

SCHEDULING YOUR LLM REINFORCEMENT LEARNING WITH REASONING TREES

Hong Wang^{1,2*} Zhezheng Hao^{1,3*} Jian Luo² Chenxing Wei¹

Yao Shu⁴ Lei Liu² Qiang Lin¹ Hande Dong^{1,2†} Jiawei Chen^{3†}

¹ Tencent ² University of Science and Technology of China ³ Zhejiang University

⁴ Hong Kong University of Science and Technology (Guangzhou)

{hwongwang, handedong}@tencent.com

{haozhezheng, sleepyhunt}@zju.edu.cn

ABSTRACT

Using Reinforcement Learning with Verifiable Rewards (RLVR) to optimize Large Language Models (LLMs) can be conceptualized as progressively editing a query’s ‘Reasoning Tree’. This process involves exploring nodes (tokens) and dynamically modifying the model’s policy at each node. When combined with data scheduling, this process yields further gains in data efficiency and accuracy. However, existing RLVR data scheduling methods typically rely on path-based metrics to rank queries, overlooking the reasoning tree structures of these queries. In this paper, we introduce a novel metric, namely **Reasoning Score** (r-score), which measures the query’s learning difficulty based on the structure of its reasoning tree. Based on the r-score, we propose the **Reasoning Tree Schedule** (Re-Schedule), a scheduling algorithm that constructs a curriculum progressing from structurally simple (high r-score) to complex (low r-score) queries. Experiments on six math-reasoning benchmarks show that Re-Schedule significantly improves average accuracy, achieving gains of up to 3.2%. These strong results validate our approach and demonstrate that a structural understanding of the reasoning tree provides a more powerful and principled foundation for RLVR data scheduling ¹.

1 INTRODUCTION

Advancing the complex reasoning capabilities of Large Language Models (LLMs) remains a significant challenge, particularly in domains like mathematical problem-solving. Reinforcement Learning with Verifiable Reward (RLVR) (Gao et al., 2024; DeepSeek-AI et al., 2025), especially through policy optimization methods like GRPO (Shao et al., 2024), has emerged as a powerful paradigm to address this challenge. As shown in Figure 1 (a), in this framework, the space of potential solution paths for a query can be modeled as a specific ‘Reasoning Tree’ (Wang et al., 2025; Yang et al., 2025), where each node represents an intermediate reasoning step and each path represents a potential solution trajectory. From this perspective, RLVR operates as a dynamic ‘node-editing’ process of the reasoning tree: by rewarding correct paths and penalizing incorrect ones, the model iteratively refines its decision policy at each tree node. This optimization process gradually prunes branches that lead to low-quality or incorrect solutions, thereby improving overall reasoning accuracy.

In this paradigm, data scheduling plays a critical role in model performance (Hu et al., 2025; Yu et al., 2025; Li et al., 2025). The concept of data scheduling originates from curriculum learning (Bengio et al., 2009), which posits that models learn more effectively when training examples (queries) are organized in a meaningful sequence. Existing data scheduling strategies typically pre-define a ‘difficulty’ metric for queries, and schedule them from easy to hard to improve data efficiency and final performance (Xi et al., 2024; Chen et al., 2025b;a; Dai et al., 2025) However, from a reasoning tree perspective, current difficulty measure strategies exhibits a critical limitation: current methods estimate difficulty primarily via final solution accuracy, overlooking richer

*Equal Contribution.

†Corresponding Authors

¹Our code is available at <https://github.com/zz-haooo/Re-Schedule>.

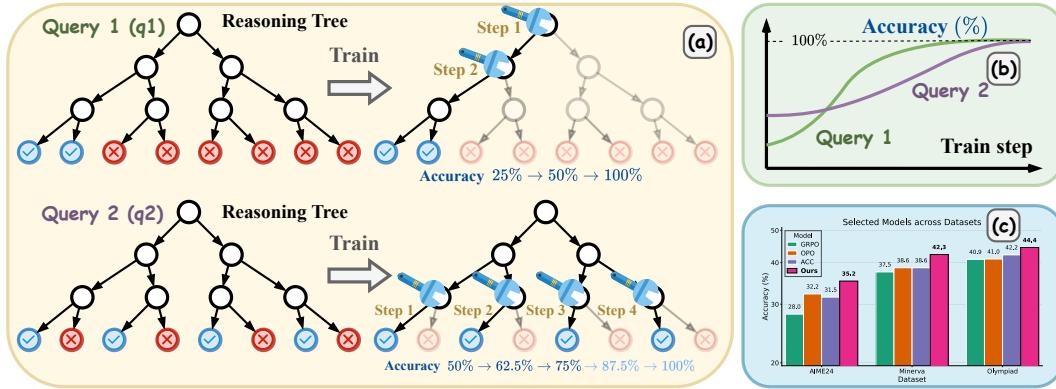


Figure 1: (a) A simple reasoning tree (q1) requires less node editing for performance improvement than a complex one (q2). (b) Consequently, q1 shows high training efficiency (steep learning curve) despite low initial accuracy, while q2’s complex structure leads to low efficiency. (c) Our method leverages this structural insight to significantly outperform baselines on various datasets.

query-level characteristics such as the structural complexity of the reasoning tree. Accuracy alone is insufficient — low accuracy does not necessarily indicate that a query is inherently hard, and high accuracy does not guarantee ease of optimization. This inconsistency can undermine the efficacy of accuracy-based scheduling approaches. We illustrate this issue with the following examples.

To illustrate, consider two representative queries, **q1** and **q2**, whose reasoning trees are shown in Figure 1(a). As depicted in Figure 1(b), LLMs may exhibit low initial accuracy on **q1**, due to the presence of many incorrect solution trajectories (reasoning paths). However, its simple tree structure means that modifying a few key decision nodes can yield substantial accuracy gains, indicating high learning efficiency despite the poor initial performance. In contrast, **q2** achieves higher initial accuracy, with roughly half of its trajectories being correct, yet these correct paths are scattered across disparate subtrees. This fragmented structure requires more extensive edits across numerous tree nodes, typically resulting in higher training difficulty and lower learning efficiency. Critically, existing path-based metrics will misinterpret **q1**’s low accuracy as high difficulty, thus assigning it a lower training weight, while incorrectly prioritizing the more difficult **q2**. Such path-based metrics may lead to a less efficient training process. This motivates our central research question: How can we move beyond path-based metrics to directly quantify a query’s true learning difficulty from its reasoning-tree structure?

To address this question, we introduce the **Reasoning Score** (r-score), a novel metric that quantifies a query’s learning potential based on its reasoning tree structure. We formalize this by framing the reinforcement learning training process as an optimization problem under a finite ‘node editing budget’, which we define as a fixed number of node editing operations. **Consequently, a query’s r-score is its maximum potential accuracy gain achievable within this limited editing budget.** This metric clearly explains the discrepancy in our example: **q1**, with its ‘concentrated’ error structure, yields a high r-score because a small budget (e.g., two edits) produces a massive accuracy gain (+75%). Conversely, **q2**’s ‘diffuse’ structure results in a low r-score, as the same budget only yields marginal improvement (+25%). Therefore, a higher r-score signifies a more tractable reasoning structure and greater learning efficiency, offering a more comprehensive assessment of difficulty than path-based metrics.

