

GAPO: Group Adaptive Policy Optimization for Real-World Code Edit

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Abstract

Reinforcement learning (RL) is widely used for post-training large language models (LLMs) in code editing, where group-relative methods like GRPO are popular for their critic-free, normalized advantage estimation. However, in real-world code-editing scenarios, reward distributions are often skewed with unpredictable outliers, leading to distorted advantage computation and increased noise. To address this issue, we propose **Group Adaptive Policy Optimization (GAPO)**, which adaptively finds an outlier-free highest-density interval (HDI) per prompt and then uses the median of that interval as an adaptive Q to replace the group mean in advantage calculation. This adaptive Q robustly handles skewed distributions while remaining plug-and-play and efficient. We validate GAPO on nine instruction-tuned LLMs (3B–14B) using a large internal dataset of 51,844 real-world, history-aware code-editing tasks across 10 languages, demonstrating consistent improvements in exact match accuracy over GRPO and its variant DAPO. Code¹ is publicly available.

Introduction

With the rapid advancement of large language models (LLMs), artificial intelligence (AI)-assisted coding has emerged as a prominent subfield and practical application (Chen et al. 2021; Li et al. 2022), demonstrating proven value in improving software engineering efficiency (Peng et al. 2023; Yetiştirten et al. 2023) and serving as a tool-generation assistant for white-collar workers across diverse domains (Schick et al. 2023; Achiam et al. 2023). Most code LLMs undergo a post-training stage, and reinforcement learning (RL) — in particular, RL from learned or human preference-based rewards — is a widely used post-training method (Christianio et al. 2017; Wang et al. 2024).

Among RL methods, Group Relative Policy Optimization (GRPO) (Shao et al. 2024) and its variants are popular choices, known for their robustness across diverse scenarios (Liu et al. 2025c). The core characteristic of the GRPO family lies in its group-relative advantage computation, which removes the need for a critic model (or value function) by sampling a group of rollouts for each input prompt and calculating advantage values as normalized rewards relative to

the mean reward within each group (Shao et al. 2024), as illustrated in Figure 1. However, in real-world code-editing scenarios with complex contexts, inter-module invocation relationships, and diverse user intents, input prompts can inevitably induce rollouts that contain outliers — rollouts that are both unpredictable (Frauenknecht et al. 2025; Wu et al. 2022) and noisy (Liu et al. 2025a). In such practical cases, the expected normal or symmetric reward distributions often shift toward left- or right-skewed forms, a phenomenon frequently observed in practice (see Figure 7 for details). Given a reward range of $[0, 1]$, when most rewards are greater than 0.5, the practical reward distribution becomes left-skewed, as unpredictable outliers tend to appear on the lower side (below 0.5). Similar for right-skewed cases.

To mitigate the negative impact of outliers, we propose **Group Adaptive Policy Optimization (GAPO)**, a group-adaptive advantage computation method designed to enhance existing GRPO and its variants (*e.g.*, DAPO (Yu et al. 2025)), as illustrated in Figure 1. In the original formulation, the mean treats all rewards uniformly—including outliers—which can distort the advantage calculation. To address this, we first adaptively identify an outlier-free sub-region within all rewards by reformulating the problem as the classical *highest-density interval* (HDI) detection task from statistics (O’Neill 2022), solved using an adapted sliding-window scan algorithm. This allows us to determine an adaptive sub-region for each input prompt. Subsequently, to further enhance robustness against outliers, we select the median within this region as the adaptive Q , replacing the original mean in the computation of group-relative advantage. As shown in Figure 1, the adaptive Q provides additional benefits. In left-skewed distributions, GAPO generates more negative rollouts than GRPO/DAPO, since Q exceeds the mean and most rewards fall below it, producing negative advantages. This is reasonable, as left-skewed distributions usually correspond to *relatively easy problems* with high rewards, where negative samples improve generalization (Mu et al. 2025; Zhu et al. 2025). Conversely, for right-skewed distributions (*relatively hard problems*), GAPO promotes more specialized learning, enhancing accuracy on these challenging cases.

We evaluate nine diverse instruction-tuned large language models (LLMs), encompassing both general-purpose and code-specialized architectures with parameter counts rang-

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†Work done during the internship at Tencent.

