

A Unified Framework for 3D Scene Understanding

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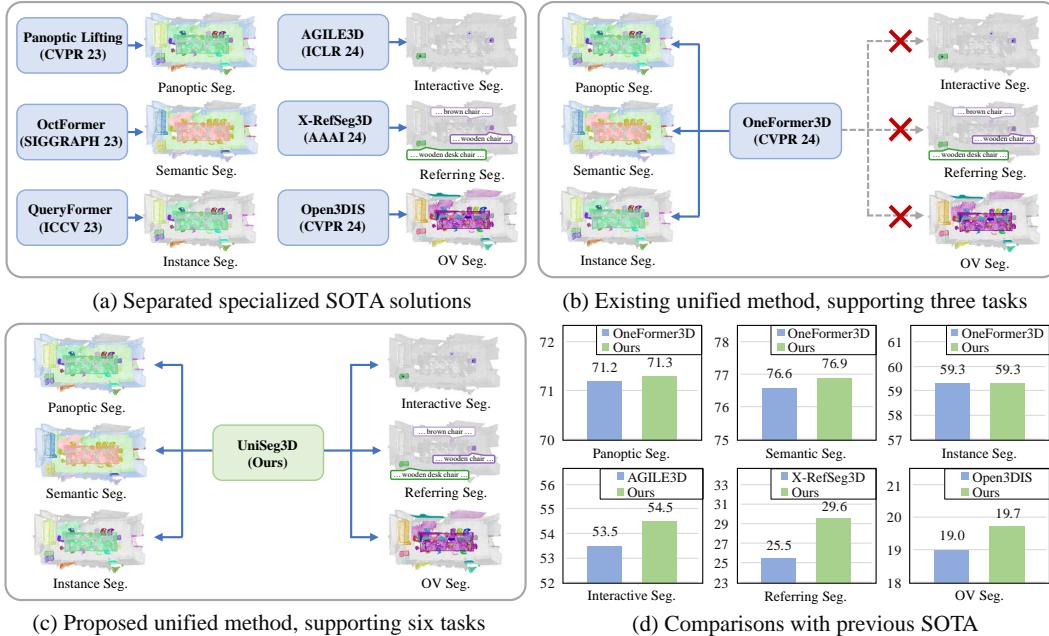


Figure 1: Comparisons between the proposed method and current SOTA approaches specialized for specific tasks. (a) Representative specialized approaches on six tasks. (b) OneFormer3D, a recent unified framework, achieves SOTA performance on three generic segmentation tasks in one inference. (c) The proposed unified framework achieves six tasks in one inference. (d) Our method outperforms current SOTA approaches across six tasks involving two modalities using a single model.

Abstract

We propose UniSeg3D, a unified 3D scene understanding framework that achieves panoptic, semantic, instance, interactive, referring, and open-vocabulary segmentation tasks within a single model. Most previous 3D segmentation approaches are typically tailored to a specific task, limiting their understanding of 3D scenes to a task-specific perspective. In contrast, the proposed method unifies six tasks into unified representations processed by the same Transformer. It facilitates inter-task knowledge sharing, thereby promoting comprehensive 3D scene understanding. To take advantage of multi-task unification, we enhance performance by establishing explicit inter-task associations. Specifically, we design knowledge distillation and contrastive learning methods to transfer task-specific knowledge across different

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tasks. Experiments on three benchmarks, including ScanNet20, ScanRefer, and ScanNet200, demonstrate that the UniSeg3D consistently outperforms current SOTA methods, even those specialized for individual tasks. We hope UniSeg3D can serve as a solid unified baseline and inspire future work. Code and models are available at <https://dk-liang.github.io/UniSeg3D/>.

1 Introduction

3D scene understanding has been a foundational aspect of various real-world applications [3, 68, 18], including robotics, autonomous navigation, and mixed reality. Among the 3D scene understanding tasks, 3D point cloud segmentation is a crucial component. Generic 3D point cloud segmentation contains panoptic, semantic, and instance segmentation (PS/SS/IS) tasks [36, 40, 58, 66, 21], which segment classes annotated in the training set. As a complement, 3D open-vocabulary segmentation (OVS) task [39, 52, 15] segments open-vocabulary classes of interest. Another group of works study to utilize user priors. In particular, 3D interactive segmentation task [23, 67] segments instances specified by users. 3D referring segmentation task [14, 43, 56, 55] segments instances described by textual expressions. The above mentioned tasks are core tasks in 3D scene understanding, drawing significant interest from researchers and achieving great success.

