

Semantic Gaussians: Open-Vocabulary Scene Understanding with 3D Gaussian Splatting

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<https://semantic-gaussians.github.io>

Abstract. Open-vocabulary 3D scene understanding presents a significant challenge in computer vision, with wide-ranging applications in embodied agents and augmented reality systems. Previous approaches have adopted Neural Radiance Fields (NeRFs) to analyze 3D scenes. In this paper, we introduce Semantic Gaussians, a novel open-vocabulary scene understanding approach based on 3D Gaussian Splatting. Our key idea is distilling pre-trained 2D semantics into 3D Gaussians. We design a versatile projection approach that maps various 2D semantic features from pre-trained image encoders into a novel semantic component of 3D Gaussians, without the additional training required by NeRFs. We further build a 3D semantic network that directly predicts the semantic component from raw 3D Gaussians for fast inference. We explore several applications of Semantic Gaussians: semantic segmentation on ScanNet-20, where our approach attains a 4.2% mIoU and 4.0% mAcc improvement over prior open-vocabulary scene understanding counterparts; object part segmentation, scene editing, and spatial-temporal segmentation with better qualitative results over 2D and 3D baselines, highlighting its versatility and effectiveness on supporting diverse downstream tasks.

Keywords: Open-vocabulary Scene Understanding · 3D Gaussian Splatting

1 Introduction

Open-vocabulary 3D scene understanding is a crucial task in computer vision. Given a 3D scene, the goal is to comprehend and interpret 3D scenes with free-form natural language, *i.e.*, without being limited to a predefined set of object categories. Allowing open-vocabulary scene queries enables machines to interact more effectively with the environment, facilitating tasks like object recognition,

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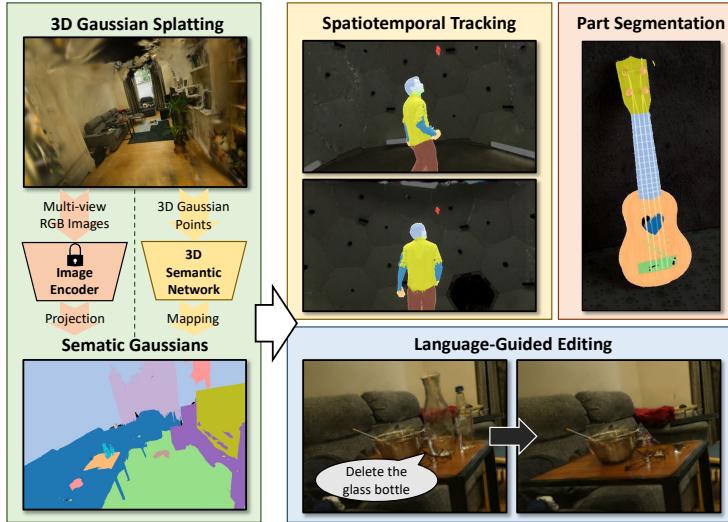


Fig. 1: Overview of our Semantic Gaussians. We inject semantic features into off-the-shelf 3D Gaussian Splatting by either projecting semantic features from pre-trained 2D encoders or directly predicting pointwise embeddings by a 3D semantic network (or fusing these two). The newly added semantic components of 3D Gaussians open up diverse applications centered around open-vocabulary scene understanding.

semantic scene reconstruction, and navigation in complex and diverse surroundings. Open-vocabulary 3D scene understanding has significant implications in various real-world applications such as robotics and augmented reality.

Various methods have been proposed to achieve open-vocabulary 3D scene understanding, relying on different 3D scene representations such as multi-view RGB images [11], point clouds [27, 33], and Neural Radiance Fields (NeRFs) [15, 21]. Approaches based on these representations have their pros and cons: Multi-view images are the most straightforward representation of 3D scenes, but allowing open-vocabulary understanding usually involves 2D vision-language models [1], which could struggle with consistency across different views, likely due to a lack of visual geometric knowledge; Point clouds are popular and well-studied, but the inherent sparsity nature of point clouds limits the application of open-vocabulary scene understanding upon them [27], *e.g.*, it is challenging to obtain a dense prediction on a 2D view; injecting open-vocabulary semantics to NeRFs could enjoy both high 2D rendering quality and dense free-form visual recognition [15], but the implicit design requires open-vocabulary recognition training for every new scene. A recent alternative scene representation is 3D Gaussian Splatting proposed by Kerbl *et al.* [14]. It utilizes 3D Gaussian points with color, opacity, and covariance matrix to represent the 3D scene, which can be learned from multi-view RGB images via gradient descent training. It attains the NeRF-level view rendering quality while preserving the explicit point-based characteristics similar to point clouds, making it suitable for open-vocabulary 3D scene understanding.