¹<https://github.com/TsingZ0/verl-GAPO>

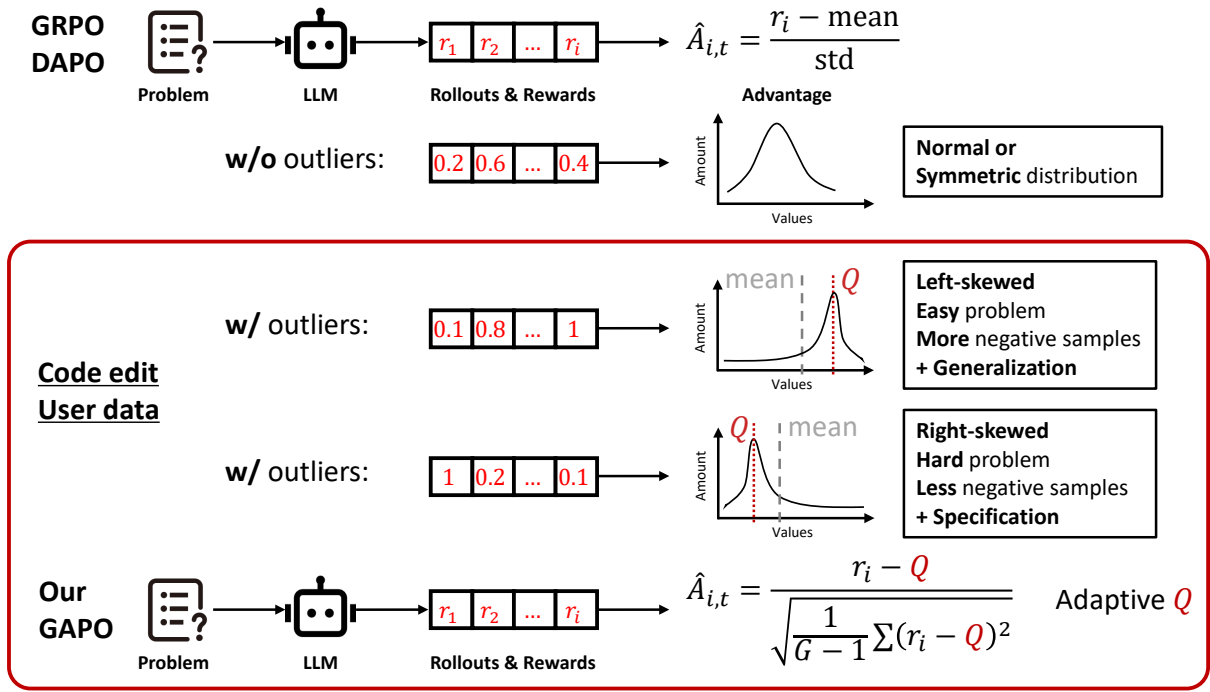


Figure 1: Illustration of GRPO/DAPO and our proposed GAPO, where r_i and $\hat{A}_{i,t}$ denote the reward and the advantage, respectively.

ing from 3B to 14B, all sourced from Hugging Face. Since no public dataset captures realistic, history-aware code editing in complex software contexts, we collected an internal dataset of 51,844 real-world code-editing tasks across 10 programming languages, with Go (37.71%), Python (22.14%), and Java (21.03%) dominating the distribution. Each example includes a rich prompt (code context, cursor range, edit history, hints) and the corresponding edited code snippet, as detailed in Table 1. Extensive experiments demonstrate the superiority of our GAPO over both GRPO and DAPO. To sum up, our contributions are:

- We empirically demonstrate that the standard group-relative advantage computation is sensitive to outliers in real-world code editing, where reward distributions are often skewed due to outliers.
- We introduce GAPO, a robust enhancement to GRPO and its variants that replaces the global mean with an adaptive Q value derived from an outlier-resistant sub-region of the reward distribution.
- We collect and release a large-scale, real-world code-editing dataset and validate GAPO’s consistent superiority over GRPO and DAPO across nine diverse LLMs (3B–14B).

Preliminaries

Problem Formulation

In code editing tasks, the model is given a lengthy input prompt q that includes the coding context, user prompt, current cursor region, historical edits, and other relevant infor-

mation. The LLM (with parameters θ) is expected to generate a code snippet $\hat{e}(q, \theta)$ that replaces the current cursor region to fulfill the user’s intent. If the model outputs special tokens indicating “no change,” no edit is applied.

During training, we assume access to the ground-truth edit e^* —i.e., the code modification the user actually intended—for each prompt q . The objective is to maximize the expected reward:

$$\mathcal{J}(\theta) = \mathbb{E}_{q \sim P(Q)}[r(\hat{e}(q, \theta), e^*)], \quad (1)$$

where $r(\cdot, \cdot)$ is a reward function that quantifies the similarity or correctness of the predicted edit relative to the ground-truth edit. We use a customized reward function that combines the exact match (em) metric and a normalized edit distance (ed) metric. Specifically, the reward function is defined as:

$$r(\hat{e}, e^*) = \frac{1}{2} \left(\mathbf{1}[\hat{e} = e^*] + \left(1 - \frac{ed(\hat{e}, e^*)}{\max\{l(\hat{e}), l(e^*)\}} \right) \right), \quad (2)$$

where \hat{e} and e^* represent two code snippets (LLM output and ground truth, respectively), $ed(\hat{e}, e^*)$ is computed using the classical dynamic programming algorithm (Lcvenshtcin 1966), and $l(\cdot)$ returns the length of a code snippet.

Group Relative Policy Optimization

GRPO is one of the most widely adopted methods in both industry and research within the field of reinforcement learning (Pennino et al. 2025; Li et al. 2025a). It is particularly effective for addressing the optimization problem in Eq. (1). A key advantage of GRPO is that it eliminates the need for

a separate value function approximation; instead, it calculates advantages using the average reward across multiple sampled responses (rollouts) generated from the same input prompt. When using GRPO from an RL view, we can rewrite Eq. (1) to be

$$\begin{aligned} \mathcal{J}_{GRPO}(\theta) &= \mathbb{E}_{q \sim P(Q), \{e_i\}_{i=1}^G \sim \pi_{\theta_{old}}(O|q)} \\ &\frac{1}{G} \sum_{i=1}^G \frac{1}{|e_i|} \sum_{i=1}^{|e_i|} [\min(\kappa_{i,t} \cdot \hat{A}_{i,t}, \rho_{i,t,\epsilon} \cdot \hat{A}_{i,t}) + C], \\ \text{s.t.}, \quad \kappa_{i,t} &= \frac{\pi_{\theta}(e_{i,t}|q, e_{i,<t})}{\pi_{\theta_{old}}(e_{i,t}|q, e_{i,<t})}, \\ \rho_{i,t,\epsilon} &= \text{clip}\left(\frac{\pi_{\theta}(e_{i,t}|q, e_{i,<t})}{\pi_{\theta_{old}}(e_{i,t}|q, e_{i,<t})}, 1 - \epsilon, 1 + \epsilon\right), \\ C &= -\beta \mathbb{D}_{KL}[\pi_{\theta} || \pi_{ref}], \end{aligned} \quad (3)$$