Previous studies [51, 8, 71, 19] in the 3D scene understanding area focus on separated solutions specialized for specific tasks, as shown in Fig. 1(a). These approaches ignore intrinsic connections across different tasks, such as the objects’ geometric consistency and semantic consistency. They also fail to share knowledge biased toward other tasks, limiting their understanding of 3D scenes to a task-specific perspective. It poses significant challenges for achieving comprehensive and in-depth 3D scene understanding. A recent exploration [22] named OneFormer3D designs an architecture to unify the 3D generic segmentation tasks, as shown in Fig. 1(b). This architecture inputs instance and semantic queries to simultaneously predict the 3D instance and semantic segmentation results. And the 3D panoptic segmentation is subsequently achieved by post-processing these predictions. It is simple yet effective. However, this architecture fails to support the 3D interactive segmentation, 3D referring segmentation, and OVS tasks, which provide complementary scene information, including user priors and open-set classes, should be equally crucial in achieving 3D scene understanding as the generic segmentation tasks. This leads to a natural consideration that *if these 3D scene understanding tasks can be unified in a single framework?*

A direct solution is to integrate the separated methods into a single architecture. However, it faces challenges balancing the customized optimizations specialized for the specific tasks involved in these methods. Thus, we aim to design a simple and elegant framework without task-specific customized modules. This inspires us to design the UniSeg3D, a unified framework processing six 3D segmentation tasks in parallel. Specifically, we use queries to unify representations of the input information. The 3D generic segmentation tasks and the OVS task, which only input point cloud without human knowledge, thus can be processed by sharing the same workflow without worrying about prior knowledge leakage. We use a unified set of queries to represent the four-task features for simplification. The interactive segmentation inputs visual point priors to condition the segmentation. We represent the point prompt information by simply sampling the point cloud queries, thereby avoiding repeated point feature extraction. The referring segmentation inputs textual expressions, which persist in a modality gap with the point clouds and are hard to unify in the previous workflows. To minimize the time consumption, we design a parallel text prompt encoder to extract the text queries. All these queries are decoded using the same mask decoder and share the same output head without the design of task-specific customized structures.

We further enhance performance by taking advantage of the multi-task design. In particular, we empirically find that the interactive segmentation outperforms the rest of the tasks in mask predictions, which is attributable to reliable vision priors. Hence, we design knowledge distillation to distill knowledge from the interactive segmentation to the other tasks. Then, we build contrastive learning between interactive segmentation and referring segmentation to connect these two tasks. The proposed knowledge distillation and contrastive learning promote knowledge sharing across six tasks, effectively establishing associations between different tasks. There are three significant strengths of the UniSeg3D: (1) it unifies six 3D scene understanding tasks in a single framework, as shown in Fig. 1(c); (2) it is flexible for that can be easily extended to more tasks by simply inputting the

additional task-specific queries; (3) the designed knowledge distillation and contrastive learning are only used in the training phase, optimizing the performance with no extra inference cost.

We compare the proposed method with task-specific specialized SOTA approaches [48, 54, 34, 67, 43, 38] across six tasks to evaluate its performance. As shown in Fig. 1(d), the UniSeg3D demonstrates superior performance on all the tasks. It is worth noting that our performance on different tasks is achieved by a single model, which is more efficient than running separate task-specific approaches individually. Furthermore, the structure of UniSeg3D is simple and elegant, containing no task-customized modules, while consistently outperforming specialized SOTA solutions, demonstrating a desirable potential to be a solid unified baseline.

In general, our contributions can be summarized as follows: **First**, we propose a unified framework named UniSeg3D, offering a flexible and efficient solution for 3D scene understanding. It achieves six 3D segmentation tasks in one inference by a single model. To the best of our knowledge, this is the first work to unify six 3D segmentation tasks. **Second**, specialized approaches limit their 3D scene understanding to task-specific perspectives. We facilitate inter-task knowledge sharing to promote comprehensive 3D scene understanding. Specifically, we take advantage of multi-task unification, designing the knowledge distillation and contrastive learning methods to establish explicit inter-task associations.

