DistRL: An Asynchronous Distributed Reinforcement Learning Framework for On-Device Control Agents

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Abstract

On-device control agents, especially on mobile devices, are responsible for operating mobile devices to fulfill users' requests, enabling seamless and intuitive interactions. Integrating Multimodal Large Language Models (MLLMs) into these agents enhances their ability to understand and execute complex commands, thereby improving user experience. However, fine-tuning MLLMs for on-device control presents significant challenges due to limited data availability and inefficient online training processes. This paper introduces *DistRL*, a novel framework designed to enhance the efficiency of online RL fine-tuning for mobile device control agents. *DistRL* employs centralized training and decentralized data acquisition to ensure efficient fine-tuning in the context of dynamic online interactions. Additionally, the framework is backed by our tailor-made RL algorithm, which effectively balances exploration with the prioritized utilization of collected data to ensure stable and robust training. Our experiments show that, on average, *DistRL* delivers a **3**$\times$ improvement in training efficiency and enables training data collection **2.4**$\times$ faster than the leading synchronous multi-machine methods. Notably, after training, *DistRL* achieves a **20%** relative improvement in success rate compared to state-of-the-art methods on general Android tasks from an open benchmark, significantly outperforming existing approaches while maintaining the same training time. These results validate *DistRL* as a scalable and efficient solution, offering substantial improvements in both training efficiency and agent performance for real-world, in-the-wild device control tasks.

1 Introduction

The integration of Large Language Models (LLMs) into agents capable of complex tasks has gained momentum with initiatives like AutoGPT [44], HuggingGPT [40], and MetaGPT [9], AutoUI [48], etc. These LLM-based agents extend beyond language processing to perform sophisticated functions, including software development and gaming, leveraging their reasoning abilities to interact with and manipulate environments effectively.

One of the key factors driving this trend is the advent of Multimodal Large Language Models (MLLMs), which can process diverse inputs such as text, images, audio, and video, thereby significantly expanding the scope of LLM applications [2, 1, 50, 16]. This versatility enables MLLM-based on-device control agents—intelligent systems embedded within mobile devices that manage and operate applications to execute user commands seamlessly—to interact more naturally and efficiently with their surroundings, completing more complex tasks that require a deeper understanding of context and the ability to learn from interactions. For instance, agents designed to operate smart-

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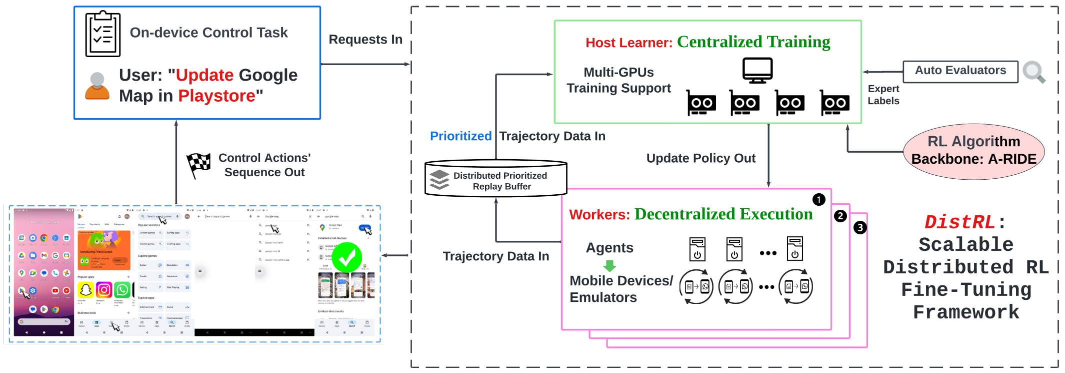

On-device Control Task
User: "Update Google Map in Playstore"
Requests In
Control Actions' Sequence Out
Host Learner: Centralized Training
Multi-GPUs Training Support
Auto Evaluators
Expert Labels
RL Algorithm Backbone: A-RIDE
Prioritized Trajectory Data In
Update Policy Out
Distributed Prioritized Replay Buffer
Workers: Decentralized Execution
Agents
Mobile Devices/ Emulators
Trajectory Data In
DistRL: Scalable Distributed RL Fine-Tuning Framework

Figure 1: Overview of On-device LLM control with *DistRL*.

phone applications can interpret screenshots from the operating system, demonstrating flexibility and adaptability that make them valuable tools in a wide range of scenarios [45, 43]. These agents are essential for tasks such as automating app interactions, managing settings, and enhancing user productivity by providing intuitive control over device functionalities.

However, a gap remains between LLMs' general reasoning capabilities and their effectiveness in GUI-based device control. While LLMs can process information, they struggle with rational behavior and error recovery in real-world environments. Previous solutions use complex wrappers, but without updating model weights, their performance remains limited [4]. Consequently, prior work in building device agents often relies on constructing complex wrappers around these models, combining them with prompting, search, or tool use. However, without updating the model's weights, the effectiveness of these agents remains inherently limited by the capabilities of the base model.

To bridge this gap, fine-tuning(type of light training) aforementioned agents on demonstrations via imitation learning [48, 27, 45] channels pre-trained abilities into actionable behaviors suitable for device control. However, the dynamic nature of devices and the web renders models trained on static data sub-optimal as ecosystems evolve. Such agents struggle to recover from mistakes in changing environments, limiting their practical utility. Therefore, building robust and reliable device-control agents necessitates an interactive approach that enables MLLMs to adapt and learn from their own experiences on devices and the Internet.

Moreover, MLLMs are prone to confidently generating incorrect content that deviates from human preferences [30, 51, 4, 42]. To address these challenges, introducing reinforcement learning (RL)-based fine-tuning methods, such as Reinforcement Learning from Human Feedback (RLHF), becomes essential. RLHF leverages human feedback to align model outputs with desired behaviors and preferences. By incorporating RL-based methods, models can learn to optimize policies that not only perform tasks effectively but also adhere to human expectations. Details of the problem formulation as an RL-based fine-tuning approach will be discussed in Sections 2.2 and 3.

One significant challenge in RL-based fine-tuning of mobile agents is the lack of support for efficient online fine-tuning. Existing offline datasets, such as **AitW** [34] and **AndroidControl** [17], provide static data that do not capture the dynamic and evolving nature of mobile apps. Frequent updates and new elements like advertisements cause distribution shifts that offline-trained agents struggle to handle, leading to failures in real-world deployments.

The second challenge is the need for Reinforcement Learning (RL) algorithms that can operate efficiently within a distributed framework. Asynchronous data collection introduces algorithmic difficulties: non-stationary data distributions hinder convergence, and delays between policy updates and data collection can cause agents to act on outdated policies, degrading performance. Ensuring consistency and stability becomes more complex when dealing with distributed agents collecting data at different rates and times, necessitating robust mechanisms to handle delayed or out-of-order updates.

To further demonstrate these challenges and the non-trivial nature of bringing MLLMs into mobile device control scenarios, our extensive case studies reveal that even the most advanced proprietary Multimodal Large Language Models (MLLMs) like GPT-4V [1], agents such as AutoUI with

Supervised Fine-Tuning (SFT), and state-of-the-art mobile control agents like DIGIRL [3] fail in numerous scenarios. A detailed analysis of these failure modes is provided in Appendix A.1.

These challenges motivate us to develop *DistRL*, as illustrated in Figure 1. *DistRL* is a novel and scalable reinforcement learning (RL) fine-tuning pipeline specifically designed for on-device mobile control agents on Android, featuring **Centralized Training** and **Decentralized Data Acquisitions**. Our main contributions are:

1. Scalable and Asynchronous Architecture for Data Acquisitions: *DistRL* introduces a decoupled and asynchronous architecture that deploys a tailor-made RL fine-tuned agent across a variety of heterogeneous worker devices and environments for remote data collection. Each worker asynchronously sends real-time interaction data back to the central learner, which continuously updates the agent. This design improves training efficiency and scalability, making DistRL highly effective for adapting control agents to dynamic environments.

2. Advanced RL Algorithm Tailored for Centralized Training: *DistRL* leverages a novel off-policy reinforcement learning algorithm, **A-RIDE** (detailed in Section 5), specifically designed for distributed and asynchronous data utlizations. Our algorithm prioritizes significant experiences to enhance sample efficiency, ensuring that the learning process focuses on the most informative data while simultaneously encouraging exploratory behavior among workers.

In practice, we validate our framework using a T5-based multimodal generation model with 1.3B parameters (details in Appendix A.5.1) to efficiently handle both vision and language inputs. To the best of our knowledge, *DistRL is the first work to scale autonomous, online RL fine-tuning for mobile device control in a distributed environment*.

2 Related Works

2.1 Multi-Modal On-device Control Agents

Recent advancements in pre-trained Large Language Models (LLMs) and Multimodal LLMs (MLLMs) have revolutionized on-device control agents, moving beyond early methods like behavioral cloning or reinforcement learning [29, 25, 41]. Early agents simulated mouse clicks and typing [41, 11] but faced scalability and adaptability challenges.

Modern approaches use pre-trained models with zero or few-shot prompting and fine-tuning for enhanced capabilities. WebGPT [27] employ fine-tuned models for web browsing, while WebAgent [8] generates web code using T5. AppAgent [45] and MobileAgent [43] act as drivers, enabling the LLMs to explore and act on mobile device environments. Training multimodal device control agents poses challenges like pixel-level interactions and variability in device ecosystems. Many rely on proprietary Vision-Language Models (VLMs) and wrappers for GUI visual grounding [6, 36], but without fine-tuning, they are limited by the base models [6].