where π_{θ} , $\pi_{\theta_{old}}$, and π_{ref} are the updating policy model, old policy model, and reference model, respectively. For each prompt q , GRPO samples a group of G edits $\{e_1, e_2, \dots, e_G\}$ from the old policy $\pi_{\theta_{old}}$. Here, ϵ and β are hyperparameters that control the optimization behavior, and \mathbb{D}_{KL} denotes the KL divergence between the current training policy and a fixed reference policy (see (Shao et al. 2024) for details).

The advantage $\hat{A}_{i,t}$ is computed based on the relative rewards of the edits within each group. Given a reward model (e.g., as defined in Eq. (2)), we score each edit to obtain a set of G rewards $\mathbf{r} = \{r_1, r_2, \dots, r_G\}$. These rewards are then normalized to yield the advantage calculation:

$$\hat{A}_{i,t} = \frac{r_i - \text{mean}(\mathbf{r})}{\text{std}(\mathbf{r})}. \quad (4)$$

Method

Motivation

As demonstrated in our experiments (see Figure 7 for details), a substantial fraction of input prompts in real-world code editing scenarios yield skewed reward distributions. This skew arises from the inherent noise, complexity, and dynamism of practical environments—often manifested through outliers—which are unavoidable and unpredictable due to factors such as rich contextual dependencies, historical user behaviors, evolving intents, and other confounding variables. These outliers introduce noise into RL training (Frauenknecht et al. 2025; Hollenstein et al. 2022) when using Eq. (4), since Eq. (4) employs an aggregation function that uniformly considers all reward values. Common approaches to mitigating the influence of outliers include using quantile-based statistics (e.g., Q1, median, Q3), which are more robust than the mean in the presence of outliers (John 2015; Rousseeuw and Hubert 2011). However, as shown in Figure 7 and Figure 8, real reward distributions across different input prompts vary—being left-skewed, normal, or right-skewed—so a single quantile or mean cannot adapt effectively to diverse cases. To address this issue, we propose a group-adaptive advantage calculation approach to enhance existing GRPO and its variants (such as DAPO (Yu

et al. 2025)); this novel RL method is termed **Group Adaptive Policy Optimization (GAPO)**.

Group Adaptive Policy Optimization

Our GAPO method does not alter the objective of existing group-relative RL approaches; instead, it only modifies the advantage computation in Eq. (4). This design makes it simple to implement and plug-and-play with any RL framework, such as `verl` (Sheng et al. 2025), requiring only a few lines of code. Specifically, we redefine the advantage as

$$\hat{A}_{i,t} = \frac{r_i - Q}{\sqrt{\frac{1}{G-1} \sum_{j=1}^G (r_j - Q)^2}}, \quad (5)$$

where the denominator represents a variant of the standard deviation, ensuring consistency with the replacement of the mean by the adaptive Q value.

The key challenge, then, is to obtain the adaptive Q value for each group corresponding to each input prompt while updating the policy models. Although the median can mitigate the effect of outliers, it is computed over the entire group and may be less adaptive to varying situations. Motivated to improve adaptability across groups with diverse reward distributions, we propose first to *identify the region free of outliers* and then *set Q as the median of this sub-region \mathcal{H}* .

To identify an outlier-free region that adapts to different reward distributions, we seek a sub-region with the highest density, which represents the majority of the data while ignoring outliers. This naturally leads us to a classical statistical problem: finding the highest-density interval (HDI) for a given probability mass (O’Neill 2022), which also identifies the narrowest interval. Formally, for a set of reward values, this can be expressed as

Highest-Density Interval (HDI)

Given G real numbers (rewards) r_1, r_2, \dots, r_G and an integer k (here $k = \lceil G\tau \rceil$), find indices $i < j$ with $j - i + 1 \geq k$ that minimize the interval length

$$L(i, j) = r_j - r_i,$$

where $r_{(1)}, r_{(2)}, \dots, r_{(G)}$ are the sorted values.

Next, to solve this problem, we use the algorithm in algorithm 1. The method first sorts the data to obtain order statistics, then applies a sliding window of fixed size k over the sorted array, computing $r_{(i+k-1)} - r_{(i)}$ for each window. The minimal such difference corresponds to the shortest interval containing k points.

Why this is optimal: any interval covering k points corresponds to a contiguous block in the sorted list; enlarging the interval beyond k points cannot make it strictly shorter, so it suffices to check only blocks of size exactly k . The computational complexity is dominated by the sorting step, which requires $\mathcal{O}(n \log n)$ time (n : number of rollouts, usually small), while the sliding window scan costs only $\mathcal{O}(n)$. Therefore, the total complexity is $\mathcal{O}(n \log n)$ time with $\mathcal{O}(m)$ extra space.

Algorithm 1: Find the Highest-Density Interval (HDI)

Require: \mathcal{G} : a group of G reward values in $[0, 1]$, $\tau \in [0, 1]$.

