# econSG: Efficient and Multi-view Consistent Open-Vocabulary 3D Semantic Gaussians

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## Abstract

The primary focus of most recent works on open-vocabulary neural fields is extracting precise semantic features from the VLMs and then consolidating them efficiently into a multi-view consistent 3D neural fields representation. However, most existing works over-trusted SAM to regularize image-level CLIP without any further refinement. Moreover, several existing works improved efficiency by dimensionality reduction of semantic features from 2D VLMs before fusing with 3DGS semantic fields, which inevitably leads to multi-view inconsistency. In this work, we propose econSG for open-vocabulary semantic segmentation with 3DGS. Our econSG consists of: 1) A Confidence-region Guided Regularization (CRR) that mutually refines SAM and CLIP to get the best of both worlds for precise semantic features with complete and precise boundaries. 2) A low dimensional contextual space to enforce 3D multi-view consistency while improving computational efficiency by fusing backprojected multi-view 2D features and follow by dimensional reduction directly on the fused 3D features instead of operating on each 2D view separately. Our econSG show state-of-the-art performance on four benchmark datasets compared to the existing methods. Furthermore, we are also the most efficient training among all the methods. We will make our source-code open source upon paper acceptance.

## 1 Introduction

The advances in neural 3D scene representation techniques have revolutionized many research and applications in computer vision and graphics. Among these neural 3D scene representation techniques, Neural Radiance Field (NeRF) (Mildenhall et al., 2021) stands out for its ability to learn 3D neural fields directly from 2D images with excellent performance in important real-world applications such novel view synthesis. Recently, the explicit 3D Gaussian Splatting (3DGS) (Kerbl et al., 2023) has been proposed as an alternative to the implicit NeRF. This technique has demonstrated remarkable reconstruction quality while maintaining high training and rendering efficiency. Concurrent to neural 3D scene representation techniques, large visual-language models (VLMs) such as the CLIP model (Radford et al., 2021) have shown extremely strong capability in zero-shot transfer to the open-world setting for various downstream tasks such as image semantic segmentation, *etc*.

The parallel rapid developments of neural 3D scene representation and large multi-modality foundation models naturally lead to research on open-vocabulary 3D scene understanding by leveraging the neural rendering capability of neural fields to align the visual-language models to 3D scenes. To this end, almost all existing works (Kerr et al., 2023; Liu et al., 2024; Qin et al., 2023; Liao et al., 2024; Shi et al., 2023; Zhou et al., 2024; Ye et al., 2023; Guo et al., 2024) unanimously adhered to the fundamental pipeline of first extracting semantic features of the given multi-view images from open-world 2D visual-language models (VLMs), followed by using the multi-view semantic features to train semantic fields appended to NeRF or 3DGS. Following the fundamental pipeline, the primary focus of most existing works is on extracting precise semantic features from the VLMs and then consolidating them efficiently into a multi-view consistent 3D neural fields representation.

Early approach LeRF (Kerr et al., 2023) leverages CLIP to get semantic features from each of the input multi-view images. However, this often results in semantic features that are incomplete or with ambiguous boundaries since CLIP is trained on image-level captions despite the attempt in LeRF to improve the granularity with multi-scale CLIP features. Several subsequent works utilize

Segment Anything Model (SAM) (Kirillov et al., 2023) or DINOv2 (Oquab et al., 2023) to improve the accuracy of the semantic features from CLIP. 3DOVS (Liu et al., 2024) and LEGaussians (Shi et al., 2023) use the semantic features with better boundaries from DINO to complement CLIP. Feature-3DGS (Zhou et al., 2024) extracts semantic features from either SAM or LSeg (Li et al., 2022). Gaussian Grouping (Ye et al., 2023) leverages only the masks from SAM, leading to class-agnostic segmentation. Semantic Gaussian (Guo et al., 2024) and OV-NeRF (Liao et al., 2024) unify 2D CLIP features with the class-agnostic instance masks generated from SAM. All the above-mentioned works over-trusted DINOv2 or SAM without making any refinement, which we show empirically (*cf.* Fig. 3 Column (b) shows missing regions in the mask proposals from SAM) to be imperfect too.

Several approaches such as OV-NeRF (Liao et al., 2024), LeRF (Kerr et al., 2023), 3DOVS (Liu et al., 2024) and Feature-3DGS (Zhou et al., 2024) naively adopt the same dimension for the 3D neural semantic fields as the high dimensional semantic features from 2D VLMs, which inevitably incurs high computational complexity for training and querying. Methods such as LangSplat (Qin et al., 2023) and LeGaussians (Shi et al., 2023) propose the use of autoencoder or quantization to reduce the dimension of the multi-view 2D semantic features, and therefore result in similar reduction of dimension in the 3D neural semantic fields for efficient training and querying. However, the reduction of feature dimension are carried out in the 2D space before lifting into the 3D space, and this can lead to multi-view inconsistency that hurts performance. Although Gaussian Grouping (Ye et al., 2023) is efficient by learning 3DGS only for class-agnostic mask rendering, it consequently lacks semantic language information for each Gaussian.

