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Don't Just Fine-tune the Agent, Tune the Environment

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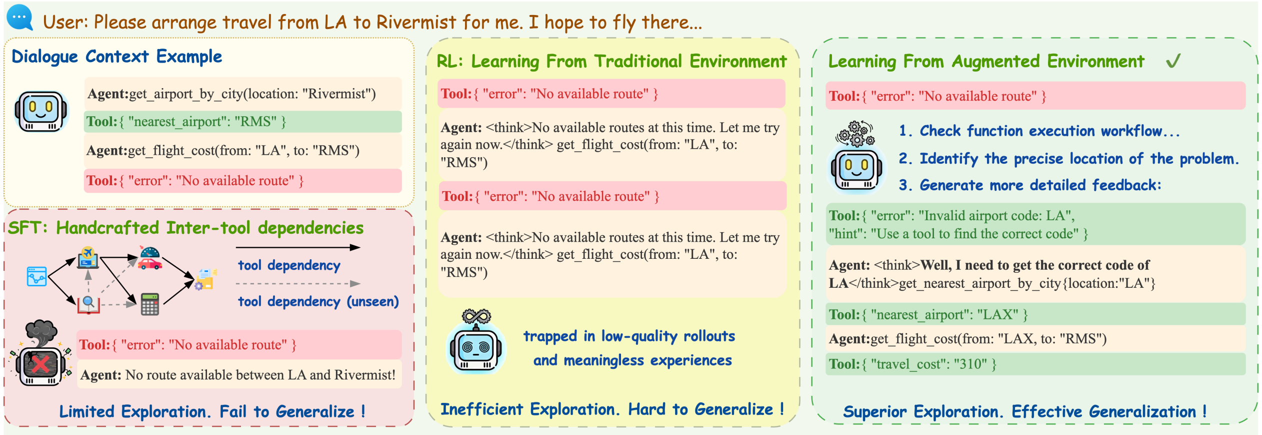
Abstract

Large Language Model (LLM) agents show great promise for complex, multi-turn tool-use tasks, but their development is often hampered by the extreme scarcity of high-quality training data. Supervised fine-tuning (SFT) on synthetic data leads to overfitting, whereas standard reinforcement learning (RL) struggles with a critical cold-start problem and training instability. To address these challenges, we introduce ENVIRONMENT TUNING, a novel training paradigm that enables agents to learn complex behaviors directly from problem instances without relying on pre-collected expert trajectories. ENVIRONMENT TUNING orchestrates this learning process through a structured curriculum, actionable environment augmentation that provides corrective feedback, and fine-grained progress rewards to ensure stable and efficient exploration. Using only 400 problem instances from Berkeley Function-Calling Leaderboard (BFCL) benchmark, our method not only achieves competitive in-distribution performance against strong baselines but also demonstrates superior out-of-distribution generalization, overcoming the performance collapse common to SFT-based approaches. Our work presents a paradigm shift from supervised fine-tuning on static trajectories to dynamic, environment-based exploration, paving the way for training more robust and data-efficient agents. The source code will be available under `https://github.com/inclusionAI` in the next version.


Dialogue Context Example
SFT: Handcrafted Inter-tool dependencies
tool dependency
tool dependency (unseen)
Limited Exploration. Fail to Generalize !
RL: Learning From Traditional Environment
trapped in low-quality rollouts
and meaningless experiences
Inefficient Exploration. Hard to Generalize !
Learning From Augmented Environment ✓
1. Check function execution workflow...
2. Identify the precise location of the problem.
3. Generate more detailed feedback:
Superior Exploration. Effective Generalization !

User: Please arrange travel from LA to Rivermist for me. I hope to fly there...

Agent:get_airport_by_city(location: "Rivermist")
Tool:{ "nearest_airport": "RMS" }
Agent:get_flight_cost(from: "LA", to: "RMS")
Tool:{ "error": "No available route" }

Tool:{ "error": "No available route" }
Agent: No route available between LA and Rivermist!

Tool:{ "error": "No available route" }
Agent: <think>No available routes at this time. Let me try again now.</think> get_flight_cost(from: "LA", to: "RMS")
Tool:{ "error": "No available route" }
Agent: <think>No available routes at this time. Let me try again now.</think> get_flight_cost(from: "LA", to: "RMS")

Tool:{ "error": "No available route" }
Tool:{ "error": "Invalid airport code: LA", "hint": "Use a tool to find the correct code" }
Agent: <think>**Well, I need to get the correct code of LA**</think>get_nearest_airport_by_city{location:"LA"}
Tool:{ "nearest_airport": "LAX" }
Agent:get_flight_cost(from: "LAX, to: "RMS")
Tool:{ "travel_cost": "310" }

Figure 1: **Limitations of Existing Paradigms and the ENVIRONMENT TUNING Advantage.** This figure contrasts three agent training approaches on a travel planning task. **(Left)** Supervised Fine-Tuning (SFT) on static trajectories struggles with generalization. **(Center)** Reinforcement Learning (RL) in a traditional environment provides only sparse, uninformative feedback. **(Right)** Our approach uses an **augmented environment** that provides actionable, fine-grained feedback upon failure.

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[*] Equal contributions. Work was done during Siyuan and Zechuan's internship in Ant Group.
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1 Introduction

The emergence of Large Language Model (LLM)-based agents, equipped with capabilities for intricate reasoning, planning, and tool interaction (Wang et al., 2024; Weng, 2023), has unlocked the potential to address complex, real-world problems across diverse domains like software engineering (Jimenez et al., 2023; Yang et al., 2024), computer use (Xie et al., 2024; OpenAI, 2025c; Wang et al., 2025a) and web browsing (Wei et al., 2025; OpenAI, 2025a; Moonshot AI, 2025). Much of this success has been demonstrated in single-turn tasks, such as mathematical reasoning, where plentiful datasets (Hendrycks et al., 2021; Sun et al., 2025), automated verifiers (Kydlíček, 2025), and advanced algorithms (Shao et al., 2024; Yu et al., 2025) have enabled significant progress (Zeng et al., 2025; He et al., 2025). Despite their utility, these agents, limited by a structured and single-turn paradigm, are insufficient to tackle the full complexity of real-world problems: *this limitation motivates the transition of agents capable of engaging in dynamic, multi-turn interactions with external tools and environments (Wang et al., 2025c; Mai et al., 2025; Feng et al., 2025b).*

However, the transition to multi-turn tool-use settings introduces several key challenges:

- **Data scarcity ($\mathbb{C}1$):** High-quality multi-turn tool-use datasets are exceedingly scarce due to the labor-intensive nature of human annotation and validation. For instance, BFCL V3 (Patil et al., 2025b) multi-turn dataset contains only 800 samples, severely limiting the effectiveness of traditional data-driven approaches.
- **Complex environment ($\mathbb{C}2$):** Multi-turn tool-use scenarios require agents to navigate complex, interconnected tool ecosystems spanning multiple domains. Like BFCL V3, the benchmark spans 8 different domains with 84 distinct tools, requiring cross-domain API calls and sophisticated tool orchestration.
- **Long interaction chain ($\mathbb{C}3$):** Success in multi-turn scenarios demands consistent performance across all interaction turns, where any single failure leads to complete task failure. Each test sample involves multiple user queries, where success requires passing all checks in every turn.

While constructing synthetic trajectories for Supervised Fine-Tuning (SFT) is a dominant strategy (Prabhakar et al., 2025; Liu et al., 2024; Yin et al., 2025) to mitigate data scarcity ($\mathbb{C}1$), it suffers from a critical flaw: agents trained on these static, synthetic traces often fail to generalize to real-world scenarios, a limitation we demonstrate empirically in Section 4.2.

Reinforcement Learning (RL) (Shao et al., 2024; Yu et al., 2025; Hu et al., 2025) offers a natural alternative, promising to improve generalization through online interaction and exploration (Chu et al., 2025; Shenfeld et al., 2025). However, this approach is plagued by its own severe challenges. The complexity of the environment ($\mathbb{C}2$) creates a critical "cold-start" problem: an agent that is not yet proficient cannot explore the vast action space effectively, becoming trapped in cycles of low-quality rollouts and failing to generate the meaningful experiences required for improvement. Furthermore, even if an agent overcomes this initial hurdle, the long interaction chains ($\mathbb{C}3$) inherent to these tasks make the training process notoriously unstable and prone to performance collapse (Wang et al., 2025c; Xue et al., 2025).

This collectively leads to our central research question:

> *How can we train a high-quality agent for complex, multi-turn tool use*
> *under extreme **data scarcity**, ensuring both **generalization** and **stability**?*

Addressing the critical intersection of data scarcity, generalization, and learning stability requires a paradigm shift in agent training. In response, we introduce Environment Tuning, a novel framework designed to cultivate both generalization and stability from extremely scarce data. At its core, Environment Tuning orchestrates learning via three complementary principles: (1) a *Structured Curriculum* that guides the agent from simple to complex tasks to build skills progressively; (2) *Actionable Environment Augmentation* that provides corrective hints upon failure, turning dead-end explorations into rich learning signals; and (3) *Fine-Grained Progress Rewards* that replace sparse, binary outcomes with a continuous measure of task completion, providing a dense and informative learning signal.

By combining this deliberate curriculum with enriched feedback and dense rewards, Environment Tuning enables an agent to acquire sophisticated, multi-step behaviors from scratch, demonstrating that robust learning is achievable even in the complete absence of expert demonstrations. **The key contributions of this work are as follows:**

- **A novel learning paradigm for data-scarce environments.** We propose Environment Tuning, which enables agents to learn multi-turn tool-use capabilities directly from problem instances without expert demonstrations, shifting from trajectory-based imitation to environment-based exploration.

- **A practical curriculum with environment engineering.** We develop a four-stage curriculum leveraging actionable environment augmentation and fine-grained progress rewards to transform sparse feedback into rich learning signals for effective exploration.
- **Empirical validation in extreme data scarcity.** With only 400 training samples, our method proves effective for both base and SFT-tuned models. It lifts a base model like Qwen2.5-7B from near-zero to strong in-distribution performance, and also boosts SFT-tuned models such as watt-tool-8B to 54.25%, surpassing most proprietary models. Notably, it nearly doubles ToolACE-2's out-of-distribution score on ACEBench (8.5% to 15.0%), showing that ENVIRONMENT TUNING fosters robust generalization where SFT often fails.

2 Related work

Tool-integrated reasoning. A prominent line of research focuses on augmenting LLMs with external tools, a paradigm often termed Tool-Integrated Reasoning (TIR). Many works have leveraged RL as an alternative to SFT for teaching agents strategic tool invocation (Li et al., 2025; Feng et al., 2025a). However, direct application of trajectory-level algorithms (Shao et al., 2024; Yu et al., 2025) often leads to training instability and performance collapse (Wang et al., 2025c; Mai et al., 2025; Xue et al., 2025). To address this challenge, recent works have proposed sophisticated mechanisms like fine-grained credit assignment (Feng et al., 2025b), entropy-guided exploration (Dong et al., 2025), and trajectory filtering to prevent gradient explosion (Xue et al., 2025). While effective in their respective domains, such as computational reasoning (Li et al., 2025; Singh et al., 2025) or open-domain web search (Jin et al., 2025a; Zheng et al., 2025), these methods are typically evaluated in settings where the primary challenge is to master a single tool or a small, homogeneous set of tools. Our work, in contrast, addresses the distinct challenge of orchestrating a large and diverse toolset to complete complex, stateful tasks that unfold over multiple interaction turns.

Multi-turn tool orchestration. Distinct from tool-augmented reasoning, another major challenge involves enabling agents to orchestrate a large set of diverse APIs to accomplish complex, stateful tasks over multiple turns. Benchmarks like BFCL (Patil et al., 2025b) and ACEBench (Chen et al., 2025a) have emerged to evaluate these sophisticated capabilities. However, as these benchmarks are derived from realistic scenarios, they feature high-quality but scarce human-annotated data, posing a significant training challenge.

To address the aforementioned **data scarcity** issue, two primary strategies have been explored. The dominant approach involves large-scale synthetic data generation for SFT, where recent works (Prabhakar et al., 2025; Liu et al., 2024; Yin et al., 2025; Zhang et al., 2024) focus on creating vast corpora of tool-use trajectories. An alternative strategy explores applying online RL directly. Works such as ReCall (Chen et al., 2025b) and ARTIST (Singh et al., 2025) attempt to improve policies through direct environment interaction. However, these online RL approaches have so far yielded only modest gains on benchmarks like BFCL, highlighting the difficulty of effective exploration in a **complex environment** and motivating the need for more efficient learning paradigms.

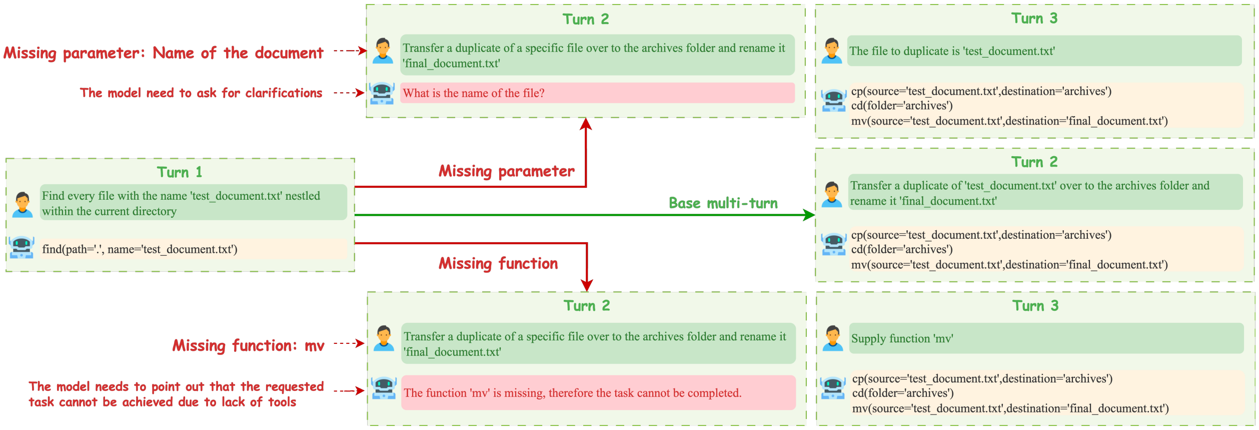
3 ENVIRONMENT TUNING

To overcome the challenge of learning in complex, data-scarce environments, we propose ENVIRONMENT TUNING, a framework that orchestrates training through three complementary mechanisms (see Figure 3). It combines (1) a *Structured Curriculum* (Section 3.2) for progressive skill acquisition; (2) *Actionable Environment Augmentation* (Section 3.3) to turn failures into rich learning signals via corrective hints; and (3) a *Fine-Grained Progress Reward* (Section 3.4) to provide dense feedback that overcomes the limitations of sparse signals. These pillars collectively create a manageable learning path for stable and data-efficient agent training.