Building on the Reasoning Score, we propose the **Reasoning Tree Schedule (Re-Schedule)**, a novel data scheduling algorithm designed to guide RLVR training more efficiently. Our method consists of three main stages. First, an offline approximation of each query’s reasoning tree is constructed by sampling multiple solution trajectories from a base model. Second, this approximated reasoning tree is used to calculate each query’s reasoning score by simulating the editing process. Finally, we integrate the r-score as a dynamic weight into the RLVR loss function to form a schedule. This schedule prioritizes high-scoring (simple) queries in the initial training phases to accelerate convergence on simple queries. As training progresses, the weighting gradually shifts to lower-scoring (difficult) queries, enabling the model to master more challenging problems.

In summary, the main contributions of this paper are:

- We introduce the Reasoning Score (r-score), a new tree-based metric that measures a query’s learning efficiency rather than its path-based solution accuracy.
- We propose Re-Schedule, a data scheduling algorithm that uses the r-score to create an effective, easy-to-hard curriculum for RLVR.
- As shown in Figure 1(c), we empirically demonstrate that our approach significantly improves average accuracy, achieving gains of up to 3.2%, on complex reasoning tasks.

2 RELATED WORK

2.1 REINFORCEMENT LEARNING WITH VERIFIABLE REWARDS IN LLMs

Reinforcement learning with verifiable reward (RLVR), where the reward is computed by a rule-based verification function, has been shown to be effective in improving the reasoning capabilities of LLMs (Gao et al., 2024; DeepSeek-AI et al., 2025; Kimi et al., 2025; Zeng et al., 2025; Wen et al., 2025; Song et al., 2025). Typically, RLVR frameworks assign a binary reward by comparing the model’s generated output against a ground-truth solution, indicating whether it is correct or incorrect. This reward design obviates the need for complex outcome-based or process-based reward models, offering a straightforward yet potent approach. Recent advancements in policy optimization algorithms, such as PPO and GRPO, have further refined this paradigm (Schulman et al., 2017; Kazemnejad et al., 2024; Yuan et al., 2025; Yue et al., 2025; Shao et al., 2024; Yu et al., 2025; Liu et al., 2025; Zhang et al., 2025; Hu, 2025). In contrast to these studies, which focus on algorithmic improvements, our work builds upon the standard GRPO framework with a primary focus on designing a more effective training data schedule.

2.2 DATA SCHEDULING ALGORITHM IN LLM REINFORCEMENT LEARNING

Various data scheduling strategies have been proposed to enhance the reasoning capabilities in LLM Reinforcement Learning. These can be broadly categorized into static selection and dynamic adjustment methods. Representative of static selection is LIMR (Li et al., 2025), which selected 1.4k examples from an 8.5k set for RLVR to match the performance of using the full set. In contrast, dynamic strategies make real-time adjustments during training. For instance, R^3 employs reverse curriculum reinforcement learning to simplify the model’s exploration space (Xi et al., 2024). LPPO dynamically adjusts data weights based on model accuracy and provides online “prompts” for challenging problems to guide exploration (Chen et al., 2025b). SEED-GRPO focuses on model uncertainty (Chen et al., 2025a), using token entropy to dynamically re-weight data. Furthermore, DELT leverages training gradients to measure the quality and learnability of data (Dai et al., 2025), subsequently adjusting sample weights. However, these existing methods primarily rely on metrics such as accuracy and diversity, which overlook the structural relationships among data samples. In contrast, our work aims to quantify the learning potential of a query by analyzing its reasoning tree.

3 PRELIMINARIES

3.1 GROUP RELATIVE POLICY OPTIMIZATION

The objective of the GRPO algorithm is to optimize a policy π_θ based on a group of generated responses (Shao et al., 2024; Yu et al., 2025). For a query q from a dataset \mathcal{D} , the policy generates G responses $\{o_i\}_{i=1}^G$. The token-level objective function is formulated as:

$$\mathcal{J}(\theta) = \mathbb{E}_{q \sim \mathcal{D}, \{o_i\}_{i=1}^G \sim \pi_{\text{old}}(\cdot|q)} \left[\frac{1}{\sum_{i=1}^G |o_i|} \sum_{i=1}^G \sum_{t=1}^{|o_i|} \min(r_{i,t} A_{i,t}, \text{clip}(r_{i,t}, 1 - \varepsilon, 1 + \varepsilon) A_{i,t}) \right], \quad (1)$$

where $r_{i,t} = \frac{\pi_\theta(o_{i,t}|q, o_{i,<t})}{\pi_{\text{old}}(o_{i,t}|q, o_{i,<t})}$ is the probability ratio of the token $o_{i,t}$ between the current and old policies. The advantage term $A_{i,t}$ is constant for all tokens within a single response and is calculated

by normalizing the response’s reward R_i relative to the other responses in the group:

$$A_{i,t} = \frac{R_i - \text{mean}(\{R_k\}_{k=1}^G)}{\text{std}(\{R_k\}_{k=1}^G) + \delta}, \quad \forall t, \quad (2)$$

where δ is a small constant for numerical stability.

Data scheduling algorithms can be formulated by introducing a weighting function $\omega(q, t)$ that modulates the contribution of each query $q \in \mathcal{D}$ and current epoch t to the overall objective. Specifically, the objective in Equation 1 is modified as follows:

$$\mathcal{J}_{\text{schedule}}(\theta) = \mathbb{E}_{q \sim \mathcal{D}, \dots} [\omega(q, t) \cdot (\text{original objective term for } q)]. \quad (3)$$

Note: In the equations above, we have abbreviated the full objective for clarity. For example, in an accuracy-based curriculum learning, the training weight ω is formulated as a function of the query’s accuracy $\text{ACC}(q)$ and current epoch t :

$$\alpha(\text{ACC}(q), t) = (1 - \gamma(t))\text{ACC}(q) + \gamma(t)(1 - \text{ACC}(q)), \quad (4)$$

$$\omega = \text{rank}(\alpha)\% \cdot \omega_{\max} + (1 - \text{rank}(\alpha)\%) \cdot \omega_{\min}. \quad (5)$$

Here, ω_{\max} and ω_{\min} are hyperparameters that define the maximum and minimum training weights (e.g., $\omega_{\max} = 0.8$, $\omega_{\min} = 0.2$); And $\text{rank}(\alpha)$ means calculating the reverse order of α in the entire dataset. The term $\gamma(t)$ is a scheduling function that progresses over time. Common choices for $\gamma(t)$ include a linear mapping, $\gamma(t) = t/T$, or a sigmoid function, $\gamma(t) = \sigma((\frac{t}{T} - 0.5))$, $\sigma(x) = (1 + e^{-x})^{-1}$, where T is the total number of epochs.

3.2 REASONING TREE

For complex reasoning tasks, the process of generating a solution can be conceptualized as traversing a ‘Reasoning Tree’. In this context, the root of the tree is the initial prompt, and each node represents a partial solution or an intermediate reasoning step. The branches extending from a node correspond to the possible next tokens or thought segments that the LLM can generate.

Due to the combinatorial explosion of possible solution paths, the complete reasoning tree is typically computationally intractable. Therefore, analysis often relies on a structured approximation (e.g., a fixed-structure k-ary reasoning tree). Formally, an approximated reasoning tree is defined as a triplet $T = (\mathcal{N}, \mathcal{E}, \mathcal{R})$, where \mathcal{N} is the set of nodes, \mathcal{E} is the set of edges, and \mathcal{R} defines the parent-child relationships.

The components of the tree are described using the following notation: $\mathcal{N}_{\text{leaf}} \subset \mathcal{N}$ is the set of leaf nodes; For a given node $n_i \in \mathcal{N}$, $C(n_i)$ denotes the set of its immediate children and $\mathcal{L}(n_i)$ denotes the set of its leaf descendants. If n_i is a leaf node, then $\mathcal{L}(n_i) = \{n_i\}$. Within this framework, each non-leaf node $n_i \in \mathcal{N} \setminus \mathcal{N}_{\text{leaf}}$ represents a partial reasoning path, while a complete path to a leaf node $n_j \in \mathcal{N}_{\text{leaf}}$ corresponds to a full solution trajectory.

From this perspective, the RLVR optimization process is a dynamic ‘node editing’ of this reasoning tree. By rewarding correct paths and penalizing incorrect ones, the policy optimization algorithm adjusts the token probabilities at each node, effectively strengthening the branches that lead to correct answers and weakening those that lead to errors. The structure of this tree—the distribution of correct and incorrect paths—is intrinsic to each problem sample and, as we will argue, is a key clue to its learning dynamics.

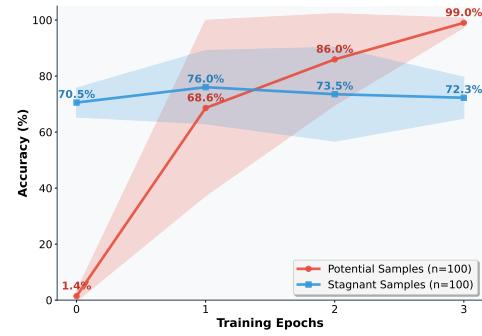


Figure 2: Accuracy Progression During Training. The solid line represents the average accuracy, and the shaded area indicates the range.

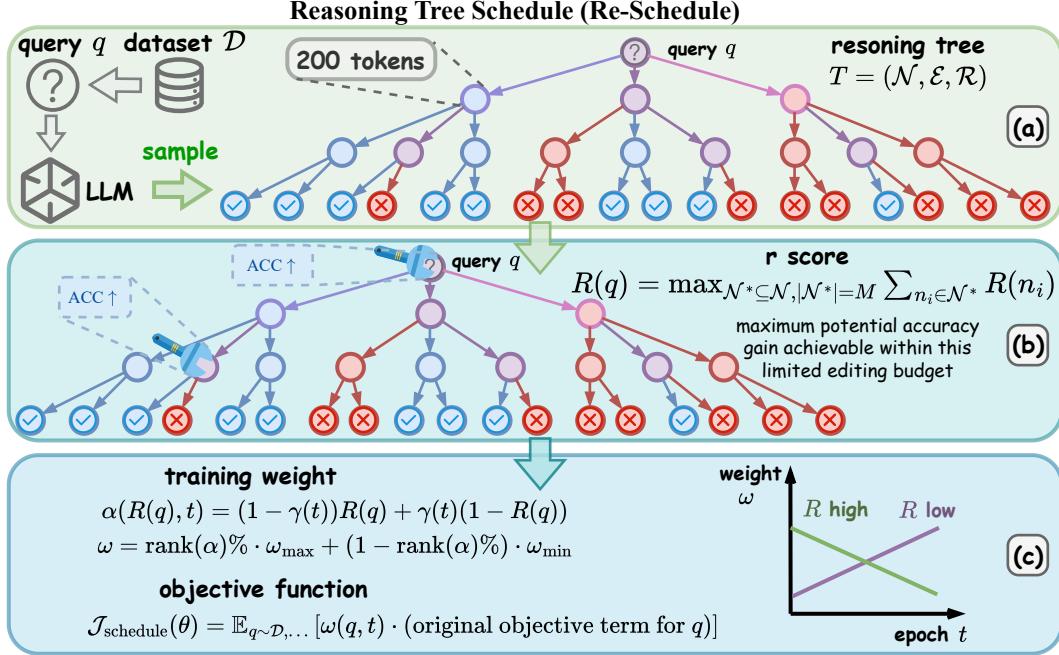


Figure 3: Overview of the **Reasoning Tree Schedule (Re-Schedule)** Algorithm. (a) **Tree Construction:** For each query, an approximate reasoning tree is constructed by sampling multiple solution paths from a base model. (b) **R-Score Calculation:** The tree’s structure is analyzed to compute the r-score, a metric quantifying the query’s learning potential. (c) **Dynamic Weighting:** The r-scores are used to dynamically weight each query during training, forming a curriculum that progresses from structurally simple (easy) to complex (hard) examples.

4 MOTIVATION

The premise of this work is that path-based metrics such as accuracy are poor indicators of a query’s true learning difficulty. To illustrate our point, we supplement the example from the introduction with an experiment. As shown in Figure 2, we selected two distinct sets of 100 queries each from the DAPA-Math-17K dataset, using the Qwen2.5-Math-7B model. The blue line represents queries that have high initial accuracy but require extensive training to show further improvement. In contrast, the red line, standing for queries with simple tree structures, begins with low accuracy but improves rapidly. Although queries for the blue line appear ‘easier’ based on their initial accuracy, queries for the red line demonstrate greater potential. This discrepancy highlights that path-based metrics, like accuracy, are biased measurements for learning difficulty. This finding motivates us to design a new metric based on the structure of the reasoning tree.

5 METHOD

As illustrated in Figure 3, the **Reasoning Tree Schedule (Re-Schedule)** enhances reinforcement learning performance by creating a curriculum based on our novel metric, the **Reasoning Score (r-score)**. The r-score quantifies a query’s learning difficulty a priori based on the structure of its reasoning tree. Next, we will introduce the specific implementation details.

5.1 TREE CONSTRUCTION

As the entire reasoning tree is computationally intractable, we construct a manageable, fixed-structure k -ary approximation for each query q . The structure of this tree, \mathcal{T} , is defined by a branching factor k , a maximum depth d , and a token interval l (e.g., $k = 4, d = 4, l = 200$).

