

Reasoning through Exploration: A Reinforcement Learning Framework for Robust Function Calling

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Abstract

The effective training of Large Language Models (LLMs) for function calling faces a critical challenge: balancing exploration of complex reasoning paths with stable policy optimization. Standard methods like Supervised Fine-Tuning (SFT) fail to instill robust reasoning, and traditional Reinforcement Learning (RL) struggles with inefficient exploration. We propose **EGPO**, a new RL framework built upon Group Relative Policy Optimization (GRPO), designed to address this challenge directly. The core of EGPO is an entropy-enhanced advantage function that integrates the entropy of the model’s Chain-of-Thought (CoT) into the policy gradient computation. This encourages the generation of diverse reasoning strategies. To maintain optimization direction, the entropy bonus is carefully constrained by a clipping mechanism. Complemented by a strict, binary reward signal, EGPO effectively guides the model towards discovering structured and accurate tool invocation patterns. On the challenging Berkeley Function Calling Leaderboard (BFCL), a 4B-parameter model trained with EGPO sets a new state-of-the-art among models of comparable size, surpassing a range of strong competitors, including GPT-4o and Gemini-2.5.

1 Introduction

Function calling represents a pivotal advancement in the evolution of Large Language Models (LLMs), transforming them from text generators into practical, interactive agents capable of addressing real-world challenges (WANG et al., 2025; QU et al., 2025). This capability is critical as it bridges the gap between an LLM’s vast internal knowledge and external, dynamic resources, thereby significantly enhancing its functionality, accuracy, and overall utility (PATIL et al., 2024; SHEN, 2024). By

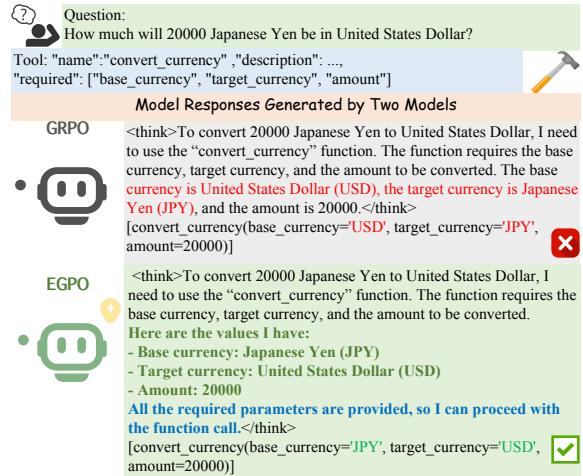


Figure 1: By employing a more structured thinking and verification process, our EGPO framework correctly identifies all required parameters for the tool call, whereas the baseline GRPO model fails by swapping the arguments.

enabling LLMs to interact with APIs, execute code, or access up-to-date information, function calling allows them to transcend the limitations of their static training data (Nguyen et al., 2024).

However, the effective training of LLMs for function calling faces a central challenge: balancing the exploration of complex reasoning paths with stable policy optimization. Prevailing training methodologies, namely Supervised Fine-Tuning (SFT) (Hao et al., 2025; Liu et al., 2024) and Reinforcement Learning (RL) (Qian et al., 2025; Zhang et al., 2025b), struggle to resolve this tension. SFT, which relies on mimicking distilled expert trajectories, often leads to superficial pattern matching rather than instilling robust reasoning capabilities (Setlur et al., 2025; Qian et al., 2025). While effective for format adherence, it fails to equip models with the adaptability required for diverse, unseen scenarios (Zeng et al., 2025; Prabhakar et al., 2025).

Reinforcement learning (RL), though theoreti-

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cally suited for exploration, encounters significant obstacles in this domain (Qian et al., 2025). First, the problem of Signal Scarcity is acute; the structured and syntactically strict nature of function calls means that random exploration rarely yields a valid Chain-of-Thought (CoT), depriving the model of a meaningful learning signal (Gao et al., 2024). Second, for base models that already possess some degree of tool-using ability, Rewarding Redundancy becomes a critical issue (Zhang et al., 2025b). Overly complex, process-based rewards often lead to suboptimal results, failing to refine the model’s performance effectively (Guo et al., 2025). The key to advancing the field is not just generating correct function calls, but effectively guiding the model to develop sound and generalizable thinking patterns (Team et al., 2025a).

In this work, we introduce **EGPO(Entropy-Guided Policy Optimization)**, a novel RL framework designed to foster strategic and diverse reasoning. Built upon Group Relative Policy Optimization (GRPO) (Shao et al., 2024), EGPO directly integrates the entropy of the model’s Chain-of-Thought into the advantage calculation, creating a policy gradient that encourages the exploration of diverse reasoning pathways. To ensure this exploration does not derail the learning process, the entropy bonus is constrained by a carefully designed clipping mechanism, which prevents it from inverting the sign of the original advantage and thus preserves a stable optimization direction. Additionally, the exploration strategy is complemented by a stringent Single-Criteria Reward mechanism, which provides an informative binary signal: a reward is granted only when the model’s output is perfect in both format and accuracy. By combining entropy-guided exploration with a clear, unambiguous reward, EGPO effectively guides models to discover superior and more structured thinking patterns for tool use (Figure 1). Our experimental results on the Berkeley Function Calling Leaderboard (BFCL) (Patil et al., 2024) and other two benchmarks (Li et al., 2023; Chen et al., 2025) demonstrate that EGPO achieves superior performance among open-source models.

Our contributions are listed as follows:

- We propose **EGPO** that integrates CoT reasoning to guide policy exploration while maintaining optimization stability.
- We show that a stringent Single-Criteria Reward is a highly effective and efficient method

for improving the tool-use capabilities of proficient foundation models.

- Our 4B model achieves state-of-the-art results among similar sized models and outperforms a series of strong competitors like GPT-4o and Gemini-2.5 on BFCLv3.

