R2D3: Imparting Spatial Reasoning by Reconstructing 3D Scenes from 2D Images

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Abstract

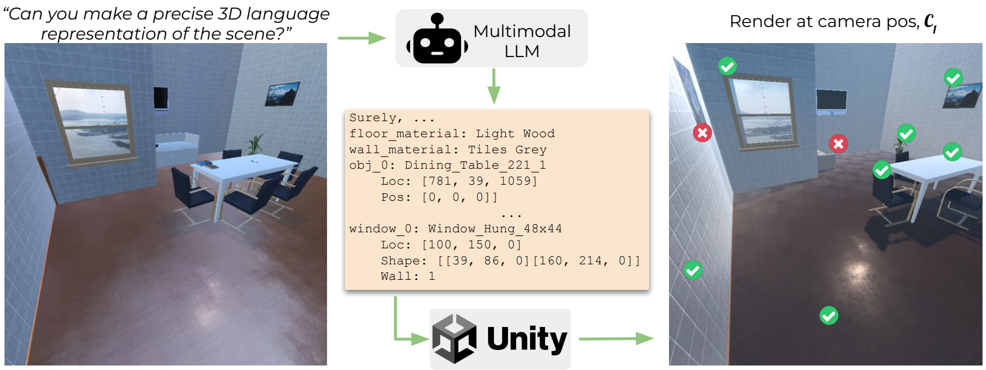
Multimodal large language models (MLMs), which have been widely adopted due to their impressive commonsense reasoning on 2D images, still struggle with 3D spatial reasoning. The research community lacks holistic evaluations that enable an analysis into what training data imparts 3D spatial capabilities. Existing benchmarks probe spatial understanding using only coarse-level spatial awareness (e.g. is something to the left or right of something else), or by predicting a bounding box for an object query. Hence, we propose R2D3, a holistic "analysis by synthesis" evaluation benchmark; R2D3 tasks an MLM to represent a 2D image as a set of semantic assets with precise 3D locations and pose such that a graphics engine can reconstruct the 3D scene. This task requires the model to have a comprehensive understanding of the elements that make up the scene and their precise 3D relative locations. Our benchmark includes 12K indoor scenes in the AI2THOR environment and is compatible with several downstream applications such as embodied AI, spatial reasoning, and navigation tasks. Using our benchmark, we explore finetuning techniques that encourage spatial reasoning. Surprisingly, we find that conventional fine-tuning on the training set of our benchmark, while enough to understand semantics, is not enough to learn the precise 3D locations and poses of the objects in a scene. However, conveying the camera-scene orientation by marking a point in the image and including its 3D coordinate in text during training allows the model to improve 3D spatial estimation at test time. We hope that the R2D3 benchmark will help drive progress in exploring design choices that improve the precise 3D spatial understanding of MLMs.

1 Introduction

Humans maintain a steady awareness of the 3D orientation of space around them to operate in the real world [78, 73]. Despite their widespread adoption, multimodal language models (MLMs) [2, 127, 67], with their impressive language and vision commonsense capabilities, still struggle to reason spatially as concluded by numerous studies [14, 45, 6]. There is a limited evaluation of what imparts 3D spatial reasoning skills to these models. Most 3D benchmarks focus on comprehending a 3D scan [41, 7, 9] while most MLMs today only accept image inputs and not 3D representations. Existing spatial tests with 2D images focus on bounding box prediction [126, 99, 9] or spatial relationship prediction [72, 34] or distance prediction [14] between two objects. Although a coarse-level spatial reasoning (left, right, behind, etc) evaluation set exists [34], there is no training data to study what factors impart precise pixel-level spatial reasoning into MLMs.

We propose a benchmark, R2D3 (Figure 1), where an MLM is tasked to represent a 2D input image such that a graphics simulator can reconstruct the 3D input scene. This task draws inspiration from fundamental schools of thought in computer vision–analysis by synthesis [120] and inverse rendering [55, 10]–that suggest that a precise reconstruction requires the model to have a comprehensive

Preprint. Under review.


"Can you make a precise 3D language representation of the scene?"
Multimodal LLM
Unity
Render at camera pos, C_l

```
Surely, ...
floor_material: Light Wood
wall_material: Tiles Grey
obj_0: Dining_Table_221_1
    Loc: [781, 39, 1059]
    Pos: [0, 0, 0]]
                   ...
window_0: Window_Hung_48x44
    Loc: [100, 150, 0]
    Shape: [[39, 86, 0][160, 214, 0]]
    Wall: 1
```

Figure 1: The task of the model is to precisely describe a 3D scene using the object names, attributes, and 3D locations that can be rendered in a graphics engine to reflect the image. We use this task to evaluate a multimodal language model's ability to understand the 3D nature of the scene holistically.

understanding of the elements that make up the scene. Precisely, the task expects the MLM to generate a structured output containing a collection of object and scene concepts with their 3D positions. The concepts are names of assets (objects, walls, windows, etc.).