In this paper, we propose efficient and multi-view consistent 3D semantic Gaussians (econSG), a simple yet effective zero-shot model for 3D semantic understanding. Our proposed econSG consists of: 1) **Confidence-region Guided Regularization (CRR)** to alleviate the incompleteness and ambiguous boundaries of the semantic features obtained from VLMs. In contrast to other approaches which over-trusted SAM or DINO, our CRR is designed to get the best from both worlds of OpenSeg (Ghiasi et al., 2022) (or LSeg) and SAM with strong 3D multi-view consistency. Specifically, our CRR first fuses backproject high confidence OpenSeg semantic features from multiple views using the depth maps obtained from Colmap (Schönberger et al., 2016). We then fit a bounding box on the fused features reprojected onto each view to prompt SAM for better region masks, which we use to guide refine the OpenSeg semantic features towards well-defined boundaries. 2) **Low-Dimensional 3D Contextual Space** to enforce 3D multi-view consistency and enhance computational efficiency. To enforce 3D multi-view consistency, we build a 3D contextual space from 3D features obtained by fusing the backprojected multi-view 2D features instead of operating on each 2D view separately. We then pre-train an autoencoder to get the low-dimensional latent semantic space for initializing the 3DGS semantic fields, where the encoder of the pre-trained autoencoder is also used to project semantic features from our CRR into the same dimension as the low-dimensional latent semantic space to supervise the 3DGS semantic fields. Our model is more efficient since we have strong initialization for the 3DGS semantic fields, and we perform optimization and rendering only in the 3D low-dimensional latent space.

We summarize our **main contributions** as follows: 1) We propose a Confidence-region Guided Regularization (CRR) to get 2D semantic features with complete and precise boundaries by mutual guidance from OpenSeg and SAM with strong awareness of multi-view consistency. 2) We design an autoencoder with one-time pretraining to get the low-dimensional 3D contextual space for initialization of the 3D neural semantic fields, and enforce multi-view consistency by backprojecting 2D features from CRR into the same dimension as the low-dimensional 3D contextual space for efficient training. 3) Our econSG show state-of-the-art performance on four benchmark datasets: Scannet (Dai et al., 2017), LeRF (Kerr et al., 2023), replica (Straub et al., 2019) and 3DOVS (Liu et al., 2024) compared to the existing methods. Furthermore, we are also the most efficient training among all the methods.

## 2 Related Work

**2D Open-vocabulary Segmentation.** 2D open-vocabulary segmentation has seen considerable growth due to the availability of vast text-image datasets and computational resources. Advancements in large visual language models (Alayrac et al., 2022; Jia et al., 2021; Radford et al., 2021)

have significantly enhanced zero-shot 2D scene understanding, even for long-tail objects in images. To enable zero-shot predictions without prior knowledge of the categories, a common approach is to use vision-and-language cross-modal encoders, which are trained to map images and text labels into a unified semantic space. However, these models often produce embeddings at the image level, which are not suitable for tasks requiring pixel-level information. Recent efforts (Ghiasi et al., 2022; Kuo et al., 2022; Li et al., 2022; Zhou et al., 2022; Rao et al., 2022) aim to bridge this gap by correlating dense image features with language model embeddings, enabling users to detect, classify or segment objects in images with arbitrary text labels. Predominant open-vocabulary segmentation methods (*e.g*. LSeg (Li et al., 2022)) often rely on distilling knowledge from large-scale pre-trained models such as image-text contrastive learning models (*e.g*. CLIP (Radford et al., 2021)) and diffusion models(Rombach et al., 2022). These approaches leverage the rich semantic information captured during pre-training to perform segmentation tasks. However, the distillation process necessitates fine-tuning on specific datasets with a limited vocabulary which undermines the open-vocabulary capability and results in reduced performance in recognizing rare classes. OpenSeg (Ghiasi et al., 2022) utilizes weak supervision through image captions without fine-tuning on a specific class set, but its vocabulary is limited compared to CLIP due to a smaller training dataset. In contrast, our method bypasses fine-tuning CLIP and effectively handles open world classes.

**3D Open-vocabulary Segmentation.** The success of 2D open-vocabulary segmentation has inspired many recent works (Peng et al., 2023; Ding et al., 2023; Nguyen et al., 2024; Takmaz et al., 2023) on 3D open-vocabulary segmentation on 3D point clouds. Many of these existing works share the same design principle of proposing a framework to align pretained 2D open-vocabulary segmentation frameworks such as LSeg (Li et al., 2022) to the feature embeddings of the point cloud. Although these works do not have to worry about 3D consistency, they primarily rely on point clouds that are relatively more difficult to obtain than multi-view images. To enable multi-view images as input, there has been a significant increase in NeRF-based (Mildenhall et al., 2021) 3D segmentation. Semantic-NeRF (Zhi et al., 2021) constructs a semantic field which enables the synthesis of semantic segmentation masks from novel views. However, this method requires a large number of annotated labels, which is non-trivial and costed. Some methods (Tschernezki et al., 2022; Fan et al., 2022) utilize the self-supervised feature extractor (*e.g*. DINO (Caron et al., 2021)) to extract 2D features and distill features into the semantic field. More recently, several NeRF-based works (Kerr et al., 2023; Liu et al., 2024; Kobayashi et al., 2022) have explored textual descriptions combined with CLIP models to achieve open-vocabulary 3D semantic understanding. LERF (Kerr et al., 2023) grounds the language field within NeRF by optimizing multiscale embeddings from CLIP into 3D scenes. 3DOVS (Liu et al., 2024) distills open-vocabulary multimodal knowledge from CLIP and object boundary information from DINO into the NeRF. Wang et al. (2024) focuses on proposing a 3D open-vocabulary segmentation framework that can generalize to unseen scenes. Despite promising results, NeRF-based approaches are marred by slow training and rending. We circumvent these issues by using the more efficient 3D Gaussian Splatting.

