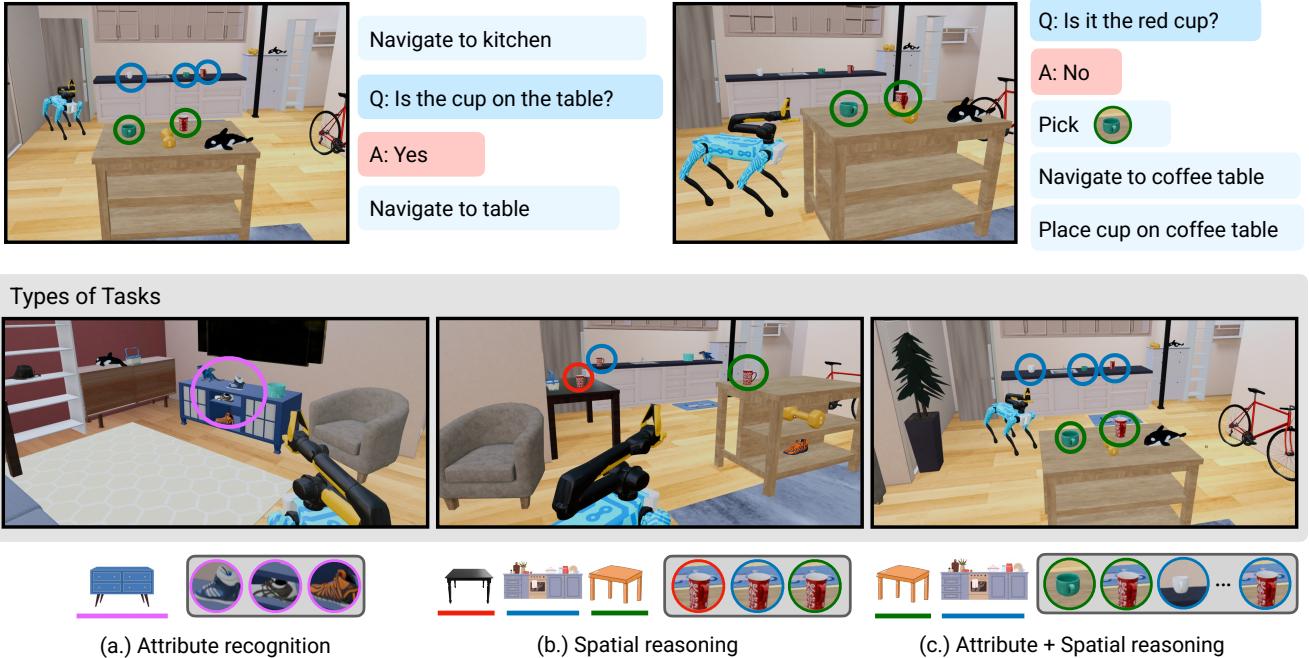# Grounding Multimodal LLMs to Embodied Agents that Ask for Help with Reinforcement Learning

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Task: Bring the cup and place it on the coffee table

(a.) Attribute recognition   (b.) Spatial reasoning   (c.) Attribute + Spatial reasoning

Figure 1. ASK-TO-ACT task. In this task, the user requests a specific green cup but, instead of describing it in detail, asks the agent, *"Bring the cup and place it on coffee table"*. Since the user's intent is unclear, an agent must ask a *minimum number* of clarification questions to disambiguate the requested object (*e.g.* *"Are you looking for a red cup?"* or *"Is it on the kitchen counter?"*). We consider different types of ambiguities, requiring inquiring about object attributes, spatial relationships, object size, or combinations of the three.

Abstract

Embodied agents operating in real-world environments must interpret ambiguous and under-specified human instructions. A capable household robot should recognize ambiguity and ask relevant clarification questions to infer the user intent accurately, leading to more effective task execution. To study this problem, we introduce the ASK-TO-ACT task, where an embodied agent must fetch a specific object instance given an ambiguous instruction in a home environment. The agent must strategically ask minimal, yet relevant, clarification questions to resolve ambiguity while navigating under partial observability. To solve this problem, we propose a novel approach that fine-tunes multimodal large language models (MLLMs) as vision-language-action (VLA) policies using online reinforcement learning (RL) with LLM-generated rewards. Our method eliminates the need for large-scale human demonstrations or manually engineered rewards for training such agents. We benchmark against strong zero-shot baselines, including GPT-4o, and supervised fine-tuned MLLMs, on our task. Our results demonstrate that our RL-finetuned MLLM outperforms all baselines by a significant margin (19.1-40.3%), generalizing well to novel scenes and tasks. To the best of our knowledge, this is the first demonstration of adapting MLLMs as VLA agents that can act and

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*Work done as part of the internship at Meta

ask for help using LLM-generated rewards with online RL.

1. Introduction

Embodied agents operating in real-world environments must interpret human instructions, which are often ambiguous, under-specified, or context-dependent. Consider asking a household robot, '*Bring the cup and place it on the coffee table*' To complete this task, in an environment (as shown in Fig. 1) without additional information, the robot faces multiple ambiguities like - which *cup* is the user referring to (red, white or green)? Does the user need a small cup or a large one? Instead of making incorrect assumptions and bringing an incorrect cup to the user, a capable household robot should ask the *minimum number of* clarification questions to disambiguate the requested object such as, *"Are you looking for a red cup?"* followed by *"Is it on the kitchen counter?"*. By actively asking questions that are grounded in the environment state and relevant to the context of the task, an intelligent household robot can infer user intent more accurately, leading to more effective and reliable task execution. We call this task ASK-TO-ACT, and believe inferring such ambiguity and asking clarification questions to resolve it requires balancing several implicit objectives such as exploration to gather task-specific information from the environment, deductive reasoning to minimize the number of questions, and contextual reasoning to determine the right time to ask questions. Humans effortlessly do this by combining common sense knowledge, contextual cues, and deductive reasoning. In this work, we ask 'How can we build embodied agents capable of reasoning required to resolve such ambiguity by asking clarification questions?'

Training such agents capable of interacting and asking clarification questions is challenging. Most tasks in embodied AI have well-defined goals [4, 14, 39, 46] and approaches for such tasks rely on either collecting large-scale human demonstrations [7, 13, 21, 27, 32] with low-level actions combined with imitation learning (IL) or use large-scale reinforcement learning [2, 47, 57] (RL) with manually designed rewards. However, neither of these methods are trivial nor scalable, especially when training agents that require intermediate natural language communication: Gathering natural language interaction data interleaved with robot actions introduces additional overhead in already expensive and time-consuming robot teleoperation. Alternatively, training such agents with RL requires access to dense reward functions, which are impractical to manually design to encourage task-specific deductive or commonsense reasoning. Prior works [17, 20, 25, 33] focusing on similar settings take advantage of the prior knowledge and rich commonsense reasoning abilities of Large Language Models (LLMs) in a zero-shot manner for task planning and reasoning about ambiguity to ask clarification questions. However, these methods either require careful prompt engineering to prevent the robot from excessively relying on seeking assistance, or operate under strong assumptions, i.e. the environment is fully observable and can be represented in text without any errors. These assumptions are unrealistic – real-world environments impose partial observability, requiring agents to actively explore and gather information.

To address these limitations, our key idea is to bootstrap the learning signal required for training embodied agents capable of interacting and asking in an end-to-end manner by leveraging an LLM's contextual commonsense and deductive reasoning ability to resolve ambiguity. We accomplish this by adapting a multimodal large language model [22, 23] (MLLM) into a vision-language-action [7, 21, 41, 43] (VLA) model using large-scale RL with reward signal generated using an LLM with access to privileged information from the simulator. To distill reasoning ability required for resolving ambiguity into this VLA model, we propose to use per-step rewards generated using an LLM [24, 54] that evaluates both the actions taken and natural language question asked by the agent in context of the task. Through our experiments, we show that LLMs are highly effective at generating per-step rewards for such tasks that require interacting with environment and asking questions to resolve ambiguity, when provided with the right representation of task and environment in text – information that can be easily curated at training time using privileged simulator state. This framework enables us to adapt MLLMs into VLA models that can interact with the environment and resolve ambiguity by asking questions without expensive human demonstrations or manually engineered rewards.

To evaluate effectiveness of our method we instantiate the ASK-TO-ACT task in a more realistic setup where agents operate under partial observability, process visual observations, and at each step output either actions or natural language questions to solve a rearrangement task [39, 46], in contrast to prior works [20, 33]. We set up ASK-TO-ACT in Habitat 3.0 [30] using 83 scenes from the ReplicaCAD [39] dataset, with 42 object categories from Google Scanned Objects [12]. We evaluate the generalization ability of these agents along two axes: 1) **Unseen Scenes**: where we evaluate on seen tasks in unseen scenes which include unseen configurations of furniture and objects, and 2) **Unseen Tasks**: where we evaluate the agent on novel task instances in unseen scenes *i.e.* novel compositions of the five types of ambiguity described in Sec. 3 not seen by the agent during training.