Our benchmark is generated using 12K indoor rooms from ProcTHOR [24], compatible with the AI2THOR [1] simulator, providing support for downstream embodied AI applications such as object manipulation, navigation, and task completion [97]. Each sample in R2D3 is a room, represented with the graphics program that generates it and a 2D image view of the room. To drive further research in image, text, and 3D understanding, we also generate natural language descriptions of the rooms and each of the object assets using GPT4-V [2]. R2D3 is larger than existing open-source evaluation benchmarks for probing 3D spatial reasoning in MLMs [34], and also includes a training set. Furthermore, since our data curation is based on procedural generation, it does not require human annotation, can be scaled up with more assets, and extended to reason about interactive tasks.

Using R2D3, we explore finetuning techniques that encourage 3D spatial reasoning in MLMs. We focus on techniques that require no change to the MLM's architecture, allowing for an easier low-resource adaptation rather than large-scale retraining of the LLM, which is infeasible for most researcher labs due to resource limitations. We adopt standard metrics from localization and adapt them to our task. Specifically, we measure the L2 distance for object placement accuracy and use standard classification accuracies for semantics. We adopt the widely-used open-sourced LLaVA 1.5-13B [67] model for our experiments. We explore two scenarios during training, one where the camera orientation is not precisely known, and the MLM must infer it from the image, and another where we know the exact camera position and orientation during training.

Our results find that LLaVA struggles to estimate the camera position and orientation if this data is not available in its training data. Since recent work shows the image encoder [27] in LLaVA lacks 3D depth capabilities [17, 8], we overlay a depth estimation mask, generated from an off-the-shelf depth estimation model [114]. We see that this significantly improves LLaVA's ability to learn to orient the scene properly when camera information is not present during training. If camera information is present, we investigate the best way to convey it to the MLM during training. Since MLLMs primarily operate on the quality of the visual or language prompt, we explore visual and language prompting. We find that a simple visual prompting strategy, i.e., marking a point in the image with the 3D location specified in language - is more effective than specifying the entire camera orientation in language. This suggests that LLaVA is better at comprehending a visual mark to calculate the 3D orientation than being able to calculate it from language alone. We see that our best adaptation reaches only 74% accuracy in placing objects correctly and 51% pose accuracy, suggesting considerable room for improvement using our benchmark.

2 Related work

Analysis by Synthesis. Our proposed R2D3 task is focused on evaluating the capability of MLMS to reason spatially about objects in a 3D environment. This falls under the general task of analysis

Dataset	Precise 3D	Real Apps	Captions/QA	Interactivity
2D Grounding Datasets [95, 65, 57]	No	Yes	No	No
3D Grounding Datasets [99, 126, 9]	Yes	Yes	No	No
ScanQA [7]	No	Yes	Yes	No
Neural De-render [113]	Yes	No	No	Yes
Spatial VLM [14]	No	Yes	Yes	No
Open EQA [72]	No	Yes	Yes	No
BLINK [34]	No	Yes	Yes	No
InverseRenderLLM [58]	Yes	No	No	Yes
R2D3 (Ours)	Yes	Yes	Yes	Yes

Table 1: Comparison of existing benchmark tasks to ours. Our dataset is aligned with AI2THOR, which enables interactive real applications like embodied AI, navigation, manipulation, as opposed to operating on simplistic domains like CLEVR or clipart. We have both precise 3D locations, pose and room layout as well natural language semantic captions and descriptions of each object. Our dataset requires no human annotation compared to many existing datasets.

by synthesis [79, 37], which aims to explain observed data such as an image using a set of physical variables. Related tasks include shape estimation of objects from images [70, 87, 101], pose estimation [125, 124, 102], multi-object scene recovery [35, 96, 26] and primitive reconstruction [105, 104, 86, 83, 85, 25, 56, 77, 106, 49, 48, 61, 38]. Based on the idea that a generative model can describe how variables produce the data, existing approaches [58, 113] propose to evaluate a model's capability to understand an image by generating an interpretable representation of it. While R2D3 is similar in nature to [113], our task focuses on images of indoor scenes instead of clip art which makes it more useful for downstream embodied AI and robotics tasks. Additionally, we are the first work to evaluate MLMs on their 3D spatial reasoning capabilities on the more application-oriented ProcThor dataset. In contrast, [58] investigate on the CLEVR [53] dataset, which contains simplified visual elements.