**3D Gaussian Splatting.** 3D Gaussian Splatting (3DGS) (Kerbl et al., 2023) has recently gained popularity as a technique for real-time radiance field rendering and 3D scene reconstruction. Inspired by the success of 3DGS in novel view synthesis, various works (Luiten et al., 2023; Yi et al., 2023; Ye et al., 2023) have adapted it for various tasks to leverage its efficient rendering process. For real-time rendering of dynamic scenes, some studies (Luiten et al., 2023; Wu et al., 2023; Yang et al., 2023a) utilize techniques such as dense scene element tracking (Luiten et al., 2023) and deformation field modeling (Yang et al., 2023b). Another line of research (Chen et al., 2023; Tang et al., 2023; Yi et al., 2023) combines Gaussian Splatting with diffusion-based models for 3D content creation, yielding high-quality generation results. DreamGaussian (Tang et al., 2023) proposes an efficient 3D text-to-3D generation method using a generative 3DGS model. However, Gaussian Splatting methods enabling object-level or semantic understanding of the 3D scene are still under-explored yet meaningful. Gaussian Grouping (Ye et al., 2023) extends Gaussian Splatting beyond mere scene appearance and geometry modeling with instance level modeling based on class-agnostic SAM masks. Feature3DGS (Zhou et al., 2024) learns high-dimensional semantic field in 3D Gaussians based on CLIP semantic features from multiple training views, leading to high computational cost. LangSplat (Qin et al., 2023) and LEGaussians (Shi et al., 2023) encode multi-view features from 2D pre-trained VLMs into 3DGS via different feature dimension reduction techniques. However, the effectivenss of these approaches is hindered by the limitations of rendering efficiency and 3D semantic inconsistency across multiple training views. In contrast, we do not directly apply

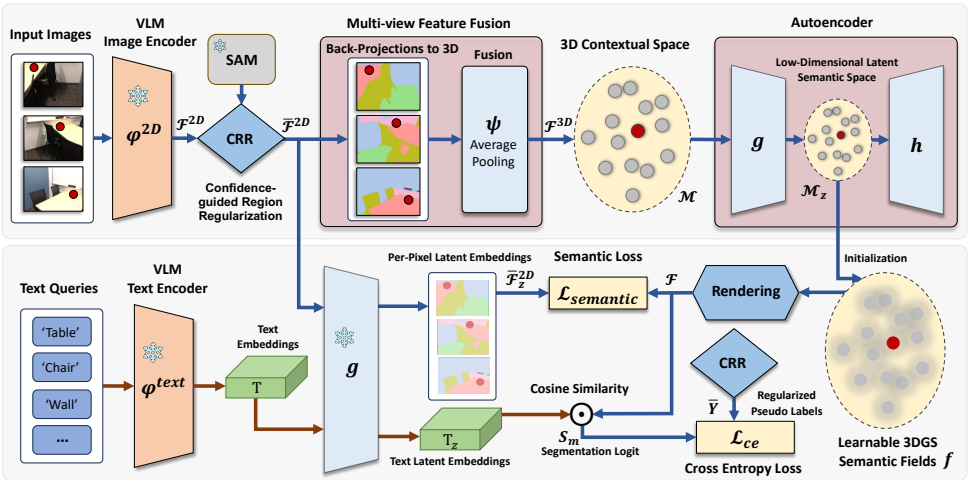


Figure 1: **Our econSG framework.** 1) Top: Building 3D contextual latent space. We use the image encode from a VLM and our CRR to get 2D features $\hat{\mathcal{F}}^{2D}$, which are then back-projected and fused in 3D to get the high dimensional 3D contextual code $\mathcal{M}$. An autoencoder $[g, h]$ is learned to map $\mathcal{M}$ into the low dimensional space $\mathcal{M}_z$. 2) Bottom: 3DGS for semantic fields. We optimize for the 3DGS semantic fields $f$ with $\mathcal{L}_{semantic}$ and $\mathcal{L}_{ce}$ supervised by the image $\hat{\mathcal{F}}^{2D}$ and text $T_z$ latent embeddings obtained by the encoder $g$, respectively. $\mathcal{M}_z$ is used to initialize $f$.

inconsistent and imprecise semantics from 2D VLMs across views to optimize 3DGS. Instead, we construct a multi-view consistent 3D embedding space for modeling the 3DGS semantic fields.

## 3 Preliminaries: 3D Gaussian Splatting

3DGS (Kerbl et al., 2023) explicitly represents the 3D scene as a set of anisotropic 3D Gaussians, which share similarity with point clouds. Each Gaussian is characterized by a center point vector $\mu \in \mathbb{R}^3$ and a covariance matrix $\Sigma \in \mathbb{R}^{3\times3}$, which influences a 3D point $x$ in the scene following the 3D Gaussian distribution: $G(x) = \frac{1}{(2\pi)^{\frac{3}{2}}|\Sigma|^{\frac{1}{2}}} e^{-\frac{1}{2}(x-\mu)^\top \Sigma^{-1}(x-\mu)}$. To ensure positive semi-definite $\Sigma$ and differential optimization, $\Sigma = RSS^\top R^\top$ is decomposed into two learnable components: a scaling matrix $S \in \mathbb{R}^3$ and a rotation quaternion matrix $R \in \mathbb{R}^4$. Additionally, each Gaussian is parameterized by an opacity value $o \in \mathbb{R}$ and an appearance feature vector defined by $n$ spherical harmonic (SH) coefficients $\mathcal{C} = \{c_i \in \mathbb{R}^3 \mid i = 1, 2, \ldots, d^2\}$, where $d^2$ is the number of coefficients of SH with degree $d$. For rendering, 3D Gaussians are projected onto the image plane of the given view by the $\alpha-$ blending function as follows: $c = \sum_{i=1}^{n} c_i \alpha_i \prod_{j=1}^{i-1}(1-\alpha_j)$. $c$ is the final color in the rendered image computed by blending $n$ ordered Gaussians that overlap onto the pixel. $c_i \in \mathbb{R}^3$ represent color computed from SH coefficients in the $i^{\text{th}}$ Gaussian. $\alpha_i$ is obtained by multiplying the projected 2D covariance matrix $\Sigma' \in \mathbb{R}^{2\times2}$ with the learned opacity. $\Sigma' = JW\Sigma W^\top J^\top$ in the camera coordinates is computed using view transform matrix $W$ and the Jacobian matrix $J$ of the affine approximation of the projective transformation.

