SceneScript: Reconstructing Scenes With An Autoregressive Structured Language Model

Armen Avetisyan[1], Christopher Xie[1], Henry Howard-Jenkins[1], Tsun-Yi Yang[1], Samir Aroudj[1], Suvam Patra[1], Fuyang Zhang[2†], Duncan Frost[1], Luke Holland[1], Campbell Orme[1], Jakob Engel[1], Edward Miller[1], Richard Newcombe[1], and Vasileios Balntas[1]

[1] Meta Reality Labs [2] Simon Fraser University
https://projectaria.com/scenescript

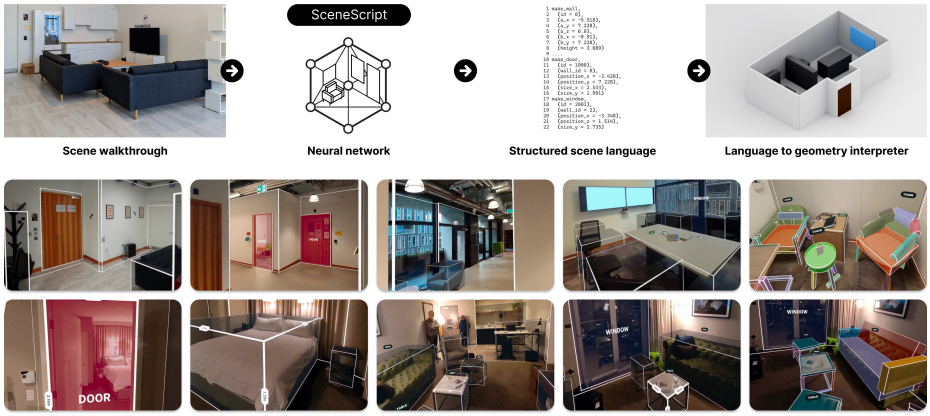

Fig. 1: (*top*) Given an egocentric video of an environment, `SceneScript` directly predicts a 3D scene representation consisting of structured scene language commands. (*bottom*) Our method generalizes on diverse real scenes while being solely trained on synthetic indoor environments. (*last column, bottom*) A notable advantage of our method is its capacity to easily adapt the structured language to represent novel scene entities. For example, by introducing a single new command, `SceneScript` can directly predict object parts jointly with the layout and bounding boxes.

Abstract. We introduce `SceneScript`, a method that directly produces full scene models as a sequence of structured language commands using an autoregressive, token-based approach. Our proposed scene representation is inspired by recent successes in transformers & LLMs, and departs from more traditional methods which commonly describe scenes as meshes, voxel grids, point clouds or radiance fields. Our method infers the set of structured language commands directly from encoded visual data using a scene language encoder-decoder architecture. To train `SceneScript`, we generate and release a large-scale synthetic dataset called *Aria Synthetic Environments* consisting of 100k high-quality indoor scenes, with photorealistic and ground-truth annotated renders of egocentric scene walkthroughs. Our method gives state-of-the art results in architectural layout estimation, and competitive results in 3D object detection. Lastly, we explore an advantage for `SceneScript`, which is the ability to readily adapt to new commands via simple additions to the structured language, which we illustrate for tasks such as coarse 3D object part reconstruction.

[†]Work done while the author was an intern at Meta.

1 Introduction

Scene representations play a crucial role in machine learning and computer vision applications, enabling accurate understanding of the environment. Over the years, researchers have explored various options such as meshes, voxel grids, point clouds, and implicit representations, aiming to represent complex real-world scenes with high-fidelity. Each of these exhibits distinct advantages and limitations that impact their suitability for different tasks. Meshes offer detailed geometric information but can be expensive in both computation and memory. Voxel grids provide a volumetric representation but suffer from a trade-off between resolution and memory requirements. Point clouds are efficient in representing sparse scenes but lack semantics and explicit connectivity information. Implicit representations, such as DeepSDF [22] and NeRF [15], can be infinitely precise but lack interpretability and editability. The selection of an appropriate representation directly impacts the performance and efficacy of various tasks including object recognition, scene understanding, and 3D reconstruction. In this paper, we propose a novel scene representation based on structured language commands as a more efficient and versatile solution.

Our motivation stems from the recent advancements in the field of Large Language Models (LLMs) and "next token prediction" autoregressive methods [20], coupled with recent works on exploring generation of sequences to represent geometric structures. For example, PolyGen [18] demonstrated the ability to describe 3D meshes as a sequence of vertices and faces generated using transformers [30]. Similarly, CAD-as-Language [11] showcased the effectiveness of generating Computer-Aided Design (CAD) primitives to represent 2D CAD sketches. Our main goal is to **directly infer a metrically accurate representation of a full scene** as a text-based sequence of specialized structured language commands.