Ensure: \mathcal{H} : the HDI covering at least τ of points.

```

1:  $\mathcal{G}' \leftarrow \text{sort}(\mathcal{G})$ 
2:  $\text{min\_length} \leftarrow \infty$ 
3:  $\text{best\_start} \leftarrow 0$ 
4:  $\text{best\_end} \leftarrow k - 1$ 
5: for  $\text{start} = 0$  to  $G - k$  do
6:    $\text{end} \leftarrow \text{start} + k - 1$ 
7:    $\text{current\_length} \leftarrow \mathcal{G}'[\text{end}] - \mathcal{G}'[\text{start}]$ 
8:   if  $\text{current\_length} < \text{min\_length}$  then
9:      $\text{min\_length} \leftarrow \text{current\_length}$ 
10:     $\text{best\_start} \leftarrow \text{start}$ 
11:     $\text{best\_end} \leftarrow \text{end}$ 
12:   end if
13: end for
14:  $\mathcal{H} \leftarrow \mathcal{G}'[\text{best\_start} : \text{best\_end} + 1]$ 
15: return  $\mathcal{H}$ 

```

Experiment

LLMs. For comprehensive evaluation, we consider *nine* large language models (LLMs) covering a diverse spectrum: **Mistral-v0.3** (Jiang et al. 2023) (general-purpose, non-reasoning; 7B), **Qwen2.5** (Qwen Team 2024) (general-purpose, non-reasoning; 3B, 7B), **Qwen3** (Yang et al. 2025) (general-purpose, reasoning; 4B, 8B), **Qwen2.5-Coder** (Hui et al. 2024) (code-specialized, non-reasoning; 3B, 7B, 14B), and **DeepSeek-Coder** (Guo et al. 2024a) (code-specialized, non-reasoning; 6.7B). All these models are instruction-tuned versions downloaded from Hugging Face (Hugging Face 2025).

Training and Evaluation Data. In this study, we focus on **code edit in real-world software engineering**, where each user maintains complex contextual codebases accompanied by multiple editing histories. These histories capture the users’ individual coding and editing preferences. After an extensive search of publicly available resources, we found *no existing dataset or benchmark* that adequately represents such realistic code editing behaviors. Therefore, we collected practical code editing data from internal users within our company, reflecting their daily software development activities.

Each data point consists of two fields: `<prompt>` and `<edit>`. The `<prompt>` field contains all necessary inputs, including the code context, user-provided hints, a sequence of edit histories, and the cursor range (*i.e.*, the code segment to be modified). The `<edit>` field includes the corresponding edited code snippet. The detailed components of each field are summarized in Table 1.

The statistics of the training dataset² are illustrated in Figure 2. The dataset comprises a total of 51,844 code-editing tasks spanning 10 distinct programming languages. The three most represented languages are Go (37.71%), Python (22.14%), and Java (21.03%), which together account for

²The evaluation dataset exhibits a similar distribution.

Field	Components
<code><prompt></code>	<code><system prompt></code> <code><user prompt></code> <code><current code></code> <code><cursor range></code> <code><sequence of edit histories></code> <code><hints></code>
<code><edit></code>	<code><edited code snippet></code>

Table 1: Components of each data point in the training and evaluation datasets.

80.88% of all samples. The remaining languages—C++, Kotlin, TypeScript, JavaScript, C, Rust, and Lua—appear less frequently, with Rust and Lua being the least represented (0.43% and 0.12%, respectively). Overall, the dataset exhibits the following characteristics:

- **Dominance of Go:** Go is the most prevalent language, reflecting its strong adoption and relevance in the analyzed software engineering contexts.
- **Secondary Languages:** Python and Java follow as major contributors, underscoring their continued prominence in contemporary development workflows.
- **Linguistic Diversity:** The inclusion of 10 programming languages demonstrates the dataset’s diversity, although the distribution is notably skewed toward the top three.
- **Niche Languages:** Rust and Lua, despite their minimal presence, may correspond to specialized use cases or emerging trends in certain domains.

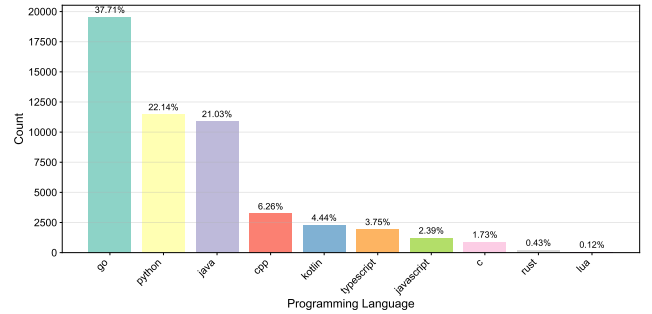


Figure 2: Language distribution statistics of the training dataset for code edit.

Baselines. Group Relative Policy Optimization (GRPO) (Shao et al. 2024) has emerged as one of the most influential RL algorithms for LLM post-training (Kumar et al. 2025; Patil and Jadon 2025; Lai et al. 2025), widely adopted in both academia and industry. Recently, Decoupled Clip and Dynamic sAmpling Policy Optimization (DAPO) (Yu et al. 2025) has gained attention as a promising extension and popular successor to GRPO. Our proposed GAPO method focuses on enhancing the group advantage computation—the