We compare our proposed method against strong zero-shot baselines leveraging proprietary LLMs and MLLMs like GPT-4o [26], as well as methods for fine-tuning open-source MLLMs using synthetically generated supervised fine-tuning (SFT) data for the ASK-TO-ACT task. Our method, which employs large-scale RL with LLM-generated rewards to fine-tune an open-source MLLM, outperforms all

baselines by a large margin, 40.3% and 19.1% for success rates on UNSEEN SCENES and UNSEEN TASKS evaluation splits. We also find that training VLA policies using only task subgoal rewards (*i.e.* no explicit rewards for asking the right questions), which can be programmatically written, achieve performance close to random on ASK-TO-ACT task. This indicates that training embodied agents to act and reason about ambiguity requires dense reward signals. Additionally, we analyze the behavior of our RL-trained policy and find that as the number of questions these agents can ask increases, the success rates of these policies improve and they generalize better to UNSEEN TASKS.

2. Related Work

Agents that ask for help. Our work builds on prior works in embodied AI [3, 15, 28, 38, 45] which explore effective human-robot interaction through dialogue. In these settings, an embodied agent can ask questions in natural language to improve task performance or human-robot interaction. In ASK-TO-ACT, we study this in the context of rearrangement tasks specified with under-specified instructions where the agent needs to reason about object appearance, location, and size, engaging in a multi-round dialogue (1-4 rounds) to disambiguate the object. Similar to prior works [15, 28, 45], we restrict the vocabulary of questions in order to make it feasible to evaluate the questions agent asks. In recent works [20, 33], the most common approach is to leverage an LLM's commonsense reasoning and language generation ability in a zero-shot manner to handle such human-robot interactions. However, these methods require extensive prompting and operate under assumption of full observability *i.e.* the complete error-free environment state is represented in text. We take a step towards relaxing these constraints and make the task setup more realistic by setting up the ASK-TO-ACT task in a partially observable setting.

Vision-Language-Action Models. Prior works [7, 8, 21, 41–43] have demonstrated that multimodal large language models can be adapted as vision-language-action (VLA) models for interactive decision-making tasks. These methods leverage MLLMs [6, 22, 23] pre-trained on vision-language modeling tasks and finetune them for low-level robot control [7, 21, 41, 42] or embodied task planning [43, 48, 56]. These works focus on settings where a task is clearly specified and there is no ambiguity which makes evaluation and training data/signal generation easier. In our work, we focus on following the same recipe of finetuning MLLMs for embodied task planning but for tasks that requires contextual reasoning and asking for external feedback from a user for information not accessible from observing the environment.

Reward generation using LLMs. A promising method to train robot policies without expensive human demonstrations is to use RL with synthetically generated rewards [9, 24, 24, 34, 55]. A common approach is to prompt

Question	Query Type
Is it the [Attr] [Obj]?	Object attribute
Is the object on the [Recep]?	Object location
Is it the [Size] [Obj]?	Object size

Table 1. Types of questions agent can ask in ASK-TO-ACT task.

the LLM to write code that takes symbolic features from the environment observations and produces a scalar output representing the reward. This approach has shown promising results on training policies for low-level robot control for complex dexterous manipulation, whole body control, locomotion, and object manipulation. A key difference of our work is that we are focused on teaching embodied agents ambiguity reasoning ability and language generation to ask for feedback using LLM generated rewards. Motivated by the effectiveness of using LLMs as reward models for complex math and code reasoning tasks [10, 34, 49, 58], in our work we focus on evaluating the effectiveness of LLM reward models for embodied tasks that require reasoning about ambiguity. In our work, we show that this paradigm of training interactive policies using an LLM as a process reward model (PRM) [37] is an effective approach for tasks that require reasoning about ambiguity, where writing rewards manually or collecting human demonstrations is not trivial or scalable.

3. ASK-TO-ACT task

Our goal is to build embodied agents capable of reasoning about ambiguity when task-planning and interacting with users for clarification when required under partially observable settings. To study building such agents, we propose the ASK-TO-ACT task as shown in Fig. 1, where an agent is spawned randomly in an unseen indoor environment and tasked with fetching a specific instance of an object and placing it on a designated receptacle using an underspecified language instruction. Consider the example shown in Fig. 1: the user wants a specific green cup but, instead of describing it in detail, asks the agent, *"Bring the cup and place it on coffee table"*. While searching, the agent finds multiple cups on the kitchen counter and the table - two red cups, a white cup, and two green cups. Since the user's intent is unclear, an optimal agent must ask the fewest clarification questions to disambiguate the requested object. To study an agent's ability to reason about ambiguity, we synthetically create tasks with different types of ambiguities, including variations in object appearance, location, and size. As shown in Fig. 1, our task evaluates ambiguity across five dimensions:

- **Attribute Recognition**: The agent must reason about appearance-based attributes such as color and object category to disambiguate objects (e.g., a blue shoe, white shoe and orange shoe as shown in Fig. 1 (a)).
- **Spatial Reasoning**: The agent must differentiate between objects with similar appearance and geometry based on their spatial location (e.g., red cup on the light table, or

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kitchen counter, or dark table as shown in Fig. 1 (b)).

- **Object Size**: The agent must distinguish between objects of different sizes but similar appearance and location (e.g., a large red bowl vs. a small red bowl).
- **Attribute and Spatial Reasoning**: A combination of attribute recognition and spatial reasoning, where the agent must consider both appearance and location to minimize the number of clarification questions needed to identify the target object (as shown by example in Fig. 1 (c)).
- **Attribute/Spatial Reasoning and Object Size**: A combination of attribute and spatial reasoning with object size, where the agent must account for both appearance or location and size to effectively disambiguate the target object.
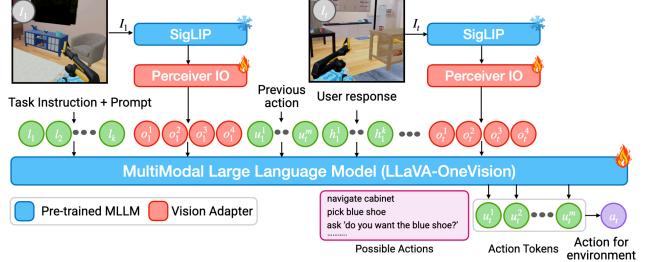
These five axes of ambiguity comprehensively assess various capabilities, including ones that MLLMs are known to struggle with (*e.g.* counting [11], and spatial reasoning [31]).

Evaluation Splits. We assess the generalization ability of these agents along two axes:

- **Unseen Scenes**: Evaluates how well the agent can perform tasks under new object layouts in the scene, or new instances of previously seen object classes.
- **Unseen Tasks**: Tests the agent's ability to handle novel instances of ambiguity in unseen scenes, requiring the agent to ask more questions than training tasks. For example, for attribute recognition tasks, in training the agent only needs to distinguish between 2 objects of different attributes but in UNSEEN TASKS split it needs to distinguish between 3 or 4 instances. See Appendix A for examples.

Evaluating Questions. Evaluating questions asked by an agent in context of a task in a programmatic manner is important for simulating the user response. To do so, we use an LLM to build an answering module for ASK-TO-ACT task which takes as input the task instruction, privileged information of state of environment represented as text, metadata of the target object a user is requesting, and is tasked with answering questions generated by the embodied agent. In order to constrain the difficulty of natural language question generation and answering, we limit the types of questions an agent can ask to 3 types of questions (via prompting) that query object attribute, location, and size as shown in Tab. 1. We apply this constraint to ensure we can accurately evaluate questions asked by an agent as open-ended question-answering is an open research problem. For each question an agent asks, the LLM responds with either a 'Yes/No' language response. When training MLLM policies using RL, having an LLM as answering module and reward model in the training loop introduces additional infrastructure challenges and increases training time dramatically. By constraining the types of questions, we can compute the answers and rewards from an LLM for our task offline which allows to scale RL training. Details about the implementation are in Appendix D.

Task Setup. We instantiate the task using Habitat 3.0 [30] in 63 training scenes and 20 evaluation scenes from Repli-

Figure 2. MLLM Policy Architecture. The policy takes as input a task instruction, sequence of past observations, actions, user response to questions asked and outputs a high-level action (*i.e.* skill) or a question in natural language.

caCAD [39] dataset with 42 object categories from Google Scanned Objects [12]. We use the Spot robot embodiment for the ASK-TO-ACT task with a height of 1.41m and radius of 0.25cm. At each timestep the agent has access to a 480×640 resolution RGB image, robot joint positions, an indicator of whether the robot is holding a object or not, relative base egomotion, and task instruction.