Our method, denoted `SceneScript`, autoregressively predicts a language of hand-designed structured language commands in pure text form. This language offers several distinct advantages: 1) As pure text, it is compact and reduces memory requirements of a large scene to only a few **bytes**. 2) It is crisp and complete since the commands are designed to result in sharp and well-defined geometry (similar to scalable vector graphics). 3) It is interpretable, editable and semantically rich by design via the use of *high-level parametric* commands such as `make_door(*door_parameters)`. 4) It can seamlessly integrate novel geometric entities by simply adding new structured commands to the language. 5) The fact that the scene representation is a series of language tokens similar to [20] opens up a plethora of potential new applications in the future such as ways to edit the scene, query it, or spin up chat interactions.

We mainly focus on the problems of architectural layout estimation and object detection as proxy tasks for the efficacy of our `SceneScript` language as a scene representation. Architectural entities such as walls, doors, and windows are highly structured entities, making them an ideal test-bed. However, one notable drawback of language models is that they require vast amounts of data for training. Since there is no existing dataset of scene walkthroughs and their cor-

responding structured language commands, we publicly released *Aria Synthetic Environments* (*ASE*), a synthetically generated dataset of 100k unique interior scenes. For each scene, we simulate egocentric trajectories with an entire suite of sensor data from Project Aria [14]. We also release multiple sources of ground truth including depth and instance segmentations. Importantly, for each rendered egocentric sequence, the architectural layout ground truth is given in our proposed `SceneScript` language.

While architectural layout serves as a test-bed, we demonstrate that our method `SceneScript` can easily be extended to new tasks via simple extensions to `SceneScript` language while keeping both the visual input and network architecture fixed. We illustrate this on the problem of 3D object detection, which results in a method that jointly infers architectural layout and 3D oriented bounding boxes. Additionally, we demonstrate more proof-of-concept experiments that show that our method results in a significantly lower barrier to entry for new tasks including representing coarse 3D object reconstruction, curved entities, composition of entities, and entity states.

Our core contributions are:

- We propose `SceneScript`, a method that jointly predicts architectural layout and object bounding boxes of a scene in the form of structured language commands given a video stream.
- We demonstrate that `SceneScript` can easily be extended to completely new tasks with simple additions of commands to our structured language, significantly lowering the barrier to entry for new tasks.
- We release a large-scale synthetic dataset, named *Aria Synthetic Environments*, comprized of **100k** unique high-quality 3D indoor scenes with GT, which will enable large scale ML training of scene understanding methods.
- We show that training `SceneScript` on *Aria Synthetic Environments* leads to generalization on real scenes (see videos/demos on the project page).

2 Related Works

2.1 Layout Estimation

Layout estimation is an active research area, aiming to infer architectural elements. Scan2BIM [17] proposes heuristics for wall detection to produce 2D floorplans. Ochmann et al. [19] formulate layout inference as an integer linear program using constraints on detected walls. Shortest path algorithms around birds-eye view (BEV) free space [3] and wall plus room instance segmentation [5] have also been explored.

Furukawa et al. [10] utilize a *Manhattan world*-based multi-view stereo algorithm [9] to merge axis-aligned depth maps into a full 3D mesh of building interiors. RoomNet [13] predicts layout keypoints while assuming that a fixed set of Manhattan layouts can occur in a single image of a room. LayoutNet [38] improves on this by predicting keypoints and optimising the Manhattan room layout inferred from them. Similarly, AtlantaNet [23] predicts a BEV floor or

Table 1: Complete set of structured language commands designed for detailing architectural layouts and object bounding boxes. Supported data types can include `int, float, bool`. It is important to note that the language's extensibility allows for easy augmentation by introducing new commands like `make_prim, make_pillar`, or enhancing existing commands, such as incorporating `is_double_door (bool)`.

make_wall (int)		make_door (int)		make_window (int)		make_bbox (int)	
id	int	id	int	id	int	id	int
a_x	float	wall0_id	int	wall0_id	int	class	int
a_y	float	wall1_id	int	wall1_id	int	position_x	float
a_z	float	position_x	float	position_x	float	position_y	float
b_x	float	position_y	float	position_y	float	position_z	float
b_y	float	position_z	float	position_z	float	angle_z	float
b_z	float	width	float	width	float	scale_x	float
height	float	height	float	height	float	scale_y	float
						scale_z	float

ceiling shape and approximates the shape contour with a polygon resulting in an *Atlanta world* prior. SceneCAD [1] uses a graph neural network to predict object-object and object-layout relationships to refine its layout prediction.