## 4 Our Method

**Objective.** We start with a set of posed views $\mathcal{I}$ and a set of text queries $\mathcal{T}$ that represent the semantic classes. Given the posed images $\mathcal{I}$ and the text queries $\mathcal{T}$, the goal is to synthesize semantic masks from novel views rendered by 3DGS parameterized by $\{x, \mu, R, S, c, f\}$, where $f$ is an additional optimizable semantic field we add to the 3DGS.

**Overview.** Fig 1 shows an overview of our econSG which consists of: 1) A **pre-training stage** where we first design the ***Confidence-guided Region Regularization (CRR)*** that mutually refines OpenSeg and SAM to get the 2D semantic features. In contrast to (Ye et al., 2023; Liao et al., 2024; Guo et al., 2024; Liu et al., 2024; Shi et al., 2023), our CRR avoids over-trusting DINO

or SAM which we empirically show to be imperfect (*cf.* Fig. 3 Column (b)). We then train an autoencoder for the ***low-dimensional 3D contextual space*** to improve training and query efficiency of the 3DGS semantic fields in the next stage. Unlike (Qin et al., 2023; Shi et al., 2023) which compress semantic features in the 2D space before 3D fusion, we enhance 3D consistency by first fusing the backprojected 2D semantic features to get the 3D contextual space followed by training an autoencoder to get the low-dimensional 3D contextual space. 2) A **training stage** where we intialize the 3DGS semantic fields with the low-dimensional 3D contextual space, and supervise the training of the rendered low-dimensional 3DGS semantic fields efficiently with the CRR semantic features mapped into the same dimension by the frozen encoder in the pretrained autoencoder. We also utilize the frozen encoder and CRR to align class semantics with the 3DGS semantic fields.

### 4.1 Image and Text Embeddings

We obtain per-pixel semantic feature $\mathcal{F}^{2D}$ from the RGB images $\mathcal{I}$ with the image encoder of a 2D VLM $\varphi^{2D} : \mathcal{I} \mapsto \mathcal{F}^{2D}$. Similarly, we use the text encoder of the 2D VLM to get the text feature $\varphi^{text} : \mathcal{T} \mapsto T$. Several 2D pre-trained models such as OpenSeg (Ghiasi et al., 2022), LSeg (Li et al., 2022), *etc*. can be used as $\varphi^{2D}$ and $\varphi^{text}$.

### 4.2 Confidence-guided Region Regularization (CRR)

As shown in Fig. 3, the semantic feature map from OpenSeg (Column (a)) and the regional mask proposals from SAM (Column (b)) can be imperfect due to complex background and occlusion, and thus leading to inconsistent and inaccurate semantics across multiple views. We design our CRR for mutual refinement of the per-pixel semantic feature from the 2D VLM and regional mask proposals from SAM as follows:

a: Select pixel embeddings $\mathcal{F}^{2D}$ across all views with confidence higher than threshold $\tau_1$:
   ▷ $\mathcal{R} \leftarrow \text{SelectConfident}(\mathcal{F}^{2D} > \tau_1)$;

b: Back-project semantic features of each pixel in $\mathcal{R}$ into 3D using depthmaps $\mathcal{D}$ from Colmap. Average-pool back-projected $\mathcal{R}$ to get multi-view consistent semantic features:
   ▷ $\bar{\mathcal{F}}^{3D} \leftarrow \text{AvgPool}(\text{BackProject}(\mathcal{R}, \text{D}))$;

c: Obtain semantic label for each 3D point according to its similarity with the text embeddings. On the reprojected points, do majority voting on the semantic labels and average-pooling on the semantic features to get a set of 2D semantic masks and their corresponding features and labels:
   ▷ $\{\mathcal{P}, \bar{\mathcal{F}}^{2D}, \bar{Y}\} \leftarrow \text{Vote-AvgPool}(\text{Project}((\text{SemanticLabel}(\mathcal{T}, \bar{\mathcal{F}}^{3D})))$;

d: Fit bounding boxes to the re-projected $\mathcal{P}$, and use as input prompts to SAM to get better regional mask proposals:
   ▷ $\mathcal{S} \leftarrow \text{PromptSAM}(\text{FitBBox}(\text{Project}(\mathcal{P})))$;

e: Retain $\mathcal{P}$ with confidence higher than threshold $\tau_2$. Assign the semantic label and feature of the high confidence $\mathcal{P}$ to the improved SAM regional mask proposal $\mathcal{S}$ with the highest IoU score:
   ▷ $\{\mathcal{S}, \bar{\mathcal{F}}^{2D}, \bar{Y}\} \leftarrow \text{MaxIoUScore}(\text{SelectConfident}(\mathcal{P} > \tau_2), \mathcal{S})$;

Note that the semantic features $\mathcal{F}^{2D}$, $\bar{\mathcal{F}}^{3D}$ and $\bar{\mathcal{F}}^{2D}$ share the same dimension since $\bar{\mathcal{F}}^{3D}$ is obtained from average pooling of $\mathcal{F}^{2D}$ from multi-view back-projections, and $\bar{\mathcal{F}}^{2D}$ is from the average-pooling of the re-projected $\bar{\mathcal{F}}^{3D}$ in each mask $\mathcal{P}$. Steps (a)-(c) enforces multi-view consistency in the semantic features from OpenSeg. Step (d) uses the multi-view consistent semantic mask to improve regional mask proposals from SAM. Finally, Step (e) uses the improved regional mask proposals from SAM to further refine the multi-view consistent semantic mask.

