
ADAPTING LLM AGENTS THROUGH COMMUNICATION

Kuan Wang^{1*}, Yadong Lu², Michael Santacroce², Yeyun Gong³,
Chao Zhang¹, Yelong Shen²

¹Georgia Institute of Technology ²Microsoft Azure AI ³Microsoft Research

{kuanwang, chaozhang}@gatech.edu

{yadonglu, misantac, yegong, yeshe}@microsoft.com

ABSTRACT

Recent advancements in large language models (LLMs) have shown potential for human-like agents. To help these agents adapt to new tasks without extensive human supervision, we propose the Learning through Communication (LTC) paradigm, a novel training approach enabling LLM agents to improve continuously through interactions with their environments and other agents. Through iterative exploration and PPO training, LTC empowers the agent to assimilate short-term experiences into long-term memory. To optimize agent interactions for task-specific learning, we introduce three structured communication patterns: **Monologue**, **Dialogue**, and **Analogue**—tailored for common tasks such as decision-making, knowledge-intensive reasoning, and numerical reasoning. We evaluated LTC on three datasets: ALFWorld (decision-making), HotpotQA (knowledge-intensive reasoning), and GSM8k (numerical reasoning). On *ALFWorld*, it exceeds the instruction tuning baseline by 12% in success rate. On *HotpotQA*, LTC surpasses the instruction tuned LLaMA-7B agent by 5.1% in EM score, and it outperforms the instruction tuned 9x larger PaLM-62B agent by 0.6%. On *GSM8k*, LTC outperforms the CoT-Tuning baseline by 3.6% in accuracy. The results showcase the versatility and efficiency of the LTC approach across diverse domains. We will open-source our code to promote further development of the community.

1 INTRODUCTION

Recent advances in large language models (LLMs) have shed light on human-like LLM agents [29, 6, 60]. Previous works have explored how to employ the LLM as the agent’s brain, which is complemented by several key components such as planning, tool use, and memory. For planning, Chain of Thought (CoT[61]) prompts the model to think step by step, decomposing complex tasks into smaller and simpler steps. ReAct [65] integrates reasoning and action within LLM, extending the action space to include both task-specific discrete actions (i.e., retrieval) and language generation. In addition, recent research has shown that LLM agents can be further augmented by using *external tools* to solve problems in interactive environments, which involve using retrieved knowledge [43, 65, 53, 17], math tools [41, 65, 23], and code interpreters [11, 54].

However, adapting LLM agents to specific tasks remains challenging. In order to adapt the generally pre-trained LLMs to task-specific environments, existing methods focus on In-context learning (ICL [5, 65, 44]) and supervised fine-tuning (SFT [29]). For example, ICL utilizes few-shot prompts as a form of short-term memory [31, 44] to adapt agents’ task-specific ability during inference, and SFT typically requires high quality supervised training data for domain adaptation. However, both of these two approaches don’t leverage the rich feedbacks (i.e., positive/negative rewards, error message, hint etc) during the interaction with environment and external tools for continuously training.

In this paper, we introduce a new training paradigm Learning through Communication (LTC), allowing the LLM agent to continuously adapt to new environments and tasks with an iterative pipeline. Each iteration of LTC consists of two distinct phases: (1) the exploration phase where the agent interact with the environments and other agents to collect diverse trajectories and feedbacks, and (2) the training phase that updates the agent model based on these trajectories.

*Work done during an internship at Microsoft

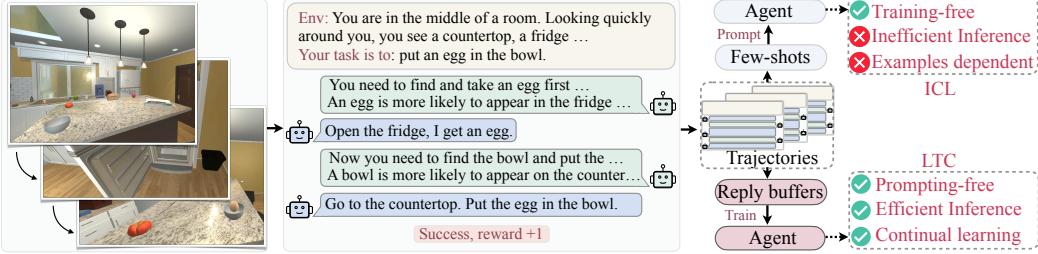


Figure 1: LTC continually adapts agents to new tasks by doing task-specific fine-tuning on the collected iterative interaction trajectories, removing the need for long and handcrafted few-shot examples as the prefix of the prompts in the inference time.

LTC method is a general learning paradigm that can be applied to diverse tasks, such as decision-making, knowledge-intensive reasoning, and numerical reasoning. To collect communication trajectories and reward signals, we designed three structured communication patterns: (1) **Monologue** allows a single agent to generate trajectories in a self-talk style and get interactive feedback from environments; (2) **Dialogue** enables the agent interacts with other agents and external tools, and utilizes feedback provided by the environments; (3) **Analogue** facilitates the agent to learn through new examples generated by the teacher agent, and also leverages feedback provided by the teacher agent instead of the environments.

In addition, the training phase is based on reinforcement learning (RL), and our training loss combines the language modeling loss and the PPO loss [29] to balance the language consistency and reward signals. We also designed a unified replay buffer to store trajectories from diverse environments, where each generated token is treated as an action in the RL formulation. We apply distinct masks to tokens generated by the system, LTC agents, and other agents, respectively. These masks are utilized to apply distinct loss functions to various token types. The replay buffer is updated after each exploration phase and a subset of the buffer is sampled for the training phase. Through this iterative process, the agent continuously adapts to new environments.

We evaluate LTC method on three representative datasets: *ALFWorld* for decision-making, *HotpotQA* for knowledge-intensive reasoning, and *GSM8k* for numerical reasoning. Throughout these experiments, LTC consistently outperforms the baselines. In *ALFWorld*, LTC outperforms the strong instruction tuning baseline by 12% on success rate, even in the challenging Pick 2 task. This shows that our communication mechanism enables the agent to learn from its experiences for task solving. On *HotpotQA*, LTC outperforms the instruction tuning baseline by 5.1% on EM score, and our LLaMA-7B based agent even obtains slightly better (0.6%) performance than the ReAct-Tuning baseline which uses 9 \times larger PaLM-62B model. On *GSM8k*, LTC also beats the CoT-Tuning baseline by 3.6% on accuracy. These results highlight the adaptability and effectiveness of LTC approach across varied domains.