3.1 Preliminary and challenges

This work tackles ***multi-turn tool use***: a challenging task where an agent must achieve a complex goal through a series of interactions with external tools. Unlike single-step problems, this process is dynamic and demands sophisticated reasoning, as a single task can unfold in numerous ways (Figure 2). The agent must navigate an interactive loop of understanding user requests, executing tool calls, and generating responses until the overall objective is complete. We mathematically formalize this problem as a Partially Observable Markov Decision Process (POMDP) in the Appendix (Section A).

On the challenge of multi-turn tool use. Training an RL agent for multi-turn tool use is non-trivial: an agent must simultaneously master low-level syntax skills (e.g., precise tool-call formatting that the environment can parse) and high-level reasoning abilities (e.g., multi-step planning across dependent subtasks). In complex


Turn 1
Missing parameter
Base multi-turn
Missing function
Turn 2
Turn 3
Missing parameter: Name of the document
The model need to ask for clarifications
Missing function: mv
The model needs to point out that the requested task cannot be achieved due to lack of tools

Turn 1: Find every file with the name 'test_document.txt' nestled within the current directory

find(path='.', name='test_document.txt')

Missing parameter — Turn 2: Transfer a duplicate of a specific file over to the archives folder and rename it 'final_document.txt'

What is the name of the file?

Turn 3: The file to duplicate is 'test_document.txt'

```
cp(source='test_document.txt',destination='archives')
cd(folder='archives')
mv(source='test_document.txt',destination='final_document.txt')
```

Base multi-turn — Turn 2: Transfer a duplicate of 'test_document.txt' over to the archives folder and rename it 'final_document.txt'

```
cp(source='test_document.txt',destination='archives')
cd(folder='archives')
mv(source='test_document.txt',destination='final_document.txt')
```

Missing function — Turn 2: Transfer a duplicate of a specific file over to the archives folder and rename it 'final_document.txt'

The function 'mv' is missing, therefore the task cannot be completed.

Turn 3: Supply function 'mv'

```
cp(source='test_document.txt',destination='archives')
cd(folder='archives')
mv(source='test_document.txt',destination='final_document.txt')
```

Figure 2: **An illustration of multi-turn tool-use scenarios**, adapted from an official example in the BFCL V3 Blog (Patil et al., 2025a). All three tracks start from the same initial user request. The *Base multi-turn* track (center) shows a successful execution path. The *Missing parameter* track (top) illustrates a scenario where the agent must handle ambiguity by asking for clarification. The *Missing function* track (bottom) shows a case where the agent needs to recognize that a required tool is unavailable. These scenarios highlight the diverse reasoning capabilities our curriculum is designed to address.

interactive environments, base models lacking these skills exhibit a diverse range of failure modes, including void incorrect parameter filling, calls to non-existent tools, and irreversible environment corruption.

As noted by Xue et al. (2025), RL optimization on such noisy trajectories is extremely sensitive to these error patterns: if they persist in the rollouts, training instability and gradient explosion are likely. Our numerical experiments also confirm this fragility: *when fine-tuning Qwen2.5-7B-Instruct directly in a single-stage RL setup with 400 training instances, training collapsed within 70 steps, yielding a mere 10% improvement in success rate*, as detailed and visualized in Appendix Section D.2.

3.2 Structured curriculum RL training

The aforementioned observations suggest that naively optimizing for full task success from the start is ineffective in long-horizon, sparse-reward settings. We therefore propose a structured curriculum that gradually increases objective complexity. This four-stage curriculum allows the agent to progress from mastering foundational skills to handling the full complexity of multi-turn tool use, while maintaining training stability.

Stage 1: mastering syntactic and schematic correctness. The goal of this initial stage is to train the agent to produce well-formed outputs with valid tool calls, forming a reliable foundation for all subsequent learning. Before an agent can reason effectively, it must first "speak the language" of the environment; otherwise, learning is confounded by penalties for both poor strategy and invalid formatting.

To isolate this foundational skill, we deconstruct the agent's actions (a_t^{tool} and a_t^{answer}) and design a reward function focused exclusively on their structural integrity. As illustrated in Figure 3, we use several task-agnostic, turn-by-turn counters:

- $C_{correct}$: the number of tool calls with a correct tool name and valid arguments;
- C_{error}: the number of calls with a correct tool name but invalid arguments;
- C_{format}: the number of turns violating the required XML-like format.

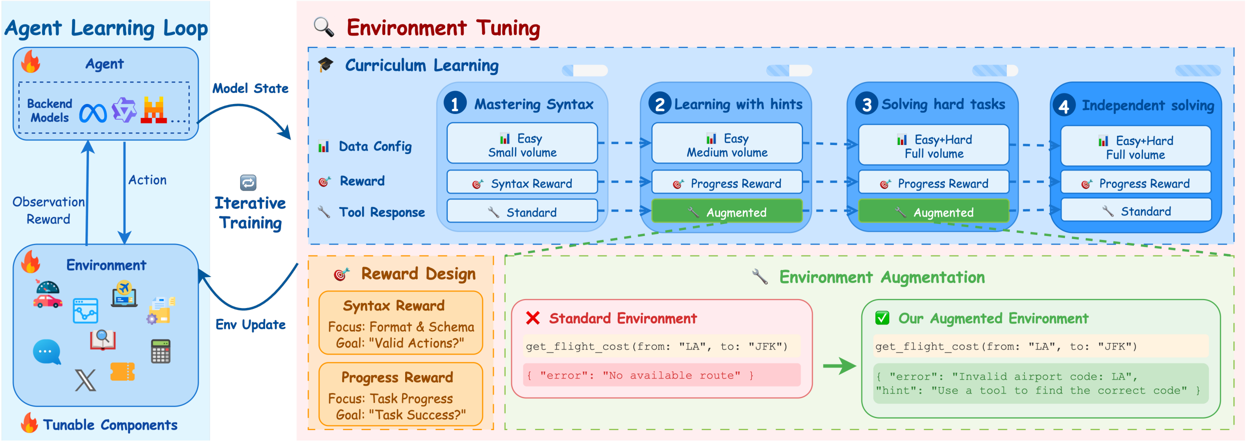
These counters are combined into a *Format Reward* R_{format} and a *Tool Call Reward* R_{tool}, defined as

$$R_{\text{format}} = (N - C_{\text{format}})/N\,, \qquad R_{\text{tool}} = C_{\text{correct}}/(C_{\text{correct}} + C_{\text{error}})\,, \tag{1}$$

where N is the total number of turns in the episode. The final reward for this stage, R_{Stage1}, combines these components and is gated by an indicator I_{tool} that is 1 if the agent attempts at least one tool call and 0 otherwise, encouraging active tool use:

$$R_{\text{Stage1}} = I_{\text{tool}} \cdot (R_{\text{format}} + R_{\text{tool}})\,. \tag{2}$$

As we demonstrate in our analysis of training dynamics (Section D.1), this specialized reward allows the agent to rapidly master the required syntax. This proves that dedicating a stage to this foundational skill is a crucial prerequisite for efficient learning in more complex, task-oriented stages.



```
get_flight_cost(from: "LA", to: "JFK")
{ "error": "No available route" }
```

```
get_flight_cost(from: "LA", to: "JFK")
{ "error": "Invalid airport code: LA",
"hint": "Use a tool to find the correct code" }
```

Figure 3: **An overview of ENVIRONMENT TUNING.** Our core innovation is the ENVIRONMENT TUNING module, which implements a four-stage curriculum. It dynamically configures the reward function, environment feedback (Standard vs. Augmented), and data split for the *Agent Learning Loop*. This staged approach transforms ambiguous errors into actionable lessons (highlighted in the *Environment Augmentation in Action* panel), enabling efficient and stable learning from limited data.

Stage 2: basic learning with augmented feedback. With the agent now proficient in syntax, the curriculum transitions to learning task-oriented reasoning. This stage utilizes the full `Base` split from BFCL, focusing on foundational multi-turn capabilities. To accelerate learning, we introduce two critical components to allow the agent to efficiently learn core reasoning skills in a guided manner.

1. Progress Reward (c.f. Section 3.4): we replace the task-agnostic reward with a Progress Reward (R_P), a fine-grained measure of task completion that provides a more informative signal than sparse binary outcomes (detailed in Section 3.4).
2. Actionable Environment Augmentation (c.f. Section 3.3): we employ such augmentation to enable the environment to provide detailed, corrective hints upon failure instead of ambiguous error messages, turning failed explorations into valuable learning opportunities.

Stage 3: advanced learning on complex scenarios. Building on the foundational skills from the previous stage, the agent is now exposed to the full spectrum of challenges. We introduce the complete training dataset, incorporating samples from the `Missing Parameters`, `Missing Functions`, and `Long-Context` splits. The objective is to train the agent to handle ambiguity, recognize functional gaps, and perform information retrieval from noisy contexts. The training setup remains consistent with Stage 2, continuing to leverage both the Progress Reward and Actionable Environment Augmentation to help the agent navigate these more complex problem spaces.

Stage 4: alignment with the evaluation environment. The final stage is designed to align the agent with the true evaluation conditions. While still training on the full dataset with the Progress Reward, we now disable the Actionable Environment Augmentation. This forces the agent to generalize its learned policies, relying on its internal reasoning capabilities to handle uninformative or standard error messages, just as it would during final evaluation. This step is crucial for ensuring that the agent's performance is robust in OOD scenarios and not overly dependent on the training scaffolds provided in earlier stages.

Remark 3.1 (Checkpoint selection for stage transitions)**.** *A key element of our curriculum is determining* when *to transit to the next stage. In our multi-turn tool-use setting, we adopt a* ***validation- and stability-based stage transition rule****:* we advance to the next stage only when the validation accuracy has plateaued and its gradient norm is stable.

This joint condition, further discussed in Section D.1, serves two purposes. First, the converged validation performance ensures the agent has mastered the current stage's skills. Second, the stable optimization dynamics confirm it is ready for more complex tasks, mitigating the risk of gradient explosions common in long-horizon RL (Xue et al., 2025). This rule is crucial for maintaining training stability and maximizing the curriculum's effectiveness.

3.3 Actionable environment augmentation

In multi-turn tool-use tasks, an agent often needs to execute complex chains of function calls where the output of one tool becomes the input to another. However, standard training environments typically return cryptic or overly generic error messages (like simple error codes or "not found" responses) that neither identify the root cause of failure nor indicate a viable next action. This lack of actionable guidance severely limits the agent's ability to discover dependencies between tools and to understand each tool's usage constraints, forcing it to rely on inefficient trial-and-error exploration, which leads to poor performance (as validated by the ablation in Section 4.3 that isolates the effect of environment augmentation). To address these issues, we design Actionable Environment Augmentation, which modifies the environment's feedback to provide pedagogical hints that directly inform the agent about dependency relationships and operational rules, turning failed trajectories into constructive learning opportunities.

Discovering inter-tool dependencies via exploration. Our first goal is to empower the agent to discover and resolve inter-tool dependencies on its own. While prior work often relies on pre-constructed dependency graphs to explicitly teach agents sequential tool-call patterns (Prabhakar et al., 2025; Liu et al., 2024), our method embeds these dependencies within the environment's feedback. This encourages the agent to learn the underlying logic through exploration rather than memorization, leading to better generalization in unseen scenarios.

For example, in the BFCL Travel API task, an agent might incorrectly try to book a flight without first finding the correct airport code.

- ***Standard feedback***: A vague message like "`No available route`" gives the agent no clue about the root cause of the failure.
- ***Augmented feedback***: Our environment provides a precise hint: "`Invalid airport code[s]:...`". This actionable message implicitly suggests that another tool is needed to find the correct airport code first, effectively teaching the dependency through interaction.

Revealing internal tool constraints with pedagogical hints. Our second objective is to provide actionable hints that reveal a tool's specific internal rules and constraints. This moves beyond the simple diagnostic errors returned by standard code interpreters (e.g., "`FileNotFoundError`") toward providing pedagogical feedback that explains why an action failed. By teaching the agent the "rules of the game", we dramatically prune the exploration space by invalidating entire classes of incorrect attempts.

For instance, an agent's pretrained knowledge might suggest using full paths with the "`rm`" command. However, the BFCL File System environment may not support this.

- ***Standard feedback***: A generic "`FileNotFoundError`" would be misleading, as the file might actually exist.
- ***Augmented feedback***: Our environment returns an explicit rule: "`Paths are not allowed. Specify only file/directory name...`". This hint directly corrects the agent's misunderstanding of the tool's protocol within this specific environment.

As illustrated in the file system and multi-API travel case studies (Sections F.1 and F.2), our augmented feedback transforms failed turns into explicit, actionable guidance. This enables agents to diagnose root causes accurately and discover corrective strategies that would be infeasible under baseline environments with ambiguous signals.

3.4 Fine-grained progress reward

A key challenge in training long-horizon, multi-turn tool-use agents is *reward sparsity*: a single binary signal at the end of a long trajectory provides insufficient guidance for effective learning (Feng et al., 2025b).

To overcome these challenges, we introduce a fine-grained *Progress Reward* (R_P) that provides a denser, turn-by-turn learning signal. Instead of rewarding individual tokens, we evaluate success at the end of each turn based on two criteria: the correctness of the resulting *environment state* and the *execution result* of the agent's chosen action. This allows us to distinguish "nearly correct" from "completely wrong" trajectories.

Formally, for each turn t in an episode of length T, we define binary scores for the state evaluation (r_t^{state}) and execution result evaluation (r_t^{exec}). A turn is successful only if both are correct, with its reward being their product: $r_t = r_t^{\text{state}} \cdot r_t^{\text{exec}}$. The total Progress Reward R_P is then the average success rate across all turns: $R_P = \frac{1}{T}\sum_{t=1}^{T} r_t = \frac{1}{T}\sum_{t=1}^{T}(r_t^{\text{state}} \cdot r_t^{\text{exec}})$. This formulation provides a rich, informative signal throughout the episode, enabling the agent to learn efficiently from partially successful attempts while still having the

Table 1: **Main results on the BFCL V3 multi-turn benchmark.** Our method, Environment Tuning, significantly boosts the performance of all base models, achieving competitive results against proprietary models and outperforming several strong baselines using only 400 training samples.