Some works fine-tune VLMs with demonstration data, e.g., AutoUI, CogAgent [13, 48], but static data-trained models may struggle with real-world variability [12]. Others use filtered imitation learning with autonomously collected data [31, 14], While DIGIRL [3] supports on-device RL fine-tuning, it encounters significant inefficiencies in parallel environments. Specifically, DigiRL's multi-machine setup relies on a fully synchronous data acquisition process, causing faster workers to idle while waiting for slower ones. This approach is impractical in real-world scenarios where task durations can vary by up to 100 times, ranging from seconds to over ten minutes. Additionally, DigiRL lacks support for efficient distributed learning algorithm designs, further hindering its scalability and performance in dynamic, parallel settings. To address this, our scalable and asynchronous RL fine-tuning pipeline, *DistRL*, offers an efficient solution for distributed mobile control agent training.

2.2 Reinforcement Learning for On-device Agent Fine-tuning

Reinforcement Learning from Human Feedback (RLHF) is widely used to fine-tune LLMs to align with human preferences [42, 30]. In device control tasks, similar approaches use imitation learning from human-labeled evaluations, but RLHF is labor-intensive due to the need for human annotations [30, 4].

Recent advances in MLLMs [2, 6, 35, 16, 49] show impressive multimodal capabilities but often produce incorrect outputs that deviate from human preferences [30, 51, 4, 42]. Reinforcement Learning from AI Feedback (RLAIF), using AI labelers as proxies, offers an alternative [5, 47, 15]. For on-device tasks, AI evaluators assess task completion using prompts and screenshots [3, 15, 47].

Previous RL research focused on single-turn tasks, limiting their effectiveness for multi-step problems [35, 21, 6]. To address this, we developed a simplified off-policy multi-turn RL algorithm, **A-RIDE**, which learns from suboptimal online interactions, reducing complexity and accelerating convergence compared to previous value-based methods [6, 27, 35, 46]. This approach is effective for large-scale applications like Android device control.

2.3 Scalable and Distributed RL Framework

Scalable reinforcement learning frameworks like *Ray RLlib* [20] enable distributed training by parallelizing policy learning across CPUs and GPUs using the *Ray* engine [19]. *Ray RLlib* supports various algorithms and efficiently manages neural network training, but it assumes that data collection can be simulated or parallelized within the same infrastructure. This assumption limits its applicability to real-world on-device control tasks involving actual mobile devices, where data collection must occur across distributed, heterogeneous devices with varying task durations and network conditions.

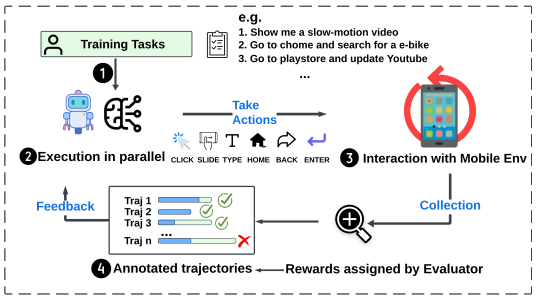
Moreoever, frameworks such as *IMPALA* [7] and *IMPACT* [23] are optimized for fast simulations, enabling efficient data collection and policy updates in highly parallelized environments. Applying these frameworks to on-device control introduces **non-trivial** challenges due to the stochastic nature of real-world interactions and the scalability constraints of mobile devices, including heterogeneous device capabilities, variable task execution times, and unreliable communication.

Our approach builds upon the foundational ideas of *IMPALA* and *IMPACT*, effectively extending their concepts to accommodate the unique challenges of on-device control. We introduce a decoupled and asynchronous architecture that supports distributed data collection from heterogeneous, real-world devices by implementing sophisticated communication protocols and optimized data utilization strategies. Furthermore, we develop a novel reinforcement learning algorithm specifically designed to handle the stochasticity and scalability inherent in mobile device environments. This algorithm enhances and maximizes the utilization of collected data while maintaining the exploration behavior of workers, addressing critical aspects that prior work utilizing A3C [24] have largely overlooked.

3 Problem Setup and Preliminaries

As presented in Figure 2, we model the on-device control problem as a finite-horizon Markov Decision Process (MDP) $M = \{S, A, T, R, \mu_0, H\}$. Here, S denotes the set of GUI states, represented by screenshots or visual observations of the device screen. A represents the set of actions available to the agent, such as touch events at specific screen coordinates. The state transition function $T : S \times A \times S \to [0, 1]$ defines the probability of transitioning from one state to another given an action. The reward function $R : S \times A \to \mathbb{R}$ provides sparse rewards, typically positive upon task completion. μ_0 is the initial state distribution, and H is the finite horizon of the episode.

At each timestep t, the mobile agent observes a state $s_t \in S$, selects an action $a_t \in A$ according to its policy $\pi(a_t|s_t)$, receives a reward $r_t = R(s_t, a_t)$, and transitions to the next state s_{t+1}. The agent's objective is to maximize the expected cumulative reward $\mathbb{E}_\pi \left[\sum_{t=0}^{H} r_t\right]$ over the episode. Given the asynchronous nature of distributed data generation in *DistRL*, trajectories are collected under behavior policies π_b and used to optimize a target policy π. This setup requires robust off-policy learning algorithms to correct for discrepancies between π_b and π.



e.g.
Training Tasks
1. Show me a slow-motion video
2. Go to chome and search for a e-bike
3. Go to playstore and update Youtube
...
1
Take Actions
2 Execution in parallel
CLICK
SLIDE
TYPE
HOME
BACK
ENTER
3 Interaction with Mobile Env
Feedback
Collection
Traj 1
Traj 2
Traj 3
...
Traj n
4 Annotated trajectories
Rewards assigned by Evaluator

Figure 2: Reinforcement Learning dynamics and auto evaluation for fine-tuning the on-device agent.

A critical component of our RL framework is the ability to obtain reliable reward signals in real-time. To achieve this, we utilize Gemini-1.5-pro [36] as an autonomous evaluator to assess whether the agent has successfully completed the task at each state. The evaluator receives the current observation, composed of the task description and a screenshot of the device, and outputs a reward signal. Specifically, the evaluator assigns a reward $r_t = 1$ if the screenshot indicates successful task completion and $r_t = 0$ otherwise. This effectively transforms the problem into a Partially

Observable MDP (POMDP), where the evaluator helps determine the termination condition based on the agent's observation. Additionally, we applied a reward penalty on unexpected behaviors like repetition which we observed many times in collected trajectories. Details of how we implemented the auto-evaluation can be found in Appendix A.2.

4 System Design

DistRL is an asynchronous distributed reinforcement learning framework for scalable and efficient training of mobile agents. By decoupling trajectory collection from policy learning and doing both in parallel, it leverages distributed working machines for CPU-intense agent-environment interactions and GPU servers for policy training. This separation optimizes efficiency, scalability, and resource utilization by aligning tasks with appropriate hardware.

This decoupled and asynchronous design offers several key advantages: it improves scalability as data collection scales naturally and linearly with more working machines providing the mobile environment, even if there are large performance gaps between them; it optimizes resource utilization by assigning tasks to suitable hardware; and it improves policy quality through richer, more diverse datasets from multiple devices, enhancing robustness and generalization capabilities. The details of our system are presented as follows:

As illustrated in Figure 3, *DistRL* employs a host-worker architecture consisting of a central **Host Learner** (Left side in Figure 3) and multiple **Workers** (Right side in Figure 3) which can be heterogeneous devices: i.e. machines of various specifications, running android emulators or being connected with mobile devices, providing the android interaction environments. These components work together to train agents through asynchronous data collection and distributed policy updates.

Host Learner: Host Learner orchestrates the policy training process using powerful GPUs. It maintains a Circular Replay Buffer (details in Appendix A.4) that stores the trajectories collected from the workers. The training loop processes this data by applying reinforcement learning algorithms to update the policy. To manage incoming data efficiently, a FIFO Trajectory Queue receives experiences from the workers and organizes them for training.

The host learner updates the policy with tailored regularization controls (details in Section 5) to encourage workers to explore a broader range of potential actions during task execution. This approach ensures diversity in the collected data, preventing convergence towards homogeneous behaviors, which is especially crucial in dynamic and complex mobile device environments. Additionally, to maximize the use of the large-scale and diverse data collected, and to avoid excessive learning on redundant or similar data, the learner employs priority-based sampling techniques (details in Section 5). These carefully curated design choices not only ensure training efficiency but also enhance the generalization capability of the policy. After updating the policy, the host learner distributes the latest version to the workers, allowing them to interact with their environments based on the latest learning updates. The training process runs continuously, with new experiences from the workers refining the policy, and the updated policy enhancing the workers' performance.

Workers: Workers operate in parallel, each managing its own Android environments with Android Emulators or actual Android devices through multi-threading. Each thread in the workers executes the policy received from the host learner and interacts with the environment through an Agent. The agent queries the environment, receives observations, and generates actions based on the current policy. Each worker collects trajectories—sequences of actions, observations, and rewards—during its interaction with the emulator.