2 Related Work

3D segmentation. The generic segmentation consists of panoptic, semantic, and instance segmentation. The panoptic segmentation [36, 57] is the union of instance segmentation [9, 31, 2, 61, 53] and semantic segmentation [42, 40, 5, 69]. It contains the instance masks from the instance segmentation and the stuff masks from the semantic segmentation. These 3D segmentation tasks rely on annotations, segmenting classes labeled in the training set. The open-vocabulary segmentation [38, 52] extends the 3D segmentation to the novel class. Another group of works explores 3D segmentation conditioned by human knowledge. Specifically, the interactive segmentation [23, 67] segments instances specified by the point clicks. The referring segmentation [14, 43] segments objects described by textual expressions. Most previous researches [62, 4, 24, 30] focus on specific 3D segmentation tasks, limiting their efficiency in multi-task scenarios, such as the domotics, that require multiple task-specific 3D segmentation approaches to be applied simultaneously. This work proposes a framework to achieve the six abovementioned tasks in one inference.

Unified vision models. Unified research supports multiple tasks in a single model, facilitating efficiency and attracting a lot of attention in the 2D area [41, 35, 28, 17]. However, rare works study the unified 3D segmentation architecture. It might be attributed to the higher dimension of the 3D data, which leads to big solution space, making it challenging for sufficient unification across multiple 3D tasks. Recent works [11, 33] explore outdoor unified 3D segmentation architectures, and some others [72, 13, 16] delve into unified 3D representations. So far, only one method, OneFormer3D [22], focuses on indoor unified 3D segmentation. It extends the motivation proposed in OneFormer [17] to the 3D area and proposes an architecture to achieve three 3D generic segmentation tasks in a single model. We note that the supported tasks in OneFormer3D can be achieved in one inference through post-processing predictions of a panoptic segmentation model. In contrast, we propose a simple framework that unifies six tasks, including not only generic segmentation but also interactive segmentation, referring segmentation, and OVS, into a single model. Additionally, we establish explicit associations between these unified tasks to promote knowledge sharing, contributing to effective multi-task unification.

3 Methodology

The framework of UniSeg3D is depicted in Fig. 2. It mainly consists of three modules: a point cloud backbone, prompt encoders, and a mask decoder. We illustrate their structures in the following.

3.1 Point Cloud Backbone and Prompt Encoders

Point cloud backbone. We represent the set of N input points as $\mathbf{P} \in \mathbb{R}^{N \times 6}$, where each point is characterized by three-dimensional coordinates x, y, z and three-channel colors r, g, b . These input

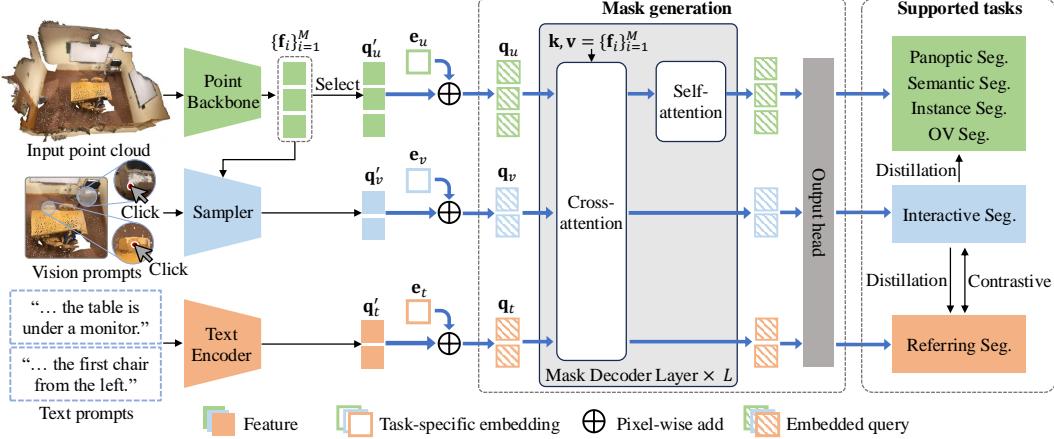


Figure 2: The framework of UniSeg3D. This is a simple framework handling six tasks in parallel without any modules specialized for specific tasks. We take advantage of multi-task unification and enhance the performance through building associations between the supported tasks. Specifically, knowledge distillation transfers insights from interactive segmentation to the other tasks, while contrastive learning establishes connections between interactive segmentation and referring segmentation.

points are then fed into a sparse 3D U-Net, serving as the point cloud backbone, to obtain point-wise features $\mathbf{F} \in \mathbb{R}^{N \times d_{in}}$, where d_{in} denotes the feature dimension. Processing dense points individually in 3D scene understanding can be time-consuming. Therefore, we downsample the 3D scenario into M superpoints and pool the point features within each superpoint to form superpoint features $\mathbf{F}_s = \{\mathbf{f}_i\}_{i=1}^M$, where each $\mathbf{f}_i \in \mathbb{R}^{d_{in}}$ and $\mathbf{F}_s \in \mathbb{R}^{M \times d_{in}}$. This procedure exhibits awareness of the edge textures [26] while reducing cost consumption.