3D Understanding and Generation. The task of holistic 3D scene understanding [39, 74, 21, 92] requires the accurate generation of object entities along with the 3D scene layout. State-of-the-art approaches are often focused on reconstructing objects of arbitrary shapes [121, 66, 36] as well as segmentation maps [116, 81, 19, 60, 80]. Such approaches are similar in spirit to recent 3D generative approaches, including [76, 54]. Existing approaches have also widely addressed other aspects of 3D understanding including object localization [88, 94], dense segmentation [11, 13, 46, 68, 93, 109, 50, 42, 54, 75, 52, 89, 108, 123] and tracking [4, 62, 64]. Our R2D3 task also bears strong similarities to existing joint 3D and language understanding tasks including but not limited to fine-grained scene captioning [16], open-vocabulary classification and localization [15, 42, 3, 31, 47, 40] and question answering [118, 7]. Unlike ScanQA [7], which addresses semantic question answering for 3D scans, our framework emphasizes understanding the 3D structure from 2D images. In contrast to existing benchmarks [126, 99, 9], which only focus on object localization within scenes, R2D3 is built off the AI2Thor engine to enable alignment with multiple interactive applications [23, 112, 22]. More importantly, our benchmark does not require any human annotations and can be arbitrarily scaled up to include more assets and tasks. Compared to LayoutNet's focus on estimating room layout from panoramas [128], R2D3 evaluates a model's understanding of the orientation of all objects and not just the scene layout. In light of potential applications in embodied AI, we focus on adapting models to perform *precise* spatial reasoning under low-resource settings. This differs from existing work such as BLINK [34], which address *coarse* spatial reasoning and Cube-LLM [17], which does large-scale pretraining. Generation of 3D scenes has also been widely explored with input conditions of different modalities. For instance, Scenescript [6] generates 3D scenes from videos while Atiss [84] autocompletes scenes based on room types and floor plans. In contrast, our task synthesizes scenes based on single images while focusing on evaluative measures. Last but not least, R2D3 diverges from rule-based systems like WordsEye [18] and SceneSeer [12] and avoids reliance on purely text-driven or heavily engineered systems such as SceneCraft [59], Holodeck [115] and Ctrl-Room [30].

Vision and Language Models. Our task has also been heavily influenced by the emergence of multimodal foundation models [90, 51, 107, 119, 33, 111, 117]. To leverage the real world knowledge in LLMs and their generative capabilities, recent approaches have proposed to adapt pretrained visual encoders with LLMs for a wide range of downstream image [103, 28, 127, 64, 5, 20] and video [122, 71, 100, 110, 63, 69] understanding tasks. These MLMS have demonstrated impressive zero-shot results on downstream tasks. Recent work [32, 42, 17] have also proposed to advance 3D understanding by augmenting LLMs to reason about 3D scenes. Adjacent to finegrained semantic analysis of vision-language models [91, 43], we focus on precise 3D perception.

3 Approach

Our goal is to explore techniques during tuning that encourage multimodal language models (MLMs) to reason about the 3D nature of 2D images. Hence, we propose a testbed, R2D3, based on the task of 2D to 3D reconstruction where researchers can tune and test MLMs to discover strategies that lead to better 3D reasoning. In R2D3, given a 2D image, an MLM is tasked to predict a precise graphics description listing the entities that make up the scene such that the 3D scene can be reconstructed using a graphics engine. Therefore, to construct our testbed, we need tuples of a 2D scene, the corresponding 3D environment, and the graphics program that generates it. Compared to existing 2D to 3D estimation benchmarks, our testbed is built using physics engines and hence, requires no human supervision while remaining accurate. Further, it allows scaling up to arbitrarily more assets and to interact and tweak the environment, which is not possible with existing benchmarks.

Below, we first describe our format for the precise graphics description (a graphics program) that represents a 3D scene using entities that construct it. Next, we outline our data curation process, where we obtain paired data of the 3D graphics description for a 2D image. Finally, since MLLMs operate based on prompts, we use our testbed to analyze visual vs language prompting baselines that improve 3D reasoning in a state-of-the-art multimodal language model, LLaVA [67].

3.1 3D Graphics Program as Scene Representation

While 3D scenes can be modeled in various ways (meshes, point clouds, nerfs [76]), a graphics program-based representation has a few key advantages when it comes to evaluating MLMs: i) interpretability, i.e. each object, its attribute, and location can be analyzed; ii) the semantic and spatial understanding of the scene is disentangled with the mesh quality and the language model doesn't need to care about mesh quality; iii) compactness, i.e. a text description is more memory efficient that meshes or point clouds and can fit into context length of common MLMs; and iv) a natural language-based representation for MLMs that already operate in the language space to make it more readily usable for other downstream reasoning tasks.

