A 3D-Language Data

A.1 More details on box-demonstration-instruction based prompting

As described in the paper, we use the boxes-demonstration-instruction method for generating task decomposition data, 3D-assisted dialog data, and navigation data. In figure 5, 6 and 7, we show the prompts for generating these data, respectively. Specifically, for each *sample* in the *fewshot_samples*, the "*bbox*" is a list of the bounding boxes of a scene, and the "*response*" refers to human-written responses for demonstration. For *bbox_new_scene*, it is a list of the bounding boxes of the scene that we query the ChatGPT to give us responses.

```
messages=[{“role”: “system” , “content”: “You are an AI visual assistant that can analyze a 3D scene. All object instances in this 3D scene are given, along with their center point position. The center points are represented by a 3D coordinate (x, y, z) with units of meters. Using the provided object instance information, design a high-level task that can be performed in this 3D scene. Besides, decomposing this high-level task into a sequence of action steps that can be performed using the instances in this 3D scene. The number of action steps should be LESS THAN TEN (< 10). \n\n Remember, the high-level task and action steps must be able to be performed in the 3D scene using the given object instances. Do not include objects that do not exist. Do not generate similar action steps. Do not include specific locations, numbers in the action steps.”}]

for sample in fewshot_samples:
   messages.append({“role”: “user”, “content”: ‘\n’.join(sample[‘bbox’])})
   messages.append({“role”: “assistant”, “content”: sample[‘response’]})

messages.append({“role”: “user”, “content”: ‘\n’.join(bbox_new_scene)})
```

Figure 5: Prompts on generating task decomposition data using boxes-demonstration-instruction method.

```
messages=[{“role”: “system” , “content”: “You are a conversation generator in a room. All object instances in this room are given, along with their center point position. The center points are represent by a 3D coordinate (x, y, z) with units of meters. You need to generate 4~10 round conversation between a human and a robot assistant. \n\n The human know all information in this room, including all objects described above and all small things that are not visible now. The human will ask the robot to do a high-level task. The robot will tell its observation and its state (e.g., location) to the human and will ask for help when it is ambiguous about the task. Remember, the high-level task should be done in this room. Do not include objects that do not exist.”}]

for sample in fewshot_samples:
   messages.append({“role”: “user”, “content”: ‘\n’.join(sample[‘bbox’])})
   messages.append({“role”: “assistant”, “content”: sample[‘response’]})

messages.append({“role”: “user”, “content”: ‘\n’.join(bbox_new_scene)})
```

Figure 6: Prompts on generating 3D-assisted dialog data using boxes-demonstration-instruction method.

```
messages=[{“role”: “system” , “content”: “You are a captioner in a room. All object instances in this room are given, along with their center point position. The center points are represent by a 3D coordinate (x, y, z) with units of meters. For each object in the room, you need to describe it using their affordances or functionality (how you can use it). You should write your sentence like "Where can I <do something>" or "Find me something that I can <do something> with" or "Where should I go for <something>".”}]

for sample in fewshot_samples:
   messages.append({“role”: “user”, “content”: ‘\n’.join(sample[‘bbox’])})
   messages.append({“role”: “assistant”, “content”: sample[‘response’]})

messages.append({“role”: “user”, “content”: ‘\n’.join(bbox_new_scene)})
```

Figure 7: Prompts on generating navigation data using boxes-demonstration-instruction method.

A.2 More details on ChatCaptioner based prompting

As for the 3D models that do not have AABB bounding box annotations, we use ChatCaptioner based prompting to generate their corresponding 3D caption. We use the 3D models in the large-scale Objaverse [15] dataset. For a 3D model, we captured images from four different angles around the model, with the model as the center, covering the front, back, left, and right directions. We observed that capturing images directly from the front angle can lead to ambiguity (such as only seeing one side of the tablet). Therefore, when capturing images, we added a 15-degree pitch angle and rotated clockwise by 45 degrees on top of the original front, back, left, and right directions. For each sampled image, we use the prompt in [54] for ChatGPT to generate a question, which is fed to BLIP-2 to get the answer according to the image content. Following [54], the first question is set to "*Descripe the 3D object in the photo*". The number of conversation rounds is set to 3. We observe that the large number of conversation rounds would bring many hallucination content. We then feed the conversation history for ChatGPT to get the caption of this image. More details about prompt design can be reffed to [54].