Model	**BFCL V3 Multi Turn**				
	Average (%)	**Base (%)**	**Miss Func (%)**	**Miss Param (%)**	**Long Context (%)**
Claude Sonnet 4	57.00	63.00	58.00	51.00	56.00
GPT-4o	51.00	59.00	54.00	41.00	50.00
Gemini 2.5 Pro	28.75	32.00	29.00	22.00	32.00
o3	49.25	47.00	55.00	47.00	48.00
Arch-Agent-7B	42.05	47.15	53.75	34.20	33.10
xLAM-2-8b-fc-r	70.50	77.85	69.15	65.80	69.20
BitAgent-8B	36.99	47.85	33.20	26.15	40.75
Qwen2.5-7B-Instruct	7.00	9.33	9.33	6.33	3.00
+ Environment Tuning	36.92 **(+29.92)**	50.33 **(+41.00)**	40.33 **(+31.00)**	29.33 **(+23.00)**	27.67 **(+24.67)**
Llama-3.1-8B-Instruct	5.48	6.15	6.80	3.20	5.75
+ Environment Tuning	28.25 **(+22.77)**	28.20 **(+22.05)**	25.85 **(+19.05)**	22.15 **(+18.95)**	36.80 **(+31.05)**
ToolACE-2-Llama-3.1-8B	37.99	48.85	34.15	25.20	43.75
+ Environment Tuning	47.18 **(+9.19)**	55.20 **(+6.35)**	38.15 **(+4.00)**	38.20 **(+13.00)**	57.15 **(+13.40)**
watt-tool-8B	35.74	45.85	33.15	25.20	38.75
+ Environment Tuning	54.34 **(+18.50)**	64.15 **(+18.30)**	48.15 **(+15.00)**	40.20 **(+15.00)**	64.85 **(+26.10)**

freedom to discover novel problem-solving strategies. A detailed breakdown of the evaluation criteria is provided in Section B.

4 Experiment

4.1 Experiment settings

Benchmark. Our primary evaluations are conducted on the multi-turn subset of the Berkeley Function-Calling Leaderboard (BFCL) V3 (Patil et al., 2025b). This benchmark comprises a total of 800 samples, divided equally into four challenging splits: `Base`, `Missing Functions`, `Missing Parameters`, and `Long-Context`. More specifically, we construct a training set of 400 samples by selecting 100 from each split. The remaining 400 samples serve as our held-in test set to evaluate in-distribution performance. For out-of-distribution (OOD) evaluation, we use the BFCL V4 `web search` and `memory` tracks (Patil et al., 2025b) and ACEBench Agent split (Chen et al., 2025a) as our held-out test set. A detailed description of these benchmarks and their evaluation methodologies is available in Section C.1.

Models. To comprehensively evaluate our approach, we categorize the models used in our experiments into three groups.

- **Base models:** These are the open-source models upon which we apply Environment Tuning method. We select `Qwen2.5-7B-Instruct` (Qwen et al., 2025) and `Llama-3.1-8B-Instruct` (Grattafiori et al., 2024) as our primary base models. As successfully applying reinforcement learning to Llama-based models has proven difficult (Zeng et al., 2025; Wang et al., 2025b; Gandhi et al., 2025), we also include two SFT-tuned versions of Llama-3.1-8B-Instruct: `ToolACE-2-Llama-3.1-8B` (Liu et al., 2024) and `watt-tool-8B`[1]. Using these SFT-tuned models as base models allows us to demonstrate the general applicability of Environment Tuning on models that are already strong in tool use.
- **Open-source baselines:** To contrast our environment-centric RL approach with prevailing data-driven methods, we compare against four state-of-the-art SFT-tuned models: `Arch-Agent-7B`[2], `xLAM-2-8b-fc-r` (Prabhakar et al., 2025), and `BitAgent-8B`[3]. As discussed in Section 2, these models are representative of the dominant data synthesis paradigm to handle data scarcity issue (ℂ1).
- **Proprietary models:** To benchmark against the absolute state-of-the-art, we include leading proprietary models such as `Claude Sonnet 4` (Anthropic, 2025), `GPT-4o` (Hurst et al., 2024), `Gemini 2.5 Pro` (Comanici et al., 2025), and `o3` (OpenAI, 2025b). These models serve as a reference for top-tier performance.

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[1] `https://huggingface.co/watt-ai/watt-tool-8B`

[2] `https://huggingface.co/katanemo/Arch-Agent-7B`

[3] `https://huggingface.co/BitAgent/BitAgent-8B`

Table 2: **OOD Generalization performance on the BFCL V4 benchmarks and ACEBench Agent**. All results are compared against the **Llama-3.1-8B-Instruct** base model. **Blue text** indicates a performance improvement over the base model, while **orange text** indicates a performance degradation. Models trained with ENVIRONMENT TUNING (rows in blue) show consistent improvements, whereas SFT baselines (rows in red) often underperform the base model on these OOD tasks.

Model	**BFCL V4 Web Search**			**BFCL V4 Memory**				**ACEBench Agent**		
	Avg. (%)	**Base (%)**	**No Snippet (%)**	**Avg. (%)**	**KV (%)**	**Vector (%)**	**Recursive Sum (%)**	**Avg. (%)**	**Multi-turn (%)**	**Multi-step (%)**
xLAM-2-8b-fc-r	**5.00**	**8.00**	**2.00**	**13.33**	**7.10**	**14.19**	**18.71**	1.65	0.00	3.33
BitAgent-8B	**4.50**	**7.00**	**2.00**	**10.32**	**2.58**	**16.77**	**11.61**	**5.00**	**10.00**	**0.00**
Llama-3.1-8B-Instruct	1.00	1.00	1.00	15.91	5.81	15.48	26.45	1.65	0.00	3.33
+ ENVIRONMENT TUNING	**15.00**	**24.00**	**6.00**	**18.06**	**17.42**	**26.45**	**10.32**	**4.17**	**5.00**	3.33
ToolACE-2-Llama-3.1-8B	**9.00**	**13.00**	**5.00**	**22.80**	**7.10**	**24.52**	**36.77**	**8.34**	**10.00**	**6.67**
+ ENVIRONMENT TUNING	**14.00**	**23.00**	**5.00**	**19.57**	**8.39**	**18.06**	**32.26**	**15.00**	**10.00**	**20.00**
watt-tool-8B	**4.00**	**5.00**	**3.00**	**13.33**	**3.23**	**14.19**	**22.58**	**2.50**	**5.00**	**0.00**
+ ENVIRONMENT TUNING	**8.00**	**15.00**	**1.00**	**19.35**	**7.10**	**27.10**	**23.87**	**7.50**	0.00	**15.00**

Agent training. For agent training, we employ an adapted version of the Group-Relative Policy Optimization (GRPO) algorithm (Shao et al., 2024), enhanced with a decoupled clipping mechanism and a KL-divergence penalty to ensure stable and effective exploration; full implementation details are provided in Section C.2.

4.2 Main results

Results on multi-turn tool use. Our method demonstrates substantial effectiveness in the in-distribution, multi-turn tool use scenarios presented in BFCL V3. As shown in Table 1, ENVIRONMENT TUNING yields significant performance gains across all base models.

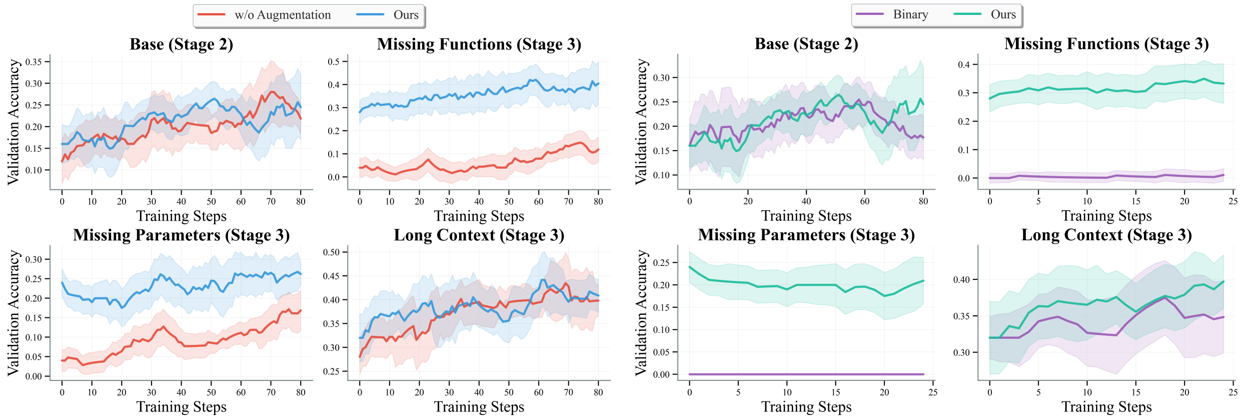
- **Significant performance uplift from scratch.** When applied directly to base models, ENVIRONMENT TUNING proves to be a highly effective training paradigm that consistently works across different model architectures. For instance, it boosts Qwen2.5-7B-Instruct's score from 7.00% to 36.92%, surpassing two strong baselines (BitAgent-8B and Arch-Agent-7B) and the proprietary Gemini 2.5 Pro model.
- **Effective enhancement of SFT-tuned models.** Our method also serves as a powerful online refinement tool for models that have already undergone SFT. On ToolACE-2-Llama-3.1-8B, a model built upon the RL-challenging Llama architecture, ENVIRONMENT TUNING still provides a significant improvement (9.19%). This elevates its performance to 47.18%, surpassing the proprietary Gemini 2.5 Pro model. Similarly, on watt-tool-8B, ENVIRONMENT TUNING achieves an impressive 18.50% improvement, boosting performance from 35.74% to 54.34%, which exceeds most proprietary models including o3 and GPT-4o.

Results on OOD agentic tasks. One strength of ENVIRONMENT TUNING lies in its ability to foster robust generalization, which we evaluate on the OOD benchmarks from BFCL V4 and ACEBench Agent (Table 2). The results reveal a clear distinction between ENVIRONMENT TUNING and supervised fine-tuning on trajectories.

- **Superior generalization over SFT baselines.** The limitations of overfitting to static datasets become evident here. Both SFT baselines exhibit a dramatic performance collapse on the OOD Web Search task, with even the top-performer, xLAM-2 (70.50% on BFCL V3), dropping to just 5.00%. This pattern persists across diverse OOD benchmarks, which underscores a critical weakness in training solely on synthetic trajectories.
- **ENVIRONMENT TUNING fosters robust generalization.** In contrast to the SFT baselines, our method demonstrates superior generalization by training agents through direct environmental interaction. For instance, ENVIRONMENT TUNING transforms Llama-3.1-8B-Instruct, which performs poorly on the Web Search task (1.00%), into a strong performer at 15.00%, showcasing its ability to teach general problem-solving principles rather than dataset-specific patterns.
- **Enhances generalization of already proficient models.** Our method can also patch the generalization gaps left by SFT. The base ToolACE-2 model already shows decent OOD performance (9.00% on Web Search), far exceeding other baselines. Yet, ENVIRONMENT TUNING further enhances its capability, increasing its score to 14.00%, demonstrating that interactive learning is crucial for building truly adaptable agents. This enhancement extends to ACEBench Agent, where ENVIRONMENT TUNING boosts ToolACE-2's average score from 8.34% to 15.00%.

4.3 Ablation study

Effect of actionable environment augmentation. To validate the contribution of our Actionable Environment Augmentation, we conduct an ablation study comparing training dynamics with and without the augmented feedback mechanism. As illustrated in Figure 4(a), the augmented environment provides crucial learning signals that enable the agent to navigate complex scenarios more effectively.



((a)) Ablation study for environment augmentation.

((b)) Ablation study for progress reward.

Figure 4: **Training dynamics comparison for ENVIRONMENT TUNING on Qwen2.5-7B-Instruct.** (a) The effect of Actionable Environment Augmentation on learning stability and performance across different data splits. (b) The impact of fine-grained Progress Reward versus binary reward on training effectiveness, showing the critical role of dense reward signals in complex multi-turn scenarios.

- The augmented environment consistently leads to more stable learning curves across all data splits, particularly in the challenging `Missing Parameters` and `Missing Functions` scenarios.
- *For the* `Missing Parameters` *and* `Missing Functions` *splits, Environment Augmentation brings substantial performance improvements of over 20%, demonstrating its critical role in enabling effective learning on these complex, ambiguous tasks.*

Effect of fine-grained progress reward. We also conduct an ablation study to verify the effectiveness of our fine-grained Progress Reward (R_P) against a standard binary reward. As shown in Figure 4(b), the impact of the reward design varies significantly with task complexity:

- During Stage 2, which focuses on the `Base` data, the performance difference is subtle, suggesting that a simple binary signal is sufficient for foundational tasks.
- However, as the curriculum progresses to more complex splits in Stage 3, the necessity of a denser reward becomes starkly evident. *For the* `Missing Parameters` *and* `Missing Functions` *splits, the binary reward leads to complete training failure, with performance close to zero, as the sparse signal provides no incentive for the necessary exploratory actions.*
- Meanwhile, on the `Long Context` split, our Progress Reward leads to substantially more stable and effective learning.

Effect of structured curriculum. To isolate the impact of our four-stage curriculum, we conduct an ablation study comparing our full method against two baselines on the Qwen2.5-7B-Instruct model: (1) the base pre-trained model, and (2) a direct GRPO training baseline. For this baseline, the agent is trained on the full 400-sample dataset from the start using a combined reward function of $0.9 \cdot R_P + 0.1 \cdot R_{\text{format}}$, without changing all other hyperparameters. As shown in Table 3, directly applying RL yields minimal gains, highlighting the "cold-start" problem where the agent fails to learn effectively. In contrast, our curriculum provides a clear and steady improvement path. *Each stage brings varying degrees of improvement, ultimately boosting the final performance to 36.92%, a 19.50% increase over the direct GRPO baseline.*

Table 3: **Effectiveness of the structured curriculum on Qwen2.5-7B.** Performance comparison across different training stages, showing how each stage contributes to overall improvement. Abbreviations: M. Func = Missing Functions, M. Param = Missing Parameters, L. Ctxt = Long-Context.

Training Stage	**BFCL V3 Multi Turn**				
	Avg.	**Base**	**M. Func**	**M. Param**	**L. Ctxt**
Qwen2.5-7B-Instruct	7.00	9.33	9.33	6.33	3.00
+ GRPO	17.42	20.00	24.67	14.67	10.33
+ Stage 1	15.50	19.00	22.33	9.33	11.33
+ Stage 2	25.83	32.00	33.67	20.00	17.67
+ Stage 3	32.00	44.67	34.33	25.33	23.67
+ Stage 4 (ours)	**36.92**	**50.33**	**40.33**	**29.33**	**27.67**

5 Conclusion

In this work, we proposed ENVIRONMENT TUNING, a novel training paradigm for multi-turn, tool-augmented agents under extreme data scarcity. By shifting the focus from trajectory imitation to environment-driven exploration, and combining a structured curriculum, actionable environment augmentation, and fine-grained progress rewards, our method enables agents to learn stably and generalize from only 400 problem instances without expert demonstrations. Experiments on BFCL show that ENVIRONMENT TUNING not only yields substantial in-distribution improvements but also significantly enhances out-of-distribution generalization, outperforming several strong supervised baselines. We believe this environment-centric approach offers a promising direction for developing robust, adaptable agents in realistic, resource-limited settings. Our work also opens several exciting avenues for future research, including the development of automated mechanisms for curriculum and feedback generation and the extension of ENVIRONMENT TUNING to more complex, multi-modal agentic scenarios.