2 Related Work

2.1 Function Call

Function calling represents a pivotal advancement in the field of LLM, transcending their traditional role of mere text generation to empower them with dynamic interaction capabilities with external environments (Zhang et al., 2024; Hao et al., 2025; Zhang et al., 2025a). This paradigm shift enables LLMs to interface seamlessly with a vast array of tools, Application Programming Interfaces (APIs), and databases, thereby unlocking a new realm of possibilities (Li et al., 2023; Chen et al., 2025). Through function calling, LLMs gain the ability to access real-time information, perform specific actions in the real or simulated environments, ensure the factual accuracy of their responses by consulting authoritative sources, and handle complex computations that are beyond their inherent symbolic manipulation capabilities (Qin et al., 2025).

Various approaches have been developed to facilitate and enhance function calling (Qian et al., 2025; Hao et al., 2025). These range from strategic prompt engineering, where specific instructions guide the LLM to recognize and utilize functions, to fine-tuning existing LLM architectures on datasets rich with function call examples (Zhang et al., 2024). More specialized architectures are also emerging that are designed from the ground up with function calling in mind. Retrieval Augmented Generation (RAG) approaches, when combined with detailed tool descriptions, enable LLMs to dynamically retrieve and employ the most appropriate tools based on the user’s query (Nguyen et al., 2024). Furthermore, advanced agentic frameworks are being developed that allow LLMs to engage in multi-step planning and execution, making autonomous decisions about when and how to use various tools (Team et al., 2025a). However, most existing approaches primarily rely on supervised learning paradigms, which may limit the model’s ability to explore diverse reasoning strategies and adapt to novel function calling scenarios (Liu et al., 2024).

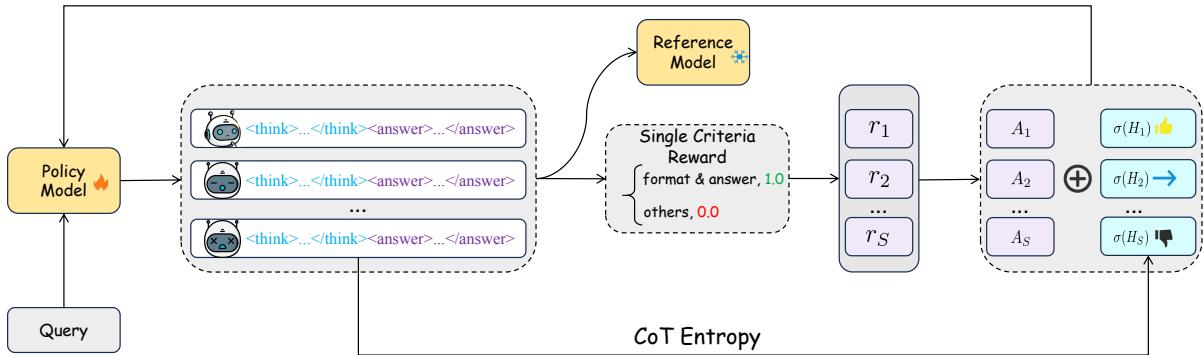


Figure 2: Overview of our EGPO framework. For a given query, EGPO calculates rewards using a single-criteria function and integrates CoT entropy with the advantage signal to guide the policy’s exploration of reasoning paths.

2.2 LLM Reasoning with RL

Reinforcement Learning plays a transformative role in significantly enhancing the reasoning capabilities of LLMs, moving them beyond mere statistical pattern matching to embody more robust and sophisticated cognitive functions, such as logical deduction, complex problem-solving, and strategic decision-making (Guo et al., 2025; Team et al., 2025b). While LLMs inherently exhibit emergent reasoning abilities, RL provides a powerful framework for refining and amplifying these nascent capabilities. Algorithms like Proximal Policy Optimization (Schulman et al., 2017) and Group Relative Policy Optimization (Shao et al., 2024) are commonly used to optimize the LLM’s policy (its decision-making process for generating text or selecting actions) based on the received rewards (Zhang et al., 2025c). This enables LLMs to learn from environmental feedback in a more nuanced and effective way.

For instance, an LLM can learn to strategically utilize external tools by being rewarded for successfully leveraging them to solve problems or retrieve accurate information (Qian et al., 2025; Zhang et al., 2025b). Similarly, RL can refine dialogue interactions, allowing LLMs to engage in more coherent, contextually aware, and goal-oriented conversations (Hu et al., 2023). Beyond just improving response quality, RL helps LLMs develop a deeper understanding of task objectives and the underlying logical structure of problems (Pternea et al., 2024; Wang et al., 2024). Nevertheless, current RL approaches for function calling often struggle with balancing exploration and exploitation, particularly when the model needs to generate both reasoning steps and precise function calls (Zhang et al., 2025b). EGPO addresses this challenge by

incorporating CoT entropy into the advantage calculation, encouraging the model to explore diverse reasoning paths while maintaining stable optimization for accurate function calling.

3 Preliminaries

This section formally defines the function calling task and introduces the Group Relative Policy Optimization (GRPO) algorithm.

3.1 Problem Definition

Let q be a user query sampled from a dataset \mathcal{D} . For each query, a set of available tools $T = \{t_1, \dots, t_N\}$ and the reference answer $g \in \mathcal{G}$ are provided. In this context, the LLM is treated as a policy π within the reinforcement learning framework, mapping environmental states to actions. Given the state comprising the query q and tool set T , the policy π generates a set of rollouts $\mathcal{O} = \{o_1, \dots, o_S\}$. Each rollout o_i consists of a Chain-of-Thought (CoT) reasoning sequence followed by the function call, denoted as $o_i = \{c_{i1}, \dots, c_{iW}, f_{i1}, \dots, f_{iL}\}$, where c_{i1}, \dots, c_{iW} are tokens in the reasoning process (enclosed within `<think>` to `</think>`) and f_{i1}, \dots, f_{iL} are the function call tokens. Each query and its rollouts are represented by a tuple (q, T, \mathcal{O}) , with q and T defining the state and \mathcal{O} encapsulating the actions produced by π .