Name	Mistral-v0.3	Qwen2.5		Qwen3*		Qwen2.5-Coder			DeepSeek-Coder
Size	7B	3B	7B	4B	8B	3B	7B	14B	6.7B
GRPO	12.93	38.80	39.05	39.47	36.80	39.69	40.05	42.64	23.32
w/ GAPO	13.58	39.96	41.36	40.09	39.62	42.70	44.40	46.25	23.85
Improvement	+0.65	+1.16	+2.31	+0.62	+2.82	+3.01	+4.35	+3.61	+0.53
Max Δ	+4.27	+17.94	+8.92	+12.71	+11.13	+18.67	+13.74	+8.27	+5.49
Max Δ step	153	139	185	459	191	121	123	102	170
DAPO	16.59	32.80	39.46	37.99	39.80	38.74	41.64	—	41.09
w/ GAPO	17.20	33.87	41.13	39.62	40.64	39.98	43.96	—	43.03
Improvement	+0.61	+1.07	+1.67	+1.37	+0.84	+1.24	+2.32	—	+1.94
Max Δ	+3.83	+13.54	+12.97	+11.43	+4.49	+15.05	+8.96	—	+7.81
Max Δ step	63	103	62	106	100	51	72	—	107

Table 2: Exact match accuracy on the evaluation set for nine LLMs. The asterisk (*) denotes reasoning LLMs. Δ denotes the performance improvement between GRPO/DAPO and our GAPO at each training step. We also record the training step at which our GAPO achieves the maximum Δ .

core mechanism of GRPO. Accordingly, we adopt both the classical GRPO and the newly introduced DAPO as our primary baselines. We demonstrate here that the **adaptive advantage computation**, at the heart of GAPO, is a generalizable framework that can be seamlessly integrated into both GRPO and DAPO, leading to consistent performance improvements.

Other Settings. We use the popular `verl` framework (Sheng et al. 2025) for RL training, which is widely adopted in industry due to its scalability. We follow most of the default settings for GRPO and DAPO in `verl` with adaptive modifications for our code edit tasks, such as an input prompt length of 4096, an output length of 1024, a rollout batch size of 512, a training batch size of 32, 8 rollouts per iteration, and a total of 10 epochs. Our GAPO method is straightforward to implement, requiring only a few lines of code by modifying the `compute_grpo_outcome_advantage` function in the GRPO and DAPO implementations (details are provided in our released code), demonstrating its high compatibility. We use the exact match (*em*) as the evaluation metric. All results are reported as the average over three trials.

Main Experiment

We begin by presenting the improvements of our GAPO over both GRPO and DAPO on **nine** LLMs, covering general-purpose and code-specific models, as well as reasoning and non-reasoning types. The original DAPO implementation suffers from out-of-memory (OOM) issues, even after batch size tuning, resulting in missing results for some models.

As shown in Table 2, our GAPO yields greater benefits for the Qwen series compared to Mistral and DeepSeek, although it also provides notable improvements for DeepSeek-Coder under the DAPO setting. Within the Qwen family, GAPO demonstrates the strongest effect on Qwen2.5-Coder, achieving up to a 4.35-point improvement in exact match accuracy. This indicates that GAPO is particularly effective for initially strong, code-specific LLMs. In contrast, its effectiveness is limited for weaker models with low baseline

performance, such as Mistral-v0.3.

The pronounced Max Δ peaks indicate that GAPO enables models to reach superior intermediate checkpoints, which is valuable for early stopping and training efficiency. While the magnitude of improvements diminishes for larger models, the gains remain consistently positive, suggesting scalable compatibility rather than overfitting to smaller LLMs. The earlier Max Δ steps observed in DAPO highlight improved efficiency in surpassing baseline performance, whereas GRPO benefits more in absolute accuracy. Moreover, due to DAPO’s dynamic sampling strategy—which discards overly easy or overly hard prompts (*i.e.*, all-pass or all-fail cases)—GAPO converges faster and exhibits greater training stability.

Performance Curves

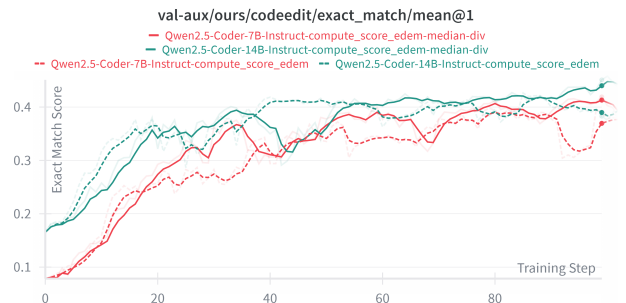


Figure 3: Performance curves on the evaluation set for GRPO, as logged by W&B. The *dotted* curves correspond to LLMs post-trained with the original GRPO. The curves labeled with “median-div” correspond to our proposed GAPO.

We also present the W&B-logged performance curves on the evaluation set in Figure 3 and Figure 4. We remove the curves of 3B models in Figure 3 for clarity. From these results, our GAPO improves the performance of both GRPO and DAPO, maintaining clear gains even after convergence.

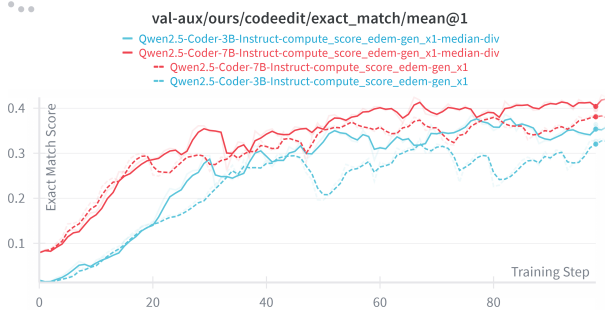


Figure 4: Performance curves on the evaluation set for DAPO, as logged by W&B. The *dotted* curves correspond to LLMs post-trained with the original DAPO.