Except for sampling images around the 3D model, for a large scene, we can also set the camera in the center of the 3D model and rotate it horizontally to sample 4 images. Since the most 3D models in Objaverse dataset are single objects, we use the former solution to sample images.

After getting caption for each image, we use the prompt shown in figure 8 for summarizing the content in all images into a 3D scene caption.

```
messages=[{“role”: “assistant” , “content”: “You are a 3D object descriptor. Given four
different descriptions of the same object from different viewpoints, summarize a concrete description in several
sentences. Avoid uncertain or negative information. Avoid describing the background. \n\n\ The four
descriptions are as follows. {descriptions}. Concrete 3D object description:”}]
```

Figure 8: Prompts on summarizing content in several views into a 3D scene caption on ChatCaptioner based method.

A.3 More details on Revision based Prompting

We use the revision based prompting method to transform the information of a 3D scene into question-answering format. Specifically, we use the prompt shown in figure 9, where *context* is the generated caption of a 3D model in objaverse dataset.

```
messages=[{“role”: “system” , “content”: “You are a writer and editor.”}]
messages=[{“role”: “user” , “content”: “Given the sentence {context}, revise it to a
question-answer pair of VQA task about it. Format: Question:<generated question>; Answer:<generated
answer>”}]
```

Figure 9: Prompts on summarizing content in several views into a 3D scene caption on ChatCaptioner based method.

B Experiments

B.1 Implementation Details

We run the models on 32 nodes, where each node has 4 V100s. The batch size is 2 for each node. The AdamW optimizer is used, with $\beta_1 = 0.9$, $\beta_2 = 0.999$, and a weight decay of 0.05. Additionally, we apply a linear warmup of the learning rate during the initial 1K steps, increasing from 10^{-8} to 10^{-4}, followed by a cosine decay with a minimum learning rate of 10^{-5}.

3D-LLMs based on pre-trained flamingo are trained using the AdamW optimizer with global norm clipping of 1, no weight decay for the perceiver resampler and weight decay of 0.1 for the other trainable parameters. The learning rate is increased linearly from 0 to 10^{-4} up over the first 5000 steps then held constant for the duration of training. The model is trained on 8 A100s. The batch size is 16. We use Distributed Data Parallel (DDP) to train the model.

B.2 Captioning Results on OpenShape

We compare our captioning model with OpenShape[34], a model trained on 3 kinds of captions on 800k Objaverse data. We evaluate on OpenShape testset using pre-trained 3D-LLMs without finetuning on their training set. We ensure o data leakage among splits. Table 5 shows the results. We also show the results on our evaluation set on Table 6

	B4	B3	B2	B1	METEOR	ROUGHL
OpenShape	1.8	3.6	8.4	19.7	5.9	18.4
3DLLM(BLIP2opt)	8.5	11.0	15.2	21.7	10.3	29.4
3DLLM(BLIP2t5)	9.0	11.4	16.7	23.6	11.0	31.3

Table 5: Results on OpenShape's evaluation set

Models	B-4	B-3	B-2	B-1	METEOR	ROUGH-L
OpenShape	0.9	2.0	4.8	11.7	4.3	14.9
3D-LLM (BLIP2-opt)	15.9	20.3	26.7	35.7	18.7	40.1
3D-LLM (BLIP2-t5)	20.1	24.7	31.0	39.8	17.7	42.6

Table 6: Results on our evaluation set

B.3 3D Grounding

In order to examine 3D-LLMs' 3D localization abilities, we carry out a held-out experiment on ScanRefer benchmark. Specifically, ScanRefer benchmark requires the models to output object locations given a referring sentence of the objects. We finetune 3D-LLMs on ScanRefer training set and report the results on ScanRefer validation sets.