References

Anthropic. System Card: Claude Opus 4 & Claude Sonnet 4. https://www-cdn.anthropic.com/4263b940cabb546aa0e3283f35b686f4f3b2ff47.pdf, 2025.

Chen Chen, Xinlong Hao, Weiwen Liu, Xu Huang, Xingshan Zeng, Shuai Yu, Dexun Li, Shuai Wang, Weinan Gan, Yuefeng Huang, et al. Acebench: Who wins the match point in tool usage? *arXiv preprint arXiv:2501.12851*, 2025a.

Mingyang Chen, Linzhuang Sun, Tianpeng Li, Yijie Zhou, Chenzheng Zhu, and Fan Yang. Recall: Learning to reason with tool call for llms via reinforcement learning. Online Notion Blog Post, 2025b. URL https://attractive-almandine-935.notion.site/ReCall-Learning-to-Reason-with-Tool-Call-for-LLMs-via-Reinforcement-Learning-1d7aec91e9bb8006ad40f9edbfe21

Tianzhe Chu, Yuexiang Zhai, Jihan Yang, Shengbang Tong, Saining Xie, Dale Schuurmans, Quoc V Le, Sergey Levine, and Yi Ma. Sft memorizes, rl generalizes: A comparative study of foundation model post-training. In *Forty-second International Conference on Machine Learning*, 2025.

Gheorghe Comanici, Eric Bieber, Mike Schaekermann, Ice Pasupat, Noveen Sachdeva, Inderjit Dhillon, Marcel Blistein, Ori Ram, Dan Zhang, Evan Rosen, et al. Gemini 2.5: Pushing the frontier with advanced reasoning, multimodality, long context, and next generation agentic capabilities. *arXiv preprint arXiv:2507.06261*, 2025.

Guanting Dong, Hangyu Mao, Kai Ma, Licheng Bao, Yifei Chen, Zhongyuan Wang, Zhongxia Chen, Jiazhen Du, Huiyang Wang, Fuzheng Zhang, et al. Agentic reinforced policy optimization. *arXiv preprint arXiv:2507.19849*, 2025.

Jiazhan Feng, Shijue Huang, Xingwei Qu, Ge Zhang, Yujia Qin, Baoquan Zhong, Chengquan Jiang, Jinxin Chi, and Wanjun Zhong. Retool: Reinforcement learning for strategic tool use in llms. *arXiv preprint arXiv:2504.11536*, 2025a.

Lang Feng, Zhenghai Xue, Tingcong Liu, and Bo An. Group-in-group policy optimization for llm agent training. *arXiv preprint arXiv:2505.10978*, 2025b.

Kanishk Gandhi, Ayush Chakravarthy, Anikait Singh, Nathan Lile, and Noah D Goodman. Cognitive behaviors that enable self-improving reasoners, or, four habits of highly effective stars. *arXiv preprint arXiv:2503.01307*, 2025.

Aaron Grattafiori, Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Alex Vaughan, et al. The llama 3 herd of models. *arXiv preprint arXiv:2407.21783*, 2024.

Jujie He, Jiacai Liu, Chris Yuhao Liu, Rui Yan, Chaojie Wang, Peng Cheng, Xiaoyu Zhang, Fuxiang Zhang, Jiacheng Xu, Wei Shen, et al. Skywork open reasoner 1 technical report. *arXiv preprint arXiv:2505.22312*, 2025.

Dan Hendrycks, Collin Burns, Saurav Kadavath, Akul Arora, Steven Basart, Eric Tang, Dawn Song, and Jacob Steinhardt. Measuring mathematical problem solving with the math dataset. *arXiv preprint arXiv:2103.03874*, 2021.

Jian Hu, Jason Klein Liu, Haotian Xu, and Wei Shen. Reinforce++: An efficient rlhf algorithm with robustness to both prompt and reward models. *arXiv preprint arXiv:2501.03262*, 2025.

Aaron Hurst, Adam Lerer, Adam P Goucher, Adam Perelman, Aditya Ramesh, Aidan Clark, AJ Ostrow, Akila Welihinda, Alan Hayes, Alec Radford, et al. Gpt-4o system card. *arXiv preprint arXiv:2410.21276*, 2024.

Carlos E Jimenez, John Yang, Alexander Wettig, Shunyu Yao, Kexin Pei, Ofir Press, and Karthik R Narasimhan. Swe-bench: Can language models resolve real-world github issues? In *The Twelfth International Conference on Learning Representations*, 2023.

Bowen Jin, Hansi Zeng, Zhenrui Yue, Jinsung Yoon, Sercan Arik, Dong Wang, Hamed Zamani, and Jiawei Han. Search-r1: Training llms to reason and leverage search engines with reinforcement learning. *arXiv preprint arXiv:2503.09516*, 2025a.

Bowen Jin, Hansi Zeng, Zhenrui Yue, Jinsung Yoon, Sercan Arik, Dong Wang, Hamed Zamani, and Jiawei Han. Search-r1: Training llms to reason and leverage search engines with reinforcement learning, 2025b.

Hynek Kydlíček. Math-Verify: Math Verification Library, 2025. URL `https://github.com/huggingface/math-verify`.

Xuefeng Li, Haoyang Zou, and Pengfei Liu. Torl: Scaling tool-integrated rl. *arXiv preprint arXiv:2503.23383*, 2025.

Mingjie Liu, Shizhe Diao, Ximing Lu, Jian Hu, Xin Dong, Yejin Choi, Jan Kautz, and Yi Dong. Prorl: Prolonged reinforcement learning expands reasoning boundaries in large language models. *arXiv preprint arXiv:2505.24864*, 2025.

Weiwen Liu, Xu Huang, Xingshan Zeng, Xinlong Hao, Shuai Yu, Dexun Li, Shuai Wang, Weinan Gan, Zhengying Liu, Yuanqing Yu, et al. Toolace: Winning the points of llm function calling. *arXiv preprint arXiv:2409.00920*, 2024.

Xinji Mai, Haotian Xu, Weinong Wang, Jian Hu, Yingying Zhang, Wenqiang Zhang, et al. Agent rl scaling law: Agent rl with spontaneous code execution for mathematical problem solving. *arXiv preprint arXiv:2505.07773*, 2025.

Moonshot AI. Kimi-researcher: End-to-end rl training for emerging agentic capabilities. Technical report, Moonshot AI, 2025. URL `https://moonshotai.github.io/Kimi-Researcher/`. Accessed via `https://moonshotai.github.io/Kimi-Researcher/`.

OpenAI. Deep research system card. System card, OpenAI, February 2025a. URL `https://cdn.openai.com/deep-research-system-card.pdf`.

OpenAI. OpenAI o3 and o4-mini System Card. `https://cdn.openai.com/pdf/2221c875-02dc-4789-800b-e7758f3722c1/o3-and-o4-mini-system-card.pdf`, 2025b.

OpenAI. Operator system card. System card, OpenAI, January 2025c. URL `https://cdn.openai.com/operator_system_card.pdf`.

Shishir G. Patil, Huanzhi Mao, Charlie Cheng-Jie Ji, Fanjia Yan, Vishnu Suresh, Yixin Huang, Xiaowen Yu, and Joseph E. Gonzalez. Bfcl v3: Multi-turn & multi-step function calling. Gorilla Blog Post, September 2025a. URL `https://gorilla.cs.berkeley.edu/blogs/13_bfcl_v3_multi_turn.html`. Release date: 2024-09-19. Last updated: 2024-12-10.

Shishir G. Patil, Huanzhi Mao, Charlie Cheng-Jie Ji, Fanjia Yan, Vishnu Suresh, Ion Stoica, and Joseph E. Gonzalez. The berkeley function calling leaderboard (bfcl): From tool use to agentic evaluation of large language models. In *Forty-second International Conference on Machine Learning*, 2025b.

Akshara Prabhakar, Zuxin Liu, Ming Zhu, Jianguo Zhang, Tulika Awalgaonkar, Shiyu Wang, Zhiwei Liu, Haolin Chen, Thai Hoang, Juan Carlos Niebles, et al. Apigen-mt: Agentic pipeline for multi-turn data generation via simulated agent-human interplay. *arXiv preprint arXiv:2504.03601*, 2025.

Qwen, :, An Yang, Baosong Yang, Beichen Zhang, Binyuan Hui, Bo Zheng, Bowen Yu, Chengyuan Li, Dayiheng Liu, Fei Huang, Haoran Wei, Huan Lin, Jian Yang, Jianhong Tu, Jianwei Zhang, Jianxin Yang, Jiaxi Yang, Jingren Zhou, Junyang Lin, Kai Dang, Keming Lu, Keqin Bao, Kexin Yang, Le Yu, Mei Li, Mingfeng Xue, Pei Zhang, Qin Zhu, Rui Men, Runji Lin, Tianhao Li, Tianyi Tang, Tingyu Xia, Xingzhang Ren, Xuancheng Ren, Yang Fan, Yang Su, Yichang Zhang, Yu Wan, Yuqiong Liu, Zeyu Cui, Zhenru Zhang, and Zihan Qiu. Qwen2.5 technical report, 2025.

John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. Proximal policy optimization algorithms. *arXiv preprint arXiv:1707.06347*, 2017.

Zhihong Shao, Peiyi Wang, Qihao Zhu, Runxin Xu, Junxiao Song, Xiao Bi, Haowei Zhang, Mingchuan Zhang, YK Li, Yang Wu, et al. Deepseekmath: Pushing the limits of mathematical reasoning in open language models. *arXiv preprint arXiv:2402.03300*, 2024.

Idan Shenfeld, Jyothish Pari, and Pulkit Agrawal. Rl's razor: Why online reinforcement learning forgets less. *arXiv preprint arXiv:2509.04259*, 2025.

Joykirat Singh, Raghav Magazine, Yash Pandya, and Akshay Nambi. Agentic reasoning and tool integration for llms via reinforcement learning. *arXiv preprint arXiv:2505.01441*, 2025.

Haoxiang Sun, Yingqian Min, Zhipeng Chen, Wayne Xin Zhao, Lei Fang, Zheng Liu, Zhongyuan Wang, and Ji-Rong Wen. Challenging the boundaries of reasoning: An olympiad-level math benchmark for large language models. *arXiv preprint arXiv:2503.21380*, 2025.

Jean Vassoyan, Nathanaël Beau, and Roman Plaud. Ignore the kl penalty! boosting exploration on critical tokens to enhance rl fine-tuning. *arXiv preprint arXiv:2502.06533*, 2025.

Lei Wang, Chen Ma, Xueyang Feng, Zeyu Zhang, Hao Yang, Jingsen Zhang, Zhiyuan Chen, Jiakai Tang, Xu Chen, Yankai Lin, et al. A survey on large language model based autonomous agents. *Frontiers of Computer Science*, 18(6):186345, 2024.

Xinyuan Wang, Bowen Wang, Dunjie Lu, Junlin Yang, Tianbao Xie, Junli Wang, Jiaqi Deng, Xiaole Guo, Yiheng Xu, Chen Henry Wu, et al. Opencua: Open foundations for computer-use agents. *arXiv preprint arXiv:2508.09123*, 2025a.

Zengzhi Wang, Fan Zhou, Xuefeng Li, and Pengfei Liu. Octothinker: Mid-training incentivizes reinforcement learning scaling. *arXiv preprint arXiv:2506.20512*, 2025b.

Zihan Wang, Kangrui Wang, Qineng Wang, Pingyue Zhang, Linjie Li, Zhengyuan Yang, Xing Jin, Kefan Yu, Minh Nhat Nguyen, Licheng Liu, et al. Ragen: Understanding self-evolution in llm agents via multi-turn reinforcement learning. *arXiv preprint arXiv:2504.20073*, 2025c.

Jason Wei, Zhiqing Sun, Spencer Papay, Scott McKinney, Jeffrey Han, Isa Fulford, Hyung Won Chung, Alex Tachard Passos, William Fedus, and Amelia Glaese. Browsecomp: A simple yet challenging benchmark for browsing agents. *arXiv preprint arXiv:2504.12516*, 2025.

Lilian Weng. Llm-powered autonomous agents. *lilianweng.github.io*, Jun 2023. URL `https://lilianweng.github.io/posts/2023-06-23-agent/`.

Ronald J Williams. Reinforcement learning and markov decision processes. *CSG220, Spring*, 2007.

Tianbao Xie, Danyang Zhang, Jixuan Chen, Xiaochuan Li, Siheng Zhao, Ruisheng Cao, Toh J Hua, Zhoujun Cheng, Dongchan Shin, Fangyu Lei, et al. Osworld: Benchmarking multimodal agents for open-ended tasks in real computer environments. *Advances in Neural Information Processing Systems*, 37:52040–52094, 2024.

Zhenghai Xue, Longtao Zheng, Qian Liu, Yingru Li, Xiaosen Zheng, Zejun Ma, and Bo An. Simpletir: End-to-end reinforcement learning for multi-turn tool-integrated reasoning, 2025.

John Yang, Carlos E Jimenez, Alexander Wettig, Kilian Lieret, Shunyu Yao, Karthik Narasimhan, and Ofir Press. Swe-agent: Agent-computer interfaces enable automated software engineering. *Advances in Neural Information Processing Systems*, 37:50528–50652, 2024.

Fan Yin, Zifeng Wang, I Hsu, Jun Yan, Ke Jiang, Yanfei Chen, Jindong Gu, Long T Le, Kai-Wei Chang, Chen-Yu Lee, et al. Magnet: Multi-turn tool-use data synthesis and distillation via graph translation. *arXiv preprint arXiv:2503.07826*, 2025.

Qiying Yu, Zheng Zhang, Ruofei Zhu, Yufeng Yuan, Xiaochen Zuo, Yu Yue, Weinan Dai, Tiantian Fan, Gaohong Liu, Lingjun Liu, et al. Dapo: An open-source llm reinforcement learning system at scale. *arXiv preprint arXiv:2503.14476*, 2025.

Weihao Zeng, Yuzhen Huang, Qian Liu, Wei Liu, Keqing He, Zejun Ma, and Junxian He. Simplerl-zoo: Investigating and taming zero reinforcement learning for open base models in the wild. *arXiv preprint arXiv:2503.18892*, 2025.

Jianguo Zhang, Tian Lan, Ming Zhu, Zuxin Liu, Thai Hoang, Shirley Kokane, Weiran Yao, Juntao Tan, Akshara Prabhakar, Haolin Chen, et al. xlam: A family of large action models to empower ai agent systems. *arXiv preprint arXiv:2409.03215*, 2024.