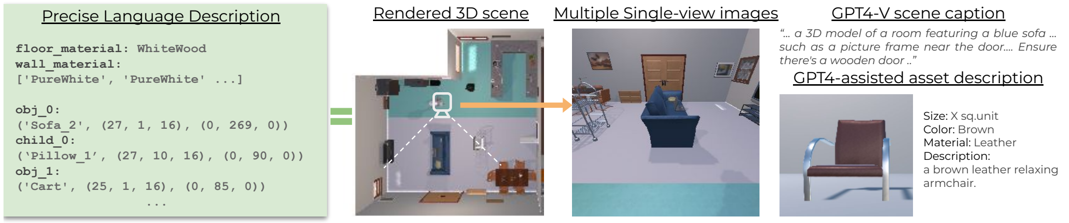
Specifically, we describe a 3D room using a standard YAML-like text file that lists the entities in the scene. For an indoor room, we start with the basic constituents that make the scene- the floor polygon, walls, objects and their children, and the windows and list them in a YAML format as shown in Figure 2 (left most block).

3.2 Generating paired image and 3D graphics program data

Figure 2 shows a summary of our curated dataset. We start with ProcTHOR scenes [24] and randomly take 12K rooms from these apartments. We formulate a light-weight graphics program for the rooms from the JSON representation of the scene in ProcTHOR [24] (see the left-most block in Figure 2). We do not use the JSON directly since it is too long (and redundant and over-parameterized) to fit into the context length for most state-of-the-art MLMs.

We render the 3D room in a graphics simulator, AI2THOR [1] (second left block in Figure 2), and take an image view of the room from the corner with the most objects visible (second right block in Figure 2). Please see the appendix to see how we calculate where to place the camera. Our camera always looks from a corner towards the opposite visible corner in the room. This 2D image view of the room and the corresponding graphics program form the basis of our curated dataset. In addition to the image, we also extract the semantic segmentation map to be of use for further research.

To drive further research in semantic understanding of 3D environments, we also generate natural language captions for the room that describe both semantics and the rough 3D relative locations of objects (rightmost block in Figure 2). Specifically, we caption the corner room view and the top-down view using GPT4-V. The corner room view caption captures the semantics of the image


Precise Language Description
Rendered 3D scene
Multiple Single-view images
GPT4-V scene caption

```
floor_material: WhiteWood
wall_material:
['PureWhite', 'PureWhite' ...]

obj_0:
('Sofa_2', (27, 1, 16), (0, 269, 0))
child_0:
('Pillow_1', (27, 10, 16), (0, 90, 0))
obj_1:
('Cart', (25, 1, 16), (0, 85, 0))
                 ...
```

"... a 3D model of a room featuring a blue sofa ... such as a picture frame near the door.... Ensure there's a wooden door .."
GPT4-assisted asset description
Size: X sq.unit
Color: Brown
Material: Leather
Description:
a brown leather relaxing armchair.

Figure 2: Method of generating our R2D3 benchmark data: We first generate a compact graphics program (left-most block) and render rooms in ProcTHOR [24]. We then render images of the rooms from corners that have the most objects visible. We also caption each of the assets and the overall semantics of the room.

being seen, and the top-down view caption is better at capturing the 3D relative locations of the objects in the scene. We also generate attribute-based phrases for each asset ID, further enabling fine-grained semantic analysis. This also makes the graphics program representation more useful for downstream reasoning and for zero-shot evaluations where a model just needs to predict the generic object class and attributes and not the exact asset ID. While generating the captions, we feed privileged information from the scene graph (such as object name) as a prompt to the GPT4-V to ensure the caption is of high accuracy.

In summary, our dataset contains 12K rooms (with an almost equal distribution of bathrooms, living rooms, bedrooms, and kitchens) composed of 996 object assets for 172 object classes, 14 kinds of windows, and 178 different wall and floor materials. On average, there are around 8 major objects and 5 children objects per room. Using MLMs' adaptation performance on this generated dataset, we wish to explore tuning strategies that lead to better 3D spatial and semantic performance.