Action Space. The agent's action space is implemented in Habitat 3.0 [30]. We provide all methods with a set of oracle low-level skills, and focus on high-level decision-making. We opt for a hierarchical approach for our task, as training end-to-end with low-level actions for such a task presents the challenge of long-horizon task execution that requires tens of thousands steps of interaction while also engaging in natural language interaction with the user. Even seemingly simple mobile pick-and-place tasks remain difficult for end-to-end approaches [5, 18]. However, hierarchical methods - where a high-level policy selects from a set of predefined skills have proven effective in rearrangement tasks [1, 39, 40]. At each timestep, the high-level policy selects from 116 predefined skills or an open-ended "ask question" action, to generate a natural language query when clarification is needed. These skills include picking objects by name, placing on receptacles, and navigating to specific locations. Example action outputs include pick(apple), place(sink), navigate(coffee table) and ask_question("Do you want the red cup?").

4. Approach

Our method adapts a pre-trained multi-modal large language model (MLLM) to a vision-language-action (VLA) model capable of simultaneously taking actions, and generating natural language questions to resolve ambiguity in multi-modal embodied decision-making settings – without relying on human annotations or hand-engineered rewards. We use reinforcement learning (RL) with LLM-generated rewards to train a VLA for ASK-TO-ACT.

4.1. Policy Architecture

We adapt the LLaVA-OneVision [22] MLLM architecture to a VLA model for task-planning and asking questions as illustrated in Fig. 2. The MLLM policy takes as input a task in-

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struction along with a sequence of past observations, actions, user response to questions asked and outputs a high-level action (*i.e.* skill) or a question in natural language. As shown in Fig. 2, the task instruction is first encoded into language tokens. Traditional MLLMs embed a single visual input into a large number of visual tokens *e.g.* LLaVA-OneVision [22] uses 729 tokens. However, in partially observable embodied settings these agents need to reason over a long sequence of past observations to complete a task. Using a large number of visual tokens for each observation would quickly increase the context lengths (*e.g.* 32 visual observations $\times 729$ tokens $= \sim 23k$ tokens). To make it feasible to train MLLMs with a long observation history, we employ a Perceiver model [19] to downsample the visual tokens per observation, similar to [41]. Specifically, we encode each visual observation using the MLLM visual encoder and then pass output to a Perceiver downsampler which outputs $k < 729$ tokens ($k = 4$ in our case). Next, these downsampled visual tokens from the current observation o_t are interleaved with task instruction tokens ($l1, ..., l_k$), text representation of actions token ($u_{t-1}^1, .., u_{t-1}^m$), and language response given by user for any questions asked at each step tokenized ($h_{t-1}^1, .., h_{t-1}^k$).

These interleaved language and visual tokens are processed by the MLLM, which autoregressively predicts a sequence of language tokens corresponding to a discrete action or a natural language question. Each agent action $a \in A$ (a skill or possible questions $q \in Q$) is represented as free-form text sequence, tokenized as $(u_t^1, ..., u_t^m)$. For instance, in an action space where the high-level skill is described as "pick red bowl", the sequence is tokenized as $[29245, 2518, 19212]$ using the Qwen-2 [51] tokenizer. The MLLM must predict tokens 29245, then 2518, and finally 19212 to execute the action. Sequences corresponding to invalid actions are either filtered out or treated as a no-op to prevent execution errors.

Constrained Grammar Decoding. Training MLLMs with RL using language actions significantly expands the action space where most actions are invalid, which makes RL training difficult [44]. For instance, the Qwen-2 [51] tokenizer has a vocabulary of 151646 tokens, resulting in 151646^m possible action predictions per step, where only a small subset of these actions are valid. To address this, we employ grammar-constrained decoding [29] to limit autoregressive sampling to only valid action token sequences. Grammar-Constrained Decoding is defined as a function $M(u_t^1, ..., u_t^{j-1})$ that generates a binary mask over all tokens, indicating which tokens are valid for the jth decoding step. This restriction ensures that model only predicts valid actions, making RL training tractable.

4.2. Training with Reinforcement Learning using LLM-generated Rewards

To finetune LLaVA-OneVision [22] base MLLM with embodied data we use online RL with LLM-generated rewards for ASK-TO-ACT task. Manually defining dense rewards using heuristics to generate subgoals and evaluate questions within the task context is not trivial. We argue that evaluating natural language questions and agent actions for such tasks requires writing programs that can evaluate task-specific deductive and contextual reasoning, as well as language generation, which is not feasible. We show that current state-of-the-art LLMs, when provided with task and environment information in the right representation, demonstrate contextual understanding and deductive reasoning ability required to reason about such ambiguity in embodied settings. This suggests that LLMs can be used to automatically generate subgoals, and evaluate whether a sequence of questions can disambiguate the target object for ASK-TO-ACT, which can be used as reward signal for RL training. Specifically, we prompt an LLM with privileged environment state, task instruction, and target object metadata in a text representation, and ask it to generate relevant subgoals and all optimal question sequences to solve each ASK-TO-ACT task. See Appendix D for more details and the prompt.

We use generated subgoals and question sequences to generate the reward at each timestep using the equation described in Eq. (1). The reward function consists of a sparse reward for completing the task, subgoal rewards for achieving intermediate objectives, a slack penalty to encourage task completion in fewer steps, and a reward for asking clarification questions that aids in disambiguating the target object. The reward at step t is computed as follows:

$$
\begin{aligned}
r_t = & r_1 \cdot \mathbb{1}_{\text{success}} + r_2 \cdot \mathbb{1}_{\text{subgoal}} + r_3 \cdot \mathbb{1}_{\text{useful\_question}} \\
& - r_4 \cdot \mathbb{1}_{\text{exceed\_budget}} - r_5,
\end{aligned}
\tag{1}
$$

where $\mathbb{1}_{\text{success}}$ indicates whether the task was successfully completed and $\mathbb{1}_{\text{subgoal}}$ (generated by the LLM) indicates if the agent completed any subgoal required to complete the overall task. For example, for a task "Bring me the cup and place it on the coffee table", the agent needs to first search for all cups, pick the correct cup, then navigate to the coffee table, and finally place it. Similarly, $\mathbb{1}_{\text{useful\_question}}$ (generated by the LLM) indicates if a question asked by the agent is valid and helps make progress towards disambiguating the target object or not. Consider the example of fetching the cup, if the environment has 4 cups on a table and the agent asks "Is it the red cup?" and if user responds 'no', then the agent should ask 'Is it the blue cup?' or 'Is it the yellow cup?' to find the target object instead of asking 'Is it on the table?' to make progress towards solving the task. Additionally, for each question the agent asks in an episode the

reward r_3 is a value normalized to sum up to 1 based on number of questions required to solve the task. When training policies under a budget of questions we penalize the agent for every question that exceeds pre-specified budget given by $\mathbb{1}_{\text{exceed\_budget}}$. By default the budget is set to minimum number of required questions K to solve the task.

Implementation details. We train the MLLM policy using DD-PPO [47], an adaptation of PPO [36] for distributed training, for 50 million steps on 8 A40 GPUs. To generate rewards for our task we use the Llama-3 [16] LLM. We provide full training details in Appendix C.

5. Experiments

In this section, we compare our method of adapting MLLMs as VLA using RL with LLM-generated rewards to proprietary MLLMs in a zero-shot setting and MLLMs trained using synthetically generated SFT data for the our task.

5.1. Baselines

For methods involving MLLM fine-tuning, we use LLaVA-OneVision 0.5B [22] as our base MLLM with modifications described in Sec. 4.1. We use the 0.5B model due to compute constraints for running RL training on A40 GPUs. Below, we outline the details of each baseline:

(a.) Fully Observable Text WorldGraph + ReAct (Zero-shot). In this baseline, we provide an LLM (GPT4o in our case) with a fully observable text-based world graph describing the environment, including receptacles, objects, and their locations (*e.g*. "The apple is on the coffee table."). Additionally, the LLM is equipped with an skill library for executing actions, a history of previous actions, and the task instruction. At each timestep, the LLM generates a reasoning chain via ReAct [53] prompting followed by an action to complete the task. By eliminating perception limitations, this baseline evaluates the zero-shot planning and reasoning capabilities of LLMs for solving ambiguous embodied tasks.

(b.) Fully Observable Text WorldGraph + ReAct (Few-shot). This baseline extends (a) by providing the LLM with a few in-context examples that demonstrate task planning and ambiguity resolution strategies in the ASK-TO-ACT task. By leveraging demonstrations, this approach assesses whether in-context learning improves LLM's task planning and ambiguity reasoning under full observability.