### 4.3 Low-dimensional 3D Contextual Space

**Multi-view Feature Fusion.** For each 3D point obtained from Structure-from-Motion (SfM) using Colmap for the intialization of 3DGS, we compute per 3D point feature $f_p^{3D} = \psi(\bar{f}_i^{2D}, \ldots, \bar{f}_{N_p}^{2D})$

from average pooling $\psi$ the multi-view features of the $N_p$ visible corresponding pixels. We build an initial 3D contextual space by consolidating all point features corresponding to the point cloud from SfM: $\mathcal{M} = \{f_1^{3D}, \ldots, f_p^{3D}\}$.

**Autoencoder.** A naive direct rendering of the feature fields is very time-consuming due to the high dimensionality of the semantic features $\mathcal{F}^{2D}$ since the latent dimensions in 2D foundation models tend to be very large. This problem is further aggravated in complex 3D scenes with a lot of dense points. We thus pretrain an autoencoder to map the high dimensional 3D contextual space $\mathcal{M}$ into a low-dimensional latent space space $\mathcal{M}_z = \{z_1^{3D}, \ldots, z_p^{3D}\}$ to improve efficiency. Specifically, the encoder $z_p^{3D} = g(f_p^{3D})$ maps feature $f_p^{3D}$ with high dimension to a lower dimension latent vector $z_p^{3D}$. The reconstruction is given by $o_p^f = h(g(f_p^{3D}))$, where $h(\cdot)$ is the decoder and $o_p^f$ is the reconstructed 3D semantic feature. The training objective of the autoencoder on the 3D point features $\mathcal{M}$ is as follows:

$$\mathcal{L}_{ae} = \mathcal{L}_{l2}(f_p^{3D}, o_p^f) + \mathcal{L}_{ce}(\hat{y}, \cos < o_p^f, \mathcal{T} >) + \mathcal{L}_{ce}(\hat{y}, \cos < z_p^f, g(\mathcal{T}) >), \tag{1}$$

where $\mathcal{L}_{l2}$ and $\mathcal{L}_{ce}$ denote $L2$ loss and cross entropy loss, respectively. Using cosine similarity, $\cos < o_p^f, \mathcal{T} >$ outputs the semantic label of the reconstructed semantic feature with the text embedding and $\cos < z_p^f, g(\mathcal{T}) >$ outputs the semantic label of the low dimension semantic feature with the encoded low dimension text embedding. $\hat{y}$ is the pseudo semantic mask generated from the 2D segmentation model.

### 4.4 3DGS Semantic Fields

After obtaining the pretrained autoencoder $[g(\cdot), h(\cdot)]$, we use the encoder $g(\cdot)$ to map: 1) The initial 3D contextual features to the low-dimensional 3D contextual space $g : \mathcal{M} \mapsto \mathcal{M}_z$; 2) Per-pixel semantic features to per-pixel low-dimensional semantic features $g : \bar{\mathcal{F}}^{2D} \mapsto \bar{\mathcal{F}}_z^{2D}$ ; 3) Text semantic features to low-dimensional text semantic features $g : \mathcal{T} \mapsto \mathcal{T}_z$.

We use the low-dimension 3D contextual space $\mathcal{M}_z$ to initialize the semantic field $f$ in each 3D Gaussians, and render the 3DGS semantic fields into each view via alpha-blending:

$$\mathcal{F} = \sum_{i \in n} f_i \alpha_i \prod_{j=1}^{i-1} (1 - \alpha_j). \tag{2}$$

We supervise the rendered semantic fields $\mathcal{F}$ by their semantic logit $S_m$ with the semantic mask label $\bar{Y}$ from CRR using a cross-entropy loss: $\mathcal{L}_{ce} = \mathrm{CE}(S_m, \bar{Y})$, where the semantic logit is obtained from the cosine similarity between the low-dimensional semantic and text features: $S_m = \cos < \mathcal{F}, \mathcal{T}_z >$. Furthermore, we optionally regularize $\mathcal{F}$ to improve feature smoothness with the low-dimensional semantic features $\bar{\mathcal{F}}_z^{2D}$ using a L2 semantic loss: $\mathcal{L}_{semantic} = \mathrm{L2}(\mathcal{F}, \bar{\mathcal{F}}_z^{2D})$.

The final supervision loss for optimizing the given scene is formulated as follows:

$$\mathcal{L} = \mathcal{L}_{color} + \lambda_{2d}\mathcal{L}_{ce} + \lambda_{sem}\mathcal{L}_{semantic} \tag{3}$$

where $\mathcal{L}_{color}$ is the 3D Gaussian image rendering loss, and $\lambda_{2d}$ and $\lambda_{sem}$ denote hyperparameters to balance the loss terms. In inference, we use Eq. 2 to render the learned 3DGS semantic fields from 3D to 2D. We deploy the encoder $g(\cdot)$ from the pre-trained autoencoder to get the text features $\mathcal{T}_z$ of the open-world text queries. By computing the activation scores between the rendered 3DGS semantic fields $\mathcal{F}$ and the text features, we can obtain the open-world segmentation predictions.

## 5 Experiments

We perform a series of experiments to demonstrate the effectiveness of our proposed method across various 3D scene understanding tasks. We evaluate our method on the 2D semantic segmentation benchmarks: ScanNet (Dai et al., 2017) and Replica (Straub et al., 2019), and 3D open-vocabulary segmentation benchmarks: LERF (Kerr et al., 2023) and 3DOVS (Liu et al., 2024) to compare with previous work, and provide results from ablation studies. We further showcase qualitative results on the Mip-Nerf360 (Barron et al., 2022) for exciting open-vocabulary applications such as 3D object localization, 3D object removal, 3D object inpainting, and language-guided editing.

