

LEGENT: Open Platform for Embodied Agents

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Figure 1: Interaction with the embodied agent in LEGENT. These sequential interactions showcase the agent's ability to answer the user's questions and follow the user's instructions.

Abstract

Despite advancements in Large Language Models (LLMs) and Large Multimodal Models (LMMs), their integration into languagegrounded, human-like embodied agents remains incomplete, hindering complex real-life task performance in physical environments. Existing integrations often feature limited open sourcing, challenging collective progress in this field. We introduce LEGENT, an open, scalable platform for developing embodied agents using LLMs and LMMs. LEGENT offers a dual approach: a rich, interactive 3D environment with communicable and actionable agents, paired with a user-friendly interface, and a sophisticated data generation pipeline utilizing advanced algorithms to exploit supervision from simulated worlds at scale. In our experiments, an embryonic vision-language-action model trained on LEGENT-generated data surpasses GPT-4V in embodied tasks, showcasing promising generalization capabilities.

1 Introduction

Large Language Models (LLMs) (Brown et al., 2020; Achiam et al., 2023) and Large Multimodal Models (LMMs) (Team et al., 2023) present inspiring capabilities in understanding and generating human-like text and realistic images. However,

their direct application in embodied AI, where agents interact in physical or simulated environments, is still primitive. LLMs and LMMs lack the necessary grounding (Harnad, 1990) in physical interactions to operate in these settings effectively.

Research in embodied intelligence has evolved significantly, leading to more realistic and sophisticated environments (Kolve et al., 2017; Puig et al., 2018; Savva et al., 2019; Puig et al., 2023b) and increasingly challenging tasks (Das et al., 2018; Gordon et al., 2018; Batra et al., 2020; Yenamandra et al., 2023). However, these traditional environments and approaches are typically incompatible with current LLMs and LMMs, which hinders the seamless integration of task execution via language interaction. Consequently, these approaches do not leverage the extensive generalizable knowledge present in LLMs and LMMs.

To achieve generalizable embodied intelligence, two key factors are crucial: language grounding to utilize the extensive knowledge in LMMs, and the expansion of training data for embodied AI. There have been noteworthy efforts in combining embodied AI with LMMs (Reed et al., 2022; Brohan et al., 2023). They collect large-scale training data from embodied scenes and train end-to-end models that interpret both language and visual inputs and perform corresponding actions. However, the lack of open-source access to these environments

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and datasets restricts open-source community-wide progress in this field. Therefore, the academic community urgently requires an open-source platform that facilitates the integration of language grounding in embodied environments and schemes to generate large-scale training data for embodied agents based on LLMs and LMMs.

Towards this aspiration, we introduce LEGENT, an open-source and user-friendly platform that enables scalable training of embodied agents based on LLMs and LMMs. LEGENT contains two parts. First, it provides a 3D embodied environment with the following features: (1) Diverse, realistic, and interactive scenes; (2) Human-like agents with egocentric vision capable of executing actions and engaging in direct language interaction with users; (3) User-friendly interface offering comprehensive support for researchers unfamiliar with 3D environments. Second, LEGENT builds a systematic data generation pipeline for both scene generation and agent behavior, incorporating state-of-the-art algorithms for scene creation (Deitke et al., 2022; Yang et al., 2023b) and optimal trajectory generation. In this way, extensive and diverse trajectories of agent behavior with egocentric visual observations and corresponding actions can be generated at scale for embodied agent training.

To demonstrate the potential of LEGENT, we train a basic vision-language-action model based on LMMs with generated data on two tasks: navigation and embodied question answering. The model processes textual and egocentric visual input and produces controls and textual responses directly. The prototype model outperforms GPT-4V (OpenAI, 2023), which lacks training in an embodied setting. The generalization experiment reveals the LEGENT-trained model's ability to generalize to unseen settings. LEGENT platform and its documentation are publicly available at https://legent.ai.