Our key contributions are summarized as follows:

- 1. Learning through Communication (LTC):** We propose a new training paradigm named Learning through Communication (LTC), allowing the LLM agent to automatically adapt to new environments and tasks with an iterative pipeline.
- 2. Task-specific Communication Patterns:** The LTC paradigm allows flexible design of communication patterns for different tasks. Three specific patterns are introduced: Monologue, Dialogue, and Analogue. These patterns are composable to help generate diverse structured interaction and feedback signals for agent training for different types of tasks.
- 3. Empirical Study and Findings:** Through rigorous studies on public benchmark tasks, we demonstrate the effectiveness of LTC, and it could be a superior approach compared with instruction-tuning or prompting baselines.

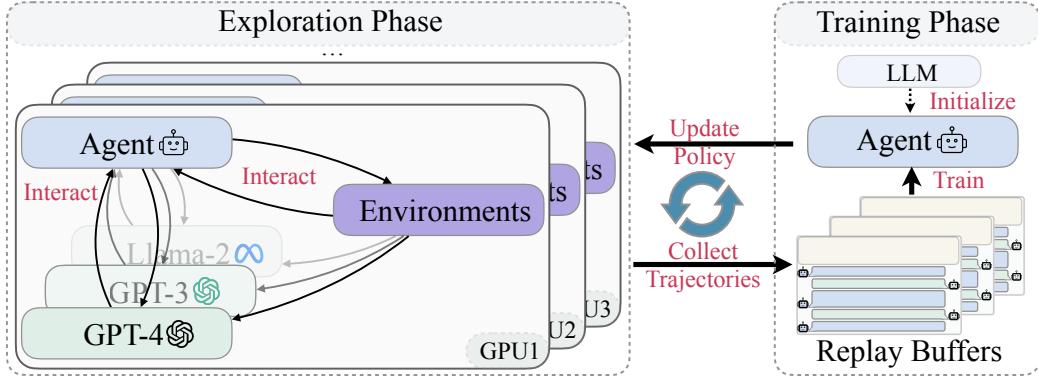


Figure 2: LTC has an iterative two-phase framework. During the exploration phase, the agent proactively explores new environments and communicates with other agents, gathering the trails to update the replay buffer. Then the agent is trained for updating the policy in the training phase.

2 RELATED WORK

2.1 INSTRUCTION TUNING

Instruction tuning (IT) is an important technique for improving the capabilities and controllability of LLMs [35, 5, 60, 34, 28, 8, 52]. Many studies have been dedicated to instruction data generation and selection [9, 57]. For instance, Unnatural Instructions [13] is created by using the Super-Natural Instructions dataset [58] as a seed to prompt InstructGPT [29]. Self-Instruct [57] employs a recursive pipeline that generates instruction data from hand-crafted seed tasks using ChatGPT [27]. Other studies focus on fine-tuning pre-trained LLMs with instruction data. BLOOMZ [26] is initialized with BLOOM [40] and then fine-tuned using the xP3 instruction dataset [26]. Flan-T5 is initialized with T5 [37] and fine-tuned with the FLAN dataset [21]. Additionally, after the release of LLaMA [52], many works have utilized it as the base model for instruction tuning, such as Alpaca [51], Vicuna [7], and GPT-4-LLM [32]. Some papers explore alignment fine-tuning using RLHF [29, 3, 48, 18]. InstructGPT [29] employs GPT-3 for supervised fine-tuning on a human-filtered instruction dataset, followed by training a reward model and using PPO [42] for RLHF. Claude investigates RLHF [3] and constitutional approaches [4] for making LLMs both harmless and helpful. DPO [36] fine-tunes the LLMs to align with human preferences by directly optimizing a classification problem on preference data instead of RLHF. While these prominent research works focus on aligning LLMs for general instruction-following, our objective is to adapt LLM agents for specific tasks or environments.

2.2 LLM AGENTS

LLMs have demonstrated the potential to act as human-like agents [29, 6, 60], and significant progress has been made in developing versatile LLM agents [62, 49, 30, 20]. For planning, Chain-of-Thought (CoT[61]) prompts the model to think step by step, by decomposing complex tasks into smaller and simpler steps. Self Consistency [55, 56] extends CoT by using ensembles of predictions to improve consistency of the LLM. Inner Monologue [16] leverages environment feedback to enhance LLMs' planning and processing capabilities in embodied robotics tasks without extra training. ReAct [65] integrates reasoning and action taking, expanding the action space to include both task-specific discrete actions and language. Reflexion [44] equips agents with dynamic memory and self-reflection capabilities to improve reasoning by using continuous trials in the same environment as feedback. Recent research has also shown that LLMs can be augmented as an autonomous agent to use *external tools* to solve problems in interactive environments. These techniques include retrieval augmentation [43, 65, 17], math tools [41, 65, 23], and code interpreters [11, 54]. Prior works also have explored using multiple LLMs in a collaborative setting to solve complex tasks [12, 33, 19, 59, 50, 1]. Open-source projects like AutoGPT [47], GPT-Engineer [2], and BabyAGI [66] also showcase the potential of LLM not just in generating content but also as a general problem solver. Most of the above methods are based on either human-designed few-shot prompting examples, or finetuning with pre-collected instruction datasets. Our LTC is not a few-shot prompting method and we focus on adapting the agent by collecting training data automatically by exploration.