Our approach stands out by requiring neither heuristics nor explicitly defined prior knowledge about architectural scene structure. In fact, our method demonstrates geometric understanding of the scene which emerges despite learning to predict the GT scene language as a sequence of text tokens.

2.2 Geometric Sequence Modelling

Recent works have explored transformers for generating objects as text-based sequences. PolyGen [18] models 3D meshes as a sequence of vertices and faces. CAD-as-Language [11] represents 2D CAD sketches as a sequence of triplets in protobuf representation, followed by a sequence of constraints. Both SketchGen [21] and SkexGen [33] use transformers to generate sketches. DeepSVG [4] learns a transformer-based variational autoencoder (VAE) that is capable of generating and interpolating through 2D vector graphics images. DeepCAD [32] proposes a low-level language and architecture similarly to DeepSVG, but applies it to 3D CAD models instead of 2D vector graphics. Our approach stands out by utilising *high-level* commands, offering interpretability and semantic richness. Additionally, while low-level commands can represent arbitrarily complex geometries, they lead to prohibitively longer sequences when representing a full scene.

The closest work to ours is Pix2Seq [6]. Pix2Seq proposes a similar architecture to ours but experiments only with 2D object detection, thus requiring domain-specific augmentation strategies. Another closely related work is Point2Seq [34] that trains a recurrent network for autoregressively regressing continuous 3D bounding box parameters. Interestingly, they find the autoregressive ordering of parameters outperforms current standards for object detection architectures, including anchors [12] and centers [36].

Fig. 2: *Aria Synthetic Environments*: (top) Random samples of generated scenes showing diversity of layouts, lights and object placements. (bottom - left to right) A top down view of a scene filled with objects, a simulated trajectory (blue path), renderings of depth, RGB, and object instances, and lastly a scene pointcloud.

3 `SceneScript` Structured Language Commands

We first describe our structured language commands that define a full scene representation including both layout and objects. After this, we introduce our corresponding large scale training dataset: *Aria Synthetic Environments*.

3.1 Commands and Parameters

We begin with a parameterization that captures the most common layout elements. For this purpose we use three commands: `make_wall`, `make_door`, and `make_window`. Each command comes with a set of parameters that results in well-defined geometry. For example, the full set of parameters for `make_wall` specifies a gravity-aligned 2D plane, while `make_door` and `make_window` specify box-based cutouts from walls. It is worth noting that this parametrization is arbitrary, and is only made in the context of presenting a proof-of-concept `SceneScript` system. There are infinitely many parametrization schemes, in this work we opt for one that prioritizes ease of use and research iteration speed.

In addition to representing these three major layout entities, we aim to jointly infer objects as oriented bounding boxes. Thus, we introduce a fourth command:

```
make_bbox: id, class, position_x, position_y,
    position_z, angle_z, scale_x, scale_y, scale_z
```

This simple parametrization represents an oriented 3D bounding box that is assumed to be aligned with gravity (assuming it points in the $-z$ direction). A summary of these commands and their respective parameters are shown in Table 1.

While we have described just four commands to capture structure and objects in an indoor environment, importantly, this text-based parametrization can readily be extended geometrically and/or even semantically to include states or other functional aspects. For example, changing the mentioned `make_door` command to include parameters such as `open_degree` allows the language to represent door states. In Section 6, we demonstrate how such extensions to the language allows for `SceneScript` to readily adapt to new tasks including coarse 3D object reconstruction.

3.2 Scene Definition

A single scene can be described as a sequence of our proposed structured language commands. The sequence requires no specific ordering, and can be of arbitrary length. From this definition, the 3D scene can easily be obtained by parsing the commands through a simple custom interpreter.

3.3 Training Dataset

To enable practical indoor scene reconstruction based on our structured language commands (Section 3.1), we publicly released a new dataset called *Aria Synthetic Environments*. It consists of a large number of training pairs of egocentric scene walkthroughs linked with corresponding ground truth command sequences.

Since transformers require vast amounts of data, we generated $100k$ synthetic scenes, which is in comparison infeasible for real-world data. Each synthetic scene comes with a floor plan model, a corresponding complete 3D scene as well as a simulated agent trajectory and a photo-realistic rendering of this trajectory. Fig. 2 illustrates the basics of *Aria Synthetic Environments*. For brevity, we refer the reader to the supplemental material for further details.