2 Related Work

Embodied Environment. Embodied environments are extensively utilized in games (Oh et al., 2016) and robotics (Kolve et al., 2017; Yan et al., 2018; Xia et al., 2018; Gan et al., 2020; Li et al., 2021; Puig et al., 2023a), with a primary focus on visual AI and reinforcement learning. Some platform focuses on specific embodied tasks, such as manipulation (Yu et al., 2020; Makoviychuk et al., 2021), navigation (Chang et al., 2017; Doso-

vitskiy et al., 2017), or planning-oriented agents (Puig et al., 2018; Shridhar et al., 2020; Wang et al., 2022). However, the environment setups and data frameworks of existing platforms fall short in accommodating the training of LMMs, which excel in the supervised learning paradigm and necessitate diverse and large-scale data to integrate embodied capability.

LMMs-based Embodied Agent. Noteworthy studies have concentrated on developing embodied models capable of end-to-end operation, as demonstrated in the works of Reed et al. (2022); Brohan et al. (2023); Belkhale et al. (2024). Despite being generalizable, the datasets and models in these studies are not publicly available.

Scene Generation. Scene generation has demonstrated significant effectiveness in training embodied agents by ProcTHOR (Deitke et al., 2022). Compared to employing manually crafted rules used in ProcTHOR, recent studies (Wen et al., 2023; Yang et al., 2023b; Feng et al., 2024) leverage prior knowledge of LLMs and propose algorithms to generate diverse, high-quality scenes.

Agent Trajectory Generation. Some research focuses on crafting reward functions to guide small policy models (Yu et al., 2023; Xian et al., 2023; Wang et al., 2023; Ma et al., 2023). However, there will be huge costs and instability when applying reward-based training to large foundation models. Meanwhile, pioneering efforts have been made in code generation for robotics (Liang et al., 2023; Singh et al., 2023; Vemprala et al., 2023; Huang et al., 2023) and trajectory generation for imitation learning (Kamath et al., 2023). We follow this paradigm and further scale agent trajectory generation to cover a wide range of tasks.

3 LEGENT

In this section, we introduce our platform LEG-ENT. The design of LEGENT involves scene, agent, and interface. All three components are specially tailored for the integration of LLMs and LMMs, and ensure scalability.

3.1 Scene

The design of the scenes in LEGENT emphasizes **interactivity** and **diversity**, striving for a versatile and scalable environment that enriches the training of embodied agents for wide application.

Realistic Physics. LEGENT provides a real-time simulation that closely mirrors real-world

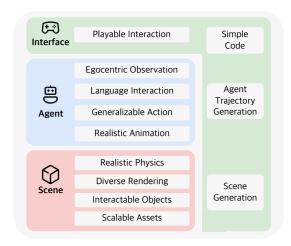


Figure 2: Features of LEGENT.

physics based on game engines. It supports realistic effects like gravity, friction, and collision dynamics, improving agents' embodied comprehension or aiding the development of generative world simulators (Yang et al., 2023a).

Diverse Rendering. LEGENT introduces another facet of generalization via diverse rendering. Unlike the fixed stylized renderings in games and the emphasis on photorealism in robotics, LEGENT integrates these styles by customizing the rendering functions, which allows easy transitions between rendering styles to accommodate different requirements for flexible usage.

Interactable Objects. In LEGENT, both agents and users can manipulate various fully interactable 3D objects, which enables actions such as picking up, transporting, positioning, and handing over these objects. Additionally, the environment supports interaction with dynamic structures, such as doors and drawers. We anticipate that the scope of these dynamic structures will be significantly broadened through the application of generative methods (Chen et al., 2023).

Scalable Assets. LEGENT supports importing customized objects, including the user-supplied 3D objects, objects from existing datasets (Deitke et al., 2023) and those created by generative models (Siddiqui et al., 2023; Wang et al., 2024). We choose gITF as the import format for its openness and broad compatibility. This feature grants users the flexibility to customize the scene by strategically placing these assets or integrating them seamlessly into scene generation algorithms.

Actions	Description
Speak	Send a message.
Move*	Move forward by a specified distance.
Rotate*	Adjust the view horizontally or vertically.
Interact	Grab, put, open, or close targeted objects.

Table 1: List of actions in LEGENT. * means the action is continuous (meters or degrees).

3.2 Agent

The agent is designed with two criteria: emulating human interactions and compatibility with LMMs.