Vision prompt encoder. Click is a kind of clear and convenient visual interaction condition that has been widely employed in previous works [20, 23, 67]. We formulate the clicks as vision prompts, as illustrated in Fig. 2. In practice, a click is first indicated by the spatially nearest point. Then, we sample a superpoint containing this point and employ its superpoint feature as vision prompt feature $\mathbf{f}_v \in \mathbb{R}^{d_{in}}$ to represent the point prompt information, thus avoiding redundant feature extraction and maintaining feature consistency with the point clouds.

Text prompt encoder. UniSeg3D is able to segment instances described by textual expressions. To process a text prompt, the initial step involves tokenizing the text sentence to obtain its string tokens $\mathbf{T} \in \mathbb{R}^{l \times c}$, where l is the sentence length and c represents the token dimension. These tokens are then fed into a frozen CLIP [44] text encoder to produce a C -dimensional text feature $\mathbf{f}_t \in \mathbb{R}^C$. This feature is subsequently projected into the d_{in} dimension using two linear layers, obtaining $\mathbf{f}_t \in \mathbb{R}^{d_{in}}$, aligning the dimension of the point features for subsequent processing.

3.2 Mask Generation

We employ a single mask decoder to output predictions of six 3D scene understanding tasks. The generic segmentation and the OVS share the same input data, *i.e.*, the point cloud without user knowledge. Therefore, we randomly select m features from M superpoint features to serve as unified queries $\mathbf{q}'_u \in \mathbb{R}^{m \times d_{in}}$ for both the generic segmentation and OVS tasks. During training, we set $m < M$ to reduce computational costs, while for inference, we set $m = M$ to enable the segmentation of every region.

The prompt information is encoded into prompt features as discussed in Sec. 3.1. We employ the prompt features as the prompt queries, which can be written as: $\mathbf{q}'_v = \{\mathbf{f}_{v,i}\}_{i=1}^{K_v}$, $\mathbf{q}'_t = \{\mathbf{f}_{t,i}\}_{i=1}^{K_t}$, where $\mathbf{q}'_v \in \mathbb{R}^{K_v \times d_{in}}$, $\mathbf{q}'_t \in \mathbb{R}^{K_t \times d_{in}}$. K_v and K_t are the number of the point and text prompts, respectively. \mathbf{q}'_u , \mathbf{q}'_v , \mathbf{q}'_t are three types of queries containing information from various aspects. Feeding them forward indiscriminately would confuse the mask decoder for digging task-specific information. Thus, we add task-specific embeddings \mathbf{e}_u , \mathbf{e}_v , and \mathbf{e}_t before further processing:

$$\mathbf{q}_u = \mathbf{q}'_u + \mathbf{e}_u, \quad \mathbf{q}_v = \mathbf{q}'_v + \mathbf{e}_v, \quad \mathbf{q}_t = \mathbf{q}'_t + \mathbf{e}_t, \quad (1)$$

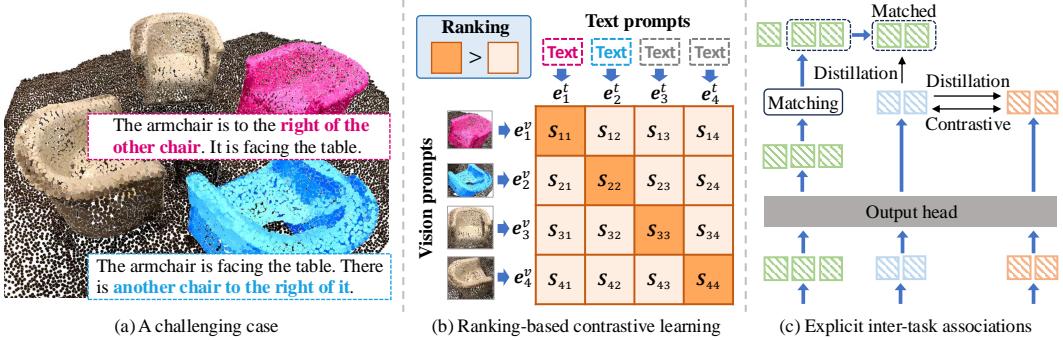


Figure 3: Illustration of the inter-task association. (a) A challenging case requiring the distinction of textual positional information within the expressions. (b) A contrastive learning matrix for vision-text pairs, where a ranking rule is employed to suppress incorrect pairings. (c) Knowledge distillation across multi-task predictions.

where $\mathbf{e}_u \in \mathbb{R}^{d_{in}}$, $\mathbf{e}_v \in \mathbb{R}^{d_{in}}$, $\mathbf{e}_t \in \mathbb{R}^{d_{in}}$, and are broadcasted into $\mathbb{R}^{m \times d_{in}}$, $\mathbb{R}^{K_v \times d_{in}}$, and $\mathbb{R}^{K_t \times d_{in}}$, respectively. The mask decoder comprises L mask decoder layers, which contain self-attention layers integrating information among queries. Prompt priors are unavailable for generic segmentation during inference. Therefore, in the training phase, we should prevent the human knowledge from leaking to the generic segmentation. In practice, the prompt queries are exclusively fed into the cross-attention layers. Output queries of the last mask decoder layer are sent into an output head, which consists of MLP layers to project dimensions d_{in} of the output queries into d_{out} . In general, the mask generation process can be formally defined as:

$$\mathbf{F}_{out} = \text{MLP}(\text{MaskDecoder}(\mathbf{q} = \text{Concat}(\mathbf{q}_u, \mathbf{q}_v, \mathbf{q}_t); \mathbf{k} = \mathbf{F}_s; \mathbf{v} = \mathbf{F}_s)), \quad (2)$$

where $\mathbf{F}_{out} = \{\mathbf{f}_{out,i}\}_{i=1}^{m+K_v+K_t}$ represents output features, with $\mathbf{f}_{out,i} \in \mathbb{R}^{d_{out}}$ and $\mathbf{F}_{out} \in \mathbb{R}^{(m+K_v+K_t) \times d_{out}}$.

Subsequently, we can process the output features to obtain the class and mask predictions. For class predictions, a common practice involves replacing class names with class IDs [22]. However, for our method to support referring segmentation, the class names are crucial information that should not be overlooked. Hence, we encode the class names into text features $\mathbf{e}_{cls} \in \mathbb{R}^{K_c \times d_{out}}$ using a frozen CLIP text encoder and propose to regress the class name features instead, where K_c denotes the number of categories. Specifically, we formulate the mask predictions mask_{pred} and class predictions cls_{pred} as follows:

$$\text{mask}_{pred} = \mathbf{F}_{out} \times \text{MLP}(\mathbf{F}_s)^\top, \quad \text{cls}_{pred} = \text{Softmax}(\mathbf{F}_{out} \times \mathbf{e}_{cls}^\top), \quad (3)$$

where $\text{mask}_{pred} = \{\text{mask}_i\}_{i=1}^{m+K_v+K_t}$ and $\text{cls}_{pred} = \{\text{cls}_i\}_{i=1}^{m+K_v+K_t}$, with $\text{mask}_{pred} \in \mathbb{R}^{(m+K_v+K_t) \times m}$ and $\text{cls}_{pred} \in \mathbb{R}^{(m+K_v+K_t) \times K_c}$. $\text{mask}_i \in \mathbb{R}^m$ and $\text{cls}_i \in \mathbb{R}^{K_c}$ represent the mask outcome and category probability predicted by the i -th query, respectively. The MLP projects $\mathbb{R}^{d_{in}}$ into $\mathbb{R}^{d_{out}}$. Given that mask_{pred} and cls_{pred} are derived from superpoints, we map the segmentation outputs for each superpoint back to the input point cloud to generate point-wise mask and class predictions.

3.3 Explicit Inter-task Association

Previous studies have overlooked the associations among 3D scene understanding tasks, resulting in task-specific approaches that fail to leverage cross-task knowledge. This limitation restricts the understanding of 3D scenes to a task-specific perspective, hindering comprehensive 3D scene understanding. We establish explicit inter-task associations to overcome these constraints.

Specifically, on the one hand, as shown in Fig. 3(a), the referring segmentation is challenging when multiple individuals of identical shapes are arranged adjacently. It requires the method to distinguish the location variations inserted in the text prompts, such as “right of the other chair” vs. “another chair to the right of it.” However, the modality gap between 3D points and linguistic texts sets significant obstructions. We propose ranking-based contrastive learning between the vision and text features to reduce the modality gap and optimize the referring segmentation.