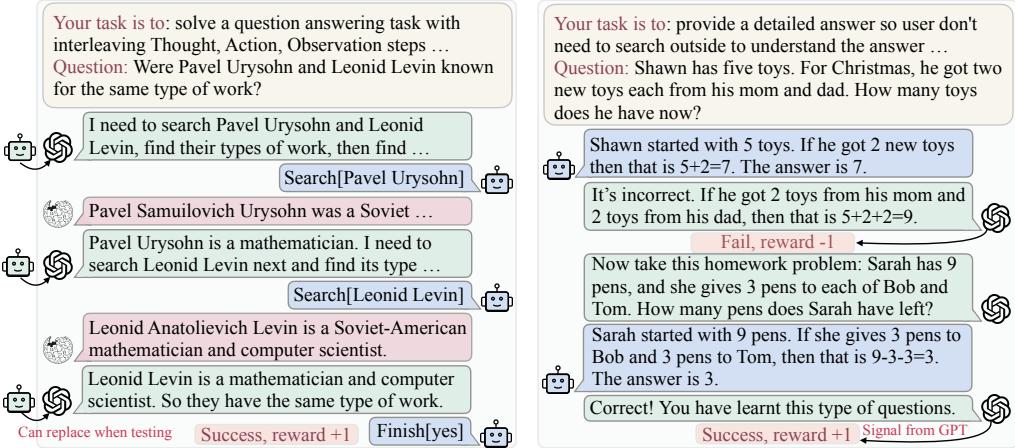


Figure 3: The toy examples to demonstrate communication patterns: 1) the left figure is the Dialogue pattern, where the GPT-4 agent play as a teacher to analyze the situation and give suggestion to the student agent who is responsible for making decisions. We can just assign the student agent to play the teacher agent when testing without GPT-4 agent. 2) the right figure is the Analogue pattern, where the student agent starts with an initial answer to the current question, and then the teacher directly corrects the answer with a reward. To help the student improve ability instead of just memorizing the solution, the teacher will generate another analogous question to ask the student. Eventually, the student gives a new answer for this analogous question and gets a new reward signal from the teacher.

3 LEARNING THROUGH COMMUNICATION

We design Learning Through Communication (LTC), an iterative training method for LLM agents to continuously adapt to new environments. As shown in Figure 2, LTC iterates between two phases: (1) An exploration phase where agents can interact with new environments and other agents to collect trial data with feedback, and (2) a training phase to fine-tune the agent to update the policy.

3.1 EXPLORATION PHASE

At the start of each iteration, the agent explores the environments to get the trajectories and the reward signal data. We denote these data as a tuple: $\mathcal{S} = (\mathcal{T}, \mathcal{M}, \mathcal{R})$, where $\mathcal{T} = \{t_1, t_2, \dots, t_n\}$ represents the text data generated by the communication process during agent exploration, $\mathcal{M} = \{m_1, m_2, \dots, m_n\}$ with $m_i \in \{0, 1, 2\}$ indicates the source of the text data (system or agents), $\mathcal{R} = \{r_1, r_2, \dots, r_n\}$ with $r_i \in \{-1, 0, 1\}$ represents the reward signals provided by either the system or the agents. We demonstrate the the details of this data structure in Figure 4, \mathcal{M} is the mask list, and \mathcal{R} is the reward list. In PPO training, both the value list and the log-prob list correspond directly to the action list. For brevity, we denote these three lists together as \mathcal{T} here. Please see Appendix A.2 for more details.

To collect the trajectories data $\mathcal{S} = (\mathcal{T}, \mathcal{M}, \mathcal{R})$ from different types of tasks, we design the communication patterns for these tasks. Here we provide three communication patterns:

- **Monologue:** Monologue is a single agent self-talk style communication pattern, designed for decision-making tasks (Algorithm 1). Figure 1 is a toy example of *ALFWorld* to demonstrate the Monologue pattern between two roles, an actor to take actions and an instructor to give suggestions. In this pattern, two roles are played by the same agent, we can view them as the different types of steps such as think and act in the ReAct formulation [65]. When the actor completes the task or achieves a maximum number of interactions, the reward will be returned from the environment and we obtain a new buffer from this pattern.
- **Dialogue:** Dialogue is a multi-agent collaborating style pattern (Algorithm 2). It is designed for knowledge-intensive tasks, where multiple knowledge sources are needed for a comprehensive answer. Similar to the Monologue, the Dialogue pattern also has multiple roles,

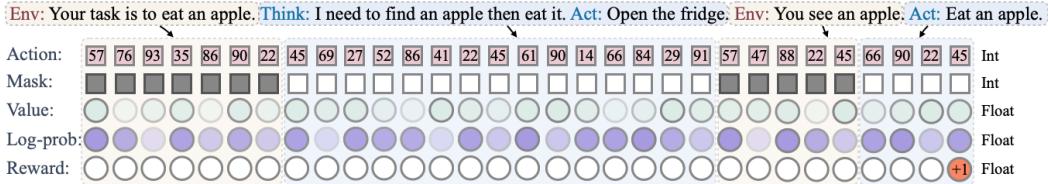


Figure 4: The buffer data is a serial of integer/float sequences. They are collected by the agent’s exploration and used for the reinforcement learning phase.

but **the roles are played by different agents**. This pattern also supports communicating with external tools and other agents, which can be easily achieved by changing the roles’ prompts or replacing the agents behind the roles. The left figure of Figure 3 is a toy example of *HotpotQA* to illustrate this pattern, where the GPT-4 agent play as a teacher to analyze the situation and give suggestions to the student agent who is responsible for making decisions. We can just assign the student agent to play as the teacher agent when testing for environments without GPT-4. So we can use this pattern to collect the buffer with GPT-4 as teacher agent and train the student to play as a teacher to improve the ability of the student agent to solve problems independently.

- **Analogue:** Dialogue is a teacher-student style pattern for powerful agents to teach the novice agents (Algorithm 3). We design the Analogue pattern for complex analytical tasks such as numerical reasoning, which require extensive analytical examples for agents to improve the specific reasoning ability lacking in the pretrained models. Similar to Dialogue, the Analogue pattern also has multiple roles played by different agents, but the teacher roles can **directly provide the reward signal and new analogous examples**, which are all provided by the system (environments) in the previous pattern. The right figure of Figure 3 is a toy example with GSM8k to demonstrate how the student agent communicates with the teacher agent in a homework-correcting style. In the math question environment, the student agent starts with an initial answer to the current question, then the teacher directly corrects the answer with a reward. To help the student improve ability instead of just memorizing the solution, the teacher will generate another analogous question to ask the student. Eventually, the student gives a new answer for this analogous question and gets a new reward signal from the teacher.

