MARFT: Multi-Agent Reinforcement Fine-Tuning

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Abstract

Large Language Model (LLM)-based Multi-Agent Systems (LaMAS) have demonstrated remarkable capabilities in addressing complex, agentic tasks requiring multifaceted reasoning and collaboration, from generating high-quality presentation slides to conducting sophisticated scientific research. Meanwhile, Reinforcement Learning (RL) has been widely recognized for its effectiveness in enhancing agent intelligence, but limited research has investigated the fine-tuning of LaMAS using foundational RL techniques. Moreover, the direct application of conventional Multi-Agent Reinforcement Learning (MARL) methodologies to LaMAS introduces significant challenges, stemming from the unique characteristics and mechanisms inherent to LaMAS. To address these challenges, this article presents a comprehensive study of LLM-based MARL and proposes a novel paradigm termed **Multi-Agent Reinforcement Fine-Tuning (MARFT)**. We introduce a brand-new MG called Flex-MG, which aligns with the LaMAS optimization in real-world applications and a universal algorithmic framework tailored specifically for LaMAS, outlining the conceptual foundations, key distinctions, and practical implementation strategies. We begin by reviewing the evolution from traditional RL to Reinforcement Fine-Tuning (RFT), setting the stage for a parallel analysis in the multi-agent domain. In the context of LaMAS, we elucidate critical differences between classical MARL and MARFT, such as asynchronous agent interactions, profile-aware agent design, and heterogeneous architectural configurations etc. These differences motivate a transition toward a novel, LaMAS-oriented formulation of RFT. Central to this work is the presentation of a robust and scalable MARFT framework. We detail the core algorithm, emphasizing its modularity and adaptability, and provide a complete, open-source implementation to facilitate adoption and further research. The latter sections of the paper explore real-world application perspectives and opening challenges in MARFT, including dynamic environment modeling, sample inefficiency, and the current lack of cohesive frameworks. By bridging theoretical underpinnings with practical methodologies, this work aims to serve as a roadmap for researchers seeking to advance MARFT toward resilient, adaptive, and human-aligned solutions in agentic systems. Our implementation of the proposed framework is publicly available at: https://github.com/jwliao-ai/MARFT.

1 Introduction

Large Language Models (LLMs) are increasingly being deployed as a new generation of autonomous agents capable of performing agentic tasks—those that require decision-making, reasoning, and interaction with complex and dynamic environments (Jin et al., 2024; Hong et al., 2024; Qian et al., 2024). These LLM-based agents are rapidly reshaping human–machine interaction and expanding the frontiers of autonomous systems. In addition to their strong natural language understanding and generation capabilities (Chowdhary, 2020), LLMs can perform retrieval-augmented generation

(RAG) (Lewis et al., 2021), and, when integrated with external tools or APIs, can accomplish more sophisticated tasks on computers and mobile platforms (Erdogan et al., 2024; Zhang et al., 2025). Furthermore, LLMs have been successfully embedded into embodied and simulated environments, functioning as agents such as robots or game players (Tan et al., 2024; Mandi et al., 2023; Carta et al., 2023). Their ability to comprehend instructions, learn from feedback, and generate context-aware outputs enables effective deployment across various domains, including healthcare, education, and software development (Dai et al., 2023; Chen et al., 2024).

Reinforcement Learning (RL) is a machine learning paradigm in which an agent learns optimal behaviors through trial-and-error interactions with an environment to maximize cumulative reward. Unlike supervised or unsupervised learning, RL is driven by feedback in the form of rewards or penalties (Sutton & Barto, 1998). The recent release of OpenAI's o1 model, trained using large-scale RL techniques, has reignited interest in the field due to its impressive reasoning abilities (OpenAI, 2024a). Following this, OpenAI expanded its broader reinforcement fine-tuning (RFT) research program focused on refining LLMs through RL approaches (OpenAI, 2024b). Distinct from conventional RL, RFT involves fine-tuning pretrained models using a relatively small set (dozens to thousands) of high-quality interaction trajectories. This process must maintain the language capabilities of the LLM while enhancing its reasoning and decision-making skills. Recent studies have shown that RFT can significantly improve the performance of LLM-based agents (DeepSeek-AI et al., 2025; Qwen-Team, 2025; Shao et al., 2024; Zeng et al., 2024; Wang et al., 2024). Notably, Shao et al. (2024) proposed a variant of Proximal Policy Optimization (PPO), termed Group Relative Policy Optimization (GRPO), which enhanced reasoning abilities and revealed intriguing phenomena such as the "Aha moment" during large-scale RL training. Building on this, Yu et al. (2025) and Yue et al. (2025) introduced DAPO and VAPO, respectively, extending GRPO with additional techniques. Collectively, these efforts highlight the centrality of the trial-and-error nature of RL in advancing LLM intelligence. Despite these advances, directly applying RFT to multi-agent LLM settings remains underexplored. Naively transferring single-agent RFT techniques to multi-agent contexts often leads to challenges such as unstable training, inactive agents, and inefficient communication. These issues underscore the need to revisit and adapt established concepts from MARL to bridge the gap between RFT and LLM-based Multi-Agent Systems (LaMAS).

Multi-Agent Systems (MAS) have consistently demonstrated superior capabilities in addressing complex agentic tasks relative to their single-agent counterparts. This is evident in the latest General AI Assistants (GAIA) leaderboard (Mialon et al., 2024), where the top-performing systems are all multi-agent frameworks. Prominent frameworks, including OpenAI Agents SDK (formerly Swarm), Microsoft AutoGen (Wu et al., 2023), Magnetic-One, CAMEL-AI OWL (CAMEL-AI.org, 2025), and Google's AI Co-Scientist (Gottweis et al., 2025), further reinforce the growing importance of multi-agent architectures. Notably, in OpenAI's vision for AGI, multi-agent systems constitute the highest organizational layer. However, as Cemri et al. (2025) illustrates, multi-agent systems are prone to a variety of failure modes—fourteen in total—related to system design, coordination, and control, where MARL is poised to address these challenges. Besides, recently Yang et al. (2025c) proposed the first framework to systematically quantify the contributions of different modules in multi-agent systems, potentially illuminating the direction for future multi-agent optimization in LLMs.

Multi-Agent Reinforcement Learning (MARL) extends standard RL to settings where multiple autonomous agents interact and learn simultaneously to achieve individual or shared objectives (Weiss, 1999; Busoniu et al., 2008; Stone & Veloso, 2000; Tuyls & Weiss, 2012). Applications of MARL span numerous domains, including swarm robotics (Hüttenrauch et al., 2019; Matignon et al., 2021), autonomous driving (Shalev-Shwartz et al., 2016), strategic games (Song et al., 2024), traffic management (K.J. et al., 2014), and distributed resource allocation (Nie et al., 2021). MARL methods can be broadly categorized into independent learning, joint learning, and coordination-based strategies (Tan, 1993; Matignon et al., 2012; Ren et al., 2005). A widely adopted paradigm is centralized training with decentralized execution (CTDE), with prominent algorithms including MADDPG (Lowe et al., 2017), MAPPO (Yu et al., 2022), and HAPPO (Kuba et al., 2022). More recently, Wen et al. (2022) pro-

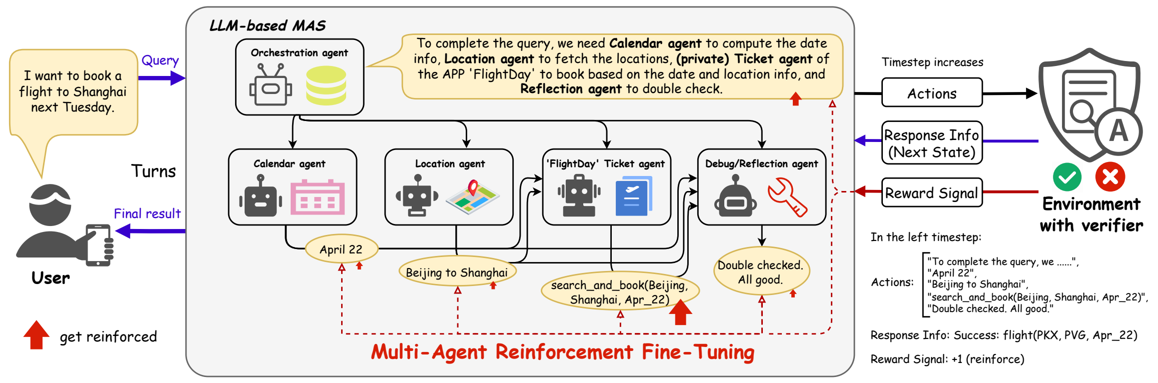

I want to book a flight to Shanghai next Tuesday.
Query
Turns
Final result
User
get reinforced
LLM-based MAS
Orchestration agent
To complete the query, we need **Calendar agent** to compute the date info, **Location agent** to fetch the locations, **(private) Ticket agent** of the APP 'FlightDay' to book based on the date and location info, and **Reflection agent** to double check.
Calendar agent
Location agent
'FlightDay' Ticket agent
Debug/Reflection agent
April 22
Beijing to Shanghai
search_and_book(Beijing, Shanghai, Apr_22)
Double checked. All good.
Multi-Agent Reinforcement Fine-Tuning
Timestep increases
Actions
Response Info (Next State)
Reward Signal
Environment with verifier
In the left timestep:
Actions: "To complete the query, we ......", "April 22", "Beijing to Shanghai", "search_and_book(Beijing, Shanghai, Apr_22)", "Double checked. All good."
Response Info: Success: flight(PKX, PVG, Apr_22)
Reward Signal: +1 (reinforce)

Figure 1: Illustration of MARFT in real-world agentic problem-solving scenarios.

posed Multi-Agent Transformer (MAT) re-framing MARL as a series of sequential decision-making problems, potentially opening new directions for research. Despite these advances, integrating LLMs into MARL settings introduces significant challenges. Unlike conventional multi-agent systems in traditional MARL tasks, LaMAS are highly flexible and complex, particularly in their communication dynamics. Addressing the challenges requires rethinking fundamental assumptions in MARL, such as agent homogeneity and communication protocols, to accommodate the unique properties of LaMAS. Though there are easy-to-use and well-established frameworks such as MALib (Zhou et al., 2023) unifying many existing MARL methods for population-based RL and OpenRLHF (Hu et al., 2024) providing implementations for most single-agent RL fine-tuning techniques, the absence of a unified framework that integrates LLMs as agents in dynamic environments with agentic tasks still constrains the swarm intelligence of LaMAS. Consequently, there remains a need for a well-established LLM-based multi-agent framework both theoretically and practically to unleash LaMAS's swarm intelligence and potential better.

Given the accelerating progress in both RFT for LLMs and LaMAS, we are motivated to introduce and formalize the concept of **Multi-Agent Reinforcement Fine-Tuning (MARFT)**. This article aims to provide a comprehensive foundation for MARFT, serving both academic and industrial audiences. The remainder of this article is organized as follows: Section 2 revisits foundational concepts in RFT, LaMAS, and MARL. Section 3 gives the problem statement and formulation and outlines the key distinctions between MARFT and existing approaches. Section 4 introduces the MARFT methodology and its basic implementation strategies. Section 5 presents preliminary experimental results and in-depth analyses. Finally, Sections 6 and 7 provide future perspectives and highlight unresolved challenges, followed by an overall conclusion of the paper in Section 8.

2 Literature Review

This section presents a comprehensive review of topics closely related to MARFT, namely RFT, LaMAS, and MARL. We begin with a discussion of the algorithmic foundations and methodological formulations of RL, followed by an in-depth review of RFT. Subsequently, we provide an overview of LaMAS and MARL from a broader perspective, thereby laying the conceptual groundwork for the introduction and development of MARFT.

2.1 Reinforcement Fine-Tuning (RFT)

RFT is a fine-tuning paradigm that harnesses the capabilities of Reinforcement Learning to refine agent behavior. While it shares foundational similarities with traditional RL, RFT places greater emphasis on achieving expert-level performance in specific tasks using limited, high-quality data and a constrained number of optimization iterations. To provide context for the discussion of RFT, we first briefly revisit the core principles, mathematical formulations, and algorithmic methodologies of standard RL.

2.1.1 Language-augmented Markov Decision Process

In most sequential decision-making scenarios, problems are typically modeled as a *Markov Decision Process (MDP)* $\langle \mathcal{S}, \mathcal{A}, \mathcal{T}, \mathcal{R}, \gamma \rangle$. In linguistic contexts, this framework can be further extended to a more specific form of language-augmented *Partial Observable Markov Decision Process (POMDP)* represented as $\langle \mathcal{V}, \mathcal{S}, \mathcal{O}, \mathcal{A}, \mathcal{T}, \mathcal{R}, \gamma \rangle$ (van Otterlo & Wiering, 2012; Carta et al., 2023). Here, $\mathcal{V}$ represents the vocabulary of a language model, which facilitates natural language understanding within an LLM. The state space $\mathcal{S}$ can be situated in a semantic space, particularly in linguistic contexts. The observation function $\mathcal{O}\colon \mathcal{S} \to \mathcal{V}^L$ and action space $\mathcal{A} \subseteq \mathcal{V}^L$ respectively denote the observations and actions, both of which are explicitly represented by sequences of L tokens from the vocabulary $w \in \mathcal{V}$. Furthermore, the action $a \in \mathcal{A}$ can be grounded to a specific tool or API call in real-world environments (Schick et al., 2023; Yan et al., 2024; Lu et al., 2024). The transition function $\mathcal{T}\colon \mathcal{S} \times \mathcal{A} \to \mathcal{S}'$, often represented as a probability distribution $\mathcal{P}$ in the form of $P(s'|s,a)$ describes the state transition following a specific action taken in a given state. However, in linguistic settings, the transition for observations can be directly achieved through sentence concatenation. The reward function $\mathcal{R}\colon \mathcal{S} \times \mathcal{A} \times \mathcal{S} \to \mathbb{R}$, typically denoted as $R(s,a,s')$, quantifies the reward for taking a particular action that induces a state transition. The discount factor γ reflects the diminishing value of rewards received over time. This constitutes the fundamental language-augmented POMDP, where a single LLM takes actions within a language-enhanced environment. For any other language-based tasks, specific POMDPs can be derived from this basic language-augmented POMDP.

