



Open3DIS: Open-Vocabulary 3D Instance Segmentation with 2D Mask Guidance

Phuc Nguyen^{1*}

Tuan Duc Ngo^{1,4*}

Evangelos Kalogerakis⁴

Chuang Gan^{2,4}

Anh Tran¹ Cuong Pham^{1,3}

Khoi Nguyen¹

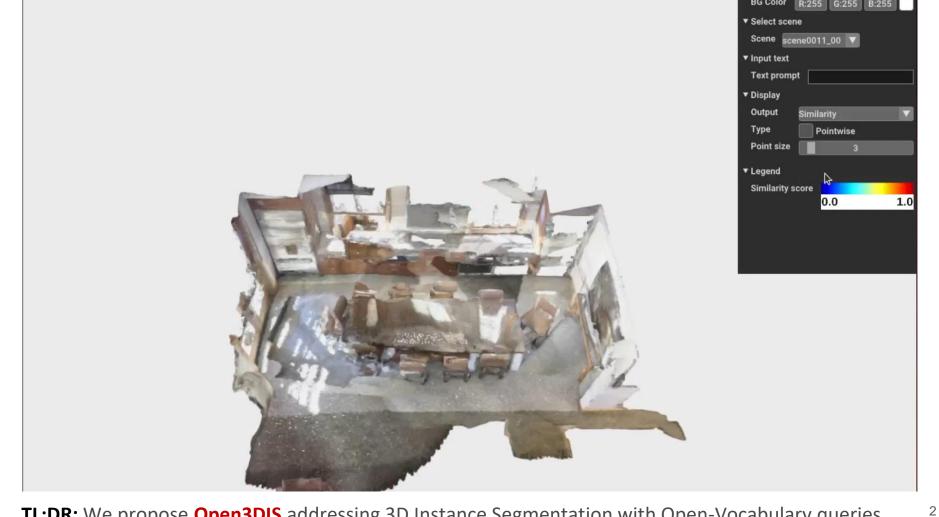
¹VinAl Research

²MIT-IBM Watson AI Lab

³Posts & Telecom Inst. of Tech.

⁴UMass Amherst

*Equal contribution



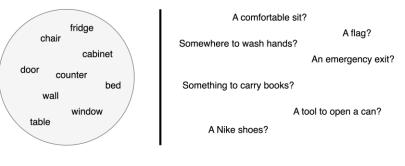
TL;DR: We propose **Open3DIS** addressing 3D Instance Segmentation with Open-Vocabulary queries

Motivations

• **3D point cloud instance segmentation** (**3DIS**) methods require extensive training data while limited to closed-set categories.



Schult et al "Mask3D: Mask Transformer for 3D instance segmentation"