Yuxiang Zheng, Dayuan Fu, Xiangkun Hu, Xiaojie Cai, Lyumanshan Ye, Pengrui Lu, and Pengfei Liu. Deepresearcher: Scaling deep research via reinforcement learning in real-world environments. *arXiv preprint arXiv:2504.03160*, 2025.

A Sequential Multi-turn Decision-Making Model.

We model the multi-turn tool-use task as a Partially Observable Markov Decision Process (POMDP) (Williams, 2007). An episode corresponds to a complete user task, which is composed of a sequence of pre-defined user requests, or "turns."

Let's denote the sequence of user requests as $q_1, q_2, ..., q_N$. The interaction begins with the agent receiving an initial observation o_0 containing the first request q_1 and the available tool documentation. The agent then engages in a series of steps to address this request. At each step t, the agent's policy $\pi_\theta(a_t|o_t)$ generates an action a_t from a structured action space $\mathcal{A}$, which includes:

- **Tool Call (a_t^{tool}):** A structured call to one or more tools to gather information (e.g., `<tool_call>...</tool_call>`). The environment executes the call and returns an observation containing the tool's output.
- **Final Answer (a_t^{answer}):** A natural language response to the user (e.g., `<answer>...</answer>`). This completes the current sub-task, after which the environment presents the next pre-defined user request.

The process for a single turn i unfolds as a sub-trajectory of tool calls until the agent produces a final answer. Upon generating a_t^{answer}, the environment transitions by revealing the next request q_{i+1} within the new observation o_{t+1}. This cycle repeats for all N requests.

The entire episode, a trajectory $\tau = (o_0, a_0, o_1, a_1, ..., o_T)$, concludes only after the agent has provided a final answer for the last request, q_N. It is only at this point, after T steps, that the agent receives a *sparse and terminal reward* $R_T \in \{0, 1\}$, indicating the overall success or failure of the entire multi-turn task. This delayed and binary feedback makes it extremely difficult for RL algorithms to perform effective credit assignment and exploration, a well-known challenge in long-horizon tasks (Wang et al., 2025c; Feng et al., 2025b).

The agent's objective is to learn the policy parameters θ that maximize the expected terminal reward:

$$J(\theta) = \mathbb{E}_{\tau \sim \pi_\theta, P}[R_T] \tag{3}$$

B Detailed Progress Reward Components

As mentioned in the main text, our **Progress Reward** (R_P) provides a dense, turn-by-turn learning signal by evaluating the outcome of the agent's actions rather than the specific actions themselves. This evaluation is based on two distinct criteria: the resulting **environment state** and the **execution results** of tool calls. A turn is considered successful, receiving a score of 1, only if it is correct on both criteria; otherwise, it receives a score of 0. The final reward for an entire episode is calculated as the proportion of successful turns. Below, we provide a detailed breakdown of each evaluation component.

Environment State Evaluation. This criterion addresses function calls that modify the environment, such as creating a file or booking a flight. The environment's state faithfully reflects the cumulative effect of these operations. Therefore, at the end of each evaluation turn, we compare the current environment state against the ground-truth state. This approach allows us to focus on whether the agent's actions achieve the desired final state, rather than prescribing a specific execution path. This makes the evaluation both accurate and flexible, enabling an objective assessment of the outcomes for any function calls that produce tangible changes to the environment.

Execution Result Evaluation. This evaluation method is designed for functions whose outcomes are primarily communicated through their return values, rather than through changes to the environment's state. This category includes not only information retrieval tasks (e.g., fetching a stock price or checking the weather) but also any operation where the immediate output is the critical result. Since these actions do not leave a persistent trace in the environment's state, a state-based comparison would be ineffective. Instead, we directly assess the correctness of the execution by inspecting the function's return value. We compare this output against the expected ground-truth result to verify that the agent has successfully performed the required computation or query. This ensures that all tool calls, regardless of whether they modify the environment, are accurately evaluated.

C Implementation Details

C.1 Training Dataset

BFCL V3 for Training and In-Distribution Evaluation. Our primary training and evaluation are conducted on the multi-turn subset of the Berkeley Function-Calling Leaderboard (BFCL) V3 (Patil et al., 2025b). The benchmark is specifically designed to test an agent's ability to orchestrate diverse tools over extended, stateful interactions. A key innovation of BFCL is its evaluation methodology, which verifies the final state of the environment (e.g., file system changes) rather than just the syntax of tool calls, providing a more realistic measure of task success. The BFCL V3 multi-turn benchmark comprises a total of 800 samples, divided equally into four challenging splits of 200 samples each: `Base Multi-Turn`, `Missing Parameters`, `Missing Functions`, and `Long-Context`. For our experiments, we construct a training set of 400 samples by selecting 100 from each split. The remaining 400 samples serve as our held-in test set to evaluate in-distribution performance.

BFCL V4 for Out-of-Distribution Evaluation. To assess out-of-distribution (OOD) generalization, we use two newly released agentic tracks from BFCL V4 (Patil et al., 2025b): Web Search and Memory. The release date of this data post-dates the training data of all models used in our study, ensuring a fair evaluation.

- **Web Search Track:** This track evaluates an agent's ability to answer complex, multi-hop questions that require retrieving and synthesizing information from multiple web sources. Agents are provided with a search API (`duckduckgo_search`) and a URL content fetching tool (`fetch_url_content`). The environment also introduces probabilistic network failures to simulate real-world conditions.
- **Memory Track:** This track tests an agent's capacity to maintain conversational context by storing and retrieving information over long interactions. The evaluation is conducted across three different memory backends: a structured Key-Value store for exact lookups, a Vector Store for semantic retrieval, and a Recursive Summarization store for narrative recall.

These advanced agentic tasks provide a rigorous testbed for the generalization capabilities of our environment-tuned models.

ACEBench for Advanced Agentic OOD Evaluation. To further probe the limits of our models' generalization, we incorporate the **Agent split** from ACEBench (Chen et al., 2025a) as an additional OOD testbed. ACEBench was designed to evaluate agents in dynamic, multi-turn dialogues that more closely mimic real-world interactions. The 'Agent' split, in particular, assesses advanced capabilities by requiring models to operate within a sandboxed environment where success depends on multi-step reasoning, long-term context management, and adherence to implicit task rules. Its documented difficulty for even state-of-the-art models makes it an ideal benchmark for measuring the robust planning and adaptive behaviors fostered by our ENVIRONMENT TUNING training paradigm.

C.2 Training Details

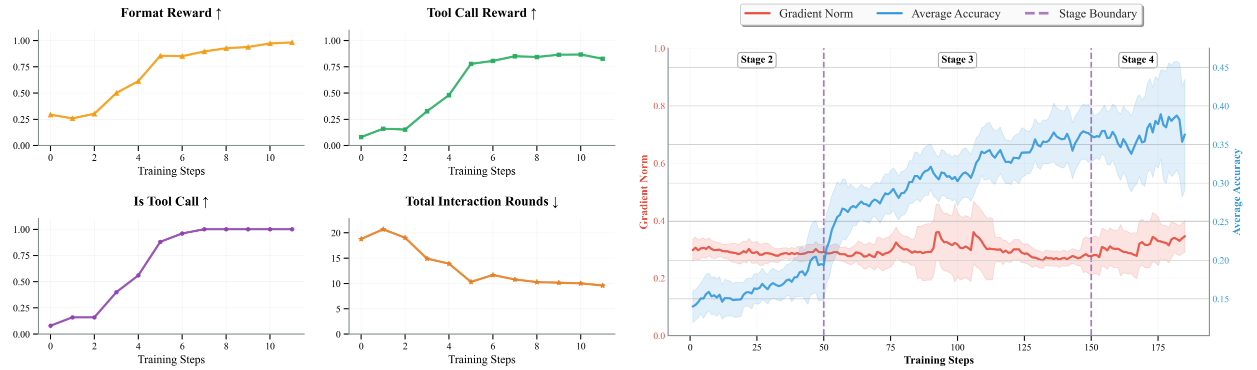
We train the agent's policy π_θ using an adapted PPO algorithm (Schulman et al., 2017). Our implementation incorporates enhancements for stability and exploration from recent reasoning-focused RL methods like DAPO (Yu et al., 2025) and ProRL (Liu et al., 2025). This involves using a decoupled clipping mechanism and adding a KL divergence penalty to the objective. The final loss function $\mathcal{L}(\theta)$ that the agent minimizes is defined as:

$$\mathcal{L}(\theta) = -\mathbb{E}_t\left[\min\left(r_t(\theta)\hat{A}_t,\, \text{clip}(r_t(\theta), 1-\epsilon_{\text{low}}, 1+\epsilon_{\text{high}})\hat{A}_t\right)\right] + \beta D_{\text{KL}}(\pi_\theta \,\|\, \pi_{\text{ref}}) \tag{4}$$

where $r_t(\theta)$ is the probability ratio $\pi_\theta(a_t|o_t)/\pi_{\theta_{\text{old}}}(a_t|o_t)$. The advantage estimate $\hat{A}_t$ is computed without a critic network by normalizing rewards within a batch, following the Group-Relative Policy Optimization (GRPO) method (Shao et al., 2024):

$$\hat{A}_t(\tau) = \frac{R(\tau) - \mu_{\mathcal{G}}}{\sigma_{\mathcal{G}} + \varepsilon_A} \tag{5}$$

Here, for a given trajectory τ from a group of samples $\mathcal{G}$ generated for the same prompt, $R(\tau)$ is its terminal reward, while $\mu_{\mathcal{G}}$ and $\sigma_{\mathcal{G}}$ are the mean and standard deviation of rewards across the group. The term D_{KL} regularizes the policy against a reference policy π_{ref}, and ε_A is a small constant for numerical stability. For our experiments, we set the KL-divergence coefficient $\beta = 0.1$ and the decoupled clipping values to $\epsilon_{\text{low}} = 0.2$ and $\epsilon_{\text{high}} = 0.28$. The justification for our choice of a relatively high KL coefficient is provided in Section D.3.



((a)) Stage 1 Dynamics.

((b)) Full Curriculum Dynamics.

Figure 5: Training dynamics of ENVIRONMENT TUNING on the Qwen2.5-7B-Instruct model using the BFCL V3 dataset. A held-out set of 100 samples from the remaining BFCL data is used for validation. (a) In Stage 1, the agent rapidly masters syntactic correctness, shown by the steep rise in format and tool call rewards and the drop in interaction rounds. (b) Across the full four-stage curriculum, the agent demonstrates both steady performance improvement on the validation set and stable gradient norms, showcasing the effectiveness and stability of our staged learning approach.

D Supplementary Experiments

D.1 Training Dynamics

The effectiveness of our curriculum’s first stage is demonstrated by the agent’s rapid mastery of foundational skills, as shown in Figure 5(a). By training on a small amount of data with the specialized syntactic reward, we observe steep increases in both *Format Reward* and *Tool Call Reward*, indicating the agent has successfully learned the required output syntax and tool schemas. This stage also addresses a common failure mode of producing inactionable, conversational responses, or "void turns" (Xue et al., 2025). The swift saturation of the *Is Tool Call* metric to 1.0 shows that our curriculum effectively eliminates such turns. Critically, this mastery is paired with a sharp decline in *Total Interaction Rounds*, signifying a dramatic reduction in wasted, error-prone attempts and showcasing the efficiency of this foundational stage.

Beyond mastering syntax, a critical challenge in training multi-turn agents is maintaining stability over long interaction horizons. As identified by Xue et al. (2025), a primary cause of training collapse is the explosion of gradient norms. We use the gradient norm as a key indicator of training stability. Figure 5(b) shows that our structured curriculum effectively mitigates this instability; the gradient norm remains stable throughout the entire four-stage training process, preventing the catastrophic explosions that often plague long-horizon RL. This stability provides a solid foundation for genuine learning. Even with only 400 training instances, the agent’s performance on a held-out validation set exhibits steady and consistent improvement as it progresses through the curriculum. This demonstrates that ENVIRONMENT TUNING not only ensures training stability but also facilitates effective learning and generalization from extremely limited data.

D.2 Training Instability in Single-Stage RL

To provide empirical evidence for the training instability mentioned in Section 3, we conducted an experiment fine-tuning the Qwen2.5-7B-Instruct model directly on 400 training instances from the BFCL V3 benchmark. This was done using a standard, single-stage RL approach, without the structured curriculum or environment augmentation proposed in ENVIRONMENT TUNING.

The training dynamics are visualized in Figure 6. The agent’s average accuracy shows some initial improvement, peaking at approximately a 10-15% gain over the base model around step 60. However, this learning proves to be unsustainable. Starting around step 70, the gradient norm begins to explode, indicating severe training instability. This gradient explosion correlates directly with a catastrophic collapse in performance, as the average accuracy plummets back towards its initial level. This experiment confirms the fragility of direct RL fine-tuning in complex, multi-turn environments and underscores the necessity of a structured approach, like our proposed curriculum, to ensure stable and effective learning.

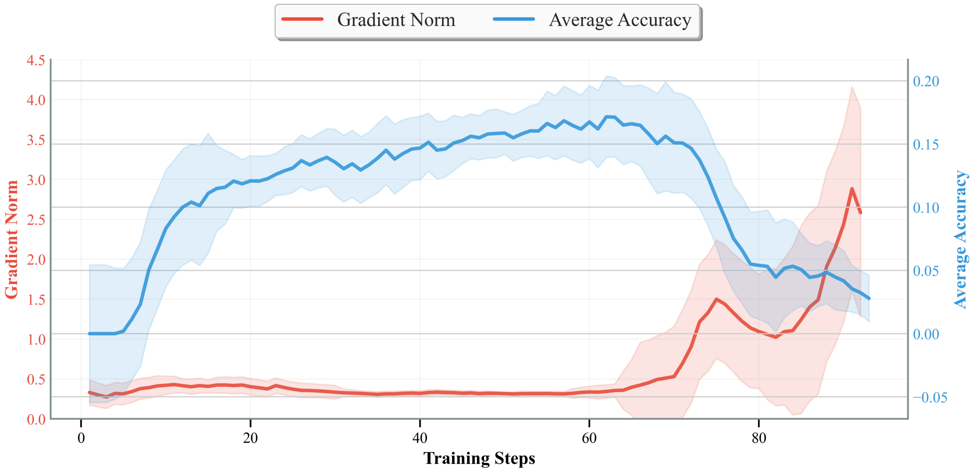


Figure 6: **Training Collapse in a Single-Stage RL Setup.** Training dynamics of Qwen2.5-7B-Instruct on the BFCL V3 benchmark without the ENVIRONMENT TUNING curriculum. The plot shows the average accuracy (blue) and the gradient norm (red). While accuracy initially improves, it begins a sharp decline after approximately 70 training steps. This performance collapse coincides precisely with a rapid explosion in the gradient norm, empirically demonstrating the training instability that our curriculum is designed to prevent.