Table 1: Comparisons of open-vocabulary segmentation on 3DOVS dataset. Best results in **bold**.

| | Dataset | 3DOVS | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Method | bed | | sofa | | lawn | | room | | bench | | overall | |
| | | mIoU | mAcc | mIoU | mAcc | mIoU | mAcc | mIoU | mAcc | mIoU | mAcc | mIoU | mAcc |
| 2D | LSeg | 56.0 | 87.6 | 04.5 | 16.5 | 17.5 | 77.5 | 19.2 | 46.1 | 06.0 | 42.7 | 20.6 | 54.1 |
| 3D | LERF | 73.5 | 86.9 | 27.0 | 43.8 | 73.7 | 93.5 | 46.6 | 79.8 | 53.2 | 79.7 | 54.8 | 76.7 |
| | 3DOVS | 89.5 | 96.7 | 74.0 | 91.6 | 88.2 | 97.3 | 92.8 | 98.9 | 89.3 | 96.3 | 86.8 | 96.2 |
| | Feature3DGS | 56.6 | 87.5 | 06.7 | 12.4 | 37.3 | 82.6 | 20.5 | 36.7 | 06.2 | 43.0 | 25.5 | 52.4 |
| | LEGaussians | 45.7 | - | 48.2 | - | 49.7 | - | 44.7 | - | 47.4 | - | 47.14 | - |
| | LangSplat | 73.5 | 89.7 | 82.3 | 98.7 | 89.9 | 95.6 | 95.0 | 99.4 | 70.6 | 92.6 | 82.3 | 95.2 |
| | econSG (Ours) | **94.9** | **97.4** | **91.6** | **98.7** | **96.3** | **98.5** | **95.8** | **99.4** | **93.0** | **97.6** | **94.3** | **98.3** |

Table 2: Comparisons of localization accuracy on LERF dataset. Best results in **bold**.

| | Dataset | LERF | | | | |
|---|---|---|---|---|---|---|
| | Method | ramen | figurines | teatime | waldo_kitchen | overall |
| 2D | LSeg | 14.1 | 08.9 | 33.9 | 27.3 | 21.1 |
| 3D | LERF | 62.0 | 75.0 | 84.8 | 72.7 | 73.6 |
| | Feature3DGS | 15.8 | 9.7 | 34.5 | 38.5 | 24.6 |
| | LangSplat | 73.2 | 80.4 | 88.1 | 95.5 | 84.3 |
| | SemanticGaussian | 6.8 | 83.1 | 89.8 | 90.9 | 85.2 |
| | LEGaussians | 78.6 | 73.7 | 85.6 | 90.1 | 82.0 |
| | econSG (Ours) | **83.2** | **89.3** | **93.4** | **96.2** | **90.5** |

### 5.1 Datasets and Experimental Setting

**Datasets.** To measure segmentation performance in open-world scenes, we evaluate the effectiveness of our approach using two established multi-view indoor scene datasets: Replica (Straub et al., 2019) and Scannet (Dai et al., 2017), and two 3D open-vocabulary segmentation datasets: LERF (Kerr et al., 2023) and 3DOVS (Liu et al., 2024). For both ScanNet and Replica, we construct training and test sets by evenly sampling sequences in each scene. Images are rendered at the resolution of $640 \times 480$. We adopt 20 different semantic class categories for Scannet by following Openscene (Peng et al., 2023), while Replica is annotated with 51 classes for evaluation as in (Engelmann et al., 2024). For LERF and 3DOVS, we follow the settings in LangSplat (Qin et al., 2023) where LERF is extended with ground truth masks annotated for language queries and 3DOVS consists of $20 \sim 30$ images for each scene with the resolution of $4032 \times 3024$. To assess 3D reconstruction quality, we applied our method to Mip-Nerf360 (Barron et al., 2022) and LERF-Localization (Kerr et al., 2023) by following Gaussian Grouping (Ye et al., 2023).

**Implementation details.** For 2D VLMs, we utilize pixel-level encoders, OpenSeg (Ghiasi et al., 2022) and LSeg(Li et al., 2022) to extract the per-pixel semantic features of each image in indoor scene datasets, and adopt Openclip (Ilharco et al., 2021) to extract image-level features for language-guided editing on Mip-Nerf360, LERF and 3DOVS datasets. We then use SAM for mutual refinement with the 2D VLMs in our CRR to get the semantic features where we set $\tau_1 = 0.45, \tau_2 = 0.6$. We use the Adam optimizer with the learning rate 0.0025 for latent semantic fields. For parameters to train the image scene, we follow the default setting in the original 3DGS (Kerbl et al., 2023). For additional parameters introduced to train the semantic scene, we set $\lambda_{sem} = 1, \lambda_{2d} = 1$. For all datasets, we train each scene for 30K iterations on one NVIDIA RTX-4090 GPU.

### 5.2 Multiview Reconstruction and Segmentation

**Open-vocabulary Segmentation Comparison.**

Tab. 1 and Tab. 2 show quantitative results of open-vocabulary segmentation on 3DOVS dataset and localization accuracy on LERF dataset. Tab. 3 shows segmentation comparison across various scenes on both Scannet and Replica. We compare with 2D-based open-vocabulary segmentation model LSeg (Li et al., 2022) along with 3D NeRF and 3DGS-based methods. LERF (Kerr et al., 2023) and 3DOVS (Liu et al., 2024) leverage the multi-scale CLIP features from the image patches as supervisions for learning NeRF-based semantic field, and thus struggle with both object boundary ambiguities for segmentation and rendering efficiency. Their performance on novel views can be

Table 3: Comparison with other methods on segmentation of novel views from Scannet and Replica. Best results highlighted in **bold**.

| Dataset | FPS | Replica | | | | Scannet | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | sparse-view | | multi-view | | sparse-view | | multi-view | |
| | | mIoU | mAcc | mIoU | mAcc | mIoU | mAcc | mIoU | mAcc |
| LERF | 0.2 | 4.312 | 17.080 | 8.285 | 22.125 | 14.059 | 38.734 | 15.349 | 40.294 |
| 3DOVS | 0.3 | 4.553 | 19.356 | 9.081 | 23.938 | 14.227 | 40.584 | 17.802 | 42.532 |
| Feature3DGS | 2.5 | 9.584 | 38.245 | 10.634 | 36.520 | 17.552 | 48.686 | 18.069 | 54.101 |
| econSG (Ours) | 156 | **25.513** | **70.716** | **33.869** | **78.564** | **39.018** | **74.805** | **48.205** | **86.178** |