2.1.2 Reinforcement Learning (RL)

The Objective of RL In classic reinforcement learning settings, an agent is capable of perceiving its environment, making decisions, and taking actions, while learning from past experiences to enhance its performance. The agent interacts with the environment until certain terminal conditions are met, generating a trajectory $\tau = (s_0, a_0, r_0, s_1, a_1, r_1, \cdots, s_T, a_T, r_T)$ of length T, with a cumulative reward expressed as $g = \sum_{t=0}^{T} \gamma^t r_t$. The primary objective is for the agent to achieve a high cumulative reward in a dynamic and uncertain environment. This is precisely what RL aims to accomplish—obtaining a policy that enables the agent to dynamically act in dynamic environments to maximize cumulative reward. Mathematically, the objective is formulated as $\max_{\pi} \mathbb{E}_{\tau \sim p_\pi(\tau)} \left[\sum_{t=0}^{T} \gamma^t R_t \right]$ (Sutton & Barto, 1998). Here, the cumulative reward from timestep t is denoted as $G_t = \sum_{t'=t}^{\infty} \gamma^{t'-t} R_{t'}$.

Value-based Methods Given that RL optimizes the policy by leveraging rewards to incentivize the policy to learn actions that yield the highest rewards, it is natural to consider a value-based approach. This value-based approach provides an elegant and effective solution to the critical credit assignment problem (Minsky, 1961; Sutton & Barto, 1998). This approach focuses on learning indirect rewards, i.e, values, which estimate the goodness of an action before receiving the reward and ideally can better optimize the policy in long-horizon and reward-sparse tasks. To this end, two vital proxies to the RL objective are introduced: the state-action value function (Q-function) and the state value function (V-function) (Sutton & Barto, 1998). Their definitions are presented respectively as

$$Q^\pi(s_t, a_t) \coloneqq \mathbb{E}_{\tau \sim p_\pi(\tau|s_t,a_t)} \left[\sum_{t'=t}^{\infty} \gamma^{t'-t} r(s_{t'}, a_{t'}) \right] = \mathbb{E}_{(s,a)_{t+1:\infty} \sim p_\pi(s,a)} \left[G_t | s_t, a_t \right],$$

$$V^\pi(s_t) \coloneqq \mathbb{E}_{\tau \sim p_\pi(\tau|s_t)} \left[\sum_{t'=t}^{\infty} \gamma^{t'-t} r(s_{t'}, a_{t'}) \right] = \mathbb{E}_{a_t \sim \pi(a_t|s_t), (s,a)_{t+1:\infty} \sim p_\pi(s,a)} \left[G_t | s_t \right].$$

Here p_π is the trajectory distribution sampled using the policy π. Obviously, from their naming and mathematical expressions, it is evident that the Q-function indicates how valuable an action a_t is at state s_t, while the V-function indicates the value of being in state s_t. Another important proxy function is the advantage function, defined as $A_\pi(s_t, a_t) := Q_\pi(s_t, a_t) - V_\pi(s_t)$ (Greensmith et al., 2001). This function quantifies how much better or worse an action a_t is compared to the average action at state s_t.

By expanding the definitions and expressing the summation terms using Q or V, we can derive two recursive equations as

$$Q^\pi(s_t, a_t) = r(s_t, a_t) + \gamma \mathbb{E}_{s_{t+1} \sim p(s_{t+1}|s_t, a_t)} \left[V^\pi(s_{t+1}) \right],$$
$$V^\pi(s_t) = \mathbb{E}_{a_t \sim \pi(a_t|s_t)} \left[Q^\pi(s_t, a_t) \right].$$

By substituting these two equations into each other, we can further derive the Bellman equations (Kirk, 1970) as

$$Q^\pi(s_t, a_t) = r(s_t, a_t) + \gamma \mathbb{E}_{s_{t+1} \sim p(s_{t+1}|s_t, a_t), a_{t+1} \sim \pi(a_{t+1}|s_{t+1})} \left[Q^\pi(s_{t+1}, a_{t+1}) \right],$$
$$V^\pi(s_t) = \mathbb{E}_{a_t \sim \pi(a_t|s_t)} \left[r(s_t, a_t) + \gamma \mathbb{E}_{s_{t+1} \sim p(s_{t+1}|s_t, a_t)} \left[V^\pi(s_{t+1}) \right] \right].$$

There are two primary methods for estimating value functions. For clarity, we focus on the V-function here, as the estimation of the Q-function can be similarly derived. The most straightforward approach is to use Monte Carlo (MC) estimation (Sutton & Barto, 1998). By performing multiple Monte Carlo samplings, we can approximate the value function as: $V(s_t) \approx \frac{1}{K} \sum_{k=1}^{K} \sum_{i=t}^{\infty} \gamma^{i-t} r\left(s_i^k, a_i^k\right)$. According to the law of large numbers (ref, 2008), this method provides an unbiased estimation of the value function. However, it can be highly inefficient, costly, and time-consuming, especially when the agent is an LLM.

A more preferable approach is to use Temporal Difference (TD) learning (Sutton, 1984). The value Bellman equation, which resembles dynamic programming, bootstraps the value function over itself at the next timestep. Therefore, we can perform Bellman backups to estimate the value function. In the context of deep learning, we typically construct a value function (also known as a critic network) (Mnih et al., 2013) and train it by minimizing the empirical Bellman error as

$$L(\phi) = \frac{1}{|\mathcal{D}|} \sum_{(o_t, a_t, o_{t+1}, r_t) \sim \mathcal{D}} \left[r_t(o_t, a_t) + \gamma V_\phi(o_{t+1}) - V_\phi(o_t) \right]^2.$$

Once the value function is obtained, the next crucial step is policy extraction, which involves deriving the policy from the value function (Watkins & Dayan, 1992). The specific policy extracted can vary widely depending on the chosen method. For instance, a greedy policy can be extracted using $\pi\left(a_t|s_t\right) = \delta\left(a_t = \text{argmax} Q\left(s_t, a_t\right)\right)$, where δ denotes the Dirac delta function. Alternatively, a soft policy can be derived as $\pi_{\text{MaxEnt}}\left(a_t|s_t\right) = \exp\left(\frac{1}{\alpha}\left(Q_{\text{soft}}\left(s_t, a_t\right) - V_{\text{soft}}\left(s_t\right)\right)\right)$, where α is a temperature parameter (Haarnoja et al., 2017). Other extraction methods can yield different policies, including mixture policies. Algorithm 1 depicts the fundamental procedure of value-based deep RL methods. However, policy extraction in the context of LLMs can be highly counterintuitive. We will elaborate on the reasons for this in Section 3.3.

Policy-based Methods Another approach to optimizing policies in RL involves directly estimating the gradient of the policy and performing gradient ascent. This method is largely based on the policy gradient (PG) theorem (Sutton et al., 1999). Recall that the objective is to maximize the expected reward: $J(\theta) = \mathbb{E}_{\tau \sim p_{\pi_\theta}(\tau)} \left[\sum_{t=0}^{\infty} \gamma^t r(s_t, a_t) \right]$.[1] According to the policy gradient theorem, the gradient of the expected reward $J(\theta)$ can be expressed as

$$\nabla_\theta J(\theta) = \mathbb{E}_{\tau \sim p_{\pi_\theta}(\tau)} \left[\sum_{t=0}^{\infty} \Psi_t \nabla_\theta \log \pi_\theta(a_t|s_t) \right],$$

[1]In other papers you may see people denote it $J(\pi_\theta)$ In fact, these two expressions are the same. You can view it as some reward J being a function of parameters θ or some reward J being a function of the policy π, which is parameterized by θ.

Algorithm 1: General value-based deep RL method

```
Input: Parameters $\phi_0$ for value function $Q$, some policy derived from value function
       e.g. $\epsilon$-greedy policy $\pi_0(a|s) = \epsilon U(a) + (1-\epsilon)\delta\left(a = \arg\max_a Q_{\phi_0}(s,a)\right)$, some initial state
       distribution $d(s_0)$, transition probability $p(s'|s,a)$, discount factor $\gamma$, learning rate $\alpha$, etc.
Output: Optimal Q function $Q^\star$ with parameters $\phi^\star$, extracted optimal policy $\pi^\star$
1  initialize parameters $\phi_0$ for value function $Q_\phi$, target value function w/o gradient $Q_{\text{targ}} \leftarrow Q_{\phi_0}$,
    some policy $\pi_0$, replay buffer $\mathcal{D} \leftarrow \emptyset$
2  for iterations $i = 0, \ldots$ do
3      initialize $s \leftarrow s_0 \sim d(s_0)$
4      while not terminal state do
5          select action using policy $a \sim \pi_i(a|s)$
6          observe next state $s' \sim p(s'|s,a)$
7          get reward $r = R(s,a)$
8          $\mathcal{D} \leftarrow \mathcal{D} \cup \{(s,a,s',r)\}$
9      end
10     sample a batch $\mathcal{B} = \{(s,a,s',r)\} \sim \mathcal{D}$
11     compute Bellman error $\boldsymbol{\epsilon} = \sum_{\mathcal{B}} \left(Q_{\phi_i}(s,a) - (r + \gamma \max_{a'} Q_{\text{targ}}(s',a')\right)$
12     update $\phi$ by minimizing $\boldsymbol{\epsilon}$: $\phi_{i+1} \leftarrow \phi_i - \alpha\nabla\boldsymbol{\epsilon}$
13     extract policy $\pi_{i+1}$ based on $Q_{\phi_{i+1}}$
14     periodically update target value function: $Q_{\text{targ}} \leftarrow Q_{\phi_i}$
15 end
```

where, in the simplest case, $\Psi_t = \sum_{t'=t}^{\infty} \gamma^{t'-t} r(s_{t'}, a_{t'})$. However, the cumulative discounted reward is often difficult to obtain directly, so Ψ_t can be approximated using other proxies, such as the Q-value $Q^\pi(s,a)$ or the advantage function $A^\pi(s_t, a_t)$ (Schulman et al., 2018).

Given the gradient of J with respect to the policy parameters θ, we can do gradient ascent to update the parameters as (1). The most classic method is REINFORCE (Williams, 1992), which utilizes MC sampling to approximate the gradient as

$$\begin{aligned} \nabla_\theta J(\theta) &\approx \frac{1}{K} \sum_{k=1}^{K} \sum_{t=0}^{T} \nabla_\theta \log \pi_\theta(a_t^k | s_t^k) G_t^k, \\ \theta &\leftarrow \theta + \alpha \nabla_\theta J(\theta). \end{aligned} \tag{1}$$

Algorithm 2 illustrates the general process of policy-based deep RL methods. And most of the time, people subtract the cumulative reward with a baseline $b(s_t)$ defined as an average over the sampled trajectories to reduce the variance (Greensmith et al., 2001).

As we can see, policy gradient does not require a value function anymore, instead, it uses the true rewards to optimize the policy directly, which is more stable compared with value-based methods, especially when the policy is an LLM. Moreover, many other variants have been proposed, *e.g.* REINFORCE++ (Hu, 2025), RLOO (Kool et al., 2019), etc., and they seem to work relatively well in LLMs.

Actor-Critic Actor-Critic (AC) (Sutton & Barto, 1998; Konda & Tsitsiklis, 1999; Degris et al., 2012; Mnih et al., 2016) architecture is a hybrid way, incorporating both value-based methods and policy-based methods, to optimize the policy. While value-based methods extract policy poorly and policy-based methods lack direct estimations to values with a result of low efficiency, Actor-Critic inherits fine-grained credit assignment from value-based methods and optimization stability from policy-based methods. Actor-Critic algorithms train the value function and policy iteratively. For each iteration, it updates the value function based on TD error and optimizes the policy via the policy gradient method

```
Algorithm 2: General policy-based deep RL method
Input: intial parameters $\theta_0$ for policy $\pi_\theta$, initial state distribution $d(s_0)$, transition probability
        $p(s'|s,a)$, discount factor $\gamma$, learning rate $\alpha$, etc.
Output: Optimal policy $\pi^\star$
1 initialize parameters $\theta_0$ for policy $\pi_\theta$, replay buffer $\mathcal{D} \leftarrow \emptyset$
2 for iterations $i = 0, \ldots$ do
3     sample intial states $\boldsymbol{s_0} \sim d(s_0)$ and generate trajectories $\boldsymbol{\tau} = \{\tau^k\} = \{(s_0, a_0, \ldots, s_H, a_H)^k\}$
        using current policy $\pi_\theta$
4     compute cumulative returns $G_t^k = \sum_{t'=t}^{H} \gamma^{t'-t} r_{t'}^k(s_{t'}^k, a_{t'}^k)$ (or some other proxy) for all
        timesteps $t$
5     estimate policy gradient $\nabla_\theta J(\theta) \approx \frac{1}{K} \sum_{k=1}^{K} \sum_{t=0}^{T} \nabla_\theta \log \pi_\theta(a_t^k|s_t^k) G_t^k$
6     update policy by gradient ascent $\theta \leftarrow \theta + \alpha \sum_{t=0}^{T} \nabla_\theta J(\theta)$
7 end
```

One of the most suitable AC algorithms that adapts well to LLMs is proximal policy optimization (PPO) (Schulman et al., 2017), which is developed upon Trust Region Policy Optimization (TRPO) (Schulman et al., 2015). TRPO gives a surrogate objective function to maximize, together with a constraint on policy update steps as

$$\underset{\theta}{\text{maximize}}\, \hat{\mathbb{E}}_t \left[\frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{\text{old}}}(a_t|s_t)} \hat{A}_t(s_t, a_t) \right], \text{ s.t. } \hat{\mathbb{E}}_t \left[\text{KL}\left[\pi_{\theta_{\text{old}}}(\cdot|s_t) \| \pi_\theta(\cdot|s_t) \right] \right] \le \delta,$$

where $\hat{A}_t$ is an estimator of the advantage function at timestep t, which is usually computed using GAE (Schulman et al., 2018), and $\hat{\mathbb{E}}_t$ is the empirical average over a finite batch of samples. By the Lagrange Multiplier, it is equivalent to the unconstrained problem as

$$\underset{\theta}{\text{maximize}}\, \hat{\mathbb{E}}_t \left[\frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{\text{old}}}(a_t|s_t)} \hat{A}_t(s_t, a_t) - \beta \text{KL}\left[\pi_{\theta_{\text{old}}}(\cdot|s_t) \| \pi_\theta(\cdot|s_t) \right] \right].$$

TRPO also gives a monotonic improvement guarantee for general stochastic policies, but for the optimization objective above, it concerns second-order optimization, including Fisher Information Matrix (FIM) computation, which can be costly. Based on TRPO, PPO emerges as a first-order algorithm that also reproduces the monotonic improvement of TRPO. PPO proposes a clipped surrogate object as

$$\underset{\theta}{\text{maximize}}\, \hat{\mathbb{E}}_t \left[\min\left(\frac{\pi_\theta(a|s)}{\pi_{\theta_{\text{old}}}(a|s)} A^{\pi_{\theta_{\text{old}}}}(s,a), \text{clip}\left(\frac{\pi_\theta(a|s)}{\pi_{\theta_{\text{old}}}(a|s)}, 1 \pm \epsilon \right) A^{\pi_{\theta_{\text{old}}}}(s,a) \right) \right].$$

And countless experiments have shown that PPO is one of the most effective RL methods for nearly all decision-making tasks, though it still suffers from inefficiency and long training time due to the on-policy method and the nature of trial-and-error (Nakibinge et al., 2024; Ouyang et al., 2022; Heess et al., 2017).