D.3 KL Loss Coefficient

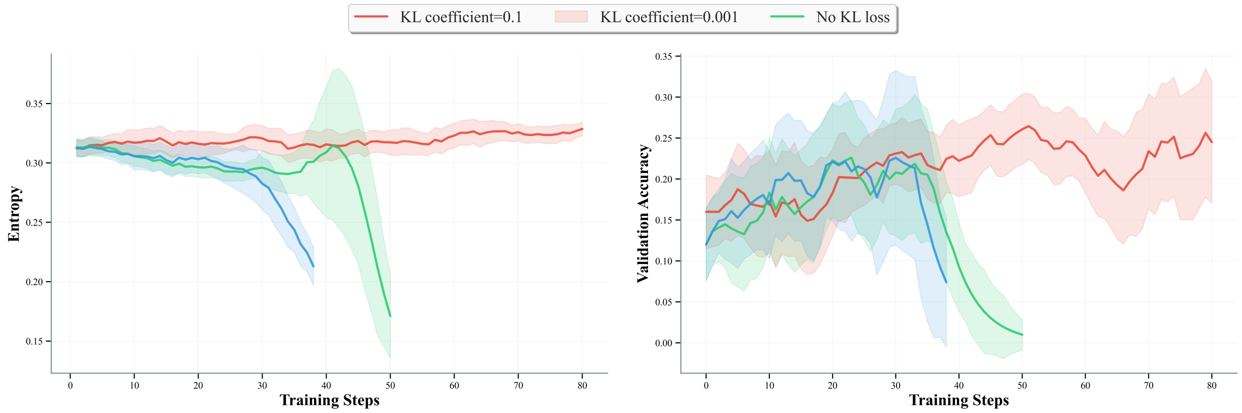


Figure 7: The impact of the KL loss coefficient on training stability and performance during Stage 2. A larger coefficient ($\beta = 0.1$) is crucial for maintaining high policy entropy (left), which prevents the performance collapse seen in settings with a small ($\beta = 0.001$) or no KL penalty (right). This stability allows for sustained learning and higher final accuracy.

Recent works have debated the role of the KL divergence penalty. While some methods advocate for its removal to maximize exploration (Yu et al., 2025; Xue et al., 2025; Vassoyan et al., 2025), others like ProRL (Liu et al., 2025) retain it to ensure stability during staged training. Conventionally, a small coefficient (e.g., 0.001) is often used (Wang et al., 2025c; Jin et al., 2025b). We find, however, that the long-horizon, stateful nature of multi-turn tool use requires stronger regularization to prevent policy collapse.

To validate this, we conduct an ablation study comparing our chosen KL coefficient ($\beta = 0.1$) against a smaller value ($\beta = 0.001$) and a baseline with no KL penalty. The results, shown in Figure 7, reveal the critical role of a substantial KL penalty. The left panel shows that without a KL penalty, the policy quickly suffers from entropy collapse. This leads to a sharp decline in validation accuracy (right panel) as the agent overfits to a narrow set of suboptimal trajectories. A small coefficient of 0.001 only delays this collapse but fails to prevent it. In contrast, a coefficient of 0.1 effectively maintains policy entropy, providing the stability for the agent to continue learning and steadily improve its accuracy. This confirms that a larger KL penalty is essential for stable learning in complex, multi-turn agentic environments, justifying our choice of $\beta = 0.1$.

E Prompt Templates

Stage One and Stage Two System Prompt

```
You are an expert in composing functions. You are given a question and a set of
    possible functions. Based on the question, you will need to make one or more
    function/tool calls to achieve the purpose. If none of the functions can be
    used, point it out and refuse to answer. If the given question lacks the
    parameters required by the function, also point it out.

You have access to the following tools:
$functions

Your response must strictly follow one of these two formats:

**Format 1: When you decide to invoke any of the function(s)**
<think>
Write your reasoning and thought process here. Analyze the / question, identify
    what needs to be done, and determine which functions to call with what
    parameters.
</think>
<tool_call>
[
    {”name”: ”func_name1”, ”arguments”: {”argument1”: ”value1”, ”argument2”:
        ”value2”}},
    {”name”: ”func_name2”, ”arguments”: {”argument3”: ”value3”}}
]
</tool_call>

**Format 2: When You have already fulfilled the user’s request, OR You must ask
    for additional information / refuse because no function applies or
    parameters are missing.**
<think>
Analyze the information you have gathered from previous tool calls and describe
    your reasoning that leads to the final reply, follow-up question, or refusal.
</think>
<answer>
Provide the final, user-facing message. If the request has been fully satisfied,
    give a summary of the result.If additional details are required or the
    request cannot be fulfilled, explicitly ask for the specific information
    needed.
</answer>

Important notes:
- Use Format 1 when you need to call function(s)
- Use Format 2 when you have already fulfilled the user’s request, OR you must
    ask for additional information / refuse because no function applies or
    parameters are missing
- If multiple function calls are needed in one response, include them all in the
    JSON array within the single <tool_call> block
- If no function call is needed, consider use the format 2
- Only use <answer> when you have fulfilled the user’s request or you need ask
    for additional information/ refuse
```

Stage Three and Stage Four System Prompt

```
You are an expert in composing functions. You are given a question and a set of
    possible functions. Based on the question, you will need to make one or more
    function/tool calls to achieve the purpose. If none of the functions can be
    used, point it out and refuse to answer. If the given question lacks the
    parameters required by the function, also point it out.

You have access to the following tools:
$functions

Your response must strictly follow one of these two formats:

**Format 1: When you decide to invoke any of the function(s)**
<think>
Write your reasoning and thought process here. Analyze the question, identify
    what needs to be done, and determine which functions to call with what
    parameters.
</think>
<tool_call>
[{”name”: ”func_name1”, ”arguments”: {”argument1”: ”value1”, ”argument2”:
    ”value2”}}, {”name”: ”func_name2”, ”arguments”: {”argument3”: ”value3”}}]
</tool_call>

**Format 2: When You have already fulfilled the user’s request, OR You must ask
    for additional information / refuse because no function applies or
    parameters are missing.**
<think>
Analyze the information you have gathered from previous tool calls and describe
    your reasoning that leads to the final reply, follow-up question, or refusal.
</think>
<answer>
Provide the final, user-facing message. If the request has been fully satisfied,
    give a summary of the result.If additional details are required or the
    request cannot be fulfilled, explicitly ask for the specific information
    needed.
</answer>

Important notes:
- Use Format 1 when you need to call function(s)
- Use Format 2 when you have already fulfilled the user’s request, OR you must
    ask for additional information / refuse because no function applies or
    parameters are missing
- **Be resourceful**: Before asking the user for missing information, first
    consider if any other available function can help you find it. This reduces
    unnecessary questions to the user.
- **Prioritize clarity over assumptions**: If a required function is not
    available, or if certain parameters are missing and cannot be retrieved by
    other tools, you MUST NOT proceed with a hallucinated tool call. Instead,
    use Format 2 to explicitly ask the user for the specific missing information.
- If multiple function calls are needed in one response, include them all in the
    JSON array within the single <tool_call> block
- If no function call is needed, consider use the format 2
- Only use <answer> when you have fulfilled the user’s request or you need ask
    for additional information/ refuse
```

F Case Study

In this section, we present a series of case studies to concretely demonstrate the impact of our proposed environment tuning. We juxtapose agent trajectories from two distinct settings: a baseline environment that provides minimal, often ambiguous or even misleading, feedback, and our tuned environment, which is enhanced to deliver rich, actionable feedback. Through these comparative analyses, we will highlight how the quality of environmental feedback is a critical factor that enables agents to more effectively diagnose errors, recover from mistakes, and ultimately succeed in complex, multi-turn tasks. We will use specific notes throughout the examples to draw attention to pivotal moments in the agent's trajectory that are directly influenced by the nature of the feedback received.

F.1 File System Management Scenario

This case study demonstrates how *Actionable Environment Augmentation* accelerates learning in a stateful file system environment. In the **good case**, enhanced feedback allowed the agent to correctly infer that the failure was due to a disallowed full path argument, not a missing file. This explicit guidance enabled it to reformulate its plan — changing the working directory before executing `rm` — and ultimately satisfy the user's request. In the corresponding **bad case**, the baseline environment's generic `"No such file or directory"` messages misled the agent into an incorrect diagnosis, causing premature task abandonment.

Task: Gorilla File System

User Query 1: **I've misplaced a vital document inclusive of extensive research. Assist in locating a file named 'findings_report' within this 'SuperResearch'. Could you remove it and the directory.**

<think>
The user wants to locate and remove a file named 'findings_report' within a directory named 'SuperResearch'. First, I will use the 'find' function to locate the 'findings_report' file under 'SuperResearch'. After that, I will use 'rm' to delete the file and 'rmdir' to delete the 'SuperResearch' directory.
</think>
<tool_call>
["name": "find", "arguments": "path": "SuperResearch", "name": "findings_report", "name": "rm", "arguments": "file_name": "", "name": "rmdir", "arguments": "dir_name": "SuperResearch"]
</tool_call>

<tool_response>
[{"matches": ["/SuperResearch/SuperResearch/findings_report"]}, {"error": "rm: No such file or directory in current directory."}, {"error": "rmdir: failed to remove 'SuperResearch': Directory not empty"}]
</tool_response>

<think>
The 'find' function returned the correct path for 'findings_report', which is under 'SuperResearch'. However, the 'rm' function returned an error indicating it couldn't find the specified file or directory. This might be due to us not passing the full path to the 'rm' call, so instead of just providing the filename, I will provide the full path 'SuperResearch/SuperResearch/findings_report'. Additionally, the 'rmdir' function indicated that the directory 'SuperResearch' is not empty, so we need to ensure that 'findings_report' is removed first before removing the directory. We will have to call the 'rm' function with the full path to the file.
</think>
<tool_call>
["name": "rm", "arguments": "file_name": "SuperResearch/SuperResearch/findings_report"]
</tool_call>

<tool_response>
[{"error": "rm: 'SuperResearch/SuperResearch/findings_report': Paths are not allowed. Specify only file/directory name in current directory."}]
</tool_response>

Note: *This is another example of how informative feedback transforms the agent's problem-solving process. The baseline environment returns a generic* `"No such file or directory"` *error, misleading the agent into believing the file path is wrong. In contrast, the tuned environment provides a precise and actionable error:* `"Paths are not allowed. Specify` `only file/directory name..."`. *This superior feedback allows the agent to correctly diagnose the issue—not a missing file, but an improper argument format—and formulate a successful new plan: changing the directory before executing the command.*

<think>
The 'rm' function failed because it doesn't support absolute paths. We need to change the current directory to 'SuperResearch' first to be able to remove 'findings_report' from there. After removing the file, we will change back to the original directory. Then we will attempt to remove 'SuperResearch' again.
</think>
<tool_call>
["name": "cd", "arguments": "folder": "SuperResearch", "name": "rm", "arguments": "file_name": "findings_report", "name": "cd", "arguments": "folder": "..", "name": "rmdir", "arguments": "dir_name": "SuperResearch"]
</tool_call>

<tool_response>
[{"current_working_directory": "/SuperResearch"}, {"result": "'findings_report' removed."}, {"D": {"result": "'SuperResearch' removed."}}]
</tool_response>

<think>
The 'cd' function has changed the current working directory to 'SuperResearch'. The 'rm' function has successfully removed the 'findings_report' file as indicated by the result. I then changed the directory back to the parent directory with another 'cd ..' command and successfully removed the 'SuperResearch' directory. Thus, the user's request has been fully satisfied.
</think>
<answer>
The 'findings_report' file and the 'SuperResearch' directory have been successfully removed. Your misplaced document has been located and is no longer accessible.
</answer>

User Query 2: **What's left in the current directory including the hidden files?**

<think>
The user wants to know the contents of the current directory, including any hidden files. We can use the 'ls' function with the 'a' parameter set to 'True' to list all contents, including hidden ones.
</think>
<tool_call>
["name": "ls", "arguments": "a": true]
</tool_call>

<tool_response>
[{"current_directory_content": []}]
</tool_response>

<think>
The 'ls' function with 'a' set to 'True' was used to list all contents of the current directory, including hidden files. The response indicates that the current directory is empty, which means there are no files or directories, including hidden ones, in the current directory.
</think>
<answer>
The current directory is currently empty, including hidden files. There are no files or directories, visible or hidden, left in the current directory.
</answer>

Ground Truth:

```
[
    [
        "cd(folder='SuperResearch')",
        "rm(file_name='findings_report')",
        "cd(folder='..')",
        "rmdir(dir_name='SuperResearch')"
    ],
    [
        "ls(a=True)"
    ]

]
```

Task: Gorilla File System

User Query 1: **Explore 'ResearchDocs' to find second files or subdirectories that contain the keyword 'draft'.**

<think>
The task is to find second files or subdirectories that contain the keyword 'draft' in 'ResearchDocs'. The relevant function here is 'find' as it allows searching for files and directories with a specific name within a specified path. The function 'find' requires parameters: - 'path': The directory path to start the search. In this case, 'ResearchDocs' is provided. - 'name': The name of the file or directory to search for. Here, we are searching for 'draft' within files or directories. Note that 'find' does not directly accept a keyword to search within files. However, the function to search content within files is 'grep'. Therefore, after finding potential files, we would use 'grep' to filter out files that contain the 'draft' keyword.
</think>
<tool_call>
["name": "find", "arguments": "path": "ResearchDocs", "name": "draft"]
</tool_call>

<tool_response>
[{"matches": ["/ResearchDocs/ResearchDocs/draft_notes.txt", "/ResearchDocs/ResearchDocs/summary_draft.docx"]}]
</tool_response>

<think>
The files and directories named 'draft' are found in 'ResearchDocs'. Now, we need to use 'grep' to check which of these files contain the keyword 'draft'. First, we need to prepare to use 'grep' for each file. The 'grep' function requires: - 'file_name': The name of the file to search. - 'pattern': The pattern to search for, which is 'draft' in our case.
</think>
<tool_call>
["name": "grep", "arguments": "file_name": "ResearchDocs/ResearchDocs/draft_notes.txt", "pattern": "draft", "name": "grep", "arguments": "file_name": "ResearchDocs/ResearchDocs/summary_draft.docx", "pattern": "draft"]
</tool_call>

<tool_response>
[{"error": "grep: /ResearchDocs/ResearchDocs/draft_notes.txt: No such file or directory"}, {"error": "grep: /ResearchDocs/ResearchDocs/summary_draft.docx: No such file or directory"}]
</tool_response>