The construction process begins at the root node (the query q) and proceeds via a periodic branching strategy during response generation. Specifically, a branch is triggered immediately at the beginning of the response and subsequently at every l -token interval. As shown in Figure 3 (a), at each trigger, the current path splits into k independent sub-paths that continue to generate in parallel. This recursive branching process continues until a predefined maximum depth d is reached. To minimize computational overhead from this multi-path sampling, we use the Key-Value (KV) Cache, as all sibling branches share the same prefix.

In RLVR tasks, a solution’s quality is determined by the correctness of its final answer, which corresponds to a leaf node in our framework. Therefore, we define the quality of any intermediate node n_i as the average accuracy of its leaf descendants, $\mathcal{L}(n_i)$. This is quantified using an accuracy function:

$$\text{ACC}(S) = \frac{\sum_{n_j \in S} \mathbb{I}(n_j \text{ is correct})}{|S|}, \quad (6)$$

where S is a set of leaf nodes and $\mathbb{I}(\cdot)$ is the indicator function. This allows us to assess quality at different levels: the quality of a reasoning segment via $\text{ACC}(\mathcal{L}(n_i))$ and the model’s aggregate performance on the query via $\text{ACC}(\mathcal{N}_{\text{leaf}})$.

5.2 R-SCORE CALCULATION

The r-score quantifies the learning potential of a node or query by measuring the maximum achievable accuracy gain under a limited policy refining cost, like a limited node editing budget. Given this idea, for any non-leaf node n_i , we define its r-score, $R(n_i)$, as the maximal accuracy gain achievable by selecting its single best child branch and pruning all others. This is formulated as:

$$R(n_i) = \max_{n_{\text{child}} \in \mathcal{C}(n_i)} \text{ACC}[\mathcal{N}_{\text{leaf}} \setminus \mathcal{L}(n_i) \cup \mathcal{L}(n_{\text{child}})] - \text{ACC}[\mathcal{N}_{\text{leaf}}]. \quad (7)$$

The overall r-score for a query, $R(q)$, estimates the total accuracy gain achievable under a budget that limits modifications to a maximum of M nodes. It is the maximum sum of r-scores from any set of M non-conflicting nodes (e.g., for a budget of $M = 4$):

$$R(q) = \max_{\mathcal{N}^* \subseteq \mathcal{N}, |\mathcal{N}^*|=M} \sum_{n_i \in \mathcal{N}^*} R(n_i). \quad (8)$$

Two nodes are considered conflicting if one is located in a subtree that is implicitly pruned by the optimal branch selection of the other.

Intuitively, solving Equation (7) represents the evaluation process of the sub-tree’s structure, while a simpler structure of reasoning tree starting from n_i yields a higher $R(n_i)$. Combining the evaluation $R(n_i)$ of each node n_i under a limited budget M , solving Equation (8) is to find the maximum achievable accuracy gain over the reasoning tree, like exploring possible combinations of M nodes and picking the best combination. Thus, a higher $R(q)$ indicates that substantial accuracy improvements can be made by correcting just a few critical reasoning steps, signifying a structurally simple and efficient-to-learn query.

5.3 DYNAMIC WEIGHTING

To strike a balance between data diversity and data scheduling, we propose a weighted scheduling framework that dynamically adjusts data prioritization. Specifically, queries are assigned adaptive weights determined by both training step t and r-score R . Specifically, when it is an early training stage, higher weights are assigned to samples with higher r-scores (indicating lower learning difficulty), stabilizing the reinforcement learning. When RL training meets the later training phase, queries’ weights will be redistributed gradually towards lower-r-score samples (higher learning difficulty) to enhance model generalization.

Motivated by this, the training weight ω of each query is formulated as

$$\alpha(R(q), t) = (1 - \gamma(t))R(q) + \gamma(t)(1 - R(q)), \quad (9)$$

$$\omega = \text{rank}(\alpha)\% \cdot \omega_{\text{max}} + (1 - \text{rank}(\alpha)\%) \cdot \omega_{\text{min}}, \quad (10)$$

where t is the current epoch; ω_{max} and ω_{min} are hyperparameters that define the maximum and minimum training weights; And $\text{rank}(\alpha)$ means calculating the reverse order of α in the entire dataset;

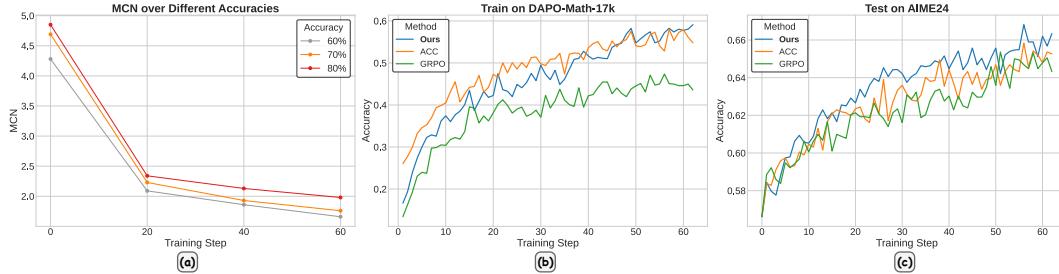


Figure 4: (a) The average MCN decreases over time, indicating successful tree optimization. (b) & (c) To compare metrics, we train models on the top 1/3 of data selected by each. The plots show the resulting (b) training accuracy and (c) test accuracy. The model used is Qwen2.5-Math-7B.

$\gamma(t)$ can be either linear mapping $\gamma(t) = \frac{t}{T}$ or sigmoid $\gamma(t) = \sigma\left(\left(\frac{t}{T} - 0.5\right)\right)$. The $\alpha(R(q), t)$ is a monotonically varying function that down-weights high-scoring (simple) queries over time while up-weighting lower-scoring (difficult) ones. This scheduling approach balances exploitation of easily learnable patterns and exploration of challenging instances, mitigating catastrophic forgetting of underrepresented data distributions.

6 ANALYSIS

6.1 TRAINING AS REASONING TREE OPTIMIZATION

To empirically validate that the training process is optimizing reasoning trees, we conducted an experiment centered on a new metric: the Minimum Corrective Nodes (MCN). This metric is defined as the minimum number of node modifications required for the reasoning tree to achieve a specified target accuracy. A single node modification is counted as one token change; thus, a lower MCN signifies a well-structured reasoning tree. In our experiment, we tracked the MCN on the DAPA-Math-17K training set during the training of Qwen2.5-Math-7B, excluding queries where the base model’s accuracy was below 10%.

As shown in Figure 4(a), the average MCN across the training set exhibits a consistent downward trend as training progresses, regardless of the target accuracy. This result demonstrates that the reinforcement learning process effectively refines the model’s policy at critical decision nodes, thereby validating our central assumption that training is a process of reasoning tree optimization.