In LLMs, we can easily analogize from typical RL tasks, *e.g.* , mujoco (Todorov et al., 2012), to language tasks. For example, an LLM is trying to complete the query a user gives, and the LLM generates actions once it receives observations, which can be the user's further responses or function call results, also maybe together with a reward signal. Based on the interaction, or in RL, i.e., trajectory, PPO or other methods can be utilized to reinforce the LLM to learn how to better tackle human queries in interactions (Zhou et al., 2025; Goldie et al., 2025).

2.1.3 From RL to RFT

Differences Though RL and RFT share foundational methodological principles, there still exist nuanced differences as listed in Table 1. RL, closely rooted in optimal control frameworks, typically

Table 1: Differences between RL and RFT.

	RL	**RFT**
Actor	Policy from scratch	Large-scale pretrained foundation model
Constraint	No constraint	Maintain original capabilities
Action Space Size	Typically small, numerable	Huge, $O(\mathcal{V}^{\|L\|})$ or $O(\mathcal{V} \times \|L\|)$
Transition	Stochastic	Deterministic and Stochastic
Granularity	Action	Action or token
Process	Reset state and sample traj.	Reset query, sample traj. and verify answer
Sample Magnitude	Large	Relatively small and high-quality

trains policy agents, such as robots, from scratch, requiring no prior domain knowledge. In contrast, RFT operates on large-scale pretrained models and adapts these models to specialized tasks. Additionally, RL trains a policy specifically for a particular task within a specific environment, while RFT enhances a model's task-specific capabilities without degrading its original abilities, such as language understanding or generative skills in LLMs. The environments also differ significantly. Conventional RL environments are entirely stochastic, whereas typical RFT agentic environments for LLMs can integrate both deterministic and stochastic transitions—deterministic for operations like sentence or token concatenation, and stochastic for environment feedback, such as tool execution results or next user queries. Since LLMs generate tokens to form sentences, RFT can operate at both the action-level (sentence-level) and token-level, whereas traditional RL settings are typically action-level. Another major difference is that RL is known for its low sample efficiency, while RFT requires relatively fewer, high-quality samples.

Implementations Since we know the difference between RFT and RL, we can introduce lots of fine-tuning techniques to better show how RFT works and what is reflected in many existing research. The first is LoRA, which freezes the base model and injects trainable rank decomposition matrices into the model. LoRA is vital for fine-tuning LLMs, especially for LaMAS, because it can optimize the policy efficiently with minimal parameter updates and also makes LLM-based multi-agent training affordable and ideal. As a single model can have different LoRA adapters for different tasks, multi-agent systems can be made using only one base model equipped with multiple adapters (2024). Secondly, it becomes necessary to implement divergence constraints during training to prevent the policy update from straying too far from the initial or reference policy, which possesses the pretrained abilities. PPO and other trust-region-related algorithms provide strong guarantees for monotonic improvement, and in their objectives, we can also modify the KL divergence from between π_{old} to between π_{ref} as GRPO (Shao et al., 2024) does in (2).

Prevailing Objective Functions To further elaborate on the objective functions used in RFT, we will introduce several prominent methods, including GRPO, DAPO, and VAPO. These objective functions are designed to optimize the policy updates while ensuring stability and efficiency during the fine-tuning process.

GRPO utilizes the objective function as shown in (2) (Shao et al., 2024). As stated in GRPO, q, o are questions and outputs sampled from the question dataset and the old policy π_{old}. This approach dispenses with the need for value function approximation, opting instead to compute a baseline through the average rewards of multiple sampled trajectories. Regularization is achieved by directly incorporating the KL divergence between the trained policy and the reference policy into the loss function.

$$J_{GRPO}(\theta) = \mathbb{E}_{[q \sim P(Q), \{o_i\}_{i=1}^{G} \sim \pi_{\theta_{\text{old}}}(O|q)]}$$
$$\frac{1}{G}\sum_{i=1}^{G}\frac{1}{|o_i|}\sum_{t=1}^{|o_i|}\left\{ \min\left[r_{i,t}(\theta)\hat{A}_{i,t}, \text{clip}\left(r_{i,t}(\theta), 1 \pm \epsilon \right)\hat{A}_{i,t}\right] - \beta \mathbb{D}_{KL}\left[\pi_\theta \| \pi_{\text{ref}} \right] \right\}, \tag{2}$$

$$\text{where } r_{i,t}(\theta) = \frac{\pi_\theta(o_{i,t}|q, o_{i,<t})}{\pi_{\theta_{\text{old}}}(o_{i,t}|q, o_{i,<t})},\ \hat{A}_{i,t} = \frac{R_i - \text{mean}(\{R_i\}_{i=1}^G)}{\text{std}(\{R_i\}_{i=1}^G)}.$$

DAPO advances upon GRPO and adopts the objective function as shown in (3) (Yu et al., 2025). It promotes exploration by increasing the ceiling clip parameter ϵ_{high}. DAPO further enhances its sampling strategy through dynamic sampling, which involves over-sampling and filtering out prompts with accuracy values of 1 and 0, ensuring that all prompts in the batch provide effective gradients. Additionally, DAPO implements a token-level policy gradient loss in the long-CoT RL scenario.

$$J_{\text{DAPO}}(\theta) = \mathbb{E}_{(q,a)\sim\mathcal{D},\{o_i\}_{i=1}^G\sim\pi_{\text{old}}(\cdot|q)}\left[\frac{1}{\sum_{i=1}^G |o_i|}\sum_{i=1}^{G}\sum_{t=1}^{|o_i|}\min\left(r_{i,t}(\theta)\hat{A}_{i,t}, \text{clip}\Big(r_{i,t}(\theta), 1-\epsilon_{\text{low}}, 1+\epsilon_{\text{high}}\Big)\hat{A}_{i,t}\right)\right],$$
$$\text{s.t. } 0 < \left|\Big\{o_i|\text{is\_equivalent}(a, o_i)\Big\}\right| < G. \tag{3}$$

VAPO extends DAPO and employs the objective function presented in (4) (Yue et al., 2025). It further enhances the training process by incorporating an additional negative log-likelihood (NLL) loss for correct outcomes sampled during training. This additional loss term improves the utilization efficiency of positive samples, thereby optimizing the overall learning performance.

$$L(\theta) = -\frac{1}{\sum_{i=1}^G |o_i|}\sum_{i=1}^{G}\sum_{t=1}^{|o_i|}\min\left(r_{i,t}(\theta)\hat{A}_{i,t}, \text{clip}\Big(r_{i,t}(\theta), 1-\epsilon_{\text{low}}, 1+\epsilon_{\text{high}}\Big)\hat{A}_{i,t}\right) + \mu * L_{\text{NLL}}(\theta),$$
$$\text{where } L_{\text{NLL}}(\theta) = -\frac{\sum_{o_i\in\mathcal{T}}\sum_{t=1}^{|o_i|}\log \pi_\theta(a_t|s_t)}{\sum_{o_i\in\mathcal{T}}|o_i|}. \tag{4}$$

2.2 LLM-based Multi-Agent Systems (LaMAS)

The concept of LaMAS has recently gained prominence (Yang et al., 2024b), with numerous applications and inference frameworks emerging to address complex agentic problems (Epperson et al., 2025). Unlike traditional MARL, where agents act synchronously with uniform decision weights, LaMAS introduces hierarchical organization and asynchronous execution. Agents in LaMAS can dynamically decompose tasks, adapt workflows based on execution dependencies, and coordinate actions in a decentralized yet goal-aligned manner.

Existing optimization methods of LaMAS can be categorized into two types as below:

- **Tuning-free techniques.** A prevalent optimization strategy for LaMAS involves tuning-free methods that do not update agent parameters. Examples include prompt engineering (Fernando et al., 2023), in-context learning (Tao et al., 2024), and self-evolution (Yang et al., 2025a; Huang et al., 2024). These techniques rely on iterative refinements of agent profiles or prompts to enhance task-specific performance.

- **Parameter fine-tuning.** A more sophisticated approach involves updating agent parameters or network configurations to optimize performance. This paradigm integrates deep learning and specific methodologies, such as multi-agent debating to generate high-quality training datasets (Subramaniam et al., 2025) or fine-tuning programming modules for improved workflow organization (Khattab et al., 2024). CORY (Ma et al., 2024) duplicates the LLM into two agents, i.e., a pioneer and an observer, that interact through knowledge transfer and role exchange, improving training stability and performance. However, many parameter fine-tuning methods lack a theoretical foundation in RL, relying instead on ad-hoc techniques. SiriuS (Zhao et al., 2025a), a self-improving, multi-agent optimization framework using bootstrapped reasoning, iteratively refines agent behaviors by leveraging successful reasoning trajectories and augmenting unsuccessful ones. The most related work, MAPoRL (Park et al., 2025), rooted in MARL, pioneers in applying multi-agent PPO to post-train LLMs, but does not consider the unique characteristics of LaMAS and assumes homogeneous agent behavior through collaborative debate, diverging from real-world scenarios where agents often perform diverse or orthogonal roles to solve complex problems. This article will focus on RFT and MARL-related methodologies in subsequent sections, providing a principled paradigm for general LaMAS reinforcement.

2.3 Multi-Agent Reinforcement Learning (MARL)

2.3.1 Decentralized Partially Observable Markov Decision Process

MARL is a variant of RL, which includes multiple agents acting **simultaneously** once receiving the environment observations, and it's often modeled by a certain form of MDP – *Decentralized POMDP (DEC-POMDP)* (Oliehoek & Amato, 2016) $\langle \mathcal{N}, \mathcal{S}, \boldsymbol{\mathcal{O}}, \boldsymbol{\mathcal{A}}, \mathcal{T}, \mathcal{R}, \gamma \rangle$, where $\mathcal{N} = \{1, \ldots, n\}$ is the set of agents **without any order constraint**, $\mathcal{S}$ is the state space, $\boldsymbol{\mathcal{O}} = \prod_{i=1}^{n} \mathcal{O}^i$ is the joint observation space, which is a product of local observation spaces at global state s, $\boldsymbol{\mathcal{A}} = \prod_{i=1}^{n} \mathcal{A}^i$ is the joint action space, which is similarly a product of local action spaces, and for the others, we can borrow the explanation from Section 2.1.1.

2.3.2 Main Approaches of MARL

Independent Learning One of the most intuitive approaches to implementing MARL is through independent learning. In this setting, each agent operates as an independent entity, possessing its own policy and value function. Other agents are treated as part of the environment, and there is no direct communication between agents. Consequently, each agent optimizes its actions based solely on its own observations and rewards, without considering the policies of other agents.

This approach allows for the direct application of single-agent reinforcement learning methods to each agent. Examples include independent Q-learning (Tan, 1993; Shoham & Leyton-Brown, 2008), independent policy gradient (Daskalakis et al., 2020), and independent AC methods. These methods are straightforward to implement and can be easily scaled to various domains. However, independent learning has significant drawbacks. It can lead to instability and difficulty in converging to an optimal solution. For instance, some agents may develop selfish policies or become "lazy" in collaborative tasks, resulting in what is known as a social dilemma.

Early experiments have demonstrated that, for certain tasks, cooperative agents outperform independent agents, especially when communication is absent (Tan, 1993). The cost of communication and the optimization of information exchange strategies require careful consideration in collaborative learning. Despite the challenges of instability and poor convergence, independent learning remains a fundamental and viable approach to MARL.

Centralized Training with Decentralized Execution Apart from independent learning, another way to MARL is by centralized training. During training, agents share a joint global value function $Q^{\boldsymbol{\pi}}(\mathbf{o}, a^1, \ldots, a^n)$ which takes into account the environment state and actions of other agents. For its design, Q can either output the value for the joint action and marginalize out for a specific action, as in COMA (Foerster et al., 2018), or directly output the value for action a^i by agent i, as in MADDPG (Lowe et al., 2017). The latter approach allows for arbitrary reward structures for separate agents. Once the value learning component is established, policy optimization can be performed using the policy gradient: $\nabla_{\theta^i} J(\theta^i) = \mathbb{E}_{s \sim p^{\boldsymbol{\mu}}, a^i \sim \boldsymbol{\pi}^i} \left[\nabla_{\theta^i} \log \boldsymbol{\pi}^i(a^i | o^i) Q^{\boldsymbol{\pi}}(\mathbf{o}, a^1, \ldots, a^n) \right]$ to update the policies.

As mentioned in Section 2.1.2, PPO has consistently been one of the most effective RL methods. Fortunately, it also extends well to multi-agent scenarios, leading to Multi-Agent PPO (MAPPO) (Yu et al., 2022). Then, the objective of MAPPO is derived as

$$\underset{\theta}{\text{maximize}} \sum_{i=1}^{n} \mathbb{E}_{s \sim \rho_{\boldsymbol{\pi}_{\theta_{\text{old}}}}, \boldsymbol{a} \sim \boldsymbol{\pi}_{\theta_{\text{old}}}} \left[\min \left(\frac{\pi_\theta^i(a^i|s)}{\pi_{\theta_{\text{old}}}^i(a^i|s)} A^{\boldsymbol{\pi}_{\theta_{\text{old}}}}(s, \boldsymbol{a}), \text{clip} \left(\frac{\pi_\theta^i(a^i|s)}{\pi_{\theta_{\text{old}}}^i(a^i|s)}, 1 \pm \epsilon \right) A^{\boldsymbol{\pi}_{\theta_{\text{old}}}}(s, \boldsymbol{a}) \right) \right].$$

However, this approach has a strong assumption that all agents share parameters, which leads to identical action spaces among agents. In the context of LLMs, it is common for different LLMs to have distinct action spaces. For instance, different LLMs may possess unique vocabularies, and some LLMs might even have different input-output formats, such as LLMs designed for ranking tasks. Moreover, MAPPO does not provide a rigorous guarantee of monotonic improvement, as a local improvement in one agent's policy can potentially degrade the overall team reward. HATRPO and HAPPO addressed this issue by sequentially updating the policies (Kuba et al., 2022).

Communication and Coordination Another intriguing approach to MARL involves directly learning the communication among agents. For instance, designing a communication module or gate module can help establish an effective explicit communication and coordination mechanism within the multi-agent system.