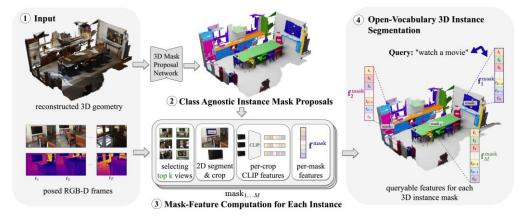


Closed-vocabulary

Open-vocabulary

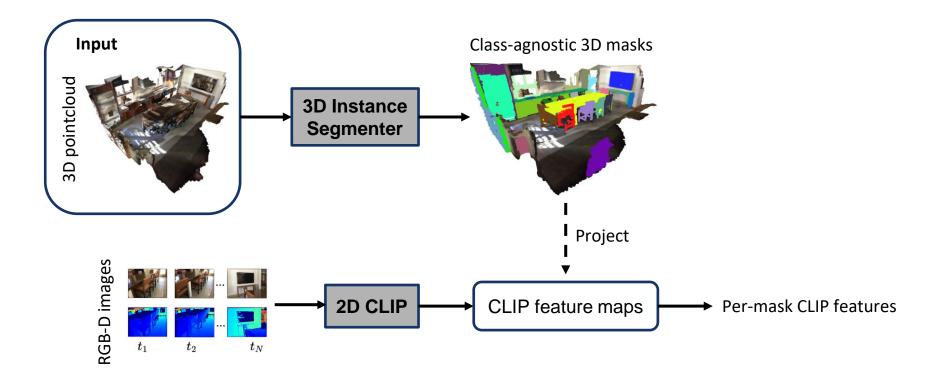
Motivations

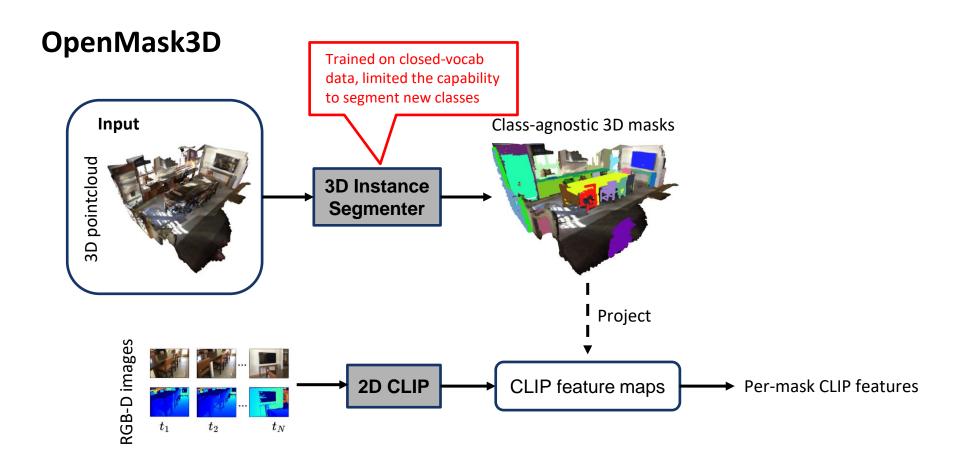
- 3D point cloud instance segmentation (3DIS) methods require extensive training data while limited to closed-set categories.
- Recent open-vocab 3DIS methods struggle with small or ambiguous instances, particularly those from uncommon classes

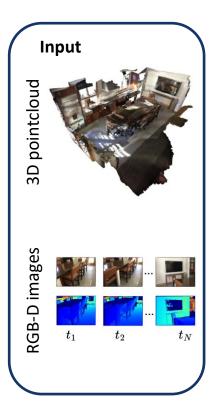


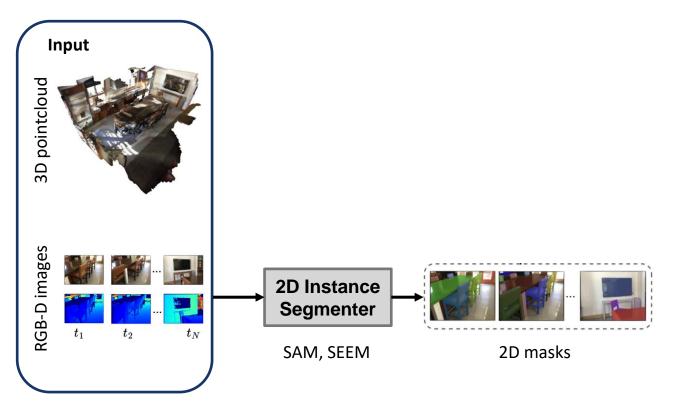
Takmaz et al "OpenMask3D: Open-vocabulary 3D Instance Segmentation"