In this work, we propose Semantic Gaussians, a novel approach to open-vocabulary 3D scene understanding building upon the benefits of 3D Gaussian Splatting. The core idea of Semantic Gaussians is to distill the knowledge from pre-trained 2D encoders into 3D Gaussians, thereby assigning a *semantic component* to each Gaussian point. To achieve this, we establish correspondence between 2D pixels and 3D Gaussian points and propose a versatile projection framework to map the semantic features of 2D pixels onto each 3D Gaussian point. Our framework is rather flexible and can leverage arbitrary pre-trained 2D models, such as OpenSeg [10], CLIP [29], VLPart [32], etc., to generate pixel-wise semantic features on 2D RGB images. Compared to the NeRF-based approach [15, 36], our method injects semantic components into 3D Gaussians without additional training, allowing for effective open-vocabulary scene queries.

In addition to projection, we further introduce a 3D semantic network that directly predicts open-vocabulary semantic components out of raw 3D Gaussians. Specifically, we employ MinkowskiNet [5], a 3D sparse convolution network to process 3D Gaussians. The 3D convolution network takes raw RGB Gaussians as input and is supervised by the semantic components of Gaussians obtained from the aforementioned projection method. As a result, we may simply run this network to obtain the semantic components, enabling faster inference. Note that the prediction of the 3D semantic network can be combined with the projected features to further improve the quality of semantic components in Gaussians and open-vocabulary scene understanding performances.

We conduct experiments on the ScanNet semantic segmentation benchmark [6], and prove our efficiency compared to 2D pre-trained models. Besides semantic segmentation, we also explore diverse applications of Semantic Gaussians, including 3D part segmentation on the MVIImgNet object dataset [35], scene editing in multi-object scenes, and spatiotemporal tracking on 4D dynamic Gaussians [24].

In summary, our contributions are three-fold:

1. We introduce Semantic Gaussians, a novel approach to open-vocabulary 3D scene understanding by bringing a novel semantic component to 3D Gaussian Splatting.
2. We propose a versatile semantic feature projection framework to map various pre-trained 2D features to 3D Gaussian points, and introduce a 3D semantic network to further allow direct prediction of these semantic components from raw 3D Gaussians;
3. We conduct experiments on the ScanNet segmentation benchmark to demonstrate the effectiveness of our method on open-vocabulary scene understanding and explore various applications including object part segmentation, scene editing, and spatiotemporal tracking.

2 Related Work

2.1 3D Scene Representation

Modeling and representing 3D scenes are crucial initial steps in understanding such environments. Before the advent of deep learning, common methods in-

volved simplifying scenes into combinations of basic elements. Classic approaches include point clouds, meshes, and voxels. Point clouds represent scenes as collections of points, where each point’s XYZ coordinates together form the scene’s geometric shape. Enhancing point clouds with RGB values, semantic labels, and other data enriches their ability to represent scenes. Meshes depict 3D scene surfaces using collections of polygons, with triangular meshes being the most common, representing surfaces as interconnected triangles. By recording the vertices and adjacency relationships of each triangle, 3D scenes can be effectively represented. Voxels discretize continuous 3D space into cubic units, extending the concept of pixels from 2D to 3D. Although these traditional methods have seen success, their limitations are increasingly apparent in today’s pursuit of realistic reconstruction and rendering.

On the other hand, implicit neural representations, represented by Neural Radiance Fields (NeRF), have made remarkable strides in various 3D computer vision tasks. NeRF was initially proposed by Mildenhall *et al.* [26] to address the problem of novel view synthesis. By extracting shape and color information from images captured from multiple viewpoints and learning a continuous 3D radiance field via neural networks, NeRF achieves photorealistic rendering of 3D scenes from arbitrary viewpoints and distances. Succeeding works demonstrate the capability of NeRF in 3D scene representation. Semantic-NeRF [36] explored encoding semantics into a NeRF to achieve 3D scene understanding. EditNeRF [23] defines a conditional NeRF where 3D objects are conditioned on shape and appearance codes to achieve scene editing. Some works [9, 28] jointly predict a canonical space and a temporal deformation field to achieve dynamic scene reconstruction.

Recently, Kerbl *et al.* [14] have proposed a new novel view synthesis method called 3D Gaussian Splatting, which represents the 3D scene with a set of 3D Gaussians. This method has demonstrated real-time rendering capabilities at 1080p resolution, achieving a remarkable 60 frames per second while maintaining state-of-the-art visual quality. The innovation behind 3D Gaussian Splatting lies in its incorporation of point-based α -blending and a differentiable tile rasterizer, enabling efficient rendering. Though it obtains a dense set of Gaussians via optimization, all parameters in these 3D Gaussians are explicit and editable. The speed enhancement and explicit parameterization position 3D Gaussian Splatting as a highly promising representation method. Building upon its success in novel view synthesis, Luiten *et al.* [24] extended the concept to Dynamic 3D Gaussians, explicitly modeling 3D Gaussians at different time steps to accommodate 4D dynamic scenes. Furthermore, Chen *et al.* [4] proposed a text-to-3D generation technique leveraging 3D Gaussian Splatting. In this study, we propose an open-vocabulary 3D scene understanding method, leveraging the advantages offered by 3D Gaussian Splatting.