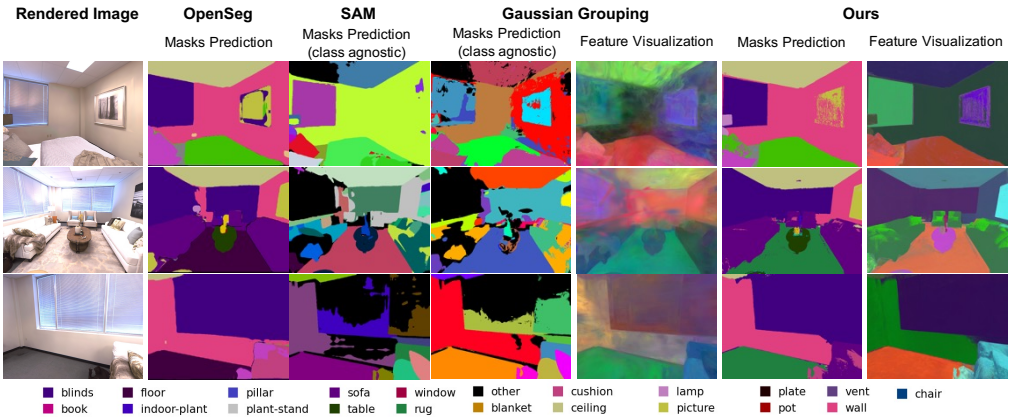


Figure 2: Qualitative comparison of our econSG with Gaussian Grouping (Ye et al., 2023) on Replica.

greatly degraded because of they generate inconsistent and imprecise ground truth semantics from multi-scale features across multiple views. Feature3DGS (Zhou et al., 2024) directly applies inconsistent and noisy semantics from training views to optimize high-dimensional semantic field in 3D Gaussians, resulting in high computation costs and inferior segmentation results. LangSplat (Qin et al., 2023) and LEGaussians (Shi et al., 2023) compress 2D features across all views to improve rendering efficiency on semantic fields, but their performance are still hindered by the inherent 3D semantic noises and inconsistency. SemanticGaussian distills noisy 2D features into an additional 3D model for learning 3D semantics while ignoring semantic consistency from the multi-view 2D images. Our model consistently shows the best performance since we introduce the 3D contextual latent space to provide sufficient 3D semantic consistency into the ground truths and design a CRR step to generate clean and complete semantic masks. These components help ensure optimization efficiency and robustness even with few input images.

In Tab. 3, we also present the inference speed under the multi-view setting in terms of the frames per second (FPS) metric. NeRF-based methods are generally constrained on rendering efficiency and slow. 3DGS-based models are inefficient from high-dimensional language features in 3D Gaussians. We also perform robustness comparison by evenly sampling sparse training views for optimization(30 images per-scene in our experiments). It shows our model consistently outperforms other methods, proving the proposed components help ensure optimization efficiency and robustness even with few input images. In Fig. 2, we visualize the learned semantic fields by showing the rendered latent embeddings in the testing views. We observe that our predictions are of better consistency across views with more complete and well-defined boundaries semantics masks.

**Ablation on CRR.** We compare our CRR with OpengSeg and SAM, and conduct ablation studies on CRR. OpenSeg in Fig. 3(a) shows issues such as ambiguous boundaries and inaccurate dense predictions. This is due to the use of noisy segmentation maps from pre-trained visual encoders for supervision. Fig. 3(b) shows that a naive over-trusting of SAM masks to refine boundaries does not work well in complex scenes. Fig. 3(c) *vs.* (d) and Fig. 3(e) *vs.* (f) show the without and with our CRR on the training and testing sets, respectively. We can see that our CRR effectively produces semantic fields with clear boundaries.

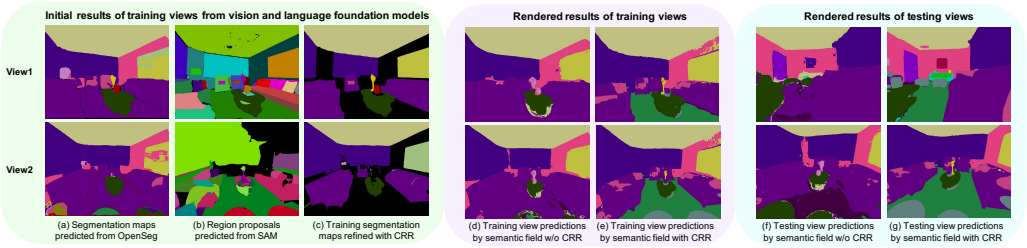


Figure 3: Ablation on confidence-guided region regularization (CRR) with qualitative results of our econSG on Replica. Panels (a)-(e) are from training views, and panels (f)-(g) are from testing views.

Figure 4: Qualitative 3D Segmentation Results and Comparison of our method. The second and fourth rows illustrate the feature visualization in 3D space.

**Analysis on 3D Contextual Latent Space.** We show qualitative results of 3D segmentation predictions and contextual feature space in Fig. 4. The 3D segmentations derived from the original OpenSeg exhibit significant coarseness and errors due to multi-view inconsistency among the predicted 2D semantic features. Gaussian Grouping shows better object-level boundaries by leveraging SAM object mask IDs as direct supervision. However, SAM can fail in complex scenes leading to incorrect masks in some views. Morever, since SAM segmentations are class-agnostic, the learned 3D semantic embeddings from Gaussian Grouping are only instance-level and cannot be queried by text embeddings. SAMPro3D (Xu et al., 2023) proposes to filter low-quality prompts and consolidate prompts inside the object. However, SAMPro3D is not applicable to open-vocabulary 3D scene understanding tasks without feature embeddings. In contrast, our model significantly improves the quality of 3D contextual space and segmentation predictions as illustrated in the last column.