To facilitate efficient simulation, workers use **Environment Snapshots**, allowing them to reset the emulator to specific states. The result trajectories from the collecting threads are asynchronously sent back to the host learner to be added to the replay buffer for training. This asynchronous design allows heterogeneous worker machines with different specifications and performance levels to collaborate naturally in improving the data collection efficiency. It prevents interference between the workers and minimizes the impact of different threads within each worker. As a result, each worker can fully contribute their performance gains as expected.

On the whole, *DistRL* employs asynchronous RL to address the challenges of online RL in dynamic, real-world settings. Each thread in workers operates independently, executing tasks and generating learning trajectories at its own pace, which accommodates variability in task durations and system latencies. Data produced by the working threads is queued and processed by the host learner, which

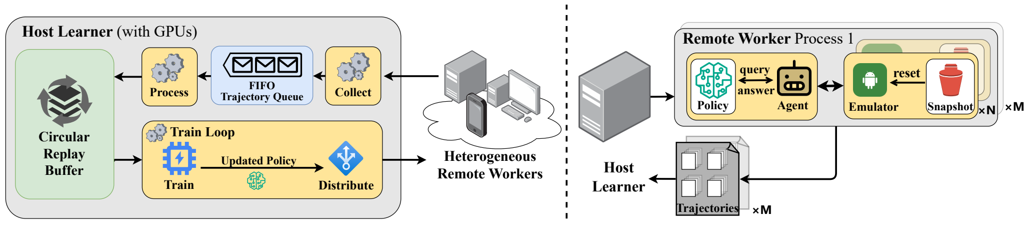


Figure 3: Illustration of the high-level workflow of DistRL System.

updates the global policy based on the collected trajectories. The updated policy is asynchronously distributed back to the workers, allowing for independent and non-blocking policy updates. This approach effectively manages temporal discrepancies between the workers and the host learner, ensuring smooth and effective learning across distributed workers. Further details regarding the communication mechanism between the host and workers are elaborated in Appendix A.3.2.

The asynchronous framework design also ensures scalability. With two 96 vCPU machines, it supports up to 32 emulators operating concurrently, and it can scale almost linearly with worker performance to handle large workloads.

5 Methodology

In this section, we introduce the core reinforcement learning algorithm employed in *DistRL* to fine-tune RL agents for device control tasks. The inherent issues of limited on-device resources, asynchronous data generation, and distributed constraints necessitate an efficient and scalable framework.

Reinforcement learning in distributed device control environments encounters significant challenges related to policy stability, convergence, and effective exploration. Stable convergence is essential for reliable agent performance, while robust exploratory behavior is crucial for discovering effective control policies in dynamic and complex settings. On-policy algorithms such as Proximal Policy Optimization (PPO) [39] and Advantage Actor-Critic (A2C) [24] are limited by their reliance on synchronous data collection and policy updates, leading to sample inefficiency and delayed learning in asynchronous, multi-agent environments.

To overcome these challenges, we introduce **A-RIDE**, an off-policy reinforcement learning algorithm tailored for distributed environments. **A-RIDE** stands for **A**dvantage-based **R**etrace **I**mproved by **D**istributed Prioritized **E**xperience Replay. It enhances exploration efficiency, maintains policy robustness, and improves training efficiency by promoting robust explorative behavior, ensuring policy stability, and prioritizing informative experiences. These advancements enable *DistRL* to achieve stable and efficient learning in real-world device control tasks.

5.1 A-RIDE: The Backbone of DistRL

Our method employs advantage-based estimations to refine policy gradient updates, as an extension of Generalized Advantage Estimation (GAE) [38], effectively balancing exploration and exploitation in the learning process. By introducing a trace decay parameter, **A-RIDE** manages the bias-variance trade-off in advantage calculations, optimizing the stability and convergence of the policy. **A-RIDE** incorporates enhancements tailored to distributed, asynchronous environments, ensuring robust policy stability and efficient learning in complex device control tasks.

While GAE has proven highly effective in synchronous environments, its reliance on synchronized data collection makes it less suitable for asynchronous settings, such as distributed control tasks on devices. To handle asynchronous trajectory generation in device control tasks, **A-RIDE** leverages an enhanced Retrace(λ) method for robust off-policy corrections inspired by [7, 26]. Unlike traditional on-policy algorithms that require synchronous data collection, **A-RIDE** is designed for distributed environments with asynchronous data.

The Retrace(λ) update is defined as: $Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \delta_t$, where the correction term δ_t is calculated as:

$$\delta_t = \sum_{k=t}^{H} \gamma^{k-t} \left(\prod_{i=t+1}^{k} c_i \right) [r_k + \gamma Q(s_{k+1}, a_{k+1}) - Q(s_k, a_k)] \,. \tag{1}$$

Here, $Q(s_t, a_t)$ is the estimated action-value function; $\gamma \in [0, 1]$ is the discount factor; H is the time horizon; $c_i = \lambda \min(1, \rho_i)$ with $\lambda \in [0, 1]$ being the trace decay parameter; $\rho_i = \dfrac{\pi(a_i|s_i)}{\mu(a_i|s_i)}$ is the importance sampling ratio between the target policy π and the behavior policy μ.

To ensure effective exploration within the action space and prevent the generation of nonsensical or invalid commands, we incorporate entropy regularization into the actor loss function. This addresses the challenge inherent in Vision-Language Models (VLMs) where purely random exploration may lead to semantically incoherent actions [18]. The actor loss is defined as:

$$\mathcal{L} = -\mathbb{E}_\mu \left[\rho_t A(s_t, a_t) \log \pi(a_t|s_t)\right] - \beta \mathbb{E}_\mu \left[\mathbb{H}(\pi(a_t|s_t))\right] + \lambda \mathbb{E}_\mu \left[\mathcal{P}_{\text{invalid}}(a_t)\right], \tag{2}$$

where the advantage function $A(s_t, a_t)$ represents how much better an action a_t is compared to the expected reward at state s_t, given the policy's understanding of the environment. It can be expressed as the difference between the action-value function $Q(s_t, a_t)$ and the state-value function $V(s_t)$: $A(s_t, a_t) = Q(s_t, a_t) - V(s_t)$. The action-value function $Q(s_t, a_t)$ estimates the expected return when taking action a_t at state s_t, while the state-value function $V(s_t)$ estimates the average expected return from state s_t under the policy π. $\mathbb{H}$ is the entropy term, $\mathcal{P}_{\text{invalid}}(a_t)$ imposes a penalty on actions deemed invalid based on task-specific criteria, β controls the strength of entropy regularization, and λ modulates the penalty's influence. The penalty is assigned using validation through pre-trained LLMs like Gemini [36]), ensuring that only contextually appropriate actions are penalized. The hyperparameters β and λ are optimized through empirical studies to balance exploration and policy robustness effectively. This formulation encourages the agent to explore a diverse set of actions while constraining it to generate valid and meaningful commands, thereby enhancing both exploration and policy robustness.

5.2 Distributed Prioritized Experience Replay (DPER)

To improve sample efficiency, we employ **Distributed Prioritized Experience Replay (DPER)**. For each trajectory $\tau = \{(s_t, a_t, r_t, s_{t+1})\}_{t=0}^{H}$, we compute the priority $p(\tau)$ as: $p(\tau) = w_1 \overline{|\delta|} + w_2 \overline{\rho} + w_3 \overline{\mathbb{H}}$, where $\overline{|\delta|}$ is the average absolute temporal-difference (TD) error over the trajectory, calculated as $\delta_t = r_t + \gamma V(s_{t+1}) - V(s_t)$; $\overline{\rho}$ is the average importance sampling ratio ρ_t; and $\overline{\mathbb{H}}$ is the average policy entropy, $\mathbb{H}_t = -\log \pi(a_t|s_t)$, encouraging exploration by encouraging policy uncertainty, thus avoiding early convergence to suboptimal policies during training in dynamic environments. The weights w_1, w_2, and w_3 balance the contributions of each component, which is selected by grid-search. Trajectories with higher priorities are replayed more frequently, focusing learning on the most informative experiences. Priorities are periodically updated based on the latest policy, recalculating them to focus learning on the most informative experiences, ensuring continual adaptation to evolving behavior policies. Details can be found in Appendix A.4.

5.3 DistRL Pipeline Implementation

As illustrated in Figure 4, *DistRL* adopts a distributed asynchronous setup where multiple worker agents generate trajectories under the behavior policy μ and send them to a central learner. The trajectory reward is computed using the Monte Carlo estimate:

$$L(V_{\text{traj}}) = -\mathbb{E}_\nu \left[r(s_H, a_H) \log V_{\text{traj}}(s_H, a_H) + (1 - r(s_H, a_H)) \log (1 - V_{\text{traj}}(s_H, a_H))\right]. \tag{3}$$

The actor is updated using policy gradients based on advantage estimates, and enhanced Retrace corrections are applied for off-policy learning. This process is distributed asynchronously across worker nodes, ensuring efficient fine-tuning in environments with sparse rewards and distributed delays.

6 Experiments

To evaluate the performance of *DistRL* on challenging Android device control tasks, we conducted extensive experiments. Our primary goal is to determine whether *DistRL* can produce agents that effectively learn from autonomous online interaction. We describe the experimental environment in Section 6.1, the baseline and benchmarks in Section 6.2, training performance in Section 6.3, and on-device task evaluations in Section 6.4. Additionally, we present ablation studies on our approach's components in Section 6.5.