6.2 THE RELATIONSHIP BETWEEN R-SCORE AND LEARNING DIFFICULTY

In this experiment, we want to see which metric best identifies valuable queries for early-stage training. The process is as follows: First, we use each metric to select the top one-third of the data, creating several distinct subsets. Second, we train a separate model on each of these subsets for a single epoch. Finally, we evaluate the resulting models on both the training and test sets.

As shown in Figure 4(b), the subset selected by the ACC-based method initially shows higher average accuracy on the training set, as expected from its selection criteria. However, as training progresses, the model trained on the r-score-selected subset quickly surpasses it. This indicates that the r-score is more effective at identifying queries with low learning difficulty, rather than just initial accuracy.

The advantage of r-score is even more evident on the test set, as shown in Figure 4(c). Here, the model trained on the r-score-selected queries consistently outperforms both the ACC-based selection and a baseline with random query selection (GRPO). This confirms that the queries identified by the r-score provide the most effective learning signal, leading to better performance improvement and validating its capability in identifying the real difficulty of queries.

7 EXPERIMENT

7.1 RL TRAINING SETUPS

Training setting We conduct experiments on two different models, including Qwen2.5-Math-7B and Qwen2.5-7B. We adapt our training codebase from verl (Sheng et al., 2025) and follow the training recipe of standard GRPO. Our training data is DAPO-Math-17k (Yu et al., 2025), containing only math problems with integer ground-truth answers. Both the KL-divergence and entropy loss terms are removed in our experiments. Generation batch size is set to 512. Training is performed with top-p value of 1.0 and temperature = 1.0.

Evaluation We evaluated our models and baselines on six widely used mathematical reasoning benchmarks: AIME24, AIME25, AMC23 (Li et al., 2024), MATH-500 (Hendrycks et al., 2021), Minerva Math (Lewkowycz et al., 2022), and OlympiadBench (He et al., 2024). Validation is performed with a top-p value of 0.7 and temperature = 1.0 across all models and test sets. We use Math-Verify for training, validation, and final evaluation.

Baselines For the throughout comparison, we compare our method against 7 baselines, including standard GRPO (Shao et al., 2024), SimpleRL-Zoo (Zeng et al., 2025), Eurus-PRIME(Cui et al., 2025), OPO (Hao et al., 2025), ACC (curriculum learning based on accuracy, using sigmoid weighting), LPPO (Chen et al., 2025b), and Seed-GRPO (Chen et al., 2025a).

Our Methods Re-Schedule is implemented with two weighting schemes: ‘linear’ and ‘sigmoid’. Unless otherwise specified, the reasoning trees in our experiments are constructed with a branching factor of $k = 4$, a maximum depth of $d = 4$, and a token interval of $l = 200$. The weighting schemes are defined as follows: 1. The ‘linear’ scheme uses $\gamma(t) = t/T$; 2. The ‘sigmoid’ scheme uses $\gamma(t) = \sigma\left(\left(\frac{t}{T} - 0.5\right)\right)$. For both, we set the total number of epochs $T = 10$.

Details of the training setup can be found in the Appendix B.

7.2 MAIN EXPERIMENT

Table 1: Main benchmark results on **Qwen2.5-Math-7B**. All values are accuracies multiplied by 100. Best results are in **bold**.

Model	AIME24	AIME25	AMC23	MATH500	Minerva	Olympiad	Avg.
Qwen2.5-Math-7B	13.8	5.3	44.6	39.6	9.9	13.8	21.2
Classical RLVR Methods							
GRPO	28.0	14.3	66.2	78.6	37.5	40.9	44.3
SimpleRL-Zoo	25.2	13.4	70.6	78.6	37.9	38.4	44.0
Eurus-PRIME	20.9	13.0	65.2	79.8	37.5	40.6	42.8
OPO	32.2	13.4	71.5	82.2	38.6	41.0	46.5
Scheduling Methods							
ACC _{sigmoid}	31.5	15.6	70.9	80.8	38.6	42.2	46.6
LPPO	32.8	14.9	63.3	79.2	39.0	40.6	45.0
Seed-GRPO	30.7	14.0	71.0	80.0	38.2	38.5	45.4
Our Methods							
Re-Schedule _{linear}	34.2	15.6	72.4	81.2	36.4	42.5	47.1
Re-Schedule _{sigmoid}	35.2	16.0	72.3	82.2	42.3	44.4	48.5

As shown in Tables 1 and 2, our Re-Schedule method consistently sets a new state-of-the-art, achieving average scores of 48.5 on Qwen2.5-Math-7B and 44.5 on Qwen2.5-7B. It significantly outperforms both scheduling baselines like ACC_{sigmoid} (by up to 3.2%) and classical RLVR methods like OPO/GRPO (by up to 3.8%). These results validate our central claim: that the reasoning tree’s structure, captured by our r-score, is a more effective way to measure the real learning difficulty of a query than path-based metrics like accuracy.

Table 2: Main benchmark results on **Qwen2.5-7B**. All values are accuracies multiplied by 100. Best results are in **bold**.

Model	AIME24	AIME25	AMC23	MATH500	Minerva	Olympiad	Avg.
Qwen2.5-7B	5.1	2.5	27.8	34.4	5.9	13.5	14.9
Classical RLVR Methods							
GRPO	15.6	8.8	62.5	78.2	38.6	40.4	40.7
SimpleRL-Zoo	15.7	8.8	65.7	76.0	33.8	38.7	39.8
OPO	16.6	8.4	64.6	74.6	31.6	40.3	39.4
Scheduling Methods							
ACC _{sigmoid}	16.7	9.8	68.6	79.0	34.2	39.4	41.3
LPPO	15.8	9.4	64.0	76.8	35.3	36.7	39.7
Seed-GRPO	13.3	6.0	63.3	76.6	32.4	36.3	38.0
Our Methods							
Re-Schedule _{linear}	18.4	12.2	68.6	80.4	41.2	42.1	43.8
Re-Schedule _{sigmoid}	18.2	14.0	69.2	81.0	41.5	43.3	44.5

7.3 ABLATION EXPERIMENT

Table 3: Ablation study on tree construction parameters. The default configuration (branching factor $k = 4$, depth $d = 4$) achieves the best performance.

Branch k	Depth d	AIME24	AIME25	AMC23	MATH500	Minerva	Olympiad	Avg.
4	4	34.2	16.0	71.1	81.8	42.3	44.4	48.3
3	5	33.8	14.8	68.4	79.6	42.3	42.8	46.9
5	3	31.7	14.2	70.4	81.0	41.9	43.0	47.0

We investigate the impact of the reasoning tree’s structure by varying the branching factor k and maximum depth d . The choice of these parameters determines the fidelity of the approximated reasoning tree. While larger values for k and d theoretically provide a more accurate approximation and thus a more effective r-score, they also introduce a significant computational overhead. As shown in Table 3, our default configuration of $k = 4$ and $d = 4$ yields the best average performance (48.3%).