2.2 Open-Vocabulary Scene Understanding

Scene understanding from 2D. Encouraged by the availability of adequate text-image datasets and the advancement in vision language models, the field of

2D open-vocabulary scene understanding has made significant progress in recent years. Prevailing approaches [18, 20, 25] distill knowledge from large-scale pre-trained foundation models (*e.g.*, CLIP [29]) to achieve zero-shot understanding, including recognizing long-tail objects and understanding synonymous labels. However, these methods are limited to small partial scenes represented by a single 2D image. When it comes to 3D scenes, the prediction result of these 2D models can hardly remain consistent between different angles of view. In contrast, our work relies on these 2D pre-trained models to achieve 3D scene understanding, segmenting, and understanding the scene from a panoptic perspective. Moreover, the proposed 3D network can perform 3D-only scene understanding in the absence of 2D pre-trained models and images.

Scene understanding from 3D. Open-vocabulary 3D scene understanding has been a long-standing challenge in computer vision. Some point-cloud-based methods [7, 12, 27] encode the semantic features from 2D pre-trained models into 3D scene points to achieve open-vocabulary 3D scene understanding. To achieve high-quality rendering and scene understanding simultaneously, feature field distillation in NeRF has been well explored. Early works such as Semantic-NeRF [36] and Panoptic Lifting [31] embed semantic labels into NeRF, resulting in precise 3D segmentation maps. Encouraged by this idea, another branch of methods such as Distill Feature Fields [17], NeRF-SOS [8], LERF [15], 3D-OVS [21] integrate pixel-wise semantic embeddings from pre-trained models such as LSeg [18], CLIP or DINO [3] into NeRFs, achieving open-vocabulary 3D scene understanding. Our work shares a similar idea with those NeRF-based methods, while the Semantic Gaussians requires no extra training for Gaussians. The explicit nature of 3D Gaussian Splatting enables Semantic Gaussians to achieve versatile projection from 2D semantic maps into 3D Gaussian points.

3 Semantic Gaussians

In this section, we illustrate the framework of our Semantic Gaussians. Fig. 2 depicts the overall framework of our method. Semantic Gaussians starts from a group of 3D Gaussians, performing scene understanding on it through 2D versatile projection and 3D semantic network processing. We first introduce our versatile projection method that projects 2D semantic embeddings from various pre-trained vision-language models into 3D Gaussian points (Sec. 3.1). We then depict the 3D semantic network that learns from the projected features and predicts the semantics of 3D Gaussians in unseen scenes (Sec. 3.2). At last, we describe the feature ensemble process and use the prediction result to support various applications (Sec. 3.3).

3.1 2D Versatile Projection

The first contribution of our approach is a versatile feature projection method. We extract pixel-level semantic maps for RGB images from a 2D pre-trained model and project them into 3D Gaussians of a scene.

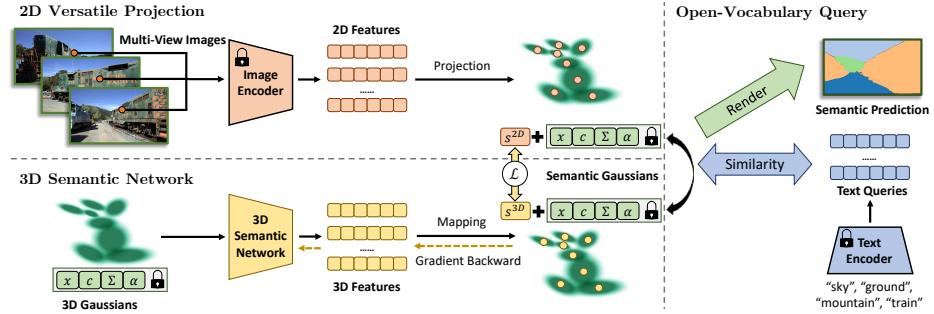


Fig. 2: An illustration of the pipeline of Semantic Gaussians. *Upper left*: our projection framework maps various pre-trained 2D features to the semantic component s^{2D} of 3D Gaussians; *Bottom left*: we additionally introduce a 3D semantic network that directly predicts the semantic components s^{3D} out of raw 3D Gaussians. It is supervised by the projected s^{2D} ; *Right*: given an open-vocabulary text query, we compare its embedding against the semantic components (s^{2D} , s^{3D} , or their fusion) of 3D Gaussians. The matched Gaussians will be splatted to render the 2D mask corresponding to the query.

Semantic Map Extraction. Our method starts from off-the-shelf 3D Gaussians \mathbf{G} of a certain scene. We can use ground-truth RGB images that are used to train 3D Gaussians or render RGB frames via the 3D Gaussians. Owing to the photorealistic rendering performance of 3D Gaussian Splatting, Semantic Gaussians can run without 2D ground-truth images. Given RGB images \mathbf{I} with a shape of $H \times W$, the aim of Semantic Gaussians is to get pixel-level semantic maps denoted by $s \in \mathbb{R}^{H \times W \times C}$ from an arbitrary 2D vision-language model \mathcal{E}^{2D} . The most straightforward avenue to obtain per-pixel semantic maps is utilizing pixel-level segmentation models such as OpenSeg. However, leveraging other encoders, *e.g.* VLPART [32] could help with object parts semantics (not covered by OpenSeg). Moreover, features from different types of models can be integrated as an ensemble to produce more accurate results. Therefore, our versatile projection method should be able to reconcile various visual features.