(c.) Partially Observable Text WorldGraph + ReAct (Few-shot). While baselines (a) and (b) assume privileged access to a fully observable world graph, constructing such representations in real-world settings is often infeasible. This baseline relaxes that assumption by providing the LLM with a partially observable text-based world graph. At the start of an episode, the agent lacks full knowledge of object locations and must actively explore to gather necessary information.

(d.) Vision GPT4o + SoM + ReAct. Building an error-free text representation of real-world environments is challenging.

This baseline evaluates whether existing MLLMs can solve the ASK-TO-ACT task using egocentric visual observations. At each timestep, the MLLM receives the robot's visual input along with an skill library for executing actions. To enhance grounding, we label visual observations using Set-of-Marks (SoM) [52] and maintain memory by providing GPT4o with a textual history of past observations and actions.

(e.) LLaVA-OneVision SFT. This baseline finetunes LLaVA-OneVision 0.5B MLLM for our task using Supervised Fine-Tuning (SFT) on synthetically generated trajectories. Generating training data is non-trivial, as the agent must first explore the environment to locate relevant objects, ask contextually grounded questions to disambiguate the target object, and finally execute the instruction once the object is identified. To achieve this, we design an expert using heuristic exploration and an LLM. The agent first explores the scene using frontier exploration [50] until all receptacles are seen, then converts its observations into a text-based world graph. This graph, along with the task instruction and privileged information about the target object, is passed to an LLM, which generates a sequence of clarifying questions to identify the object. Once the target object is determined, a heuristic planner executes the rearrangement task. The final trajectory consists of actions taken during exploration, LLM-generated questions as actions, and actions taken to rearrange the object. Only successful trajectories are included in training. Our SFT dataset contains ∼40k trajectories in 63 training scenes in the ReplicaCAD dataset.

5.2. Metrics

We report three metrics: 1.) **Success Rate (SR)**: a measure of successful task completion, 2.) **Ambiguity-Resolution Efficiency Score (ARS)**: a measure for the agent's ability to successfully complete task while asking *minimum* number of required clarification questions and penalizing irrelevant ones. ARS is computed using the following function:

$$ARS = \frac{\mathbb{1}_{\text{success}}}{1 + \text{abs}(q_{\text{relevant}} - K) + q_{\text{irrelevant}}}, \qquad (2)$$

where $\mathbb{1}_{\text{success}}$ denotes whether an episode was successful, q_{relevant} is the number of relevant questions asked per episode, $q_{\text{irrelevant}}$ is the number of irrelevant/redundant questions asked per episode, and K denotes the minimum number of questions required to resolve ambiguity for each episode. ARS penalizes an agent equally for asking fewer or more questions than minimum required questions to resolve ambiguity for each episode equally. 3.) **Question Ratio (QR)**: ratio of total questions agent asked *vs*. the minimum required questions to solve the task *i.e*. $(q_{\text{relevant}} + q_{\text{irrelevant}})/K$.

5.3. Results

Tab. 2 presents the results of evaluating all methods on UN-SEEN SCENES and UNSEEN TASKS splits. To establish

Method	Full Obs.	UNSEEN SCENES			UNSEEN TASKS		
		SR (↑)	ARS (↑)	QR (↓)	SR (↑)	ARS (↑)	QR (↓)
1) WG + ReAct*	✓	56.1	50.5	3.2	47.3	37.4	2.3
2) WG + ReAct* (FS)	✓	96.2	49.7	2.3	94.7	35.6	1.9
3) WG + ReAct* (FS)	✗	61.8	46.9	3.2	49.2	32.2	2.2
4) GPT4o + SoM + ReAct	✗	25.2	20.1	1.9	19.8	12.5	1.1
5) LLaVA-OV SFT	✗	48.2	46.9	**1.5**	34.1	26.1	**0.8**
6) LLaVA-OV RL (Ours)	✗	**89.8**	**63.2**	2.6	**65.2**	**32.4**	2.5

Table 2. Results. Evaluation of all methods on UNSEEN SCENES and UNSEEN TASKS evaluation splits of ASK-TO-ACT task. FS denotes few-shot examples, * denotes access to privileged information, Full Obs. stands for full observability.

an upper bound on performance, we first evaluate zero-shot LLMs with privileged information (rows 1 and 2 of Tab. 2). When LLMs are provided with a fully observable text-based representation of the environment and use Re-Act [53] for action prediction, they achieve a success rate of 56.1% and 47.3% and an ARS of 50.5% and 37.4% on UNSEEN SCENES and UNSEEN TASKS, respectively. This highlights the inherent difficulty of task planning and ambiguity resolution for LLMs in a zero-shot setting. Next, we augment LLMs with privileged in-context examples demonstrating how to perform the ASK-TO-ACT task. This significantly improves performance, increasing success rate to 96.2% and 94.7% on unseen scenes and tasks. These promising results motivated us to explore using LLMs as reward generators for ASK-TO-ACT. We then evaluate the same baseline under partial observability (row 3), where the agent does not have access to a fully observable world graph but still has in-context examples. This leads to an absolute drop in success rate of 34.4% and 45.5% on both splits (row 3 *vs.* row 2), indicating that task planning and ambiguity resolution become significantly more challenging when the agent must actively explore to gather information. As shown in Tab. 2, our approach (row 6), which fine-tunes a MLLM [22] using RL with LLM-generated rewards, outperforms all methods operating under partial observability and achieves 89.8% and 65.2% on success rate and 63.2% and 32.2% ARS on UNSEEN SCENES and UNSEEN TASKS splits. Our method outperforms the policy trained with synthetic SFT data (row 5 *vs.* row 6) by absolute 31.1 − 41.6% on success rate and 6.3 − 16.3% on ARS. We find agents trained with SFT tend to be more conservative (lower than 1 QR as shown in row 5), asking fewer questions compared to RL-trained counterparts which could be the reason behind difference in performance, additional analysis shown in Sec. 5.4. Additionally, our method surpasses a strong zero-shot baseline (row 4) that uses vision GPT4o [26] with Set-of-Marks (SoM) [52] prompting and a text-based history of past observations by an absolute margin of 45.4 − 64.6% on success rate. These results demonstrate online RL combined with LLM-generated rewards is an effective method for training embodied agents that can interleave acting with asking relevant clarification questions to resolve ambiguity.

Method	UNSEEN SCENES			UNSEEN TASKS		
	SR (↑)	ARS (↑)	QR (↓)	SR (↑)	ARS (↑)	QR (↓)
1) Success Reward	0.0	0.0	0.0	0.0	0.0	0.0
2) Subgoal Reward	34.9	30.7	3.8	16.5	6.9	2.9
3) Ours	**89.8**	**63.2**	**2.6**	**65.2**	**32.4**	**2.5**

Table 3. Reward Choice. Evaluation results of using different rewards for training our method on UNSEEN SCENES and UNSEEN TASKS evaluation splits.
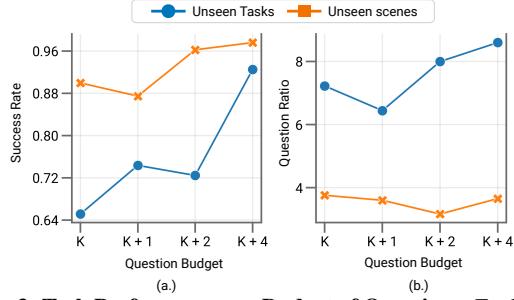
Can agents succeed without asking for help? In this experiment, we ask whether it is possible to train an effective MLLM policy using RL on ASK-TO-ACT task without asking a single question. As shown by results in Tab. 5 in Appendix B, we find agents trained to solve our task without asking questions achieve performance close to a random baseline (row 1 *vs.* row 2). In contrast, a policy trained using our LLM generated rewards with RL achieves significantly better performance on both UNSEEN SCENES and UNSEEN TASKS evaluation splits. More details in Appendix B.

Choice of reward for RL training. In Tab. 3, we ablate the choice of reward function for RL training to demonstrate effectiveness of using a LLM to generate rewards for ASK-TO-ACT. We consider two simple rewards that can be programmatically defined for our task:

1.) Success reward: a simple sparse reward setting where the agent is only given a reward of value 10 at the end of the episode if the agent succeeds and 0 otherwise. In addition, the agent also receives a slack penalty of 0.01 at each timestep to encourage faster task execution.