One seminal work in this area is CommNet (Sukhbaatar et al., 2016), which introduced a novel trainable controller $\mathbf{\Phi}$ that maps global state-views s to joint policies a. In this mapping, each agent has access to the hidden states of other agents, thereby influencing its own policy. This approach can be seamlessly integrated with RL algorithms and ideally results in an optimal communication module.

In the context of LLM-based multi-agent systems, such communication modules can take the form of an "orchestra agent". This agent is specifically designed and trained to act as a task and information router, facilitating effective collaboration among the agents. Currently, a popular solution involves designing a well-structured multi-agent framework that includes a planner or orchestration agent to enhance collaboration. However, most of these attempts focus on improving performance during inference without incorporating further training.

Sequential Modeling Another intriguing perspective on understanding MARL is through sequential modeling (SM). The connection between MARL and SM is grounded in the Multi-Agent Advantage Decomposition Theorem (Kuba et al., 2021) as below:

Theorem 1 (Multi-Agent Advantage Decomposition Theorem (Kuba et al., 2021)). *For any predefined permutation of n agents, for any state $s \in \mathcal{S}$ and joint action $\boldsymbol{a} \in \boldsymbol{\mathcal{A}}$, the following always holds:*

$$A^{\boldsymbol{\pi}}(s, \boldsymbol{a}^{1:n}) = \sum_{m=1}^{n} A^{\boldsymbol{\pi}}(s, \boldsymbol{a}^{1:m-1}, \boldsymbol{a}^{m}). \tag{5}$$

This theorem reveals that if an agent is aware of the actions taken by its predecessors, maximizing the agent's local advantage is equivalent to maximizing the joint advantage. Building on this insight, a new multi-agent sequential decision-making paradigm has been proposed, exemplified by the Multi-Agent Transformer (MAT) (Wen et al., 2022). Within this paradigm, the approach to approximating the value function remains consistent with conventional MARL methods, specifically by minimizing the empirical Bellman error below[2] as

$$L(\phi) = \frac{1}{nT} \sum_{i=1}^{n} \sum_{t=0}^{T-1} \left[r_t(\boldsymbol{o}_t, \boldsymbol{a}_t) + \gamma V_{\bar{\phi}}(\hat{\boldsymbol{o}}_{t+1}^{i}) - V_{\phi}(\hat{\boldsymbol{o}}_t^{i}) \right]^2,$$

where $\bar{\phi}$ is the parameters of the target network, which are non-differentiable and updated at intervals. But for the policy optimization, the modified clipping PPO objective goes as

$$L(\theta) = \frac{1}{nT} \sum_{i=1}^{n} \sum_{t=0}^{T-1} \min \left[\boldsymbol{r}_t^i(\theta) \hat{A}_t, \text{clip}\left(\boldsymbol{r}_t^i(\theta), 1 \pm \epsilon \right) \hat{A}_t \right], \text{where } \boldsymbol{r}_t^i(\theta) = \frac{\pi_\theta^i \left(a_t^i | \hat{\boldsymbol{o}}_t^{1:n}, \hat{\boldsymbol{a}}_t^{1:i-1} \right)}{\pi_{\theta_{\text{old}}}^i \left(a_t^i | \hat{\boldsymbol{o}}_t^{1:n}, \hat{\boldsymbol{a}}_t^{1:i-1} \right)}.$$

An intuitive way to understand this paradigm is to consider that, before acting **simultaneously**, agents make decisions (not take actions) sequentially in an arbitrary order or permutation, based on what their predecessors have planned or decided to do. They then execute their actions accordingly. For instance, in a football game, it is akin to players stating their intended actions one by one during halftime. Once on the field, they follow through with the sequential decisions they have just made.

[2]In MAT, the *hat* $\hat{}$ means some encoding of the variable.

Networked Agents One more novel cooperative MARL paradigm involves networked agents, which operate in fully decentralized settings. In this framework, agents perceive local environmental observations and synchronize information locally with neighboring agents over a network (Zhang et al., 2018). A consensus mechanism has been introduced to the paradigm, expanding its applicability to real-world domains with strict privacy requirements (Chen et al., 2022; Varela et al., 2025). By enabling localized information sharing and coordination, networked agents enhance system robustness and adaptability while preserving data privacy, making this paradigm particularly promising for applications in decentralized and privacy-sensitive environments, especially for LaMAS in use.

3 MARFT Overview

Based on the review of RFT, LaMAS, and MARL, in this section, we will extend this foundation to the context of MARFT, highlighting the problem statement, unique considerations, and additional complexities that arise in this domain.

3.1 Problem Statement and Flex-MG

MARFT integrates the three key principles comprehensively reviewed in Section 2, adapting them to the context of RFT for LaMAS. In MARFT, agents operate within a framework that allows asynchronous yet coordinated execution, reflecting the dependencies inherent in agentic problem-solving (as detailed in Section 2.2). This design is particularly suitable for addressing complex tasks where execution dependencies necessitate dynamic adaptation and partial observability. Thus, the algorithms developed for MARFT serve dual objectives: optimizing concurrent actions and learning systemic organization and dynamic task decomposition workflow.

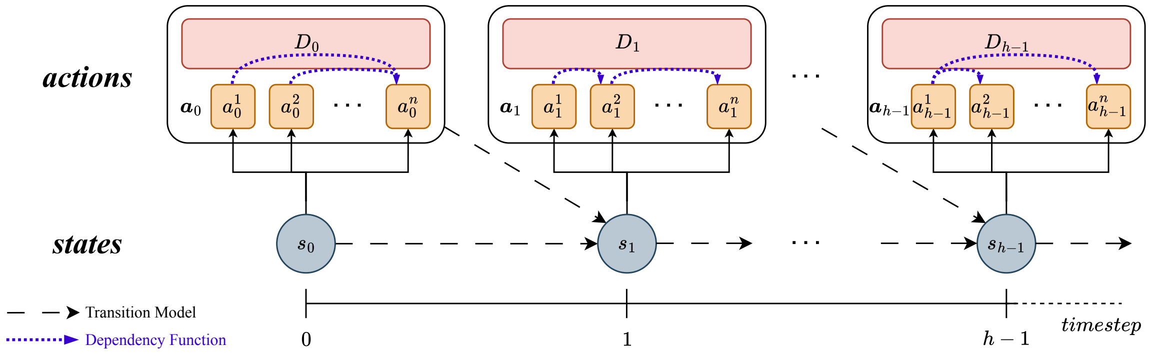


Figure 2: A detailed illustration of the dynamics of a Flex-MG. The dependency function (dashed purple line) can vary across timesteps.

To enhance problem formulation and accommodate MARFT, we propose *Flexible Markov Game (Flex-MG)*, illustrated in Figure 2 and denoted as $\langle \mathcal{V}, \mathcal{N}, \mathcal{S}, \boldsymbol{\mathcal{A}}, \mathcal{T}, \mathcal{R}, \gamma, \mathcal{D} \rangle$. Here, $\mathcal{V}$ is the vocabulary, $\mathcal{N} = \{1, ..., n\}$ is the agent composition of a LaMAS **with some organization**, i.e., some order constraint among agents, $\mathcal{S}$ is the state space, and $\boldsymbol{\mathcal{A}} = \prod_{i=1}^{n} \mathcal{A}^i$ is the joint action space. The transition function $\mathcal{T} \colon \mathcal{S} \times \boldsymbol{\mathcal{A}} \to \mathcal{S}'$, written as $P(s'|s, \boldsymbol{a})$, models state changes given joint actions. The reward function $\mathcal{R} \colon \mathcal{S} \times \boldsymbol{\mathcal{A}} \to \mathbb{R}$, denoted $R(s, \boldsymbol{a})$, assigns rewards based on states and joint actions. The discount factor γ accounts for temporal reward decay.

Flex-MG is distinguished by its introduction of a **dependency function** $\mathcal{D} \colon \boldsymbol{\mathcal{A}} \times \boldsymbol{\mathcal{A}} \to \{0, 1\}$, which explicitly models inter-agent dependencies. Specifically, $\mathcal{D}(a^i, a^j) = 1$ indicates that the action of agent j is conditionally dependent on the action of agent i. As a result, the decision-making process of agent j is influenced not only by the global state s but also by the actions of all agents k such that $k \in \{l | \mathcal{D}(a^l, a^j) = 1\}$. These dependencies can be integrated into agent j's input via concatenation or other fusion methods, thereby forming an enriched input for the agent's policy. Crucially, the dependency function $\mathcal{D}$ can vary across timesteps, potentially governed by an orchestration agent or a dynamic routing mechanism. This flexibility captures the evolving coordination structures in LaMAS and embodies the "flexible" nature of the proposed framework. Notably, when $\mathcal{D}(a^i, a^j) = 0$ for all i, j, Flex-MG reduces to a standard multi-agent decentralized setting where agents act independently.

3.2 Categorizations of LaMAS in MARFT

In the context of MARFT, the unique characteristics of LaMAS necessitate a detailed categorization. We classify LaMAS based on three key dimensions: parameter sharing, execution synchronicity, and update scheme. This categorization not only captures the distinct features of LaMAS but also provides a clear direction for the development of MARFT algorithms.

Parameter sharing Parameter sharing is a critical consideration in multi-agent systems, particularly in traditional MARL. However, in LaMAS, parameter differentiation strategies introduce additional complexity. Agents may either share parameters or maintain distinct configurations, each with unique implications for optimization.

For parameter sharing, agents share an identical base model, which can be fully fine-tuned or LoRA fine-tuned on a single adapter for task-specific roles. For non-parameter sharing, agents may use different base models with fine-tuning (full or LoRA) or share a common base model with role-specific adapter modules. While parameter sharing streamlines optimization and alleviates memory pressure, it can introduce challenges such as opposite optimization directions or parameter drift, where conflicting updates degrade performance. Despite these risks, parameter sharing remains essential for efficient LaMAS fine-tuning, particularly when combined with techniques like LoRA, which isolate task-specific adaptations from the base model.

Execution synchronicity Execution synchronicity represents another critical dimension for classifying LaMAS. Unlike traditional cooperative games in multi-agent systems, where agents typically act synchronously, LaMAS often operates under asynchronous or hybrid execution paradigms. This distinction arises from the inherent dependencies in agentic tasks, where execution outcomes frequently rely on partial or sequential results.

In synchronous LaMAS, agents execute actions concurrently, assuming full observability and independence of execution results, while in asynchronous LaMAS, agents act independently, with execution triggered by task-specific dependencies or environmental signals. The latter paradigm is prevalent in real-world applications, as it accommodates dynamic workflows and partial observability. Hybrid LaMAS combines synchronous and asynchronous elements to balance efficiency and flexibility.

Update simultaneity In addition to execution synchronicity during inference, the choice of update scheme during training further distinguishes LaMAS configurations. Specifically, LaMAS can be categorized into two types based on how agent updates are orchestrated.

In a LaMAS with synchronous update manner, all agents are updated concurrently. Though simple and easy to implement, it introduces non-stationarity into the optimization process and suffers from severe off-policy issues as later agents may base their updates on outdated policies of earlier agents. Each agent's policy updates are based on rapidly changing system dynamics, complicating convergence and potentially leading to oscillations in performance. On the other hand, in sequential (i.e., agent-by-agent) update LaMAS, agents are updated sequentially, with each agent's update based on the most current policies of others. This method ensures monotonic improvement of both individual agents and the overall system by reducing non-stationarity and minimizing off-policy effects. However, it may increase computational overhead due to the sequential nature of updates.

3.3 Differences and Resulting Challenges

Due to the distinct characteristics of LaMAS compared to traditional multi-agent systems in MARL, implementing large-scale LaMAS within a MARL framework presents significant challenges, and classic MARL methods often fail to effectively enhance the performance of LaMAS.[3] Below, we list the key differences between MARFT and traditional MARL in table 2, and expand the discussion in detail, which hopefully can guide the methodology and implementation in the following section.

Table 2: Differences between MARFT and traditional MARL.

	MARL	**MARFT**
Execution Asynchronicity	Synchronous	Asynchronous
Utilities	Task-specific only	Agentic with original language ability
Agent Identity	Unspecified, usually id	Specified profiles
Heterogeneity	Parameters	In-out formats, externals, parameters
System Organization	Static	Dynamic
Optimization Space	Small	Large and variable

Execution Asynchronicity One of the most significant differences between conventional MARL and MARFT is the nature of agent action executions. In traditional cooperative MARL, agents' actions are typically executed simultaneously. However, in MARFT, they are executed asynchronously. In some cases, the actions of certain agents may even depend on the outcomes of other agents' actions. For example, in a collaborative coding assistant system, one LLM agent generates a function prototype, and another agent asynchronously refines it based on the first agent's output, demonstrating both asynchronicity and result dependency. As a result, conventional MARL methods, which assume synchronous actions, may not be directly applicable or effective in LLM-based multi-agent systems.

Utilities Unlike agents in typical MARL problems, LLMs are initially designed for language processing rather than specific agentic tasks. However, the value- or reward-guided nature of RL means that when using value-based RL algorithms to optimize or extract policies, the derived optimal policy often prioritizes actions that maximize the value function. This can lead to policies that generate high-reward actions or tokens but are incomprehensible to humans. Though some attempts to extract a policy together with entropy regularization have been made to improve its agentic intelligence without harming the text capability (Wen et al., 2024a), it is still a point that requires additional attention when we try to implement value-based methods to optimize LLMs.

Characteristic Profiles The transition from single-agent to multi-agent systems in typical MARL benchmarks, such as Multi-Agent MuJoCo, often involves splitting a single agent into multiple components without additional modifications. In contrast, LLMs require a more nuanced approach. When decomposing tasks into orthogonal sub-tasks, each LLM agent needs a profile to define its role and capabilities, enabling it to generate actions consistent with its assigned character. This profile can be human-specified or learned by the agent through natural evolution. Consequently, the joint observation space in MARFT is augmented with profiles, taking the form `[agent profile + env observation (+ agent-specific guidance)]`. This modification is crucial when designing a MARL training framework.

Heterogeneity In conventional MARL benchmarks, heterogeneity is typically characterized by differences in agent structures and non-parameter-sharing schemes. However, LLM-based systems introduce a higher level of complexity. First, LLMs themselves can vary significantly in terms of model structures, parameters, input and output formats (*e.g.* , LLMs vs. Vision-Language Models),

[3]In fact, there is very little research about implementing classic MARL methods, such as COMA, MADDPG, MAPPO, HAPPO, etc., to LaMAS.

and vocabularies. Second, agents may have access to different external tools or devices, reflecting real-world scenarios. For instance, in designing a multi-agent system for a mobile operating system, some agents may have access to both local and remote search engines, while others may rely on proprietary databases or tools from other companies. This heterogeneity complicates training, making it more difficult and unstable.

