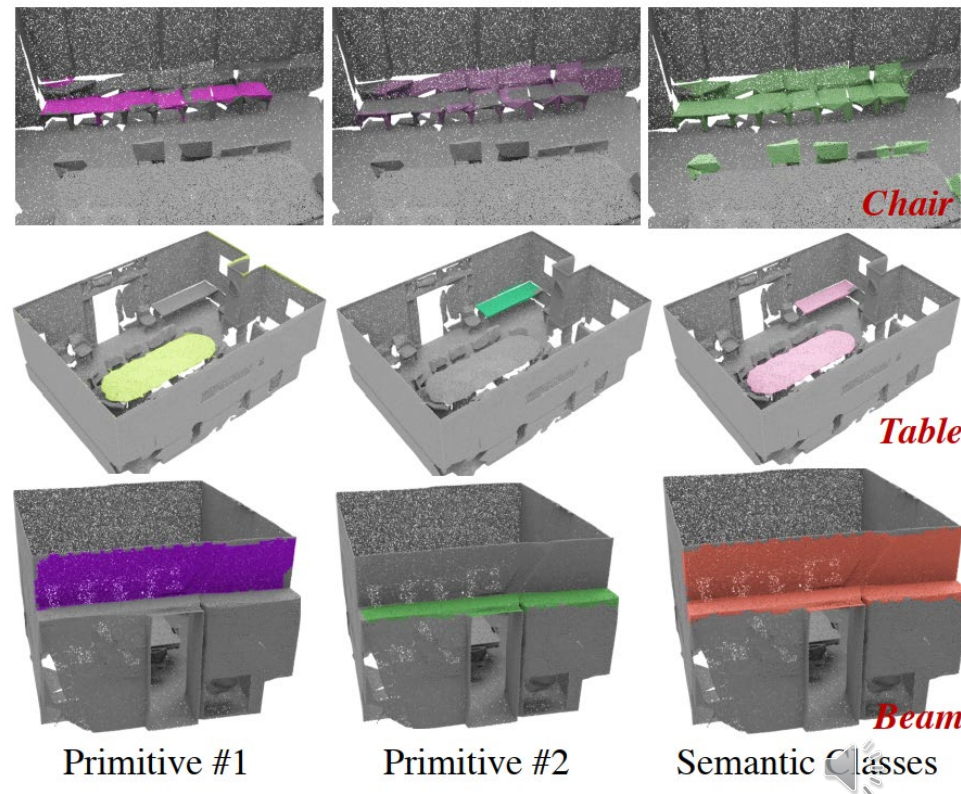
S3DIS → ScanNet:

<i>model trained on</i> →	Areas 2/3/4/5/6	Areas 1/3/4/5/6	Areas 1/2/4/5/6	Areas 1/2/3/5/6	Areas 1/2/3/4/6	Areas 1/2/3/4/5
IIC [23]	3.5±0	3.4±0	3.7±0.1	3.5±0.1	3.5±0	3.6±0
IIC-S [23]	3.9±0.1	3.9±0.1	4.0±0.1	3.9±0	3.9±0.1	3.9±0
PICIE [7]	5.6±0.2	5.1±0.1	5.0±0.1	5.9±0.3	6.0±0.3	5.5±0.2
PICIE-S [7]	6.9±0.3	6.9±0.7	6.9±0.8	8.1±0.4	8.4±0.3	6.7±0.9
GrowSP (Ours)	16.9±0.6	17.8±0.6	16.4±0.5	16.1±0.6	17.1±0.8	15.3±0.3

ScanNet → S3DIS:

<i>test on</i> →	Area-1	Area-2	Area-3	Area-4	Area-5	Area-6
IIC [23]	3.7±0.5	3.8±0.4	3.8±0.2	4.0±0.5	3.8±0.2	3.7±0.4
IIC-S [23]	6.7±0.1	5.7±0	6.4±0.2	5.8±0	5.9±0	6.5±0.1
PICIE [7]	13.5±0.1	12.7±0.2	13.4±0.1	12.8±0.1	11.3±0.4	13.1±0.1
PICIE-S [7]	14.7±0.9	13.9±0.8	15.1±0.7	14.7±0.4	14.2±0.3	15.8±0.2
GrowSP (Ours)	28.2±1.4	22.9±2.5	31.4±1.5	25.2±1.0	28.6±2.5	30.6±2.0

- Learned Semantic Primitives



Experiments:

- Visualizations:

