# **OVIR-3D: Open-Vocabulary 3D Instance Retrieval Without Training on 3D Data**

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21k categories as

text queries

t = 0

Region

**Proposals** 

3D Projection

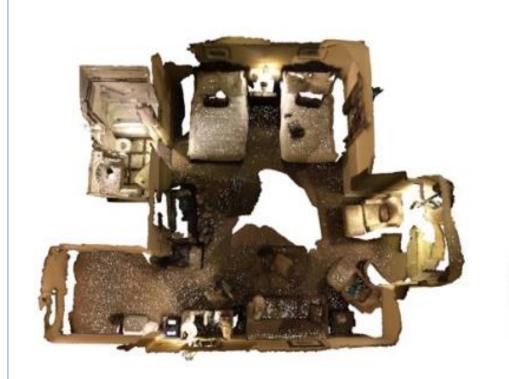
Instance Fusion



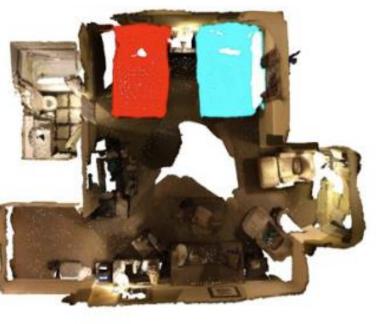
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### Introduction

Recent progress on open-vocabulary (language-driven, without a predefined set of categories) 3D segmentation addresses the problem mainly at the semantic level. Nevertheless, robotic applications, such as manipulation and navigation, often require 3D object geometries at the instance level. This work provides a solution for open-vocabulary 3D instance retrieval, which returns a ranked set of 3D instance segments given a 3D point cloud reconstructed from an RGB-D video and a language query.



a) Original scan





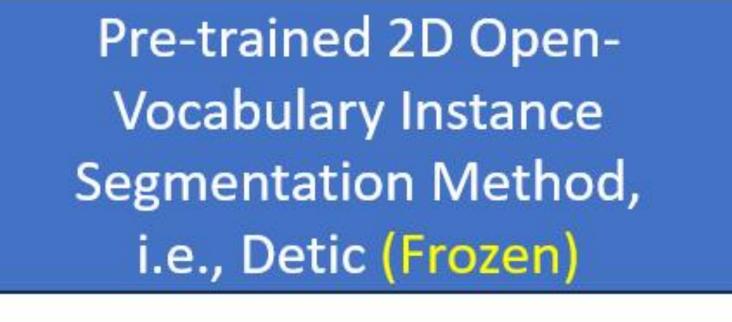
b) Top 2 instances retrieved given the query: "bed"

c) Top 3 instances retrieved given the query: "lamp"

# **Key Takeaways**

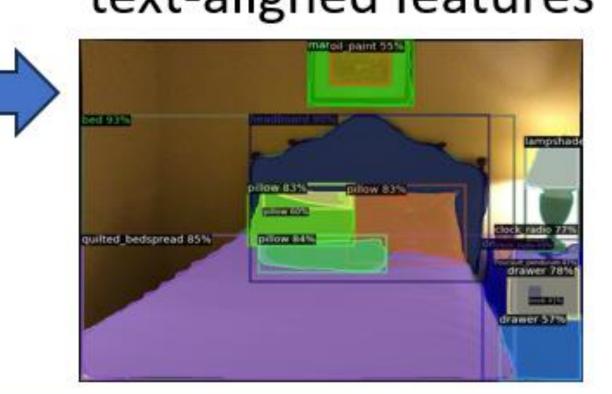
Directly training an open-vocabulary 3D segmentation model is hard due to the lack of annotated 3D data with enough category varieties. Instead, this work views this problem as a 3D fusion problem from language-guided 2D region proposals, which could be trained with extensive 2D datasets, and provides a straightforward yet effective method to project and fused 2D instance information in the 3D space for fast retrieval.

## **Overall Pipeline**



a) Text-aligned 2D Region
Proposal Generation

2D region proposals with text-aligned features





Post-processing

b) 2D-to-3D Instance Fusion

# Query: "Sofa" Text Feature Ranking Memory Bank

Top 1 is shown in blue.

### Quantitative Results

Memory Bank of Queryable 3D Instances

Periodic filtering and merging of instances in the memory bank

The proposed method outperforms existing methods on both ScanNet200 (200 classes) and YCB-Video (21 classes) using mAP metric.

	ScanNet200 [25]		YCB-Video [29]			
Method	$mAP_{50}$	mAP	$mAP_{50}$	mAP		
OpenScene [23]	0.190	0.089	0.333	0.116		
Fusion++ [19]	0.253	0.094	0.464	0.120		
PanopticFusion [21]	0.370	0.150	0.378	0.136		
Ours	0.443	0.211	0.801	0.427		
Table 1. D14 CNI-4200 [25] 1 VOD VI.1 [20]						

Table 1: Results on ScanNet200 [25] and YCB-Video [29]

### **Ablation Studies**

	COCO	ScanNet200	LVIS	ImageNet21k		
$mAP_{50}$	0.228	0.419	0.429	0.443		
	ImageNet21k - ScanNet200					
$mAP_{50}$	0.410					

Table 2: Results on ScanNet200 [25] with different input queries to the region proposal network.

	Average	KMeans(16)	KMeans(64)		
$mAP_{50}$	0.428	0.429	0.443		
	Feature from largest 2D detection				
$mAP_{50}$	0.380				

Table 3: Results on ScanNet200 [25] with different feature ensemble strategies