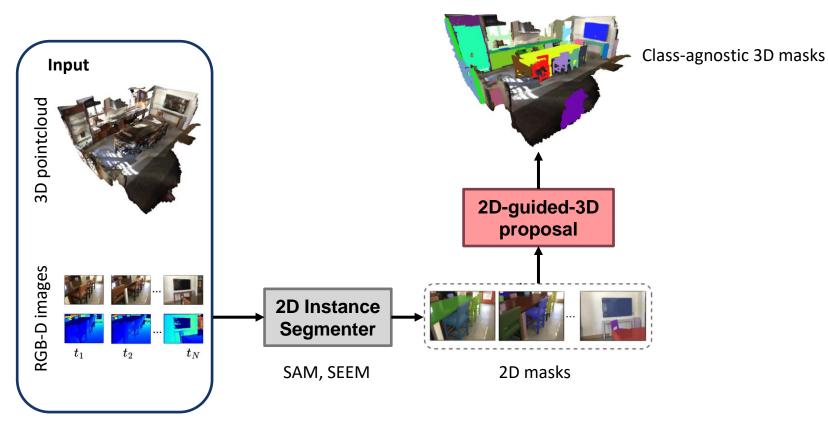
OpenMask3D

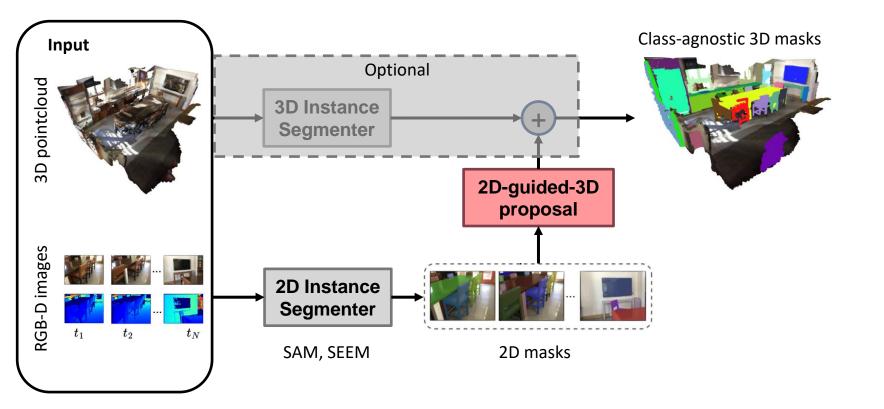


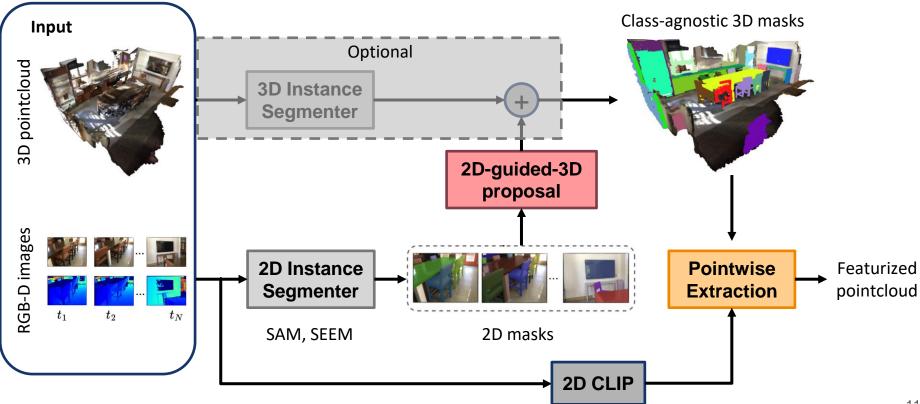


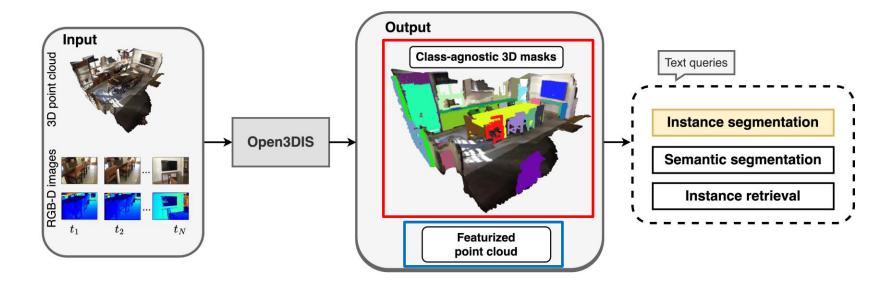






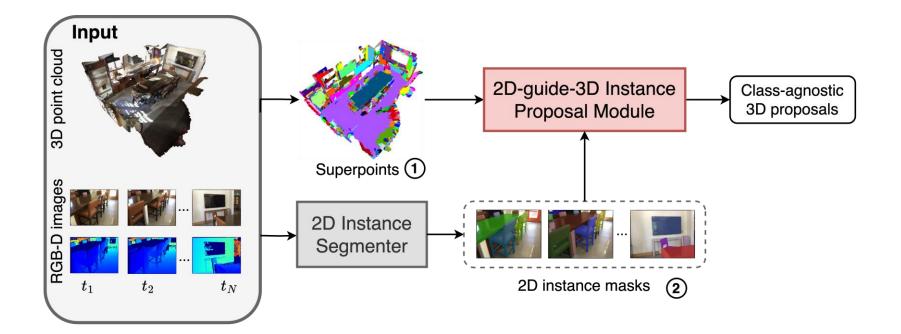






Given a **3D point cloud** with the corresponding **RGB-D sequences**, Open3DIS generates a set of **class-agnostic 3D proposals** and a **featurized point cloud** for open-vocabulary queries

How to obtain 3D instance proposals?



3D Superpoints

Original images



Super-pixels

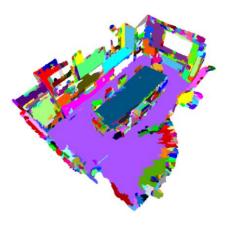


3D Superpoints

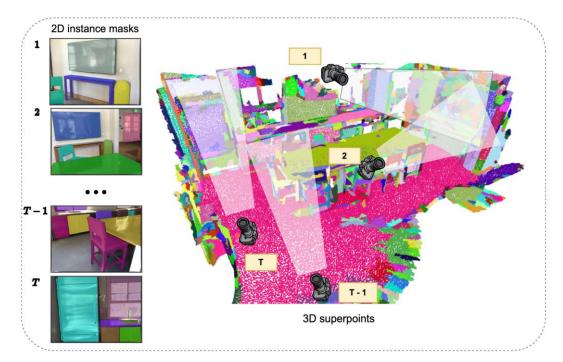


Original point cloud





Per-frame superpoints merging



1. Use SAM to obtain a set of **2D masks** of every RGB frame

2. For each 2D mask *m*, we project **superpoints** onto their image planes and calculate the IoUs with predicted **2D masks**

Per-frame superpoints merging

2D masks



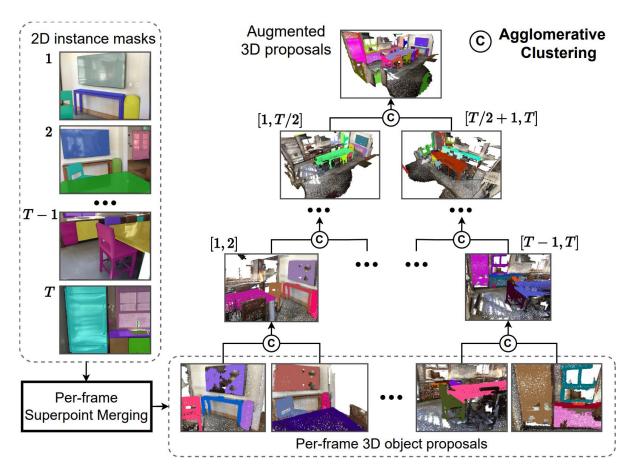
Per-frame 3D proposals



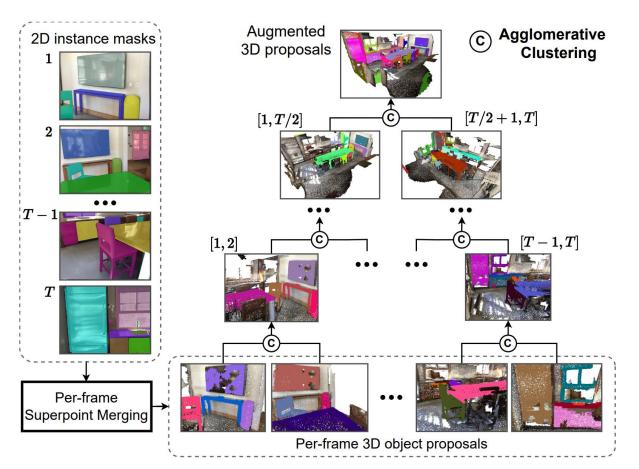
1. Use SAM to obtain a set of **2D masks** of every RGB frame

2. For each 2D mask *m*, we project **superpoints** onto their image planes and calculate the IoUs with predicted **2D masks**

3. We merge all superpoints having sufficient overlap to create an initial **3D proposal of mask** *m*

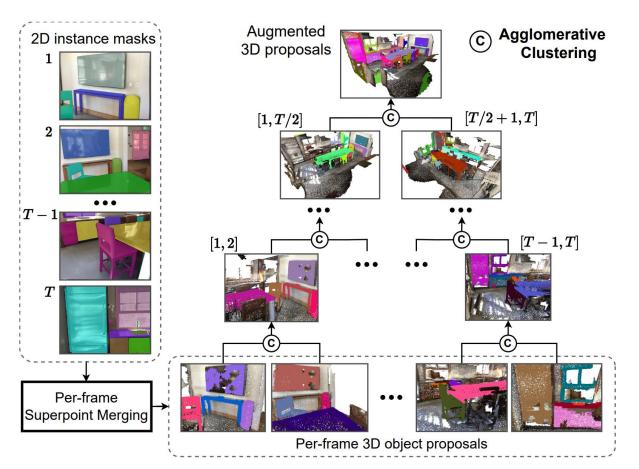


1. We merge point cloud regions from different frames in a bottom-up manner.



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2. Agglomerative clustering is chosen to combine proposals from pairs of frames.