In Table 7, we show the results on. As we can see, our 3D-LLMs can have decent performances on grounding and referring, and outperform most of the baselines, showing that 3D-LLMs have the ability of 3D localization. Notably, the baseline models use ground-truth bounding boxes, or a pre-trained object detector to propose bounding boxes and classes for object proposals. Then, they use scoring modules to vote for the most likely candidate. Our method does not use any explicit object proposal module or ground truth bounding boxes, but outputs the locations of the bounding boxes directly using LLM losses for predicting tokens, while still outperforming most of the baselines. We could also see from the Avg. Dist metric the bounding boxes we predict is very close to the ground-truth brounding boxes. In Figure 10, we show some grounding results.

	OCRand	Vote+Rand	SCRC	One-stage	ScanRefer	3D-LLM (flamingo)	3D-LLM (BLIP2-opt)	3D-LLM (BLIP2-flant5)
ACC@0.25	29.9	10.0	18.7	20.4	41.2	21.2	29.6	30.3

Table 7: Experimental Results on ScanRefer

B.4 Object Navigation

We show the ability of our 3D-LLM to progressively understand the environment and navigate to a target object. We formulate the navigation process as a conversation. At each time step, we online build a 3D feature from the partially observed scene. We feed this feature, current agent location, and history location to the 3D-LLM for predicting a 3D waypoint the agent should go for. We then use an off-the-shelf local policy [49] to determine a low-level action (*e.g.*, go forward, turn left or right) for navigating to the waypoint. The 3D-LLM predicts "stop" if it believes the agent has reached the target object. We finetune our 3D-LLM on the object navigation episodes built on Habitat-ObjNav dataset [4].

In Figure 11, we visualize a conversation process and its corresponding navigation trajectory. At the beginning when the target object is not observed, the 3D-LLM predicts a waypoint that leads the agent to explore the area most likely containing the target object. When the agent observes the target object (*i.e.*, red box in the partially observed scene), the 3D-LLM predicts a waypoint leading the agent to it. The example episode is performed on the HM3D dataset [42] using Habitat simulator [44].

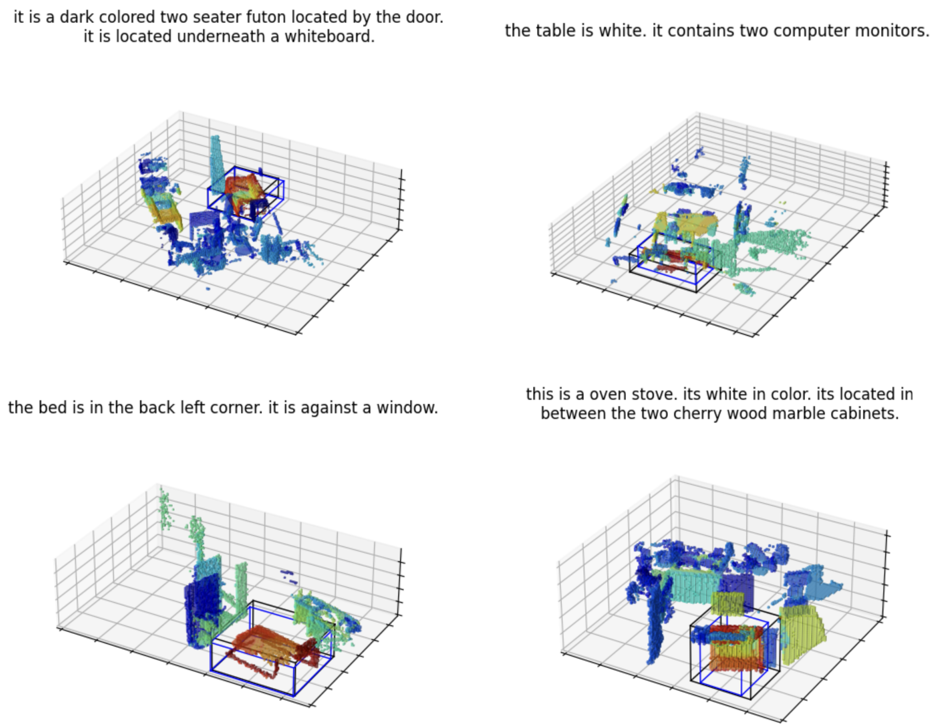
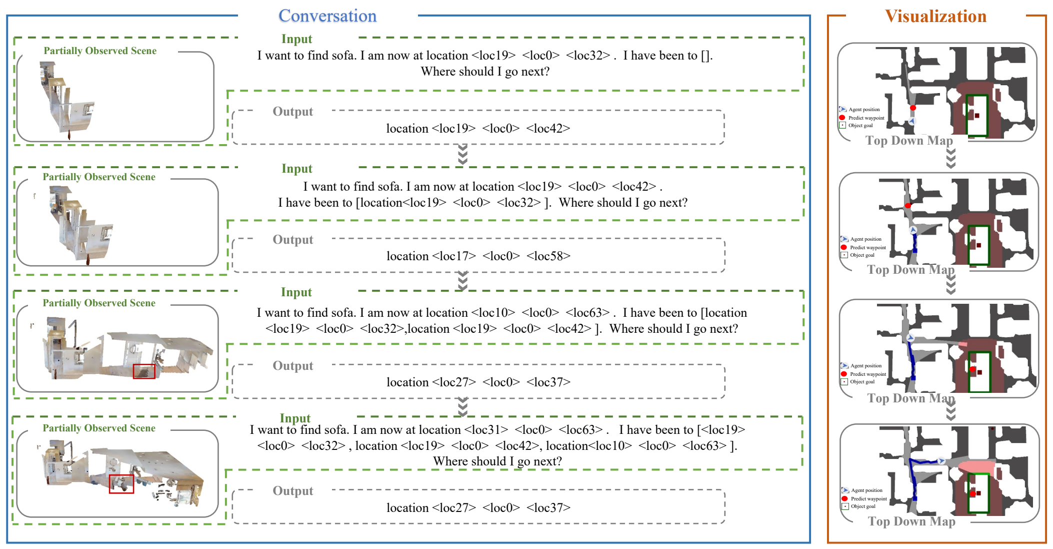