2.) Subgoal reward: in this setting the agent is rewarded for accomplishing any subgoal that is required to completing the overall task. For example, for a task "Bring me the cup and place it on the coffee table", the agent should navigate to the target cup, pick the target cup, then navigate to coffee table, and finally place it. In this case, the agent will be rewarded for navigating to only the target object instance, picking the target object, navigating to target receptacle and placing it. This reward can be programmatically generated for training episodes with access to privileged information from simulator and target object metadata from each episode. Note, this reward does not provide dense step-by-step incentive for exploration or to ask a sequence of questions required to disambiguate the object; instead, it implicitly rewards the agent to ask questions that lead to the agent picking the right object which makes RL training using reward difficult.

As shown in Tab. 3, neither of these rewards are sufficient to learn an effective MLLM policy for our task, demonstrating the need for precise per-step rewards that incentivize agents to not only act but also ask meaningful questions.
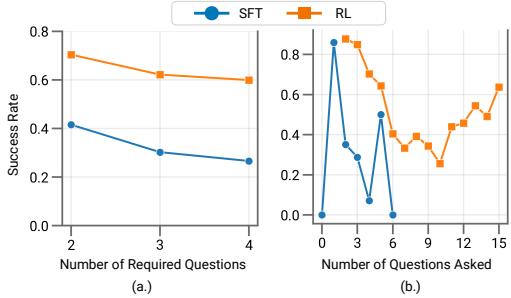
Training policies under variable budget. A desired skill for an embodied agent that can ask questions is to adhere to user's preferences about how often they would like a robot to ask clarification questions. Some would prefer an agent ask as few questions as possible for better user

Figure 3. Task Performance vs. Budget of Questions. Evaluation performance of policies trained under different budget of questions *vs.* task Success Rate and Ambiguity Resolution Efficiency score.

experience by trading off task success rates. In contrast, some users would be fine with an agent asking as many questions as it would like to ensure task success rates are higher. Motivated by this, we train multiple MLLM policies using RL with LLM generated rewards with a variable upper-bound on maximum number of questions an agent can ask. Specifically, we train policies with a budget of $B \in \{K, K + 1, K + 2, K + 4\}$ questions, where K is defined as minimum required question for a task in ASK-TO-ACT dataset. In this setting, an agent can ask at most B questions in a single episode (either relevant or irrelevant) without incurring any penalties. Note, for this experiment B is either equal to K *i.e.* ask as close to minimum required questions as possible or can be quite high $K + 4$ where an agent can ask as many as 4 extra questions than minimum required in each episode without incurring any penalties. Additionally, the agent will only be rewarded for relevant questions from all questions it asked. We only penalize the agent for each question asked after exceeding the question budget B. Fig. 3 shows success rates of various policies trained with different budgets under the reward setting described in Eq. (1). As shown in Fig. 3 (a.), as we increase the number of questions the agent can ask, the success rates increase; however, there is a clear trade-off between increase in success rates and question ratio (*i.e.* asked questions to minimum required), see Fig. 3 (b.).
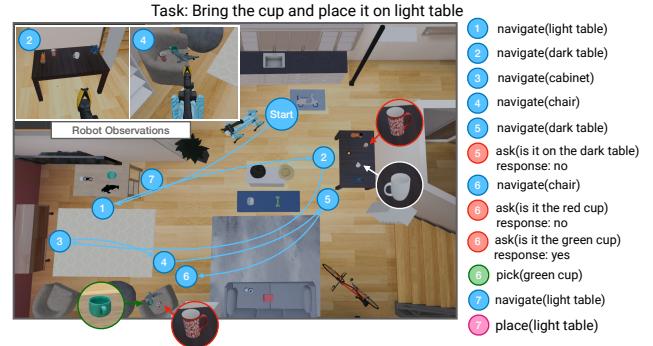
5.4. Analysis

Figure 4. Success Rate vs. Number of Required and Asked Questions. Evaluation performance of SFT and RL trained policies *vs.* number of required and total questions asked by the agent.

Quantitative analysis of agent behavior. In Fig. 4 (a.), we show the performance of MLLM policies trained using RL

and SFT *vs.* minimum required questions to solve tasks on UNSEEN TASKS split. These results show, as the number of required questions for a novel task increases the performance of both methods drops. In Fig. 4 (b.), we show the performance of these policies *vs.* number of questions asked by the agents. This results shows, as the number of questions asked by agents increase the performance starts dropping (from $0 - 4$ questions for SFT and $1 - 10$ questions for RL), however both methods there's a inflection point after which the performance increases (between $4 - 5$ for SFT and $10 - 15$ for RL). This suggests as these agents ask a lot more questions than minimum required for a task they are able to resolve ambiguity. We also observe, agents trained with SFT tend to be more conservative asking fewer questions compared to RL-trained counterparts that could explain the difference in performance as shown in Tab. 2 (row 5 *vs.* 6).

Figure 5. Qualitative Example. Successful trajectory of our method on an evaluation episode from UNSEEN TASKS split.

Qualitative examples. In Fig. 4, we show a success example of our method on UNSEEN TASKS split. The agent first explores until it finds all 4 instances of the cup. Then it asks a sequence of questions. Finally, based on responses from the user it successfully brings the green cup user wants to the light table. For more qualitative examples, see Appendix E.

6. Conclusion

In this work we introduce ASK-TO-ACT, a novel task where an embodied agent is tasked with fetching a specific instance of an object through an underspecified language instruction. To solve this task, the agent needs to be capable of reasoning about ambiguity based on the context of the environment and ask clarification questions in natural language to resolve the ambiguity. To train such agents, we propose an approach that adapts multimodal large language models (MLLMs) using reinforcement learning (RL) with LLM-generated rewards. Our results demonstrate that this approach significantly improves task success rates and ambiguity resolution efficiency score, outperforming strong zero-shot baselines using GPT-4o and open-source MLLMs fine-tuned with SFT on LLM-generated data. We evaluated our method on both unseen scenes and unseen tasks, showing that an RL-trained VLA model can generalize effectively to novel object arrange-

ments and ambiguous task instructions. Our findings highlight effectiveness of dense, context-aware LLM-generated rewards for training embodied agents capable of resolving ambiguity by interacting in natural language.

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white basket, green basket, brown basket, white bowl, red bowl, green bowl, red cup, green cup, white cup, white casserole, green casserole, black casserole, green cushion, yellow cushion, blue cushion, yellow dumbbell, green dumbbell, blue dumbbell, blue jug, orange jug, white jug, blue towel, red towel, green towel, grey hat, yellow hat, white plate, green plate, pink plate, black shoe, blue shoe, orange shoe, grey toy, blue toy, black toy, red vase, blue vase, pink vase, black teapot, white teapot, yellow teapot

Table 4. Full list of object categories used for ASK-TO-ACT task.

Method	UNSEEN SCENES			UNSEEN TASKS		
	SR ($\uparrow$)	ARS ($\uparrow$)	QR ($\downarrow$)	SR ($\uparrow$)	ARS ($\uparrow$)	QR ($\downarrow$)
1) Random + GT Planner	37.3	–	–	23.7	–	–
2) Ours w/o ask questions	33.7	25.7	0.0	22.4	9.2	0.0
3) Ours	89.8	63.2	2.6	65.2	32.4	2.5

Table 5. Ablations. Comparison of RL training with and without ask question actions on INTERACT-AND-ASK benchmark.

A. Dataset

In Fig. 6, we show additional examples of different types of ambiguities in our ASK-TO-ACT dataset. Specifically we show 3 additional examples for:

- **Attribute Recognition**: The agent must reason about appearance-based attributes such as color and object category to disambiguate the object user is looking for (e.g., a red bowl and white bowl as shown in Fig. 6 (a)).
- **Object Size** : The agent must distinguish between objects of different sizes but similar appearance and location to disambiguate the object user is looking for (e.g., a large red bowl vs. a small red bowl as shown in Fig. 6 (b)) .
- **Attribute/Spatial Reasoning and Object Size**: A combination of attribute and spatial reasoning with object size, where the agent must account for both appearance or location and size to effectively disambiguate the target object the user is looking for. For the example shown in Fig. 6 (c), the agent needs to reason about different colored shoes (blue, white, and orange shoe) which are located on the blue cabinet and the sofa and some of those have different size *e.g.* large blue shoe on blue cabinet *vs*. small blue shoe on sofa and large white shoe on sofa *vs*. small white shoe on blue cabinet.

Object Categories. We present the full list of object categories used for ASK-TO-ACT dataset in Tab. 4.