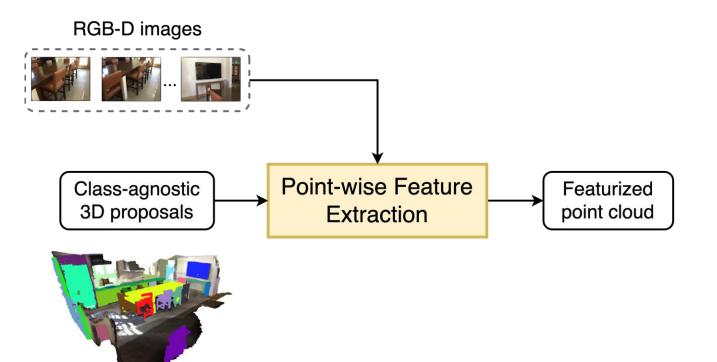


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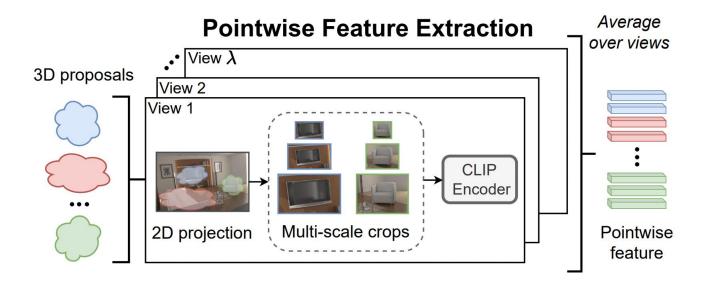
2. Agglomerative clustering is chosen to combine proposals from pairs of frames.

How to obtain featurized point cloud?

Point-wise feature extraction



Point-wise feature extraction



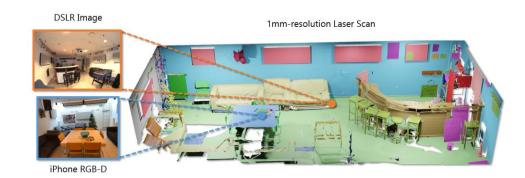
Experiments

Datasets:

- ScanNet++ and ScanNet200
- ARKitScenes
- S3DIS
- Replica

Metrics:

- AP (Average Precision)
- AR (Average Recall)







Quantitative Results: ScanNet200

Method	Setting	3D Proposal	AP	AP ₅₀	\mathbf{AP}_{25}	AP _{head}	AP _{com}	AP _{tail}
ISBNet [36] Mask3D [42]	Fully-sup		24.5 26.9	32.7 36.2	37.6 41.4	38.6 39.8	20.5 21.7	12.5 17.9
OpenScene [37] + DBScan [10] [†]	Open-vocab	None	2.8	7.8	18.6	2.7	3.1	2.6
OpenScene [37] + Mask3D [42]		Mask3D [42]	11.7	15.2	17.8	13.4	11.6	9.9
SAM3D [†] [57]		None	6.1	14.2	21.3	7.0	6.2	4.6
OVIR-3D [†] [33]		None	13.0	24.9	<u>32.3</u>	14.4	12.7	11.7
OpenMask3D [45]		Mask3D [42]	15.4	19.9	23.1	17.1	14.1	14.9
Ours (only 2D)	Open-vocab	None	18.2	<u>26.1</u>	31.4	18.9	16.5	<u>19.2</u>
Ours (only 3D)		ISBNet [36]	<u>18.6</u>	23.1	27.3	<u>24.7</u>	<u>16.9</u>	13.3
Ours (2D and 3D)		ISBNet [36]	23.7	29.4	32.8	27.8	21.2	21.8

Our method surpasses previous OV-3DIS approaches by a large margin, having competitive performance with fully-supervised methods

Quantitative Results: Replica & S3DIS

Method	3D Proposal	AP	AP ₅₀	\mathbf{AP}_{25}
OpenScene + Mask3D	Mask3D	10.9	15.6	17.3
OpenMask3D	Mask3D	13.1	18.4	24.2
OVIR-3D [†]	None	11.1	20.5	27.5
Ours	None	18.1	26.7	30.5