Table 4: Ablation study on the weight function hyperparameters, ω_{\min} and ω_{\max} . The default setting (0.5, 2.0) performs best.

ω_{\min}	ω_{\max}	AIME24	AIME25	AMC23	MATH500	Minerva	Olympiad	Avg.
0.5	2.0	35.2	16.0	72.3	82.2	42.3	44.4	48.5
0.5	1.5	31.4	15.4	72.3	81.8	38.1	42.5	46.9
0.5	3.0	33.5	15.0	69.1	81.8	37.5	41.0	46.3
0.8	2.0	36.6	13.6	71.1	81.6	37.1	43.8	47.3
0.2	2.0	33.5	13.9	71.0	80.0	38.2	41.6	46.4

We analyze the sensitivity of our method to the minimum ω_{\min} and maximum ω_{\max} weight hyperparameters, which control the dynamic range of the curriculum. Results in Table 4 show that our default setting of $\omega_{\min} = 0.5$ and $\omega_{\max} = 2.0$ achieves the highest average score (48.5). Decreasing the dynamic range by either reducing ω_{\max} (to 1.5) or increasing ω_{\min} (to 0.8) leads to performance degradation. This indicates that a sufficiently large weighting range is crucial for the curriculum to effectively differentiate between easy and hard samples. Conversely, an overly extreme range (e.g., $\omega_{\min} = 0.2$) also degrades performance, possibly because the curriculum excessively under-weights

difficult queries. By assigning them a minimal weight for a prolonged period, the model is prevented from learning difficult queries. Furthermore, for additional experiments on the design choices for the r-score calculation, please see Appendix C.

8 CONCLUSIONS

In this work, we challenged the reliance on path-based metrics for RLVR data scheduling. We introduced the r-score, a novel metric that quantifies learnability based on the structure of a query’s reasoning tree, and proposed Re-Schedule, a curriculum learning algorithm built upon it. Extensive experiments demonstrated that Re-Schedule consistently outperforms classical RLVR and existing scheduling methods, validating that r-score is a more effective proxy for learnability than path-based accuracy. Our findings establish that a structural understanding of the reasoning process provides a more powerful and principled foundation for creating efficient training curricula in RLVR.

ETHICS STATEMENT

We have manually reevaluated the dataset we created to ensure it is free of any potential for discrimination, human rights violations, bias, exploitation, and any other ethical concerns.

REPRODUCIBILITY STATEMENT

To ensure the reproducibility of our findings, all source code and datasets used in our experiments are included in the supplementary material. The provided materials are sufficient to replicate the main results presented in this paper.

REFERENCES

- Yoshua Bengio, Jérôme Louradour, Ronan Collobert, and Jason Weston. Curriculum learning. In *Proceedings of the 26th annual international conference on machine learning*, pp. 41–48, 2009.
- Minghan Chen, Guikun Chen, Wenguan Wang, and Yi Yang. Seed-grpo: Semantic entropy enhanced grpo for uncertainty-aware policy optimization. *arXiv preprint arXiv:2505.12346*, 2025a.
- Xinjie Chen, Minpeng Liao, Guoxin Chen, Chengxi Li, Biao Fu, Kai Fan, and Xinggao Liu. From data-centric to sample-centric: Enhancing llm reasoning via progressive optimization. *arXiv preprint arXiv:2507.06573*, 2025b.
- Ganqu Cui, Lifan Yuan, Zefan Wang, Hanbin Wang, Wendi Li, Bingxiang He, Yuchen Fan, Tianyu Yu, Qixin Xu, Weize Chen, Jiarui Yuan, Huayu Chen, Kaiyan Zhang, Xingtai Lv, Shuo Wang, Yuan Yao, Xu Han, Hao Peng, Yu Cheng, Zhiyuan Liu, Maosong Sun, Bowen Zhou, and Ning Ding. Process reinforcement through implicit rewards. *CoRR*, abs/2502.01456, 2025. doi: 10.48550/ARXIV.2502.01456. URL <https://doi.org/10.48550/arXiv.2502.01456>.
- Yalun Dai, Yangyu Huang, Xin Zhang, Wenshan Wu, Chong Li, Wenhui Lu, Shijie Cao, Li Dong, and Scarlett Li. Data efficacy for language model training. *arXiv preprint arXiv:2506.21545*, 2025.
- DeepSeek-AI, Daya Guo, Dejian Yang, Haowei Zhang, Junxiao Song, Ruoyu Zhang, Runxin Xu, Qihao Zhu, Shirong Ma, Peiyi Wang, and et al Xiao Bi. Deepseek-r1: Incentivizing reasoning capability in llms via reinforcement learning. *CoRR*, abs/2501.12948, 2025. doi: 10.48550/ARXIV.2501.12948. URL <https://doi.org/10.48550/arXiv.2501.12948>.
- Jiaxuan Gao, Shusheng Xu, Wenjie Ye, Weilin Liu, Chuyi He, Wei Fu, Zhiyu Mei, Guangju Wang, and Yi Wu. On designing effective RL reward at training time for LLM reasoning. *CoRR*, abs/2410.15115, 2024. doi: 10.48550/ARXIV.2410.15115. URL <https://doi.org/10.48550/arXiv.2410.15115>.
- Yaru Hao, Li Dong, Xun Wu, Shaohan Huang, Zewen Chi, and Furu Wei. On-policy rl with optimal reward baseline. *arXiv preprint arXiv:2505.23585*, 2025.
- Chaoqun He, Renjie Luo, Yuzhuo Bai, Shengding Hu, Zhen Leng Thai, Junhao Shen, Jinyi Hu, Xu Han, Yujie Huang, Yuxiang Zhang, Jie Liu, Lei Qi, Zhiyuan Liu, and Maosong Sun. Olympiadbench: A challenging benchmark for promoting AGI with olympiad-level bilingual multimodal scientific problems. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar (eds.), *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, ACL 2024, Bangkok, Thailand, August 11-16, 2024, pp. 3828–3850. Association for Computational Linguistics, 2024. doi: 10.18653/V1/2024.ACL-LONG.211. URL <https://doi.org/10.18653/v1/2024.acl-long.211>.
- Dan Hendrycks, Collin Burns, Saurav Kadavath, Akul Arora, Steven Basart, Eric Tang, Dawn Song, and Jacob Steinhardt. Measuring mathematical problem solving with the MATH dataset. In Joaquin Vanschoren and Sai-Kit Yeung (eds.), *Proceedings of the Neural Information Processing Systems Track on Datasets and Benchmarks 1, NeurIPS Datasets and Benchmarks 2021, December 2021, virtual*, 2021. URL <https://datasets-benchmarks-proceedings.neurips.cc/paper/2021/hash/be83ab3ecd0db773eb2dc1b0a17836a1-Abstract-round2.html>.

