# REWARDING THE JOURNEY, NOT JUST THE DESTINATION: A COMPOSITE PATH AND ANSWER SELF-SCORING REWARD MECHANISM FOR TEST-TIME REINFORCEMENT LEARNING

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#### **ABSTRACT**

Reinforcement Learning (RL) has emerged as a powerful paradigm for advancing Large Language Models (LLMs), achieving remarkable performance in complex reasoning domains such as mathematics and code generation. However, current RL methods face a fundamental scalability bottleneck due to their heavy reliance on human-curated preference data or labeled datasets for reward modeling. To overcome this limitation, we explore RL on unlabeled data where models learn autonomously from continuous experience streams. The core challenge in this setting lies in reliable reward estimation without ground-truth supervision. Existing approaches like Test-Time RL address this through self-consistent consensus, but risk reinforcing incorrect pseudo-labels derived from majority voting. We introduce COMPASS (Composite Path and Answer Self-Scoring), a novel test-time reward mechanism that operates without external supervision. COM-PASS integrates two complementary components: the Dual-Calibration Answer Reward (DCAR), which stabilizes training by establishing trustworthy pseudolabels through confidence and credibility calibration, and the Decisive Path Reward (DPR), which directly optimizes the reasoning process quality beyond mere outcome supervision. By jointly reinforcing trustworthy consensus answers and highly decisive reasoning chains, the **COMPASS** systematically enhances the model's analytical capabilities. Extensive experiments show that COMPASS achieves significant and consistent performance gains across diverse reasoning tasks and model architectures, advancing a more scalable direction for LLMs to learn from continuous experience.

# 1 Introduction

Reinforcement Learning (RL) (Kaelbling et al., 1996; Dong et al., 2024) has emerged as a powerful paradigm for advancing the capabilities of pre-trained Large Language Models (LLMs), driving

significant progress in complex reasoning domains, e.g., mathematics Setlur et al. (2024); Gao et al. (2024); Albright & Andemicael (2025) and code generation (Guo et al., 2025; Achiam et al., 2023; Team, 2025; Wang et al., 2024; Islam et al., 2024). However, current RL approaches predominantly rely on explicit external supervision through ground-truth labels (Luong et al., 2024; Ouyang et al., 2022; Shao et al., 2024) or human preference data to construct reward functions. This dependency creates a fundamental scalability bottleneck: as tasks grow in complexity and volume, large-scale annotation becomes increasingly impractical, hindering the continuous evolution of state-of-the-art models.

This limitation naturally motivates an alternative paradigm where LLMs autonomously improve through RL on unlabeled data, learning directly from continuous experience streams (Zhang et al., 2025c; Xiong et al., 2025; Huang et al., 2024). However, the core challenge in this paradigm lies in reward estimation during inference without access to ground-truth information. Test-Time Reinforcement Learning (TTRL) (Zuo et al., 2025) formalizes this setting by enabling parameter updates using unlabeled test data—a promising direction that has recently gained significant attraction. TTRL addresses the reward challenge by sampling multiple responses per problem and constructing pseudo-labels through self-consistency consensus via majority voting. The approach relies on the model's intrinsic confidence as a proxy metric when external rewards are unavailable: answers consistently reproduced across multiple trials are considered higher-confidence and thus more likely to be correct. This mechanism mirrors human problem-solving, where conclusions verified through diverse methods strengthen our confidence in their validity.

While using confidence as a correctness proxy aligns with cognitive principles, a critical question remains: how is confidence actually manifested in the reasoning process of LLMs? TTRL(Zuo et al., 2025) adopts self-consistency via majority voting as its confidence proxy. However, this choice has clear limitations. When initial pseudo-labels derived from voting are biased or incorrect, reflecting flaws in the pre-trained model's prior knowledge, the model risks reinforcing erroneous consensus. This raises an important motivation for our work: can we exploit other forms of prior knowledge within LLMs to mitigate these limitations and obtain more reliable self-reward signals? Since LLMs fundamentally operate as next-token predictors, their most direct internal state evidence resides in the probability distribution over candidate tokens. Different measures of this distribution naturally yield alternative notions of model confidence. For instance, the entropy of the distribution reflects uncertainty—lower entropy indicates higher confidence. Similarly, the probability assigned to the top-1 token represents the model's certainty in its preferred choice. Moreover, the margin between the top-1 and top-2 token probabilities captures decisiveness; a larger margin implies the model is less hesitant, and thus more confident.