3.2 GRPO

Group Relative Policy Optimization (GRPO) serves as an efficient alternative to Proximal Policy Optimization (PPO), leveraging Generalized Advantage Estimation (GAE) without the need to learn a separate value function (Schulman et al., 2015, 2017; Shao et al., 2024). Instead, it estimates

advantages by using the average reward across multiple sampled outputs for the same query as a baseline, followed by normalization. For a set of rewards $\{r_1, \dots, r_S\}$ corresponding to S rollouts for a given query, the advantage A_i for rollout o_i with reward r_i is computed as:

$$A_i = \frac{r_i - \text{mean}(\{r_1, \dots, r_S\})}{\text{std}(\{r_1, \dots, r_S\})}. \quad (1)$$

The policy is optimized by maximizing a clipped surrogate objective:

$$\begin{aligned} \mathcal{J} = & \mathbb{E}_{q \sim \mathcal{D}, o \sim \pi_{\text{old}}(O|q)} \sum_{t=1}^S \left[\right. \\ & \min\left(\rho_t \hat{A}_t, \text{clip}\left(\rho_t, 1-\varepsilon, 1+\varepsilon\right) \hat{A}_t\right) \\ & \left. - \beta \text{KL}(\pi \| \pi_{\text{ref}})\right], \end{aligned} \quad (2)$$

where $\rho_t = \frac{\pi(o_t|q, o_{\leq t})}{\pi_{\text{old}}(o_t|q, o_{\leq t})}$ is the likelihood ratio between the current policy π and the old policy π_{old} , \hat{A}_t denotes the estimated advantage, and ε, β are hyperparameters controlling the clipping range and KL divergence penalty, respectively. This formulation promotes stable policy updates while encouraging alignment with a reference policy π_{ref} .

4 Method

In this section, we describe our proposed EGPO method in detail, including the design of the reward and CoT entropy guided policy exploration. An overview of the EGPO framework is presented in Figure 2.

4.1 Reward Design

We design a straightforward yet effective reward function to conduct reinforcement learning. For a given query q with reference answer g , the model’s generated answer o_i is evaluated as follows: If o_i involves a tool call, o_i is deemed correct only if it is correct by performing Abstract Syntax Tree (AST) evaluation, exactly matches g , and adheres to the required reasoning template. Conversely, if g does not involve a tool call, o_i is correct only if it fails AST parsing and complies with the reasoning template. In all cases, any output that fails to follow the thinking template will be directly deemed an incorrect answer.

The reward is thus defined as:

$$r(o_i) = \begin{cases} 1, & \text{format \& answer are correct} \\ 0, & \text{otherwise.} \end{cases} \quad (3)$$

This binary reward emphasizes the holistic integrity of the output, ensuring not only semantic accuracy but also precise structural compliance, which is critical for downstream processing. For non-tool-calling scenarios, the AST failure condition implicitly confirms that the response is appropriately textual and avoids spurious tool invocations.

4.2 Entropy-Guided Policy Optimization (EGPO)

To enhance exploration in the Chain-of-Thought (CoT) reasoning process within the RL framework, our EGPO method incorporates CoT entropy into the advantage calculation. For a query q and a set of rollouts $\mathcal{O} = \{o_1, \dots, o_S\}$, where $o_i = \{c_{i1}, \dots, c_{iW}, f_{i1}, \dots, f_{iL}\}$ (with c as CoT tokens and f as final answer tokens), the vocabulary is denoted as \mathcal{V} and the average CoT entropy of rollout o_i is computed as:

$$E_i = -\frac{1}{W} \sum_{j=1}^W \sum_{v \in \mathcal{V}} \pi(v | q, c_{i,j}) \log \pi(v | q, c_{i,j}) \quad (4)$$

This entropy term is then scaled and clipped before integration with the advantage function:

$$A_i^{\text{new}} = A_i + \min\left(\lambda E_i, \frac{|A_i|}{\alpha}\right), \quad (5)$$

where $\lambda > 0$ is a scaling factor for entropy weighting, and $\alpha > 1$ governs the clipping threshold. The clipping via $\frac{|A_i|}{\alpha}$ prevents the entropy adjustment from inverting the sign of the original advantage A_i , thereby maintaining the optimization direction while fostering diverse CoT explorations—particularly when A_i is small (Shao et al., 2024; Schulman et al., 2015; Cheng et al., 2025). This mechanism strikes a balance between directed learning and exploratory reasoning, enhancing the model’s robustness in function calling tasks.

5 Experiments

In this section, we first introduce a simple RL data filtering on public datasets. Then, we elaborate on experimental settings and main results. Ablation study and a deep analysis are presented at the end.

5.1 Data Preparation

Our data preparation pipeline is engineered to refine high-quality samples for reinforcement learning in function calling tasks. For each initial input

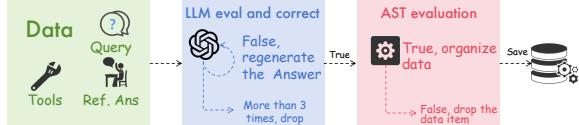


Figure 3: Implementation of the data cleaning pipeline for reinforcement learning in function calling. We begin with LLM-based evaluation and correction, followed by Abstract Syntax Tree (AST) evaluation. Data is retained only after passing all stages or discarded after three regeneration attempts.

tuple (q, T, g) , q denotes the user query, T represents a set of available tools, and g is the reference answer. The data undergoes a rigorous two-stage evaluation process, as depicted in Figure 3. The pipeline consists of the following evaluations:

- 1. LLM Evaluation and Correction:** An initial assessment is conducted using GPT4-o (Hurst et al., 2024) to evaluate the query-tool-answer tuple. If discrepancies or errors are detected, the LLM regenerates the answer to rectify them. To maintain data quality, a strict dropout mechanism is enforced: samples are discarded if regeneration exceeds three attempts. This stage yields a binary outcome, denoted as $\text{Eval}_{\text{LLM}}(q, T, g) \in \{\text{True}, \text{False}\}$.
- 2. Abstract Syntax Tree (AST) Evaluation:** Following a successful LLM evaluation, an AST-based assessment is performed on the reference answer. A sample is discarded if: (i) the query cannot be addressed by any tool in T , but g parses as a valid tool call via AST; or (ii) the query requires a tool call, but g is free-form text that fails AST parsing. This stage also produces a binary result, denoted as $\text{Eval}_{\text{AST}}(q, T, g) \in \{\text{True}, \text{False}\}$. The details of the AST are shown in Appendix D.