4 `SceneScript` Network Architecture

Our pipeline is a simple encoder-decoder architecture that consumes a video sequence and returns `SceneScript` language in a tokenized format. Figure 3 illustrates a high-level overview of our method.

We examine three encoder variants: a pointcloud encoder, a posed image set encoder, and a combined encoder. The decoder remains the same in all cases.

4.1 Input Modalities and Encoders

The encoder computes a latent scene code in the form of a 1D sequence from video walkthrough of the scene. The decoder is designed to consume these 1D sequences as input. This enables the integration of various input modalities within a unified framework. As a preliminary, for each scene we assume access to a set of M posed camera images $\{\mathbf{I_1}, ..., \mathbf{I_M}\}$, e.g., *SLAM* output.

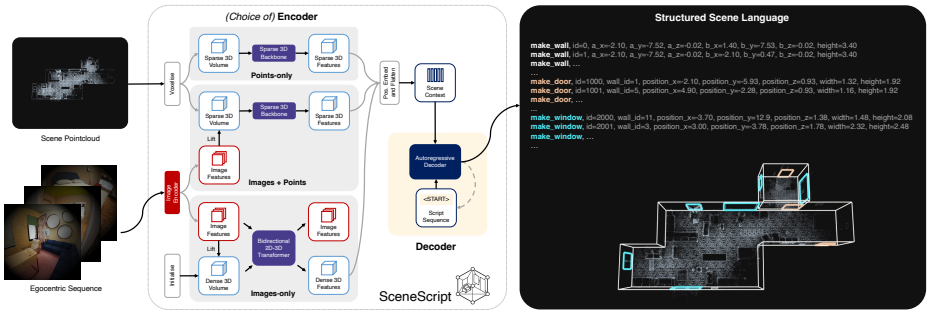

Fig. 3: `SceneScript` core pipeline overview. Raw images & pointcloud data are encoded into a latent code, which is then autoregressively decoded into a sequence of commands that describe the scene. Visualizations are shown using a customly built interpreter. Note that for the results in this paper, the the point clouds are computed from the images using Aria MPS [25] – i.e. are not using a dedicated RGB-D / Lidar sensor.

Point Clouds. A point cloud $\mathbf{P} = \{\mathbf{p_1}, ..., \mathbf{p_N}\}$ consists of N points, where $\mathbf{p_i}$ is a 3D point coordinate. It can come from passive images using *SLAM* or *SfM*, or RGB-D / Lidar sensors.

Specifically, we use the Semi-dense Pointclouds from Project Aria's Machine Perception Services [25], that are obtained from a visual-inertial SLAM system using Aria's monochrome cameras and IMUs. We discretize the point cloud to 5cm resolution, then employ a sparse 3D convolution library [26,27] to generate pooled features. The encoder $\mathcal{E}_{geo}$ applies a series of down convolutions, resulting in a reduction of the number of points in the lowest level.

$$\mathbf{F}_{geo} = \mathcal{E}_{geo}(\mathbf{P}), \quad \mathbf{P} \in \mathbb{R}^{N\times 3}, \mathbf{F}_{geo} \in \mathbb{R}^{K\times 512} \tag{1}$$

where $K \ll N$. $\mathbf{F}_{geo}$ is a condensed latent representation of the point cloud that contains the necessary scene context. For later use in the transformer decoder, we treat $\mathbf{F}_{geo}$ as a sequence of feature vectors where the entries $\mathbf{f_i}$, $i \in 1...K$ are sorted lexicographically according to the coordinate of the active site $\mathbf{c_i}$, $i \in 1...K$. To incorporate positional encoding, we append the coordinates of the active sites to their respective feature vectors $\mathbf{f}_i \leftarrow \texttt{cat}(\mathbf{f_i}, \mathbf{c_i})$.

Point Clouds with Lifted Features. We additionally explore augmenting the point cloud with image features. From the original egocentric sequence and associated trajectory, we sample a set of M keyframes, $\mathbf{I}_i$ where $i \in 1...M$, and compute a set of image features $\mathbf{F}_i$ for each. We then project each point into the set of keyframe cameras and retrieve the feature vector (output by a CNN) at the pixel location:

$$\mathbf{f}_{ip} = F_i(\pi(\mathbf{p})) \qquad \mathbf{p} \in \mathbf{P}, i \in 1...M, \tag{2}$$

where $\pi(\cdot)$ represents the projection function of a 3D point into the camera. If $\pi(\mathbf{p})$ falls outside the image bounds, no feature is retrieved. We combine the set

of lifted features for a point through an average, resulting in a single feature vector for each point: $\mathbf{f}_p = 1/M \sum_{i=1}^{M} \mathbf{f}_{ip}$.