4 Experiments

Using the R2D3 task we described above, we investigate tuning techniques that encourage accurate 3D spatial reasoning in a widely used MLM, LLaVA [67]. At test time, we only focus on the model's ability to estimate the 3D relative locations of objects without having access to the full 3D orientation of the camera. To keep the coordinate scale and range consistent with the GT for easier evaluation, we input the room polygon bounds and the corner position from which the image was taken (this can be thought of as a noisy approximate camera position). The model is then tasked to orient the image (and all objects in it) in that space. This intrinsically also requires the model to estimate the precise camera orientation to accurately align the image in the polygon layout. Specifically, here is the prompt we use at test time:

```
<image> The room polygon is [(x,z)...].  Image taken from corner (x, z) looking
inside the room.  Plausible 3D coordinates (x, y, z) for the image shown:
```

The model is then tasked to predict the graphics program as described in Section 3.1. While training the model for the task, we experiment with designing the multimodal prompt containing additional information that allows accurate estimation of the 3D scene in the MLM. The key intuition behind designing our prompt is to make it easier for the MLM to perform the spatial conversion of the 2D image scene to the 3D coordinates. Specifically, we analyze two scenarios: 1) Can LLaVA learn to estimate 3D without precise camera orientation during training, i.e., just from data alone? This would be useful for training on data with noisy camera information. 2) If we do have precise camera orientation during training, what is the best way to convey it to the MLM? Based on these questions, we describe the adaptation strategies we experiment with below.

4.1 Adaptation Strategies Explored

4.1.1 Learning without precise camera orientation in training

Specifically, we use the image and the prompt specifying the room polygon and only the coordinate from which the picture was taken- the exact angle is not specified, and the model needs to learn to

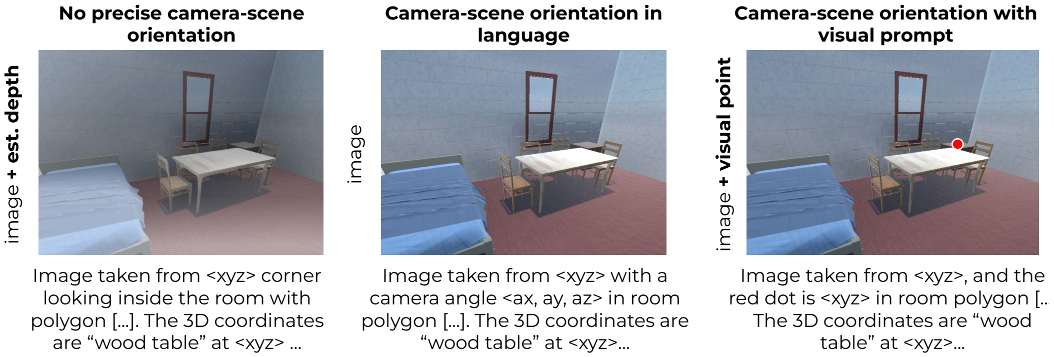

No precise camera-scene orientation
Camera-scene orientation in language
Camera-scene orientation with visual prompt
image + est. depth
image
image + visual point
Image taken from <xyz> corner looking inside the room with polygon […]. The 3D coordinates are "wood table" at <xyz> …
Image taken from <xyz> with a camera angle <ax, ay, az> in room polygon […]. The 3D coordinates are "wood table" at <xyz>…
Image taken from <xyz>, and the red dot is <xyz> in room polygon [.. The 3D coordinates are "wood table" at <xyz>…

Figure 3: Various ways to convey the 3D camera-scene orientation during training. Experiments show that overlaying depth helps when we do not have access to precise camera-scene orientation helps. When we do have precise camera-scene orientation, conveying it by marking a point in the image makes it easier for LLaVA to learn 3D estimation.

approximate how to orient the image it sees to the polygon shape. The model is then tuned to predict the precise 3D locations of all the entities in the scene. This method is denoted as **FT** in the tables.

Since recent work [8] shows ViT [27] in LLaVA lacks 3D perception, we explore whether we can simply convey depth alongside the ViT [27] features using a depth estimation model. Hence, we infer depth using the DepthAnything [114] model and overlay it on the image as shown in Figure 3 (left). The details for how we scale and overlay it can be found in the appendix. We denote this method as **Depth** in the tables.

Finally, as another ablation, recent work [17] suggests that switching out ViT [27] for DinoV2 [82] in LLaVA may improve 3D estimation. Hence, we also experiment with the same, but in a low-resource LORA [44] tuning setting and not full pretraining. This approach is denoted as **w/ Dino FT**.

4.1.2 How to best convey camera orientation during training?

We explore the setting where we do train with precise camera orientation. Since MLMs operate on language and visual promoting, we explore the two modalities to prompt to effectively convey the precise camera orientation to MLMs.

Conveying camera orientation using language. First, we experiment with feeding in the exact camera position and rotation angle specified in the language. Specifically, we add the following to the prompt: `... Image taken from corner (x,z) with a rotation around y of angle <a>. Plausible 3D coordinates ..`. This approach is denoted as **Orient Language** (Figure 3, middle).