Only samples that pass both evaluations (i.e., $\text{Eval}_{\text{AST}}(q, T, g) \wedge \text{Eval}_{\text{LLM}}(q, T, g)$) are retained in the database. For our experiments, we refine the xlam-function-calling-60k dataset (Zhang et al., 2024) and Open-Agentic-tool-use (Aworld team, inclusionAI, 2025) dataset.

5.2 Experiment Setting

Training Data. We conduct experiments by using xlam-function-calling-60k (Zhang et al., 2024) and Open-Agentic-tool-use (Aworld team, inclusionAI, 2025) datasets, the former provides 60,000

single-turn samples, and the latter provides 30,000 multi-turn samples. The first stage of data filtering is employed with GPT-4o (Hurst et al., 2024), and the second stage is to conduct an objective evaluation based on AST. Table 2 summarizes the data statistics after each processing stage.

Models. To evaluate EGPO’s generalizability, we experiment with diverse base models: Llama-3.2-3B-Instruct (Grattafiori et al., 2024) from Llama family and Qwen3-4B-Instruct-2507 from Qwen family. In experiments, we compare against strong open-sourced specialized tool-calling models like ToolACE-2-8B (Liu et al., 2024), BitAgent-8B, ToolACE-MT (Zeng et al., 2025), and watt-tool-8B. We also include general-purposed models like GPT-4o (Hurst et al., 2024), Gemini-2.5-Pro (Comanici et al., 2025), and Grok-4-0709 as strong baselines.

Benchmarks. We evaluate both Single-Turn and Multi-Turn tool calling performance on the Berkeley Function Calling Leaderboard (BFCLv3) (Patil et al., 2024). Our evaluation is reported in terms of accuracy (%), which is calculated using the official script. To further evaluate our model, we also report the results on more function call specialized benchmarks, ACEBench (Chen et al., 2025) and APIBank (Li et al., 2023).

Implementation Details. We train models for 5 epochs with a learning rate of 1×10^{-6} and inference temperature of 0.7 by using the Verl framework (Sheng et al., 2025). Training is performed on 32 H200 GPUs with a batch size of 1,024, 8 rollouts and reserving 5% of data for validation. We set the KL coefficient to 0.001 and the maximum response length to 8192 tokens. The hyperparameters λ and α are set to 0.4 and 2.

5.3 Experimental Results

Results on BFCL. We present the detailed experimental results in Table 1. In the critical Multi-Turn evaluation, which requires complex state tracking and error recovery, EGPO-4B achieves the best performance. Our model, with only 4 billion parameters, attains an Overall score of 56.25%, substantially outperforming all other evaluated models, including major proprietary models like GPT-4o (42.50%) and Grok-4 (36.12%). When compared to similarly sized open-source models (e.g., ToolACE-MT (Zeng et al., 2025) with 8B parameters, scoring 40.25%), EGPO-4B demonstrates a remarkable 15.0 point advantage, validating the efficacy of the EGPO approach. Its superior performance is consistent across challenging sub-metrics.

Models	Parameter Counts	Multi-Turn					Single-Turn		
		Overall	Base	Miss Func	Miss Param	Long Context	Overall	Non-Live	Live
GPT-5-2025-08-07	/	28.50	33.50	29.50	23.00	28.00	65.59	72.92	58.25
GPT-4o-2024-11-20	/	42.50	55.50	34.50	29.00	<u>51.00</u>	77.21	83.88	70.54
Gemini-2.5-Pro	/	25.00	25.50	26.00	24.50	24.00	74.50	85.04	63.95
o3-2025-04-16	/	38.38	44.00	40.50	31.50	37.50	53.01	39.98	66.03
Amazon-Nova-Pro-v1:0	/	34.75	42.50	24.50	27.50	44.50	81.78	85.25	78.31
Grok-4-0709	/	36.12	44.00	31.00	26.00	43.50	79.80	85.21	74.39
Moonshotai-Kimi-K2-Inst	1000B	41.25	51.00	43.00	31.00	40.00	80.80	84.02	77.57
DeepSeek-R1-0528	671B	<u>44.50</u>	54.50	41.00	36.50	46.00	78.22	75.73	<u>80.90</u>
Qwen3-235B-A22B-Inst-2507	245B	39.62	53.50	34.50	27.50	43.00	<u>83.37</u>	90.12	76.61
Llama-4-Maverick	400B	17.88	23.50	18.00	14.00	16.00	80.90	88.15	73.65
Qwen3-32B	32B	47.50	53.00	50.50	<u>40.00</u>	46.50	84.21	87.96	80.46
ToolACE-2-8B	8B	37.00	47.00	31.00	28.00	42.00	82.54	87.87	77.20
BitAgent-8B	8B	37.75	46.50	37.50	24.00	43.00	81.71	87.33	76.09
watt-tool-8B	8B	37.88	45.50	39.00	24.00	43.00	81.71	87.54	75.87
ToolACE-MT	8B	40.25	<u>57.50</u>	31.50	34.00	38.00	78.23	84.94	71.52
Qwen3-4B-Inst-2507	4B	15.75	19.00	15.50	12.50	16.00	78.19	86.35	70.02
EGPO-4B	4B	56.25	63.50	54.50	48.00	59.00	84.92	<u>88.50</u>	81.34

Table 1: Performance on BFCL (last updated August 26, 2025), with all metrics calculated using the official script. The best result within each category is highlighted in **bold**. The second best results are underlined.

Processing Stage	Samples
xLAM+Open-Agentic	90,000
After LLM Evaluation	89,641
After AST Evaluation	88,759

Table 2: Data statistics in two-stage data preparation.

Notably, it leads in the two difficult error recovery scenarios: 1) Miss Func (missing certain required functions, 54.50%). This demonstrates our model’s ability to identify when no function is available to satisfy the user’s request and to request additional tools. 2) Miss Param (missing certain required parameters, 48.00%). This shows that the model can detect missing key information in a user’s request and request clarification rather than making unfounded assumptions, which is crucial for real-world robustness. Furthermore, EGPO also achieves the highest score in the Long Context metric (59.00%), indicating that EGPO effectively improves the model’s ability to maintain coherence and leverage historical context in extended conversations. For the Base test, EGPO-4B also secures the top result at 63.50%, confirming a strong foundational capability.