System Organization Traditional MARL tasks are often set in static simulated environments. In contrast, LLM-based multi-agent systems are designed for real-life agentic tasks with higher uncertainty. These tasks can be decomposed in various ways, leading to different multi-agent systems with distinct populations and roles. Moreover, agents may exhibit sequential dependencies and contextual relationships when solving sub-tasks. For example, one agent's action may depend on the outcome of another agent's action. This dynamic organization can be either human-designed or agent-explored (*e.g.* , through training), adding another layer of complexity to the design process.

Optimization Space If we take one LLM generation as an action, the observation space is exponentially vast as $o \in \mathcal{O} \subseteq \mathcal{V}^L$, whose complexity is $O(|\mathcal{V}|^L)$, where $\mathcal{V}$ is the vocabulary of the acting LLM and N is the token length of the generated action, and both of them vary with different acting LLMs. It makes the value function hard to converge with stability. If we take one token as an action, the complexity can be reduced to $O(|\mathcal{V}| \times L)$, but it will become a task with super sparse reward outcome so that the value function should also be meticulously learned, as L can be extremely large. This is also reflected in VAPO and is mitigated by value pretraining (Yue et al., 2025). Fortunately, not all LLM-related tasks face such large optimization spaces. For instance, in embodied AI with LLMs, predefined actions (*e.g.* , "go to the kitchen," "grab a coffee") are often provided, significantly narrowing the action space (Carta et al., 2023; Tan et al., 2024).

These differences collectively make the optimization of LaMAS more complex than traditional MARL problems. MARFT is designed to tackle the difficulties. To generally optimize the LaMAS regardless of the highly dynamic workflow or organization, MARFT reframes the problem as a sequential decision-making problem despite the dynamic organization. It preserves pretrained utilities by applying clipping, preventing excessive policy drift. Agent profiles are encoded to activate specific capabilities, and no modality assumptions are made, as all agent actions are expressed in tokens from their respective vocabularies.

4 Multi-Agent Reinforcement Fine-Tuning

Building on the formulations outlined in the previous section, we now turn to the core methodologies that enable MARFT to address the unique challenges of optimizing LaMAS.

4.1 MARFT Instantiations

Inheriting the SM-style re-modeling via the multi-agent advantage decomposition theorem introduced in the last section, MARFT follows the procedure demonstrated in Figure 3. Given any organizational or task-solving workflow of a LaMAS, theorem (5) allows MARFT to reframe it as a sequential decision-making process. When collecting interactive trajectories, the LaMAS generates actions with an auto-regressive problem-solving style. The "encoder" constructs local roll-out states using agent profiles and other relevant information, while the "decoder" combines these states with dependent predecessors' actions to generate the current agent's action $a^m \sim p_{\pi^m}(a^m|s, a^{1:m-1})$.

MARFT-A To instantiate the framework, we further present Action-level MARFT (MARFT-A), a variant designed for targeted, action-level policy optimization in LaMAS. During training, MARFT-A adopts an optimization objective in (6)[4]. Notably, in MARFT-A, each agent optimizes within a trust

[4]Our current MARFT instantiation employs a sequential decision-making process for scalability. Extending it to handle the parallel rollouts permitted by Flex-MG (i.e., a general DAG structure) would necessitate a more complex optimization objective to tackle off-policy problems, which we leave as a direction for future work.

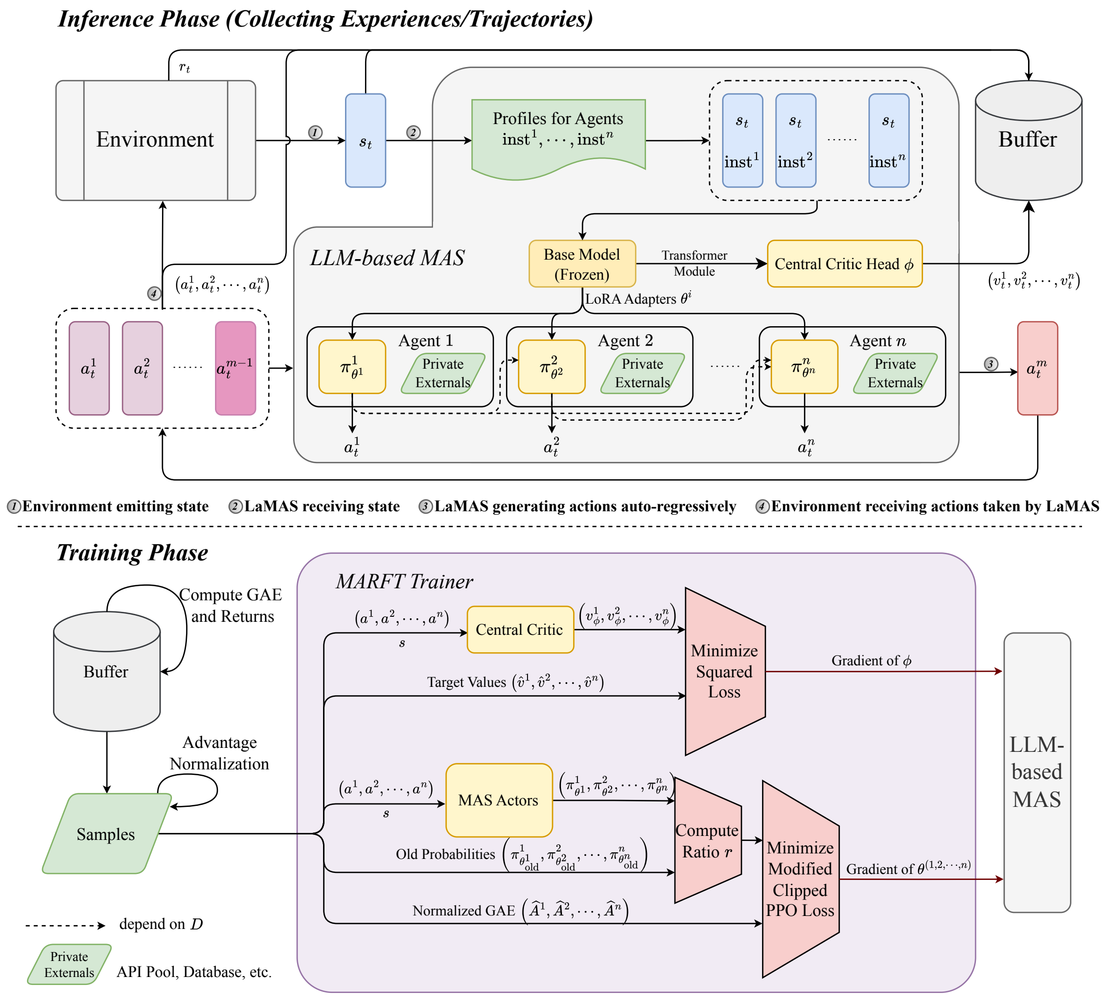

Inference Phase (Collecting Experiences/Trajectories)
Environment
r_t
s_t
Profiles for Agents inst^1, ⋯, inst^n
s_t inst^1
s_t inst^2
s_t inst^n
Buffer
LLM-based MAS
Base Model (Frozen)
Transformer Module
Central Critic Head ϕ
$(v_t^1, v_t^2, \cdots, v_t^n)$
LoRA Adapters θ^i
Agent 1
Agent 2
Agent n
Private Externals
$(a_t^1, a_t^2, \cdots, a_t^n)$
a_t^m
①Environment emitting state
②LaMAS receiving state
③LaMAS generating actions auto-regressively
④Environment receiving actions taken by LaMAS
Training Phase
Compute GAE and Returns
Buffer
Advantage Normalization
Samples
MARFT Trainer
Central Critic
Target Values $(\hat{v}^1, \hat{v}^2, \cdots, \hat{v}^n)$
Minimize Squared Loss
Gradient of ϕ
MAS Actors
Old Probabilities
Compute Ratio r
Minimize Modified Clipped PPO Loss
Normalized GAE $(\hat{A}^1, \hat{A}^2, \cdots, \hat{A}^n)$
Gradient of $\theta^{(1,2,\cdots,n)}$
LLM-based MAS
depend on D
API Pool, Database, etc.

Figure 3: The procedure of Multi-Agent Reinforcement Fine-Tuning. Inference and training are conducted in an alternating manner. Each agent within the MAS can have its own private APIs, tool pool, database, and other resources.

region conditioned on predecessor actions, akin to MAT, thus ensuring monotonic improvement as in HAPPO's sequential update scheme.

$$L(\boldsymbol{\theta}) = \frac{1}{nT} \sum_{i=1}^{n} \sum_{t=0}^{T-1} \min \left[\boldsymbol{r}_t^m(\boldsymbol{\theta}) \hat{A}_t, \operatorname{clip}\left(\boldsymbol{r}_t^m(\boldsymbol{\theta}), 1 \pm \epsilon\right) \hat{A}_t \right], \tag{6}$$

$$\text{where } \boldsymbol{r}_t^m(\boldsymbol{\theta}) = \frac{\pi_{\theta^m}^m \left(a_t^m | s_t, \hat{\boldsymbol{a}}_t^{1:m-1}\right)}{\pi_{\theta_{\text{old}}^m}^m \left(a_t^m | s_t, \hat{\boldsymbol{a}}_t^{1:m-1}\right)}.$$

Action Normalization. As shown in equation (7), the probability of each token $P(w|\cdot)$ is less than (or equal to) 1. As a result, longer action tends to have a lower joint probability, even though it is more reasonable than other actions in the task. To address the issue, Tan et al. (2024) proposed token normalization and word normalization by dividing the joint action probability in (7) by a constant related to its token or word length. It gets rid of the strong assumption that all the actions have similar lengths, which in LLMs, can be an evil condition, because in agentic tasks, it is all too common that solutions generated can be either super long with a chain-of-thought or super short with a direct answer.

$$\begin{aligned}\log P_{\pi^i}\left(a^i|s,\boldsymbol{a}^{\mathcal{N}(i)}\right) &= \log P_{\pi^i}\left(w^{i,1},\ldots,w^{i,L^i}|s,\boldsymbol{a}^{\mathcal{N}(i)}\right)\\ &= \sum_{j=1}^{L^i}\log P_{\pi^i}\left(w^{i,j}|s,\boldsymbol{a}^{\mathcal{N}(i)},w^{i,1},\ldots,w^{i,j-1}\right).\end{aligned} \tag{7}$$

Agent-by-agent Update. Updating every policy during each training epoch may introduce implicit off-policy issues, which can potentially compromise the monotonic improvement guarantee of PPO for individual agents' policies. This problem can be exacerbated in LaMAS, where agents often have dependencies on the results of other agents' actions. Drawing on the approach of A2PO (Wang et al., 2023), an agent-by-agent update scheme can be employed to restore monotonic improvement for each agent and facilitate stable convergence.

Trajectory-level Optimization. For language models, the definition of action from the RL perspective can be dynamic. Direct trajectory-level optimization, such as GRPO with outcome supervision (Shao et al., 2024) and its variant DAPO (Yu et al., 2025), can be viewed as an action-level optimization with non-zero reward only at the end of the trajectory in the MDP or a normal action-level optimization in a single-step variant of the MDP. Consequently, trajectory-level optimization can be seamlessly integrated into MARFT by following the same idea.

MARFT-T On top of the credit assignment of each agent on its action, we can also give a more fine-grained credit assignment by naturally treating every token as an action, leading to another token-level instantiation of MARFT named MARFT-T. In this situation, we need to define the token-level multi-agent state value functions as

$$Q^{\boldsymbol{\pi}}\left(s_t,\boldsymbol{a}_t^{i-1},w_t^{i,j-1},w_t^{i,j}\right) := \mathbb{E}_{\tau\sim p_{\boldsymbol{\pi}}\left(\tau|s_t,\boldsymbol{a}_t^{i-1},w_t^{i,j-1},w_t^{i,j}\right)}\left[\sum_{k=t}^{\infty}\gamma^{k-t}R_k(s_k,\boldsymbol{a}_k)|s_t,\boldsymbol{a}_t^{i-1},w_t^{i,j-1},w_t^{i,j}\right].$$

$$V^{\boldsymbol{\pi}}\left(s_t,\boldsymbol{a}_t^{i-1},w_t^{i,j-1}\right) := \mathbb{E}_{\tau\sim p_{\boldsymbol{\pi}}\left(\tau|s_t,\boldsymbol{a}_t^{i-1},w_t^{i,j-1}\right)}\left[\sum_{k=t}^{\infty}\gamma^{k-t}R_k(s_k,\boldsymbol{a}_k)|s_t,\boldsymbol{a}_t^{i-1},w_t^{i,j-1}\right].$$

And then the token-level Bellman backup can be spontaneously derived as

$$Q^{\boldsymbol{\pi}}(s_t,\boldsymbol{a}_t^{i-1},w_t^{i,1:j-1},w_t^{i,j}) \leftarrow \begin{cases}0+\gamma\max\limits_{w_t^{i,j+1}} Q^{\boldsymbol{\pi}}(s_t,\boldsymbol{a}_t^{i-1},w_t^{i,1:j},w_t^{i,j+1}) & \text{if } j<|a_t^i|\\ 0+\gamma\max\limits_{w_t^{i+1,1}} Q^{\boldsymbol{\pi}}(s_t,\boldsymbol{a}_t^{1:i},w_t^{i+1,1}) & \text{if } j=|a_t^i|\ \&\ i+1<n\\ R(s_t,\boldsymbol{a}_t^{1:i})+\gamma\max\limits_{w_{t+1}^{1,1}} Q^{\boldsymbol{\pi}}(s_{t+1},\boldsymbol{a}_t^{1:i},w_{t+1}^{1,1}) & \text{if } j=|a_t^i|\ \&\ i=n\end{cases},$$

$$V^{\boldsymbol{\pi}}(s_t,\boldsymbol{a}_t^{i-1},w_t^{i,1:j}) \leftarrow \begin{cases}0+\gamma V^{\boldsymbol{\pi}}(s_t,\boldsymbol{a}_t^{1:i-1},w_t^{i,1:j+1}) & \text{if } j<|a_t^i|\\ 0+\gamma V^{\boldsymbol{\pi}}(s_t,\boldsymbol{a}_t^{1:i},w_t^{i+1,1}) & \text{if } j=|a_t^i|\ \&\ i<n\\ R(s_t,\boldsymbol{a}_t^{1:i})+\gamma V^{\boldsymbol{\pi}}(s_{t+1},\boldsymbol{a}_t^{1:i},\emptyset) & \text{if } j=|a_t^i|\ \&\ i=n\end{cases}.$$

This type of modified token-level Bellman backup guides the computations of TD errors and the advantages of tokens, thereby leading to token-level value training and policy optimization. In the context of the MARFT-T approach, each token is treated as an individual action, thereby introducing a new MG formulation, where the reward function is highly sparse and assigns zero rewards to all intermediate tokens and preceding agents, with the reward being allocated solely to the final token of the entire multi-agent system. Although this sparsity in the reward signal poses challenges for learning the value function, it significantly reduces the optimization complexity from $O\left(|\mathcal{V}|^L\right)$ to $O\left(|\mathcal{V}|\times L\right)$, which is discussed in Section 3.3. However, due to the introduction of the different MG, MARFT-T optimizes inconsistently with the original optimization problem (Wen et al., 2024b).