- Jian Hu. REINFORCE++: A simple and efficient approach for aligning large language models. *CoRR*, abs/2501.03262, 2025. doi: 10.48550/ARXIV.2501.03262. URL <https://doi.org/10.48550/arXiv.2501.03262>.
- Jingcheng Hu, Yinmin Zhang, Qi Han, Dixin Jiang, Xiangyu Zhang, and Heung-Yeung Shum. Open-reasoner-zero: An open source approach to scaling up reinforcement learning on the base model, 2025. URL <https://arxiv.org/abs/2503.24290>.
- Amirhossein Kazemnejad, Milad Aghajohari, Eva Portelance, Alessandro Sordoni, Siva Reddy, Aaron C. Courville, and Nicolas Le Roux. Vineppo: Unlocking RL potential for LLM reasoning through refined credit assignment. *CoRR*, abs/2410.01679, 2024. doi: 10.48550/ARXIV.2410.01679. URL <https://doi.org/10.48550/arXiv.2410.01679>.
- Kimi, Angang Du, Bofei Gao, Bowei Xing, Changjiu Jiang, Cheng Chen, Cheng Li, Chenjun Xiao, Chenzhuang Du, Chonghua Liao, Chuning Tang, Congcong Wang, Dehao Zhang, Enming Yuan, Enzhe Lu, Fengxiang Tang, Flood Sung, Guangda Wei, Guokun Lai, Haiqing Guo, Han Zhu, Hao Ding, Hao Hu, Hao Yang, Hao Zhang, Haotian Yao, Haotian Zhao, Haoyu Lu, Haoze Li, Haozhen Yu, Hongcheng Gao, Huabin Zheng, Huan Yuan, Jia Chen, Jianhang Guo, Jianlin Su, Jianzhou Wang, Jie Zhao, Jin Zhang, Jingyuan Liu, Junjie Yan, Junyan Wu, Lidong Shi, Ling Ye, Longhui Yu, Mengnan Dong, Neo Zhang, Ningchen Ma, Qiwei Pan, Qucheng Gong, Shaowei Liu, Shengling Ma, Shupeng Wei, Sihan Cao, Siying Huang, Tao Jiang, Weihao Gao, Weimin Xiong, Weiran He, Weixiao Huang, Wenhao Wu, Wenyang He, Xianghui Wei, Xianqing Jia, Xingzhe Wu, Xinran Xu, Xinxing Zu, Xinyu Zhou, Xuehai Pan, Y. Charles, Yang Li, Yangyang Hu, Yangyang Liu, Yanru Chen, Yejie Wang, Yibo Liu, Yidao Qin, Yifeng Liu, Ying Yang, Yiping Bao, Yulun Du, Yuxin Wu, Yuzhi Wang, Zaida Zhou, Zhaoji Wang, Zhaowei Li, Zhen Zhu, Zheng Zhang, Zhexu Wang, Zhilin Yang, Zhiqi Huang, Zihao Huang, Ziyao Xu, and Zonghan Yang. Kimi k1.5: Scaling reinforcement learning with llms. *CoRR*, abs/2501.12599, 2025. doi: 10.48550/ARXIV.2501.12599. URL <https://doi.org/10.48550/arXiv.2501.12599>.
- Aitor Lewkowycz, Anders Andreassen, David Dohan, Ethan Dyer, Henryk Michalewski, Vinay V. Ramasesh, Ambrose Sloane, Cem Anil, Imanol Schlag, Theo Gutman-Solo, Yuhuai Wu, Behnam Neyshabur, Guy Gur-Ari, and Vedant Misra. Solving quantitative reasoning problems with language models. In Sanmi Koyejo, S. Mohamed, A. Agarwal, Danielle Belgrave, K. Cho, and A. Oh (eds.), *Advances in Neural Information Processing Systems 35: Annual Conference on Neural Information Processing Systems 2022, NeurIPS 2022, New Orleans, LA, USA, November 28 - December 9, 2022*, 2022. URL http://papers.nips.cc/paper_files/paper/2022/hash/18abbeef8cfe9203fdf9053c9c4fe191-Abstract-Conference.html.
- Jia Li, Edward Beeching, Lewis Tunstall, Ben Lipkin, Roman Soletskyi, Shengyi Huang, Kashif Rasul, Longhui Yu, Albert Q Jiang, Ziju Shen, et al. NuminaMath: The largest public dataset in ai4maths with 860k pairs of competition math problems and solutions. *Hugging Face repository*, 13:9, 2024. URL http://faculty.bicmr.pku.edu.cn/~dongbin/Publications/numina_dataset.pdf.
- Xuefeng Li, Haoyang Zou, and Pengfei Liu. LIMR: less is more for RL scaling. *CoRR*, abs/2502.11886, 2025. doi: 10.48550/ARXIV.2502.11886. URL <https://doi.org/10.48550/arXiv.2502.11886>.
- Zichen Liu, Changyu Chen, Wenjun Li, Penghui Qi, Tianyu Pang, Chao Du, Wee Sun Lee, and Min Lin. Understanding r1-zero-like training: A critical perspective. *CoRR*, abs/2503.20783, 2025. doi: 10.48550/ARXIV.2503.20783. URL <https://doi.org/10.48550/arXiv.2503.20783>.
- John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. Proximal policy optimization algorithms. *CoRR*, abs/1707.06347, 2017. URL <http://arxiv.org/abs/1707.06347>.
- Zhihong Shao, Peiyi Wang, Qihao Zhu, Runxin Xu, Junxiao Song, Mingchuan Zhang, Y. K. Li, Y. Wu, and Daya Guo. Deepseekmath: Pushing the limits of mathematical reasoning in open language models. *CoRR*, abs/2402.03300, 2024. doi: 10.48550/ARXIV.2402.03300. URL <https://doi.org/10.48550/arXiv.2402.03300>.

Guangming Sheng, Chi Zhang, Zilingfeng Ye, Xibin Wu, Wang Zhang, Ru Zhang, Yanghua Peng, Haibin Lin, and Chuan Wu. Hybridflow: A flexible and efficient rlhf framework. In *Proceedings of the Twentieth European Conference on Computer Systems*, pp. 1279–1297, 2025.

Mingyang Song, Mao Zheng, Zheng Li, Wenjie Yang, Xuan Luo, Yue Pan, and Feng Zhang. Fastcurl: Curriculum reinforcement learning with progressive context extension for efficient training r1-like reasoning models. *CoRR*, abs/2503.17287, 2025. doi: 10.48550/ARXIV.2503.17287. URL <https://doi.org/10.48550/arXiv.2503.17287>.

Shenzhi Wang, Le Yu, Chang Gao, Chujie Zheng, Shixuan Liu, Rui Lu, Kai Dang, Xionghui Chen, Jianxin Yang, Zhenru Zhang, et al. Beyond the 80/20 rule: High-entropy minority tokens drive effective reinforcement learning for llm reasoning. *arXiv preprint arXiv:2506.01939*, 2025.