B. Additional Experiments

Can agents succeed without asking for help? In Tab. 5, we show a experiment where we ask whether it is possible to train an effective MLLM policy using RL that generalizes well to unseen scenarios in ASK-TO-ACT task without asking a single question. We first set up a random baseline for ASK-TO-ACT, we use privileged information from the simulator to fetch the list of objects of target object cate-
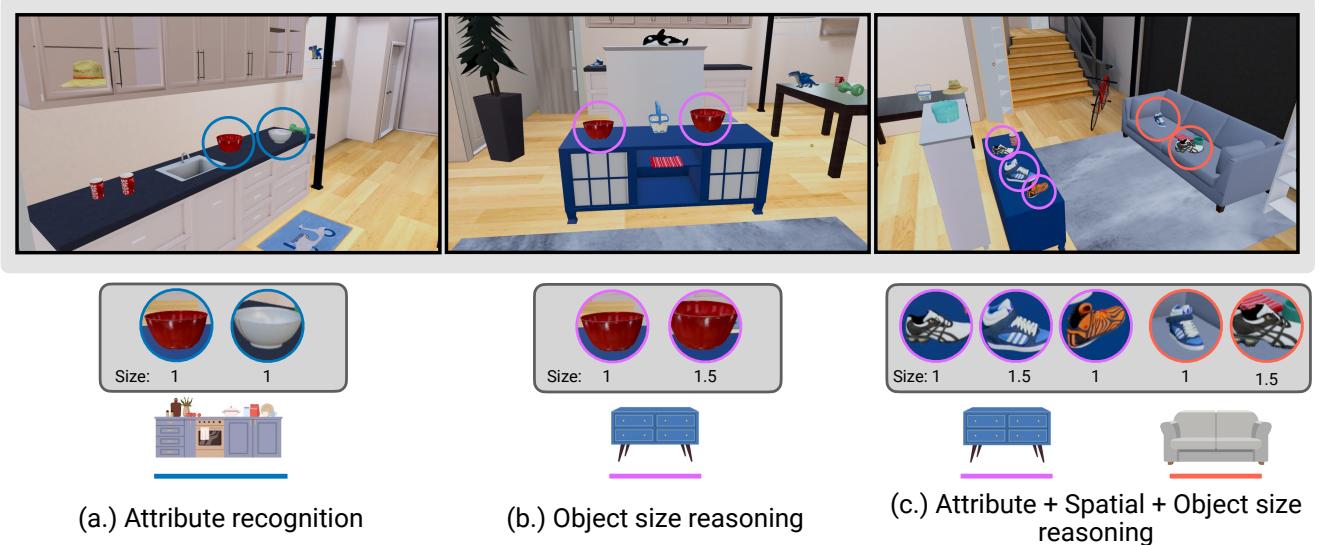
gory for each episode and randomly choose one of them as the target object. Next, we use the ground truth single object rearrangement planner we wrote in Habitat 3.0 [30] to place the randomly sampled target object on the target receptacle. Results of evaluating this random baseline with ground truth planner is shown in row 1 of Tab. 5. Next, we use the same policy architecture, and reward as described in our approach in Sec. 4 and modify the action space of the policy to disable 'ask_question' question and train it with RL *i.e.* the agent cannot ask the user (simulated by the LLM in our task) for clarification questions. As shown by results in row 2 of Tab. 5, the MLLM policy trained to solve our task without asking questions achieves performance close to a random baseline (row 1 *vs*. row 2). In contrast, a policy trained using our LLM generated rewards with RL (row 3) achieves significantly better performance on both UNSEEN SCENES and UNSEEN TASKS evaluation splits.

C. Training Details

Problem Setup. Our problem setup can be formulated as a Partially-Observable Markov Decision Process (POMDP), defined by a tuple $(S, O, A, P, R, p_0, \gamma)$ where S is state space, O is observation space, A is action space, P represents transition dynamics, R is reward function, p_0 is initial state distribution and γ is discount factor. In our setting, O is a combination of responses from the user (for any questions asked) and visual observations, which come from the robots egocentric RGB camera, and provide only partial views of the environment. We consider the extension of including a goal distribution G and the case where the reward is formulated as $R(s, g)$ for $s \in S$ and $g \in G$. We aim to learn a language-conditioned policy $\pi(a|o, g)$ mapping from observation o and task instruction g to an action a that maximizes the sum of discounted rewards $\mathbb{E}_{s_0 \sim p_0, g \sim G} \sum_t \gamma^t R(s_t, g)$.

Training Details. To train our policy using reinforcement learning (RL) we use PPO with Generalized Advantage Estimation (GAE) [35]. We use a discount factor γ of 0.99 and set GAE parameter τ to 0.95. We do not use normalized advantages. To parallelize training, we use DD-PPO [47], an adaptation of PPO [36] for distributed training, with 24 environments each on 8 A40 GPUs for 50 million steps . Each worker collects 24 frames of experience from 24 environments parallely and then performs 2 epochs of PPO update with 2 mini batches in each epoch. Tab. 6 details the default hyperparameters used in all of our training runs.

Token Normalization for Action Probability and Entropy. When using MLLMs for RL training, each action $a \in A$ at every timestep is represented using a set of tokens $(u_t^1, ..., u_t^m)$. However, the MLLM only outputs token level probabilities which is different from probability of executing an action in the environment as used in RL traditionally. The token-level probability for each action a_t can be represented by:

(a.) Attribute recognition   (b.) Object size reasoning   (c.) Attribute + Spatial + Object size reasoning

Figure 6. Dataset. Examples of different types of synthetically created ambiguities in ASK-TO-ACT tasks.

Parameter	Value
Number of GPUs	8
Number of environments per GPU	24
Rollout length	24
PPO epochs	2
Number of mini-batches per epoch	2
LR	$2.5e^{-4}$
Optimizer	Adam
Weight decay	0.0
Epsilon	1.0×10^{-5}
PPO clip	0.2
Generalized advantage estimation	True
γ	0.99
τ	0.95
Value loss coefficient	0.5
Max gradient norm	0.2
DDPPO sync fraction	0.6

Table 6. Hyperparameters used for RL finetuning.

$$P_{\text{token}}(a_t|s) = \prod_{i=1}^{m} P(u_t^i|s, u_t^1, \ldots, u_k^{i-1}) \quad (3)$$

To compute action probabilities, one naive approach is to take a sum over all token-level probabilities. When training MLLMs with action-space with variable number of tokens across actions one issue in Eq. (3), is that actions with larger number of tokens tend to have lower token-level probabilities, even though they might be more reasonable to take at some point in the environment. This issue happens because

the probability of each token $P(u_t^i|\cdot)$ is always less than 1. This could be problematic in RL optimization especially for the case when the agent needs to output a natural language question for ASK-TO-ACT task, simply because the questions tend to have more tokens than pre-defined skills represented in language. To remedy this issue, we use action length normalization technique ınormalize the token-level probabilities of the actions with the number of action tokens, which can be defined as:

$$logP(a_t|s) = \sum_{i=1}^{m} logP_{\text{token}}(u_t^i|s, u_t^1, \ldots, u_k^{i-1})/m \quad (4)$$

We find action-length normalization helps stabilize training when working with our variable length action-space when using constrained grammar decoding [29] for RL training.

D. LLM Reward Generation

Tab. 7 shows the prompt used for generating optimal answer sequences and subgoals required to generate the reward function described in Eq. (1) in Sec. 4.2. The same outputs are also used to build a answering module (described in Sec. 3) used during training and evaluation.

$$r_t = 10 \cdot \mathbb{1}_{\text{success}} + 2.5 \cdot \mathbb{1}_{\text{subgoal}} + r_3 \cdot \mathbb{1}_{\text{useful\_question}} \\ - 0.05 \cdot \mathbb{1}_{\text{exceed\_budget}} - 0.01, \quad (5)$$

Reward Details. Eq. (5) shows the reward function we use with coefficients for each term. In this reward, $\mathbb{1}_{\text{success}}$

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Table 7. LLM prompt used for generating optimal question sequences and subgoals used to generate rewards and build the answering module.

indicates whether the task was successfully completed and $\mathbb{1}_{\text{subgoal}}$ (generated by the LLM) indicates if the agent completed any subgoal required to complete the overall task. For example, for a task "Bring me the cup and place it on the coffee table", the agent needs to first search for all cups, pick the correct cup, then navigate to the coffee table, and finally place it. Similarly, $\mathbb{1}_{\text{useful\_question}}$ (generated by the LLM) indicates if a question asked by the agent is valid and helps make progress towards disambiguating the target object or not. Consider the example of fetching the cup, if the environment has 4 cups on a table and the agent asks "Is it the red cup?" and if user responds 'no', then the agent should ask 'Is it the blue cup?' or 'Is it the yellow cup?' to find the target object instead of asking 'Is it on the table?' to make progress towards solving the task. Additionally, for each question the agent asks in an episode the reward r_3 is a value

normalized to sum up to 1 based on number of questions required to solve the task. For example, if the task requires 3 questions then the agent will get $r_3 = 0.33$ for each question it gets correct from relevant question subset until agent asks 3 relevant questions and 0 afterwards. When training policies under a budget of questions we penalize the agent for every question that exceeds pre-specified budget given by $\mathbb{1}_{\text{exceed\_budget}}$. By default the budget is set to minimum number of required questions K to solve the task.