Conveying camera and scene orientation using a visual prompt. Next, instead of specifying the camera position and rotation angle in language, we specify only the camera position in language and mark the 3D location of one random object in the image using a red dot as shown in Figure 3 (right). We specify the 3D location of the dot in the prompt like: `The red circular mark in the image is at 3D coordinates (x, y, z)`. The intuition is that the coordinate of the point marked along with the coordinate of the camera in the prompt gives the model a way to orient the image in the 3D space. Compared to specifying the rotation angle in language and making the model estimate 2D to 3D using that information, we wish to check if MLMs can perform the estimation better with the visual information instead. This approach is denoted as **Visual Point**.

4.2 Metrics

Recall that for all settings, we wish to evaluate both the spatial and semantic accuracy of the MLM. We display the spatial accuracy results in Table 2 and the semantic accuracy results in Table 3.

Semantics

For semantics, we measure standard metrics used in classification - object recall. We measure the recall of both the broad class of object (chair, fridge etc) (denoted as **Class** under **Object Recall** in

Tuning Strategy	Absolute		Relative		Pose	
	ACC ↑	L2 ↓	ACC ↑	L2 ↓	ACC (<10°) ↑	ERR (deg) ↓
a. FT	0.5805	0.1466	0.7024	0.0917	0.3880	75.68
b. w/ Dino FT	0.2110	0.3198	0.4299	0.1643	0.1262	100.46
c. Depth	0.6541	0.1176	0.7503	0.0781	0.4409	71.63
d. Orient Language	0.6960	0.1100	0.7595	0.0801	0.4804	66.71
e. Visual Point	**0.7421**	**0.0973**	**0.7782**	**0.0748**	**0.5102**	**61.98**

Table 2: Table showing the spatial accuracy of reconstructing the full 3D scene from a single image. Overlaying depth helps when precise camera orientation is not known over simply fine-tuning. If camera orientation is known, marking a visual point is better than specifying in language.

Tuning Strategy	Object Recall		Count Acc ↑	WallMaterial ↑	FloorMaterial ↑
	Class ↑	Finegrained ↑			
a. FT	0.8733	0.6250	0.6038	0.7545	0.8283
b. w/ Dino FT	0.7328	0.1240	0.1240	0.6338	0
c. Depth	0.8803	0.6238	0.5964	0.7784	0.8343
d. Orient Language	0.8823	0.6386	0.6101	0.7645	0.8703
e. Visual Point	0.8815	0.6496	0.6128	0.7645	0.8403

Table 3: Table showing the semantic accuracy of the entities in the scene. All tuning approaches are good at understanding semantics. Our prompts do not affect the accuracy significantly.

the tables) as well as the fine-grained asset based on the attributes (e.g. armchair01) (denoted as **Finegrained**). We also measure the count error of the objects between predicted and GT - denoted by **Count Err** in the tables. Finally, we also measure the material accuracy of the walls (denoted as **WallMaterial**) and the floors (**FloorMaterial**).

Spatial

We measure the spatial accuracy of the objects placed in two ways - Absolute and Relative. For **Absolute**, we compute the location distances for each object class between prediction and GT. In AI2THOR, we only need to provide the center coordinate of an asset, and each asset is a fixed size. Hence, for each object class in GT, we compute the L2 distances of object centers between predicted and GT after Hungarian matching (as commonly done in standard detection tasks). We normalize the L2 distances by the max dimension of the room. We consider an object to be placed correctly if the normalized error is below 10% of the max dimension (reported as **ACC** in the tables).

Since we would like our approach to be generalizable to scene generations at arbitrary coordinate spaces (especially for cases without precise camera orientation), we also introduce the **Relative** metric. To evaluate the relative positions of objects, we compute the L2 distance between every object-object pair in the image for pairs of object classes in the GT. For each object class, we compare the pairwise distances to all other objects classes for the predicted and GT scenes. If the predicted layout of objects is similar to GT, the hope is that all pairwise relative distances should be similar. Once again, we report the average pairwise **L2** and **ACC** ($< 10\%$ L2 normalized by max dimension).

For pose, we measure the error in degrees for rotation along the y-axis (vertical height axis). Once again, an absolute degree error less than 10 degrees counts as accurate placement. We report both **ACC** and degree **ERR** under **Pose** in Tables 2.