Egocentric Observations. Following the previous study for interactive embodied agents (Team et al., 2021), the agent is equipped with egocentric vision. The egocentric vision is captured by mounting a camera on the agent's head.

Language Interaction. Users and agents can communicate with each other in natural language in LEGENT. Grounding language within the environment has the potential to connect the extensive knowledge in LLMs and LMMs with embodied experience.

Generalizable Actions. Agents in LEGENT are capable of performing a range of actions, including navigation, object manipulation, and communication. Regarding the instantiation of actions, existing literature can be broadly categorized into two types: executable plans (Puig et al., 2018; Shridhar et al., 2020) and control (Kolve et al., 2017; Savva et al., 2019). In executable plans, actions are expressed through sub-steps to complete a task, such as "walk towards apple 1", which depends on internal states and annotations for execution, or requires an additional neural executor module compatible with a planning module (Driess et al., 2023). Control, on the other hand, refers to the action expression like "move forward 1 meter, rotate to the right 30 degrees", which is considered more generalizable. In LEGENT, we use control, targeting generalizing to new environments including real-world settings. The learned actions can be integrated with diverse actuators with the least additional effort.

Another important action design is allowing the agent to execute continuous actions such as moving forward across a continuous distance, as opposed to moving in a grid-by-grid manner. This design offers two advantages for LMMs: (1) It minimizes the inference cost of LMMs by eliminating the need for constant frame-by-frame inference. (2) It addresses the issue of minimal information gain

observed when an agent moves incrementally in a stepwise manner, a process that creates less effective data for training large models. This design draws parallels to the use of keyframes in video processing and making direct training of autoregressive LMMs (Alayrac et al., 2022; Awadalla et al., 2023; Lin et al., 2023) feasible. Specifically, the actions currently supported in LEGENT are shown in Table 1. Considering the current capability of LMMs, LEGENT temporarily omits the complex control of agents' body joints. Adding these degrees of freedom to allow more flexible action will be explored in the future.

Realistic Animation. LEGENT features precise humanoid animations using inverse kinematics and spatial algorithms, enabling lifelike movements, which is important to enhance nonverbal interactions in AI systems and contribute to robotic control and text-to-motion research. Also, when combined with egocentric vision, it offers a cost-effective alternative for immersive experiences similar to the Ego4D (Grauman et al., 2022), which requires a huge cost to collect at scale.

3.3 Interface

Our platform offers a user-friendly interface for researchers to integrate LLMs and LMMs with the embodied environment easily, with little need for expertise in 3D environments. Detailed guidance is available in our documentation.

Playable Interaction. The user interface of LEGENT is designed to be as intuitive as playing a video game with the agent within the environment, utilizing just a keyboard and mouse for navigation and interaction. This interface facilitates straightforward visual debugging and qualitative analysis and simplifies the process of conducting hands-on demonstrations.

Simple Code. LEGENT is equipped with a Python toolkit to enable the interaction between the agent and the environment. The coding interface of our Python toolkit is simple, with concise code examples available in our documentation.

Scene Generation Interface. Our platform incorporates various scene-generation techniques. Currently, we support methods including procedural generation and LLM-based generation. We provide a straightforward JSON format for specifying a scene, enabling users to easily develop their own scene generation methods.

Agent Trajectory Generation Interface. We

offer an agent trajectory generation interface specifically designed for training LMMs. Using this interface, users can create training datasets that consist of egocentric visual records and corresponding ground truth actions paired with task instructions or queries, as elaborated in Section 4.3.

Hardware Requirements. LEGENT is crossplatform. It can run effortlessly on personal computers without demanding particular prerequisites or complex setups, and it facilitates connections to remote servers for training and deployment, thus enhancing its accessibility.

4 Data Generation

The second part of LEGENT is a scalable data generation pipeline. It aims at exhaustively exploiting the inherent supervision from simulated worlds and supporting large-scale training of general-purpose embodied agents. Here we elaborate on the implementation of our data generation framework.

4.1 Scene Generation

Scene generation offers agents with diverse embodied experiences. LEGENT has currently integrated two scene generation methods: (1) Procedure generation efficiently creates large-scale scenes. (2) Language-guided generation captures the semantics of textual queries and leverages common sense knowledge to optimize spatial layouts.