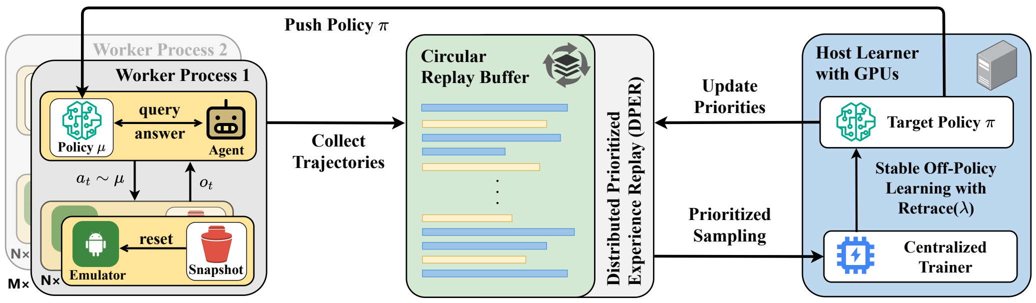


Figure 4: Backbone of DistRL: A-RIDE - Reinforcement Learning-based Fine-Tuning

6.1 Evaluation Environment

Our evaluation environment consists of a host learner with 4 NVIDIA V100 GPUs for intensive policy training and two worker machines with 8 NVIDIA Tesla T4 GPUs and 96 vCPUs each, supporting parallel emulation. This setup leverages 192 vCPUs to run multiple emulators concurrently, enabling scalable distributed reinforcement learning experiments. The worker machines handle inference and data collection, asynchronously communicating with the host learner to exchange trajectories and updated model weights. This configuration allows us to assess *DistRL*'s scalability and performance in a realistic large-scale distributed environment.

6.2 Benchmarks and Baseline Methods

To comprehensively validate our approach, we utilize both the *General* and *web shopping* tasks for training and testing. Specifically, our training set is derived from enhanced online task instructions, which are composed of **AitW** [34], **AndroidWorld** [33], and expert-curated task sets. We fine-tune our model on this combined training set and evaluate performance on the corresponding test subsets derived from **AitW**. Our analysis focuses on training efficiency using the *General Tasks*, which include fundamental application operations and information retrieval tasks. Additionally, we assess the agent's performance on both *General Tasks* and *Web Shopping Tasks* to evaluate its capability in handling domain-specific instructions, addressing the significant task distribution gap. Detailed descriptions of the datasets used are provided in Appendix A.5. Our baseline methods[3] include:

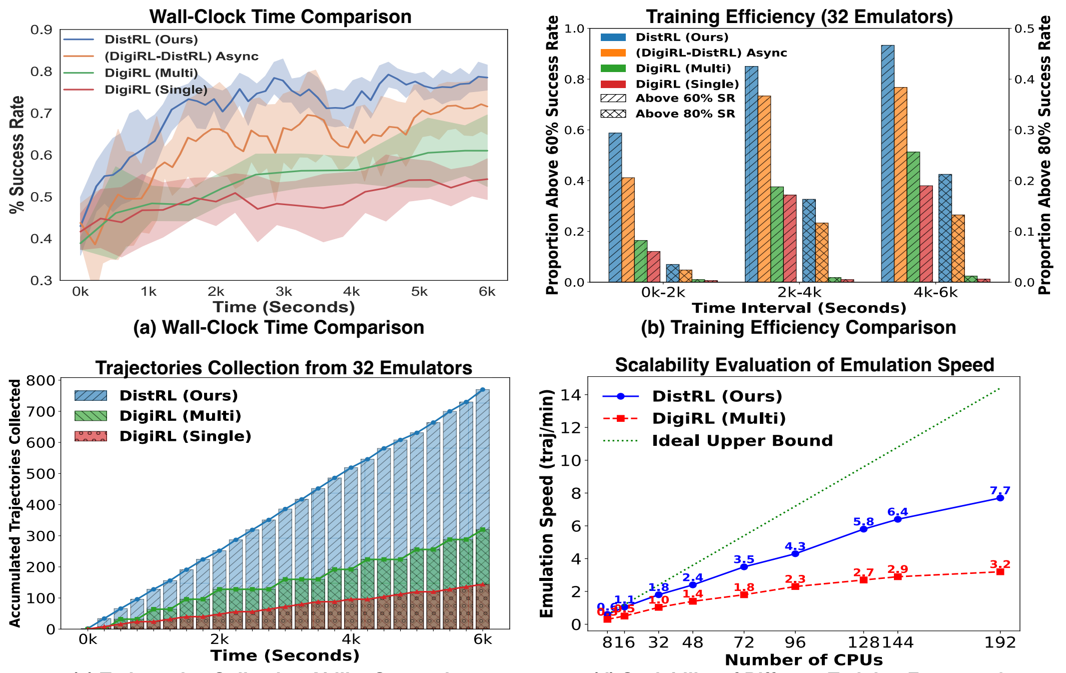
- DigiRL [3]: The state-of-the-art framework prior to our work, which integrates RL fine-tuning with visual language models (VLMs) and provides a reproducible training process. We consider its both single and multi-machine settings in online mode.
- AutoUI [48]: A simple explorative mobile agent equipped with VLMs under supervised fine-tuning.
- GPT-4V [28] and Gemini 1.5 Pro [36]: Equipped with exploration drives-AppAgent [45] to facilitate learning from the environments.

6.3 Training Performance

Training efficiency is crucial in reinforcement learning, particularly in complex environments, and is measured by the rate of improvement over time. We compared *DistRL* with the existing DigiRL framework. Our results show that *DistRL* significantly boosts training efficiency with its distributed, asynchronous design, leveraging multiple machines and GPUs.

In subfigure (a), by 6k seconds, *DistRL* achieves a success rate 30% and 40% higher than DigiRL in multi- and single-machine settings, respectively. Even compared with DigiRL that is enhanced with our asynchronous framework (by integrating the DigiRL algorithm into the *DistRL* framework to isolate the framework's benefits-named as *DigiRL-DistRL Async*), *DistRL* achieves 10% higher result with faster convergence speed. Subfigure (b) illustrates the proportions of success rates above 60% and 80% in different training phases, representing key stages in the learning curve. *DistRL* maintains higher proportions of success rates above these thresholds compared to DigiRL, showing a faster convergence and higher stability. These improvements are attributed to our asynchronous architecture and tailor-made algorithm for efficient data collection and sampling.

[3]A qualitative comparison among methods and more details can be found in Table 3 in Appendix A.5.1



(a) Wall-Clock Time Comparison

(b) Training Efficiency Comparison

(c) Trajectories Collection Ability Comparison

(d) Scalability of Different Training Frameworks

Figure 5: Training performance (32 emulators) between the current state-of-the-art method (DIGIRL) and *DistRL*, highlighting the enhanced efficiency of *DistRL*'s distributed framework during online training. **(a)** Wall-clock time comparison **(b)** Training efficiency comparison. **(c)** Accumulated trajectories collection ability comparison. **(d)** Scalability of different training frameworks

Subfigure (c) highlights *DistRL*'s superior data collection efficiency, accumulating 800 trajectories in 6k seconds, compared to DIGIRL's 300 in a multi-machine setting. While subfigure (d) demonstrates *DistRL*'s scalability. It achieves a collection speed of approximately 7.7 trajectories per minute with 192 CPUs, with nearly linear scalability, closely approaching the ideal upper bound—perfect linear scalability with no overhead from communication or error handling. This ideal upper bound is determined by assuming each CPU operates independently and continuously with a stable speed, profiled by measuring the collection speed when a single CPU handles the task.

Additionally, Table 1 also presents the final training performance at convergence or after extended training time budgets (will be explained in the subsequent subsection), demonstrating the superior long-term performance of *DistRL* compared to the baselines.

6.4 On-Device End-to-end Agent Performance Evaluation

We evaluate the end-to-end performance of agents trained with *DistRL* against other frameworks, including on-device control agents, using subsets of both the **AitW** training and test sets. The primary metric for evaluation is the success rate across *General* and *Web Shopping* tasks. To ensure a fair comparison, we allocate extensive fine-tuning time for DIGIRL in single-machine and synchronous multi-machine configurations, typically allowing 2 times the convergence time required by our asynchronous *DistRL* multi-machine setup. Despite this generous tuning period, baseline methods often fail to achieve stable performance due to inherent inefficiencies in their synchronous designs, which hinder effective utilization of additional training time.

The results in Table 1 and Figure 6.(a) demonstrate the superior performance of our *DistRL* framework over other agents across all evaluated settings. In the *General* test set, *DistRL* achieves a success rate of 73.2%, showing a relative improvement of approximately 19.6% over DIGIRL (MULTI) and 22.2% over DIGIRL (SINGLE). In the *Web Shopping* test set, *DistRL* attains a success rate of 68.5%, outperforming DIGIRL (MULTI) by about 14.4% and DIGIRL (SINGLE) by 14.9%. This significant enhancement is attributed to *DistRL*'s design for pure asynchronous task collection procedures and its advanced algorithm for efficiently utilizing diverse incoming trajectories, leading to better generalization and higher success rates.