We form our lifted-feature point cloud, $\mathbf{P'} = \{\mathbf{p'_1}, ..., \mathbf{p'_M}\}$, by concatenating each point's lifted feature with the original XYZ location: $\mathbf{p'} = \texttt{cat}(\mathbf{f}_p, \mathbf{p})$. $\mathbf{P'}$ is then encoded into a context sequence using sparse 3D convolutions, with only the input feature channels adjusted to match the new point feature dimension.

End-to-end Encoding of Posed Views. In order to encode the egocentric sequence more directly without a pre-computed point cloud, we adopt a 2D $\leftrightarrow$ 3D bidirectional transformer encoder following the form defined in RayTran [29].

In this formulation, we initialize a volume representation of the scene as a dense voxel grid of features, $\mathbf{V}$, that coincides with the scene geometry. In turn, we sample a subset of M keyframes, $\mathbf{I}_i$ where $i \in 1...M$, from the full stream of posed images. And for each of these keyframes we compute image features from a CNN, $\mathbf{F}_i$. Repeated layers of bidirectional attention enable the image and voxel grid features to be refined iteratively in successive transformer blocks through the aggregation of view-point and global-scene information. As in RayTran [29], the interaction between the two representations is guided by the image-formation process by leveraging known camera parameters and poses. Attention in these transformer blocks is restricted by patch-voxel ray intersections, where each image patch attends to the voxels it observes and each voxel location attends to all the patches that observe it. The resulting voxel grid of features is flattened, concatenated with an encoded represention of its XYZ location, and passed to the decoder.

4.2 Language Decoder

We utilize a transformer decoder [30] to decode the scene latent code into a sequence of structured language commands. The sequence of tokens passes through an embedding layer, followed by a positional encoding layer. Together with the encoded scene code (Section 4.1), the embedded tokens are passed into the several transformer decoder layers where a causal attention mask is used to ensure autoregressive generation. More implementation details can be found in Appendix **??**.

4.3 Language Tokenization

We refer to the serialization the structured language into a sequence of tokens as **tokenization**. The goal is to construct a bijective mapping between a sequence of structured language commands (Section 3) and a sequence of integer tokens that can be predicted by the transformer decoder architecture. We utilize the following schema:

$$[\texttt{START}, \texttt{PART}, \texttt{CMD}, \texttt{PARAM\_1}, \texttt{PARAM\_2}, \ldots, \texttt{PARAM\_N}, \texttt{PART}, \ldots, \texttt{STOP}]$$

For example, a sample sequence for a `make_door` command may look like:

$$[\texttt{START}, \texttt{PART}, \texttt{MAKE\_DOOR}, \texttt{POSITION\_X}, \texttt{POSITION\_Y}, \texttt{POSITION\_Z}, \texttt{WALL0\_IDX}, \texttt{WALL1\_IDX}, \texttt{WIDTH}, \texttt{HEIGHT}, \texttt{PART}, \ldots, \texttt{STOP}]$$

This schema enables 1D packing of tokens without requiring fixed-size slots or padding like other sequence modelling methods such as [32]. Additionally, it does not impose any limitations on the number or the hierarchy of sub-sequences, as they are flexibly separated by a `PART` token. This allows for arbitrarily complex scene representations.

The tokenized sequence is discretized into integers at a 5cm resolution, then translated into a sequence of embeddings via learnable lookup table. Note that by designing the `SceneScript` language, we also design the tokenization. This tokenization scheme is notably different from standard NLP tokenization, which involves Byte-Pair Encodings (BPE) [20].

5 Results

In this section, we introduce the metrics we define to measure performance, and we discuss some qualitative and quantitative results that give insights to our proposed `SceneScript` method.

5.1 Metrics

To evaluate accuracy of the layout estimation, we make use of geometric metrics applied between the ground-truth room layout and our predicted `SceneScript` language. To do so, we define an *entity distance*, d_E, between a pair of entities of the same class. Each entity, E, is represented as a 3D plane segment comprising of 4 corners $\{c_1, c_2, c_3, c_4\}$. The distance between two entities, E and E' is computed as the maximum Euclidean distance between each corner and its counterpart assigned via Hungarian mathcing, i.e.: $d_E(E, E') = \max\{||c_i - c'_{\pi(i)}|| : i = 1, ..., 4\}$, where $\pi(i)$ is the permutation also found via Hungarian matching.

We threshold d_E to define the success criteria for the predicted entities. We compute the following metrics:

- F1 Score @ *threshold* – the F1 score of the set of predictions is computed at a single d_E threshold.
- Average F1 Score – the F1 score is computed across a range of entity distance thresholds and averaged.

