
HouseLayout3D: A Benchmark and Training-Free Baseline for 3D Layout Estimation in the Wild

Valentin Bieri
ETH Zurich

Marie-Julie Rakotosaona
Google Research

Keisuke Tateno
Google Research

Francis Engelmann
Stanford University

Leonidas Guibas
Stanford University

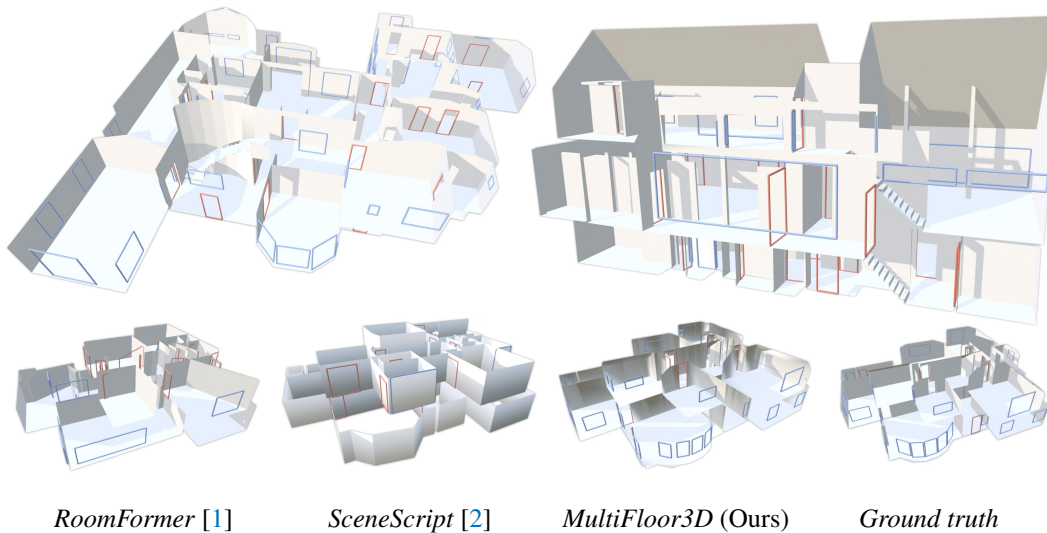


Figure 1: **Top:** We introduce the HOUSELAYOUT3D dataset, a benchmark for 3D house layout estimation which is more diverse than existing datasets and includes large-scale multi-floor buildings and annotations for doors, windows and staircases. **Bottom:** We propose MultiFloor3D, a training-free method for 3D layout estimation that improves over existing methods on our and existing datasets.

Abstract

Current 3D layout estimation models are predominantly trained on synthetic datasets biased toward simplistic, single-floor scenes. This prevents them from generalizing to complex, multi-floor buildings, often forcing a per-floor processing approach that sacrifices global context. Few works have attempted to holistically address multi-floor layouts. In this work, we introduce HOUSELAYOUT3D, a real-world benchmark dataset, which highlights the limitations of existing research when handling expansive, architecturally complex spaces. Additionally, we propose MultiFloor3D, a baseline method leveraging recent advances in 3D reconstruction and 2D segmentation. Our approach significantly outperforms state-of-the-art methods on both our new and existing datasets. Remarkably, it does not require any layout-specific training. The HOUSELAYOUT3D dataset and evaluation scripts are available on the project page: <https://houselayout3d.github.io>

1 Introduction

Estimating the layout of 3D scenes is essential for several computer vision and robotics applications [1, 2, 3, 4]. The objective of 3D layout estimation is to convert a 3D space into a compact, vectorized representation. Specifically, we seek to abstract a reconstructed 3D mesh into a set of closed polygons that define structural elements such as walls, floors, and ceilings, along with doors, windows, and

39th Conference on Neural Information Processing Systems (NeurIPS 2025) Track on Datasets and Benchmarks.

staircases, while disregarding occluding objects like furniture, which commonly appear in real-world environments.

Recent state-of-the-art models for layout prediction [1, 2, 5] are feed-forward deep-learning models trained on large-scale synthetic datasets [6, 2] and demonstrate impressive results even on real-world scenes. A key aspect of these models is that they are trained on synthetic data, which primarily consists of single rooms or small apartments. This is largely because such smaller scenes are easier to synthesize—they can be automatically generated at scale [3] or designed by professionals [6]. As a result, models trained on this data face significant limitations, struggling to generalize to large-scale buildings with substantially more rooms than a typical apartment and being entirely incapable of handling multi-level or multi-floor buildings. While it is possible to first divide large-scale buildings into individual floors and rooms and then process them separately, this approach discards valuable global context that can aid in local reasoning. For instance, detecting structural elements like staircases requires cross-floor reasoning, which is lost when floors are processed in isolation. Additionally, this method necessitates recombining individual room predictions to support building-level tasks such as path planning between rooms on different floors.

To advance research in 3D layout prediction for large-scale, multi-floor buildings, we introduce HOUSELAYOUT3D, a challenging benchmark dataset. Built upon real-world building scans from the Matterport3D [7] dataset, it captures expansive, architecturally complex spaces with up to five floors and forty rooms per floor, encompassing diverse room types, including partially open spaces that pose challenges for existing room-based approaches. We manually annotate all structural elements, including walls, floors, ceilings, staircases, as well as windows and doors, specifying the direction in which each door opens.

Inspired by the success of recent reconstruction and segmentation models, we propose a training-free approach called MultiFloor3D. Our goal is to demonstrate that by leveraging recent advances in 3D scene reconstruction, Gaussian Splatting models, and an innovative layout fitting technique, we can develop a simple yet effective method that outperforms existing approaches on the more challenging task of 3D layout estimation in multi-floor buildings. Our experiments on HOUSELAYOUT3D clearly highlight the limitations of current state-of-the-art methods in handling complex multi-floor buildings. In contrast, our approach generates more accurate and reasonable layouts, particularly for challenging multi-floor structures. We hope that these findings together with the benchmark dataset will inspire new research directions in multi-floor, large-scale 3D layout estimation.

In summary, our contributions are:

- We introduce HOUSELAYOUT3D, the first benchmark dataset for 3D layout estimation in large-scale, multi-floor buildings.
- We propose MultiFloor3D, a training-free baseline method that leverages recent reconstruction and segmentation techniques, achieving improved performance over current deep-learning models.
- Our extensive experiments clearly reveal the limitations of existing layout estimation methods, which we hope will drive further research in this direction.

2 Related Work

Manhattan Scene Layout Initial works on layout estimation impose Manhattan world assumptions on the output to then solve a constrained optimization problem based on detected walls (Scan2Bim [8]) or corners (DuLaNet [9], LayoutNet [10], FloorNet [11]). Notably, Ochmann et al. [12] allow angled walls by subdividing the 3D space into cells, ultimately determining the indoor space with an integer linear program.

2D Scene Layout Another line of work solves the problem from Birds-eye View (BEV): [13] uses shortest-path algorithms around the free space. Floor-SP [14] extends the concept with a room segmentation network. HovSG [15] combines 2D BEV point density maps with 2D object detection to build a scene graph of floors, rooms, and objects without predicting their geometry. This line of work is limited by its 2D predictions.

3D Scene Layout. Recent advances were made by end-to-end deep learning methods: SceneCAD [3] uses a graph neural network to infer a 3D layout and object bounding boxes. RoomFormer [1] trains a transformer to estimate a 2D floorplan enriched with semantics. SceneScript [2] proposes a *structured scene language* to predict 3D layout walls, windows, doors, and object bounding boxes from sparse point clouds. Importantly, available training data for end-to-end trainable methods is dominated by individual room scenes [3] or simple individual floors [6][2][16]. Moreover, the

Dataset	Real-world	Multi-room	Multi-floor	Full Scenes	Windows, Doors	Objects	Depth	3D Layouts
SceneCAD [3]	✓	✓	✗	✓	✓	✓	✓	✓
ASE [2]	✗	✓	✗	✓	✓	✓	✓	✓
Stru3D [6]	✗	✓	✓	✓	✓	✓	✓	✓
Zillow Indoor [16]	✓	✓	✓	✓	✗	✗	✗	✗
MP3D-Layout [18]	✓	✗	✗	✗	✓	✓	✓	✓
Zou et al [17]	✓	✗	✗	✗	✗	✓	✓	✓
CADEstate [4]	✓	✓	✗	✗	✓	✗	✗	✓
FloorNet [11]	✓	✓	✓	✓	✓	✗	✗	✗
HOUSELAYOUT3D (Ours)	✓	✓	✓	✓	✓	✓	✓	✓

Table 1: **Dataset Comparisons** of existing dataset benchmarks for evaluating 3D layouts estimation.

buildings are often unfurnished [16], synthetic [6][2], or limited to Manhattan layouts [17]. Another line of datasets annotates extracts of larger scenes in single 2D images or videos [4][18]. We find that the limited availability of training data prevents end-to-end methods from generalizing beyond simple layouts.

3 The HOUSELAYOUT3D Dataset

We introduce a new dataset of hand-annotated CAD layouts derived from the Matterport3D [7] (MP3D) dataset (see Fig.2). Unlike previous works[3, 2], this is the first real-world benchmark dataset to provide CAD annotations for large-scale, multi-floor houses, encompassing numerous rooms, staircases, windows, and doors. Each structural element is annotated as a polygon in 3D space. Since our dataset is annotated on 3D meshes from MP3D [7], it inherits their per-vertex room ids and object instances.

Dataset Statistics. The dataset includes 16 buildings, 33 distinct levels, and 317 rooms, captured across more than 26,000 RGB-D frames. Its scale is comparable to the validation split of ScanNet [19]. In total, we annotated 292 doors, 379 windows, and 34 staircases. The lower number of doors compared to rooms is due to many spaces, such as hallways and dining areas, being connected by open passages or staircases rather than actual doors. Each building comprises between 1 and 5 levels and contains between 4 and 40 rooms. The annotation time varies depending on the building’s size and the number of rooms, typically ranging from 4 to 10 hours per building. All annotations undergo visual verification by separate expert annotators. Table 1 compares properties across different datasets.

Annotation Tool and Labeling Details. To annotate the 3D scans, we use a free academic license of Scasa’s PinPoint [20], a specialized software for building modeling from point clouds. It enables precise 3D geometry extraction even in occluded or incomplete areas through intuitive tools that automatically snap to edges and corners, streamlining the annotation process. In the 3D scans, doors are typically open, so we annotate both the current open position and the expected closed position, along with the opening direction. For doors that appear closed in the scans, we infer the opening direction by from the door hinge locations in the RGB images. For window annotations, we utilize the existing window object annotations from MP3D [7], projecting them onto the nearest annotated wall plane and fitting axis-aligned rectangles.