Unifying Various 2D Features with SAM. Accommodating a variety of 2D pre-trained features is **non-trivial** as they can be pixel-level segmentation network (*e.g.*, OpenSeg [10], LSeg [18]), instance-level recognition network (*e.g.*, GroundingDINO [22], VLPART [32]), or image-level classification network (*e.g.*, CLIP [29]). Semantic Gaussians utilizes Segment Anything (SAM) [16] to produce fine segmentation maps for each model. For pixel-level models, SAM can refine the segmentation boundary. Given an RGB image \mathbf{I} , we use everything prompt in SAM to generate N binary masks $\mathbf{M}_1, \dots, \mathbf{M}_N$. We calculate the average pooling of embeddings in each mask \mathbf{M}_i , and assign it as the embedding of all pixels in this mask: $s[\mathbf{M}_i] = \text{AvgPool}(s[\mathbf{M}_i])$. For instance-level models, we use SAM as the postprocessing module to get fine masks. Similar to Grounded-SAM [30], we use the prediction result from the pre-trained model as the box prompt of SAM. After getting the binary mask, we assign the CLIP embedding of this instance to all the pixels within the instance region. For image-level

models, SAM can be a preprocessing module to get region proposals. We use the “everything” prompt in SAM to get various proposed regions. Each region is padded, cropped, and resized to 224×224 , and fed into the image-level model to get semantic embeddings. Similarly, the semantic embeddings are assigned to all pixels within each proposed region.

2D-3D Projection and Fusion. After acquiring per-pixel semantic maps, Semantic Gaussians projects them into 3D Gaussians to obtain the semantic components. For each pixel $\mathbf{u} = (u, v)$ in a semantic mapping s , Semantic Gaussians tries to find if there are corresponding 3D Gaussian points $\mathbf{p} = (x, y, z)$ in the space. This can be achieved when the camera intrinsic matrix K and world-to-camera extrinsic matrix E are provided. Under the pinhole camera model, the projection can be formulated as $\tilde{\mathbf{u}} = K \cdot E \cdot \tilde{\mathbf{p}}$, where $\tilde{\mathbf{u}}$ and $\tilde{\mathbf{p}}$ are the homogeneous coordinates of \mathbf{u} and \mathbf{p} . After this projection, every pixel \mathbf{u} will correspond to a beam of ray in the 3D space. As we only expect to project 2D semantics to the surface points in 3D space, we perform depth rendering of 3D Gaussians to get the depth map of the 3D scene. During splatting and volume rendering, the opacity is accumulated from near to far. Therefore, we set an opacity threshold α_d , and when the opacity surpasses α_d , the ray of view is occluded by some opaque objects, where we can record the depth. Note that we do not need ground-truth depth from datasets.

When 2D pixels and 3D Gaussian points are paired, assuming that a certain Gaussian point \mathbf{p} in 3D spaces has a group of 2D semantics $\{s_1, \dots, s_K\}$ from K different views, these semantics can be fused by average pooling: $s_{\mathbf{p}}^{2D} = AvgPool(s_1, \dots, s_K)$. By repeating this process for all 3D Gaussian points, we can construct a group of semantic Gaussians for a 3D scene.

3.2 3D Semantic Network

In addition to projecting 2D pre-trained features onto 3D Gaussians, we alternatively explore a more direct approach – predicting the semantic components from the raw 3D Gaussians. In this section, we build a 3D semantic network f^{3D} to do exactly that. Specifically, given the input 3D Gaussians \mathbf{G} , our 3D network f^{3D} predict the point-wise semantic component s^{3D} , which can be formulated as Eqn. 1:

$$s^{3D} = f^{3D}(\mathbf{G}). \quad (1)$$

We use fused features from Sec. 3.1 (denoted by s^{2D}) to supervise the 3D model. The loss function is the cosine similarity loss:

$$\mathcal{L} = 1 - \cos(s^{3D}, s^{2D}). \quad (2)$$

We use MinkowskiNet [5] as the backbone of our 3D model. MinkowskiNet is a 3D sparse convolution network designed for point clouds. Due to the similarity between 3D point clouds and 3D Gaussians, it can be utilized to process 3D

Gaussians. Opacities, colors, and covariance matrixes are set as input features of our 3D model, and the output is the semantic embeddings s^{3D} of every Gaussian point.

Though the supervised target entirely comes from pre-trained 2D encoders, the 3D model recognizes the scene by processing 3D geometric information rather than multiple 2D views, making the result more consistent. Experiments in Sec. 4.2 show that the 3D prediction s^{3D} can complement 2D projection features s^{2D} . Also, the inference speed of our 3D semantic model is much faster than 2D projection.