Notably, GAPO yields more stable improvements for DAPO than for GRPO, because DAPO’s dynamic sampling filters out prompts with zero variance, increasing the proportion of outliers that appear among the remaining prompts. These filtered prompts often introduce noise, which can destabilize the exploration and exploitation processes of RL.

Policy Training Curves

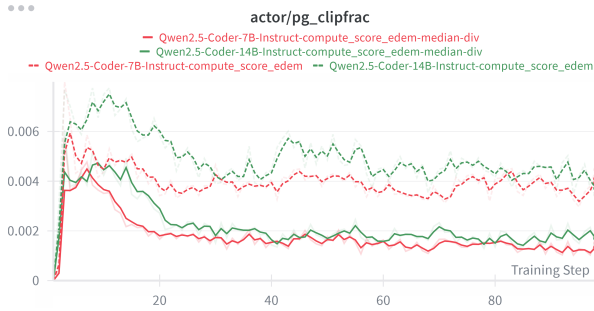


Figure 5: Clip fraction curves on the training set for GRPO, as logged by W&B.

The clip fraction curves in Figure 5 and Figure 6 illustrate the proportion of actions whose probability ratios were clipped during gradient updates. A low `pg_clipfrac` indicates that few updates reach the clipping threshold, implying gentler policy changes and greater training stability. For both the peak and converged values, our GAPO consistently exhibits lower `pg_clipfrac` than GRPO or DAPO. Moreover, smaller models generally show lower clip fractions than larger ones.

Distribution Analysis

We investigate the reward distributions of rollouts for all input prompts in the training set, with the resulting statistics shown in Figure 7. The pie chart indicates that most input prompts (68.4%) induce rollouts with approximately normal distributions, while a substantial portion (19.9%) exhibits skewed distributions, roughly evenly split between

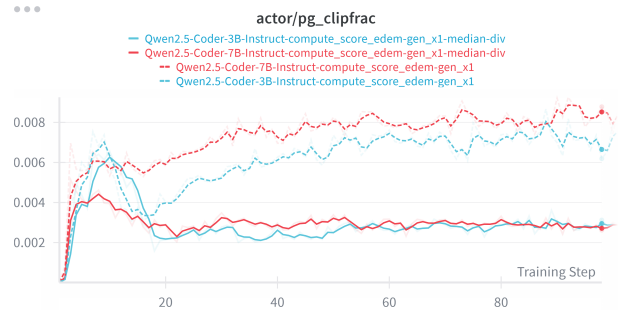


Figure 6: Clip fraction curves on the training set for DAPO, as logged by W&B.

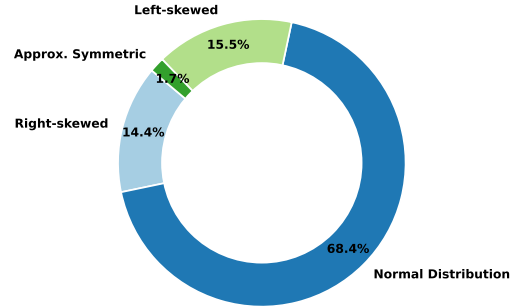


Figure 7: Pie chart showing the reward distribution of rollouts before training using Qwen2.5-Coder-14B.

left-skewed and right-skewed. This skew arises from the inherent noise, complexity, and dynamism of real-world environments—often manifesting as unavoidable and unpredictable outliers driven by complex context, user history, evolving intents, and other confounding factors. When computing advantage values as in Eq. (4) for these skewed distributions, outliers can have a negative impact, introducing noise (Frauenknecht et al. 2025; Hollenstein et al. 2022). In contrast, our GAPO method employs an adaptive Q value to locate the center of the dense region in the reward distribution, thereby mitigating the influence of outliers and reducing noise in the computation of advantage values.

Furthermore, we visualize representative examples sampled from input prompts that exhibit four types of reward distributions in Figure 8, providing a closer look at the skewed cases. Noticeable gaps exist between the mean and median for the left-skewed, right-skewed, and approximately symmetric distributions, while outliers primarily appear in the left- and right-skewed cases. By further analyzing the relationship between the mean–median difference and the sign of the advantages computed in Eq. (4) and Eq. (5), we find that our GAPO method generates more negative rollouts than the original GRPO/DAPO in left-skewed distributions. This occurs because Q is larger than the mean in such cases, causing most rewards to fall below Q and thus produce negative advantages. This behavior is reasonable, as