Our analysis indicates that the token-level probability distribution encodes rich internal signals that extend beyond simple majority voting, providing a principled basis for guiding the model's optimization toward more reliable reasoning and answers. To systematically leverage these signals, we introduce **COMPASS** (**Com**posite **P**ath and **A**nswer **S**elf-**S**coring), a novel reward mechanism that combines answer-level calibration with path-level evaluation. **COMPASS** consists of two components: the Dual-Calibration Answer Reward (DCAR) and Decisive Path Reward (DPR). First, DCAR refines majority voting by incorporating confidence measures and assessing the credibility of pseudo-labels, effectively enhancing learning stability and efficiency. Furthermore, DPR moves beyond the final answer to scrutinize each step of the generation process. Through an entropyweighting mechanism, it encourages the model to make more decisive choices (high decisiveness) at critical junctures of high uncertainty (high entropy), providing a direct and dense supervisory signal for optimizing the reasoning path. Our contributions can be summarized as follows:

- We propose **COMPASS**, a novel self-scoring reward mechanism for reinforcement learning on unlabeled data that enables LLM self-evolution through intrinsic evaluation of both final answers and intermediate reasoning paths.
- We design a composite reward function featuring two innovative components: DCAR, which dual-calibrates consensus for more reliable answer rewards, and DPR, which introduces process-centric evaluation through dense rewards for decisive token generation during uncertain reasoning steps.
- Extensive experiments across diverse reasoning benchmarks demonstrate **COMPASS**'s effectiveness and superiority, marking a significant advancement in learning from continuous experience streams.

# 2 RELATED WORK

#### 2.1 RL FOR REASONING

RL plays a critical role in enhancing the instruction-following and reasoning capabilities of LLMs (Guo et al., 2025; Ouyang et al., 2022). Over time, research in this direction has evolved through three main paradigms, each progressively reducing reliance on external supervision. Reinforcement Learning from Human Feedback (RLHF) (Ouyang et al., 2022; Zheng et al., 2023; Dai et al., 2023), aligns base models with human preferences using learnable reward models trained on annotated preference data. Methods such as Proximal Policy Optimization (PPO) (Schulman et al., 2017) are widely employed, but the dependence on large-scale human feedback limits scalability. Reinforcement Learning with Verifiable Rewards (RLVR) (Luong et al., 2024; Shao et al., 2024), replaces preference-based supervision with rule-based reward functions grounded in gold-standard answers. This class of methods, which has been particularly effective for math and code generation tasks, reduces the need for nuanced human feedback but still requires labeled datasets to provide ground-truth answers. Reinforcement Learning from Internal Feedback (RLIF) (Zhang et al., 2025a; Zuo et al., 2025; Zhao et al., 2025), eliminates explicit supervision altogether by leveraging intrinsic signals from LLMs themselves. The underlying idea is that LLMs already possess a substantial amount of knowledge, which—if effectively organized—can support correct reasoning. However, direct inference after supervised training often fails to fully exploit this potential, requiring reinforcement learning to discover strategies that better coordinate and utilize existing knowledge. Conceptually, RLIF aims to formalize this intuition by framing the organization and utilization of pre-existing knowledge within LLMs as a policy optimization problem, wherein intrinsic feedback signals serve as implicit rewards guiding the emergence of more effective reasoning strategies. For example, EMPO (Zhang et al., 2025a) incentivizes reasoning by minimizing entropy in a latent semantic space, while TTRL (Zuo et al., 2025) generates pseudo-labels via self-consistency consensus among multiple sampled responses and uses them to compute rewards. These approaches mark a shift toward self-rewarding reinforcement learning, aiming to enable LLMs to improve directly from unlabeled data. Our work also falls within the scope of RLIF.

### 2.2 CONFIDENCE-BASED REWARD

In fully unsupervised settings (Zhang et al., 2025b; Wei et al., 2025), where ground-truth labels are unavailable, directly optimizing for the correctness of Large Language Model (LLM) outputs is infeasible. A natural alternative is to exploit intrinsic proxy metrics that correlate strongly with correctness. Among these, model confidence (Xiong et al., 2023; Tripathi et al., 2025; Tian et al., 2025) has emerged as a particularly informative indicator, mirroring human cognition, in which confidence serves as an internal estimate of reliability in the absence of external supervision. Current confidence-based reward methods have evolved along three complementary trajectories. One paradigm quantifies confidence through the log-likelihood of generated sequences, rewarding responses that the model assigns higher probability; for instance, RLSC (Li et al., 2025) reinforces generation by maximizing sequence log-likelihood. Another paradigm centers on entropy minimization, where lower entropy implies greater certainty—an idea instantiated by RENT (Prabhudesai et al.), which encourages more decisive and coherent outputs. A third direction evaluates selfconsistency across multiple samples, as in TTRL (Zuo et al., 2025), which derives pseudo-labels via consensus among sampled responses and reinforces outputs consistent with the emergent majority. While these confidence-based methods have yielded notable gains in reasoning and stability, they predominantly rely on a single dimension of confidence—whether likelihood, entropy, or consensus. This leaves open an important question: how can multiple complementary confidence signals be integrated to construct more reliable and fine-grained self-reward mechanisms? Our work addresses this gap by proposing a unified reward framework that leverages diverse intrinsic feedback sources to guide more robust self-improvement in LLMs.