3.3 Inference

After obtaining the semantic components of 3D Gaussians, we can perform language-driven open-vocabulary scene understanding. In this section, we will detail the inference process. Given a free-form language query, we use the CLIP text encoder to encode the prompts into text embedding \mathbf{t} . We calculate the cosine similarity between the text embedding and the semantic component of every 3D Gaussian point and the matched Gaussians will be viewed as corresponding to the query. Take semantic segmentation and part segmentation as an example, labels of N semantic classes are encoded as $\mathbf{t}_1, \dots, \mathbf{t}_N$. We calculate the cosine similarity between these text embeddings and the semantic embedding of 3D Gaussians:

$$c_n^{2D} = 1 - \cos(s^{2D}, \mathbf{t}_n), c_n^{3D} = 1 - \cos(s^{3D}, \mathbf{t}_n) \quad (3)$$

When 2D and 3D semantic components s^{2D} and s^{3D} both exists, we choose the larger value in c_n^{2D} and c_n^{3D} as the cosine similarity of the class \mathbf{t}_n . The similarities $\{c_1, \dots, c_n\}$ after the softmax function can be the confidence score of each class. To get a 2D semantic segmentation map, the confidence scores are splatted onto 2D views, which is similar to RGB splatting.

4 Experiments

In this section, we conduct various experiments to demonstrate the effectiveness of Semantic Gaussians on open-vocabulary 3D scene understanding and other applications. We first evaluate and compare our method on the ScanNet 2D semantic segmentation benchmark which is constructed on 3D scenes. Then, we exhibit qualitative results on some applications, including part segmentation, spatiotemporal tracking, and language-guided editing. We also provide ablation study results.

4.1 Experimental Setup

For comparisons on semantic segmentation task, we select ScanNet [6] dataset as our 2D segmentation benchmark. ScanNet is a large-scale segmentation benchmark of indoor scenes, with calibrated RGBD trajectories, 3D point clouds, and

ground-truth semantic label maps. We train 3D RGB Gaussians for all 1,201 scenes. We train our 3D semantic network on ScanNet train set and evaluate our performance on the validation set.

For qualitative evaluations, we choose MVIImgNet [35] dataset as our part segmentation dataset, and CMU Panoptic [13] dataset as our spatiotemporal tracking dataset. MVIImgNet is a multi-view single-object dataset containing 238 classes of objects with camera parameters and sparse point clouds. CMU Panoptic dataset is a large-scale dataset for multi-people engaging in social activities. To evaluate Semantic Gaussians on 4D Gaussians, we follow the work of Dynamic 3D Gaussians [24] to construct Gaussians with temporal information. For language-guided editing, we choose some scenes in the Mip-NeRF 360 [2] dataset to show our performance.

4.2 Semantic Segmentation

Comparisons on ScanNet-20. We first evaluate our approach on the 2D semantic segmentation task. We compare our method with OpenSeg [10], an open-vocabulary 2D segmentation model. We report mIoU and mAcc as the metrics of semantic segmentation on the ScanNet-20 benchmark. As we only process off-the-shelf 3D Gaussians and do not care about their training process, we do not report any metrics about rendering quality. The training of 3D Gaussian Splatting follows the official setting. As we are only concerned about semantic segmentation performance, in our method, we extract semantic features from OpenSeg to conduct 2D projection and 3D network training. Consequently, the result in this section will show how much our method will improve from 2D vision-language models.

Table 1: 2D semantic segmentation results on the ScanNet-20 validation set. We report the mean IoU and the mean accuracy on all 20 classes.

	mIoU	mAcc
OpenSeg	45.3	62.0
2D Projection s^{2D}	48.3	65.8
3D Semantic Network s^{3D}	47.2	62.9
2D+3D Ensemble	49.5	66.0

We compare our method to the ScanNet-20 segmentation benchmark. ScanNet-20 benchmark has 20 canonical classes (wall, floor, table, *etc.*) with ground truth semantic labels on each posed 2D image. Table 1 shows the performance of the OpenSeg 2D model and our Semantic Gaussians. We observe that both our 2D projection (Sec. 3.1) and our 3D network (Sec. 3.2) surpass the pre-trained OpenSeg model, even though all of our knowledge comes from it and relies on no ground truth labels. We assume the reason lies in the multi-view information integration, keeping the prediction consistent and mitigating some errors in low-quality views. Moreover, we notice that though the mIoU and mAcc of

our 3D network are lower than the 2D projection, the 2D and 3D ensemble will further improve our performance. We conjecture that some objects in certain scenes cannot be correctly recognized by 2D models in all views due to their low quality, while the 3D network could recognize them by utilizing geometric details.

Ablation Study. We conduct ablation studies to figure out the efficiency of our method. As the performance of 2D projection and 3D network is presented in Sec. 4.2, in this section, we ablate the performance of reducing input features to our 3D network. Points in 3D Gaussian Splatting have many features, *i.e.*, coordinates, colors, rotations, scales, and opacities. If we only use coordinates and colors, they degrade to point clouds. Table 2 shows the comparisons of different inputs. We observe that if we reduce the input features, the mIoU and mAcc of our 3D networks will become much lower, even lower than the OpenSeg pre-trained model in Table 1. This implies that the extra features in 3D Gaussian Splatting are important, and provide more information than RGB point clouds.