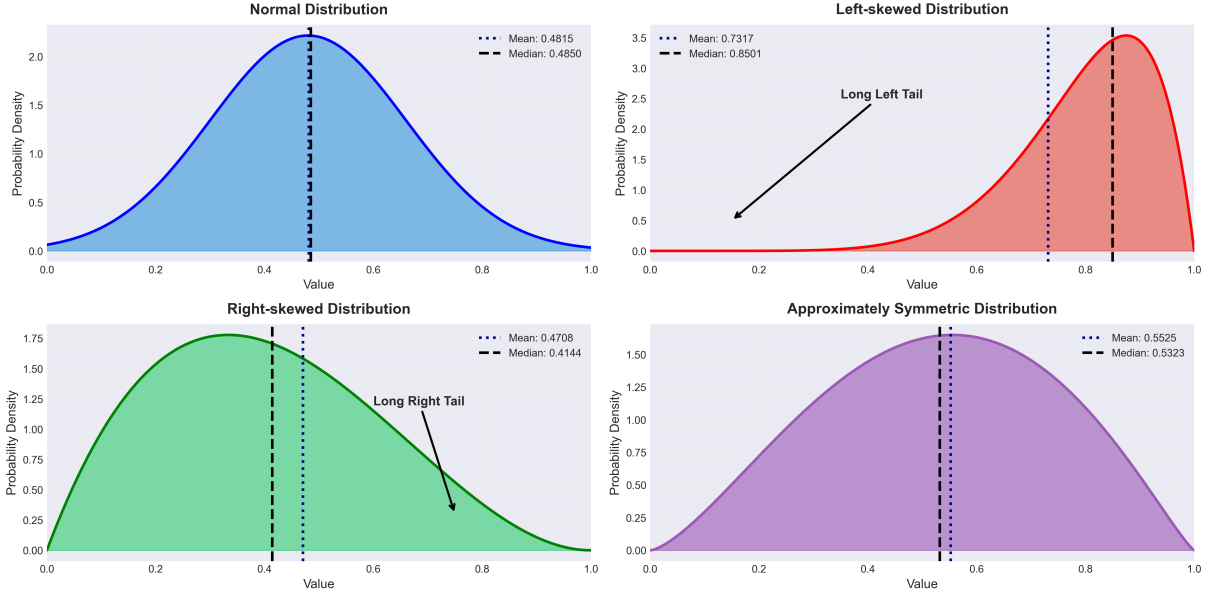


Figure 8: Examples of four types of reward distribution of rollouts before training using Qwen2.5-Coder-14B.

left-skewed distributions typically correspond to *relatively easy problems* with generally higher rewards, where more negative samples promote better generalization during training (Mu et al. 2025; Zhu et al. 2025). Conversely, for right-skewed distributions (*relatively hard problems*), GAPO encourages more specialized learning, leading to improved accuracy on these challenging cases. These trends align with our post-training goals.

Hyperparameter Study

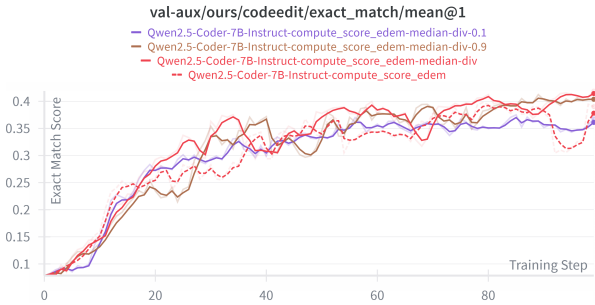


Figure 9: Performance curves on the evaluation set for GRPO with τ values of 0.1, 0.5 (default), and 0.9, as logged by W&B.

The only hyperparameter of our GAPO method is τ , which defines the percentage range of the dense region. We study its effects on Qwen2.5-Coder-7B, with the results shown in Figure 9, Figure 4, Figure 5, and Figure 6. Across these figures, we observe that the default value of $\tau = 0.5$ achieves the best overall performance. While $\tau = 0.9$ produces similar learning curves, it exhibits higher instability, as indicated

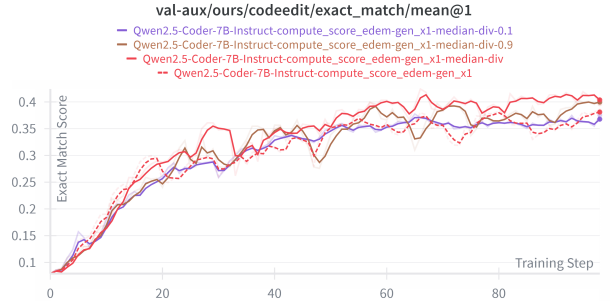


Figure 10: Performance curves on the evaluation set for DAPO with τ values of 0.1, 0.5 (default), and 0.9, as logged by W&B.

by larger `pg_clipfrac` values in both GRPO and DAPO frameworks. Conversely, $\tau = 0.1$ yields lower accuracy but demonstrates the best stability, evidenced by smoother learning curves and smaller `pg_clipfrac` values. Therefore, τ can be tuned within the range 0.1–0.5 to balance accuracy and stability according to different requirements.

Ablation Study

In addition to using the median within the adaptive dense region as our adaptive Q —denoted GAPO (median, div), which modifies both the numerator and denominator in the original advantage computation of GRPO (Eq. (4))—we consider two variants:

1. GAPO (median, std): replaces only the numerator with the median while keeping the denominator unchanged (*i.e.*, still based on the standard deviation);
2. GAPO (mean, div): uses the mean instead of the median

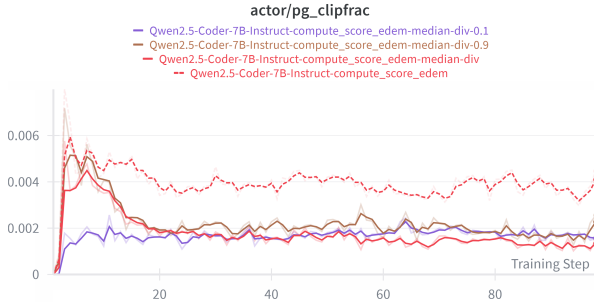


Figure 11: Clip fraction curves on the training set for GRPO with τ values of 0.1, 0.5 (default), and 0.9, as logged by W&B.

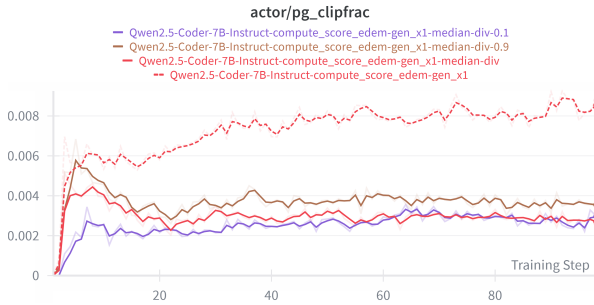


Figure 12: Clip fraction curves on the training set for DAPO with τ values of 0.1, 0.5 (default), and 0.9, as logged by W&B.

within the adaptive dense region to compute Q .