Figure 10: Qualitative examples of grounding. Black box denotes ground truth and blue box denotes predicted results. We also show the heatmap by calculating the similarity between 3D features and language features.



Input
I want to find sofa. I am now at location <loc19> <loc0> <loc32> . I have been to []. Where should I go next?

Output
location <loc19> <loc0> <loc42>

Input
I want to find sofa. I am now at location <loc19> <loc0> <loc42> . I have been to [location<loc19> <loc0> <loc32>]. Where should I go next?

Output
location <loc17> <loc0> <loc58>

Input
I want to find sofa. I am now at location <loc10> <loc0> <loc63> . I have been to [location <loc19> <loc0> <loc32>,location <loc19> <loc0> <loc42>]. Where should I go next?

Output
location <loc27> <loc0> <loc37>

Input
I want to find sofa. I am now at location <loc31> <loc0> <loc63> . I have been to [<loc19> <loc0> <loc32> , location <loc19> <loc0> <loc42>, location<loc10> <loc0> <loc63>]. Where should I go next?

Output
location <loc27> <loc0> <loc37>

Figure 11: **Visualization of an object navigation episode.**

B.5 Held-In Evaluation

B.5.1 3D Dense Captioning

In Table 8, we show the results of 3D dense captioning. Specifically, given a 3D bounding box, models are expected to output the caption describing what's in that region. We can see that our 3D-LLMs outperform image-based baselines.

	BLEU-1	BLEU-2	BLEU-3	BLEU4	METEOR	ROUGH-L
flamingo-SingleImage	21.5	10.5	6.9	4.1	11.1	23.4
flamingo-MultiView	24.4	12.3	7.1	4.6	11.9	25.8
BLIP-SingleImage	23.0	11.7	7.7	4.6	11.3	23.8
BLIP-MultiView	25.3	14.1	9.0	5.6	12.5	24.9
3D-LLM (flamingo)	29.6	16.8	10.6	5.9	11.4	29.9
3D-LLM (BLIP2-opt)	32.5	18.7	11.9	6.5	11.7	31.5
3D-LLM (BLIP2-flant5)	34.3	20.5	13.2	8.1	13.1	33.2

Table 8: Experimental Results on Held-In 3D Dense Captioning Dataset.