Method	B8 /	'N4	B6/N6			
	\mathbf{AP}^B_{50}	\mathbf{AP}_{50}^N	\mathbf{AP}^B_{50}	\mathbf{AP}_{50}^N		
LSeg-3D [8]	58.3	0.3	41.1	0.5		
PLA [8]	59.0	8.6	46.9	9.8		
Lowis3D [7]	58.7	13.8	51.8	15.8		
Ours	60.8	26.3	50.0	29.0		

Replica

S3DIS

Quantitative Results: ScanNet++

Method	AP	AP ₅₀	\mathbf{AP}_{25}	AR	AR ₅₀	\mathbf{AR}_{25}	NOTE
ISBNet [50] (3D)	6.2	10.1	16.2	10.9	16.9	25.2	pretrained Scannet200
SAM3D [78]	7.2	14.2	29.4				
SAM-guided Graph Cut [18]	12.9	25.3	43.6				
Segment3D [26]	12.0	22.7	37.8				
SAI3D [82] (SAM)	17.1	31.1	49.5				
Ours (SAM)	18.5	33.5	44.3	35.6	63.7	82.7	100 frames per scene
Ours (SAM)	20.7	38.6	47.1	40.8	75.7	91.8	all frames per scene

Qualitative Results on ARKitScenes



Picture of a Horse



Qualitative Results on ARKitScenes



Blue letter M



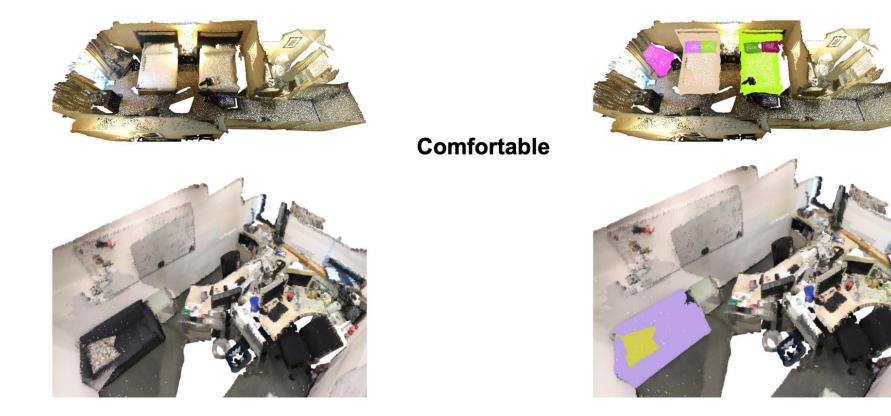
Qualitative Results on ARKitScenes



Watering plants



Qualitative Results on ScanNet200



Qualitative Results on ScanNet200



Wash your hand



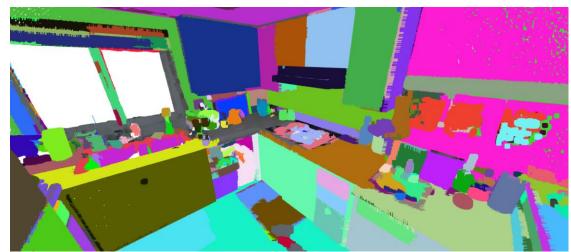
Qualitative Results on ScanNet200



Qualitative Results on ScanNet++

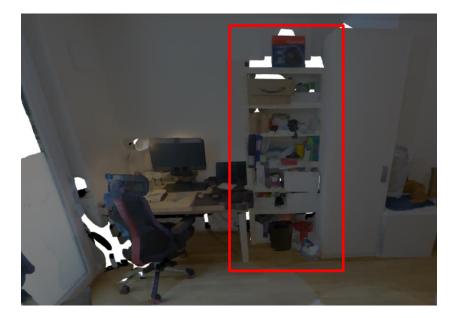


SAM Class-agnostic 3D Instance Segmentation



Qualitative Results on ScanNet++

SAM Class-agnostic 3D Instance Segmentation





Summary

• We introduce **Open3DIS** to address the open-vocabulary 3D instance segmentation task with a novel strategy to generate high-quality 3D proposals from pretrained 2D model.

Our approach achieves state-of-the-art performance on 5 different datasets.

 Future research on adapting Open3DIS for other 3D representation such as 3D Gaussian Splatting would be an interesting exploration.



Thank you!