4.2 Implementations

4.2.1 Base Algorithm

The detailed algorithm implementation of MARFT-A is illustrated as algorithm 3, and the details are demonstrated in the Appendix A with highlighted comments as explanations. For the design of the value function V_ϕ, we base it with a frozen transformer module, which proceeds the sequence information and outputs the final hidden state vector of the sequence, and add an extra trainable multilayer perceptron (MLP) with parameters ϕ to map the hidden vector to a specific value. A common instantiation of the transformer module can be the base model of an agent. For the design of the agents, we usually resort to LoRA fine-tuning to avoid overwhelming pressure on computing resources. If the agents share the same base model, we can assign separate but same-structured LoRA adapters to them, but if the agents have different base models, even different modalities, we then have to give them distinguished LoRA adapters.

Algorithm 3: Action-level Multi-Agent Reinforcement Fine-Tuning (MARFT-A)

```
Input: Agent population $n$, agent profiles inst$^i$, the initial joint policy $\boldsymbol{\pi}_{\boldsymbol{\theta}_0}$ with parameters $\theta_0^i$
       for each policy $\pi^i_{\theta^i}$, initial parameters $\phi_0$ for the critic network $V_\phi$, hyper-parameters
       including maximum interaction steps $T$ in one roll-out, clip parameter $\epsilon$, discount factor
       $\gamma$, GAE $\lambda$, etc.
Output: Optimized joint policy $\boldsymbol{\pi}$ and critic network $\phi$
1  initialize policy $\boldsymbol{\pi}_{\boldsymbol{\theta}} \leftarrow \boldsymbol{\pi}_{\boldsymbol{\theta}_0}$, critic network $V_\phi \leftarrow V_{\phi_0}$ and buffer $\mathcal{D} \leftarrow \emptyset$
2  for episode $= 0, \dots$ do
3      for $t = 0, \dots, T-1$ do
4          collect $s_t$
5          for $i = 1, \dots, n$ do
6              generate action $a^i \sim p_{\pi^i_{\theta^i}}(a^i|s, \boldsymbol{a}^{1:i-1})$
7          end
8          $s_{t+1} \sim \mathcal{T}(\cdot|s_t, \boldsymbol{a}_t)$
9          $r_t = R(s_t, \boldsymbol{a}_t)$
10         $\mathcal{D} \leftarrow \mathcal{D} \cup \{(s_t, \boldsymbol{a}_t, r_t, s_{t+1})\}$
11     end
12     compute advantage estimate $\hat{A}$ via GAE and compute value network target $\hat{V}$ in $\mathcal{D}$
13     for n epoches do
14         sample a batch $\mathcal{B} = \{(s_t, \boldsymbol{a}_t, r_t, s_{t+1}, \hat{A}, \hat{V})\} \sim \mathcal{D}$
15         update $\phi$ by minimizing $\sum_{n=1}^N \left\| V_\phi(s_n) - \hat{V}_n \right\|^2$
16         update $\boldsymbol{\theta}$ by maximizing the objective (6)
17     end
18 end
```

For the implementation of action normalization, we can directly count the token length or word length as Z and divide the sum of the log probabilities of generated tokens by Z.

$$\text{Norm}\left(\log P_{\pi^i_{\theta^i}}\left(a^i|s, \boldsymbol{a}^{1:i-1}\right)\right) = \frac{\log P_{\pi^i_{\theta^i}}\left(a^i|s, \boldsymbol{a}^{i-1}\right)}{Z}.$$

To implement agent-by-agent update, this sequential update mechanism involves updating only one policy per training epoch and cycling through the policies alternatively.

4.2.2 Token-level Adaptations

For the implementation of MARFT-T, the overall procedure mirrors that of Algorithm 3, with the primary modification being the storage of all token logits and values, rather than just the joint action probabilities and values, during the trajectory rollout phase. Subsequently, the token-level Bellman backup is utilized to determine the target values for the critic network and to calculate the TD errors. Additionally, GAE (Schulman et al., 2018) is employed to estimate the advantage values for each token. The optimization objectives remain consistent with those outlined in the general framework.

5 Experiments

To verify the feasibility and effectiveness of the MARFT paradigm, we implement MARFT-A and MARFT-T that follows general principles of MARFT and conduct a series of experiments, including main experiments of fine-tuning LaMAS in math problem-solving and coding environments. We demonstrate the learning dynamics and evaluation results[5] for further analysis. More experiments and experiment details are presented in Appendix B.

5.1 Setups

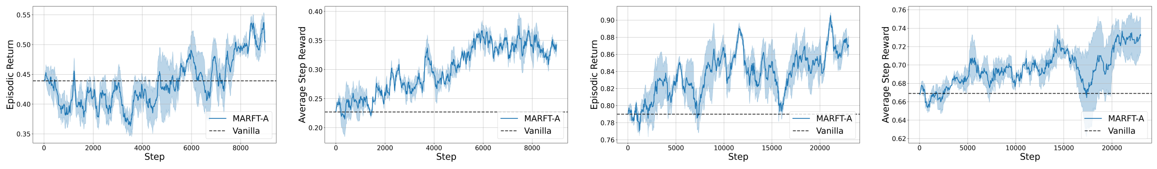
Task Environments The environments are supported by specific datasets and reset by randomly sampling a (problem, answer, or test cases) pair from the dataset. The LaMAS takes actions, and the environment verifier checks the correctness. The reward in math problem-solving environment is 1 for correct answers and 0 otherwise, and the reward in coding environment is the test case pass rate.

Datasets and Benchmarks For math problem-solving, we train on the MATH (Hendrycks et al., 2021) (7.5k entries) and CMATH (Wei et al., 2023) (600 entries) training sets. We evaluate on MATH500, the CMATH test set, and the out-of-domain GSM8K (Cobbe et al., 2021) test set. For coding, we use the CodeForces (Penedo et al., 2025) dataset with 1339 training and 377 test entries.

Base Model and LaMAS Setups For math experiments, we use Qwen2.5-Coder-3B-Instruct (Yang et al., 2024a; Hui et al., 2024) as the base model[6]. Solo represents a single-agent setup, while Duo represents a LaMAS with two agents (Reasoner → Actor) collaborating on problem-solving. For coding experiments, we use Qwen2.5-3B-Instruct (Yang et al., 2024a; Hui et al., 2024) as the base model. On top of the Duo setting used in the math scenario, we add a Trio that represents a LaMAS with three agents (Reasoner → Coder → Reviewer). Each agent is equipped with a dedicated LoRA adapter. Profile configurations for these experiments are detailed in Appendix B.3.

5.2 Learning Dynamics

Figure 4 shows the training dynamics of MARFT-A of Duo in environments supported by MATH and CMATH. The episodic return (ER) is the correctness of solving the math problem. The average step reward (ASR) is calculated by dividing the episodic return by the steps taken to solve the problem.



(a) ER (MATH). (b) ASR (MATH). (c) ER (CMATH). (d) ASR (CMATH).

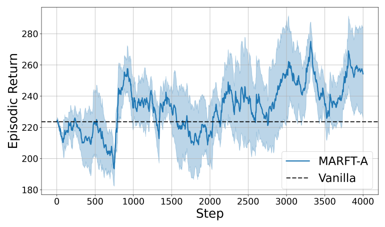
Figure 4: Learning dynamics of MARFT-A of Duo on MATH and CMATH.

[5]The mean and standard error of all curves are computed over 3 random seeds. The mean and standard error of evaluation results are calculated over 10 random seeds with temperature 0.1.

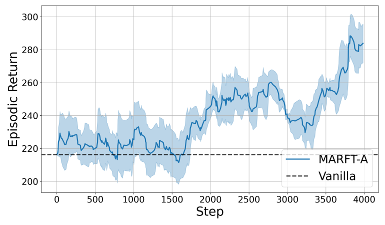
[6]The models were specifically chosen to avoid data leakage.

We observe that in math problem-solving environments, the episodic return exhibits a clear improvement up to about 8 p.p.[7] (~18.45%). However, during the early stages of training, the episodic return demonstrates noticeable oscillations. This instability can be explained by the behavior of the value loss, which display high losses during the initial phase. Besides, we observe a constant improvement in average step reward, which means Duo not only tries to achieve high episodic return but also learns to solve the problem more efficiently.

Figure 5 shows the training dynamics of MARFT-A of Duo and Trio in coding environments built by CodeForces. We observe that the scores undergo a certain oscillation in the beginning and then increase stably from about 220 to about 260 (~18.18%) and 280 (~27.27%) respectively for Duo and Trio.



(a) Duo.



(b) Trio.

Figure 5: Learning dynamics of MARFT-A on CodeForces.

5.3 Evaluation Results

On top of the learning dynamics of MARFT-A in the environment supported by the train set, we also conduct evaluations on the test set. Table 3 presents the performance of Solo, Duo, and MARFT-A-tuned Duo on the MATH500, CMATH, and GSM8K test sets, including in-domain and out-of-domain assessments. And Table 4 gives a comparison of total scores between vanilla LaMAS and the MARFT-A-tuned ones on the test set.

Solo vs. Multi-Agent For mathematical tasks, by comparing Solo and Duo, we observe that Duo significantly outperforms Solo on the MATH500 benchmark by approximately 7.5 p.p. (~20.58%). However, their performance is comparable on CMATH and GSM8K, likely because these datasets consist of relatively simpler problems. In such cases, a more complex solving process may hinder performance. These results suggest that a LaMAS like Duo is more effective than a single agent in solving complex mathematical problems. For coding tasks, Solo and Duo perform close to each other, but Trio falls behind by about one point, which proves that overcomplicating a system for a task with modest difficulty can harm the system's performance.

Table 3: Evaluation results (in percentages) of Solo, Duo and MARFT-A-tuned Duo on mathematical benchmarks. MARFT-A Duo-MATH and MARFT-A Duo-CMATH mean MARFT-A-tuned Duo in the environments supported by MATH train set and CMATH train set.

Benchmarks	Solo	Duo	MARFT-A	
			Duo-MATH	Duo-CMATH
MATH500	36.44 ± 1.35	43.9 ± 1.09	47.14 ± 1.31	$\mathbf{47.18 \pm 0.10}$
CMATH	80.24 ± 0.62	79.00 ± 0.98	81.26 ± 0.55	$\mathbf{81.82 \pm 0.85}$
GSM8K	68.45 ± 1.68	74.23 ± 0.63	$\mathbf{77.24 \pm 0.94}$	76.76 ± 0.55

Vanilla vs. MARFT-A For mathematical tasks, on in-domain benchmarks, MARFT-A enhances Duo's performance by about 3 p.p.. Additionally, MARFT-A improves Duo's effectiveness in out-of-domain settings, demonstrating its capability to foster collaborative behavior within Duo. This indicates that MARFT-A can further augment the performance of multi-agent systems. Duo-MATH and Duo-CMATH, fine-tuned on English and Chinese datasets respectively, both generalize well across domains: Duo-CMATH scores 49.4% on MATH500, and Duo-MATH reaches 83.0% on CMATH. Both also improve performance on GSM8K, indicating that MARFT enhances not only

[7] p.p. is the abbreviation for percentage points.

Table 4: Evaluation results of Solo, Duo, Trio, and the MARFT-A-tuned ones on CodeForces.

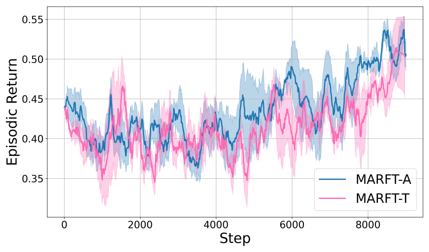
Setup	Vanilla	MARFT-A
Solo	27.21 ± 2.84	28.92 ± 2.07
Duo	27.45 ± 1.60	$\mathbf{31.50 \pm 1.16}$
Trio	26.58 ± 2.47	28.39 ± 1.58

in-domain accuracy but also cross-lingual and out-of-domain generalization. For coding problems, we see that MARFT-A-tuned Duo obtains a significant improvement of about 4 scores (~14.75%) and surpasses MARFT-A-tuned Solo by about 2.5 scores (~8.92%). Though we notice that vanilla Trio falls behind the other two, we still see Trio get improved by about 2 scores (~6.81%) by using MARFT-A, which validates the effectiveness of MARFT, regardless of the over-complicated LaMAS design.

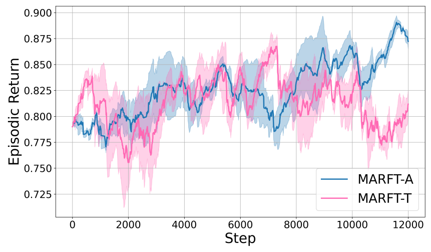
5.4 Ablation Experiments

5.4.1 Optimization Granularity

Figure 6 (Supplementary Figure 8 in Appendix) shows the performance of MARFT-A and MARFT-T while fine-tuning Duo, in mathematical environments. From both subfigures, we see that MARFT-A is overall better than MARFT-T. Specifically, MARFT-A achieves a higher episodic return than MARFT-T in the end and has a more stable and faster improvement. This kind of superiority of MARFT-A over MARFT-T can be theoretically deduced from the inconsistency of their optimality, which is caused by the different MG (Wen et al., 2024b).



(a) Episodic Return (MATH).



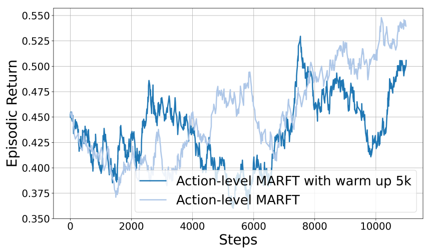
(b) Episodic Return (CMATH).

Figure 6: Curves of episodic return during Duo MARFT with different optimization granularity (computed over 3 random seeds).