B.6 More Ablative Studies

B.6.1 Ablative Studies on Flamingo Perceiver

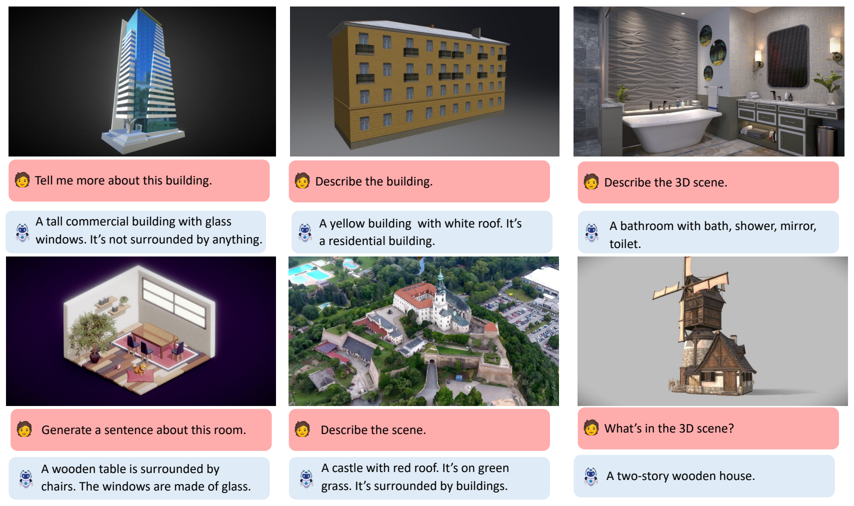
We first examine how the perceiver resampler of Flamingo benefits the training. We carry out an ablative experiment where we take out the perceiver of the flamingo model. Table 9 shows the results. From the table, we can see that the perceiver module is indeed beneficial for the training of 3D-LLM.

	BLEU-1	BLEU-2	BLEU-3	BLEU-4	METEOR	ROUGH_L	CIDER	EM
wo/ perceiver	29.2	17.2	11.2	7.4	11.4	30.4	58.9	20.6
w/ perceiver	30.3	17.8	12	7.2	12.2	32.3	59.2	20.4

Table 9: Ablative Study on the Perceiver of Flamingo Model.

B.7 More Qualitative Examples

We show more qualitative examples in Figure 12, 13, 14.



Tell me more about this building.

A tall commercial building with glass windows. It's not surrounded by anything.

Describe the building.

A yellow building with white roof. It's a residential building.

Describe the 3D scene.

A bathroom with bath, shower, mirror, toilet.

Generate a sentence about this room.

A wooden table is surrounded by chairs. The windows are made of glass.