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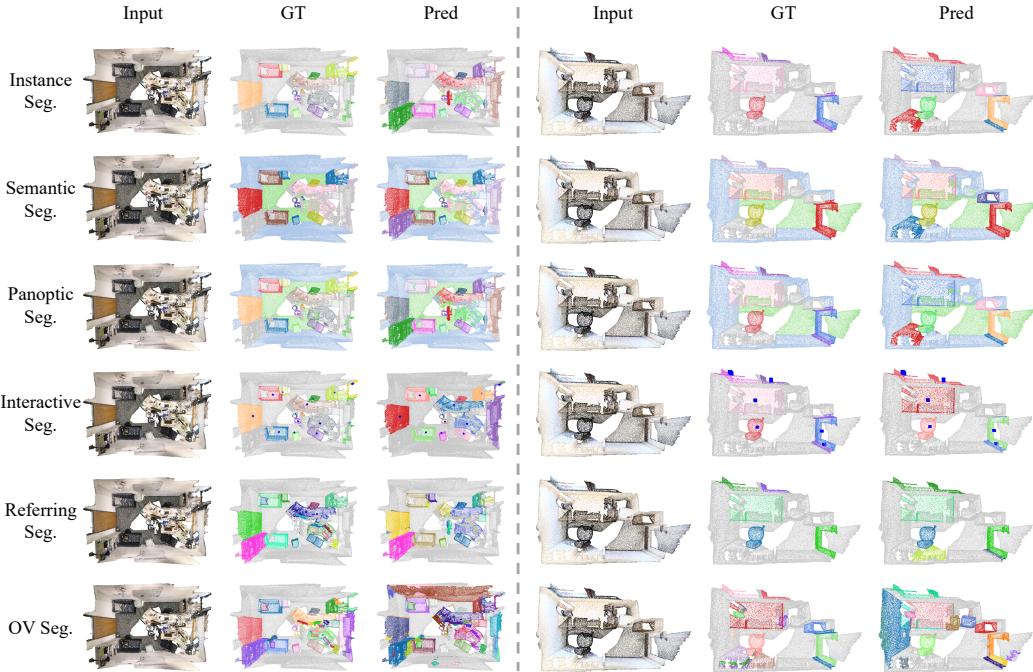


Figure I: Visualization of segmentation results obtained by UniSeg3D on ScanNet20 validation split.

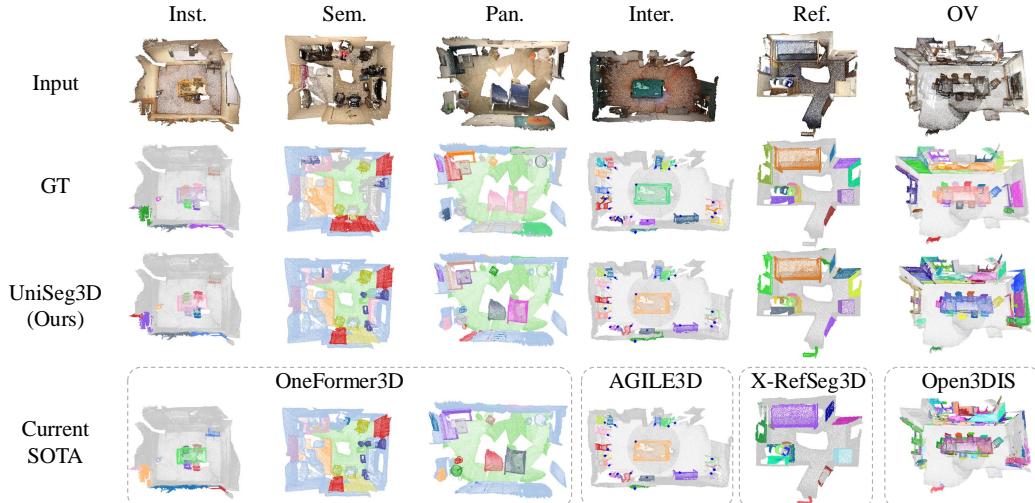


Figure II: Visualization of segmentation results obtained by UniSeg3D and current SOTA methods on ScanNet20 validation split.



Figure III: Visualization of open capabilities. **Red prompts** involve categories not presented in the ScanNet20 annotations, while **blue prompts** describe the attributes of various objects, such as affordances and color.