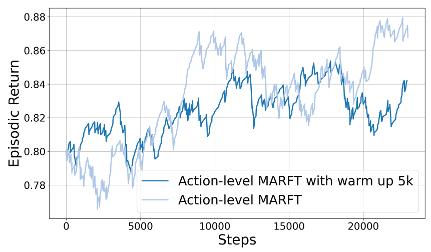
5.4.2 Value Pretraining (Warm-up)

We investigate the impact of value pertaining, also known as warm-up, where for the first few steps, only the critic network is updated while all agents stay frozen. Figure 7 shows comparisons between MARFT with warm-up and without warm-up settings.

Value pretraining aims to reduce the oscillations commonly seen in the early stages of training. As shown in the figures, it mitigates the sharp initial drops caused by a randomly initialized critic. While warm-up stabilizes early learning, it also slows performance improvement. Since reinforcement learning depends on exploration and exploitation, an overly long warm-up can lead to overfitting on a narrow and limited distribution of observations. Overall, its impact is modest and largely determined by the number of warm-up steps.



(a) Episodic Return (MATH).



(b) Episodic Return (CMATH).

Figure 7: Curves of episodic return during Duo MARFT with and without warm-up.

5.5 Future Experiments

Hyperparameter settings have a significant impact on MARFT. We include more experimental results in Appendix B.1 with more hyperparameter configurations, and these experiments, and we will collate the data and update the experiments in time.

Given the preliminary nature of our experiment on the only MATH (Hendrycks et al., 2021), CMATH (Wei et al., 2023) and CodeForces (Penedo et al., 2025), we outline a series of future experiments to further explore the capabilities and robustness of MARFT:

- **MARFT on agentic tasks**: Apply MARFT to agentic tasks and benchmarks like WebShop (Yao et al., preprint) and RoCo (Mandi et al., 2023). These environments will assess MARFT's effectiveness in scenarios requiring extended interaction and decision-making over multiple steps and turns.
- **Hyper-parameter sensitivity analysis**: Conduct extensive experiments to explore the impact of hyperparameters, particularly as the number of agents increases. This will involve testing various hyperparameter configurations to identify optimal settings that enhance stability and performance in multi-agent systems. The hyperparameter settings for the conducted experiments are listed in Appendix B.2.
- **LaMAS population scale.** Extend the experimental scope to investigate the scalability of LaMAS by varying the number of agents. Specifically, conduct experiments with agent populations of 4, 6, 8, 12, and beyond to comprehensively explore the potential of LaMAS in handling larger and more complex multi-agent scenarios. This analysis will provide insights into the system's performance and limitations as the number of agents increases.

Through these planned experiments, we aim to validate MARFT's versatility and generalization ability, and address its sensitivities, ensuring its applicability across a wider range of tasks and environments.

6 Perspectives

From this section onward, we shift our focus from the technical aspects of MARFT to discussing its perspectives and challenges.

Powerful Capabilities for Solving Complex Agentic Tasks Agentic tasks are significantly more complex than traditional language tasks, requiring capabilities such as autonomous decision-making, collaboration, and adaptive reasoning. While a standalone LLM-based agent may lack the breadth of skills needed to address these multifaceted challenges, MARFT empowers LaMAS to overcome these limitations. By leveraging RFT, MARFT enables the efficient decomposition of complex instructions into executable sub-tasks, distributing them among specialized agents within the LaMAS framework. This allows heterogeneous LLM-based agents to contribute their unique intelligence while dynamically sharing goals, negotiating strategies, and aligning team objectives through natural language interactions. MARFT further enhances this process by optimizing both individual agent policies and collective system performance, ensuring efficient coordination and adaptability. For example, in a logistics scenario, MARFT fine-tunes agents to collaboratively solve the task of "delivering emergency supplies" by dynamically assigning sub-tasks such as route planning, inventory allocation, and risk assessment to specialized agents, thereby maximizing the system's overall effectiveness.

Scalability and Robust Generalization MARFT offers significant scalability. Agentic multi-agent problems are highly flexible, allowing for various ways to decompose tasks and design corresponding multi-agent systems. As the agent population, environmental complexity, and task scale increase, the key challenge is to maintain efficient and stable learning performance and coordination capabilities. MARFT not only enhances the overall performance of the multi-agent system but also increases the intelligence of each agent by enabling more dynamic role-playing. Even if the system organization changes significantly, the problem can be re-decomposed to allow agents to function within a multi-agent system similar to the one they were trained in.

Enhanced Privacy and Federated Learning In a unified multi-agent system, agents do not have access to each other's local data. Instead, they contribute their unique intelligence to the system through their actions, thereby enhancing the system's collective intelligence. This setup aligns with many real-world scenarios where entities are willing to share their powerful agents but are highly concerned about data privacy. While this resembles federated learning, MARFT places greater emphasis on improving system performance through better collaboration among agents.

Integration with Blockchain Technology MARFT's decentralized nature and privacy-preserving capabilities make it a natural fit for blockchain. In blockchain systems, MARFT can enable secure and efficient multi-agent collaboration without requiring agents to share sensitive data. For example, in smart contract execution, MARFT can coordinate multiple agents to validate transactions, manage decentralized autonomous organizations (DAOs), or optimize resource allocation in decentralized finance (DeFi) platforms. The ability of MARFT to dynamically adapt to changing environments and agent populations ensures robust performance in the unpredictable and adversarial settings typical of blockchain ecosystems. Additionally, MARFT's emphasis on preserving pretrained capabilities while adapting to new tasks aligns well with the need for agents to maintain trustworthiness and reliability in blockchain-based systems. This integration opens new avenues for enhancing transparency, security, and efficiency in blockchain applications while leveraging the collective intelligence of LaMAS.

7 Open Problems

Despite the advantages and potential of MARFT paradigm, both academia and industry face numerous challenges that impede the development of more effective MARFT algorithms.

Lack of Dynamic Environments for Training A significant challenge in advancing MARFT is the absence of well-established, easy-to-implement, and scalable dynamic interactive environments designed for solving agentic tasks. There are two primary difficulties in this regard. First, creating such environments with complex agentic tasks demands substantial engineering expertise, comparable to developing fundamental environments like VirtualHome (Puig et al., 2018) or Overcooked (Carroll et al., 2019) from scratch. Second, designing reward feedback mechanisms for multi-agent systems in highly dynamic environments with complex agentic tasks is exceedingly challenging. The reward signals can be multi-dimensional, and balancing the weights among different goals is a delicate task. Although there are several "dynamic" benchmarks available, such as the Berkeley Function Calling Leaderboard (Yan et al., 2024; Patil et al., 2023), ToolSandBox (Lu et al., 2024), and GAIA (Mialon et al., 2024), converting these into dynamic environments that support MARL training remains an unresolved issue.

Low Sample Efficiency and Lack of High-Quality Synthetic Data RL, particularly on-policy RL, is known for its low sample efficiency. Algorithms like PPO and TRPO, which guarantee monotonic improvement, require frequent switching between sampling trajectories and training. This process is especially problematic and time-consuming when applied to LLMs. Potential solutions may include adopting ideas like Dyna (Sutton, 1991) to enhance sample efficiency or developing algorithms that effectively utilize stale trajectories. Another issue stemming from low sample efficiency is the scarcity of high-quality synthetic data. Effective multi-agent trajectories need to achieve high success rates while also demonstrating efficient communication and coordination. Currently, the field lacks such data for multi-agent cold starts.

Lack of an Established MARFT Framework Developing engineering solutions that integrate LLMs and MARL is highly challenging. While there exist user-friendly, efficient, and scalable frameworks such as verl (Sheng et al., 2024), OpenRLHF (Hu et al., 2024) for LLM fine-tuning and MALib (Zhou et al., 2023), ReMA (Wan et al., 2025), PettingLLMs (Zhao et al., 2025b) for MARL training, a comprehensive framework specifically designed for MARFT is notably absent. The creation of such a framework would require significantly more effort than developing either of the aforementioned frameworks individually. This is because it must effectively integrate both LLMs and MARL components, each of which presents its own set of complexities. While this article introduces a MARFT framework, it is still in its early stages and offers significant room for further development and refinement.

Lack of a Unified Communication Mechanism or Protocol Recent advancements have led to the development of numerous agent communication protocols (Yang et al., 2025b), such as MCP (Model Context Protocol) (Anthropic, 2024), A2A (Agent-to-Agent) (Surapaneni et al., 2025), and ANP (Agent Network Protocol) (Gaowei Chang, 2025). These protocols are essential for enabling effective collaboration among agents and facilitating interactions with users. They also address the critical need for agents to contribute to shared goals while preserving their own data and knowledge, reflecting the future vision of a decentralized, privacy-preserving agent ecosystem. However, the proliferation of these protocols has resulted in a fragmented landscape, lacking a unified and efficient communication pipeline. This fragmentation may hinder the seamless integration and interoperability of diverse agents, particularly in dynamic and heterogeneous environments typical of LaMAS. The absence of a standardized communication framework not only complicates system design and scalability but also introduces inefficiencies and potential bottlenecks in real-world applications.

8 Conclusion

In this article, we propose a novel paradigm termed **Multi-Agent Reinforcement Fine-Tuning (MARFT)**, together with a brand-new MG called Flex-MG to better align with the LaMAS optimization in realistic scenarios, and present a universal algorithmic framework, MARFT, that integrates RFT, LaMAS, and MARL to advance the capabilities of LaMAS systems. MARFT addresses several fundamental challenges in adapting conventional MARL to LaMAS, including asynchronous agent interactions, profile-aware architecture design, heterogeneity across agents, and the dynamic organization of multi-agent systems. Through the fusion of RFT with sequential decision-making paradigms, trust-region optimization techniques, and token-level adaptation mechanisms, MARFT enables efficient coordination and policy refinement while preserving the foundational capabilities of pretrained LLMs.

Preliminary experimental results on mathematical problem-solving tasks illustrate the potential of MARFT to surpass traditional single-agent strategies, demonstrating improved accuracy through emergent swarm intelligence, even in the presence of training instabilities. These findings suggest that MARFT holds significant promise for agentic tasks requiring complex, well-organized, distributed reasoning and acting.

The paradigm's intrinsic scalability, privacy-preserving characteristics, and alignment with decentralized system architectures make it a compelling foundation for real-world deployment in domains ranging from logistics and collaborative robotics to blockchain-based ecosystems. Nevertheless, numerous theoretical and practical challenges remain. Key open problems include the development of dynamic environment designs with agentic tasks tailored for LaMAS, improvement of sample efficiency, and the absence of standardized and well-established frameworks for MARFT and a unified multi-agent communication protocol.

Future research directions may include the creation of unified benchmarks and development toolkits for MARFT, the construction of high-quality synthetic datasets to simulate multi-agent LLM interactions, and the design of hybrid learning strategies to boost data efficiency, etc. By addressing these open challenges, we envision MARFT as a stepping stone toward realizing generalizable, human-aligned, and collaboratively adaptive agent systems, paving the way for scalable AGI capable of tackling complex open-world problems with robust agentic behavior and human-like adaptability.

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A Detailed Framework Code Explanation

Abstract runner code:

```
for episode in range(episodes):
    for step in range(self.episode_length):
        # rollout/sample trajectories
        rollout_obs, actions, action_tokens, values, log_probs = self.mas.
            infer_for_rollout(self.buffer.obs[self.buffer.cur_batch_index,
            step])
        next_obs, rewards, dones, infos = self.envs.step(actions)
        # insert trajectory data into buffer
        data = next_obs, rollout_obs, rewards, dones, values, actions,
            action_tokens, log_probs
        self.insert(data)
    # compute target values before training
    self.before_update() # implements bellman backup and computes GAE
    train_infos = self.trainer.train(self.buffer, steps) # training
    self.buffer.after_update() # on-policy, move buffer pointer
```

Abstract action-level Bellman backup and GAE computation code in buffer:

```
def compute_gae_and_returns(self, next_value):
    self.action_level_v_values[self.cur_batch_index, -1] = next_value
    gae = 0
    for step in reversed(range(self.episode_length)):
        for agent in reversed(range(self.num_agents)):
            # computing deltas and GAE values based on the method proposed
                in the GAE paper
            if agent == self.num_agents - 1:
                delta = self.rewards[self.cur_batch_index, step, :, agent] +
                     self.gamma * self.action_level_v_values[self.
                    cur_batch_index, step + 1, :, 0] * self.masks[self.
                    cur_batch_index, step + 1, :, 0] - self.
                    action_level_v_values[self.cur_batch_index, step, :,
                    agent]
                gae = delta + self.gamma * self.gae_lambda * self.masks[self
                    .cur_batch_index, step + 1, :, 0] * gae
            else:
                delta = self.rewards[self.cur_batch_index, step, :, agent] +
                     self.gamma * self.action_level_v_values[self.
                    cur_batch_index, step, :, agent + 1] * self.masks[self.
                    cur_batch_index, step, :, agent + 1] - self.
                    action_level_v_values[self.cur_batch_index, step, :,
                    agent]
                gae = delta + self.gamma * self.gae_lambda * self.masks[self
                    .cur_batch_index, step, :, agent + 1] * gae
            # restore target V values for critic update
            self.action_level_returns[self.cur_batch_index, step, :, agent]
                = self.action_level_v_values[self.cur_batch_index, step, :,
                agent] + gae
            # restore advantage values for policy optimization
            self.action_level_advantages[self.cur_batch_index, step, :,
                agent] = gae
    # move the pointer
    self.cur_num_batch = self.cur_num_batch + 1 if self.cur_num_batch < self
        .max_batch else self.max_batch
```

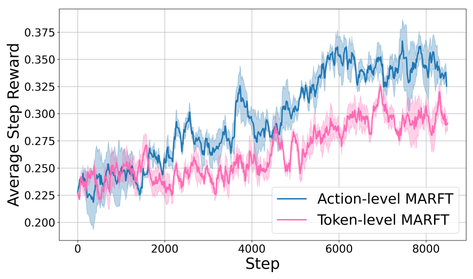
Then, for token-level Bellman backup and GAE computation, we just need to modify the operations within the innermost *for* loop.