Table 2: Performance of different input features on the ScanNet-20 validation set. "XYZ+RGB" means the input of the 3D network only contains the coordinate and the color information of 3D Gaussians, and "Full Gaussians" keeps the same setting as our main experiments. "3D" and "2D+3D" denote our 2D projection method and the 2D-3D ensemble method.

		mIoU	mAcc
3D	Only XYZ+RGB	44.8	59.2
	Full Gaussians	47.2	62.9
2D+3D	Only XYZ+RGB	47.7	63.9
	Full Gaussians	49.5	66.0

4.3 Part Segmentation

In this section, we show the application of our Semantic Gaussians on part segmentation. As OpenSeg cannot tell object parts correctly, here we extract features from VLPart [32] and use SAM [16] to refine the segmentation result. The experiments are conducted on the MVIImgNet dataset, which has different types of single objects suitable for part segmentation. The MVIImgNet dataset does not have ground truth segmentations, so we compare our methods with other baseline models. Specifically, we compare our method with 2D vision-language models including OpenSeg and VLPart, and LERF [15], a NeRF-based method that distills knowledge from multi-scale CLIP.

Fig. 3 shows the qualitative result of part segmentation. From the result, we find that OpenSeg and LERF cannot distinguish object parts correctly, as their capabilities are limited by their training data. By contrast, VLPart is trained on object part segmentation dataset and it can tell parts effectively. However,

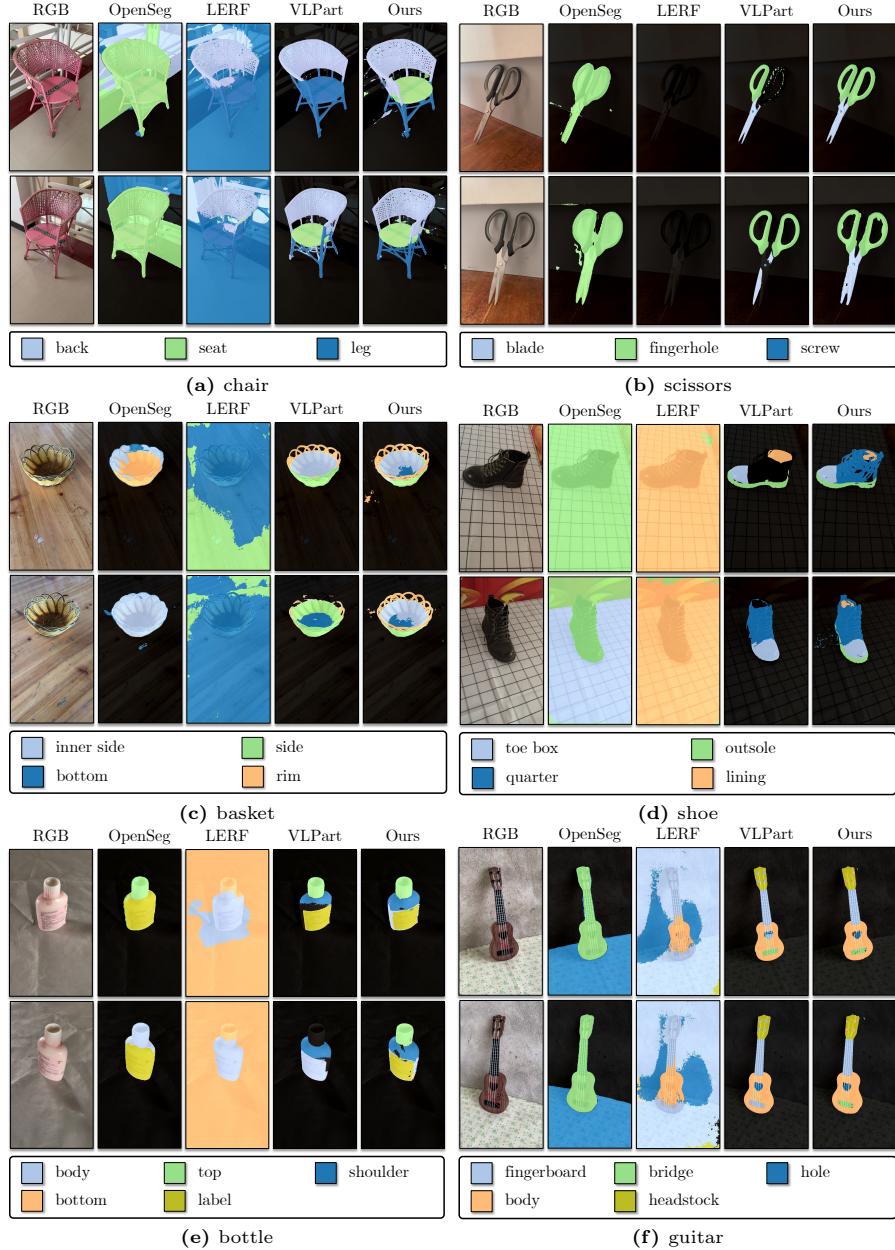


Fig. 3: Qualitative comparisons of different methods on the MVImgNet part segmentation task. We choose 6 classes of objects with 3, 4 and 5 parts to show the part segmentation performance.