Tuning details We split our dataset into a training set of 11K rooms, a validation set of 500 rooms, and test set of 500 rooms. All numbers reported in the tables are on the test set. Since we focus on low-resource adaptation techniques, we use LORA tuning [44] with a rank of 16 and alpha 32 on the entire model, instead of fully tuning the LLM and vision encoder backbones. During training, we feed in the entire sequence of image tokens, language prompt, and graphics program of the scene and compute cross-entropy loss for the next token prediction. During testing, we input the image and prompt and generate the language representation of the scene using a greedy algorithm. We keep the generation parameters standard to the official implementation of LLaVA [67]. More details are in the

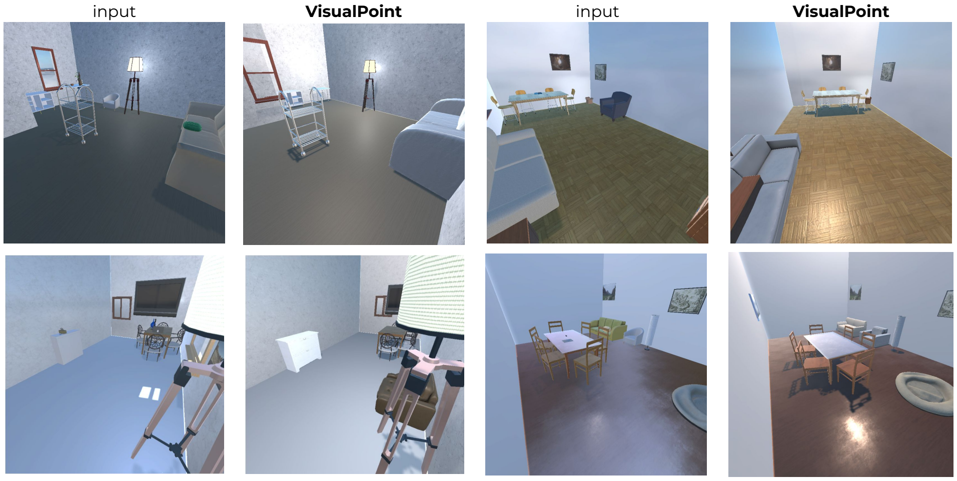
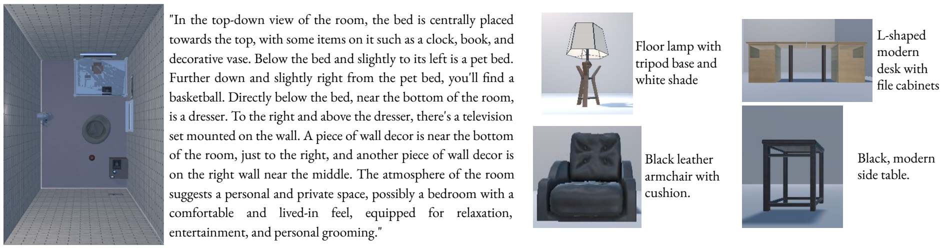


Figure 4: Qualitative results showing the input 2D image and the view rendered from the graphics program output of our VisualPoint strategy. VisualPoint is accurate at reconstructing the scene, although there are occasional errors in pose and object hallucination.


"In the top-down view of the room, the bed is centrally placed towards the top, with some items on it such as a clock, book, and decorative vase. Below the bed and slightly to its left is a pet bed. Further down and slightly right from the pet bed, you'll find a basketball. Directly below the bed, near the bottom of the room, is a dresser. To the right and above the dresser, there's a television set mounted on the wall. A piece of wall decor is near the bottom of the room, just to the right, and another piece of wall decor is on the right wall near the middle. The atmosphere of the room suggests a personal and private space, possibly a bedroom with a comfortable and lived-in feel, equipped for relaxation, entertainment, and personal grooming."

Floor lamp with tripod base and white shade
L-shaped modern desk with file cabinets
Black leather armchair with cushion.
Black, modern side table.

Figure 5: Some examples of the GPT4-V[2] generated captions for the 3D relative locations of assets in the rooms (left) and the attribute-based description of the ProcTHOR [24] assets.

appendix. In all our experiments, due to GPU memory constraints for context length, we only predict the major objects per room (around 8 per room on average) from a choice of 472 assets across 172 object classes.

5 Results

Overlaying depth can help LLaVA estimate camera orientation significantly. As seen in Table 2, rows a vs c, overlaying the estimated depth helps spatial estimation of the objects by 7% absolute and 5% relative. Both these approaches assume access to no precise camera-scene orientation data, and the model must learn to estimate it based on the image it sees and the knowledge of the corner the image was taken from in the room polygon. While standard fine-tuning underperforms to learn from the 3D locations in GT, estimating the depth improves the ability to orient the image correctly.

Having precise camera-scene orientation during training is beneficial to estimate it during testing. As seen in Table 2, specifying the exact camera-scene orientation parameters during training in the language prompt (row d) understandably helps significantly over training approaches without (row a, c). Recall that we only assume access to noisy camera-scene orientation during test time.