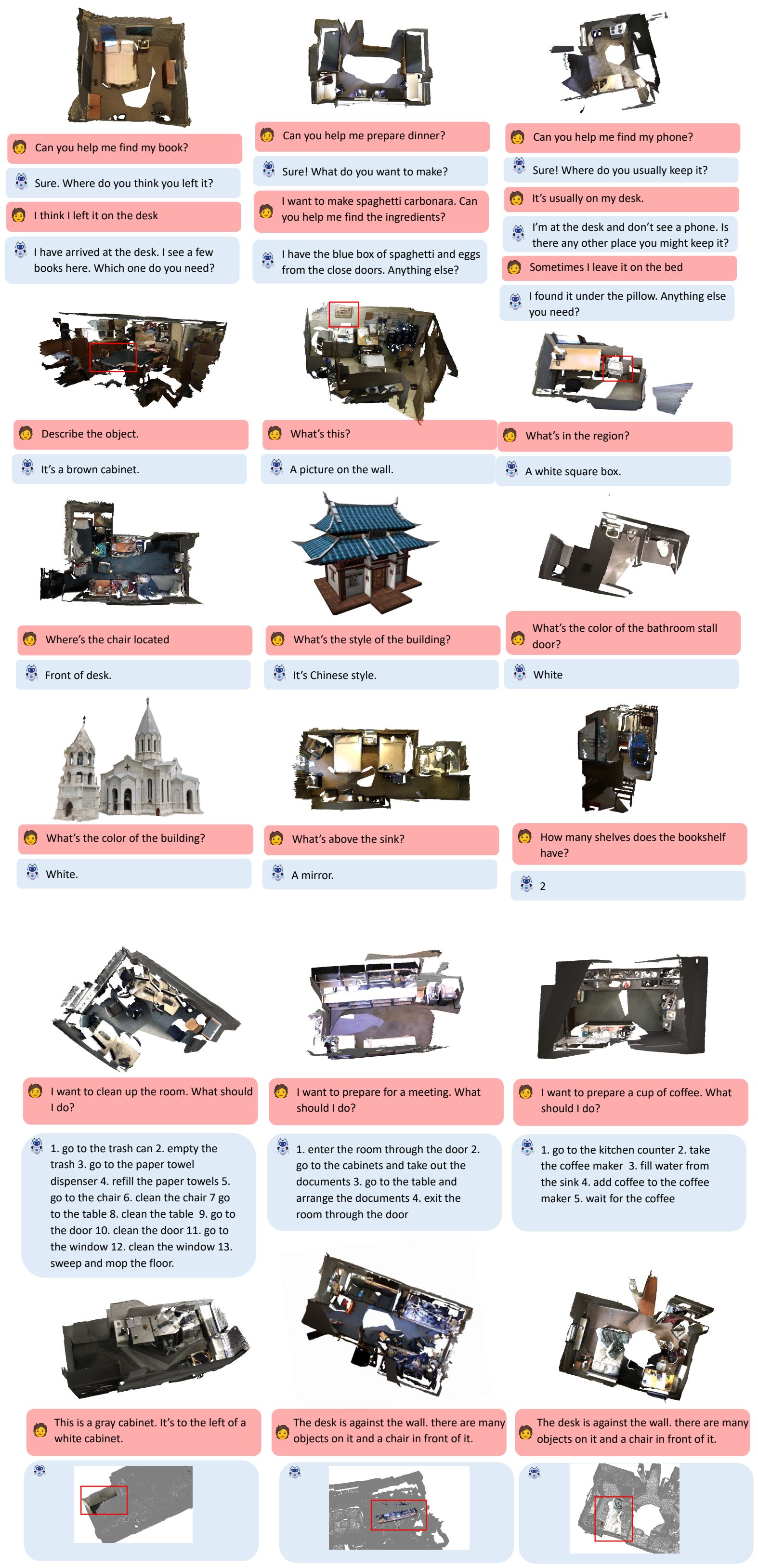
Describe the scene.

A castle with red roof. It's on green grass. It's surrounded by buildings.

What's in the 3D scene?

A two-story wooden house.

Figure 12: Qualitative Examples on 3D Captioning



Can you help me find my book?

Sure. Where do you think you left it?

I think I left it on the desk

I have arrived at the desk. I see a few books here. Which one do you need?

Can you help me prepare dinner?

Sure! What do you want to make?

I want to make spaghetti carbonara. Can you help me find the ingredients?

I have the blue box of spaghetti and eggs from the close doors. Anything else?

Can you help me find my phone?

Sure! Where do you usually keep it?

It's usually on my desk.

I'm at the desk and don't see a phone. Is there any other place you might keep it?

Sometimes I leave it on the bed

I found it under the pillow. Anything else you need?

Describe the object.

It's a brown cabinet.

What's this?

A picture on the wall.

What's in the region?

A white square box.

Where's the chair located

Front of desk.

What's the style of the building?

It's Chinese style.

What's the color of the bathroom stall door?

White

What's the color of the building?

White.

What's above the sink?

A mirror.

How many shelves does the bookshelf have?

2

I want to clean up the room. What should I do?

1. go to the trash can 2. empty the trash 3. go to the paper towel dispenser 4. refill the paper towels 5. go to the chair 6. clean the chair 7 go to the table 8. clean the table 9. go to the door 10. clean the door 11. go to the window 12. clean the window 13. sweep and mop the floor.

I want to prepare for a meeting. What should I do?

1. enter the room through the door 2. go to the cabinets and take out the documents 3. go to the table and arrange the documents 4. exit the room through the door

I want to prepare a cup of coffee. What should I do?