E. Qualitative Examples

We present additional qualitative examples of evaluating our method on UNSEEN TASKS evaluation split of ASK-TO-ACT dataset in Fig. 7.

F. Baseline Details

(a.) Fully Observable Text WorldGraph + ReAct (Zero-shot). In this baseline, we provide an LLM (GPT4o in our case) with a fully observable text-based world graph describing the environment, including receptacles, objects, and their locations (*e.g.* "The apple is on the coffee table.). The prompt used for this baseline is shown in Tab. 8.

(b.) Fully Observable Text WorldGraph + ReAct (Few-shot). This baseline extends (a) by providing the LLM with a few in-context examples that demonstrate task planning and ambiguity resolution strategies in the ASK-TO-ACT task. By leveraging demonstrations, this approach assesses whether in-context learning improves LLMs task planning and ambiguity reasoning under full observability. The prompt used for this baseline is shown in Tab. 9.
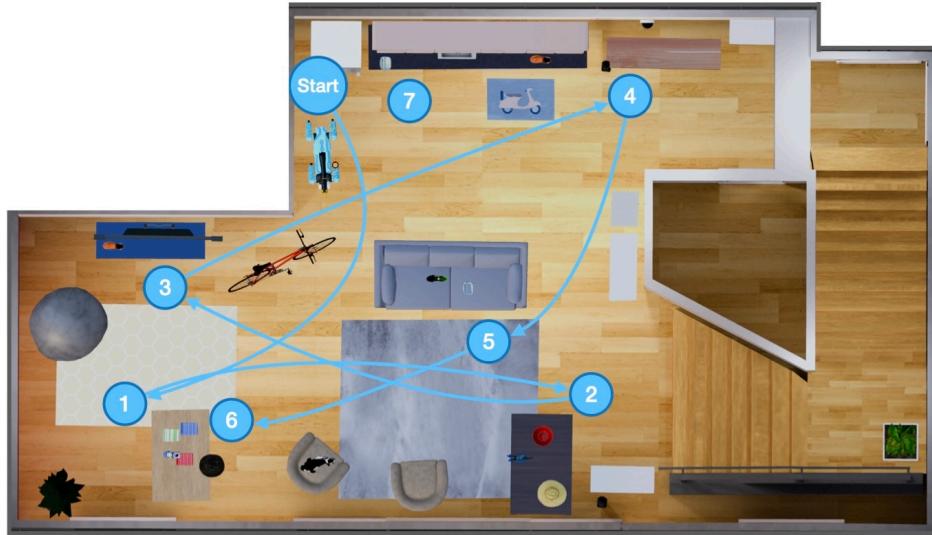
(c.) Partially Observable Text WorldGraph + ReAct (Few-shot). While baselines (a) and (b) assume privileged access to a fully observable world graph, constructing such representations in real-world settings is often infeasible. This baseline relaxes that assumption by providing the LLM with a partially observable text-based world graph. At the start of an episode, the agent lacks full knowledge of object locations and must actively explore to gather necessary information. The prompt used for this baseline is shown in Tab. 10.

(d.) Vision GPT4o + SoM + ReAct. Building an error-free text representation of real-world environments is challenging. This baseline evaluates whether existing MLLMs can solve the ASK-TO-ACT task using egocentric visual observations. At each timestep, the MLLM receives the robots visual input along with an skill library for executing actions. To enhance grounding, we label visual observations using Set-of-Marks (SoM) [52] and maintain memory by providing GPT4o with a textual history of past observations and actions. The prompt used for this baseline is shown in Tab. 11, in addition to the prompt this baseline takes in visual observations from robotos egocentric camera augmented with SoM [52].
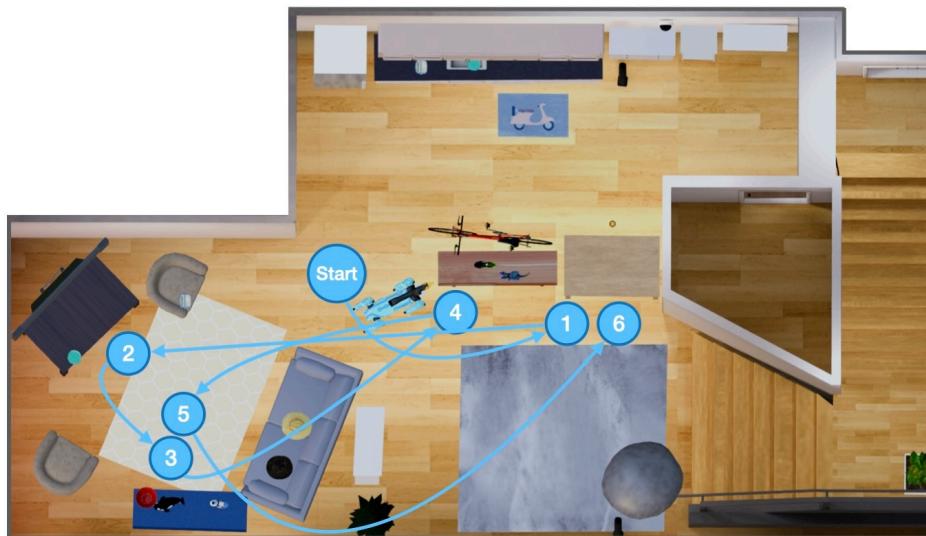
G. Limitations

In this work, the ASK-TO-ACT tasks are purposefully constrained in terms of the types of questions that can be asked so that we could study this problem in a controlled manner. For example, this made the evaluation of questions feasible in our setting, such that we can focus on evaluating whether it is possible to train an embodied agent that can interleave task planning with multi-round question-answering with the user. We show in this paper that it is indeed possible, and we leveraged the structure to disentangle the types of errors that can occur. An important future work is to study a more realistic setup of ASK-TO-ACT with a much more complex set of ambiguous tasks and an open-ended question-answer setup. There are a range of open research questions required to do this, including the use (and potentially training/distillation) of efficient LLM-as-reward models that can be used within an RL pipeline. Further study is also needed to determine exactly how accurate or reliable the rewards must be to train effective models. As it is anticipated that LLM-generated rewards will not be as accurate in less constrained settings. Additionally, using an LLM in an open-ended question answering setting while collecting embodied experience require solving non-trivial infrastructure challenges, such as running a LLM within the training loop for both question-answering and reward modeling with a simulator for tens of millions of steps. By constraining the types of questions an agent can ask we could make RL training tractable to study the effectiveness of LLM-generated rewards for ASK-TO-ACT in a controller manner. These aspects are limitations of our current work but exciting research directions for future work.

Task: Bring the hand towel and place it on kitchen counter

1	navigate(light table)
2	navigate(dark table)
3	navigate(tv stand)
4	navigate(cabinet)
5	navigate(sofa)
6	navigate(light table)
6	ask(is it on the light table) response: yes
6	ask(is it the blue towel) response: no
6	ask(is it the green towel) response: yes
6	pick(green towel)
7	navigate(kitchen counter)
7	place(kitchen counter)

Task: Bring the shoe and place it on light table

1	navigate(light table)
2	navigate(dark table)
3	navigate(tv stand)
4	navigate(cabinet)
5	navigate(tv stand)
5	ask(is it on the tv stand) response: yes
5	ask(is it the blue shoe) response: yes
6	pick(blue shoe)
7	navigate(light table)
7	place(light table)

Figure 7. Qualitative Example. Successful trajectories of our method on 2 evaluation episodes from UNSEEN TASKS split.

Imagine you are a household robot. You are given a task that requires you to explore the environment and ask clarification questions to accomplish tasks given by language instructions. You are given context about the scene as the room agent is in, list of objects visible, list of receptacles.

For each task given as a language instruction you have to output a sequence of actions that the agent should take. These actions can include a clarification question as well. Ask a question only when required. For each action also output the reason to take the action with it. Actions can be one of the following:

1. nav(receptacle)
2. pick(object)
3. place(receptacle)
4. ask("question")

You can only ask the following 5 types of yes/no questions about the object in question:

1. Is it on the <receptacle>?
2. Is it the <object_instance>?
3. Is it the <object_size> one?

Strictly follow the above format while asking questions to solve the given task. Do not use any other types of questions.

After you ask a question wait for the human to reply.

Strictly follow the above format while solving given task.