In the Single-Turn evaluation, which measures immediate response accuracy and precision, EGPO-4B maintains its competitive standing. The model secures the best Overall Single-Turn accuracy among all evaluated models, achieving 84.92%. This performance surpasses near large

open-sourced competitor, Qwen3-235B (83.37%), and far exceeds the strong baselines like GPT-4o (77.21%). This result highlights that the EGPO approach enhances Multi-Turn function call skills without sacrificing the core Single-Turn precision.

These results demonstrate that the EGPO-4B’s parameter efficiency among LLMs. By achieving the highest Overall score in both the complex Multi-Turn evaluation (56.25%) and the challenging Single-Turn evaluation (84.92%), our method successfully bridges the performance gap between small, resource-efficient models and large-scale proprietary or publicly available models, even those orders of magnitude larger in parameter count.

Results on ACEBench and APIBank. Figure 4a illustrates the models’ performance on the ACEBench Benchmark, including Single-Turn and Multi-Turn subsets. In the Single-Turn tasks, the EGPO-4B model achieves the highest accuracy at 80.00%, demonstrating a slight edge over other models, which are closely clustered. GPT-4o scores 78.00% and GPT-4o-mini scores 76.00%. The superiority of EGPO-4B is more pronounced in the Multi-Turn subset, which requires sophisticated conversational coherence. EGPO-4B leads with an accuracy of 74.00%, creating a larger performance gap over GPT-4o (68.00%) and GPT-4o-mini (66.50%). Figure 4b presents the results on the APIBank Benchmark, which evaluates function-calling capabilities and is segmented into Level-1 (Call) and Level-2 (Retrieve+Call). In the Level-1

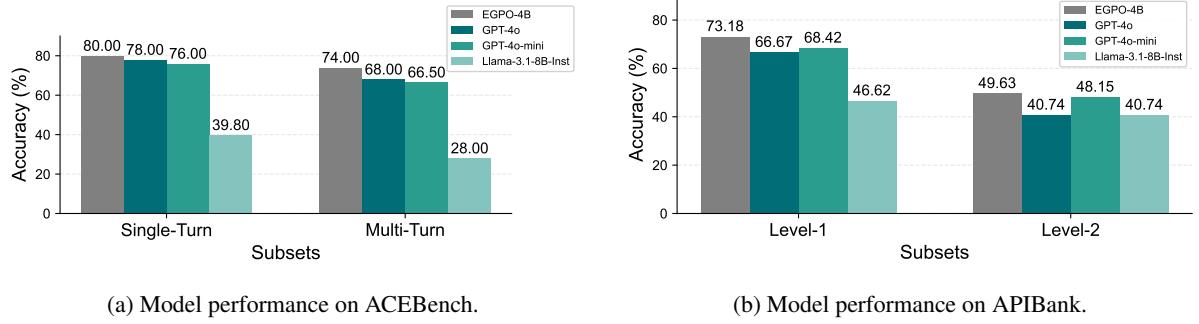


Figure 4: Performance on ACEBench and APIBank with all metrics calculated using the official scripts.

tasks, EGPO again exhibits the top performance with 73.18% accuracy. GPT-4o and GPT-4o-mini are competitive, achieving 66.67% and 68.42%, respectively. Llama-3.1-8B-Instruct is noticeably lower at 46.62%. In the more demanding Level-2 subset, which involves more complex function-calling scenarios, all models experience a decline in accuracy, but EGPO maintains its leading position with 49.63%. Intriguingly, on this harder subset, GPT-4o and GPT-4o-mini score identically at 40.74%. Our results show that models trained via the proposed EGPO method generalize well across different tool-calling scenarios, unlocking new chances to improve performance scaling in LLM tool-augmented learning.

5.4 Ablation Study

In the ablation study, we adopt consistent configurations across all experiments to ensure fair comparisons and select the GRPO method as the baseline to evaluate the performance of each module.

Comparison of EGPO and GRPO. In Figure 6, we present a comparative analysis by using two different models. After training models by using the EGPO and GRPO with the same Single-Criteria Reward, evaluated on the Single-Turn and Multi-Turn subsets of BFCL. Across both the Qwen3-4B model and Llama3.2-3B model, the EGPO approach consistently yields the highest accuracy in all four sub-categories, demonstrating its effectiveness and generalizability. Crucially, the advantage of EGPO is most pronounced in the difficult Multi-Turn tasks. For the Qwen model, EGPO scores 56.25% compared to the Base model’s mere 15.75%, and for the Llama model, EGPO achieves 36.62% compared to the Base model’s collapse at just 2.00%, underscoring that entropy from the CoT provides a dramatic and vital boost in handling complex, sequential Multi-Turn conversations.

Training Dynamics. We present the visualized Qwen3-4B learning curves in Figure 5, including Average Reward, KL Divergence, Actor Entropy, and Average Response Length. During the training steps, the reward curve in Figure 5a of EGPO is consistently above that of GRPO, which demonstrates the training stability and excellent performance of EGPO. During the middle and later stages of training in Figure 5b, the KL divergence of EGPO is significantly higher than that of GRPO, deviating further from the base model, implying that introducing the entropy of the CoT in the advantage computation allows the model to better explore a thinking pattern suitable for function calling scenarios. From the perspective of the Actor Entropy in Figure 5c, unlike GRPO, where the entropy consistently decreases and then plateaus. EGPO’s curve first declines and then rises, according to (Yu et al., 2025), the entropy of the actor model with such a trend change is associated with the model’s exploration capability, maintaining a trend of slow entropy increase is conducive to the model generating diverse answers and achieving improved performance. Finally, from the perspective of response length in Figure 5d, the responses generated by EGPO are longer than those by GRPO. This additional token budget enables the model to produce responses with better quality.