Liang Wen, Yunke Cai, Fenrui Xiao, Xin He, Qi An, Zhenyu Duan, Yimin Du, Junchen Liu, Lifu Tang, Xiaowei Lv, Haosheng Zou, Yongchao Deng, Shousheng Jia, and Xiangzheng Zhang. Light-r1: Curriculum sft, DPO and RL for long COT from scratch and beyond. *CoRR*, abs/2503.10460, 2025. doi: 10.48550/ARXIV.2503.10460. URL <https://doi.org/10.48550/arXiv.2503.10460>.

Zhiheng Xi, Wenxiang Chen, Boyang Hong, Senjie Jin, Rui Zheng, Wei He, Yiwen Ding, Shichun Liu, Xin Guo, Junzhe Wang, Honglin Guo, Wei Shen, Xiaoran Fan, Yuhao Zhou, Shihan Dou, Xiao Wang, Xinbo Zhang, Peng Sun, Tao Gui, Qi Zhang, and Xuanjing Huang. Training large language models for reasoning through reverse curriculum reinforcement learning. In *Forty-first International Conference on Machine Learning, ICML 2024, Vienna, Austria, July 21-27, 2024*. OpenReview.net, 2024. URL <https://openreview.net/forum?id=t82Y3fmRtk>.

Zhicheng Yang, Zhijiang Guo, Yinya Huang, Xiaodan Liang, Yiwei Wang, and Jing Tang. Treerpo: Tree relative policy optimization. *arXiv preprint arXiv:2506.05183*, 2025.

Qiyi Yu, Zheng Zhang, Ruofei Zhu, Yufeng Yuan, Xiaochen Zuo, Yu Yue, Tiantian Fan, Gaohong Liu, Lingjun Liu, Xin Liu, Haibin Lin, Zhiqi Lin, Bole Ma, Guangming Sheng, Yuxuan Tong, Chi Zhang, Mofan Zhang, Wang Zhang, Hang Zhu, Jinhua Zhu, Jiaze Chen, Jiangjie Chen, Chengyi Wang, Hongli Yu, Weinan Dai, Yuxuan Song, Xiangpeng Wei, Hao Zhou, Jingjing Liu, Wei-Ying Ma, Ya-Qin Zhang, Lin Yan, Mu Qiao, Yonghui Wu, and Mingxuan Wang. DAPO: an open-source LLM reinforcement learning system at scale. *CoRR*, abs/2503.14476, 2025. doi: 10.48550/ARXIV.2503.14476. URL <https://doi.org/10.48550/arXiv.2503.14476>.

Yufeng Yuan, Yu Yue, Ruofei Zhu, Tiantian Fan, and Lin Yan. What's behind ppo's collapse in long-cot? value optimization holds the secret. *CoRR*, abs/2503.01491, 2025. doi: 10.48550/ARXIV.2503.01491. URL <https://doi.org/10.48550/arXiv.2503.01491>.

Yu Yue, Yufeng Yuan, Qiyi Yu, Xiaochen Zuo, Ruofei Zhu, Wenyuan Xu, Jiaze Chen, Chengyi Wang, TianTian Fan, Zhengyin Du, Xiangpeng Wei, Xiangyu Yu, Gaohong Liu, Juncai Liu, Lingjun Liu, Haibin Lin, Zhiqi Lin, Bole Ma, Chi Zhang, Mofan Zhang, Wang Zhang, Hang Zhu, Ru Zhang, Xin Liu, Mingxuan Wang, Yonghui Wu, and Lin Yan. Vapo: Efficient and reliable reinforcement learning for advanced reasoning tasks, 2025. URL <https://arxiv.org/abs/2504.05118>.

Weihao Zeng, Yuzhen Huang, Qian Liu, Wei Liu, Keqing He, Zejun Ma, and Junxian He. Simplerl-zoo: Investigating and taming zero reinforcement learning for open base models in the wild. *CoRR*, abs/2503.18892, 2025. doi: 10.48550/ARXIV.2503.18892. URL <https://doi.org/10.48550/arXiv.2503.18892>.

Xiaojiang Zhang, Jinghui Wang, Zifei Cheng, Wenhao Zhuang, Zheng Lin, Minglei Zhang, Shaojie Wang, Yinghan Cui, Chao Wang, Junyi Peng, et al. Srpo: A cross-domain implementation of large-scale reinforcement learning on llm. *arXiv preprint arXiv:2504.14286*, 2025. URL <https://arxiv.org/abs/2504.14286>.

A USAGE OF LLMs

Throughout the preparation of this manuscript, Large Language Models (LLMs) were utilized as a writing and editing tool. Specifically, we employed LLMs to improve the clarity and readability of the text, refine sentence structures, and correct grammatical errors. All final content, including the core scientific claims, experimental design, and conclusions, was conceived and written by us, and we take full responsibility for the final version of this paper.

B DETAILS OF EXPERIMENTAL SETUP

All algorithms are implemented based on the official GRPO codebase within the VeRL framework. We use a learning rate of 1e-6 without warm-up across all experiments. At each rollout step, we generate 8 answers for each of 512 sampled questions, then split the data into 16 mini-batches and train the policy network for 16 gradient steps. Models are trained for at most 150 rollout steps. Unless otherwise specified, we follow GRPO’s default design choices with token-level loss normalization without dynamic sampling and KL regularization. For all models, the maximum input length is 1024 and the minimum input length is 3072. All the experiments were conducted on H20 GPUs.

Note: The authors of Eurus-PRIME only published results from training on Qwen2.5-Math-7B. Therefore, we do not include results for the Qwen2.5-7B model in our comparison.

C SUPPLEMENTARY EXPERIMENT: EFFECT OF METRIC SELECTION

Table 5: Ablation study comparing our proposed node-level modification metric (‘Fix’) with a branch-level ‘Pruning’ metric. ‘Fix’ consistently outperforms ‘Pruning’, validating our fine-grained approach.

Model	AIME24	AIME25	AMC23	MATH500	Minerva	Olympiad	Avg.
Fix							
Re-Schedule (linear)	34.2	15.6	72.4	81.2	36.4	42.5	47.1
Re-Schedule (sigmoid)	34.2	16.0	71.1	81.8	42.3	44.4	48.3
Pruning							
Re-Schedule (linear)	35.7	14.6	73.7	81.0	34.9	41.6	46.9
Re-Schedule (sigmoid)	33.1	16.7	71.1	82.0	39.0	42.4	47.4

We validate our core design choice for the r-score calculation. Our proposed method (‘Fix’) defines an ‘edit’ as a single node modification. We compare this against an alternative (‘Pruning’), where an ‘edit’ is defined as pruning an entire sub-branch from a decision point. Table 5 shows that the ‘Fix’ method consistently outperforms ‘Pruning’ for both linear (47.1% vs. 46.9%) and sigmoid (48.3% vs. 47.4%) schedules. This result shows that compared with the branch ‘Pruning’, the node ‘Fix’ is more consistent with the training process of reinforcement learning.