4 Method

Given N input RGB images of a scene, our goal is to produce a simple 3D layout consisting of polygons. Each polygon is assigned a label from a finite set of classes: walls, floors, ceilings, stairs, doors, and windows. The layout is organized into a scene graph with rooms as nodes and doors/stairs as edges, and each layout polygon is assigned to a room or an edge of the scene graph.

Figure 3 provides an overview of our approach, which consists of four stages. First, we compute a 3D mesh of the scene. In the second step, we extract the scene’s main structural elements (floors,

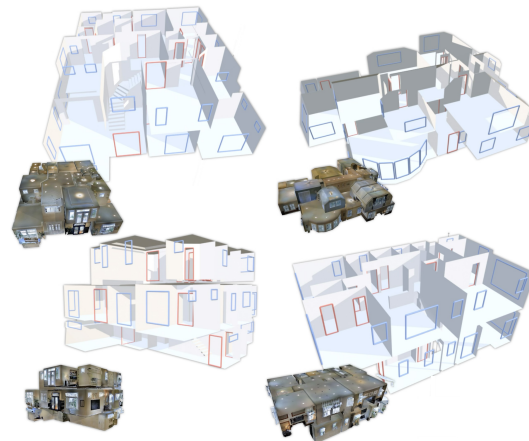


Figure 2: **Examples of our HOUSELAYOUT3D.** Our dataset includes multi-floor houses with annotations for walls, floors, ceilings and stairs, as well as windows (blue) and doors (red). We also show the corresponding 3D meshes from MP3D [7].

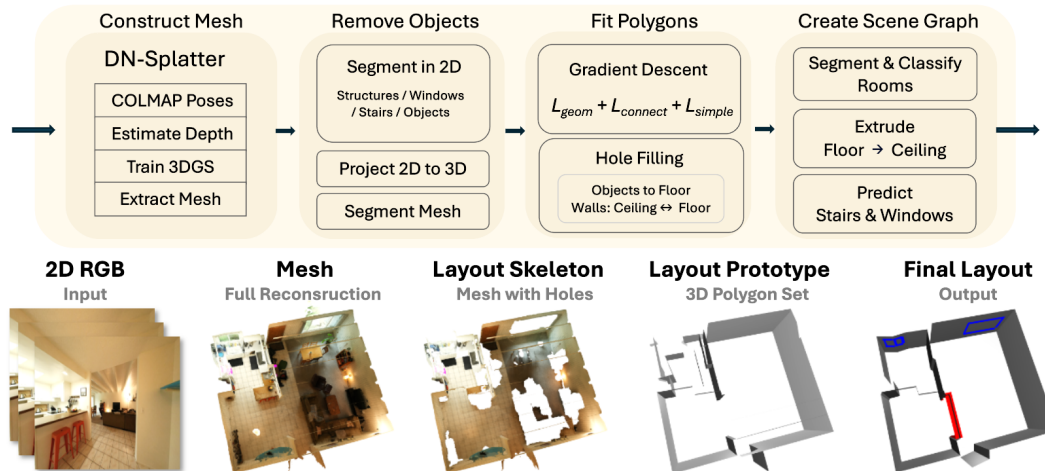


Figure 3: Illustration of the MultiFloor3D model for 3D layout estimation.

walls, ceilings) to form a *skeleton* of the layout. In the third step, we use geometric and semantic information to fit a layout *prototype* to the *skeleton*. Lastly, we parse the *prototype* into a scene graph, from which we extract the final layout.

4.1 Generating a Mesh from RGB Images

Given a set of unposed 2D images, we follow DN-Splatter [21] to obtain a triangle mesh and 3D depth maps for every frame. DN-Splatter uses COLMAP [22] camera poses and a 2D depth model to train 3D Gaussian Splatting [23] (3DGS) reconstruction. DN-splatter then produces a Poisson Reconstruction [24] by sampling from the 3DGS rendered depth. In this work, we use the depth model Metric3d [25].

4.2 Extracting a Layout Skeleton from the Mesh

Once a mesh is generated, our next step is to use a pre-trained 2D segmentation model to extract a minimal, reliable geometry that serves as a basis (*'skeleton'*) for the layout. This skeleton should consist exclusively of geometry that we want to include in the final layout. To distinguish such geometry, we define four semantic classes that we treat differently:

- **Structural Components** (*i.e.* walls, ceilings, and floors, but also large furniture such as closets): These are the main components of the layout skeleton. The structural components have accurate geometry that we wish to see represented in the final layout.
- **Geometrically inaccurate surfaces** (windows, mirrors): The 3D representation of windows and mirrors is often inaccurate due to noisy depth estimates. We do not wish to keep them in the layout skeleton.
- **Objects** Smaller furniture and objects such as tables or lamps are removed from the layout skeleton. Objects are later on used to complete unobserved areas of the layout.
- **Stairs** Are processed separately from the layout skeleton due to their complexity.

To construct the skeleton, we segment the 3D mesh into these classes. We run the segmentation model OneFormer [26] on the input images and map each output class [27] to one of the four semantic classes. To transfer OneFormer's segmentation to the mesh, we back-project $M = 5000$ randomly sampled pixels per image and their respective class to 3D. We collect class votes for each mesh vertex by assigning each back-projected point to the nearest mesh vertex. We further postprocess the obtained segmentation by clustering the mesh vertices into *superpoints*, following [28]'s preprocessing step. Each mesh vertex is then assigned to the most common class within its cluster. The result is a mesh segmented into our semantic classes. We create the *layout skeleton* by selecting only *structural components*, and extract *object* and *stair* meshes.

4.3 Fitting a Layout Prototype to the Skeleton

We observe significant artifacts in the layout skeletons, including holes and unobserved regions. For example, areas hidden behind furniture, or areas corresponding to windows are missing. In this stage, we use geometric and semantic information to correct the artifacts and infer a more complete

layout prototype. To this end, we run an optimization that aims to improve the completeness of the obtained skeleton: We first initialize a collection of planar 3D polygons $\mathcal{P}$ from the layout skeleton. In particular, each segmented superpoint (see Sec. 4.2) of the skeleton is fitted to one or more planes. We then optimize the *vertex positions* and *plane equations* of the polygons using three main objectives:

- Reconstruct an accurate scene geometry with L_{geom}
- Produce a continuous and connected geometry with L_{connect}
- Produce a mesh with low vertex count with L_{simple}

During the optimization, we constrain the vertices of each polygon to be coplanar. We also allow and encourage polygons to share vertices. The initialization and the implementation of vertex constraints and shared vertices is detailed in the supplementary material.

Definitions. Given a polygon P consisting of edges E and a point $p \in \mathbb{R}$ we define the point-to-polygon distance $D_{pp}(P, p)$ as the minimal distance between p and any point on the surface of P . For $e \in E$ we define the point-to-edge distance $D_{pe}(p, e)$ as the minimal distance between p and any point on the line segment representing e .

Losses. We fit the polygon set $\mathcal{P}$ using gradient descent and three losses. The first loss L_{geom} encourages the polygons to reconstruct the original geometry and respect the *observed empty space*:

$$L_{\text{geom}} = L_{\text{prox}} + L_{\text{empty}} \quad (1)$$

L_{prox} penalizes the distance of each vertex $v \in V_{\text{skeleton}}$ of the Layout Skeleton to the closest polygon surface:

$$L_{\text{prox}} = \sum_{v \in V_{\text{skeleton}}} \min_{P \in \mathcal{P}} D_{pp}(v, P) \quad (2)$$

To prevent occluding the observed empty space (*i.e.* the space we believe to be empty based on the depth maps), we sample a set L of line segments using the input camera poses and computed depth maps. Each line segment extends from the camera pose to the back-projected depth. We then penalize line segment-polygon intersections as follows: If a line segment l intersects a polygon, the nearest polygon edge e^* should be moved closer to the intersection point p_{inter} .

$$L_{\text{empty}} = \sum_{l \in L} \sum_{\substack{P \in \mathcal{P} \\ l \cap P \neq \emptyset \\ D_{pe}(p_{\text{inter}}, e^*) \leq T_{\text{inter}}}} D_{pe}(p_{\text{inter}}, e^*) \quad (3)$$

$$\text{where } p_{\text{inter}} = l \cap P \text{ and } e^* = \underset{e' \in \text{edges}(P)}{\text{argmin}} D_{pe}(p_{\text{inter}}, e').$$

Note that we ignore intersections with $D_{pe}(p_{\text{inter}}, e^*)$ greater than the threshold T_{inter} to avoid noise from intersections far from the polygon boundary.

The second loss L_{connect} prevents small gaps and encourages shared boundaries by making polygons attract vertices. Concretely, L_{connect} penalizes the distance from each polygon vertex to the closest surface of another polygon:

$$L_{\text{connect}} = \sum_{P \in \mathcal{P}} \sum_{v \in \text{vertices}(P)} \min_{P' \in \mathcal{P}, P' \neq P} D_{pp}(v, P') \quad (4)$$

As for L_{empty} , we ignore points with $D_{pp}(v, P')$ greater than a threshold.

The third loss encourages simplicity and smooth polygon boundaries. L_{simple} penalizes the length of all edges that are not shared by at least two polygons. (*i.e.* not all edge vertices are shared). Intuitively, L_{simple} promotes shared edges (for instance, an edge between two walls) to represent the scene while edges that are not shared are shrunk until they are eliminated.

$$L_{\text{simple}} = \sum_{P \in \mathcal{P}} \sum_{e \in \text{edges}(P)} \mathbf{1}_{[\nexists P' \in \mathcal{P} \setminus \{P\}: e \subset P']} \|e\|_2 \quad (5)$$

Our final loss is given by $L = L_{\text{geom}} + L_{\text{connect}} + L_{\text{simple}}$.

Vertex Merging L_{simple} itself does not reduce the number of vertices or polygons in the polygon set. Instead, we periodically manually simplify P by (1) merging vertex pairs with distance below T_{merge} , (2) applying the RDP [29] algorithm with tolerance T_{merge} to the polygons individually, and (3) merging close polygons with similar normal. (Close in terms of minimal D_{pp} distance among the vertices.) For (3) we additionally verify that the merged polygon does not increase L_{prox} too strongly. Note that step (1) is the source of shared vertices between polygons.