Framework Type	Framework Name	General		Web Shopping	
		Training	Test	Training	Test
Prompting	AppAgent + GPT-4v	41.4	43.0	31.2	35.2
	AppAgent + Gemini	39.1	45.3	30.5	32.0
Learning	AutoUI	38.3	40.6	42.2	44.5
	DigiRL (single,online)	64.6 ± 1.5	59.9 ± 2.1	63.3 ± 1.5	59.6 ± 3.1
	DigiRL (multi)	67.7 ± 1.3	61.2 ± 2.4	64.5 ± 1.1	59.9 ± 2.8
	DistRL (Ours)	$\mathbf{75.5 \pm 0.2}$	$\mathbf{73.2 \pm 1.1}$	$\mathbf{69.8 \pm 0.5}$	$\mathbf{68.5 \pm 1.7}$

Table 1: Main comparisons regarding the **success rate** of different agents across various settings. Each experiment is repeated three times and the mean and standard deviation are reported. Results are evaluated with our autonomous evaluator with the 128 user instructions in the train and test set.

The prompting-based methods, such as AppAgent combined with GPT-4V or Gemini, show considerably lower success rates, not exceeding 45.3% in any test setting. These methods lack adaptive learning capabilities on real-time large-scale interaction data, leading to poorer performance and higher susceptibility to task variability. AutoUI, another learning-based agent fine-tuned by supervised knowledge, also underperforms with success rates below 45%, likely due to less efficient exploration strategies and inadequate handling of diverse user instructions.

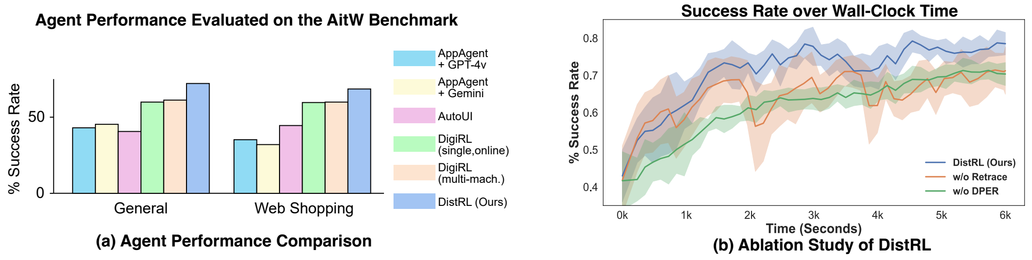


Figure 6: (a) Comparison of trained agent performance when evaluated on the **AitW** benchmark.**(b)** Ablation Study of DistRL

6.5 Ablation Studies

To understand the contributions of different components in *DistRL*, we conduct ablation studies by systematically removing or altering key elements of the algorithm, such as the enhanced Retrace algorithm and Distributed Prioritized Experience Replay (DPER). The results, summarized in Figure 6.(b), demonstrate the significant impact of each component on the task success rate.

Distributed Prioritized Experience Replay (DPER) is crucial for accelerating training convergence. Removing DPER results in an 8% decrease in the success rate, indicating that prioritizing trajectories with higher TD errors and smaller policy discrepancies enables faster and more efficient learning by focusing updates on the most informative experiences. With the entropy term, the prioritization mechanism promotes exploration based on the evolving policy distribution, preventing stagnation during training.

Retrace Algorithm is essential for maintaining training stability. Ablating the Retrace algorithm leads to a 6% drop in success rate and causes sharp decreases in performance during training. This instability arises because Retrace provides off-policy correction, ensuring stable updates even when the agent receives a large number of diverse trajectories.

Overall, the ablation results confirm that both DPER and the Retrace algorithm are integral to the efficiency and robustness of *DistRL*.

7 Conclusion and Future Work

In this paper, we introduce *DistRL*, an efficient distributed reinforcement learning framework tailored for mobile-based agents tasked with user instructions. Our primary contribution is the development of a robust and scalable pipeline that seamlessly bridges the gap between real-time interactions on mobile devices or emulators and distributed training infrastructures, ensuring efficient and adaptive learning.

For future work, we aim to extend the generalization capabilities of *DistRL* to a broader range of tasks, focusing on enhancing both the training pipeline and the underlying algorithmic architecture. Additionally, we envision evolving *DistRL* into a core backbone for integrating many more Multimodal Large Language Models (MLLMs), allowing for a wider range of applications and evaluations on diverse benchmarks.

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A Appendix

A.1 Case Study

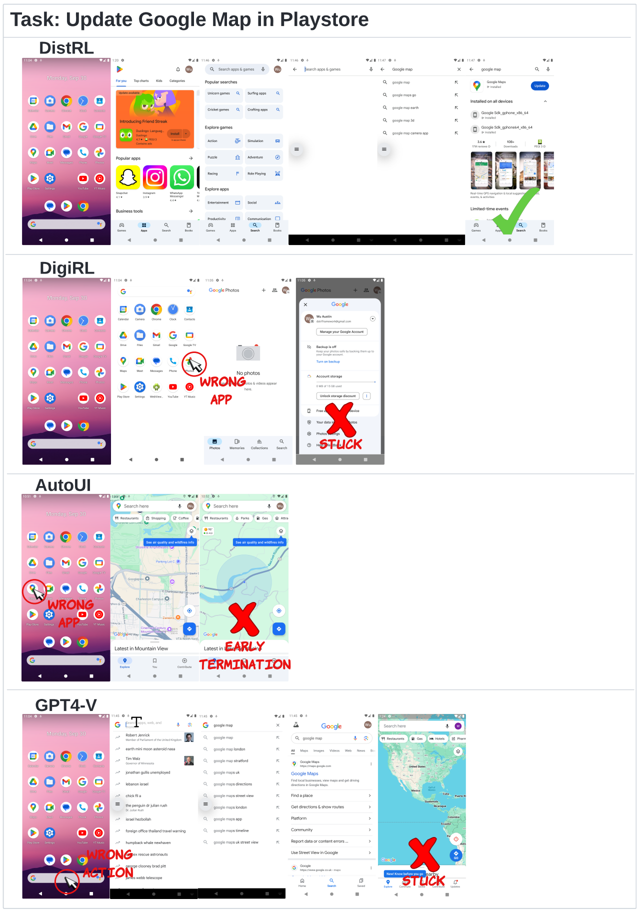

Figure 7: Case study on general app operation tasks.

Figure 7 illustrates a type of common case where baseline methods always fails, highlighting the challenges for these device-control agent in real-time app operation tasks.

DIGIRL, which was trained on older versions of the system, fails due to discrepancies between its learned knowledge and the current environment. This mismatch in training data leads to a significant error: DIGIRL mistakenly opens Google Photos instead of the Play Store. Since the two apps share similar icon features. After opening the wrong app, DIGIRL continues to operate within the incorrect environment, ultimately getting stuck in the settings menu of Google Photos. This reveals a significant limitation of offline-training-only agent in adapting to updated environments, especially when visual similarities between app icons lead to misclassification. AutoUI shares a similar issue where it struggles to correctly identify the target application. In this case, it opens Google Maps directly instead of navigating through the Play Store. Its lack of adaptability to new tasks or novel instructions results in failure.

The AppAgent with GPT-4V takes an alternate route by resorting to web searching, which diverges from the intended method of updating the app. Eventually, this leads to the agent becoming stuck within the Google Maps application itself, indicating that while GPT-4V was able to explore different avenues to achieve the goal, it did not follow the expected approach due to the lack of app-specific knowledge.

While the *DistRL*, which was actively trained on the real-time newly-updated environment through online-training, could conduct the intended operations accurately and successfully.

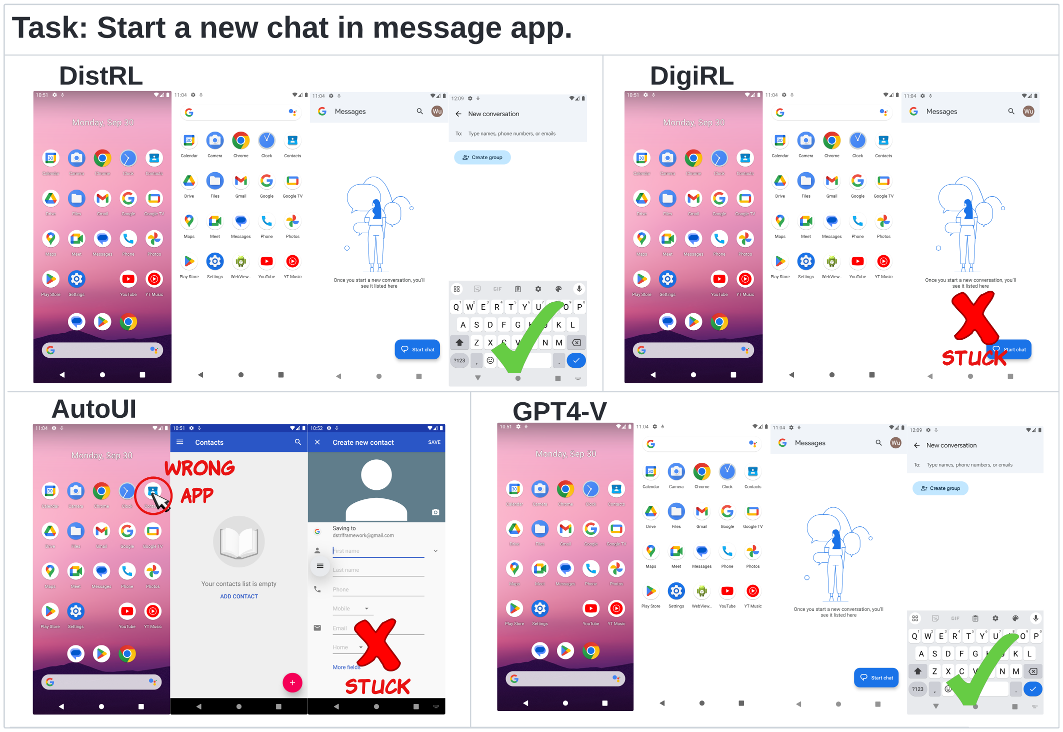

Figure 8: Case study on general app operation tasks.