Marking the 3D location of a random object is an effective way to convey camera-scene orientation. As seen in Table 2, we see that marking a random object with the 3D coordinate (row e) during training outperforms specifying the exact camera-scene orientation in the language (row e). This suggests that LLaVA is better at estimating the camera-scene orientation by interpolating between the camera position and the visual point marked in the image than at interpreting the position and angle specified in language alone.

For LORA-based tuning, providing estimated depth is much better than switching ViT for DinoV2. While recent work [8] suggests DinoV2 [82] has superior 3D capabilities to ViT [27], we see that LLaVA has a difficult time interpreting DinoV2 features if not pre-trained completely like in CubeLLM [17]. As seen in Table 2 and 3 (rows b vs c), LLaVA with DinoV2 [27] tuned using LORA [44] underperforms in all metrics.

Pose accuracy leaves room for improvement. We see that in Table 2, the pose accuracy of our best method is only at 51%. On average, we see a $61°$ error in the pose for objects, leaving considerable room for improvement.

There is no significant change in semantic accuracy between standard FT and our prompting methods. As seen in Table 3, there is no significant change in the semantic capabilities of the standard LLaVA, whether we fine-tune or use our prompting strategies. This suggests that while our prompting methods do not affect the semantic accuracy of LLaVA, they improve the spatial accuracy (Table 2).

LLaVA is good at object classes, but not at fine-grained recognition and counting. In Table 3, a high object recall suggests that LLaVA is already pretty good at recognizing broad classes of objects. However, the accuracy of fine-grained recognition is lower. The accuracy is also lower for counting objects precisely across all adaptation methods.

Qualitative examples of our results and data While our dataset is procedurally generated using physics engines (which is always accurate), we show some qualitative examples of the captions generated by GPT4-V (which may be noisy) for the rooms and the assets in Figure 5. We also show some qualitative results of our best-performing model outputs in Figure 4. The input is from our R2D3 dataset, and the corresponding rendering is from the graphics program output of our MLM. While locations are mostly accurate, there are errors in pose and object hallucination.

6 Discussion

Limitations Our work fine-tunes LLaVA. Hence, understandably, LLaVA loses some general question-answering and conversational capabilities. However, the lessons from the adaptation can be applied to a larger-scale adaptation where we mix in some of the original natural language data to retain the original LLM capabilities. Our task and benchmark are also based on simulators and graphics engines. While recent works [29, 98] show that training in simulation can transfer to real, further investigation is needed to analyze transfer to real environments and other downstream tasks. Further analysis is also required to test other state-of-the-art MLMs [2, 127, 20].

Future work While we use our benchmark here to reconstruct 3D scenes from a 2D image, it can be extended in various ways. Interesting avenues for future work can look at utilizing the interactive nature of our scenes and reasoning about tasks using them. We can also view our work as image to 3D interactive scene generation. In that case, an exciting future work would be to look into generalizing real apartment images in the wild to create digital replicas.

Conclusion We hope that our benchmark paves the way to explore strategies that impart better 3D reasoning in multimodal language models (MLMs) and improve further on our baselines to make them deployable for real-life applications.

Acknowledgments and Disclosure of Funding

This project was partially funded by Amazon Science and NSF award number 2120322. We wish to thank Devdeep Ray and Jang Hyun Cho for helpful discussions on 3D and depth estimation. The contents of the paper do not represent the views of the US Government or the funding agencies.

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Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes]
   (c) Did you discuss any potential negative societal impacts of your work? [NA] Our dataset is a synthetic benchmark to test spatial perception in MLMs. Hence, we do not deal with any individual, cultural, or societal topics. The only bias could be that our apartment indoor scenes reflect primarily North American homes.
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]
2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [NA] We have no theoretical results. Only empirical.
   (b) Did you include complete proofs of all theoretical results? [NA]
3. If you ran experiments (e.g. for benchmarks)...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes] . In the supplementary.
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] . In the supplementary.
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [No] Our training runs are computationally expensive and hence we only run them a couple times. The differences in accuracy are large for our case and evaluated on a relatively large number of 3d rooms (500). Hence, we do not compute error bars from multiple runs. However, we will release training code and checkpoints for reproducibility.
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes]
4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
   (a) If your work uses existing assets, did you cite the creators? [Yes]
   (b) Did you mention the license of the assets? [Yes]
   (c) Did you include any new assets either in the supplemental material or as a URL? [No]
   (d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? [NA] . We use publicly available open-source datasets.
   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [NA] . Our datasets are synthetic and no personally identifiable content is present.
5. If you used crowdsourcing or conducted research with human subjects...
   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [NA] . Our dataset is synthetically generated and doesn't need any human annotation.
   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [NA]
   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [NA] .