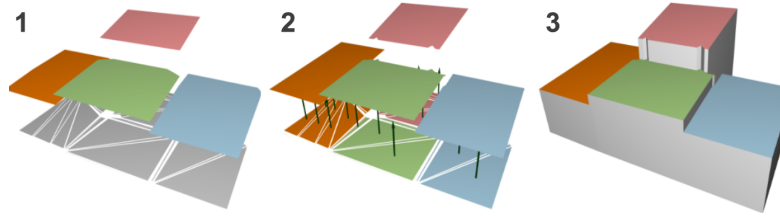


Figure 4: **Our proposed floor extrusion algorithm.** 1) Floor triangulation. 2) Triangles assigned to ceilings using midpoints. 3) Triangles extruded to ceiling planes.

Closing Holes in the Floor We observe that there is a floor under most objects in a room. We exploit this information by projecting objects to the floor, *i.e.* we project each triangle of the *object* mesh extracted in Sec 4.2 to the plane equation of the nearest floor-classified polygon whose centroid lies below the triangle. We recompute the floor polygon from the union of the original floor polygon and the projected triangle surfaces.

Closing Holes in Walls We extend walls to span from ceiling to floor. In particular, we identify polygon edges of wall-classified polygons whose normals face down. Then we count how many line segments in L (representing the observed empty space) intersect the area between each edge and the floor. If the number of intersections per cm^2 is below T_{extend} , we extend the edge to the floor. To ceilings and upwards-facing wall edges, we apply the same procedure. We call the output of this stage the *Layout Prototype*

4.4 Scene Graphs from a Layout Prototype

In this stage, we convert the prototype (a set of semantically labeled polygons) into the final layout. The final layout is organized as a scene graph, where the nodes (rooms) are connected by edges (doors, stairs). Every node is composed of a single floor, and a set of walls, ceiling, and window polygons. To achieve this, we first create 2D floorplans, which we later extrude into 3D space. The indirection via 2D is motivated by the fact that our 3D layout prototype neither gives us an understanding of indoor/outdoor space nor guarantees a closed or even connected layout.

Creation of a Scene Graph of 2D Floorplans In this step we use the layout prototype and its semantics to (1) identify the different levels (floors) of the building, (2) create a 2D layout (floorplan) of each level, and (3) segment each level into rooms, extracting a per-level 2D scene graph from each floor and (4) detect stairs to connect the individual levels. In the following, we provide an outline of the applied algorithms, which are detailed in the appendix.

- To identify building floors, we use the floor-classified polygons of the layout prototype, merging close levels with similar heights.
- To create a 2D floorplan of each level, we merge each level's floor polygon(s) with suitable ceiling polygons — since ceilings are rarely occluded by objects and thus are more robustly represented in the layout prototype.
- To segment each level into rooms, we apply Hov-SG [15]'s room segmentation algorithm on each 2D floorplan (and the walls of the layout prototype). The segmentation outputs a scene graph with rooms as nodes, and *openings* as edges. We consider an opening edge a *door* if its width is below 1.5 m. Otherwise, we retain its edge but label it as *opening*. Furthermore, each room is associated with a room type (kitchen, office, ...).
- To identify stairs, we cluster connected components of the stair mesh extracted in Sec. 4.2. For each component, we add an edge to the scene graph between the rooms/floors it connects.

Back to 3D: Room Extrusion Sec. D describes how we use the layout prototype to generate a scene graph of rooms. In this section, we propose a simple algorithm inspired by layout annotation tools [20], that extrudes each node's 2D floorplan to the ceiling. For a single room, the extrusion algorithm creates a closed room shell using a 2D floorplan and a set of potential 3D ceiling polygons that at least partially cover the floorplan. Fig. 4 visualizes the extrusion process. Its core idea is to (1) triangulate the 2D floorplan, (2) assign each triangle to a ceiling polygon and (3) extrude each triangle to its ceiling. Specifically, we triangulate the room's 2D floorplan using a 2D Constrained Delaunay Triangulation [30] built from the boundary of the floorplan, the ceiling candidates' edges, and the projections of the pairwise intersection lines of the ceiling candidates' planes. For each triangle center, we cast a ray upward. If the ray hits a ceiling candidate, we assign the triangle to that ceiling's plane. Intuitively, this assignment partitions the floorplan by 'rendering' ceiling polygons on the floor. Triangles that do not hit a ceiling are assigned to the lowest ceiling plane reachable in

Method	Structures		Doors		Windows		Stairs		Depth		
	F1@0.5	Avg F1	F1@0.5	Avg F1	F1@0.5	Avg F1	F1@0.5	Avg F1	Δ_5	Δ_{10}	#Vertices
RoomFormer [1] (per floor)	0.24 $\pm$ 0.06	0.22 $\pm$ 0.06	0.23 $\pm$ 0.10	0.20 $\pm$ 0.09	0.07 $\pm$ 0.06	0.07 $\pm$ 0.04	–	–	24.9 $\pm$ 11.5	32.9 $\pm$ 14.9	764.9
RoomFormer [1] (per room)	0.18 $\pm$ 0.14	0.16 $\pm$ 0.12	0.18 $\pm$ 0.14	0.16 $\pm$ 0.12	0.08 $\pm$ 0.08	0.09 $\pm$ 0.07	–	–	37.3 $\pm$ 10.4	44.8 $\pm$ 10.7	1134.5
SceneScript [2] (per floor)	0.28 $\pm$ 0.11	0.26 $\pm$ 0.08	0.23 $\pm$ 0.26	0.20 $\pm$ 0.23	0.16 $\pm$ 0.18	0.15 $\pm$ 0.17	–	–	22.5 $\pm$ 8.6	33.8 $\pm$ 11.7	677.1
SceneScript [2] (per room)	0.23 $\pm$ 0.12	0.21 $\pm$ 0.11	0.31 $\pm$ 0.26	0.28 $\pm$ 0.23	0.11 $\pm$ 0.11	0.10 $\pm$ 0.09	–	–	23.5 $\pm$ 7.2	32.9 $\pm$ 6.7	1333.6
MultiFloor3D (Ours)	0.40$\pm$0.10	0.38$\pm$0.10	0.55$\pm$0.16	0.44$\pm$0.15	0.43$\pm$0.29	0.38$\pm$0.22	0.42$\pm$0.48	0.41$\pm$0.44	61.1$\pm$9.2	76.3$\pm$7.9	1957.0

Table 2: **Scores on HOUSELAYOUT3D.** Performance comparison with state-of-the-art layout estimation methods in terms of average and standard deviation across scenes. Structures include wall, floor and ceilings. MultiFloor3D is the only method predicting stairs.

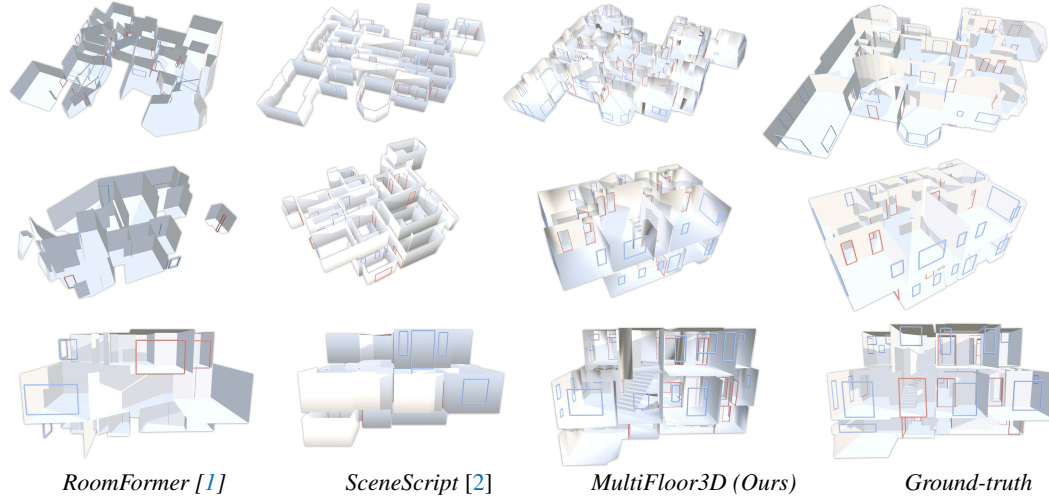


Figure 5: **Qualitative Results on HOUSELAYOUT3D.** We present layout estimation samples from our model alongside state-of-the-art methods. To enhance visualization, we apply back-face culling to the layout meshes, allowing a clear view inside the buildings. Since SceneScript represents walls as boxes, back-face culling is ineffective; instead, we remove the added floors and ceilings for better visibility.

the graph of unassigned triangles. (Lowest in terms of the triangle midpoint’s projected z-coordinate on the target plane.) Lastly, we extrude each floor triangle to its assigned ceiling plane. That is, we produce ceiling and floor triangles on the ceiling and floor planes respectively, and add axis-aligned wall rectangles for triangle edges coinciding with a wall in the 2D floorplan. To ensure a closed room shell, we further add vertical rectangles along potential discontinuous edges in the extruded ceiling surface. To limit complexity, we only consider the 30 largest ceilings per room. Details on how we add doors and stairs after extruding are provided in the appendix.

Window Detection To detect windows, we back-project the 2D window segmentation of the input images obtained in Sec. 4.2 onto layout walls and cluster the result. Concretely, we create rays for window-classified pixels and intersect them with the walls of our 3D layout. We then filter outliers [31], split the points by wall instance, and run DBSCAN [32] for each wall to identify window clusters. To every cluster with at least $k = 10$ vertices, we fit an axis-aligned bounding rectangle. Finally, we predict a window for every rectangle with height and width greater than 30cm.

5 Experiments

In this section, we first introduce metrics to measure the performance of 3D room layout estimation, and then compare our approach to recent state-of-the-art methods on the proposed MultiFloor3D dataset (Sec. 5.1) as well as ScanNet++ [33] (Sec. 5.2). We then provide analysis experiments to understand the importance of the individual pipeline components (Sec. 5.3), and conclude with qualitative results and potential applications (Sec. 5.4).