The case study in Figure 8 further illustrates the comparative performance on a simpler general app operation task — starting a new chat in the messaging app.

DistRL successfully completes the task by efficiently navigating through the app's interface. It opens the correct messaging app and enters the "New Conversation" screen without getting stuck.

In contrast, DIGIRL manages to open the correct messaging app but fails to proceed, getting stuck when attempting to start the new chat. This is due to DIGIRL's reliance on outdated training data, as it was trained on an older version of the app's interface. In the outdated UI, the intended action (starting a chat) involved interacting with elements in a different layout, and DIGIRL cannot adapt to the updated version. This demonstrates the pitfalls of relying primarily on offline data for training without sufficient online fine-tuning to adapt to new UI changes, as seen in modern apps that frequently update their designs.

AutoUI, on the other hand, fails immediately by selecting the wrong app. It opens the Contacts app instead of the messaging app, leading to a failure in completing the task from the very beginning. This reflects a limitation in AutoUI's task understanding and its inability to differentiate between similar apps, further highlighting the weakness of frameworks that lack a robust decision-making process or real-time adaptability.

GPT-4V, though not specifically trained for app-specific tasks, performs well in this scenario due to its generalization capability. It opens the correct messaging app and navigates to the "New Conversation" screen successfully. GPT-4V is more flexible and suitable for simpler, general-purpose tasks. However, this general-purpose approach may not scale well for more complex tasks where app-specific expertise and interaction nuances are required.

The real cases in the figures emphasizes the critical importance of efficient real-time online learning.

Figure 9 shows a case study on the web shopping task.

DistRL demonstrates relatively smooth and fluid operations, progressing through the steps without hesitation. While it ultimately encounters early termination due to reaching the step limit (horizon), it performs each step with clear transitions and effectively navigates through the sequence. *DistRL* shows strong task comprehension and adaptation throughout, but its misunderstanding on the task

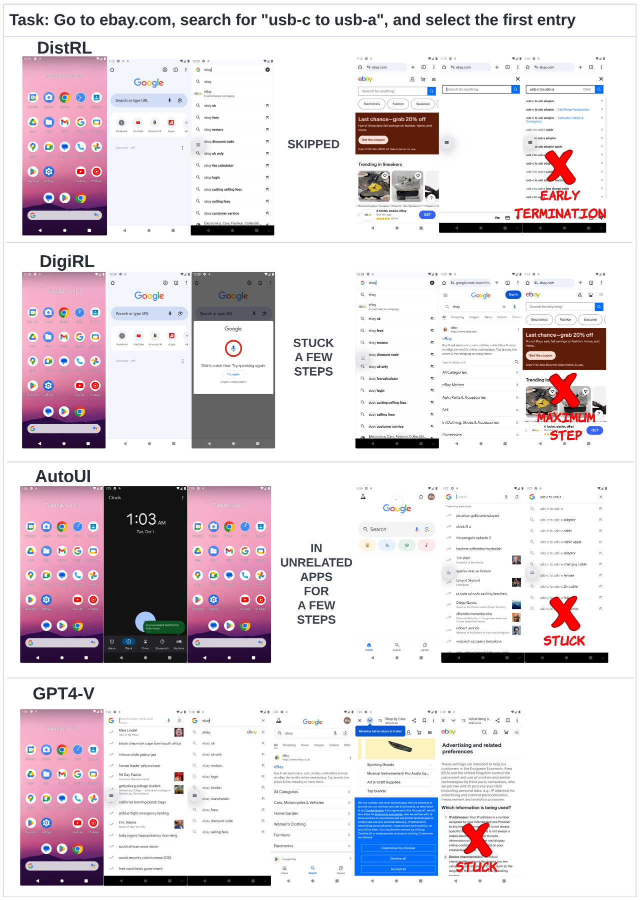
Task: Go to ebay.com, search for "usb-c to usb-a", and select the first entry
DistRL
SKIPPED
EARLY TERMINATION
DigiRL
STUCK A FEW STEPS
MAXIMUM STEP
AutoUI
IN UNRELATED APPS FOR A FEW STEPS
STUCK
GPT4-V
STUCK

Figure 9: Case study on web shopping tasks.

requirement prevents it from fully completing the task. This behavior emphasizes the efficiency of *DistRL*'s operations and its capacity to generalize across unseen web shopping tasks, even though the task is terminated early.

In contrast, DIGIRL faces several challenges during the task. It frequently steps back and forth between pages, struggling with the microphone input. These actions result in unnecessary delays and inefficiencies, which eventually lead it to reach its step budget without successfully completing the task. The back-and-forth behavior indicates a lack of robust policy adaptation, which causes it to get stuck in a loop, unable to make meaningful progress.

AutoUI, on the other hand, wanders into unrelated apps before eventually returning to the task. The lack of focus results in it spending multiple steps outside the task's scope, which ultimately contributes to its failure. This signifies weaknesses in both task planning and execution, as it struggles with distractions and incorrect app selections.

GPT-4V follows a similarly smooth approach as *DistRL*, but it becomes stuck after selecting a wrong entry into eBay, which triggers the cookie settings of the website. Although GPT-4V successfully navigates through several steps, it ultimately fails to get around the emergent pop-up, highlighting its limitation in handling web-specific tasks that require precision and app-specific understanding.

In summary, while *DistRL* and GPT-4V demonstrate smoother task execution, only *DistRL* manages to maintain a consistently structured progression, even though it faces early termination. Meanwhile, DIGIRL struggles significantly, exhibiting inefficient operations that lead to step budget exhaustion without meaningful progress. This case study emphasizes the importance of the ability to adapt policies in dynamic environments to complete tasks successfully within budgeted steps.

A.2 Auto Reward Labeling

A.2.1 Evaluation with Auto-Evaluator

To generalize the evaluator across a wide range of tasks without manual rule definitions, we leverage a pre-trained LLM with appropriate prompting. The prompt is designed to instruct the LLM to act as an expert evaluator, i.e., Gemini-1.5-Pro [36], in our practice. An example of such a prompt is provided below:

```
You're an expert in evaluating whether the Screenshot successfully completes the Task.
=====Examples=====
Screenshot: {train_1.png}
Task: Send a message to Evelyn.
Q: What should I expect to see on the screenshot if I've sent a message to Evelyn?
A: I should expect to see an open messaging app with a conversation window showing
a message sent to "Evelyn." The screenshot, however, shows the messaging app's contact list,
but no message has been sent.
Status: failure
```

In this prompt, the evaluator compares the expected outcome of the task with the actual screenshot. By analyzing the visual content and reasoning about the task, the LLM determines task completion.

A.2.2 Reward Penalty

To capture long-term dependencies in the device control setting, Monte-Carlo (MC) rollouts were employed to compute cumulative returns, which are then propagated backward to inform updates across each transition. However, during the experiments, we observed frequent repeated nonsense actions even in successful trajectories when doing roll-out with AutoUI agent, which sometimes causes unstable convergence during the asynchronous online learning. Thus, we further deployed a reward penalty on unexpected behaviors: accumulative penalty on repetitions and hard penalty on invalid actions.

A.3 System Design

A.3.1 Detailed System Description

DistRL is a distributed reinforcement learning framework designed for scalable, efficient training of mobile agents. It decouples trajectory collection from policy learning, utilizing working machines for agent-environment interactions and GPU servers for policy training. The working devices handle inference and CPU-intense data collection, transmitting data asynchronously to GPU servers for training large language models (LLMs). This separation optimizes efficiency, scalability, and resource utilization by aligning tasks with appropriate hardware.

This decoupled design offers several key advantages. First, it enhances efficiency by preventing resource contention: mobile devices focus on interaction tasks without being slowed by training, and GPUs dedicated to training perform updates without interruption. Notably, different types of GPUs are used; lightweight GPUs or CPUs handle inference and data collection, while high-performance GPUs are employed for intensive training computations. Second, scalability improves as more mobile devices are added, allowing data collection to scale naturally without single-machine hardware limitations. Third, resource utilization is optimized by aligning tasks with suitable hardware, maximizing performance. Dedicated training resources achieve faster convergence by efficiently processing larger batches and complex models. Cost efficiency is enhanced by leveraging existing devices for data collection and appropriately allocating GPU resources based on task requirements, reducing unnecessary hardware investments. Finally, the quality of learned policies improves due to the richer and more diverse dataset collected from multiple devices, enhancing robustness and generalization capabilities.

A.3.2 Communication between Host Learner and Workers

In our *DistRL* framework, communication between the Host Learner and Workers is crucial for synchronizing policy updates and collecting trajectories. We have opted to use SCP (Secure Copy Protocol) over SSH to transfer LoRA weights between the Host Learner and Workers. This choice is based on several practical considerations related to bandwidth, overhead, and deployment flexibility.