#### 2.3 TEST-TIME ADAPTATION

Test-Time Adaptation (TTA) (Sun et al., 2017; Maria Carlucci et al., 2017; Schneider et al., 2020) refers to updating a model on unlabeled test data during inference, aiming to mitigate performance degradation caused by distribution shifts between training and testing environments. Early studies in computer vision primarily explored unsupervised objectives that promote robustness to domain

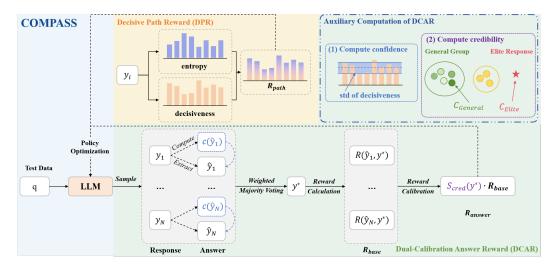


Figure 1: The Composite Path and Answer Self-Scoring (COMPASS) reward mechanism. Given a prompt q, the policy LLM samples multiple candidate responses  $\{y_1, y_2, \cdots, y_N\}$ . The Dual-Calibration Answer Reward (DCAR) firstly constructs a consensus pseudo-label  $y^*$  via confidence-calibrated self-consistency, where each response's contribution is weighted by its decisiveness-derived confidence. DCAR further evaluates the credibility of this consensus by comparing the confidence of the general supporting group against the most confident elite response, yielding a reliability-calibrated answer reward  $R_{answer}$ . Complementarily, the Decisive Path Reward (DPR) assesses the reasoning process quality by computing step-wise entropy and decisiveness measures to generate the path reward  $R_{path}$ . Together, DCAR and DPR form a unified intrinsic reward framework that reinforces both trustworthy answers and high-quality reasoning processes.

shifts. More recently, the TTA paradigm has been extended to LLMs and reasoning tasks. For instance, Tent (Wang et al., 2020) adapts models by minimizing the entropy of predictions, under the assumption that well-adapted models should produce certain (i.e., low-entropy) outputs on test samples. Similarly, TTRL (Zuo et al., 2025) introduces test-time reinforcement learning, where rewards are derived from self-consistency via majority voting among sampled responses. Despite these advances, most existing TTA approaches remain limited in scope: they either focus on generic uncertainty reduction or rely on outcome-level consensus, offering only indirect supervision over the underlying reasoning process. This limitation highlights the need for more expressive test-time reward mechanisms that can jointly assess both answer reliability and reasoning quality, thereby enabling stronger and more principled adaptation in LLMs.

# 3 COMPOSITE PATH AND ANSWER SELF-SCORING

This section introduces the proposed COMPASS framework for reinforcement learning on unlabeled data. COMPASS is motivated by the observation that the token-level probability distribution of LLMs encodes multiple internal signals, e.g., uncertainty, confidence, and decisiveness, which can serve as intrinsic feedback for guiding optimization. COMPASS systematically integrates these signals to provide more reliable and fine-grained rewards. Specifically, given a state represented by the prompt q, the model acts by producing an output y sampled from a policy  $\pi_{\theta}(y \mid q)$  parameterized by  $\theta$ . To construct reward signals without ground-truth labels, we generate multiple candidate responses and extract the corresponding answers  $\{\hat{y}_1, \hat{y}_2, \dots, \hat{y}_N\}$  from the model through repeated sampling. A consensus output  $y^*$  is derived through *confidence-calibrated self-consistency*, serving as a proxy for the optimal action. The environment then provides a reward  $R(\hat{y}_i, y^*)$  based on the alignment between the sampled action  $\hat{y}_i$  and the consensus action  $y^*$ . To further stabilize RL training, we propose a *credibility* metric to assess the quality of generated pseudo-labels. In addition to the aforementioned outcome-based Dual-Calibration Answer Reward (DCAR), we also introduce the process-based Decisive Path Reward (DPR) to evaluate the reasoning quality of each candidate response. As shown in Figure 1, the proposed COMPASS consisting of DCAR and DPR achieves reinforcement learning on data without explicit labels.