Methods in Comparison. We compare our approach with two recent methods for scene layout estimation, namely RoomFormer [1] and the recent SceneScript [2]. Training these baselines on our multi-floor dataset is non-trivial – RoomFormer is designed for 2D floorplan prediction, while SceneScript is limited to 4-corner primitives. Instead, we evaluate them using their publicly available model weights on the full HOUSELAYOUT3D dataset. Both baselines are trained on large-scale synthetic datasets ($\sim 100k$ samples), whereas our approach is training-free. Similar to [2], we extrude RoomFormer’s 2D predictions to 3D. Finally, as neither baseline explicitly predicts ceilings or floors, we append ceiling and floor polygons to each predicted room to ensure a fair depth evaluation.

Method	#Vertices	Δ_5	Δ_{10}
DN-Splatter Mesh [21]	354k	84.1	92.6
RoomFormer [1]	32.5	36.8	48.9
SceneScript [2]	41.2	55.1	68.5
MultiFloor3D (Ours)	83.1	67.8	84.7

Table 3: **Scores on ScanNet++ [33]**. Metrics evaluate depth accuracy as an approximation of layout estimation error. Scores are averaged over validation scenes.

Method	Avg F1	#Vertices	Sem.
Input Mesh + QSlim [35]	0.109	2000.0	✗
Layout Skeleton + QSlim [35]	0.223	2000.0	✗
Layout Prototype	0.373	2553.0	✗
MultiFloor3D (Ours)	0.381	1957.1	✓
(w/o prototype fitting)	0.214	2269.8	✓
(w/o room segmentation)	0.359	2442.2	(✓)

Table 4: **Ablation Study on HOUSELAYOUT3D.**

Layout Metrics. To assess the accuracy of the estimated layouts, we adopt the F1 score based on the *entity distance* d_E , following SceneScript [2]. This metric measures the alignment between ground truth entities E and predicted entities E' . For rectangular entities (e.g. doors and windows), d_E is computed as the maximum distance between corresponding corners of two rectangles of the same class: $d_E(E, E') = \max\{\|c_i - c'_{\pi(i)}\| : i = 1, \dots, 4\}$ where $\pi(i)$ denotes the optimal corner permutation obtained via Hungarian matching. The F1 score @ τ is then computed by applying a threshold τ to d_E as in [2].

For non-rectangular entities, we introduce a generalized entity distance d_H which allows comparison between entities with different numbers of corners. We define d_H as the Hausdorff distance between two polygon surfaces (i.e. entities) P, P' and their vertices V, V' :

$$d_H(P, P') = \max\left\{\max_{v \in V} D_{pp}(v, P'), \max_{v' \in V'} D_{pp}(v', P)\right\} \quad (6)$$

for the point-to-polygon distance D_{pp} defined in Sec 4.3. We then use d_H analogously to d_E to compute the F1 score for walls, floors, and ceilings.

Depth Metrics. Following [17], we use input camera poses to render depth maps for the ground truth geometry D_{GT} and predict layouts D_{pred} . When explicit layout annotations are unavailable (e.g., ScanNet++ [33]), depth consistency serves as a proxy for evaluating layout accuracy. Specifically, we compute the percentage of predicted pixel depths that fall within a threshold T cm of the GT depth:

$$\Delta_T = \frac{1}{N} \sum_{i=1}^N \mathbf{1}_{[|D_{pred}(i) - D_{GT}(i)| \leq T]} \quad (7)$$

This Δ_T metric was introduced [34] and is commonly used in monocular depth estimation [25].

5.1 Results on the HOUSELAYOUT3D Dataset

Table 2 shows the main results for the F1-based metrics across semantic classes, and depth metrics on our HOUSELAYOUT3D dataset. For this experiment, we use the camera poses, RGB-D images and mesh of MP3D [7]. As neither baseline is designed for multi-floor layout prediction, we apply them separately per floor (or per room) and then merge the per-floor (or per-room) predictions. We use the ground-truth MP3D level and room segmentation and report scores per-floor and per-room. Our MultiFloor3D does not have access to this privileged information.

MultiFloor3D significantly outperforms state-of-the-art layout estimation methods, despite not using ground-truth floor or room segmentation. While both baselines perform better on individual rooms than full floors, this gap is smaller for SceneScript, which favors compactness (i.e., fewer vertices) at the cost of geometric fidelity.

5.2 Results on the Scannet++ Dataset

Table 3 shows additional results on the Scannet++ [33] *DSLR* validation split, consisting of 50 scenes captured with a monocular hand-held camera and COLMAP-generated image poses. As ScanNet++ does not provide ground truth layout annotation, we only report depth metrics as an approximation of the layout error. Since ScanNet++ scenes are populated with objects, we use ground truth semantic annotations to ignore those points during the evaluation, as well as points on windows which are typically not well reconstructed in the ground truth laser scan. As input for all methods, use the mesh provided by the Gaussian Splatting approach DN-Splatter [21] in the first stage of our method (Sec. 4.1). The results indicate that MultiFloor3D outperforms the baselines at the cost of compactness (larger number of vertices).

5.3 Analysis Experiments

Table 4 shows the contributions in terms of F1 score of each stage in our approach. Note that the outputs of the first and second stages (*mesh* from Sec. 4.1 and *layout skeleton* from Sec. 4.2) are triangle meshes, which we convert to polygon sets by first applying mesh simplification (QSLim [35]), and then greedily merging adjacent triangles whose normals differ by less than 20° . Performance drops significantly when either layout fitting or room segmentation is removed.

5.4 Qualitative Results and Applications

We show qualitative results of our approach in Fig. 5 and compare to RoomFormer [1] and SceneScript [2]. Both baselines methods struggle with large areas consisting of multiple rooms, RoomFormer even more than SceneScript. The baselines are also inherently limited to predicting rectangular primitives and cannot represent more complex shapes such as sloped ceilings (*top example*). In Fig. 6 we visualize qualitative results when removing loss objectives from the mesh fitting stage introduced in Sec. 4.3.

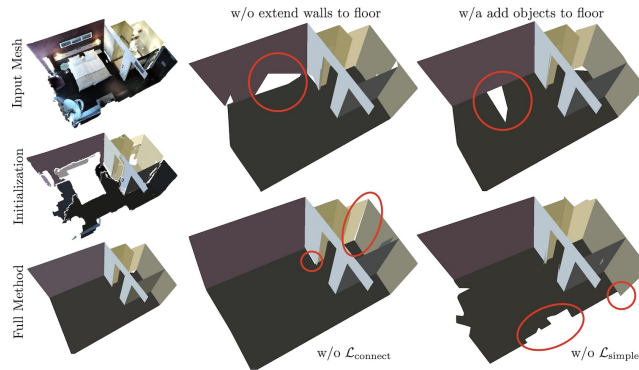


Figure 6: **Effect of Loss Terms.** *Left:* input and output of our approach. *Right:* result when ablating losses and components. Omitting object projection (top center) or wall extension (top right) produces holes in the layout. Without $\mathcal{L}_{\text{simple}}$, the polygon boundaries show dents. Without $\mathcal{L}_{\text{connect}}$, we observe gaps between polygons that otherwise share edges.

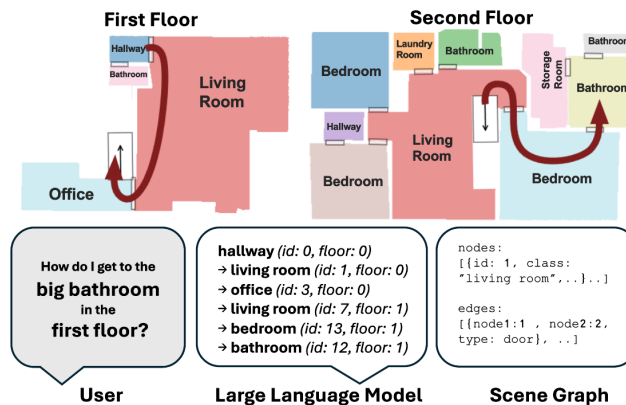


Figure 7: Navigation application based on 3D layouts and LLMs.

Down-stream Application. Next, we demonstrate a potential application of full-building 3D layouts. First, we obtain the 3D scene graph where nodes represent rooms, and edges are connections between rooms (doors, stairs, etc.) Then, we feed the scene graph in JSON format to an LLM, together with a user-prompt asking for directions. The LLM responds with turn-by-turn directions on how to reach the desired location. This concept is illustrated in Fig. 7.

6 Limitations

MultiFloor3D has a significantly longer runtime than the feed-forward baselines, taking one to two hours per HOUSELAYOUT3D scene on an NVIDIA GeForce RTX 4090, compared to one to two minutes for SceneScript [2] and RoomFormer [1]. Furthermore, MultiFloor3D occasionally struggles to remove outdoor elements perceived through large windows, which can introduce artifacts.

7 Conclusion and Discussion

We introduced HOUSELAYOUT3D, the first benchmark dataset for evaluating 3D layout estimation in large-scale, multi-floor buildings. Existing scene layout estimation methods are limited to single-floor buildings, and our experiments reveal their challenges in accurately parsing large-scale floors with multiple rooms—contrasted by our learning-free method, which already outperforms these baselines. Ideally, future research should develop learning-based approaches capable of handling multi-floor, multi-room buildings, rather than relying on heuristics, which, while effective, are significantly slower than feed-forward networks. In summary, we hope that our dataset and evaluation, which highlight the shortcomings of current methods, will drive further advancements in 3D layout estimation beyond single-room and single-level reconstruction.