3.2 TRAINING PHASE

In the training phase, the LLM agent model could be optimized through the conversation sessions collected in the exploration stage. Given a example session $\mathcal{S} = (\mathcal{T}, \mathcal{M}, \mathcal{R})$, we mainly utilize two training objects for model training.

- Language model Objective: \mathcal{L}_{LM} encourages the model to learn from the trajectory \mathcal{T} , serving as an unsupervised learning schema to help model for behavior cloning from other agents’ response or predicting system feedbacks.
- Reinforcement Objective: $\mathcal{L}_{\text{reinforce}}$ optimizes the model by maximizing the expectation reward provided by environment or a teacher agent (i.e., GPT-4 [28]). It is an goal-oriented objective, and allows the model to learn through both positive and negative signals in the communication session.

Thus, the overall training objective for LTC combines the above two terms:

$$\mathcal{L}_{\text{LTC}}(\mathcal{S}) = \beta \mathcal{L}_{\text{LM}}(\mathcal{T}) + \mathcal{L}_{\text{reinforce}}(\mathcal{S}), \quad (1)$$

where β is a balancing hyper-parameter. The off-policy PPO algorithm [42] is utilized for optimizing $\mathcal{L}_{\text{reinforce}}(\mathcal{S})$, and it can be further breakdown into policy loss, value loss and policy entropy regularization terms in implementation. The vanilla PPO algorithm takes the triplet (state, action, rewards) for training. In this case, we sample from the trajectories $(\mathcal{T}_{<i}, t_i)$ for simulating the state-action pairs, specifically, we only keep the tokens generated by agent model itself as actions for policy updating.

4 EXPERIMENTS

4.1 DATASETS

We conducted experiments on three datasets: *ALFWorld* [46], *HotpotQA* [64], and *GSM8k* [10]. Each of these datasets represents a different task type, namely decision-making, knowledge-intensive reasoning, and numerical reasoning, respectively. And different communication patterns are used: Monologue for *ALFWorld*, Dialogue for *HotpotQA*, and Analogue for *GSM8k*.

ALFWorld *ALFWorld* (Figure 1) is a text-based game that follows the ALFRED benchmark [45]. In this game, agents are presented with six types of tasks that involve navigating a simulated household environment using textual actions. With over 50 locations to explore, these tasks demand strategic planning and thorough exploration. Following [46], we utilize the train set that consists of 3553 environments for training our model and the baselines; and we use the unseen test set that comprises 134 environments for evaluation.

HotpotQA *HotpotQA* is a question-answering dataset that focuses on multi-hop reasoning based supporting facts, with the goal of improving the explainability of QA systems. In this dataset, agents are required to reason across two or more Wikipedia passages to derive answers. We initialize the environments using only the text of the questions, meaning that agents are provided with the question and task description but do not have access to supporting paragraphs. To support their reasoning, agents must either rely on their internal knowledge or interact with an external Wikipedia tool to retrieve the necessary information. For training, we sample the environments from the training set, which consists of 90,447 QA-pairs. For evaluation, we run 500 random examples from the test set, following [65].

GSM8k The *GSM8k* dataset is a collection of 8.5K math problems for grade school students. These problems have been crafted by human experts to ensure linguistic diversity. The dataset is divided into two sets: 7.5K problems for training and 1K problems for testing. Each problem in the dataset requires 2 to 8 steps of reasoning to arrive at the solution. The problems primarily focus on fundamental arithmetic operations like addition, subtraction, multiplication, and division.

4.2 SETTINGS

Model Architecture We use a modified version of LLaMA [52] as the base model. To generate state values corresponding to the action tokens, we introduce an additional linear layer to serve as the value head. This value head acts as an auxiliary output module, and the output values are processed using the *tanh()* function to ensure they fall within the range of (-1, 1). This adaptation for RL has also been discussed in prior studies [39].

Agent Pre-training We use the LLaMA-7B model [52] for our LLM agent. To enhance the agent’s ability to follow task-specific instructions, we initialize it by instruction fine-tuning (IT). And this initialized agent works as the baseline for a fair comparison. This step is crucial because the original LLaMA-7B model, without prior instruction fine-tuning, struggled to follow task instructions and generate sensible actions in the environments. To collect data for instruction fine-tuning, we employ GPT3/4 as our agent to explore the environments created from the training set. We then filter out negative examples and retain positive examples to train the initial agent. For both the *ALFWorld* and *HotpotQA* datasets, we leverage GPT3 (specifically, text-davinci-003). However, for the *GSM8k* dataset, we use GPT4 due to GPT3’s inadequate performance in handling mathematical problems, which resulted in a scarcity of positive examples.

Training details We utilize the AdamW optimizer [22] with a batch size of 32. The learning rate is set to 2e-4. In each iteration, the sizes of new environments for agents to explore are: 256 for *ALFWorld*, 512 for *GSM8k*, and 1024 for *HotpotQA*. For parameter-efficient fine-tuning, we employ LoRA [14] with hyperparameters $R = 16$ and $\alpha = 16$. For distributed training, we utilize 4 nodes with $8 \times$ A100 GPUs on *HotpotQA* and *GSM8k*. For the experiments on *ALFWorld*, we use 1 node with $2 \times$ A100 GPUs due to the dataset’s small scale.

Baselines We compare the agents trained by LTC with existing prompting and instruction tuning methods, including ReAct [65], ReAct-IM [16], CoT [61], CoT-SC [55, 56], BUTLER [24]. The detailed of these baselines are described in Appendix A.7. Most of these methods focus on few-shot

prompting, and different pre-trained models are used. To ensure a fair comparison, we include the additional baselines named ReAct-Tuning and CoT-Tuning by fine-tuning the LLaMA-7B model using the collected trajectories as fine-tuning data mentioned in 4.2. In addition, GPT-4 are not used in the test time, and all the results reported are obtained by the trained agent itself.