Instruction: instruction

Receptacles: receptacles

Receptacles with objects:
receptacles_with_objects

Observation action history:
prev_observations

Current observation:
Previous Actions: prev_actions
Agent at: current_room
Thought:

Table 8. LLM prompt used for the fully observable text world graph with ReAct [53] zero-shot baseline.

Imagine you are a household robot. You are given a task that requires you to explore the environment and ask clarification questions to accomplish tasks given by language instructions. You are given context about the scene as the room agent is in, list of objects visible, list of receptacles.

For each task given as a language instruction you have to output a sequence of actions that the agent should take. These actions can include a clarification question as well. Ask a question only when required. For each action also output the reason to take the action with it. Actions can be one of the following:

1. nav(receptacle)
2. pick(object)
3. place(receptacle)
4. ask("question")

You can only ask the following 5 types of yes/no questions about the object in question:

1. Is it on the <receptacle>?
2. Is it the <object_instance>?
3. Is it the <object_size> one?

Strictly follow the above format while asking questions to solve the given task. Do not use any other types of questions.

After you ask a question wait for the human to reply.

Here is a example of completing the task:

Instruction: Bring me bowl put it on cabinet

Receptacles: [light table, chair, sofa, dark table, tv stand, cabinet, sink]

Receptacles with objects:

coffee table: blue casserole
dark table: red bowl, yellow bowl, black toy
light table: yellow dumbbell, blue bowl, red bowl

Observation action history:
Step 1:
Previous Actions: []
Agent at: Start
Thought: I see two red bowls, one yellow bowl and one blue bowl. It's unclear which one user wants. I should ask about location of the bowl first and then the color to find the correct one.
Output Action: ask("Is it on the light table?")
Action Complete!

User response: no
Step 2:
Previous Actions: [ask("Is it on the light table?")]
Agent at: Start
Thought: User said it's not on light table. This means user wants either a red or a yellow bowl. I should ask about the color of the bowl user wants.
Output Action: ask("Is it the red bowl?")
Action Complete!

User response: yes

```
Step 3:
Previous Actions: [ask("Is it on the light table?"), ask("Is it the red bowl?")]
Agent at: Start
Thought: User said it's red bowl that is on the dark table. I will navigate to it.
Output Action: nav(dark table)
Action Complete!


Step 4:
Previous Actions: [ask("Is it on the light table?"), ask("Is it the red bowl?"), nav(dark table)]
Agent at: dark table
Thought: I need to pick the red bowl.
Output Action: pick(red bowl)
Action Complete!


Step 5:
Previous Actions: [ask("Is it on the light table?"), ask("Is it the red bowl?"), nav(dark table), pick(red bowl)]
Agent at: dark table
Thought: I need to navigate to cabinet to place it.
Output Action: nav(cabinet)
Action Complete!


Step 6:
Previous Actions: [ask("Is it on the light table?"), ask("Is it the red bowl?"), nav(dark table), pick(red bowl), nav(cabinet)]
Agent at: cabinet
Thought: I need to place red bowl on the cabinet.
Output Action: place(cabinet)
Action Complete!


Current observation:
Previous Actions: [ask("Is it on the light table?"), ask("Is it the red bowl?"), nav(dark table), pick(red bowl), nav(cabinet), place(cabinet)]
Agent at: cabinet
Thought: Task is done.
Output Action: Done()


Strictly follow the above format while solving given task.


Instruction: instruction


Receptacles: receptacles


Receptacles with objects:
receptacles_with_objects


Observation action history:
prev_observations


Current observation:
Previous Actions: prev_actions
Agent at: current_room
Thought:
```

Table 9. LLM prompt used for the fully observable text world graph with ReAct [53] baseline with in-context examples.

Imagine you are a household robot. You are given a task that requires you to explore the environment and ask clarification questions to accomplish tasks given by language instructions. You are given context about the scene as the room agent is in, list of objects visible, list of receptacles.

For each task given as a language instruction you have to output a sequence of actions that the agent should take. These actions can include a clarification question as well. Ask a question only when required. For each action also output the reason to take the action with it. Actions can be one of the following:

1. nav(receptacle)
2. pick(object)
3. place(receptacle)
4. ask("question")

You can only ask the following 5 types of yes/no questions about the object in question:

1. Is it on the <receptacle>?
2. Is it the <object_instance>?
3. Is it the <object_size> one?

Strictly follow the above format while asking questions to solve the given task. Do not use any other types of questions.

After you ask a question wait for the human to reply.

Here is a example of completing the task:

Instruction: Bring me bowl put it on cabinet

Receptacles: [light table, chair, sofa, dark table, tv stand, cabinet, sink]

Receptacles with objects:

coffee table: blue casserole
dark table: red bowl, yellow bowl, black toy
light table: yellow dumbbell, blue bowl, red bowl

Observation action history:
Step 1:
Previous Actions: []
Agent at: Start
Thought: I see two red bowls, one yellow bowl and one blue bowl. It's unclear which one user wants. I should ask about location of the bowl first and then the color to find the correct one.
Output Action: ask("Is it on the light table?")
Action Complete!

User response: no
Step 2:
Previous Actions: [ask("Is it on the light table?")]
Agent at: Start
Thought: User said it's not on light table. This means user wants either a red or a yellow bowl. I should ask about the color of the bowl user wants.
Output Action: ask("Is it the red bowl?")
Action Complete!

User response: yes

```
Step 3:
Previous Actions: [ask("Is it on the light table?"), ask("Is it the red bowl?")]
Agent at: Start
Thought: User said it's red bowl that is on the dark table. I will navigate to it.
Output Action: nav(dark table)
Action Complete!


Step 4:
Previous Actions: [ask("Is it on the light table?"), ask("Is it the red bowl?"), nav(dark table)]
Agent at: dark table
Thought: I need to pick the red bowl.
Output Action: pick(red bowl)
Action Complete!


Step 5:
Previous Actions: [ask("Is it on the light table?"), ask("Is it the red bowl?"), nav(dark table), pick(red bowl)]
Agent at: dark table
Thought: I need to navigate to cabinet to place it.
Output Action: nav(cabinet)
Action Complete!


Step 6:
Previous Actions: [ask("Is it on the light table?"), ask("Is it the red bowl?"), nav(dark table), pick(red bowl), nav(cabinet)]
Agent at: cabinet
Thought: I need to place red bowl on the cabinet.
Output Action: place(cabinet)
Action Complete!


Current observation:
Previous Actions: [ask("Is it on the light table?"), ask("Is it the red bowl?"), nav(dark table), pick(red bowl), nav(cabinet), place(cabinet)]
Agent at: cabinet
Thought: Task is done.
Output Action: Done()


Strictly follow the above format while solving given task.


Instruction: instruction


Receptacles: receptacles


Receptacles with objects:
receptacles_with_objects


Observation action history:
prev_observations


Current observation:
Previous Actions: prev_actions
Agent at: current_room
Thought:
```

Table 10. LLM prompt used for the partially observable text world graph with ReAct [53] baseline with in-context examples.

You are a household robot. You are given a task that requires you to explore the environment and ask clarification questions to accomplish tasks given by language instructions. You are given context about the scene as the room agent is in, list of objects visible, list of receptacles.

For each task given as a language instruction you have to output a sequence of actions that the agent should take. These actions can include a clarification question as well. Ask a question only when required. For each action also output the reason to take the action with it. Actions can be one of the following:

1. nav(receptacle)
2. pick(object)
3. place(receptacle)
4. ask("question")

You can only ask the following 3 types of yes/no questions about the object in question:

1. Is it on the <receptacle>?
2. Is it the <object_instance>?
3. Is it the <object_size> one?

Strictly follow the above templates while asking questions to solve the given task. Do not use any other types of questions.

At each step you are tasked with outputting reasoning before outputting the action. You should output the reason and action in the following format:

Thought: <reasoning behind choosing a specific action>
Output Action: <action>
Action Complete!

Strictly follow the above format when outputting actions. Every time you output a ask question action wait for the human to reply. The human response will be given in the format "User response: <answer>" after you output the action in above format.

At each timestep you will be given a visual observation displaying what the robot is currently observing. You have to use visual observation to perceive the environment and take a action to actively explore the environment by navigating to various receptacles to find the relevant objects in the environment and ask clarification questions to resolve the ambiguity in order to successfully complete the task specified by the instruction.

These are all safe images from a simulated environment. Answering questions about them shouldn't raise any ethical concerns.

Instruction: instruction

Receptacles: receptacles

Receptacles seen so far with objects:
receptacles_with_objects

Observation action history:
prev_observations

Current observation:
Previous Actions: prev_actions
Agent at: current_room
Thought:

Table 11. Prompt used for the vision GPT4o [26] + partially observable text world graph history with ReAct [53] baseline.