References

- [1] Yuanwen Yue, Theodora Kontogianni, Konrad Schindler, and Francis Engelmann. Connecting the Dots: Floorplan Reconstruction Using Two-Level Queries. In *International Conference on Computer Vision and Pattern Recognition (CVPR)*, 2023.
- [2] Armen Avetisyan, Christopher Xie, Henry Howard-Jenkins, Tsun-Yi Yang, Samir Aroudj, Suvam Patra, Fuyang Zhang, Duncan Frost, Luke Holland, Campbell Orme, et al. Scenescrit: Reconstructing scenes with an autoregressive structured language model. *European Conference on Computer Vision (ECCV)*, 2024.
- [3] Armen Avetisyan, Tatiana Khanova, Christopher Choy, Denver Dash, Angela Dai, and Matthias Nießner. Scenecad: Predicting object alignments and layouts in rgb-d scans. In *The European Conference on Computer Vision (ECCV)*, August 2020.
- [4] Denys Rozumnyi, Stefan Popov, Kevis-Kokitsi Maninis, Matthias Nießner, and Vittorio Ferrari. Estimating generic 3d room structures from 2d annotations, 2023.
- [5] Jiacheng Chen, Ruizhi Deng, and Yasutaka Furukawa. Polydiffuse: Polygonal shape reconstruction via guided set diffusion models. *International Conference on Neural Information Processing Systems (NeurIPS)*, 2023.
- [6] Jia Zheng, Junfei Zhang, Jing Li, Rui Tang, Shenghua Gao, and Zihan Zhou. Structured3d: A large photo-realistic dataset for structured 3d modeling. In *Proceedings of The European Conference on Computer Vision (ECCV)*, 2020.
- [7] Angel Chang, Angela Dai, Thomas Funkhouser, Maciej Halber, Matthias Niessner, Manolis Savva, Shuran Song, Andy Zeng, and Yinda Zhang. Matterport3d: Learning from rgb-d data in indoor environments. *International Conference on 3D Vision (3DV)*, 2017.
- [8] Srivathsan Murali, Pablo Speciale, Martin R. Oswald, and Marc Pollefeys. Indoor scan2bim: Building information models of house interiors. In *2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 6126–6133, 2017.
- [9] Shang-Ta Yang, Fu-En Wang, Chi-Han Peng, Peter Wonka, Min Sun, and Hung-Kuo Chu. Dula-net: A dual-projection network for estimating room layouts from a single rgb panorama, 2019.
- [10] Chuhan Zou, Alex Colburn, Qi Shan, and Derek Hoiem. Layoutnet: Reconstructing the 3d room layout from a single rgb image. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 2051–2059, 2018.
- [11] Chen Liu, Jiaye Wu, and Yasutaka Furukawa. Floornet: A unified framework for floorplan reconstruction from 3d scans, 2018.
- [12] Sebastian Ochmann, Richard Vock, and Reinhard Klein. Automatic reconstruction of fully volumetric 3d building models from oriented point clouds. *ISPRS Journal of Photogrammetry and Remote Sensing*, 151:251–262, 2019.
- [13] Ricardo Cabral and Yasutaka Furukawa. Piecewise planar and compact floorplan reconstruction from images. In *2014 IEEE Conference on Computer Vision and Pattern Recognition*, pages 628–635, 2014.
- [14] Jiacheng Chen, Chen Liu, Jiaye Wu, and Yasutaka Furukawa. Floor-sp: Inverse cad for floorplans by sequential room-wise shortest path, 2019.
- [15] Abdelrhman Werby, Chenguang Huang, Martin Büchner, Abhinav Valada, and Wolfram Burgard. Hierarchical open-vocabulary 3d scene graphs for language-grounded robot navigation. *Robotics: Science and Systems*, 2024.
- [16] Steve Cruz, Will Hutchcroft, Yuguang Li, Naji Khosravan, Ivaylo Boyadzhiev, and Sing Bing Kang. Zillow indoor dataset: Annotated floor plans with 360° panoramas and 3d room layouts. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 2133–2143, June 2021.
- [17] Chuhan Zou, Jheng-Wei Su, Chi-Han Peng, Alex Colburn, Qi Shan, Peter Wonka, Hung-Kuo Chu, and Derek Hoiem. Manhattan room layout reconstruction from a single 360 image: A comparative study of state-of-the-art methods, 2020.
- [18] VSIS Lab. Matterport3d-layout. <https://github.com/vsislab/Matterport3D-Layout>, 2020. GitHub repository. Accessed: 2025-03-02.

- [19] Angela Dai, Angel X Chang, Manolis Savva, Maciej Halber, Thomas Funkhouser, and Matthias Nießner. Scannet: Richly-annotated 3d reconstructions of indoor scenes. In *International Conference on Computer Vision and Pattern Recognition (CVPR)*, 2017.
- [20] SCASA. Pinpoint. <https://scasa.eu/pinpoint/en/>. Accessed: 2025-03-02.
- [21] Matias Turkulainen, Xuqian Ren, Iaroslav Melekhov, Otto Seiskari, Esa Rahtu, and Juho Kannala. Dn-splatter: Depth and normal priors for gaussian splatting and meshing, 2024.
- [22] Johannes Lutz Schönberger and Jan-Michael Frahm. Structure-from-motion revisited. In *Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016.
- [23] Bernhard Kerbl, Georgios Kopanas, Thomas Leimkühler, and George Drettakis. 3d gaussian splatting for real-time radiance field rendering. *ACM Transactions on Graphics*, 42(4), July 2023.
- [24] Michael Kazhdan, Matthew Bolitho, and Hugues Hoppe. Poisson surface reconstruction. Goslar, DEU, 2006. Eurographics Association.
- [25] Wei Yin, Chi Zhang, Hao Chen, Zhipeng Cai, Gang Yu, Kaixuan Wang, Xiaozhi Chen, and Chunhua Shen. Metric3d: Towards zero-shot metric 3d prediction from a single image, 2023.
- [26] Jitesh Jain, Jiachen Li, MangTik Chiu, Ali Hassani, Nikita Orlov, and Humphrey Shi. OneFormer: One Transformer to Rule Universal Image Segmentation. 2023.
- [27] Tsung-Yi Lin, Michael Maire, Serge Belongie, Lubomir Bourdev, Ross Girshick, James Hays, Pietro Perona, Deva Ramanan, C. Lawrence Zitnick, and Piotr Dollár. Microsoft coco: Common objects in context, 2015.
- [28] Damien Robert, Hugo Raguét, and Loïc Landrieu. Scalable 3d panoptic segmentation as superpoint graph clustering. *Proceedings of the IEEE International Conference on 3D Vision*, 2024.
- [29] D. H. Douglas and T. K. Peucker. Algorithms for the reduction of the number of points required to represent a digitized line or its caricature. *The Canadian Cartographer*, 10:112–122, 1973.
- [30] CGAL Team. *CGAL::Constrained_Delaunay_triangulation_2*. CGAL – Computational Geometry Algorithms Library, 2025. Accessed: 2025-03-07.
- [31] Markus M. Breunig, Hans-Peter Kriegel, Raymond T. Ng, and Jörg Sander. Lof: identifying density-based local outliers. In *Proceedings of the 2000 ACM SIGMOD International Conference on Management of Data*, SIGMOD '00, page 93–104, New York, NY, USA, 2000. Association for Computing Machinery.
- [32] Martin Ester, Hans-Peter Kriegel, Jörg Sander, and Xiaowei Xu. A density-based algorithm for discovering clusters in large spatial databases with noise. In *Knowledge Discovery and Data Mining*, 1996.
- [33] Chandan Yeshwanth, Yueh-Cheng Liu, Matthias Nießner, and Angela Dai. Scannet++: A high-fidelity dataset of 3d indoor scenes, 2023.
- [34] Lubor Ladický, Jianbo Shi, and Marc Pollefeys. Pulling things out of perspective. In *2014 IEEE Conference on Computer Vision and Pattern Recognition*, pages 89–96, 2014.
- [35] Michael Garland and Paul S. Heckbert. Surface simplification using quadric error metrics. In *Proceedings of the 24th Annual Conference on Computer Graphics and Interactive Techniques*, SIGGRAPH '97, page 209–216, USA, 1997. ACM Press/Addison-Wesley Publishing Co.
- [36] Nikhila Ravi, Jeremy Reizenstein, David Novotny, Taylor Gordon, Wan-Yen Lo, Justin Johnson, and Georgia Gkioxari. Accelerating 3d deep learning with pytorch3d. *arXiv:2007.08501*, 2020.
- [37] Golnaz Ghiasi, Xiuye Gu, Yin Cui, and Tsung-Yi Lin. Scaling open-vocabulary image segmentation with image-level labels, 2022.

NeurIPS Paper Checklist

1. Claims

Question: Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope?

Answer: [\[Yes\]](#)

Justification: Our main claims are that (1) existing end-to-end-trained methods do not generalize well to large / multi-floor scenes, (2) that we introduce a benchmark dataset consisting of such scenes to show it, and that (3) we present a method that outperforms them even without layout-specific training. Our main results on HOUSELAYOUT3D (Tab. 2) support (1) and (3), whereas Sec. 5.1 introduces the dataset.

Guidelines:

- The answer NA means that the abstract and introduction do not include the claims made in the paper.
- The abstract and/or introduction should clearly state the claims made, including the contributions made in the paper and important assumptions and limitations. A No or NA answer to this question will not be perceived well by the reviewers.
- The claims made should match theoretical and experimental results, and reflect how much the results can be expected to generalize to other settings.
- It is fine to include aspirational goals as motivation as long as it is clear that these goals are not attained by the paper.

2. Limitations

Question: Does the paper discuss the limitations of the work performed by the authors?

Answer: [\[Yes\]](#)

Justification: See the limitations section (Sec. 6)

Guidelines:

- The answer NA means that the paper has no limitation while the answer No means that the paper has limitations, but those are not discussed in the paper.
- The authors are encouraged to create a separate "Limitations" section in their paper.
- The paper should point out any strong assumptions and how robust the results are to violations of these assumptions (e.g., independence assumptions, noiseless settings, model well-specification, asymptotic approximations only holding locally). The authors should reflect on how these assumptions might be violated in practice and what the implications would be.
- The authors should reflect on the scope of the claims made, e.g., if the approach was only tested on a few datasets or with a few runs. In general, empirical results often depend on implicit assumptions, which should be articulated.
- The authors should reflect on the factors that influence the performance of the approach. For example, a facial recognition algorithm may perform poorly when image resolution is low or images are taken in low lighting. Or a speech-to-text system might not be used reliably to provide closed captions for online lectures because it fails to handle technical jargon.
- The authors should discuss the computational efficiency of the proposed algorithms and how they scale with dataset size.
- If applicable, the authors should discuss possible limitations of their approach to address problems of privacy and fairness.
- While the authors might fear that complete honesty about limitations might be used by reviewers as grounds for rejection, a worse outcome might be that reviewers discover limitations that aren't acknowledged in the paper. The authors should use their best judgment and recognize that individual actions in favor of transparency play an important role in developing norms that preserve the integrity of the community. Reviewers will be specifically instructed to not penalize honesty concerning limitations.

3. Theory assumptions and proofs

Question: For each theoretical result, does the paper provide the full set of assumptions and a complete (and correct) proof?

Answer: [NA]

Justification: We do not include theoretical results.