4.3 RESULTS

ALFWorld As shown in Table 1, LTC outperforms the previous best methods* on all of tasks of *ALFWorld*. We can see that Instruction Fine-tuning is already a strong baseline outperforming others, yet our LTC achieves a success rate of 91%, remarkably outperforming the best Instruction Tuning baseline (78%). Notably, on both Cool and Look tasks, LTC obtains a 100% success rate. Even on the hardest Pick Two & Place task (e.g., “put two pencils in the drawer”), it achieves a decent 76% success rate. The Pick Two task requires the agent to perform two sequences of “pick and place” actions in one task, while keeping track of the desired type and the location. The combined sequences and the need to remember the previous location make this task challenging. This may be the reason why baselines achieve lower success rates on this task. In contrast, our LTC agent, which further trains the agent with self-exploration significantly outperforms other agents. This underscores the effectiveness of the communication mechanism in LTC.

Method \ Task	Pick	Clean	Heat	Cool	Look	Pick 2	All
ReAct (avg)	65	39	83	76	55	24	57
ReAct (best of 6)	92	58	96	86	78	41	71
ReAct-IM (avg)	55	59	60	55	23	24	48
ReAct-IM (best of 6)	62	68	87	57	39	33	53
BUTLER _g (best of 8)	33	26	70	76	17	12	22
BUTLER (best of 8)	46	39	74	100	22	24	37
ReAct-Tuning (avg)	83	91	91	90	72	8	77
ReAct-Tuning (best of 3)	92	97	96	95	78	24	78
LTC (avg)	89	91	93	97	96	67	90
LTC (best of 3)	92	97	96	100	100	76	91

Table 1: AlfWorld success rates (%) for 6 tasks. The results of the bottom block are obtained by fine-tuning LLaMA-7B model.

Model	Method	EM score
PaLM-540B	CoT [61]	29.4
	CoT-SC [55]	33.4
	ReAct [65]	27.4
	ReAct → CoT-SC	35.1
GPT3-175B	ReAct	30.8
PaLM-62B	ReAct-Tuning	32.6
	CoT-Tuning	25.2
PaLM-8B	ReAct-Tuning	25.0
	CoT-Tuning	14.1
LLaMA-7B	ReAct-Tuning	28.1
	LTC	33.2

Table 2: EM scores on HotpotQA with prompt and tuning methods. Methods that use fine-tuning are marked by “-Tuning”.

Model	Method	Accuracy
PaLM-540B	CoT [61]	56.5
	CoT-SC [55]	74.4
GPT3-175B	CoT [61]	60.1
	CoT-SC [55]	78.0
LLaMA-7B	CoT [52]	11.0
	CoT-SC [52]	18.1
LLaMA-7B	CoT-Tuning	37.7
	LTC	41.3

Table 3: Accuracy on GSM8k. The results of the bottom block are obtained by fine-tuning LLaMA-7B model, while the others are prompting methods without fine-tuning.

HotpotQA As shown in Table 2, LTC outperforms the instruction tuning baseline[†] by 5.1% on Exact Match (EM) score, and it even outperforms ReAct and CoT on their default settings. Note that ReAct and CoT use PaLM-540B and GPT3-175B as the pre-trained LM model, which is 77x and 25x larger than our the LLaMA-7B model we used. By sampling 21 CoT trajectories during inference and adopting the majority answer, CoT-SC is slightly better (0.2%) than LTC, and their combined method ReAct → CoT-SC surpasses LTC by 1.9%. Compared to other models with tuning,

*For *ALFWorld*, ReAct and ReAct-IM results are from Table 3 of [65]. BUTLER and BUTLER_g results are from Table 4 of [46], and they are trained with DAgger [38].

[†]For HotPotQA, Prompting method results without fine-tuning are from Table 1&5 of [65]. PaLM-8B and PaLM-62B scores are estimates from Figure 3 of [65].

our LLaMA-7B based agent even obtains slightly better (0.6%) performance than the ReAct-Tuning baseline with $9\times$ larger PaLM-62B model.

GSM8k As shown in Table 3, LTC outperforms the instruction fine-tuning baseline by 3.6% on accuracy. It also outperforms CoT and CoT-SC baselines with the same LLaMA-7B model. However, LTC underperforms CoT and CoT-SC with the much larger models (PaLM-540B and GPT3-175B). This phenomenon is because numerical reasoning requires a larger model size and sufficient pretraining data, as observed in [28]. Unfortunately, due to computational resource limitations, we can only train the relatively small LLaMA-7B model but were unable to train larger-scale models. Nevertheless, we believe that exploring LTC with larger models is promising for future research.

5 DISCUSSION

Efficiency As mentioned above, prompting-based methods such as ReAct [65] and CoT [61] use a subset of exemplary trajectories from the given task as few-shot prompts during inference. However, these few-shot prompts are often long, which leads to increased inference cost and limited context length for user queries. As shown in Table 4, we compare the number of input tokens for each task. We compute the CoT prompts for **GSM8k**, and we use ReAct for the other two tasks. All the few-shot prompts are sourced from the original paper. As shown, our LTC agents used only 12.8%, 8.6%, and 10.8% of the input tokens required by the ICL methods on the three tasks, respectively.

Method	GSM8k (CoT)	Hotpot-QA (ReAct)	Alfworld (ReAct)
ICL	836	1937	1744
LTC	107	167	189

Table 4: Average number of tokens of the input prompts on test sets. LTC does not use any few shot examples in the prompt, hence uses only a fraction of tokens compared to ICL.

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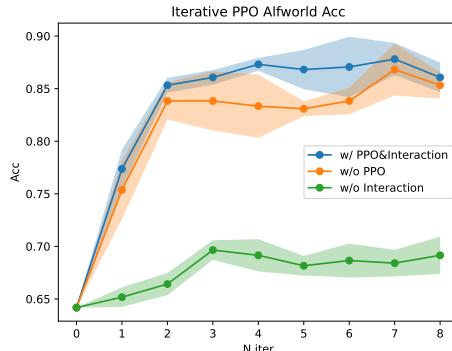


Figure 5: The accuracy curves of PPO training.

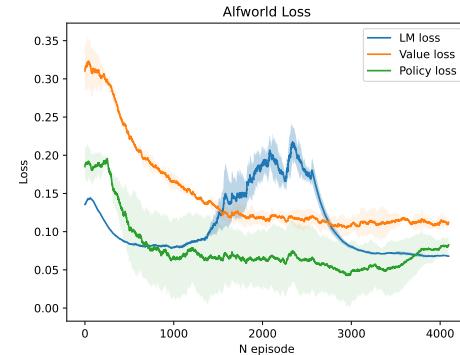


Figure 6: The loss curves of PPO training.