The scores are computed for each class independently and averaged to overall score. In addition, scores are computed for each scene and averaged across the dataset. We use the following range of thresholds (cm) for the average F1 scores: $T = \{1, 2, ..., 9, 10, 15, 25, 30, 50, 75, 100\}$.

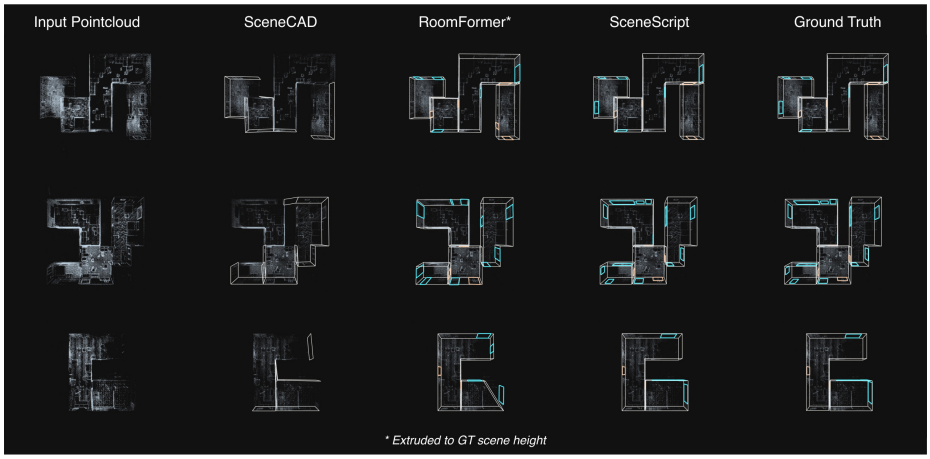

Fig. 4: Qualitative samples between our model and SOTA methods on *Aria Synthetic Environments*'s test set. Hierarchical methods like SceneCAD suffer from error cascading which leads to missing elements in the edge prediction module. RoomFormer (a 2D method extruded to 3D) primarily suffers from lightly captured scene regions which leave a unnoticeable signal in the density map.

Table 2: Layout Estimation on *Aria Synthetic Environments* Quantitative comparison between our method and related recent work.

	F1 @5cm				Avg F1			
Method	mean	wall	door	window	mean	wall	door	window
SceneCAD '20 [1]	-	0.048	-	-	-	0.275	-	-
RoomFormer '23 [37]	0.139	0.159	0.148	0.110	0.464	0.505	0.481	0.407
Ours (Point cloud)	0.848	0.930	0.922	0.692	0.784	0.816	0.811	0.724
Ours (Lifted features)	**0.903**	**0.943**	**0.959**	**0.806**	**0.801**	**0.818**	**0.822**	**0.764**
Ours (Image-only)	0.661	0.687	0.798	0.497	0.719	0.727	0.772	0.658

5.2 Layout Estimation

We perform scene layout estimation with the the three encoder variants of `SceneScript`: a baseline model with sparse3d convolution pointcloud encoder, an RGB RayTran-based feature volume encoder [29], and our proposed lifted feature point encoder. The same transformer decoder is being used in all three scenarios.

To provide comparison to existing works, we include results from two baseline methods, namely SceneCAD [1] and the recent RoomFormer [37]. For these experiments SceneCAD and RoomFormer were both trained on *Aria Synthetic Environments*. Note that SceneCAD only predicts walls.

Table 2 shows the main results for our F1-based metrics on *Aria Synthetic Environments*. `SceneScript` exhibits a substantial performance advantage over SOTA layout estimation baselines across multiple metrics.

Table 3: 3D Object Detection Performance comparison against state-of-the-art methods on an 3D object detection task trained and evaluated by F1-score at 0.25 and 0.5 IoU thresholds. By simply adding a `make_bbox` command `SceneScript` can achieve competitive object detection results.

(a) *Aria Synthetic Environments*

Method	Input	F1 @.25 IoU	F1 @.50 IoU
3DETR '21 [16]	Points	0.201	0.078
Cube R-CNN '23 [2]	RGB	0.394	0.228
ImVoxelNet '22 [24]	RGB	0.584	0.516
Ours	Points	**0.620**	**0.577**

(b) ScanNet [8]

Method	Input	F1 @.25 IoU	F1 @.50 IoU
3DETR '21 [16]	Points	0.480	0.349
3DETR-m '21 [16]	Points	0.536	0.407
SoftGroup '22 [31]	RGB Points	**0.622**	**0.573**
Ours	RGB Points	0.506	0.406

Both baseline methods encounter a significant decline in accuracy when dealing with finer details. See Figure 4 for qualitative comparisons between our method and baseline methods.