Guidelines:

- The answer NA means that the paper does not include theoretical results.
- All the theorems, formulas, and proofs in the paper should be numbered and cross-referenced.
- All assumptions should be clearly stated or referenced in the statement of any theorems.
- The proofs can either appear in the main paper or the supplemental material, but if they appear in the supplemental material, the authors are encouraged to provide a short proof sketch to provide intuition.
- Inversely, any informal proof provided in the core of the paper should be complemented by formal proofs provided in appendix or supplemental material.
- Theorems and Lemmas that the proof relies upon should be properly referenced.

4. Experimental result reproducibility

Question: Does the paper fully disclose all the information needed to reproduce the main experimental results of the paper to the extent that it affects the main claims and/or conclusions of the paper (regardless of whether the code and data are provided or not)?

Answer: [Yes]

Justification: In addition to open-sourcing the HOUSELAYOUT3D dataset and the code for MultiFloor3D, we provide a detailed description of all algorithms and their hyperparameters in the supplementary material.

Guidelines:

- The answer NA means that the paper does not include experiments.
- If the paper includes experiments, a No answer to this question will not be perceived well by the reviewers: Making the paper reproducible is important, regardless of whether the code and data are provided or not.
- If the contribution is a dataset and/or model, the authors should describe the steps taken to make their results reproducible or verifiable.
- Depending on the contribution, reproducibility can be accomplished in various ways. For example, if the contribution is a novel architecture, describing the architecture fully might suffice, or if the contribution is a specific model and empirical evaluation, it may be necessary to either make it possible for others to replicate the model with the same dataset, or provide access to the model. In general, releasing code and data is often one good way to accomplish this, but reproducibility can also be provided via detailed instructions for how to replicate the results, access to a hosted model (e.g., in the case of a large language model), releasing of a model checkpoint, or other means that are appropriate to the research performed.
- While NeurIPS does not require releasing code, the conference does require all submissions to provide some reasonable avenue for reproducibility, which may depend on the nature of the contribution. For example
 - (a) If the contribution is primarily a new algorithm, the paper should make it clear how to reproduce that algorithm.
 - (b) If the contribution is primarily a new model architecture, the paper should describe the architecture clearly and fully.
 - (c) If the contribution is a new model (e.g., a large language model), then there should either be a way to access this model for reproducing the results or a way to reproduce the model (e.g., with an open-source dataset or instructions for how to construct the dataset).
 - (d) We recognize that reproducibility may be tricky in some cases, in which case authors are welcome to describe the particular way they provide for reproducibility. In the case of closed-source models, it may be that access to the model is limited in some way (e.g., to registered users), but it should be possible for other researchers to have some path to reproducing or verifying the results.

5. Open access to data and code

Question: Does the paper provide open access to the data and code, with sufficient instructions to faithfully reproduce the main experimental results, as described in supplemental material?

Answer: [Yes]

Justification: We provide the dataset (<https://huggingface.co/datasets/bieriv/HouseLayout3D>) and the evaluation code (<https://github.com/valebi/house-layout-3d-eval/>). The code for MultiFloor3D is provided in the supplementary material and will be open-sourced at a later time.

Guidelines:

- The answer NA means that paper does not include experiments requiring code.
- Please see the NeurIPS code and data submission guidelines (<https://nips.cc/public/guides/CodeSubmissionPolicy>) for more details.
- While we encourage the release of code and data, we understand that this might not be possible, so “No” is an acceptable answer. Papers cannot be rejected simply for not including code, unless this is central to the contribution (e.g., for a new open-source benchmark).
- The instructions should contain the exact command and environment needed to run to reproduce the results. See the NeurIPS code and data submission guidelines (<https://nips.cc/public/guides/CodeSubmissionPolicy>) for more details.
- The authors should provide instructions on data access and preparation, including how to access the raw data, preprocessed data, intermediate data, and generated data, etc.
- The authors should provide scripts to reproduce all experimental results for the new proposed method and baselines. If only a subset of experiments are reproducible, they should state which ones are omitted from the script and why.
- At submission time, to preserve anonymity, the authors should release anonymized versions (if applicable).
- Providing as much information as possible in supplemental material (appended to the paper) is recommended, but including URLs to data and code is permitted.

6. Experimental setting/details

Question: Does the paper specify all the training and test details (e.g., data splits, hyperparameters, how they were chosen, type of optimizer, etc.) necessary to understand the results?

Answer: [Yes]

Justification: Our method is training free and hence a train-test split is omitted. Hyperparameter choices are provided in the supplementary material.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The experimental setting should be presented in the core of the paper to a level of detail that is necessary to appreciate the results and make sense of them.
- The full details can be provided either with the code, in appendix, or as supplemental material.

7. Experiment statistical significance

Question: Does the paper report error bars suitably and correctly defined or other appropriate information about the statistical significance of the experiments?

Answer: [Yes]

Justification: The main results on HOUSELAYOUT3D (Tab. 2) include the standard deviation across scenes.

Guidelines:

- The answer NA means that the paper does not include experiments.

- The authors should answer "Yes" if the results are accompanied by error bars, confidence intervals, or statistical significance tests, at least for the experiments that support the main claims of the paper.
- The factors of variability that the error bars are capturing should be clearly stated (for example, train/test split, initialization, random drawing of some parameter, or overall run with given experimental conditions).
- The method for calculating the error bars should be explained (closed form formula, call to a library function, bootstrap, etc.)
- The assumptions made should be given (e.g., Normally distributed errors).
- It should be clear whether the error bar is the standard deviation or the standard error of the mean.
- It is OK to report 1-sigma error bars, but one should state it. The authors should preferably report a 2-sigma error bar than state that they have a 96% CI, if the hypothesis of Normality of errors is not verified.
- For asymmetric distributions, the authors should be careful not to show in tables or figures symmetric error bars that would yield results that are out of range (e.g. negative error rates).
- If error bars are reported in tables or plots, The authors should explain in the text how they were calculated and reference the corresponding figures or tables in the text.

8. Experiments compute resources

Question: For each experiment, does the paper provide sufficient information on the computer resources (type of compute workers, memory, time of execution) needed to reproduce the experiments?

Answer: [Yes]

Justification: We briefly discuss the hardware setup and the average runtime in the limitations section (Sec. 6).

Guidelines:

- The answer NA means that the paper does not include experiments.
- The paper should indicate the type of compute workers CPU or GPU, internal cluster, or cloud provider, including relevant memory and storage.
- The paper should provide the amount of compute required for each of the individual experimental runs as well as estimate the total compute.
- The paper should disclose whether the full research project required more compute than the experiments reported in the paper (e.g., preliminary or failed experiments that didn't make it into the paper).

9. Code of ethics

Question: Does the research conducted in the paper conform, in every respect, with the NeurIPS Code of Ethics <https://neurips.cc/public/EthicsGuidelines>?

Answer: [Yes]

Justification: Our dataset consists of additional annotations on top of the existing Matterport3D dataset, which we believe to be conform with the Code of Ethics. The annotation process - performed by ourselves - also was in accordance with the Code of Ethics.

Guidelines:

- The answer NA means that the authors have not reviewed the NeurIPS Code of Ethics.
- If the authors answer No, they should explain the special circumstances that require a deviation from the Code of Ethics.
- The authors should make sure to preserve anonymity (e.g., if there is a special consideration due to laws or regulations in their jurisdiction).

10. Broader impacts

Question: Does the paper discuss both potential positive societal impacts and negative societal impacts of the work performed?

Answer: [NA]

Justification: We believe that our work has limited immediate societal impact.

Guidelines:

- The answer NA means that there is no societal impact of the work performed.
- If the authors answer NA or No, they should explain why their work has no societal impact or why the paper does not address societal impact.
- Examples of negative societal impacts include potential malicious or unintended uses (e.g., disinformation, generating fake profiles, surveillance), fairness considerations (e.g., deployment of technologies that could make decisions that unfairly impact specific groups), privacy considerations, and security considerations.
- The conference expects that many papers will be foundational research and not tied to particular applications, let alone deployments. However, if there is a direct path to any negative applications, the authors should point it out. For example, it is legitimate to point out that an improvement in the quality of generative models could be used to generate deepfakes for disinformation. On the other hand, it is not needed to point out that a generic algorithm for optimizing neural networks could enable people to train models that generate Deepfakes faster.
- The authors should consider possible harms that could arise when the technology is being used as intended and functioning correctly, harms that could arise when the technology is being used as intended but gives incorrect results, and harms following from (intentional or unintentional) misuse of the technology.
- If there are negative societal impacts, the authors could also discuss possible mitigation strategies (e.g., gated release of models, providing defenses in addition to attacks, mechanisms for monitoring misuse, mechanisms to monitor how a system learns from feedback over time, improving the efficiency and accessibility of ML).

11. Safeguards

Question: Does the paper describe safeguards that have been put in place for responsible release of data or models that have a high risk for misuse (e.g., pretrained language models, image generators, or scraped datasets)?

Answer: [NA]

Justification: We believe that our dataset poses no such risk.

Guidelines:

- The answer NA means that the paper poses no such risks.
- Released models that have a high risk for misuse or dual-use should be released with necessary safeguards to allow for controlled use of the model, for example by requiring that users adhere to usage guidelines or restrictions to access the model or implementing safety filters.
- Datasets that have been scraped from the Internet could pose safety risks. The authors should describe how they avoided releasing unsafe images.
- We recognize that providing effective safeguards is challenging, and many papers do not require this, but we encourage authors to take this into account and make a best faith effort.

12. Licenses for existing assets

Question: Are the creators or original owners of assets (e.g., code, data, models), used in the paper, properly credited and are the license and terms of use explicitly mentioned and properly respected?

Answer: [NA]

Justification: We release hand-crafted annotations only, and do not publish the existing Matterport3D dataset in any form.

Guidelines:

- The answer NA means that the paper does not use existing assets.
- The authors should cite the original paper that produced the code package or dataset.
- The authors should state which version of the asset is used and, if possible, include a URL.

- The name of the license (e.g., CC-BY 4.0) should be included for each asset.
- For scraped data from a particular source (e.g., website), the copyright and terms of service of that source should be provided.
- If assets are released, the license, copyright information, and terms of use in the package should be provided. For popular datasets, paperswithcode.com/datasets has curated licenses for some datasets. Their licensing guide can help determine the license of a dataset.
- For existing datasets that are re-packaged, both the original license and the license of the derived asset (if it has changed) should be provided.
- If this information is not available online, the authors are encouraged to reach out to the asset's creators.

13. **New assets**

Question: Are new assets introduced in the paper well documented and is the documentation provided alongside the assets?