Study of Reward Patterns. As shown in Table 3, we also use two series of models for reward pattern exploration and find that reward patterns with Reasoning Format often fail to achieve optimal results. Here, we set up an additional reward of 0.5 if the model outputs the correct Reasoning Format (i.e., enclosing the CoT within <think> and </think> tags), but in our experiments, this reward pattern does not yield the best results. This suggests that for the models with instruction-following capability, format reward setting will cause reward

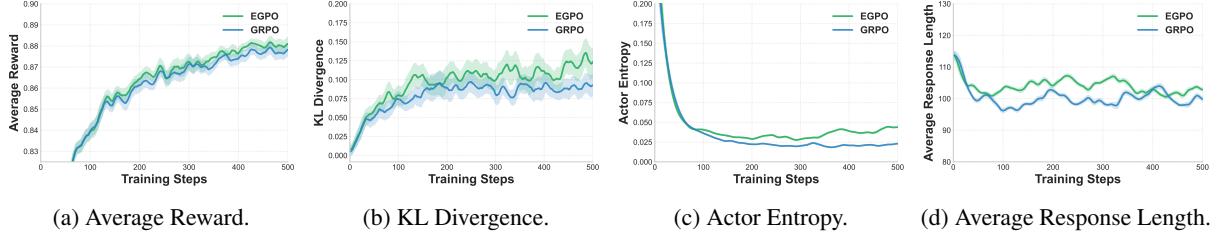


Figure 5: Visualization of the learning curves for EGPO and GRPO during training. We report the Average Reward, KL Divergence, Actor Entropy and Average Response Length.

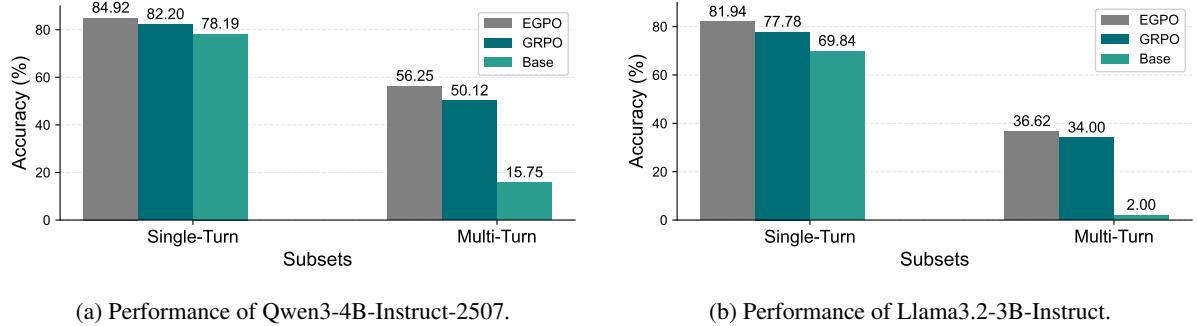


Figure 6: Performance of two series models trained by EGPO and GRPO on BFCL.

redundancy and fail to achieve optimal results.

Subsets	Qwen3-4B		Llama-3-3B	
	w/ RF	w/o RF	w/ RF	w/o RF
Single-Turn	84.36	84.92	77.69	81.94
Multi-Turn	53.25	56.25	32.50	36.62

Table 3: Performance comparison of different models with or without Reason Format reward.

5.5 Further Analysis

In Figure 5d, we observe that EGPO-trained models exhibit longer CoT compared to GRPO. To further investigate this, we randomly sampled 100 pieces from the BFCL simple Python subset and compared EGPO with GRPO. Unlike GRPO, the EGPO-trained model self-generates two types of special actions: structural parameter checks, used to verify parameter correctness, and verification, used for validation of the final answer. As shown in Figure 7, these action tokens account for over 20% of the total tokens in the CoT, suggesting that EGPO induces the model to adopt a distinct thinking pattern. This behavior is likely driven by the entropy reward in EGPO, which encourages more exploration, resulting in structural and verification actions that enhance overall model performance.

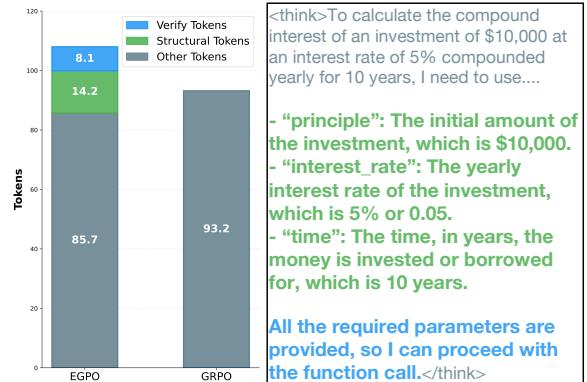


Figure 7: Statistical results of the special action tokens generated by EGPO.

6 Conclusion

This work presents EGPO, a novel and effective RL framework for LLM function calling. By encouraging diverse reasoning paths while maintaining optimization stability, EGPO enables models to develop more sophisticated parameter extraction and verification strategies. EGPO achieves state-of-the-art results among similar sized models and outperforms a series of strong competitors like GPT-4o and Gemini-2.5 with only 4B parameters, representing a significant advancement towards building more intelligent and reliable LLMs for real-world tool interaction.

Limitations

While EGPO demonstrates strong performance on multiple function calling benchmarks, two key limitations remain. First, EGPO relies on high-quality CoT reasoning during training, which may not generalize effectively to domains where structured reasoning is less natural or poorly defined. Second, the stringent binary reward design, though effective in promoting format correctness and semantic accuracy, may be too rigid for tasks requiring nuanced partial credit or multi-step reasoning with intermediate feedback.

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A Q & A Template

The following Q & A Template in Figure 8, with its predefined set of instructions, guidelines, and constraints, plays a pivotal role in standardizing the behavior, output format of the model being trained and evaluated. It ensures that during the training phase, the model learns in a consistent manner aligned with the desired objectives, and during the evaluation, the performance is generated under a unified set of rules.