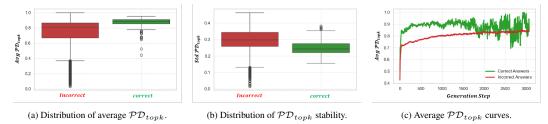


Figure 2: Analysis of  $\mathcal{PD}_{topk}$  indicators validating confidence-calibrated self-consistency. (a) Distribution of average  $\mathcal{PD}_{topk}$  values, showing systematic differences between correct and incorrect responses. (b) Distribution of  $\mathcal{PD}_{topk}$  stability throughout generation trajectories, demonstrating more consistent decisiveness in correct answers. (c) Average  $\mathcal{PD}_{topk}$  curves across generation steps, revealing that correct responses maintain higher and more stable decisiveness throughout reasoning. These empirical findings confirm that the probability difference between top-1 and top-2 tokens strongly correlates with answer correctness.

#### 3.1 DUAL-CALIBRATION ANSWER REWARD (DCAR)

A central challenge in RL on unlabeled data is ensuring the reliability of pseudo-labels for stable optimization. To address this, we design the DCAR, which refines consensus answers by integrating two complementary signals: confidence and credibility. Our approach begins with a key hypothesis: more confident responses should contribute more significantly to the final decision. As shown in Figure 2, this hypothesis is supported by our correlation analysis, which reveals that  $\mathcal{PD}_{topk}$ , i.e., the probability difference between top-1 and top-2 tokens across the generation trajectory, strongly correlates with final answer correctness, capturing the model's predictive stability and decisiveness. Building on this insight, we implement confidence-calibrated self-consistency, where more decisive responses receive higher weighting in pseudo-label formation. Therefore, we first define the confidence of a trajectory  $\hat{y}_i$  as:

$$\mathcal{PD}_{topk}(x_t) = p(x_t^1 | x_{< t}) - p(x_t^2 | x_{< t}), \tag{1}$$

$$c(\hat{y}_i) = \exp\left(-\operatorname{std}_t \mathcal{P}\mathcal{D}_{topk}(x_t)\right),\tag{2}$$

where  $x_t^1$  and  $x_t^2$  represent the top-1 and top-2 tokens at timestep t. And we then define *confidence* as the negative exponential of the standard deviation (std), which ensures lower std yields higher confidence and guarantees positive weights required for self-consistency. Finally, for a given answer y, we design the *confidence-calibrated self-consistency* score  $\mathcal{S}_{ccsc}$  as the confidence-weighted sum:

$$S_{ccsc}(y) = \frac{\sum_{i:\hat{y}_i = y} c(\hat{y}_i)}{\sum_{i=1}^{N} c(\hat{y}_i)}.$$
(3)

The final pseudo-label  $y^*$  is determined as the answer with the highest calibrated score:

$$y^* = \arg\max_{y} \mathcal{S}_{ccsc}(y). \tag{4}$$

To further enhance the reliability of our confidence-calibrated pseudo-label  $y^*$ , we introduce a *credibility* score  $\mathcal{S}_{cred}$  that assesses consensus quality relative to the most confident response, effectively implementing soft curriculum learning. This approach is grounded in a key hypothesis: *a consensus derived from high-confidence responses is more reliable than one based on diverse low-confidence outputs*. Building on this principle, we define the credibility metric using two fundamental concepts: *General Group*  $\mathcal{C}_{General}$  and *Elite Response*  $\mathcal{C}_{Elite}$ . Specifically, the *General Group* contains all responses that agree with the pseudo-label  $y^*$ . The group's confidence  $\mathcal{C}_{General}$  is defined as the maximum confidence within this subset, representing the strongest supporting evidence for the consensus, and the  $\mathcal{C}_{Elite}$  is the response among all N candidates with the highest confidence:

$$C_{\text{General}} = \max_{i:\hat{y}_i = y^*} c(\hat{y}_i), \quad C_{\text{Elite}} = \max_{i=1,\dots,N} c(\hat{y}_i). \tag{5}$$

The *credibility* of the pseudo-label  $y^*$  is the ratio of these two confidence scores:

$$S_{cred}(y^*) = \frac{C_{General}}{C_{Elite}}.$$
 (6)