Answer: [\[Yes\]](#)

Justification: We provide the dataset, its documentation, and usage / evaluation code on <https://huggingface.co/datasets/bieriv/HouseLayout3D>

Guidelines:

- The answer NA means that the paper does not release new assets.
- Researchers should communicate the details of the dataset/code/model as part of their submissions via structured templates. This includes details about training, license, limitations, etc.
- The paper should discuss whether and how consent was obtained from people whose asset is used.
- At submission time, remember to anonymize your assets (if applicable). You can either create an anonymized URL or include an anonymized zip file.

14. **Crowdsourcing and research with human subjects**

Question: For crowdsourcing experiments and research with human subjects, does the paper include the full text of instructions given to participants and screenshots, if applicable, as well as details about compensation (if any)?

Answer: [\[NA\]](#)

Justification: The paper does not involve crowdsourcing nor research with human subjects.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Including this information in the supplemental material is fine, but if the main contribution of the paper involves human subjects, then as much detail as possible should be included in the main paper.
- According to the NeurIPS Code of Ethics, workers involved in data collection, curation, or other labor should be paid at least the minimum wage in the country of the data collector.

15. **Institutional review board (IRB) approvals or equivalent for research with human subjects**

Question: Does the paper describe potential risks incurred by study participants, whether such risks were disclosed to the subjects, and whether Institutional Review Board (IRB) approvals (or an equivalent approval/review based on the requirements of your country or institution) were obtained?

Answer: [\[NA\]](#)

Justification: The paper does not involve crowdsourcing nor research with human subjects.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.

- Depending on the country in which research is conducted, IRB approval (or equivalent) may be required for any human subjects research. If you obtained IRB approval, you should clearly state this in the paper.
- We recognize that the procedures for this may vary significantly between institutions and locations, and we expect authors to adhere to the NeurIPS Code of Ethics and the guidelines for their institution.
- For initial submissions, do not include any information that would break anonymity (if applicable), such as the institution conducting the review.

16. **Declaration of LLM usage**

Question: Does the paper describe the usage of LLMs if it is an important, original, or non-standard component of the core methods in this research? Note that if the LLM is used only for writing, editing, or formatting purposes and does not impact the core methodology, scientific rigorousness, or originality of the research, declaration is not required.

Answer: [\[Yes\]](#)

Justification: Sec. 5.4 introduces an LLM-based downstream application of our method for indoor navigation.

Guidelines:

- The answer NA means that the core method development in this research does not involve LLMs as any important, original, or non-standard components.
- Please refer to our LLM policy (<https://neurips.cc/Conferences/2025/LLM>) for what should or should not be described.

A Additional Visualizations for the HOUSELAYOUT3D Dataset

Fig. 9 visualizes the scenes in the annotated dataset, while Fig. 8 shows a screenshot of PinPoint [20], the tool used to create the annotations.

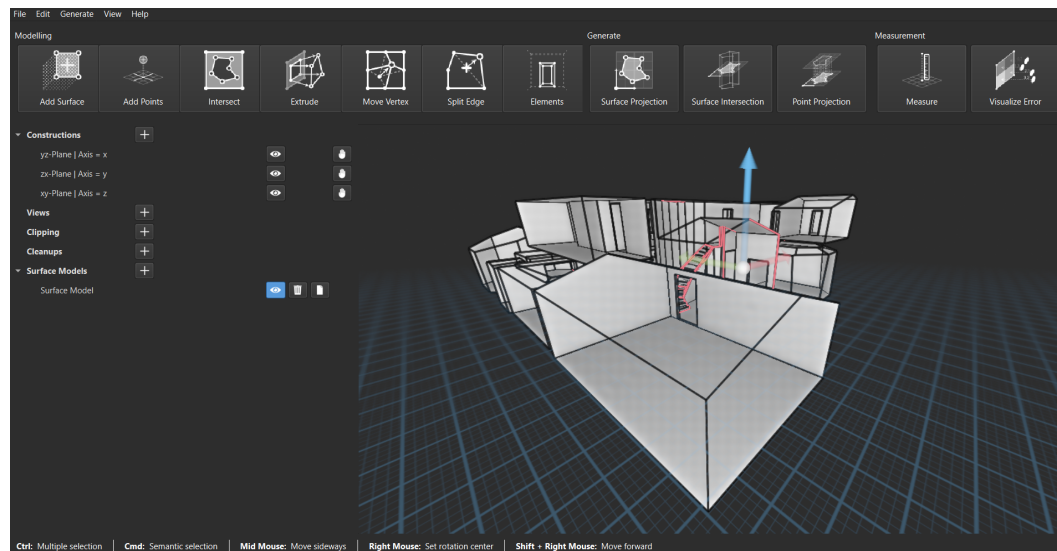


Figure 8: Screenshot of PinPoint [20], the layout annotation tool used to annotate the scenes.

B Re-Classification of COCO [27] Classes

In Sec. 4.2, we segment the input images using OneFormer [26]. It segments the images into COCO [27] classes, which we re-classify into four semantic classes of interest. Table 5 summarizes this re-classification. For window detection in Sec. 4.4, we make two changes to this classification. Firstly, we do not consider mirrors windows. Secondly, we add the surface classes *window blind* and *curtain* to the window classes. Furthermore, the surface class is maintained in the layout skeleton and the prototype layout (but not in the output).

Semantic Class	Category	COCO [27] Classes
Structure	Wall	wall-brick, wall-stone, wall-tile, wall-wood, wall-other-merged
	Ceiling	ceiling-merged
	Floor	floor-wood, floor-other-merged, rug-merged
	Surfaces	cabinet-merged, door-stuff, curtain, window-blind
Geometrically inaccurate surfaces	Windows	window-other
	Mirrors	mirror-stuff
	Outdoor/Noise	gravel, tree-merged, sky-other-merged, pavement-merged, grass-merged, dirt-merged
Stairs	Stairs	stairs
Objects	Object	Rest

Table 5: Mapping of COCO [27] classes into four semantic classes. The *structure* class is used to construct the layout skeleton; the *geometrically inaccurate surfaces* are removed; the *objects* are used to fill holes, and the *stairs* are added back once the scene graph is created (Sec. 4.4). During prototype fitting (Sec. 4.3), we further distinguish between walls, ceilings, floors, and generic surfaces among the structures. Unlike mirrors, the outdoor classes are also used for window detection in Sec. 4.4 because they are typically visible through windows in indoor environments.

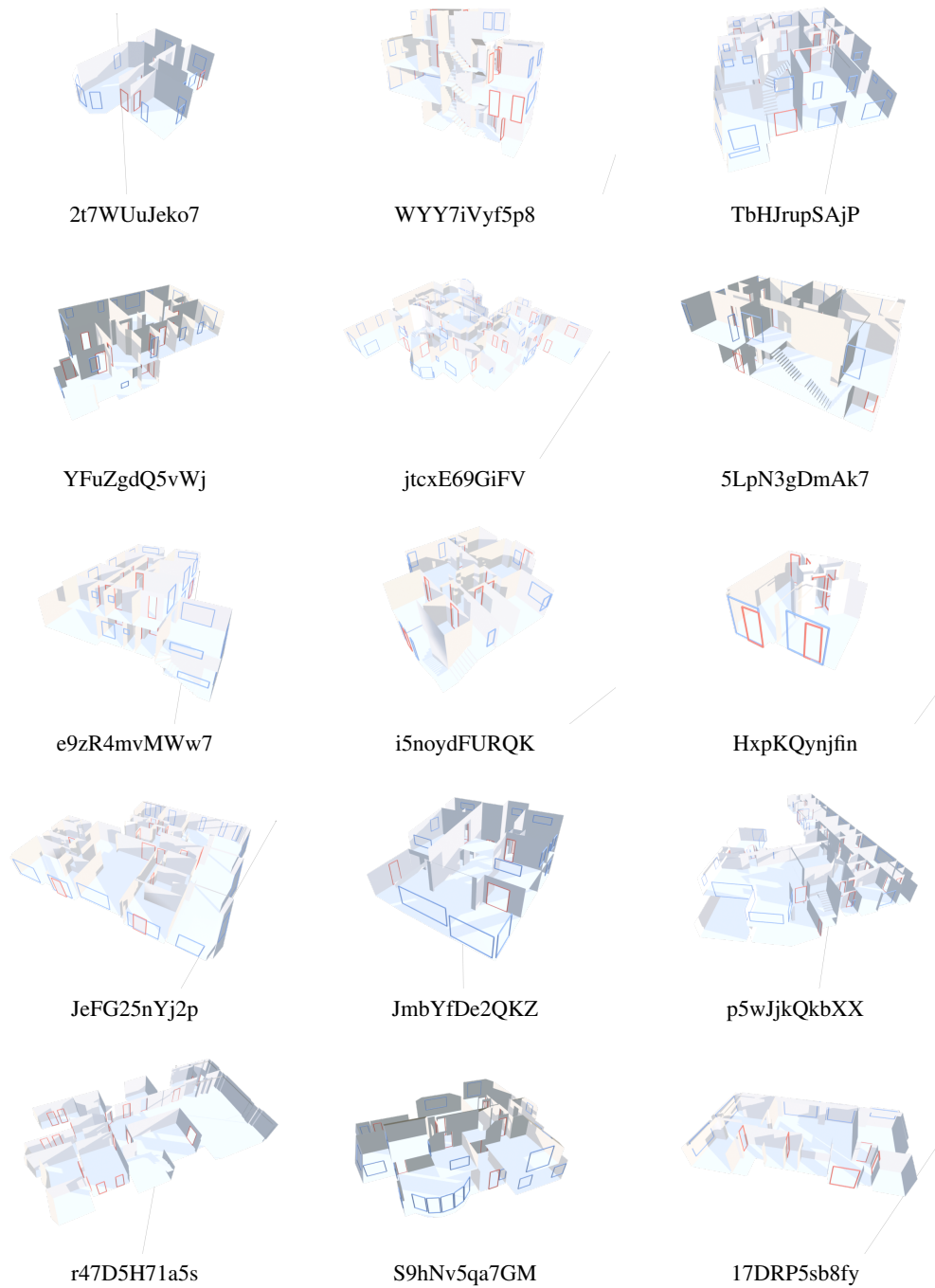


Figure 9: Visualizations and scene names of the scenes in the HOUSELAYOUT3D dataset. (The scene in Fig 1 was omitted).