**Training Efficiency Analysis.** In Tab. 4 , we show training and inference time on the "sofa scene" of 3DOVS dataset at different feature dimensions. Compared with LangSplat, our model achieves a significant speed increase in inference (LangSplat:401.9s *vs.* Ours:4.9s). This is because LangSplat performs evaluation on the original high-dimensional space while our model directly makes predictions in the low-dimensional latent contextual space. Our model can achieve promising efficiency and accuracy due to the low-dimensional 3D latent contextual space that avoids the need for training high-dimensional 3DGS semantic fields. The last column of Tab 4 shows that the high-dimensional features (*e.g.* 512 for CLIP features) pose huge memory and computation demands especially on training when the autoencoder is removed.

### 5.3 Applications

**3D Scene Editing.** Fig. 5 (Right) shows examples of language-guided editing on a object scene from the Bear data (Ye et al., 2023) and a room scene from Mip-NeRF360 (Barron et al., 2022). We utilize

Table 4: Training efficiency analysis on the sofa scene of the 3DOVS dataset.

| Methods | LERF | 3DOVS | Langsplat | Feature3DGS | Ours | | | Ours (remove autoencoder) |
|---|---|---|---|---|---|---|---|---|
| Feature dimension | 512 | 512 | 3 | 128 | 6 | 16 | 32 | 512 |
| mIoU (%) | 27.0 | 74.0 | 82.3 | 06.7 | 91.6 | 91.8 | 91.8 | OOM |
| Training time (min) | 19.4 | 78 | 66 | 87 | 29 | 32 | 43 | OOM |
| Inference (s) | 121.4 | 6.6 | 401.9 | 6.0 | 4.9 | 5.2 | 5.3 | OOM |

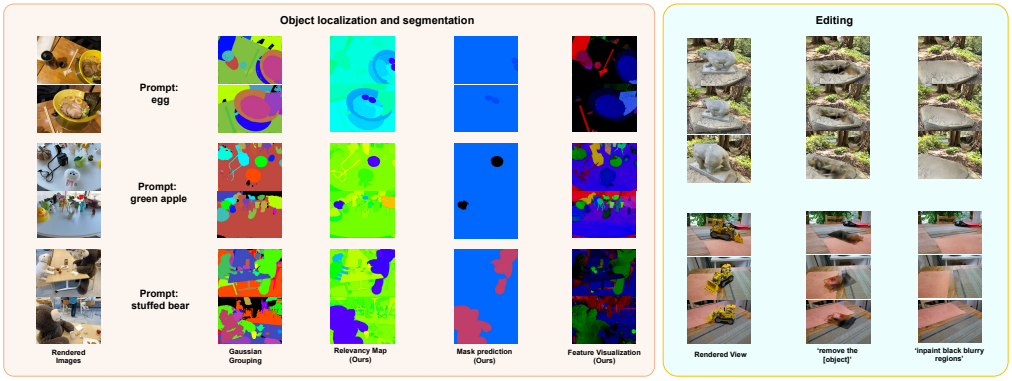


Figure 5: Qualitative examples of language-guided segmentation and editing. Segmentation results of the rendering views are compared with Gaussian Grouping on LERF-localization dataset.

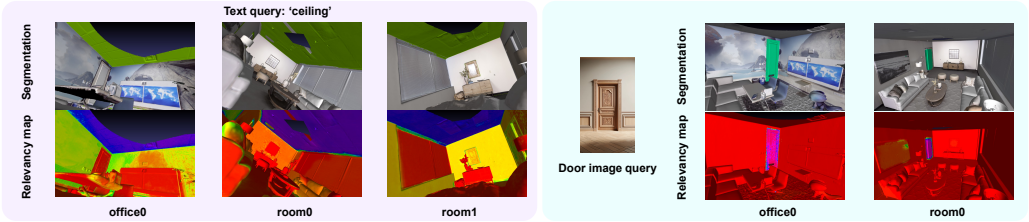


Figure 6: A 3D scene can be queried using text prompt embedding or images to locate matching 3D points. Colors of image query outlines indicate corresponding matches in the 3D point cloud.

the text encoder to embed the object category names to identify the corresponding 3DGS points and adjust their attributes such as coordinates and colors. We first detect regions that are invisible in all views after deletion and then inpaint these specific areas instead of the entire 2D object regions. We then use the 2D inpainted image in each rendering view to guide the learning of new 3D Gaussians.

**Open-Vocabulary 3D Object detection.** Fig. 5 (Left) shows examples of object localization and segmentation with text queries. In Fig. 6, we query a 3D scene database to retrieve examples based on their similarity to a given input image. We first encode the query text or image using CLIP image encoder and then threshold the cosine similarities between the CLIP features and the 3DGS semantic fields to produce a 3D object detection and mask.

## 6 Conclusion

In this paper, we propose econSG for open-vocabulary semantic segmentation of 3D scenes. Specifically, we propose CRR to get 2D semantic features with complete and precise boundaries by mutual guidance from OpenSeg and SAM with strong awareness of multi-view consistency. We design an autoencoder with one-time pretraining to get the low-dimensional 3D contextual space for initialization of the 3D neural semantic fields, and enforce multi-view consistency by backprojecting 2D features from CRR into the same dimension as the low-dimensional 3D contextual space for efficient training. Our econSG show state-of-the-art performance on four benchmark datasets compared to the existing methods. Furthermore, we are also the most efficient training among all the methods.

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