Algorithm 1: The Complete Composite Path and Answer Self-Scoring Reward.

```
Input: Prompt q, policy \pi_{\theta}, number of samples N
Output: Final rewards \{R(y_i)\}_{i=1}^N
Initialize: trajectories Y, answers \hat{Y}, confidences C, decisiveness sequences D, entropy sequences H
/* -----DCAR: Dual-Calibration Answer Reward-----
for i \leftarrow 1 to N do
     Sample y_i \sim \pi_{\theta}(\cdot|q), extract answer \hat{y}_i
     Compute confidence c(\hat{y}_i) = \exp(-std_t \cdot \mathcal{PD}_{topk}(x_t))
     Append to Y, \hat{Y}, C:
Find unique answers A = \text{unique}(\hat{Y}), initialize S[a] \leftarrow 0
foreach a \in A do
 S[a] \leftarrow \sum_{\hat{y}_i = a} c(\hat{y}_i)
y^* = \arg\max_{a \in A} S[a]
\mathcal{C}_{\text{General}} \leftarrow \max(\{\mathbf{c}(\hat{y}_i) \mid \hat{y}_i = y^*\})
C_{\text{Elite}} \leftarrow \max(\{\mathbf{c}(\hat{y}_i)\})
\mathcal{S}_{cred}(y^*) \leftarrow \mathcal{C}_{General}/\mathcal{C}_{Elite}
for i \leftarrow 1 to N do
  \begin{bmatrix} R_{\text{base}} \leftarrow \mathbb{I}[\hat{y}_i = y^*] \\ R_{\text{answer}}(y_i) \leftarrow \mathcal{S}_{cred}(y^*) \cdot R_{\text{base}} \end{bmatrix} 
/* -----DPR: Decisive Path Reward-----
for i \leftarrow 1 to N do
     for t \leftarrow 1 to T do
           d_t \leftarrow \mathcal{PD}_{topk}(x_t)
       h_t \leftarrow -\sum_j p(x_t^j|x_{< t}) \log p(x_t^j|x_{< t})
Append d_t to D[i], h_t to H[i]
     w_t \leftarrow \frac{e^{h_t}}{\sum_{j=1}^T e^{h_j}}
    R_{\text{path}}(y_i) \leftarrow \sum_{t=1}^{T} w_t \cdot d_t
for i \leftarrow 1 to N do
   L R(y_i) \leftarrow R_{\text{answer}}(y_i) + R_{\text{path}}(y_i) 
return \{R(y_i)\}_{i=1}^N;
```

This ratio quantifies the consensus strength relative to the most confident individual response. A value of 1 indicates perfect alignment between the consensus and the most confident opinion, signifying high reliability, whereas values below 1 reveal the presence of highly confident dissenters, thereby reducing trust in the consensus outcome. The final outcome reward  $R_{\rm answer}$  in our DCAR module integrates the base reward  $R_{\rm base}(\hat{y}_i)$  with the credibility score  $\mathcal{S}_{cred}$  through multiplicative modulation:

$$R_{\text{answer}}(\hat{y}_i) = \mathcal{S}_{cred}(y^*) \cdot R_{\text{base}}(\hat{y}_i), \tag{7}$$

where  $R_{\rm base}(\hat{y}_i)$  is a binary indicator that equals 1 if  $\hat{y}_i$  matches the pseudo-label  $y^*$  and 0 otherwise. This formulation transforms the sparse binary reward into a continuous signal within [0,1], implementing a soft curriculum learning mechanism that directs the model's focus toward high-credibility pseudo-labels, thereby promoting more stable and reliable optimization.

# 3.2 DECISIVE PATH REWARD (DPR)

While DCAR provides robust outcome-level supervision, effective reasoning requires complementary process-level guidance. To address this, we introduce the DPR to encourage decisive actions at critical reasoning junctures to ensure the integrity of the entire reasoning chain. DPR operates by providing dense per-token feedback that directly optimizes reasoning trajectories through entropy-weighted decisiveness scoring. Specifically, we evaluate two complementary metrics at each generation step t: decisiveness  $d_t$ , quantifying the model's confidence in its token selection, and uncertainty  $h_t$ , measuring the entropy of the predictive distribution. The decisiveness at each position is defined as:

$$d_t = \mathcal{PD}_{topk}(x_t), \tag{8}$$

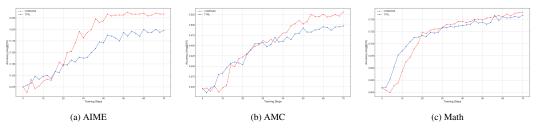


Figure 3: Performance comparison on AIME/AMC/MATH using Qwen2.5-7B.

with higher values  $d(x_t)$  indicating more confident and unambiguous decisions. Our central hypothesis posits that decisiveness carries greater importance during high-uncertainty moments, where confident actions provide more informative signals when multiple alternatives appear viable. Based on this premise, we define the process reward  $R_{\text{path}}(y_i)$  by dynamically weighting each step's decisiveness by its corresponding uncertainty:

$$w_t = \frac{e^{h_t}}{\sum_{i=1}^T e^{h_i}}, \quad R_{\text{path}}(y_i) = \sum_{t=1}^T w_t \cdot d_t.$$
 (9)