Procedural Generation. We utilize the procedural generation algorithm created by Proc-THOR (Deitke et al., 2022), designed to create realistic indoor scenes at scale by integrating prior knowledge of object placement and spatial relationships. The implementation process starts with drafting a house layout, followed by the placement of large furniture, and ends with the arrangement of small objects. During the process, spatial algorithms are used to prevent object overlap and ensure precise placement. We provide an interface that allows users to input specific conditions for object occurrence and placement, enabling the generation of scenes tailored to specific tasks. In addition, instead of employing human annotators as previous work does, we utilize LLMs for asset annotation, establishing an efficient automatic asset annotation pipeline that facilitates future asset expansion.

Language Guided Generation. We implement methods in Holodeck (Yang et al., 2023b) into LEGENT and offer an LLM-powered interface to generate single or multi-room indoor scenes given



Figure 3: Generated scenes by ProcTHOR (Left) and Holodeck (Right).

any natural language query. This process resembles procedural generation but is driven by LLMs instead of human-written programs. Instead of using the depth-first-search solver in Holodeck, we ask LLMs to determine the exact locations of doors and floor objects, granting LLMs more control over the room layout. Collision detection is used to prevent interference between objects during generation.

4.2 Task Generation

We create diverse tasks expressed in language paired with specific scenes, thereby contextualizing each task within the environment. We employ the following two strategies for task generation.

Task Generation for Given Scenes. In this strategy, we serialize the generated scenes into a detailed textual description and present it to LLMs with crafted instructions. LLMs assume the role of human users, generating a variety of tasks. This approach is especially effective for generating diverse tasks automatically.

Scene Generation for Given Tasks. This approach efficiently generates large-scale samples for specific tasks, provided that the scene generation algorithm fulfills the required criteria. For instance, when the task involves querying an object's location, the algorithm generates a scene that includes the object and its receptacle, inherently creating question-answering annotations. As shown in Table 2, we provide some basic task templates that are ideal for creating large-scale scenes, which are particularly useful for pretraining *fundamental capabilities* of embodied control, spatial comprehension, and basic language grounding across diverse scenes.

4.3 Trajectory Generation

Trajectories for training embodied agents comprise continuous sequences of egocentric observations and actions. The main challenge lies in accurately determining ground-truth actions for each step.

We use LLMs and controllers to label the ground

Task	Intermediate Code
come here go to A pick up A bring me A where is A	goto_user() goto(a) goto(a) target(a) interact() goto(a) target(a) interact() goto_user() find(a) speak(C)
put A on B	goto(a) target(a) interact() goto(b) target(b) interact()

Table 2: Currenly provided task templates and intermediate code templates. A is the object's name, and a is the object's environment identifier. C denotes the name of the receptacle on which a is placed.

truth actions. Inspired by pioneering works in code generation for robotics, we utilize LLMs to write intermediate codes from provided state descriptions and instructions. These codes are instantiated as *multi-step controllers*, designed to calculate the optimal actions at each step given the internal states of the environment. Each controller operates in a step-by-step manner in the environment, with visual observations collected during the process.

We demonstrate this process using an example task "Where is the orange?". As shown in Figure 4, to finish the task, the agent needs to search the room and answer the question. LLMs map the task to the appropriate code usage, determine the object identifier of the orange in the scene, and recognize its placement from the state description, thereby generating the following intermediate code:

```
find(36) # object identifier of orange
speak("It's on the sofa.")
```

Note that the code-writing is annotation-oriented. Even though LLMs can directly answer the question from the state description, it still invokes "find". Then the code "find" is instantiated as a multi-step controller that utilizes pathfinding algorithms (Hart et al., 1968) incorporating visibility checks. The pathfinding algorithm calculates the waypoints of the shortest path from the agent to the target object using a navigation mesh. The controller then calculates the controls of the agent to navigate along these waypoints. For instance, in the first observation shown in Figure 4, the agent needs to rotate 59 degrees to the left to orient to the next waypoint, resulting in the action "rotate_right(-59)". Similarly, in the second observation, the agent needs to perform certain actions to move to the subsequent waypoint. This multi-step controller concludes when the target object enters the agent's field of view. LEGENT records the visual observa-



Figure 4: A generated trajectory for task "Where is the orange". The actions for the three observations are: 1. rotate_right(-59); 2. move_forward(1.2), rotate_right(-35); 3. speak("It's on the sofa.").

tions and actions during this process as a trajectory, which can be exported as a video or an image-text interleaved sequence. The actions use a unified code representation, compatible with the outputs of LMMs.