B Dataset

B.1 Data Source

The single-turn part is from the xlam-function-calling-60k (Zhang et al., 2024) and the multi-turn part comes from the Open-Agentic-tool-use (Aworld team, inclusionAI, 2025). The Open-Agentic-tool-use dataset is an open-source project focusing on multi-turn tool-use learning and serving as a reproduction of Kimi K2’s Large-Scale Agentic Data Synthesis for Tool Use Learning (Team et al., 2025a). Built based on 8 environments, it currently has over 30000 open-sourced data and is suitable for both SFT and RL training. Its data generation process involves constructing API relationship graphs for environments, sampling APIs with random parameter construction, verifying API executability in the environment, generating user questions via a user agent based

Q & A Template

System Prompt

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

Tool

Here is a list of functions in JSON format that you can invoke:

```
{functions}
```

In each action step, you MUST:

1. Think about the reasoning process in the mind and enclosed your reasoning within `<think></think>` XML tags.

2. Then, provide a function call with function names and arguments. i.e.,
`[func_name1(params_name1=params_value1, params_name2=params_value2...), func_name2(params)]`

3. Make sure both the reasoning and the tool call steps are included together in one single reply.

A complete reply example is:

```
<think>reasoning process here</think>
```

answer here

Please make sure the type of the arguments is correct and reject to answer if the function can not solve the user's question.

User Query

Please ...

Answer

```
<think>reasoning process here</think>
```

answer here

Figure 8: Q & A Template used in the experiments.

on sampled APIs and environment feedback. The xlam-function-calling-60k is a high-quality, verifiable synthetic text dataset designed for training and evaluating LLM function-calling capabilities. Comprising 60,000 entries, it includes 33,659 entries generated by DeepSeek-V2-Chat and the rest by Mixtral-8x22B-Inst, leveraging 3,673 executable APIs across 21 categories; each entry undergoes three-stage verification (format checking, function execution, semantic validation), resulting in over 95% accuracy in human evaluation (with minor issues like inaccurate arguments in the remaining 5%). Structurally, each JSON entry links a plain-language query (user request), an array of tools (available APIs with names, descriptions, and parameter details like type/required status), and an answers array (correct API calls + arguments). It supports tasks like question answering, text generation, and reinforcement learning for LLM Agents.

C Full Results on Leader Boards

C.1 Single-Turn Results on BFCL

Here, we show all models’ full Single-Turn results in Table 4, where EGPO-4B attains superior performance with scores of 88.50% and 81.34% on Non-Live and Live sections. The results surpass all similar scale models and achieve great enhancement on Parallel and Parallel Multiple subsections, which indicates that our model has achieved excellent tool-calling capabilities under complex single-turn queries.

C.2 ACEBench

Table 5 presents the comprehensive results of various models on the ACEBench normal metric, encompassing multiple evaluation dimensions. For the Single-Turn task, EGPO-4B stands out with the highest accuracy of 80.0%. In the Multi-Turn task, EGPO-4B again performs best, obtaining an accuracy of 74.0%.

C.3 Results on BFCLv4

BFCLv4 evaluates the model’s agentic capability with two sections, Web Search and Memory. We test our model, EGPO-4B, on the two corresponding test sets in Table 6. We do not use any datasets related to search or memory, but still improve the scores in both sections by 10.5% and 5.16%.

D Abstract Syntax Tree Parser

The Abstract Syntax Tree (AST) parser is a foundational component of a compiler or interpreter, responsible for transforming the linear stream of tokens from a lexer into a tree-like, hierarchical representation of the program’s structure. This AST is crucial because it abstracts away details like punctuation and whitespace, providing a clean, logical map of code elements that is far easier for later stages—such as optimization and code generation—to process than raw text. The function call evaluation process uses this AST in two phases: first, Function Matching strictly verifies the function name and parameter signature, enforcing specific rules for data types (e.g., direct boolean matching, order-dependent list matching), with multi-function checks using an all-or-nothing principle; second, Executable Evaluation verifies function output, checking non-REST tests for completeness or structural criteria, and REST tests for API validity and response structure, also strictly adhering to the all-or-nothing rule for multi-function execution. A simple example of Abstract Syntax Tree Parser is shown in Figure 9.

E Case Study

We further show some cases where the EGPO model uses additional special action tokens to assist in reasoning during the inference process in Figure 10 and Figure 11. We refer to the tokens related to structural output as structural tokens and mark them in green, while those related to verification are called verify tokens and marked in blue. These special action tokens indicate that our model is executing tasks with new thinking patterns in tool-using scenarios; that is, EGPO helps the model explore better domain-specific thinking patterns.

Models	Non-Live					Live				
	Overall	Simple	Multiple	Parallel	Parallel Multiple	Overall	Simple	Multiple	Parallel	Parallel Multiple
	Close-Sourced Models									
GPT-5-2025-08-07	72.92	58.67	76.00	84.00	73.00	58.25	61.63	57.45	50.00	62.5
GPT-4o-2024-11-20	83.88	76.5	91.00	90.00	78.00	70.54	70.54	70.75	62.50	66.67
Gemini-2.5-Pro	85.04	68.67	91.00	91.50	89.00	63.95	75.58	60.40	81.25	83.33
o3-2025-04-16	39.98	71.42	88.50	0.00	0.00	66.03	69.77	67.62	0.00	0.00
Amazon-Nova-Pro-v1:0	85.25	71.50	93.50	92.00	84.00	78.31	80.62	77.87	87.50	66.67
Grok-4-0709	85.21	73.33	92.50	89.50	85.50	74.39	77.91	73.69	68.75	70.83
Open-Sourced Models										
Moonshotai-Kimi-K2-Inst	84.02	79.08	93.00	76.00	88.00	77.57	86.05	75.78	81.25	62.50
DeepSeek-R1-0528	86.52	71.58	96.00	91.00	87.50	77.65	83.72	76.16	87.50	70.83
Qwen3-235B-A22B-Inst-2507	90.12	80.50	95.00	95.50	89.50	76.61	83.72	75.02	75.00	70.83
Llama-4-Maverick	88.15	76.08	95.00	92.50	89.00	73.65	84.50	71.04	75.00	70.83
Qwen3-32B	87.96	76.83	94.50	90.00	90.50	80.46	84.88	79.87	81.25	58.33
ToolACE-2-8B	87.87	75.00	92.00	92.50	92.00	77.20	70.16	79.30	75.00	62.5
BitAgent-8B	87.33	76.33	95.00	93.00	85.00	76.09	78.29	75.59	87.50	66.67
watt-tool-8B	87.54	76.17	94.50	94.00	85.50	75.87	77.52	75.59	87.50	62.50
Base Models										
Qwen3-4B-Instruct-2507	86.35	76.42	91.50	88.00	89.50	70.02	73.64	69.61	81.25	41.67
Llama-3.2-3B-Inst	81.94	71.25	92.00	87.00	77.50	57.74	63.57	57.26	25.00	37.50
Ours										
EGPO-4B	88.50	76.50	95.00	93.50	89.00	81.34	85.66	79.49	87.50	75.00
EGPO-3B	87.38	72.00	96.00	89.00	92.50	76.50	74.42	75.12	81.25	70.83