This formulation provides dense, per-token feedback that incentivizes decisive actions at critical high-uncertainty junctures, fostering more robust reasoning paths. The complete COMPASS reward combines both components (see Algorithm 1):

$$R(y_i) = R_{\text{answer}}(y_i) + R_{\text{path}}(y_i). \tag{10}$$

#### 4 EXPERIMENTS

# 4.1 EXPERIMENTAL SETUP

Benchmarks. To comprehensively evaluate COMPASS's generalizability, we employ diverse backbone models spanning different scales and specializations: LLaMA-3.2-1B-Instruct (Meta, 2024) as an instruct-tuned model, Qwen2.5-Math-1.5B (Yang et al., 2025) as a mathematically specialized base model, and Qwen2.5-7B (Yang et al., 2025) as a general-purpose base model. We conduct evaluation on GPQA-Diamond (Rein et al., 2024), a challenging subset of the Graduate-Level Google-Proof Question Answering benchmark, alongside three mathematical reasoning benchmarks: AIME 2024 (Yuan et al., 2024), AMC (Yuan et al., 2024), and MATH-500 (Hendrycks et al., 2021). As TTRL (Zuo et al., 2025) pioneered the test-time reinforcement learning paradigm, we primarily compare COMPASS against both backbone models and TTRL baselines to validate its effectiveness in enabling autonomous self-improvement.

**Metrics.** We evaluate COMPASS independently on each benchmark using the pass@k protocol following DeepSeek-R1 (Guo et al., 2025), reporting pass@1 scores with non-zero temperature sampling. Specifically, we generate 16 responses per question (4 for 32k context length) using temperature 0.6 and top-p 0.95. The pass@1 score is computed as: pass@1 =  $\frac{1}{k} \sum_{i=1}^{k} p_i$ , where  $p_i \in 0, 1$  indicates the correctness of the i-th response.

Implementation Details. We implement COMPASS using GRPO (Shao et al., 2024) independently on each benchmark. For optimization, we employ AdamW with a cosine learning rate schedule (peak  $5 \times 10^{-7}$ ). During rollout, we sample 64 responses (temperature 0.6, except 1.0 for Qwen2.5-Math) for pseudo-label estimation via voting, then downsample to 32 responses per prompt for training. This design maintains computational efficiency while achieving strong performance. For models with fewer than 7B parameters, we follow TTRL settings with 10, 30, and 80 episodes for MATH-500, AMC, and AIME 2024 respectively, scaled by dataset size. For Qwen2.5-7B, we reduce epochs to 2, 8, and 20 (approximately 20% of TTRL's budget) to evaluate efficiency in computationally constrained regimes.

Table 1: Performance comparison on test-time reinforcement learning on various benchmarks. \* indicates our reproduction of TTRL; † denotes an evaluation with a reduced number of training epochs compared to the original TTRL paper, a condition applied to both methods for a fair comparison.

Name	AIME	AMC	MATH	GPQA
	Instr	uct Models		
LLaMA3.2-1B-Instruct	1.5	9.8	24.7	23.8
TTRL	6.7	19.2	27.8	24.0
COMPASS	3.5	20.1	28.7	25.8
$\Delta$	-3.1	+0.9	+0.9	+1.8
	Math	Base Models		
Qwen2.5-Math-1.5B	7.7	28.6	32.7	24.9
TTRL	15.8	47.4*	$72.4^{*}$	26.1
COMPASS	18.3	48.6	73.1	29.3
$\Delta$	+2.5	+1.2	+0.7	+3.2
	Vanilla	Base Models		
$Qwen2.5-7B^{\dagger}$	7.5	34.6	60.9	30.5
TTRL	20.0	50.2	76.6	31.1
COMPASS	23.5	53.2	76.9	31.7
$\Delta$	+3.5	+3.0	+0.3	+0.6

#### 4.2 MAIN RESULTS

COMPASS performs well on most tasks and models. Table 1 presents the main results. We apply COMPASS to 3 models spanning 3 model families, 2 model types, and 3 model sizes, consistently demonstrating obvious improvements across 4 highly challenging benchmarks. On the AIME 2024 and GPQA benchmarks, COMPASS achieves significant improvements of 15.8% and 12.3%, respectively, over TTRL when using Qwen2.5-Math-1.5B. For experiments with the larger Qwen2.5-7B base model, both TTRL and COMPASS were trained for approximately 20% of the epochs specified in the original TTRL paper due to computational constraints. Despite this reduced training schedule, our method demonstrates a clear and consistent performance advantage over TTRL, as evidenced by both the final evaluation metrics in Table 1 and the performance trend curves illustrated in Figure 3. However, we note an exception with the LLaMA3.2-1B-Instruct model on the AIME 2024 dataset. We attribute this performance drop to the model's insufficient foundational knowledge. For such a model, the high-entropy states targeted by our process reward (DPR) likely signify fundamental confusion rather than meaningful reasoning junctures. Reinforcing these spurious signals inadvertently degrades performance, highlighting that the efficacy of our method relies on the base model possessing a solid knowledge foundation.