VLPart cannot keep segmentation consistency across different views, while our

Semantic Gaussians distills knowledge from VLPart, and can keep high-quality segmentations in all views.

4.4 Spatiotemporal Tracking

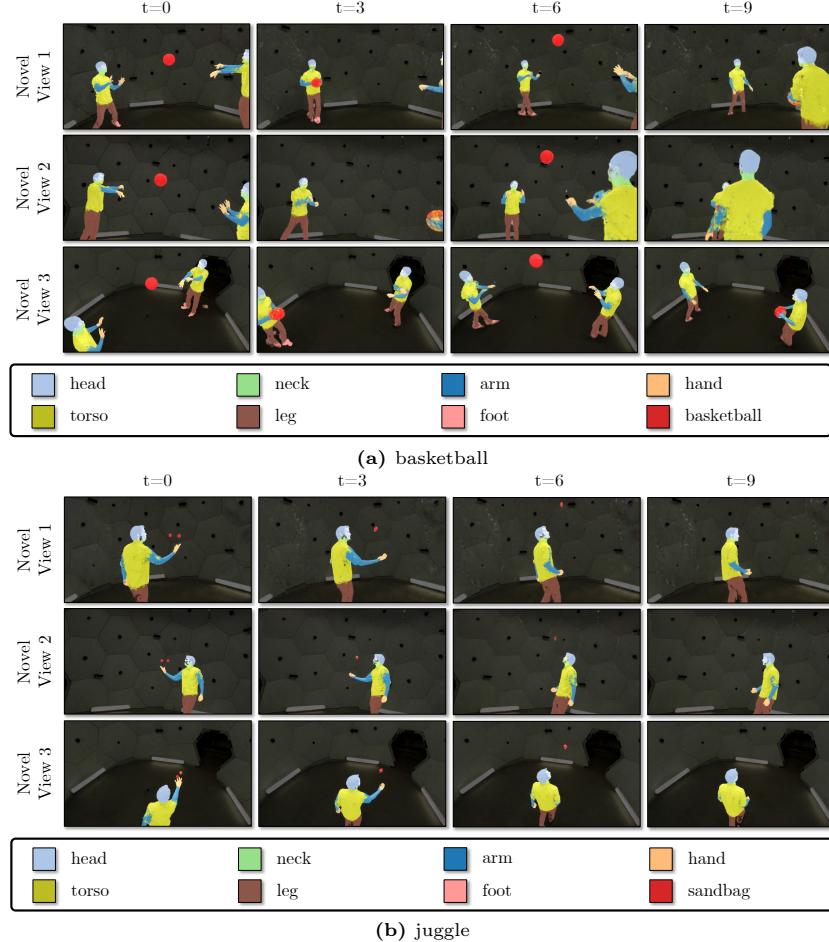


Fig. 4: Qualitative results of spatiotemporal tracking on the CMU Panoptic dataset.

In this section, we show the performance of our Semantic Gaussians on spatiotemporal tracking. 3D Gaussian Splatting is originally designed to represent a static scene, while some succeeding works [19, 24, 34] ameliorate it to support 4D dynamic scenes. We follow the work of Dynamic 3D Gaussians [24] to represent