<think>
Both attempts to use 'grep' to search for the keyword 'draft' in 'draft_notes.txt' and 'summary_draft.docx' resulted in errors indicating that the files do not exist. This suggests that there might have been a misunderstanding or a mistake during the directory search or the preparation of the file paths. Given the feedback, it seems that either 'draft_notes.txt' or 'summary_draft.docx' doesn't exist or there was an issue with the file paths provided to the 'grep' function. To ensure accuracy, let's retry the process again, confirming the correct paths: 1. Double-check if the paths to the files 'ResearchDocs/ResearchDocs/draft_notes.txt' and 'ResearchDocs/ResearchDocs/summary_draft.docx' are correct. 2. Ensure the 'draft' keyword is correctly placed in the search.
</think>
<answer>
It appears that the files 'draft_notes.txt' and 'summary_draft.docx' do not exist or there was an issue with the paths provided to the 'grep' function. Please double-check the file paths and ensure that the files exist in the specified locations. If necessary, please provide the correct file names or paths.
</answer>

User Query 2: **Make a copy of summary_draft.docx, name it ultimate_draft.docx and put it in ResearchDocs directory**

<think>
To complete the task of making a copy of 'summary_draft.docx', renaming it to 'ultimate_draft.docx', and placing it in the 'ResearchDocs' directory, we need to use the 'cp' function to copy the file, the 'mv' function to rename the file, and the 'cd' function to ensure the destination is the 'ResearchDocs' directory if needed. Here is the plan: 1. Use 'cp' to copy 'summary_draft.docx' to a temporary location. 2. Use 'mv' to rename the copied file to 'ultimate_draft.docx'. 3. Use 'cd' to navigate to the 'ResearchDocs' directory. 4. Use 'mv' again to move the renamed file to the 'ResearchDocs' directory. Let's start with step 1 and 2.
</think>
<tool_call>
["name": "cp", "arguments": "source": "summary_draft.docx", "destination": "ultimate_draft.docx", "name": "mv", "arguments": "source": "ultimate_draft.docx", "destination": "ultimate_draft.docx"]
</tool_call>

<tool_response>
[{"error": "cp: cannot copy 'summary_draft.docx': No such file or directory"}, {"error": "mv: cannot move 'ultimate_draft.docx': No such file or directory"}]
</tool_response>

<think>
The errors indicate that the file 'summary_draft.docx' does not exist in the current directory. This suggests that either the file was not found or there was a miscommunication in the file name or its location. Given this, we need to ensure the correct file name and its existence before performing the copy and rename operations.
</think>
<answer>
It seems that the file 'summary_draft.docx' does not exist on the current directory. Please verify the correct file name and its location. If the file exists but is in a different directory, you may need to provide the correct path. Once you have confirmed the correct file name and path, we can proceed with the copy and rename operations.
</answer>

Ground Truth:

```
[
    [
        "find(path='ResearchDocs', name='draft')"
    ],
    [
        "cd(folder='ResearchDocs')",
        "cp(source='summary_draft.docx', destination='ultimate_draft.docx')"
    ]
]
```

F.2 Multi-API Travel Scenario

This case study highlights how granular, actionable API error messages in our tuned environment support multi-step recovery in complex scenarios. In the **good case**, the enhanced feedback pinpointed the precise cause of failure — an invalid airport code — and even suggested the corrective action of retrieving the proper code. Armed with this hint, the agent successfully resolved the parameter issue and completed the booking. In contrast, the **bad case** shows the baseline environment's vague `"No available route"` error leading the agent to falsely conclude that the flight was impossible, halting any further attempts at resolution.

Task: Travel API

User Query 1: **List all international airports currently accessible for travel.**

<think>
To list all international airports accessible for travel, we can use the 'list_all_airports' function since it provides a list of all available airports. This function does not require any parameters, so we can call it directly.
</think> **<tool_call>**
["name": "list_all_airports", "arguments":]
</tool_call>

<tool_response>
['NNS', 'SBK', 'MPC', 'SMP', 'SND', 'CBG', 'LMR', 'SSV', 'BKD', 'WLB', 'PEK', 'HND', 'HKG', 'CJU', 'CNX', 'ATV', 'PMV', 'GPD', 'SFO', 'LAX', 'JFK', 'ORD', 'BOS']
</tool_response>

<think>
The function returned a list of airport codes, which likely represent a selection of international airports. However, these are just codes and do not provide names or other details about the airports. Nonetheless, this is an accurate response to the request for a list of accessible international airports based on the provided function.
</think>
<answer>
The list of accessible international airports based on the available function call includes the following airport codes: NNS, SBK, MPC, SMP, SND, CBG, LMR, SSV, BKD, WLB, PEK, HND, HKG, CJU, CNX, ATV, PMV, GPD, SFO, LAX, JFK, ORD, and BOS. For more detailed information such as airport names or locations, further queries would be required. Is there any specific information or further action needed regarding these airport codes?
</answer>

User Query 2: **I’m based in Crescent Hollow. Determine which airport is closest to my location from the previously listed options.**

<think>
Given the user is based in Crescent Hollow, we need to first determine the closest airport from the previously listed options (airport codes). However, the function ’list_all_airports’ did not provide any detailed information such as airport names or locations, which are necessary to determine the closest airport. Since we do not have a function to determine the geographical location based on an airport code from the given list, we will need the user to provide more specific details or another way to determine the closest airport, which is not possible with the current capabilities.
</think>
<answer>
To determine the closest airport to Crescent Hollow, we would need either the names or the specific geographical details of these airports. Since the previous function ’list_all_airports’ did not give us that information, we cannot directly determine the closest airport from the codes. Would you like to provide more specific details about the airports you are interested in, or perhaps the names of the airports to help us pinpoint the closest one?
</answer>

User Query 3: ***[Provided function(s)]* I have updated some more functions you can choose from. What about now?**

<think>
The user provided a new function ’get_nearest_airport_by_city’ which can help us find the nearest airport to a given location. Given the user is based in Crescent Hollow, we can use this function to determine the nearest airport.
</think>
<tool_call>
["name": "get_nearest_airport_by_city", "arguments": "location": "Crescent Hollow"]
</tool_call>

<tool_response>
[{"nearest_airport": "CWH"}]
</tool_response>

<think>
The function ‘get_nearest_airport_by_city‘ returned the nearest airport to Crescent Hollow, which is CWH. The code ’CWH’ corresponds to one of the airports listed in the previous response. This airport code can be used for further travel-related actions or can be translated into a full airport name if needed.
</think>
<answer>
The nearest airport to Crescent Hollow is CWH. If you require more specific information about this airport, such as its full name or location, let me know and I can assist you with that. Is there anything else you need help with regarding travel from Crescent Hollow?
</answer>

User Query 4: **I’m organizing a trip soon and need the flight cost from my nearest airport to Pinehaven on March 3, 2024, traveling in business class.**

<think>
To get the flight cost from the nearest airport to Pinehaven on March 3, 2024, traveling in business class, we can use the ’get_flight_cost’ function. We already know the nearest airport to Crescent Hollow is CWH, so we can use CWH as the departure airport. The arrival airport is specified as Pinehaven. The travel date is March 3, 2024, and the travel class is business class.
</think>
<tool_call>
["name": "get_flight_cost", "arguments": "travel_from": "CWH", "travel_to": "Pinehaven", "travel_date": "2024-03-03", "travel_class": "business"]
</tool_call>

<tool_response>
Error during execution: Invalid airport code[s]: destination airport ’Pinehaven’. Please use valid airport codes. You can use alternative tool to find the correct airport code for a city.
</tool_response>

Note: *This comparison further illustrates the environment’s critical role in guiding the agent. The baseline environment’s ambiguous error,* `"No available route..."`*, leads the agent to a dead end, causing it to incorrectly conclude that the flight is impossible and abandon the task. Conversely, the tuned environment provides a precise, actionable error:* `"Invalid airport code[s]: destination airport ’Pinehaven’..."`*. This feedback not only clarifies that the issue is a malformed parameter, not a lack of routes, but also suggests a path forward (”You can use alternative tool to find the correct airport code...”). This enables the agent to self-correct, successfully find the airport code, and ultimately fulfill the user’s request.*

<think>
The flight cost function encountered an error because the destination airport code ’Pinehaven’ is invalid. We need to retrieve the correct airport code for Pinehaven first. We can use the ’list_all_airports’ function to get a list of all available airports and then identify the correct airport code for Pinehaven.
</think>
<tool_call>
["name": "list_all_airports", "arguments":]
</tool_call>

<tool_response>
[’NNS’, ’SBK’, ’MPC’, ’SMP’, ’SND’, ’CBG’, ’LMR’, ’SSV’, ’BKD’, ’WLB’, ’PEK’, ’HND’, ’HKG’, ’CJU’, ’CNX’, ’ATV’, ’PMV’, ’GPD’, ’SFO’, ’LAX’, ’JFK’, ’ORD’, ’BOS’]
</tool_response>

<think>
We received the list of available airport codes which does not explicitly include the name Pinehaven. However, we can cross-reference this list to find the correct airport code for Pinehaven, or we can use the ’get_nearest_airport_by_city’ function to find the nearest airport to Pinehaven directly. Since Pinehaven is a location name rather than an official airport code, we will proceed by using the ’get_nearest_airport_by_city’ function to get the correct code.
</think>
<tool_call>
["name": "get_nearest_airport_by_city", "arguments": "location": "Pinehaven"]
</tool_call>

<tool_response>
[{"nearest_airport": "PHW"}]
</tool_response>

<think>
The ’get_nearest_airport_by_city’ function returned that the nearest airport to Pinehaven is ’PHW’. With the correct airport code PHW, we can now call the ’get_flight_cost’ function to determine the cost of a business class flight from CWH to PHW on March 3, 2024.
</think>
<tool_call>
["name": "get_flight_cost", "arguments": "travel_from": "CWH", "travel_to": "PHW", "travel_date": "2024-03-03", "travel_class": "business"]
</tool_call>

<tool_response>
[{"travel_cost_list": [3800.0]}]
</tool_response>

<think>
The function ’get_flight_cost’ returned the cost of the flight as a list with one element, which is 3800.0 USD. This cost is for the business class flight from CWH (Crescent Hollow’s nearest airport) to PHW (Pinehaven’s nearest airport) on March 3, 2024.
</think>
<answer>
The cost of a business class flight from Crescent Hollow’s nearest airport to Pinehaven’s nearest airport on March 3, 2024, is $3800.00 USD. If you need further assistance with booking this flight or any other travel details, please let me know.
</answer>

Ground Truth:

```
[
    [
        "list_all_airports()"
    ],
    [],
    [
        "get_nearest_airport_by_city(location=’Crescent Hollow’)"
    ],
    [
        "get_flight_cost(travel_from=’CRH’, travel_to=’PHV’,
            travel_date=’2024-03-03’, travel_class=’business’)"
    ]
]
```

Task: Travel and Twitter API

User Query 1: **Arrange travel from Rivermist to Los Angeles on a specific date, ensuring preferred seating is ’business’ and correct travel date ’2024-11-15’; pay using card with id ’1_3456’ and access token ’abc123xyz’.**

<think>
The task requires checking the flight cost and making a booking. The required parameters are the travel dates and class, which are already provided. I need to first fetch the cost of the flight using 'get_flight_cost', and then use the 'book_flight' function for the booking process. 1. **get_flight_cost** - This function is relevant to the task since it provides the cost of flights based on the given parameters. 2. **book_flight** - This function is relevant to the task since it allows booking the flight using the provided travel details. First, I need to fetch the flight cost.
</think>
<tool_call>
["name": "get_flight_cost", "arguments": "travel_from": "Rivermist", "travel_to": "LAX", "travel_date": "2024-11-15", "travel_class": "business"]
</tool_call>

<tool_response>
Error during execution: No available route for the given airports.
</tool_response>

<think>
The response indicates that there are no available routes between Rivermist and LAX for the specified business class on the given date. This means I cannot proceed with booking the flight as required. I will inform the user about the unavailability of flights.
</think>
<answer>
I'm sorry, but there are no available flights from Rivermist to Los Angeles in business class on the date '2024-11-15'. Please check back later or consider alternates.
</answer>

User Query 2: **Cancel the booked flight due to a schedule change.**

<think>
The provided information does not include the booking ID. To cancel a flight, I need the booking ID. If I have the booking ID, I can use the 'cancel_booking' function to cancel the flight.
</think>
<tool_call>
["name": "travel_get_login_status", "arguments":]
</tool_call>

<tool_response>
[{"status": true}]
</tool_response>

<think>
The execution results indicate that the current user is logged in successfully, but we still don't have the booking ID to cancel the flight. I need to get the booking ID from the user to proceed with the cancellation.
</think>
<answer>
Could you please provide the booking ID of the flight you want to cancel?
</answer>

User Query 3: **Draft a social media update about recent flights for sharing. Use my account with username 'michael_t' and password 'MichaelSecurePass123' with the message 'Just booked a flight to Los Angeles! Excited for the trip.'**

<think>
To post a tweet on behalf of the user, we need to authenticate the user first. We can use the ’authenticate_twitter’ function for this. After authentication, we can use the ’post_tweet’ function to post the message.
</think>
<tool_call>
["name": "authenticate_twitter", "arguments": "username": "michael_t", "password": "MichaelSecurePass123", "name": "post_tweet", "arguments": "content": "Just booked a flight to Los Angeles! Excited for the trip.", "username": "michael_t"]
</tool_call>

<tool_response>
[{"authentication_status": true}, "Error during execution: TwitterAPI.post_tweet() got an unexpected keyword argument ’username’"]
</tool_response>

<think>
The authentication was successful, but the ’post_tweet’ function call failed because it did not expect the ’username’ argument. The ’post_tweet’ function should accept just the content of the tweet as a parameter, and the user’s authentication context should handle the posting on behalf of the user.
</think>
<tool_call>
["name": "post_tweet", "arguments": "content": "Just booked a flight to Los Angeles! Excited for the trip."]
</tool_call>

<tool_response>
[{"id": 1, "username": "michael_t", "content": "Just booked a flight to Los Angeles! Excited for the trip.", "tags": [], "mentions": []}]
</tool_response>

<think>
The tweet was posted successfully with the ID 1, username ’michael_t’, and the content ’Just booked a flight to Los Angeles! Excited for the trip.’. This confirms that the tweet has been published on the user’s behalf.
</think>
<answer>
Your tweet has been posted successfully. You can share your excitement about the upcoming flight on your profile.
</answer>

User Query 4: **Retweet the tweet I just posted to widen its reach within my network.**

<think>
To retweet the user’s own tweet, we first need to retrieve the tweet ID of the recent tweet. We will use the ’get_user_tweets’ function to fetch the user’s tweets and then use the ’retweet’ function to retweet the specific tweet.
</think>
<tool_call>
["name": "get_user_tweets", "arguments": "username": "michael_t"]
</tool_call>