Encoder Ablation. The results demonstrate that `SceneScript` is robust to the encoding strategy chosen to encode the egocentric capture. It is able to infer highly accurate scene layouts in all configurations tested, and in each case `SceneScript` outperforms the included baselines by a significant margin.

Relative comparison of the encoder strategies reveals that leveraging the pointclouds from a highly specialized and well-tuned system is still able to offer advantages of an, almost, entirely learned approach such as RayTran [29]. A light extension in the form of lifted image features can widen this gap even further. In particular, we observe that the discrepancy between the encoders becomes particularly apparent as the complexity of the scene increases in the form of increased room count. In the Appendix, we also show a quantitative evaluation of per-entity error distances, which aids in further attribution of relative performance gains between the encoding methods.

5.3 Object Detection

In this section, we perform evaluation of `SceneScript` for object detection on both *Aria Synthetic Environments* and ScanNet [8]. For comparison, we include recent and state-of-the-art baseline methods, namely Cube-RCNN [2], ImVoxelNet [24], 3DETR [16], and SoftGroup [31].

Worth noting is that `SceneScript` does not predict a confidence score for each `make_bbox` command. This means that fair computation of the conventional mAP metric for this task is not possible, as detections cannot be ranked across scenes. Among other issues, this results in a metric that varies with the order in which scenes are evaluated. We therefore report F1-score-based metrics, which do not exhibit this order variance. Further discussion of this, and mAP numbers for the baselines for reference, can be found in the Appendix.

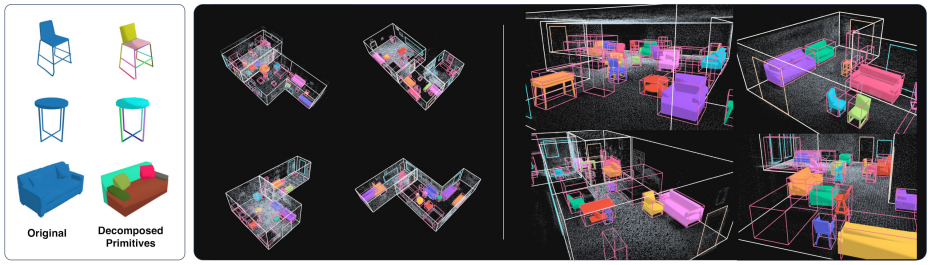

Fig. 5: Example scene reconstructions on scenes from *Aria Synthetic Environments*. (left) Visualisation of the decomposed meshes used to create `make_prim` training pairs. (right) Views of full scene predictions, as well as close ups highlighting the fidelity of object reconstruction through the prediction volumetric primitives enabled by `make_prim`.

In Table 3a, all methods were trained on *Aria Synthetic Environments*. 3DETR performs poorly due to its encoder being designed for relatively clean datasets such as ScanNet [8], while semi-dense point clouds from *Aria Synthetic Environments* exhibit more noise and less uniformity (see Figure 3 for an example). Cube R-CNN and ImVoxelNet both operate on RGB images, and detections are tracked for the entire sequence via a tracker [2] to provide competitive performance. In Table 3b, our method provides similar performance to both 3DETR and SoftGroup.

Through the addition of the `make_bbox` command, `SceneScript` demonstrates object detection performance on par with SOTA baselines on multiple object detection datasets. This result illustrates the extensibility of a token-based approach, and that our proposed `SceneScript` language representation does not suffer compared to specialised object detection network architectures.

6 Extending the `SceneScript` Structured Language

A key advantage offered by `SceneScript`'s structured language prediction paradigm is that the expressiveness of its reconstruction can be tailored without requiring a change to the method. Up to now, we have focussed on showcasing the efficacy of `SceneScript` for representing simple layout elements and objects as bounding boxes. In this section, we showcase this characteristic by increasing the fidelity of our scene representation by introducing coarse 3D object reconstruction.

6.1 Objects as Volumetric Primitives

We turn to a language based on volumetric primitives, motivated by works such as [28, 35]. Using simple primitives such as cuboids and extruded cylinders, enables us to coarsely represent arbitrary object categories while maintaining object semantics (e.g. tabletops can be represented by a single cuboid). Thus, this language can describe many object categories simultaneously.