Shortcuts One interesting observation is that the GPT-4 agent sometimes employs "shortcuts" to solve problems when serving as a teacher to generate new training data. These shortcuts rely on the internal knowledge acquired during its pretraining process. To illustrate this, we present a case study from *HotpotQA* in Figure 7. In this case, the GPT-4 agent quickly retrieves the answer by leveraging its memorized knowledge about the second entry after receiving the Wikipedia page of the first entry. On the other hand, the bottom of Figure 7 demonstrates a comparison with LLaMA-7B, which was trained using our LTC method with the GPT-4 agent in the loop. LLaMA-7B does not employ shortcuts and instead performs a search for the second entry. This case study demonstrates that communication mechanism in LTC provide additional benefits during learning, compared to solely relying on data generated by GPT-4.

Ablation We conducted ablation studies on the loss design of LTC. Figure 5 illustrates the success rate of agents on the *ALFWorld* dataset under different loss settings. Without using our communication pattern for interactions and merely sampling pre-collected instruction data for training, the improvement was limited. However, when we incorporated our communication pattern to gather data, the model's performance quickly surpassed 80%. Furthermore, employing PPO to handle



Figure 7: GPT-4 can use shortcuts to solve the problem, while the LLaMA-7B agent cannot mimic it.

positive and negative samples separately resulted in faster and more significant improvement (blue line). In Figure 6, we present the separate curves of the three main losses during training. Initially, the LM loss showed a decreasing trend. Interestingly, as training iterations progressed, both the value loss and policy loss gradually decreased, which possibly causes the LM loss to increase temporarily. After the value loss and policy loss reached a certain threshold, the LM loss continued to decrease till convergence.

6 CONCLUSION

We introduced Learning-Through-Communication (LTC), a paradigm that adapts LLM agents to new tasks and environments via communication-based iterative learning. Within this LTC framework, we have designed three communication modes for common tasks including decision-making, knowledge-intensive reasoning, and numeric reasoning. These communication modes facilitate interactions between LLM agents and their environments, as well as other agents such as GPT-4 and humans. The history of these interactions can be autonomously organized into training data for PPO training so that the agent can adapt to the new task. Our approach represents a closed loop where the agent self-interacts with the environment or other agents, and learning to improve itself with minimal human intervention. Empirically, we have demonstrated that LTC performs strongly in success rate and efficiency across three different tasks: AlfWorld, HotpotQA, and GSM8k. It consistently outperforms existing LLM agent and instruction tuning baselines, showing the promise of the LTC paradigm in adapting LLM agents to new tasks and environments with minimal human effort. As for future work, we plan to explore more diverse communication patterns for different tasks, and involve the communication with human during the iterative learning process. We will open source our code to facilitate further research in this line.

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Algorithm 1 The Python-style algorithm to demonstrate Monologue pattern

```
# agent: LLaMA agent
# input: Task description
# output: S = (T, M, R)

# initialization
T, M, R = [input], [0], [0]

i = 0
while i < max_steps:
    T += ["think:"]
    thought = agent.api(T)
    T.append(thought)
    M.append(1) # agent message mask
    R.append(0)

    T += ["act:"]
    action = agent.api(T)
    T.append(action)
    M.append(1) # agent message mask
    R.append(0)

    response = env.execute(action)
    reward = parse(response)
    T.append(response)
    M.append(0) # system message mask
    R.append(reward)

    i += 1
    if reward != 0:
        break
S = (T, M, R)
return S
```

A APPENDIX

A.1 COMMUNICATION PATTERNS

To collect the trajectories and the reward signal data from different types of tasks, we design the communication patterns for these tasks and unified the data format as described in Figure 4. Here we use three python-syle algorithms (Algorithm 1 Algorithm 2 Algorithm 3) to demonstrate how three types of communication patterns help the agent collect exploration data.

A.2 BUFFER STRUCTURE

The communication data will be saved as replay buffers for the training phase, and the buffer data format is a serial of tokens sequences demonstrated in Figure 4. We treat each token as the action unit in our reinforcement learning formula, and each exploration trail is processed into 5 data sequences $[S_a, S_m, S_v, S_l, S_r]$:

- S_a : A list of integers representing the generated token ids encoded by the tokenizer. All the valid text trajectories are recorded as a queue, including system texts like environment descriptions, feedback, and agent texts like parsed actions, thinking processes, and hints from other agents. While the invalid generated text of the agent will be skipped, such as nonsense string and action text can not be parsed. These tokens are treated equally as the input for the LLM, but they have different masks to apply different losses.
- S_m : The system mask to mask different types of input tokens to control the training loss. We set 0 as the default mask for system texts like environment descriptions, system feedback, and system prompts, the actions encoded from these kinds of texts are not actions we want the agent to learn, so they will be masked out both policy loss and value loss in the PPO algorithm. We set 1 as the mask for agents-generated tokens like the keywords of decisions and the thinking process, which are the main supervising objects of our reinforcement learning pipeline, so they will be assigned full policy loss and value loss. We set 2 as the mask for hints or feedback from other agents, which are the actions we also want our own agent to learn but without instant state values since they are not generated by our agent. So

Algorithm 2 The Python-style algorithm to demonstrate Dialogue pattern

```
# agent1: LLaMA agent
# agent2: GPT-4 agent
# input: Task description
# output: S = (T, M, R)

# initialization
T, M, R = [input], [0], [0]

i = 0
while i < max_steps:
    T += ["think:"]
    thought = agent2.api(T)
    T.append(thought)
    M.append(2) # teacher agent message mask
    R.append(0)

    T += ["act:"]
    action = agent1.api(T)
    T.append(action)
    M.append(1) # student agent message mask
    R.append(0)

    response = env.execute(action)
    reward = parse(response)
    T.append(response)
    M.append(0) # system message mask
    R.append(reward)

    i += 1
    if reward != 0:
        break
S = (T, M, R)
return S
```