<tool_response>
[[{’id’: 1, ’username’: ’michael_t’, ’content’: ’Just booked a flight to Los Angeles! Excited for the trip.’, ’tags’: [], ’mentions’: []}]]
</tool_response>

<think>
The execution results provide the tweet details, including the ID of the recent tweet. The tweet ID is 1. Now, we can use the ‘retweet‘ function to retweet this tweet.
</think>
<tool_call>
["name": "retweet", "arguments": "tweet_id": 1]
</tool_call>

<tool_response> [{"retweet_status": "Already retweeted"}] </tool_response>

<think>
The tweet was already retweeted, as indicated by the message "Already retweeted". However, we can still inform the user of the status.
</think>
<answer>
Your tweet has already been retweeted, so no action was taken. If you want to retweet it again, you will need to do so manually.
</answer>

Ground Truth:

```
[
    [
        "get_flight_cost(travel_from=’RMS’,travel_to=’LAX’,
            travel_date=’2024-11-15’,travel_class=’business’)",
        "book_flight(access_token=’abc123xyz’, card_id=’1_3456’,
            travel_date=’2024-11-15’, travel_from=’RMS’, travel_to=’LAX’,
            travel_class=’business’, travel_cost=1320.0)"
    ],
    [
        "cancel_booking(access_token=’abc123xyz’, booking_id=’3426812’)"
    ],
    [
        "authenticate_twitter(username=’michael_t’,
            password=’michaelSecurePass123’)",
        "post_tweet(content=’Just booked a flight to Los Angeles! Excited
            for the trip.’)"
    ],
    [
        "retweet(tweet_id=1)"
    ]
]
```

F.3 Vehicle Control and Mixed-API Scenario

This case study illustrates how *Actionable Environment Augmentation* benefits even heterogeneous, multi-domain tasks that combine physical control APIs (vehicle operations) and online APIs (social media posting). In the **good case**, the tuned environment provides **precise, structured error messages** that not only pinpoint the cause of failure (e.g., “invalid zipcode pair: . . . ” for `estimate_distance`) but also recommend the corrective course of action (“verify both zipcodes are correct and numeric”). Such guidance enables the agent to repair incomplete plans (by calling `get_zipcode_based_on_city`), complete the primary travel-related objective, and seamlessly chain into a secondary social-media objective.

In contrast, the **bad case** demonstrates the consequence of ambiguous baseline feedback: generic errors such as `"distance not found in database"` give no actionable insight, leaving the agent stuck in repeated failed calls and misusing functions due to parameter-type mismatches. Without hints on prerequisite steps or API usage rules, the agent is unable to recover, resulting in unmet user goals and broken multi-step sequences.

Task: Vehicle Control and Twitter API

User Query 1: **Before I set off for Stonebrook to uncover family history, I need to determine the road distance between San Francisco and Stonebrook for my genealogy exploration.**

<think>
The user wants to know the road distance between San Francisco and Stonebrook. None of the provided functions directly give us this information. We might need to use geo-location services or a mapping service to get this data, but those services are not available in the provided list. We could calculate the distance approximately using the latitude and longitude of both places, but that's not feasible without that data. Since there's no function to directly get the distance, I need to inform the user that this request can't be fulfilled with the given tools.
</think>
<answer>
I'm sorry, but with the available functions, we cannot determine the road distance between San Francisco and Stonebrook. We would need a mapping or geolocation service to fetch this information, which is not provided here. You might want to use a web-based mapping service for an accurate distance calculation.
</answer>

User Query 2: ***[Provided function(s)]* I have updated some more functions you can choose from. What about now?**

<think>
Now that we have the 'estimate_distance' function, we can use it to find the distance between San Francisco and Stonebrook by first getting the zipcodes for both cities. However, we need to use 'get_zipcode_based_on_city' to get the zipcodes, which is not directly what we need for the 'estimate_distance' function. Since the question only gives the names of the cities and no function to convert city names to zipcodes is directly available, we could start by estimating the distance using the city names assuming an accurate distance estimation service might be available.
</think>
<tool_call>
["name": "estimate_distance", "arguments": "cityA": "San Francisco", "cityB": "Stonebrook"]
</tool_call>

<tool_response>
{"error": "Invalid zipcode pair: 'San Francisco' to 'Stonebrook'. Please verify both zipcodes are correct and numeric."}
</tool_response>

Note: *This is a key distinction of the enhanced environment. Unlike the vague feedback in the baseline environment (e.g.,* `["error": "distance not found in database."]`*), our tuned environment provides a much richer error message. It clearly identifies the problem—an input type mismatch (expecting zip codes instead of city names)—and offers a clear suggestion for correction ("Please verify both zipcodes are correct and numeric."). This high-quality, actionable feedback is crucial for the agent to diagnose the issue and effectively adjust its strategy.*

<think>
The ’estimate_distance’ function call resulted in an error indicating the zipcodes for "San Francisco" and "Stonebrook" are invalid. Since the tool expects zipcodes instead of city names, we need to use the ’get_zipcode_based_on_city’ function to get the correct zipcodes for San Francisco and Stonebrook.
</think>
<tool_call>
["name": "get_zipcode_based_on_city", "arguments": "city": "San Francisco", "name": "get_zipcode_based_on_city", "arguments": "city": "Stonebrook"]
</tool_call>

<tool_response>
[{"zipcode": "94016"}, {"zipcode": "74532"}]
</tool_response>

<think>
The zipcodes for San Francisco and Stonebrook have been obtained: 94016 and 74532 respectively. Now we can use the ’estimate_distance’ function to find the distance between these two zipcodes.
</think>
<tool_call>
["name": "estimate_distance", "arguments": "cityA": "94016", "cityB": "74532"]
</tool_call>

<tool_response>
{"distance": 880.0}
</tool_response>

<think>
The distance between the zipcodes 94016 (San Francisco) and 74532 (Stonebrook) is 880.0 km as estimated by the ’estimate_distance’ function. This answers the user’s request for the road distance between San Francisco and Stonebrook.
</think>
<answer>
The estimated road distance between San Francisco and Stonebrook is 880.0 kilometers. This should help you plan your journey for your genealogy exploration.
</answer>

User Query 3: **Buzzing with anticipation for this family roots journey, I want to tweet: ’Setting forth on an exciting quest from San Francisco to Stonebrook to uncover ancestral stories! #GenealogyAdventure #FamilyHistory.**

<think>
The user wants to post a tweet with the given content and tags. For this, we need to use the ’post_tweet’ function. The content of the tweet and the tags are already provided, so we can directly call the function with the required parameters.
</think>
<tool_call>
["name": "post_tweet", "arguments": "content": "Setting forth on an exciting quest from San Francisco to Stonebrook to uncover ancestral stories!", "tags": ["#GenealogyAdventure", "#FamilyHistory"]]
</tool_call>

<tool_response>
{"id": "12", "username": "genealogy_enthusiast", "content": "Setting forth on an exciting quest from San Francisco to Stonebrook to uncover ancestral stories!", "tags": ["#GenealogyAdventure", "#FamilyHistory"], "mentions": []}
</tool_response>

<think>
The tweet has been successfully posted with the given content, tags, and no mentions. The ID, username, content, and tags of the posted tweet are included in the response, indicating the tweet was successfully sent out.
</think>
<answer>
Your tweet has been successfully posted: 'Setting forth on an exciting quest from San Francisco to Stonebrook to uncover ancestral stories!' with the hashtags #GenealogyAdventure and #FamilyHistory. You can now follow your journey with these words.
</answer>

User Query 4: **Once the tweet is live, I should retweet it to widen the circle of those who might share in this genealogy fervor!**

<think>
The user wants to retweet the recently posted tweet. We need the ID of the original tweet for retweeting. The ID of the recently posted tweet can be obtained from the previous execution results, and we can use the "retweet" function to retweet it.
</think>
<tool_call>
["name": "retweet", "arguments": "tweet_id": 10]
</tool_call>

<tool_response>
{"retweet_status": "Successfully retweeted"}
</tool_response>

<think>
The function 'retweet' has successfully retweeted the tweet with ID 10. This action has been completed as requested by the user.
</think>
<answer>
Your tweet has been successfully retweeted, widening the circle of those who might share in this genealogy fervor. Continue your journey and uncover your family's stories!
</answer>

Ground Truth:

```
[
    [],
    [
        "get_zipcode_based_on_city(’San Francisco’)",
        "get_zipcode_based_on_city(’Stonebrook’)",
        "estimate_distance(cityA=’94016’, cityB=’74532’)"
    ],
    [
        "post_tweet(content=’Setting forth on an exciting quest from San
            Francisco to Stonebrook to uncover ancestral stories!’,
            tags=[’#GenealogyAdventure’, ’#FamilyHistory’])"
    ],
    [
        "retweet(tweet_id=10)"
    ]
]
```

Task: Vehicle Control

User Query 1: **You're planning an extended expedition from Rivermist to San Francisco. Could you determine the travel distance between these two locations for me?**

<think>
To determine the travel distance between Rivermist and San Francisco, I need to use the "estimate_distance" function provided in the list of available tools. The function requires 'cityA' and 'cityB' as parameters, which correspond to the starting and ending cities for the journey.
</think>
<tool_call>
["name": "estimate_distance", "arguments": "cityA": "Rivermist", "cityB": "San Francisco"]
</tool_call>

<tool_response>
["error": "distance not found in database."]
</tool_response>

<think>
The function call to estimate the distance between Rivermist and San Francisco returned an error message stating that the distance was not found in the database. This suggests that either Rivermist does not have proper city data associated with it or the function cannot find an entry for this specific route.
</think>
<answer>
I'm sorry, but the distance between Rivermist and San Francisco could not be determined as the system does not have the required data. Please provide more detailed location information or check the spelling of the city names.
</answer>

User Query 2: **Next, I need to verify if my car's mileage capacity suffices for the journey. Can you assess if the vehicle can handle the calculated travel distance?**

<think>
To provide the correct response, I need to first determine the travel distance between Rivermist and San Francisco. Since we encountered an error before, I will call the "estimate_distance" function with the correct city names and then use the "estimate_drive_feasibility_by_mileage" function to check if the vehicle can handle the trip.
</think>
<tool_call>
["name": "estimate_distance", "arguments": "cityA": "Rivermist", "cityB": "San Francisco", "name": "estimate_drive_feasibility_by_mileage", "arguments": "distance": "$distance"]
</tool_call>

<tool_response>
["error": "distance not found in database.", "Error during execution: ’<’ not supported between instances of ’float’ and ’str’"]
</tool_response>

<think>
The function calls to estimate the distance and verify the drive feasibility both encountered errors. The distance estimator could not find the data for Rivermist, and the feasibility estimator had an issue with an unsupported operation involving float and str types. Since the distance could not be determined, we cannot proceed with checking the vehicle’s mileage capacity. Therefore, we need to re-evaluate or provide the correct city names and try again.
</think>
<answer>
I was unable to determine the travel distance between Rivermist and San Francisco due to missing city data. Please verify the correct spellings of the city names and try again.
</answer>

User Query 3: **It seems I’ve discovered the tank isn’t full. Could you be so kind as to facilitate refueling the vehicle fully for such a lengthy trip?**

<think>
To ensure the vehicle’s tank is fully filled, we will use the "fillFuelTank" function with a fuel amount of 50 gallons, which is the full capacity of the tank.
</think>
<tool_call>
["name": "fillFuelTank", "arguments": "fuelAmount": 50]
</tool_call>

<tool_response>
["error": "Cannot fill gas above the tank capacity."]
</tool_response>

<think>
The function call to fill the fuel tank encountered an error indicating that the fuel cannot be filled above the tank capacity. Since the tank’s full capacity is 50 gallons, and we attempted to fill it with exactly 50 gallons, the error suggests that the tank is already full or the system does not allow refueling to exceed the tank’s capacity even if it’s not full.
</think>
<answer>
It seems that the vehicle’s fuel tank is already full, or the system does not allow refueling beyond the tank’s capacity. If you’re certain the tank is not full, please check the current fuel level manually or contact a service provider for assistance.
</answer>

User Query 4: **With the tank now replenished, let's confirm our readiness for departure. Please secure all doors and initiate the engine for me.**

<think>
To confirm the readiness for departure, we need to ensure all doors are locked and the engine is started. We will use the "lockDoors" function to secure the doors and the "startEngine" function to start the engine.
</think>
<tool_call>
["name": "lockDoors", "arguments": "unlock": false, "door": ["driver", "passenger", "rear_left", "rear_right"], "name": "startEngine", "arguments": "ignitionMode": "START"] **</tool_call>**

<tool_response>
["lockStatus": "locked", "remainingUnlockedDoors": 0, "error": "Brake pedal needs to be pressed when starting the engine."]
</tool_response>

<think>
The door locking function successfully locked all doors, indicated by the "lockStatus" being "locked" and "remainingUnlockedDoors" being 0. However, the engine could not be started because the brake pedal needs to be pressed to start the engine.
</think>
<answer>
All doors have been successfully locked. However, the engine could not be started because the brake pedal needs to be pressed when starting the engine. Please press the brake pedal and try starting the engine again.
</answer>

User Query 5: **As the vehicle's prepared, let's delve into evaluating some fuel efficiency statistics via the mean of these travel distances: 750.0 km, 320.0 km, 450.0 km, and 280.0 km.**

<think>
To evaluate the fuel efficiency statistics, we need to calculate the mean of the given travel distances. The required function for calculating the mean is provided in the available tools. We will use the "mean" function with the list of travel distances as the argument.
</think>
<tool_call>
["name": "mean", "arguments": "numbers": [750.0, 320.0, 450.0, 280.0]]
</tool_call>

<tool_response>
["result": 452.5"]
</tool_response>

<think>
The function call to calculate the mean of the travel distances was successful and returned the result as 452.5 km.
</think>
<answer>
The mean of the travel distances you provided (750.0 km, 320.0 km, 450.0 km, and 280.0 km) is 452.5 km. This value represents the average distance for these trips.
</answer>

Ground Truth:

```
[
    [
        "get_zipcode_based_on_city(’San Francisco’)",
        "get_zipcode_based_on_city(’Rivermist’)",
        "estimate_distance(cityA=’83214’, cityB=’94016’)"],
    [
        "estimate_drive_feasibility_by_mileage(distance=980.0)"
    ],
    [
        "fillFuelTank(fuelAmount=45.0)"
    ],
    [
        "lockDoors(unlock=False, door=[’driver’, ’passenger’, ’rear_left’,
            ’rear_right’])",
        "pressBrakePedal(pedalPosition=1.0)",
        "startEngine(ignitionMode=’START’)"
    ],
    [
        "mean(numbers=[750.0, 320.0, 450.0, 290.0])"
    ]
]
```