Table 4: The evaluation details on the BFCL benchmark (last updated August 26, 2025), with all metrics calculated using the official script.

Models	Atom	Single-Turn	Multi-Turn	Similar API	Preference
GPT-4o-2024-11-20	90.0	78.0	68.0	80.0	78.0
Llama3.1-70B-Inst	83.7	71.5	61.0	74.0	66.0
ToolACE-MT-8B	83.0	64.0	51.0	68.0	68.0
Base Models					
Qwen3-4B-Instruct-2507	67.7	60.0	52.0	68.0	64.0
Llama3.2-3B-Inst	27.0	19.0	7.0	38.0	30.0
Ours					
EGPO-4B	83.0	80.0	74.0	80.0	50.0
EGPO-3B	66.3	40.0	42.0	58.0	30.0

Table 5: Full result of the accuracy of ACEBench normal examples. The best result within each category is highlighted in **bold**.

Models	Web Search			Memory			
	Overall	Base	No Snippet	Overall	KV	Vector	Recursive Sum
Qwen3-4B-Instruct-2507	5.00	4.00	6.00	12.69	11.61	11.61	14.84
EGPO-4B	15.50	15.00	16.00	17.85	8.39	0.65	44.52

Table 6: Performance of EGPO-4B on BFCLv4.

AST Parser Example

Example:

```
[calculate_triangle_area(base=10, height=5)]
```

Parse:

```
Module(body=[  
    Expr(value=List(elts=[  
        Call(  
            func=Name(id='calculate_triangle_area', ctx=Load()),  
            args=[],  
            keywords=[  
                keyword(arg='base', value=Constant(value=10)),  
                keyword(arg='height', value=Constant(value=5))  
            ]  
        )  
    ], ctx=Load()))  
, type_ignores=[])
```

Figure 9: AST Parser Example.

Case Study 1

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

Tool

Here is a list of functions in JSON format that you can invoke:

```
[{"name": "calculate_compound_interest",
 "description": "Calculates the compound interest of an
                 investment over a given time period.",
 "parameters": {
   "type": "dict",
   "properties": {
     "principle": {
       "type": "integer",
       "description": "The initial amount of the investment."
     },
     "interest_rate": {
       "type": "float",
       "description": "The yearly interest rate of the
                     investment."
     },
     "time": {
       "type": "integer",
       "description": "The time, in years, the money is
                     invested or borrowed for."
     },
     "compounds_per_year": {
       "type": "integer",
       "description": "The number of times the interest is
                     compounded per year. Default is 1."
     }
   },
   "required": ["principle", "interest_rate", "time"]
 }]
```

In each action step, you MUST:....

User: Calculate the compound interest of an investment of \$10,000 at an interest rate of 5% compounded yearly for 10 years.

Assistant: <think> To calculate the compound interest of an investment of \$10,000 at an interest rate of 5% compounded yearly for 10 years, I need to use the calculate_compound_interest function. The function requires the following parameters:

- principle: The initial amount of the investment, which is \$10,000.
- interest_rate: The yearly interest rate of the investment, which is 5% or 0.05.
- time: The time, in years, the money is invested or borrowed for, which is 10 years.
- compounds_per_year: The number of times the interest is compounded per year, which is 1 since it is compounded yearly.

All the required parameters are provided, so I can proceed with the function call. </think>
[calculate_compound_interest(principle=10000, interest_rate=0.05, time=10, compounds_per_year=1)]

Figure 10: Example 1 of EGPO.

Case Study 2

System: You are an expert in composing functions. You are given a question and a set of possible functions. Based on the question, you will need to make one or more function/tool calls to achieve the purpose. If none of the functions can be used, point it out. If the given question lacks the parameters required by the function, also point it out. You should only return the function calls in your response. If you decide to invoke any of the function(s), you MUST put it in the format of [func_name1(params_name1=params_value1, params_name2=params_value2...), func_name2(params)]. You SHOULD NOT include any other text in the response.

Here is a list of functions in JSON format that you can invoke:

```
[{"name": "convert_currency",
  "description": "Converts an amount from a particular currency\n  to another currency.",
  "parameters": {
    "type": "dict",
    "properties": {
      "base_currency": {
        "type": "string",
        "description": "The base currency in which the original\n          amount is present."
      },
      "target_currency": {
        "type": "string",
        "description": "The currency to which you want to\n          convert."
      },
      "amount": {
        "type": "integer",
        "description": "The amount you want to convert."
      }
    },
    "required": ["base_currency", "target_currency", "amount"]
  }
}]
```

In each action step, you MUST:...

User: How much will 20000 Japanese Yen be in United States Dollar?

Assistant: <think> To convert 20000 Japanese Yen to United States Dollar, I need to use the convert_currency function. The function requires the base currency, target currency, and the amount to be converted. Here are the values I have:

- Base currency: Japanese Yen (JPY)
- Target currency: United States Dollar (USD)
- Amount: 20000

All the required parameters are provided, so I can proceed with the function call. </think>
[convert_currency(base_currency='JPY', target_currency='USD', amount=20000)]

Figure 11: Example 2 of EGPO.