Algorithm 3 The Python-style algorithm to demonstrate Analogue pattern

```
# agent1: LLaMA agent
# agent2: GPT-4 agent
# input: Question description
# output: S = (T, M, R)

# initialization
T, M, R = [input], [0], [0]

i = 0
while i < max_steps:
    T += ["answer_the_question_step_by_step:"]
    answer1 = agent1.api(T)
    query = T + answer1 + ["the_answer_is_correct, yes_or_no? also_gives_a_better_answer"]
    response = agent2.api(query)
    reward, answer2 = parse(response)
    T.append(answer1)
    T.append(answer2)
    M.append(1) # student agent message mask
    M.append(2) # teacher agent message mask
    R.append(reward)
    R.append(+1) # assume teacher is correct

    query = query + response + ["please_generate_a_similar_qa_pair_to_teach_the_student:"]
    response = agent2.api(query)
    new_question, teacher_answer = parse(response)
    new_question += "answer_the_question_step_by_step:"
    student_answer = agent1.api(new_question)
    reward = parse(student_answer, teacher_answer)
    T.append(new_question + student_answer)
    M.append(1) # student agent message mask
    R.append(reward)

    i += 1
S = (T, M, R)
return S
```

the tokens with mask 2 will be mask out only the value loss and supervised by the policy loss.

- S_v : The state values corresponding to the actions obtained by the value head our the agent model. The value head is an addition layer inserted to the original pre-trained LLM architecture, we implement it by inserting a linear layer after the second-to-last LlamaDecoderLayer as the auxiliary output module and the output values are processed by a $\tanh()$ function to keep it range inside $(-1, 1)$.
- S_r : The rewards corresponding to the actions. The rewards are very sparse, most of the actions are zero-reward, and only when the current task is finished or the token length of the current buffer has just overflowed it will be non-zero value: +1 for positive, -1 for negative.

A.3 ALGORITHM OF LTC

The implementation of LTC can be summarized as Algorithm 4, we unveil the structural framework that embodies the Learning Through Communication (LTC) paradigm, meticulously crafted to facilitate autonomous and progressive learning through iterative cycles. At the outset, the pre-trained Large Language Model (LLM) agent undergoes a fine-tuning phase to align its initial configuration with the intended learning tasks. Following this, an exploration phase is initiated where a batch of training environments is sampled and subsequently engaged by the agent to generate trial data asynchronously, leveraging the power of parallel computing across multiple GPUs to enhance efficiency. This newly generated data is synchronized across all GPUs to foster a cohesive learning base, which is stored in a replay buffer for further utilization. As the agent iterates through this process, it continually samples from this replay buffer during the training phase, employing the Proximal Policy Optimization (PPO) algorithm in a distributed data parallel (DDP) setting to refine its strategies and adapt dynamically. This code snippet, therefore, encapsulates the innovative asynchronous and distributed nature of the LTC paradigm, marking a significant stride in fostering intelligent, adaptive, and collaborative artificial intelligence agents.

A.4 TRAINING LOSS

After exploration in each iteration, we update the replay buffer by incorporating the newly collected trajectories and then sample the most recent trajectories to train the parameters π_θ of the LLM agent. We design our training objective to combine: 1) the standard language modeling loss \mathcal{L}_{LM} , 2) the policy loss \mathcal{L}_{policy} , 3) the value loss \mathcal{L}_{value} , and 4) the entropy loss $\mathcal{L}_{entropy}$. The overall training objective is formulated as:

$$\mathcal{L}_{total} = \mathcal{L}_{LM} + \beta(\mathcal{L}_{policy} + \lambda\mathcal{L}_{value} + \mathcal{L}_{entropy})$$

where β and λ are weighting hyperparameters.

The different losses in the above are described as follows:

- The LM loss \mathcal{L}_{LM} is defined as the cross entropy between the agent and its generations which have a positive reward, akin to self-improving model schemes [15, 36]. By training on these generations, the agent is further encouraged to give generations which yield positive rewards.
- The policy loss \mathcal{L}_{policy} is introduced to supervise the agent’s actions. The policy loss \mathcal{L}_{policy} is calculated using a masked version of the surrogate objective defined in [42] with advantage estimates \hat{A} ,

$$\mathcal{L}_{policy}(\theta) = -\mathbb{E}[m_{policy} * \min(r(\theta)\hat{A}, \text{clip}(r(\theta), 1 - \epsilon, 1 + \epsilon)\hat{A}],$$

Algorithm 4 Python-style code of LTC

```
# agent: Pre-trained LLM agent
# n_gpu: total number of GPUs
# env_cls: the class of environments
# n_gen: the generation size for one iteration
# n_train: the train size for one iteration

# initialization
agent = instruction_finetune(agent)
replay_buffer = []
i = 0
while i < max_iteration:
    i += 1
    # Exploration Phase
    envs = env_cls(sample(data, n_gen//n_gpu))
    # asynchronously generate
    new_buffer = generate_trials(agent, envs)
    # dist.gather and dist.broadcast
    new_buffer = sync_all_gpus(new_buffer)
    replay_buffer.append(new_buffer)

    # Training Phase
    rollouts = sample(replay_buffer, n_train)
    # distributed training with ppo
    agent = ppo_ddp_train(agent, rollouts)
```

where $r(\theta)$ is the output probability ratio $r(\theta) = \frac{\pi_\theta(a|s)}{\pi_{\text{old}}(a|s)}$ of the agent with its previous version π_{old} . We define binary mask m_{policy} to mask out the encoded system message in PPO loss (marked by $S_m = 0$ in buffers A.2). For example, let $\{x_1, y_1, x_2, y_2, \dots, x_n, y_n\}$ be a token buffer consisting of system messages $x_n \in X$ and agents' messages (include the target trained agent and the other teacher agents) π_θ output $y_n \in Y$, then the binary mask $m_{\text{policy}} = \{0, 1, 0, 1, \dots, 0, 1\}$.