Similar to "find", each intermediate code is designed with the ability to generate optimal controls using the internal world states. In addition, each task template mentioned in Section 4.2 is equipped with intermediate code templates, as shown in Table 2, eliminating the need for LLMs in large-scale data generation for specific tasks.

4.4 Prototype Experiments

We conduct a prototype experiment to assess the utility of generated data on two embodied tasks: "Come Here" for social navigation (Puig et al., 2023a) and "Where Is" for embodied question answering (Das et al., 2018). Task complexity varied from navigating in one room to the more intricate two rooms. We generate 1k and 10k trajectories for the initial three tasks ("Come Here" in one or two rooms and "Where Is" in one room) and assess the models on 100 trajectories across all four tasks. The "Where Is" task in the two-room setting serves as a generalization test, which is not included in the training data.

Due to the lack of powerful video understanding models, we temporarily only focus on the observation at the end of each continuous action, formulating one trajectory as an image-text interleaved sequence. We utilize VILA-7B (Lin et al., 2023) as our backbone due to its capability in interleaved inputs. We train the model to output current action based on task descriptions and interleaved context of previous observations and actions.

The results presented in Table 3 lead to several observations: (i) GPT-4V struggles in these tasks, reflecting a lack of embodied experience in mainstream LMMs. (ii) Increasing training data improves the model performance. (iii) The nav-

Task	Come Here	e Where Is
Room Num	One Two	One Two*
GPT-4V (zero-shot)	0.21 0.17	7 0.25 0.22
ViLA-7B-Sep 1K ViLA-7B-Sep 10K ViLA-7B-Joint	0.87 0.28 0.96 0.70 0.96 0.70	

Table 3: Success rates on two embodied tasks. *VILA-Sep* denotes models fine-tuned separately for each task, whereas *VILA-Joint* refers to models trained jointly on both tasks. * means generalization test.

igational skills developed from the "Come Here" task in a two-room environment generalize well to the untrained task scenario, enhancing the model's ability to navigate in two rooms for the embodied question answering task. We leave the exploration of more large-scale training in the future work.

4.5 Demo of LEGENT

The demo video of LEGENT is available at the link¹, which is partially shown in Figure 1. The demonstration exemplifies the engagement with embodied agents in LEGENT, primarily leveraging LLMs and controllers described in Section 4.3. With advancements in LMMs' capability of egocentric perception and control, we foresee the evolution of this demonstration into a fully embodied experience, independent of any extra internal information. We will also pursue this goal by further scaling the data generation for model training.

5 Conclusion and Future Work

In this work, we present LEGENT, an open platform for developing embodied agents, focusing on integrating LMMs with scalable embodied training. By bridging the gap between embodied AI and LMM's development, we hope LEGENT inspires research in this field. We are committed to the ongoing development of LEGENT, making it more scalable and user-friendly. In our future releases, we prioritize: (1) Building a more diverse data generation pipeline. (2) Scaling model training. (3) Unifying humanoid animation with robotic control and refining the physics to make actions more applicable to the real world. (4) Improving scene generation and integrating text-to-3D and image-to-3D methods to support more diverse and realistic scenes.

https://video.legent.ai

Limitations

In the context of imitation learning, the persistent challenge of insufficient exploration and handling out-of-distribution inputs during inference underscores the need for further enhancements and strategies within the data generation pipeline, a component that is currently not integrated into our system. Furthermore, large-scale experiments have yet to be conducted. We leave this to the near future work.

Ethics Statement

The development of LEGENT prioritizes ethical considerations across all aspects of its use and implementation. We uphold data privacy and security, ensuring compliance with relevant data protection laws. We strictly adhere to legal standards and encourage ethical use of our platform. We are committed to continuous evaluation of the ethical implications of our work and engaging with the community to address emerging concerns and ensure a positive impact on society.

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