As shown in Table 3, both variants perform worse than the default GAPO, and in most cases even underperform the original GRPO/DAPO—particularly GAPO (median, std). In GAPO (median, std), only the numerator of the advantage computation differs from that of GRPO/DAPO, which introduces a shift in the advantage values. This shift cannot eliminate the negative impact of outliers; instead, it introduces noise and ultimately degrades performance. Larger models (e.g., 14B) appear more robust to this advantage shift.

In contrast, replacing the median with the mean in both the numerator and denominator—i.e., GAPO (mean, div)—results in less performance degradation than GAPO (median, std). This is because GAPO (mean, div) leverages statistics from the dense (outlier-free) sub-region to represent the entire (potentially outlier-contaminated) action distribution, reducing the influence of outliers. The fact that GAPO (median, div) outperforms GAPO (mean, div) demonstrates that the median better suppresses the impact of outliers than the mean, yielding a more robust advantage calculation.

Size	3B	7B	14B
GRPO	39.69	40.05	42.64
w/ GAPO (median, div)	42.70	44.40	46.25
w/ GAPO (median, std)	39.42	40.23	44.43
Δ to GRPO	-0.27	+0.18	+1.79
Δ to w/ GAPO	-3.28	-4.17	-1.82
w/ GAPO (mean, div)	41.72	42.54	45.10
Δ to GRPO	+2.03	+2.49	+2.46
Δ to w/ GAPO	-0.98	-1.86	-1.15
DAPO	38.74	41.64	—
w/ GAPO (median, div)	39.98	43.96	—
w/ GAPO (median, std)	37.32	40.65	—
Δ to DAPO	-1.62	-0.99	—
Δ to w/ GAPO	-2.86	-3.31	—
w/ GAPO (mean, div)	38.96	41.11	—
Δ to DAPO	+0.22	-0.53	—
Δ to w/ GAPO	-1.02	-2.85	—

Table 3: Exact match accuracy of GAPO’s variants on the evaluation set using Qwen2.5-Coder (3B, 7B, 14B).

Related Work

Stabilized Variants of GRPO

To address the instability and limited exploration of GRPO, recent studies have proposed improvements from multiple perspectives. For instance, (Wei et al. 2025) highlights GRPO’s gradient instability and mitigates it by dithering discrete reward signals with random noise. GMPO (Zhao et al. 2025) replaces the arithmetic mean with a geometric mean to reduce outlier sensitivity. Dr. GRPO (Liu et al. 2025b) corrects training bias by jointly considering response length and question difficulty. GSPO (Zheng et al. 2025) mitigates high variance in Mixture-of-Experts models via sequence-level importance sampling. Other works (Cui et al. 2025; Hao et al. 2025b) stabilize training and alleviate entropy collapse by regulating entropy dynamics.

Beyond token-level optimization, another line of work enhances GRPO stability through refined advantage computation. OPO (Hao et al. 2025a) achieves stable policy optimization via a variance-minimizing bias term. BNPO (Xia et al. 2025) adaptively normalizes rewards using a Beta distribution for low-variance gradient estimation. (Wang et al. 2025b) employs Kalman filtering to estimate latent reward baselines and uncertainty. GRPO-MA (Wang et al. 2025a) reduces variance by averaging multi-answer rewards, while (Wu et al. 2025a) introduces a group-wise K -quantile baseline for entropy-safe reasoning.

Despite these efforts, stability in LLM reinforcement learning for code scenarios remains underexplored. Moreover, these methods rely on discrete validation rewards derived from mathematical reasoning, which fundamentally differ from the continuous rewards in the code-editing tasks addressed in this work.

LLM for Code Edit

Code editing (Li et al. 2023; Guo et al. 2024b; Nam et al. 2025) is more challenging than basic code refinement, as it depends not only on the user prompt but also on the coding context, cursor position, and historical edits. To tackle this challenge, Self-Edit (Zhang et al. 2023) fine-tunes a fault-aware neural editor in a generate-and-edit manner, improving code quality and accuracy. EDITLORD (Li et al. 2025b), in contrast, avoids direct prompting or fine-tuning; it first uses an LLM to extract transformation rules from training data and then trains a second LLM to apply these rules to code pairs. IterPref (Wu et al. 2025b) leverages offline preference learning for iterative debugging, enabling context-aware code editing based on user feedback. LEDEX (Jiang et al. 2024) automatically collects refinement trajectories and enhances LLMs’ self-debugging ability via supervised fine-tuning and reinforcement learning. Finally, RLEF (Gehring et al. 2024) performs code editing with real-time execution feedback, optimizing refinement through end-to-end reinforcement learning.

Conclusion

We propose GAPO, a robust enhancement to GRPO-like methods that replaces the global mean with an adaptive Q —the median of the highest-density interval of rewards—to handle skewed, outlier-prone reward distributions in real-world code editing. Evaluated on various tasks across 10 languages and nine LLMs (3B–14B), GAPO consistently outperforms GRPO and DAPO in exact match accuracy, with minimal overhead. It improves generalization on left-skewed tasks and specialization on right-skewed ones, offering a plug-and-play solution for stable, effective RL-based code LLM post-training.

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