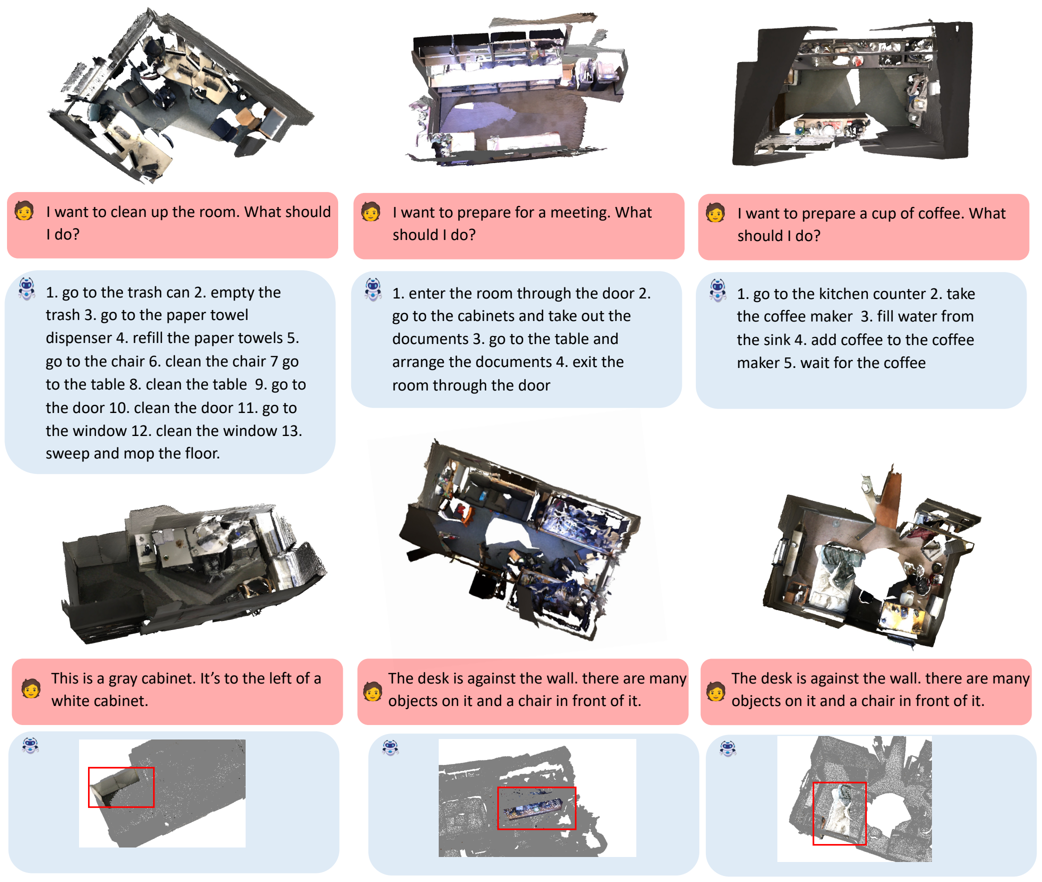
1. go to the kitchen counter 2. take the coffee maker 3. fill water from the sink 4. add coffee to the coffee maker 5. wait for the coffee

This is a gray cabinet. It's to the left of a white cabinet.

The desk is against the wall. there are many objects on it and a chair in front of it.

The desk is against the wall. there are many objects on it and a chair in front of it.

Figure 13: Qualitative Examples on 3D-Assisted Dialog, 3D Dense Captioning and Question Answering.



I want to clean up the room. What should I do?

1. go to the trash can 2. empty the trash 3. go to the paper towel dispenser 4. refill the paper towels 5. go to the chair 6. clean the chair 7 go to the table 8. clean the table 9. go to the door 10. clean the door 11. go to the window 12. clean the window 13. sweep and mop the floor.

I want to prepare for a meeting. What should I do?

1. enter the room through the door 2. go to the cabinets and take out the documents 3. go to the table and arrange the documents 4. exit the room through the door

I want to prepare a cup of coffee. What should I do?

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The desk is against the wall. there are many objects on it and a chair in front of it.

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Figure 14: Qualitative Examples on Task Decomposition and Grounding (Referring).