Within the AWS environment, network bandwidth between instances can exceed 500 Mbps. As illustrated in Table 2, transferring the LoRA weights (approximately 100 MB) using SCP takes less than 2 seconds on average. This communication overhead is negligible compared to the time required for trajectory collection and policy training.

Table 2: Communication Time for Transferring LoRA Weights via SCP

Network Bandwidth	LoRA Weight Size	Transfer Time
500 Mbps	100 MB	1.6 seconds
1 Gbps	100 MB	0.8 seconds

Each Worker thread completes approximately 6–10 trajectories per minute. Concurrently, training the policy on the Host Learner, even utilizing 4 V100 GPUs, takes around 120 seconds to perform a single model update. Consequently, the communication time of a few seconds for transferring weights is significantly lower than both the data collection and training durations, introducing no noticeable bottlenecks.

Alternative high-performance communication options like InfiniBand (IB) or RDMA over Converged Ethernet (RoCE) were considered. However, these technologies require specialized hardware and configurations, which are not always available or practical—especially when Workers (mobile devices or emulators) are dispersed across different physical locations or data centers. SCP over SSH offers a flexible and widely supported solution that operates effectively across diverse environments.

In summary, the minimal communication overhead introduced by using SCP over SSH does not adversely affect the overall performance of the *DistRL* framework. The simplicity, reliability, and broad compatibility of this approach make it a reasonable and efficient choice for our distributed reinforcement learning system.

A.4 Methodology Details

A.4.1 Limitations of Traditional Methods

On-policy algorithms such as Proximal Policy Optimization (PPO [39]) and Advantage Actor-Critic (A2C [24]) require synchronous data collection and updates, leading to inefficiencies in distributed and large-scale environments due to low sample efficiency and synchronization delays.

Standard off-policy methods like V-trace have been popular in distributed RL frameworks (e.g., **IMPALA** [7]) but can be suboptimal when the divergence between the behavior policy μ and the target policy π is either too small or too large due to clipping mechanisms.

These weights were empirically validated to provide a robust trade-off between bias and variance, enhancing the overall learning efficiency and stability of the reinforcement learning agent in our distributed, asynchronous setting.

A.4.2 Implementation Details

Circular Replay Buffer We utilize a **Circular Replay Buffer** with fixed capacity N to store experience tuples $(s_t, a_t, r_t, s_{t+1}, a_{t+1})$. When the buffer is full, new experiences overwrite the oldest ones, ensuring that the buffer contains the most recent experiences, which is effective in non-stationary environments.

The buffer index i is updated as:

$$i \leftarrow (i+1) \bmod N. \tag{4}$$

Enhanced Retrace Algorithm Retrace(λ) adjusts the importance sampling corrections based on policy divergence. When policies are similar, it fully exploits trajectories through λ-returns. When they differ significantly, it truncates importance sampling ratios to control variance, ensuring stable and unbiased updates.

Temporal-Difference Error Calculation The temporal-difference (TD) error for each step is calculated as:

$$\delta_t = r_t + \gamma V(s_{t+1}) - V(s_t), \tag{5}$$

which represents the discrepancy between predicted and actual rewards, guiding the learning updates.

Priority-Based Sampling in DPER In **Distributed Prioritized Experience Replay (DPER)**, trajectories are sampled based on their computed priority to focus on the most informative experiences. The probability of sampling a trajectory τ is proportional to its priority $p(\tau)$, calculated as:

$$P(\tau) = \frac{p(\tau)^\alpha}{\sum_i p(\tau_i)^\alpha},$$

where $\alpha = 0.5$ controls the extent to which prioritization is applied. A value of $\alpha = 0.5$ provides a balance between uniform sampling (when $\alpha = 0$) and full prioritization (when $\alpha = 1$), allowing the model to benefit from both the prioritization of informative trajectories and a degree of randomness. This ensures that less prioritized but potentially useful experiences still have a chance to be replayed, helping prevent overfitting to a narrow subset of the replay buffer.

Policy Update Mechanism The actor (policy network) is updated using gradients derived from the advantage estimates (without consideration of penalties on low-scored outputs):

$$\nabla_\theta \mathcal{L} = -\mathbb{E}_\mu \left[\rho_t A(s_t, a_t) \nabla_\theta \log \pi_\theta(a_t|s_t)\right] - \beta \nabla_\theta \mathbb{E}_\mu \left[\log \pi_\theta(a_t|s_t)\right], \tag{6}$$

where θ represents the parameters of the policy network.

A.4.3 Hyperparameter Tuning for Distributed Prioritized Experience Replay

To enhance sample efficiency in our **Distributed Prioritized Experience Replay (DPER)** framework, it is crucial to appropriately balance the contributions of the average temporal-difference (TD) error ($\overline{|\delta|}$), the average importance sampling ratio ($\overline{\rho}$), and the average policy entropy ($\overline{H}$). These components inherently operate on different scales, necessitating careful normalization to ensure that no single component disproportionately influences the priority calculation.

Each component contributing to the priority score is normalized to a common scale based on their statistical properties observed during preliminary training runs. The normalization process is as follows:

- **Average Absolute TD Error ($\overline{|\delta|}$)**: Normalized by dividing by the maximum absolute TD error observed across all trajectories in the training set. This scaling ensures that $\overline{|\delta|}$ ranges between 0 and 1.
- **Average Importance Sampling Ratio ($\overline{\rho}$)**: As importance sampling ratios naturally fall within the range [0, 1], no additional scaling is required.
- **Average Policy Entropy ($\overline{H}$)**: Normalized by dividing by the maximum observed entropy value during training, ensuring that $\overline{H}$ also ranges between 0 and 1.

This normalization facilitates a balanced contribution from each component when computing the overall priority, preventing any single factor from dominating the priority score.

The weights w_1, w_2, and w_3 are critical in determining the influence of each normalized component on the priority calculation. To identify the optimal values for these weights, we employed a grid search strategy on a validation set, exploring the following empirical ranges: $w_1 \in \{0.01, 0.1, 0.5, 1.0, 2.0, 5.0, 10.0\}$, $w_2 \in \{0.01, 0.10.3, 0.5, 0.7, 1.0\}$, $w_3 \in \{0.01, 0.1, 0.3, 0.5, 0.7, 1.0\}$.

These ranges were selected based on insights from prior research [37, 10] and preliminary experiments that indicated effective performance within these intervals.

The chosen weights effectively balance the three components, ensuring that:

- **Learning from High-TD Error Trajectories**: By assigning a higher weight to $\overline{|\delta|}$, the framework emphasizes replaying experiences where the model's predictions were significantly off, facilitating targeted learning and faster convergence.
- **Maintaining Exploration**: The weight on policy entropy ensures that the agent continues to explore diverse actions, preventing premature convergence to suboptimal policies.
- **Correcting for Distributional Shifts**: The importance sampling ratio weight allows the algorithm to adjust for changes in the policy distribution, maintaining unbiased updates despite using prioritized replay.

A.5 Experimental Details

A.5.1 Baseline Methods

We evaluate proprietary vision-language models (VLMs), GPT-4V [28] and Gemini 1.5 Pro [36], using the AppAgent framework. By applying the prompt from [45], we enable these models to interact effectively with the environment. We assessed the AppAgent [45] in a augmented prompting setting, where the agent explores the environment and gathers experience ahead of inference phase. This collected experience is appended to the test-time prompt, enhancing the model's decision-making capabilities. Unlike learning-based approaches, these methods rely on advanced prompting strategies to accomplish tasks without extensive training. Additionally, our framework *DistRL* integrates **GPT-2** [32] for policy learning and **ROBERTA-base** [22] for the critic model [4]

In Table 3, we compare *DistRL* with other frameworks based on scalability, task diversity, and training efficiency.

Table 3: Comparison among on-device agents' frameworks based on scalability, task diversity, and training efficiency.

	DistRL (Ours)	DIGIRL	**AutoUI**	**AppAgent+MLLMs**
Type	Async.	Sync.	N/A	N/A
Scalability	++	+	N/A	N/A
Task Diversity	General	Limited	Limited	General
Training Eff.	High	Low	Low	N/A
Multi-GPUs Sup.	✓	✓✗ (offline only)	✗	✗

A.5.2 Training and Test Data

The dataset used in this work is based on the Android in the Wild (**AitW**) [34] and **AndroidWorld** [33] task set, with enhancements for practical use in fine-tuning agents to control mobile devices and interact with real-world applications. We trained two separate models using two distinct subsets for *General Tasks* and *Web Shopping Tasks*. Each model was trained on its corresponding training subset and evaluated on the respective test subset drawn from **AitW**.

For training, we utilized the *General Tasks* subset from **AitW**, augmented with tasks selected from **AndroidWorld** and several expert curated ones, which includes tasks that require basic to complex application usage and information retrieval. For *Web Shopping Tasks*, we used the subset from **AitW** directly. Each training set consists of more than 400 tasks, allowing the agent to learn from a broad range of apps and websites operations and promote robust learning without overfitting to specific task types.

To avoid cold start issues in our asynchronous reinforcement learning framework, we constructed a warmup trajectory dataset for each task type, each consists of 128 trajectories collected with an initial version of the AutoUI agent. These sets will be fed into the replay buffer at the beginning of the online training.

During testing, we evaluated the models on their respective test sets: 128 tasks for *General Tasks* and 128 tasks for *Web Shopping Tasks*, both sourced from **AitW**. This approach ensures that each model is assessed on the task domain it was trained on, addressing the task distribution gap between general user instructions and domain-specific web shopping instructions.