Abstract MARFT-A training code in the trainer. (For token-level training, we just need to modify the policy loss computation to take token logits as input):

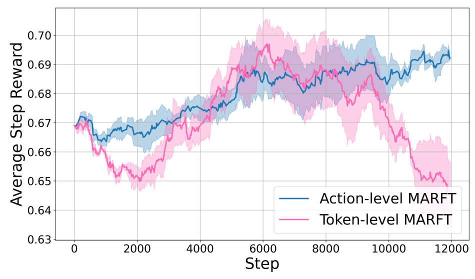
```python
def ppo_update(self, sample, global_steps: int):
    # compute the agent to train for agent-by-agent training
    agent_to_train = None
    if self.agent_iteration_interval > 0:
        time_slice = global_steps // self.agent_iteration_interval
        agent_to_train = time_slice % self.num_agent
    # sample preprocess, including advantage normalization and moving data
        onto the CUDA device.
    observations, actions, rollout_observations, log_probs, value_preds,
        returns, advantages, action_tokens = sample
    advantages_copy = advantages.copy()
    advantages_copy[advantages_copy == 0.0] = np.nan
    mean_advantages = np.nanmean(advantages_copy)
    std_advantages = np.nanstd(advantages_copy)
    advantages = (advantages - mean_advantages) / (std_advantages + 1e-8)
    actions, rollout_observations, log_probs, value_preds, returns,
        advantages, action_tokens = to_cuda((actions, rollout_observations,
        log_probs, value_preds, returns, advantages, action_tokens))
    # compute gradient accumulation batch size
    batch_size = rollout_observations.shape[0]
    cp_batch_size = int(batch_size // self.gradient_cp_steps)
    if cp_batch_size == 0:
        print(f"gradient_cp_steps␣>␣batch_size,␣set␣cp_batch_size␣=␣1")
        cp_batch_size = 1
    # critic update with gradient accumulation
    self.critic_optimizer.zero_grad()
    value_loss = 0
    for start in range(0, batch_size, cp_batch_size):
        end = start + cp_batch_size
        if end > batch_size:
            end = batch_size
        cp_weight = (end - start) / batch_size  # weight for the chunk loss
        cp_obs_batch, cp_value_preds_batch, cp_returns_batch =
            rollout_observations[start:end], value_preds[start:end], returns
            [start:end]
        values_infer = self.mas.get_action_values(cp_obs_batch)
        cp_value_loss = self.cal_value_loss(values_infer,
            cp_value_preds_batch, cp_returns_batch)
        cp_value_loss *= cp_weight  # scale the loss by the chunk weight
        cp_value_loss.backward()
        value_loss += cp_value_loss.item()
    # gradient clipping
    if self._use_max_grad_norm:
        critic_grad_norm = nn.utils.clip_grad_norm_(self.mas.critic.
            parameters(), self.max_grad_norm)
    else:
        critic_grad_norm = get_gard_norm(self.mas.critic.parameters())
    self.critic_optimizer.step()
    critic_grad_norm = critic_grad_norm.item()
    # MAS update
    for optimizer in self.policy_optimizer.values(): optimizer.zero_grad()
    total_approx_kl = 0.
    total_entropy = 0.
    policy_loss = 0.
    total_policy_grad_norm = 0.
    for start in range(0, batch_size, cp_batch_size):
        end = start + cp_batch_size
        if end > batch_size:
            end = batch_size
        cp_weight = (end - start) / batch_size
        cp_obs_batch, cp_act_batch, cp_adv_batch, cp_log_probs_batch = rollout_observations[start:end], action_tokens[start:end], advantages[start:end], log_probs[start:end]
        log_prob_infer, cp_entropy = self.mas.get_joint_action_log_probs(cp_obs_batch, cp_act_batch, agent_to_train)
        # if agent-by-agent training, only compute the loss on the actions or tokens generated by the agent
        if agent_to_train is not None:
            cp_log_probs_batch = cp_log_probs_batch[:, agent_to_train: agent_to_train + 1]
            cp_adv_batch = cp_adv_batch[:, agent_to_train: agent_to_train + 1]
        cp_policy_loss, approx_kl = self.cal_policy_loss(log_prob_infer, cp_log_probs_batch, cp_adv_batch, cp_entropy)
        total_approx_kl += approx_kl * cp_weight
        total_entropy += cp_entropy.mean().item() * cp_weight
        cp_policy_loss = cp_policy_loss * cp_weight
        cp_policy_loss.backward()
        policy_loss += cp_policy_loss.item()
    # trust-region hard cut, the value can be specific to the method -- 0.02 is not a fixed value
    if total_approx_kl > 0.02:
        return value_loss, critic_grad_norm, 0, 0, total_approx_kl, total_entropy
    if agent_to_train is not None:
        self.mas.agents.set_adapter(self.mas.profiles[agent_to_train]['role'])
        policy_grad_norm = nn.utils.clip_grad_norm_(self.mas.agents.parameters(), self.max_grad_norm)
        self.policy_optimizer[self.mas.profiles[agent_to_train]['role']].step()
        total_policy_grad_norm = policy_grad_norm.item()
    else:
        for profile in self.mas.profiles:
            self.mas.agents.set_adapter(profile['role'])
            policy_grad_norm = nn.utils.clip_grad_norm_(self.mas.agents.parameters(), self.max_grad_norm)
            self.policy_optimizer[profile['role']].step()
            total_policy_grad_norm += policy_grad_norm.item()

    return value_loss, critic_grad_norm, policy_loss, total_policy_grad_norm, total_approx_kl, total_entropy
```

B Experiment Details

B.1 More Experiment Curves

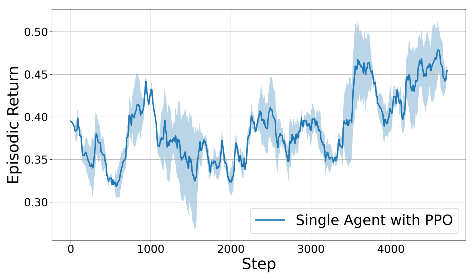


(a) Average Step Reward (MATH).

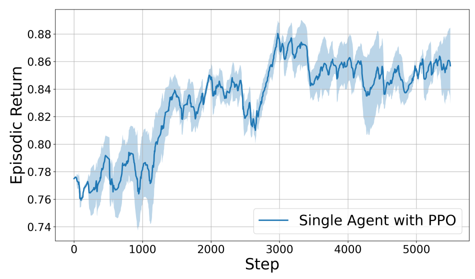


(b) Average Step Reward (CMATH).

Figure 8: Curves of average step reward during Duo MARFT with different optimization granularity (computed over 3 random seeds).

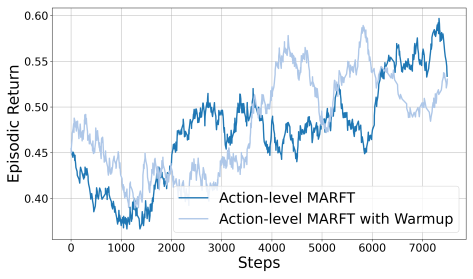


(a) Episodic Return (MATH).

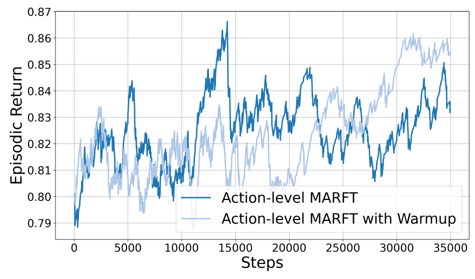


(b) Episodic Return (CMATH).

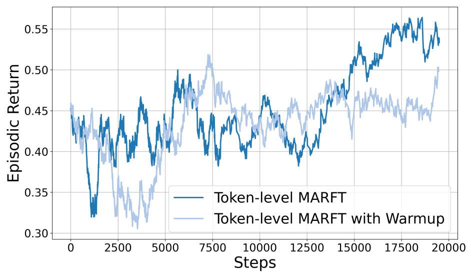
Figure 9: Curves of episodic return during Solo MARFT (computed over 3 random seeds).



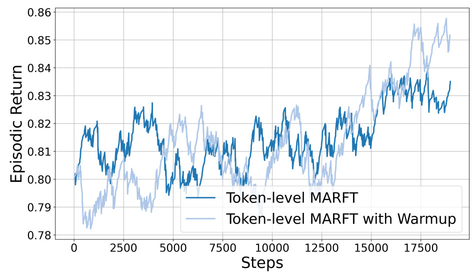
(a) Episodic Return (MATH).



(b) Episodic Return (CMATH).



(c) Episodic Return (MATH).



(d) Episodic Return (CMATH).

Figure 10: Curves of episodic return during Duo MARFT with and without warm-up. The `warm-up steps` is set to 1k.

B.2 Hyperparameter Configurations for Experiments

Table 5: Hyperparameter configuration for learning dynamics in Figure 4.

Hyperparameter	Value	Hyperparameter	Value	Hyperparameter	Value
MAS learning rate	1e-6	critic learning rate	1e-5	use gae	True
rollout threads	1	num mini-batch	1	ppo epoch	1
max horizon	2	hidden size	64	episode length	8
optim eps	1e-5	critic loss coef	1	entropy coef	1e-3
gamma	0.99	gae gamma	0.95	max grad norm	0.5
context window	2456	max new tokens	512	clip param	0.2

Table 6: Hyperparameter configuration for learning dynamics in Figure 5.

Hyperparameter	Value	Hyperparameter	Value	Hyperparameter	Value
MAS learning rate	1e-6	critic learning rate	1e-5	use gae	True
rollout threads	4	num mini-batch	1	ppo epoch	1
max horizon	1	hidden size	64	episode length	30
optim eps	1e-5	critic loss coef	1	entropy coef	1e-3
gamma	0.99	gae gamma	0.95	max grad norm	0.5
context window	4096	max new tokens	1024	clip param	0.2

Table 7: Hyperparameter configuration for MARFT-T in Figure 6.

Hyperparameter	Value	Hyperparameter	Value	Hyperparameter	Value
MAS learning rate	3e-6	critic learning rate	1e-5	use gae	True
rollout threads	1	num mini-batch	1	ppo epoch	1
max horizon	2	hidden size	64	episode length	8
optim eps	1e-5	critic loss coef	1	entropy coef	1e-3
gamma	0.99	gae gamma	0.95	max grad norm	0.5
context window	2456	max new tokens	512	clip param	0.2

Table 8: Hyperparameter configuration for warm-up ablation in Figure 7.

Hyperparameter	Value	Hyperparameter	Value	Hyperparameter	Value
MAS learning rate	1e-6	critic learning rate	1e-5	use gae	True
rollout threads	1	num mini-batch	1	ppo epoch	1
max horizon	2	hidden size	64	episode length	8
optim eps	1e-5	critic loss coef	1	entropy coef	1e-3
gamma	0.99	gae gamma	0.95	max grad norm	0.5
context window	2456	max new tokens	512	warmup steps	5000

B.3 Profiles

For the profiles that define distinct agent characteristics, we have designed two configurations for math problems and three configurations for coding problems as below:

For math problem-solving scenario:

Solo (Single-agent) profile:

```
[
    {
        "role": "actor",
        "prompt": "<|im_start|>system: You are the **Actor**, an LLM agent
           responsible for solving math problems. Analyze the problem,
           determine the optimal solution path, execute calculations, and
           provide the final answer within \\boxed{{}}.<|im_end|>\n",
        "with_answer": true
    }
]
```

Duo (Duo LaMAS) profiles:

```
[
    {
        "role": "reasoner",
        "prompt": "<|im_start|>system: Two LLM agents (Reasoner -> Actor)
           collaborate step-by-step to solve math problems. You are the **
           Reasoner**: Analyze the original problem, historical actions,
           and reflection data (if provided) to determine the critical next
            step. Guide the Actor by providing concise reasoning for the
           optimal operation.<|im_end|>\n",
        "with_answer": false
    },
    {
        "role": "actor",
        "prompt": "<|im_start|>system: Two LLM agents (Reasoner -> Actor)
           collaborate step-by-step. You are the **Actor**: Execute
           operations using the original problem, action history, and
           Reasoner's guidance. Provide final answer within \\boxed{{}}.<|
           im_end|>\n",
        "with_answer": true
    }
]
```

For coding scenario:

Solo (Single-agent) profile:

```
[
    {
        "role": "coder",
        "prompt": "<|im_start|>You are the **Coder**: Solve the coding
           problem using efficient, correct, and clean Python code. Handle
           edge cases, respect problem constraints, and structure your
           solution for clarity.\nAlways use Python.<|im_end|>",
        "with_answer": true,
    }
]
```

Duo (Duo LaMAS) profiles:

```
[
    {
        "role": "reasoner",
        "prompt": "<|im_start|>system: Two LLM agents (Reasoner -> Coder)
           collaborate to solve Codeforces Python coding problems. You are
           the **Reasoner**: Analyze the problem statement, constraints,
           and expected behavior. Identify edge cases, break the problem
```

```
            into logical steps, and suggest an algorithmic plan. You may
            include helpful pseudocode, but do **not** write actual Python
            code.<|im_end|>",
        "with_answer": false,
    },
    {
        "role": "coder",
        "prompt": "<|im_start|>system: Two LLM agents (Reasoner -> Coder)
            collaborate to solve Codeforces problems using Python. You are
            the **Coder**: Implement the Reasoner's plan using efficient,
            correct, and clean Python code. Handle edge cases, respect
            problem constraints, and structure your solution for clarity.\
            nAlways use Python.<|im_end|>",
        "with_answer": true,
    }
]
```

Trio (Trio LaMAS) profiles:

```
[
    {
        "role": "reasoner",
        "prompt": "<|im_start|>system: Three LLM agents (Reasoner -> Coder
            -> Reviewer) collaborate to solve Codeforces Python coding
            problems.\nYou are the **Reasoner**: Analyze the problem
            statement, constraints, and expected behavior.\nIdentify edge
            cases, break the problem into logical steps, and suggest a high-
            level algorithmic plan.\nYou may include helpful pseudocode and
            edge case analysis, but do **not** write actual Python code.<|
            im_end|>",
        "with_answer": false,
    },
    {
        "role": "coder",
        "prompt": "<|im_start|>system: Three LLM agents (Reasoner -> Coder
            -> Reviewer) collaborate to solve Codeforces Python coding
            problems.\nYou are the **Coder**: Implement the Reasoner's plan
            using efficient and correct Python code.\nHandle edge cases,
            follow the provided strategy, and ensure clarity and correctness
            .\nAlways use Python.\nPlace your complete solution below the
            line starting with 'Answer:'.<|im_end|>",
        "with_answer": false,
    },
    {
        "role": "reviewer",
        "prompt": "<|im_start|>system: Three LLM agents (Reasoner -> Coder
            -> Reviewer) collaborate to solve Codeforces Python coding
            problems.\nYou are the **Reviewer**: Carefully review the Coder'
            s solution.\n1. Check for correctness against the problem and
            Reasoner's plan.\n2. Identify and add any missing test cases,
            especially edge cases.\n3. Suggest or perform optimizations if
            needed (e.g. time or memory improvements).\n4. Provide a final,
            polished version of the code if improvements are made.\nStart
            your message with 'Review:', and include improved Python code (
            if any) below 'Final Answer:'.<|im_end|>",
        "with_answer": true,
    }
]
```