- The value loss is defined in [42] as the mean squared error between calculated value and estimated advantages masked by another binary mask m_{value} (marked by $S_m = 1$ in buffers A.2). For example, let $\{z_1, y_1, z_2, y_2, \dots, z_n, y_n\}$ be a token buffer consisting of all other messages (except the agent-generated messages) $z_n \in X$ and trained agent-generated messages π_θ output $y_n \in Y$, then the binary mask $m_{\text{policy}} = \{0, 1, 0, 1, \dots, 0, 1\}$.
- $\mathcal{L}_{\text{entropy}}$ is an entropy bonus to ensure sufficient exploration, as suggested in past work [63, 25]. This entropy is computed as a small negative factor times the entropy of the policy distribution : $\mathcal{L}_{\text{entropy}} = 0.01 \times \sum_a \pi_\theta(a|s) \log \pi_\theta(a|s)$.

A.5 IMPLEMENTATION DETAIL

A.6 ASYNCHRONOUSLY DISTRIBUTED GENERATING

The exploration data is generated in an asynchronous style, so that the agent can handle the environments with open-end exploration space. The training data are pre-processed into interactive environments which are capable for agents to observe the states, take actions, and get immediate feedback. According to the number of GPU threads, these environments are divided into corresponding portions and then distributed to each GPU. Subsequently, these GPUs begin to explore these environments asynchronously in parallel with the same agent trained by the latest data. Since the lengths of the generated contents are varied and the interactions inside the environments are generally open-ended, the time cost for the agent to explore each environment is also varied, some GPU threads may process the data faster than others. A barrier is set for all the GPU threads so that the early finished GPU threads can wait for the others until the total accumulated buffers generated by the environments achieve a preset number S_g , which is the quantity of the new training buffers we want to add to the replay buffers in one iteration. After all the GPU threads reach the barrier, we get enough buffers then gather the buffers from each GPU thread and merge them together, and broadcast the new buffers to each GPU thread to update their local replay buffers. The updated replay buffers will be used in the training phase for training the agents of the next iteration.

A.7 BASELINES

ReAct [65] uses a subset of training cases as prompts for different tasks, in the format of thought-action-observation sequences. For knowledge-intensive reasoning tasks like *HotpotQA*, ReAct designs an action space that includes search, lookup, and finish actions, enabling the agent to interact with Wikipedia to retrieve necessary information. On the other hand, **ReAct-IM** adopts Inner Monologue (IM) [16] style prompting. Chain-of-thought prompting (**CoT**) [61], enhances the reasoning capabilities of Language and Vision models (LLMs) by generating a sequence of intermediate reasoning steps. This can be considered as a reasoning-only baseline of ReAct, excluding actions and observations. Additionally, **CoT-SC** [55, 56] is a follow-up work of CoT, serving as a self-consistency baseline. It is worth noting that most of these methods employ greedy decoding, except for BUTLER [24], which utilizes beam search. Most of these methods focus on few-shot prompting, and different pre-trained models are used. To ensure a fair comparison, we include the additional baselines named ReAct-Tuning and CoT-Tuning by fine-tuning the LLaMA-7B model using the collected trajectories as fine-tuning data mentioned in 4.2. In addition, GPT-4 are not used in the test time, and all the results reported are obtained by the trained agent itself.

A.8 LOSSES

We conducted ablation studies on the loss design of LTC. Figure Figure 5 illustrates the success rate of agents on the *ALFWorld* dataset under different loss settings. Without using our communication pattern for interactions and merely sampling pre-collected instruction data for training, the improvement was limited. However, when we incorporated our communication pattern to gather data, the

System: Interact with a household to solve a task. Here is the task:
System: You are in the middle of a room. Looking quickly around you, you see a a countertop 1, a fridge 1, cabinet 6, a cabinet 5, a cabinet 4, a cabinet 3, a cabinet 2, a cabinet 1, a coffeemachine 1, a drawer 3, a drawer 2, a drawer 1, a garbagecan 1, a microwave 1, a shelf 3, a shelf 2, a shelf 1, a sinkbasin 1, a stoveburner 4, a stoveburner 3, a stoveburner 2, a stoveburner 1, and a toaster 1.
System: Your task is to: put an egg in the bowl.

(LLaMA) Think: To solve the task, you need to find and take an egg, then find a bowl to put the egg in. An egg is more likely to appear in fridge (1).
(LLaMA) Act: go to fridge 1
System: The fridge 1 is closed.
(LLaMA) Act: open fridge 1
System: You open the fridge 1. The fridge 1 is open. In it, you see a bowl 1, a cup 2, a cup 1, a egg 1, a lettuce 1, a mug 2, a plate 2, a potato 2, a potato 1, and a tomato 1.
(LLaMA) Act: take egg 1 from fridge 1
System: You pick up the egg 1 from the fridge 1.
(LLaMA) Think: Now you take an apple (1). Next, you need to find the bowl and put the egg in. A bowl is more likely to appear on the countertop.
(LLaMA) Act: go to the countertop 1
System: On the countertop 1, you see a bowl 1, apple 2, a apple 1, a mug 3, a potato 3, and a spatula 1.
(LLaMA) Act: Put egg 1 in/on bowl 1
System: Success, reward +1

Figure 8: The text version of the toy example in Figure 1 for Monologue pattern of ALFWorld.

model’s performance quickly surpassed 80%. Furthermore, employing PPO loss to handle positive and negative samples separately resulted in faster and more significant improvement (blue line). In Figure Figure 6, we present the separate curves of the three main losses during training. Initially, the LM loss showed a decreasing trend. Interestingly, as training iterations progressed, both the value loss and policy loss gradually decreased, which possibly causes the LM loss to increase temporarily. After the value loss and policy loss reached a certain threshold, the LM loss continued to decrease till convergence.

A.9 CASES STUDY

One interesting observations is that the GPT-4 agent sometimes employs ”shortcuts” to solve problems when serving as a teacher to generate new training data. These shortcuts rely on the internal knowledge acquired during its pretraining process. To illustrate this, we present a case study from *HotpotQA* in Figure Figure 7. In this case, the GPT-4 agent quickly retrieves the answer by leveraging its memorized knowledge about the second entry after receiving the Wikipedia page of the first entry. On the other hand, the bottom of Figure Figure 7 demonstrates a comparison with LLaMA-7B, which was trained using our LTC method with the GPT-4 agent in the loop. LLaMA-7B does not employ shortcuts and instead performs a search for the second entry. This case study demonstrates that communication mechanism in LTC provide additional benefits during learning, compared to solely relying on data generated by GPT-4.