General Tasks The *General Tasks* subset consists of tasks that involve basic application operations and information retrieval. Examples include searching for the latest news, retrieving information about locations, and interacting with mobile apps. To force the agent to operate more on the various applications instead of searching everything through web, we augmented the task set for training with several instructions from **AndroidWorld** and some expert curated tasks, which are typically more complex and application-specific. The training set contains 600 tasks, and the test set includes 128 tasks from **AitW**, facilitating a robust evaluation of *General Tasks* performance. Each task allows a maximum of 15 steps to complete. Example tasks from the *General Tasks* subset are shown in Table 4.

[4]We adopt the same baseline agent (AutoUI-driven agent) and VLMs models as used in DIGIRL to validate the advantages of our fine-tuning framework and algorithm

Task Set	Task Example
AitW	What is the capital of Norway? Play some music on YouTube.
AndroidWorld	Run the stopwatch. Create a new contact for Jack. Their number is 0123456789.
Expert Curated	Check today's events in the calendar. Check if there is any app to update in Playstore.

Table 4: Examples of task descriptions in the General Tasks subset.

Web Shopping Tasks The *Web Shopping Tasks* subset includes tasks that simulate real-world shopping activities such as searching for products, navigating e-commerce websites, and interacting with shopping carts. Task complexity ranges from simple web navigation to multi-step operations involving product searching and browsing. The training set consists of 500 tasks, and the test set includes 128 tasks from **AitW**, enabling the evaluation of the agent's ability to handle domain-specific instructions. Each task permits up to 20 steps to complete. Example tasks from the *Web Shopping Tasks* subset are presented in Table 5.

Difficulty	Task Example
1	Go to ebay.com
1	Go to costco.com
2	Go to ebay.com, search for "asus zenbook"
2	Go to walmart.com, search for "corsair k70"
3	Go to bestbuy.com, search for "dell xps", and select the first entry
3	Go to newegg.com, search for "bose soundlink mini", and select the first entry

Table 5: Examples of task descriptions in the Web Shopping Tasks subset.

A.5.3 Detailed Performance Comparison

Other methods struggle to achieve comparable performance. DIGIRL, both in single and multi-machine settings, suffers from inefficiencies in data collection and utilization. The multi-machine version requires extensive collection time due to its low efficiency, hindering its ability to train effectively on diverse tasks, while the single-machine version struggles with scalability issues. These inefficiencies lead to higher variance in performance, as evidenced by the higher standard deviations (up to $\pm 3.1\%$) compared to *DistRL*.

Overall, the low variance and high success rates of *DistRL* demonstrate its robustness and effectiveness in generalizing across different tasks, emphasizing the advantages of our distributed reinforcement learning approach over existing methods, especially in large-scale, asynchronous settings.

A.6 Additional Quantitative Experiments

A.6.1 Failure Modes Analysis

Figure 10 presents a comparative analysis of failure rates across different approaches on the **AitW** *General* and *Web Shopping* subsets. Among the evaluated frameworks, *DistRL* consistently exhibits the lowest failure rates across all failure categories, notably excelling in recovering from mistakes and achieving the correct goal.

For the *General* subset, *DistRL* demonstrates exceptional performance with failure rates as low as 4% in recovering from mistakes, 12% in getting stuck midway, and 2% in arriving at an incorrect goal. These rates are at least three times lower than those observed in alternative approaches such as AutoUI and DIGIRL. This significant reduction in failure rates can be attributed to *DistRL*'s robust asynchronous distributed reinforcement learning (RL) framework, which facilitates more nuanced and adaptive policy learning. The distributed nature of *DistRL* allows for parallel exploration and exploitation of the state-action space, leading to a more comprehensive understanding of task dynamics and improved decision-making accuracy.

Similarly, on the *Web Shopping* subset, *DistRL* maintains low failure rates of 3% in recovering from mistakes, 7% in encountering mid-task obstacles, and 4% in goal misalignment. These figures represent at least a twofold improvement over competing frameworks, highlighting *DistRL*'s superior capability in managing complex and dynamic task environments. The ability to effectively

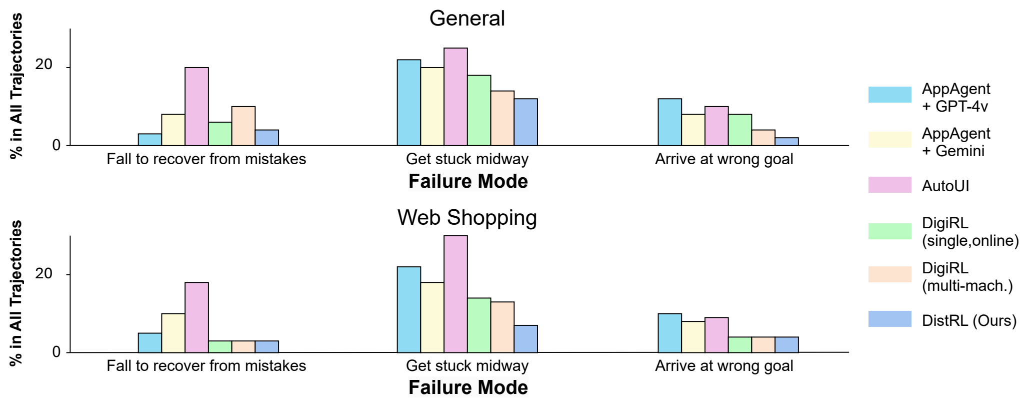

Figure 10: Comparison of **failure modes** across different frameworks on the AitW General and Web Shopping subsets.

handle task complexities is further reinforced by the asynchronous updates in *DistRL*, which mitigate issues such as delayed feedback and non-stationary environments that often plague distributed learning systems.

In contrast, frameworks like AutoUI and DIGIRL exhibit higher failure rates, which may stem from their less sophisticated policy learning mechanisms or limited scalability in distributed settings. These higher failure rates suggest that these approaches may struggle with tasks that involve intricate dependencies or require rapid adaptation to changing conditions. The limitations observed in these frameworks underscore the importance of advanced distributed learning architectures in developing resilient and efficient agents capable of navigating complex, real-world environments.

Overall, the superior performance of *DistRL* across multiple failure modes underscores its effectiveness in building robust agents. This robustness is crucial for applications where reliability and precision are paramount, such as automated web interactions and general task execution. Future work may explore further enhancements to the distributed framework, such as incorporating more sophisticated exploration strategies or leveraging transfer learning to extend capabilities to even more diverse task domains.

A.6.2 Generalization Performance on AitW Subsets

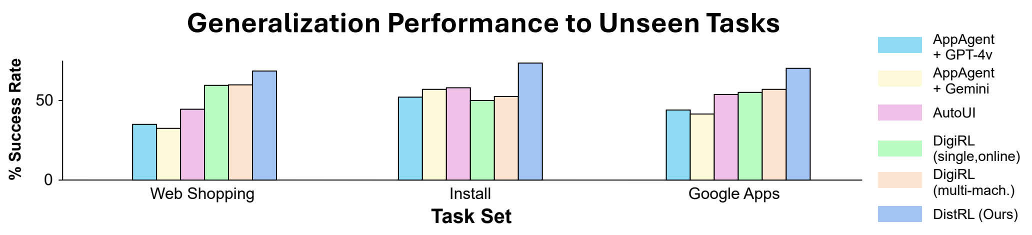

Figure 11: Generalization performance across different AitW subsets. The agents were trained on the General task set and evaluated on 128 tasks per subset.

Figure 11 illustrates the generalization performance of various frameworks across the *Web Shopping*, *Install*, and *Google Apps* subsets of the **AitW** dataset. The agents were trained exclusively on the *General* task set, and their ability to generalize was assessed on the first 128 tasks within each respective subset.

DistRL consistently outperforms its counterparts, achieving accuracies of 68.5% on *Web Shopping*, 73.5% on *Install*, and 70.2% on *Google Apps*. These results highlight *DistRL*'s superior generalization capabilities, which can be largely attributed to its robust distributed learning approach. The asynchronous distributed RL framework employed by *DistRL* enables the agent to learn from a diverse set of experiences concurrently, fostering a more versatile and adaptable policy that can transfer effectively across different task domains.

In contrast, frameworks such as DIGIRL and AppAgent exhibit markedly lower generalization performance. DIGIRL and AppAgent struggle particularly with adapting to the *Install* and *Google Apps* subsets, where task structures and requirements may differ significantly from the training set. This limitation suggests that these frameworks may be overfitting to the *General* task set or lacking the necessary mechanisms to capture the underlying transferable features essential for effective generalization.

The ability of *DistRL* to generalize across diverse task subsets is a critical advantage, especially in real-world applications where agents are often required to operate in varied and unforeseen environments. This generalization strength is likely a result of the extensive exploration and varied experiences facilitated by the distributed learning process, which allows *DistRL* to build a more comprehensive and flexible policy.

These findings have significant implications for the development of autonomous agents. The demonstrated generalization capabilities of *DistRL* suggest that distributed RL frameworks can be a promising direction for creating agents that are not only proficient in specific tasks but also adaptable to a wide range of scenarios without the need for extensive retraining. Future research could investigate the integration of additional generalization techniques, such as meta-learning or multi-task learning, with distributed RL to further enhance performance across even more diverse and complex task domains.