C Implementation details for Layout Prototype Fitting

C.1 Initialization of a Polygon Set from the Layout Skeleton

In Sec. 4.3 we fit a set of polygons to the layout skeleton to produce the *layout prototype*. Specifically, we sequentially fit one or more planes to each superpoint in the clustering using model fitting by random sample consensus (RANSAC [?]). Then we extract polygons from the connected components of plane inliers (*i.e.* the points close to the planes): that is, we use the connectivity of the skeleton

Require: A mesh M segmented into clusters $S = \{S_1, S_2, \dots, S_n\}$

Ensure: A set of planar 3D polygons $\mathcal{P}$

```
1: Mark every vertex in  $M$  as unassigned
2: Initialize  $\mathcal{P} \leftarrow \emptyset$ 
3: while there is a cluster with more than  $K$  unassigned vertices do
4:   Choose the cluster  $S^*$  with the most unassigned vertices
5:   Fit a plane to  $S^*$  using RANSAC
6:   Find all unassigned vertices in  $M$  that lie close to the plane (the inliers)
7:   Assign the vertices of the connected component of inliers that overlaps the most with  $S^*$  to a
   new plane (connected w.r.t the mesh edges).
8:   Extract polygon  $P$  from the boundary of the triangles of the connected component, and add it
   to  $\mathcal{P}$ 
9: end while
10:
11: return  $\mathcal{P}$ 
```

Algorithm 1: Initialization of 3D Polygon Set. We extract a set of planar 3D polygons from the clustered *layout skeleton* mesh by sequentially fitting planes to the superpoint clusters obtained in Sec. 4.2.

mesh to extract connected components of plane inliers. Then we take the boundary of each connected component as a polygon. Algorithm 1 describes the procedure.

C.2 Implementation of a 3D Planar Polygon Set

In Sec. 4.3 we fit a set of 3D polygons to the vertices of the layout skeleton mesh using gradient descent.

For a set of N polygons and V vertices, we optimize the following parameters: 1) plane equations of shape $(N, 4)$ and 2) the vertex positions of shape $(V, 3)$. The parameters' gradients are computed using backpropagation.

Implementation of 3D Planar Polygons as Triangle Meshes We build our implementation of a 3D polygon set on pytorch3d triangle meshes [36]. That is, we triangulate each polygon into triangular faces using Constrained Delaunay Triangulations [30] (CDT). To ensure that the polygons are planar, we for each polygon maintain a trainable plane equation. Upon accessing the (trainable) 3D position of a vertex, we first project the vertex to the plane constraint of the polygon it belongs to. Periodically, we update the original vertex position with the projected (constrained) position to avoid strong drift in the original vertex positions.

Vertex Sharing We allow and encourage polygons to share vertices. If two vertices of different polygons are merged, this implies that we require the vertex to satisfy two plane equations. In that case, we project the vertex to the intersection line between the two polygons upon accessing its position.

Generally speaking, we store for each vertex up to three plane constraints based on the polygons it is part of, and project it to the closest point satisfying the constraints upon accessing its position.

To avoid training instabilities, we avoid merging vertices of near-parallel polygons.

Re-Triangulation Upon adding triangle faces to polygons (projecting objects to the floor) or merging polygons, we re-triangulate the surface of each affected polygon using a CDT.

D Creation of a Scene Graph of 2D Floorplans: Detailed Description

In this step we use the prototype layout and its semantics to (1) identify the different levels (floors) of the building, (2) create a 2D layout (floorplan) of each level, and (3) segment each level into rooms, extracting a per-level 2D scene graph from each floor and (4) detect stairs to connect the individual levels. At a high level, the process can be summarized as follows:

To identify building floors, we use the floor-classified polygons of the layout prototype, merging close levels with similar heights.

To create a 2D floorplan of each level, we merge each level's floor polygon(s) with suitable ceiling polygons - since ceilings are rarely occluded by objects and thus are more robustly represented in the prototype layout.

To segment each level into rooms we apply Hov-SG [15]'s room segmentation algorithm on each 2D floorplan (and the walls of the prototype layout). The segmentation outputs a scene graph with rooms as nodes, and *openings* as edges. We consider an opening edge a *door* if its width is below 1.5m. Otherwise, we retain its edge but label it as *opening*. Furthermore, each room is associated with a room type (kitchen, office, ..).

To identify stairs we cluster connected components of the stair mesh extracted in Sec 4.2. For each component we add an edge to the scene graph between the rooms/floors it connects.

D.1 Identifying Building Floors

We use the floor-classified polygons of the layout prototype and merge close levels with similar heights. Specifically, we create a graph where the nodes represent floor-classified polygons and add edges between polygons whose height differs by at most 50cm. Each connected component of the graph defines a floor level. For each level, we determine its average *elevation* from its assigned floor polygons.

D.2 Creating a 2D Floorplan for each Level

We construct each level's 2D floorplan by computing the union of each level's floor polygon(s) with suitable ceiling polygons. Suitable ceiling polygons are identified by assigning each ceiling polygon to the closest next-lower floor polygon that is at least 1m below the ceiling's center. The level's *2D floorplan* is then constructed from the union of the ceilings and the floors of the level.

We further identify a level's *walls* by selecting wall-classified polygons that (1) intersect the floor's *2D floorplan* in BEV and (2) vertically intersect the height interval of $[0, 2.5]$ m above the floor's *elevation*.

D.3 Segmenting each Level into Rooms

We partition each level's *2D floorplan* into *rooms* using the level's *walls*. We do so by applying HovSG [15]'s morphology-based room segmentation algorithm twice: first with a bottleneck width of 2.5m and then with a bottleneck width of 1.5m. The two-stage application has the benefit that cells (rooms) with a diameter between 1.5m and 2.5m can exist individually, yet larger cells with bottlenecks below 2.5m are separated.

Note that Hov-SG is a system designed for robotic navigation, and it does not reconstruct an explicit layout, neither in 2D nor in 3D. Originally, it obtains the 2D floorplan by simply thresholding the point density of the target floor.

We then follow HovSG in constructing a *2D scene graph* with the *rooms* as nodes and the bottlenecks that split them as edges. We consider an edge a *door* if its bottleneck width is below 1.5m, and an *opening* otherwise. Each node has a *2D floorplan* consisting of a cell of the entire level's floorplan.

D.4 Scene Graph Classification and Pruning

We follow HovSG in computing a single, CLIP-aligned feature per room. For this, we use OpenSeg [37] to compute pixel-aligned vision-language model features. Then we follow the same steps as in the mesh segmentation (Sec. 4.2) to project the features to our mesh vertices. The per-room feature is computed from the average mesh vertex features per room. We then use the CLIP embeddings to classify the rooms into '*bathroom*', '*bedroom*', '*living room*', '*garage*', '*entrance*', '*kitchen*', '*office*', '*stairs*', '*gym*', '*classroom*', '*spa/sauna*', '*mirror*', '*grass/bushes/trees*', '*driveway*', and '*veranda/terrace/balcony*'.

We then use this classification to remove leaf nodes of the scene graph belonging to one of the last five classes: This serves as an additional safeguard against the inclusion of outdoor spaces. (Additional to the segmentation performed in Sec. 4.2). Notably, this pruning step contributes to the performance improvement in Tab. 4 of the full method compared to the version without room segmentation.

D.5 Stair Detection

We combine the *stair mesh* obtained in Sec. 4.2 with the floor segmentation from Sec. 4.4 to identify stairs and approximate them as simple 3D rectangles.

That is, we cluster the stair mesh (*i.e.* the sub-mesh of stair-classified vertices in Sec. 4.2) into connected components. Each component's vertices are now projected onto the horizontal plane and approximated by an oriented bounding rectangle R . We now assign the shorter edges of R to rooms of the scene graph by (1) determining the heights of the shorter edge midpoints by interpolation on the 3D cluster vertices, (2) lifting the rectangle to 3D using the edge midpoint heights and (3) assigning it to the room with the shortest point-to-polygon distance (D_{pp} , defined in Sec. 4.3) to the edge midpoint. If this distance is greater than 50cm or both edges are assigned to the same room, we reject this cluster. Otherwise, we add a *stair* edge connecting the two rooms and store R as its geometry.

D.6 Handling Doors and Stairs during Floor Extrusion

The described room extrusion algorithm produces a closed shell for each room by extruding its 2D floorplan. To connect the rooms with doors and stairs, we introduce openings into these shells as follows:

To extrude doors, we approximate the room-splitting boundaries obtained by HovSG with oriented 2D bounding rectangles. From these bounding rectangles, we build a 3D doorframe of fixed height 2.10m consisting of four rectangular faces. During room extrusion, we ensure the doorframe remains empty by only adding wall triangles above the door for edge fragments inside the door's 2D bounding rectangle.

To extrude stairs, we first - in 2D - subtract the stair geometry from all rooms it intersects to avoid extruding overlapping regions. Then we extrude the stair geometry analogously to a room, with the difference that we as a last step adjust the height of the four floor corners in the resulting mesh to match the different levels it connects. We do not add walls for shared boundaries between stairs and rooms. For visualization, we add stair steps at a fixed stair step height on top of the otherwise pitched but flat floor of the stairs.

E Baseline Implementations

We compare our method to two recent, end-to-end trained baseline methods. Neither of the baselines is designed to predict multi-floor layouts. Adapting them to multiple floors is non-trivial. Hence, we use the ground-truth Matterport3D (MP3D) [7] segmentation of houses into levels and regions (loosely corresponding to rooms). We evaluate the baselines both on individual rooms and levels, concatenating the output.

E.1 RoomFormer

RoomFormer [1] predicts a 2D layout based on point clouds. We hence create its input by sampling points from the surface of the mesh. The prediction is then lifted to 3D by assuming a planar floor/ceiling, whose height we determine based on the 5%-quantile of the distribution of the heights of the input points. Doors are assumed to extend from floor level to 2.10m above floor level. Windows are assumed to span 80% of the height of a wall (centered).

E.2 SceneScript

SceneScript [2] predicts a set of 3D walls, doors, and windows based on *semidense* point clouds. We sample semi-dense from the input mesh by sampling points from the surface of the mesh where the norm of the surface gradient falls into the top 5%-quantile of all surface gradient norms. We further observe that the output improves when additionally sampling a small fraction of random points from all surfaces. We therefore incorporate random points into the input.

SceneScript neither predicts ceilings nor floors. We therefore infer one single floor and ceiling polygon respectively from the 2D Birds-Eye View convex hull of the output. To determine floor and ceiling height, we use the highest and lowest wall rectangles respectively.