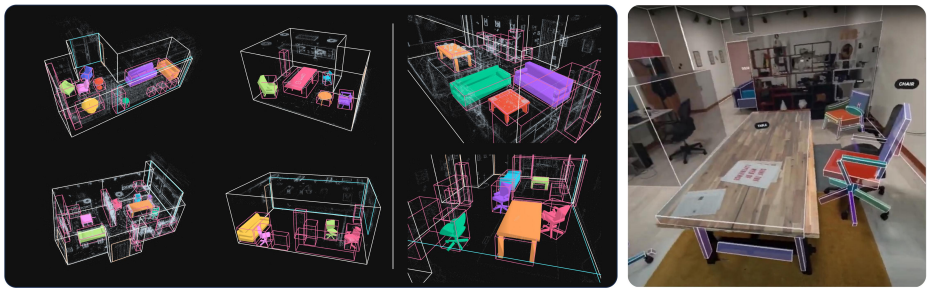

Fig. 6: Example scene reconstructions on **real scenes** with the addition of the `make_prim` command. Note that `SceneScript` was trained only on synthetic data.

This representation requires only one additional command over the layout and box commands already discussed previously, namely:

```
make_prim: bbox_id, prim_num, class, center_x, center_y
    , center_z, angle_x, angle_y, angle_z, scale_x,
    scale_y, scale_z
```

This command and its parameters describe a volumetric primitive (cuboid or extruded cylinder) via its 3D center, 3D rotation, and 3D scale. The `prim_num` parameter can be associated with semantics, e.g. tabletops of different tables typically have the same `prim_num`.

Dataset. To obtain ground truth `make_prim` commands that align with the objects in *Aria Synthetic Environments*, we first run an extension of Yang *et al*. [35] to obtain cuboid and extruded cylinder primitives of a database of 3D CAD models (ABO [7], which was used to populate *Aria Synthetic Environments*). See Figure 5 (left) for example decompositions. For this proof-of-concept experiment, we use three categories: *table*, *chair*, and *sofa*. We then convert these decomposed primitives into `make_prim` commands that are aligned with the objects in the dataset, which results in training pairs.

Results. We show qualitative results on *Aria Synthetic Environments* in Figure 5. In Figure 6, we show inferences in a few real-world environments despite only having trained on our simulated dataset. These results demonstrate that `SceneScript`'s general purpose architecture is capable of coarsely reconstructing objects of multiple categories through addition of a new command.

6.2 Further Extensions

In this section, we have explored just one extension of `SceneScript`'s structured scene language in order to demonstrate its flexibility. The result was greatly increased expressiveness of the scene reconstruction. In the Appendix, we include

additional explorations that can further increase the fidelity and accuracy of the reconstructions. These explorations include reconstructing curved walls, inferring object states (e.g., door opening angles), as well as direct prediction of parametric models using object models deployed commonly by tech artists (e.g., blender geometry nodes) for object reconstruction.

7 Interactive Scene Reconstruction

Scene reconstruction often occurs offline, on pre-recorded walkthroughs of an environment, or derivatives of them, such as a point cloud. However, we take advantage of `SceneScript`'s inference occurring at an interactive rate, which takes between 2-5s depending on the size of the environment, by implementing streaming of `SceneScript`'s live reconstructions into a modern VR headset. This enables an interactive experience where the user can see the reconstruction overlaid onto the environment they are exploring in real-time. See the video recording on the website for examples. Visualisations of this interface are included in Figure 1.

8 Limitations and Future Work

`SceneScript` exhibits certain limitations that should be acknowledged. First, the structured language commands are manually defined, which requires human intervention at this stage. Secondly, due to the higher-level nature of our commands, it can be challenging to capture fine-grained geometric details with extremely high precision (i.e. mm). As a consequence, the resulting reconstructions based on this representation tend to lead to simpler and coarser geometries, potentially missing intricate nuances at the very high detail level. These limitations potentially highlight areas for future research and optimization, aiming to automate the command definition process and explore techniques to enhance the representation's ability to capture intricate geometric details accurately. However, we believe that the ability to built scene representations that are based on structured language commands will be a key part in complex and efficient methods of scene reconstruction in the future.

9 Conclusion

We introduced `SceneScript`, a novel reconstruction method that is based on a tokenized scene representation. `SceneScript` autoregressively predicts a sequence of structured scene language commands given a video stream of an indoor space. This tokenized scene representation is compact, editable and intepretable. In addition, we showed that a strength of `SceneScript` is the ability to extend to arbitrary elements (e.g. Bezier curves, object part decomposition) with minimal changes. This research opens up new directions in representing 3D scenes as language, bringing the 3D reconstruction community closer to the recent advances in large language models such as GPT-class models [20].

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