COMPASS naturally scales. As shown in Table 1, another noteworthy observation is that as the model size increases ( $1B \rightarrow 1.5B \rightarrow 7B$ ), performance consistently improves, highlighting the natural scaling behavior of COMPASS: larger models can produce more accurate rewards during self-improvement, which leads to more effective learning on new data.

COMPASS achieves sustainable self-evolution through online and RL. To understand the mechanisms of our proposed COMPASS framework, we analyzed its training dynamics against the TTRL baseline as shown in Figure 4, focusing on pseudo-label accuracy and majority ratio. The results highlight COMPASS's superior learning process. Our method achieves significantly higher pseudo-label accuracy, confirming that its advanced reward system—which combines the outcome-based Dual-Calibration Answer Reward (DCAR) and process-based Decisive Path Reward (DPR), and generates more effective training signals. In contrast, the baseline's accuracy stagnates at a much lower level. Simultaneously, COMPASS maintains a consistently lower majority ratio. This demonstrates that it successfully avoids the baseline's tendency to prematurely converge on the most frequent answer, a common pitfall of naive majority voting. Instead of simply reinforcing the consensus, COMPASS values diverse and high-quality reasoning paths. This dual dynamics of increasing label accuracy while reducing reliance on a single popular answer provides strong evidence for COMPASS's effectiveness. It cultivates a more robust self-evolution by considering

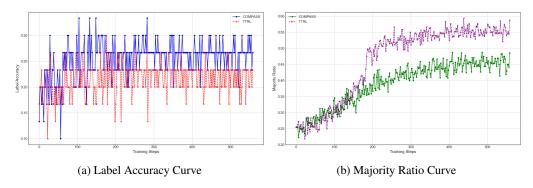


Figure 4: Training dynamics comparision on AIME using Qwen2.5-Math-1.5B.

both the intrinsic quality of reasoning paths and the popularity of final answers, leading to a more reliable self-improving model.

## 4.3 ABLATION RESULTS

We performed sequential ablation experiments by progressively removing model components: we first removed the credibility calibration from COMPASS, then further excluded the process reward (DPR), and finally removed the confidence calibration, which reduced the model to the baseline TTRL. The performance curves across training steps (Figure 5) show that each component contributes positively to model performance. Among them, the confidence calibration yields the most substantial improvement, as indicated by the largest vertical gap between the red and green curves.

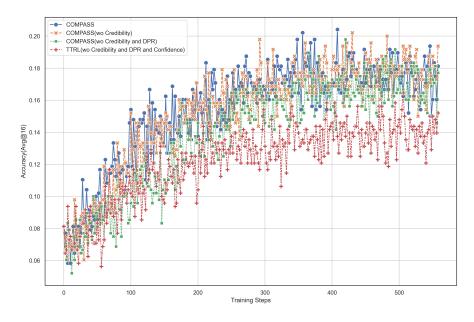


Figure 5: Ablation Results of COMPASS on AIME using Qwen2.5-Math-1.5B.

#### 4.4 CASE STUDY

To validate the effectiveness of COMPASS, we present two case studies—DCAR (Figure 6) and DPR (Figure 7). DCAR establishes trustworthy pseudo-labels through confidence and credibility calibration, while DPR directly evaluates reasoning quality via entropy-weighted decisiveness. Together, these two components demonstrate how COMPASS achieves robust self-evolving reinforcement learning on unlabeled data.

#### 4.4.1 DUAL-CALIBRATION ANSWER REWARD (DCAR)

#### **Problem**

Every morning Aya goes for a 9-kilometer-long walk and stops at a coffee shop afterwards. When she walks at a constant speed of s kilometers per hour, the walk takes her 4 hours, including t minutes spent in the coffee shop. When she walks s + 2 kilometers per hour, the walk takes her 2 hours and 24 minutes, including t minutes spent in the coffee shop. Suppose Aya walks at  $s + \frac{1}{2}$  kilometers per hour. Find the number of minutes the walk takes her, including the t minutes spent in the coffee shop.