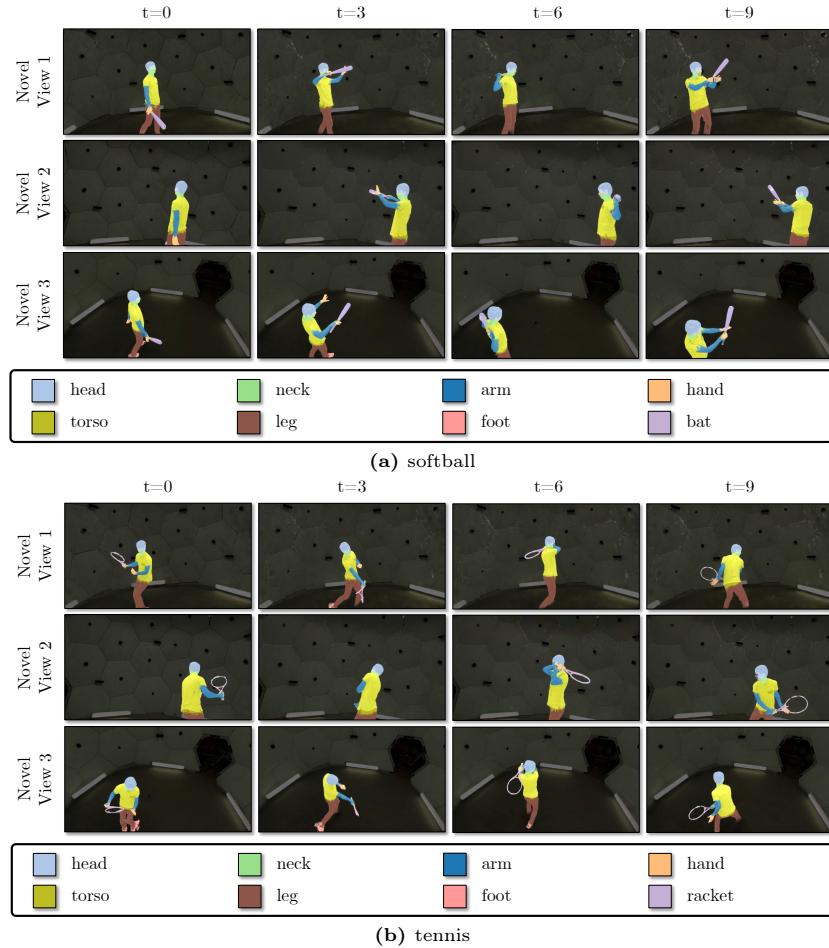


Fig. 5: More qualitative results of spatiotemporal tracking on the CMU Panoptic dataset.

a spatiotemporal scene and use their pre-trained scenes from the CMU Panoptic dataset [13] to evaluate our tracking performance.

Fig. 4 and Fig. 5 show the qualitative result of our spatiotemporal tracking. As the scene often contains 1 2 humans and a dynamic object, we use VLPart in 2D projection and perform human part segmentation simultaneously. For each dynamic 3D Gaussian, we conduct our method at every frame to avoid looking at future frames. We render some novel views to show our capability of spatial tracking. The results show that our Semantic Gaussians can track human parts and objects with a high accuracy between different views and timesteps.

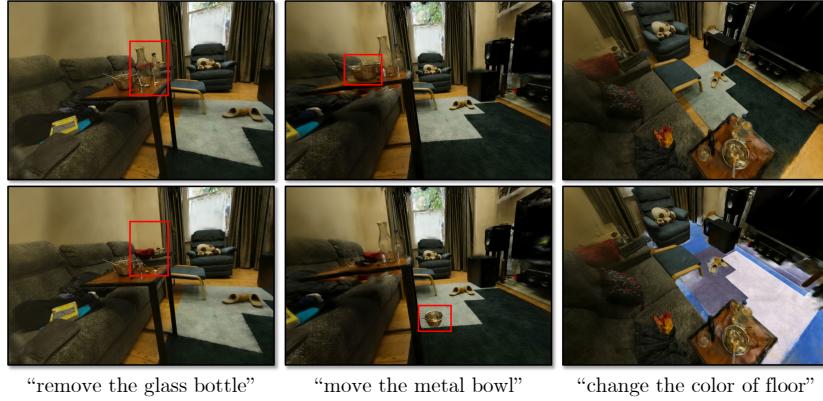


Fig. 6: Qualitative examples of language-guided editing. We perform object removal, movement, and color change on Mip-NeRF 360 room scene.

4.5 Language-guided Editing

In this section, we show the application of language-guided editing of our Semantic Gaussians. Our method can predict semantic embeddings for each 3D Gaussian point, and thus we can choose certain points by language query. Fig. 6 shows some qualitative examples of language-guided editing on the room scene in the Mip-NeRF 360 dataset [2]. In this example, we use CLIP text embeddings of "glass bottle", "metal bowl" and "floor" to query and choose certain 3D Gaussian points in the scene, and we edit them by modifying their properties such as coordinates, colors, opacities, *etc.* Examples in Fig. 6 demonstrate our effectiveness in language-guided editing.

5 Conclusion

In this work, we propose Semantic Gaussians, a novel approach to open-vocabulary 3D scene understanding via 3D Gaussian Splatting. Semantic Gaussians distill knowledge from pre-trained 2D encoders by projecting 2D pixel-level embeddings to 3D Gaussian points. Moreover, we introduce a 3D sparse convolutional network to predict semantic components with the input of RGB Gaussians, thus achieving zero-shot generalization to unseen 3D scenes. We conduct experiments on the ScanNet segmentation benchmark to prove its effectiveness and exhibit downstream applications such as part segmentation, spatiotemporal tracking, and scene editing. Our work paves the way for real-world applications of 3D Gaussian Splatting, such as embodied agents and augmented reality systems.

Albeit the advantages we have demonstrated, our Semantic Gaussians framework does have limitations. The scene understanding performance is bottlenecked by the performance of 2D pre-trained models and off-the-shelf 3D Gaussians. On the one hand, if the 2D pre-trained model completely fails to recognize the scene, Semantic Gaussians will fail either. Our proposed 3D semantic network can help lift the performances to some extent. Further, we may reconcile features

from multiple 2D pre-trained encoders. On the other hand, if the 3D Gaussians cannot generalize well to a needed novel view, *i.e.*, the 3D Gaussian-based scene representation is weak, Semantic Gaussians will not be able to provide robust scene understanding with that novel view as well. This limitation belongs to 3D Gaussian Splatting, as we do not modify any property of 3D Gaussians. Fortunately, 3D Gaussian Splatting is gaining much popularity recently, and we believe the progress made on 3D Gaussian Splatting will improve the performance of our Semantic Gaussians.

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