#### **Ground Truth**

204

#### **Confidence-Calibrated Self-Consistency (CCSC)**

Answer Candidate	Count	Correct	Individial Confidence	molecular of $S_{ccsc}$
204	3	✓	0.824, 0.817, 0.815	2.455
36	3	X	0.824, 0.802, 0.788	2.414
360	2	X	0.815, 0.803	1.618
54	1	X	0.840(Elite)	0.840
	7	X		

## Motivation

CCSC aims to refine pseudo-labels by weighting each candidate answer according to its internal confidence rather than raw vote frequency. This helps the model resolve ambiguous cases where majority voting fails.

#### Analysis

- ✓ <u>Ambiguity under majority voting</u>: Both 204 ( ✓ ) and 36 ( X ) receive three votes each, leading to a tie.
- ✓ CCSC resolves ambiguity: The  $S_{ccsc}$  (only molecular) of 204 and 36 is 2.455 and 2.414 respectively, so the correct answer (204) is identified despite equal vote counts.

### Credibility-Calibrated Answer Reward (CCAR)

## Motivation

While CCSC identifies the consensus pseudo-label, CCAR determines how much that pseudolabel should influence learning by assessing its reliability relative to the most confident response.

# **Analysis**

- ✓ Elite inconsistency detection: The most confident sample (answer 54, conf 0.840) is incorrect due to a setup error (*Initially, the total time of 4 hours was miscalculated as 360 minutes instead of 240 minutes*.).
- ✓ Consensus reliability check: When the confidence of the consensus group (answer 204, conf 0.824) is lower than that of the most confident sample (answer 54, conf 0.840), the reward is reduced, preventing unstable updates.
- ✓ <u>Soft curriculum behavior</u>: High-credibility pseudo-labels drive stronger reinforcement, while the low-credibility labels contribute less, stabilizing optimization.

Figure 6: Case Study for Dual-Calibration Answer Reward (DCAR)

## 4.4.2 DECISIVE PATH REWARD (DPR)

#### Problem

Find the largest possible real part of the expression below, where z is a complex number with |z| = 4.

$$(75 + 117i)z + \frac{96 + 144i}{z}$$

#### **Ground Truth**

540

#### **Decisive Path Reward (DPR)**

#### **Motivation**

While DCAR focuses on outcome-level accuracy, DPR provides process-level supervision to ensure reasoning stability. It rewards decisive and confident reasoning steps, especially in high-uncertainty situations, guiding the model toward more consistent reasoning trajectories.

#### Overview

Two model-generated responses achieve the same correct final answer but receive vastly different DPR scores—0.849 (high) vs. 0.093 (low)—demonstrating that DPR distinguishes reasoning quality beyond correctness.

#### Analysis

ightharpoonup High-Quality Path (DPR = 0.849):

To solve the problem, we start by letting  $z=4e^{i\theta}$  where  $\theta$  is a real number. The goal is to find the largest possible real part of the expression  $(75+117i)z+\frac{96+144i}{z}$ ... The real part of this expression is:  $324cos\theta-432sin\theta$ ...

- ✓ Reasoning Behavior: The model immediately adopts the optimal representation  $z = 4e^{i\theta}$  and proceeds in a clear, stepwise manner—deriving real and imaginary components efficiently.
- ✓ <u>Interpretation</u>: DPR assigns a high reward due to consistent, coherent reasoning and minimal uncertainty throughout the trajectory.
- $\triangleright$  Low-Quality Path (DPR = 0.093):

Author x, let  $z = 4e^{i\theta}$ , where t is a real variable. Then  $75 + 117i = (117 + i(3\sqrt{3} - 75))/2$  (modulus 2), so as z is in the upper half plex 75 + 117i has imaginary part  $3\sqrt{3}$  and hence looks like  $(re^{i\theta} + ire^{-i\theta})/2$  in the upper half plex.mousePosition Depending on your intuition based on this, you could proceed...

- ✓ <u>Reasoning Behavior</u>: The model drifts through <u>irrelevant or incoherent statements</u> before converging to the correct result, showing lack of logical focus.
- ✓ <u>Interpretation</u>: DPR yields a low reward, penalizing erratic reasoning transitions despite the correct final answer.

Figure 7: Case Study for Decisive Path Reward (DPR).

# 5 Conclusion

In this work, we introduced **COMPASS**, a novel self-scoring reinforcement learning framework designed to enable Large Language Models to learn from unlabeled data. By integrating two complementary reward components—Dual-Calibration Answer Reward (DCAR) and Decisive Path Reward (DPR)—COMPASS jointly optimizes the reliability of final answers and the decisiveness of reasoning trajectories. Our experiments demonstrate the strong potential of COMPASS, achieving

consistent improvements across a variety of tasks and models. We view COMPASS as a further step toward Reinforcement Learning with self-labeled rewards, marking an important direction of learning from continuous streams of self-experience.

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