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Not All Rollouts are Useful: Down-Sampling Rollouts in LLM Reinforcement Learning

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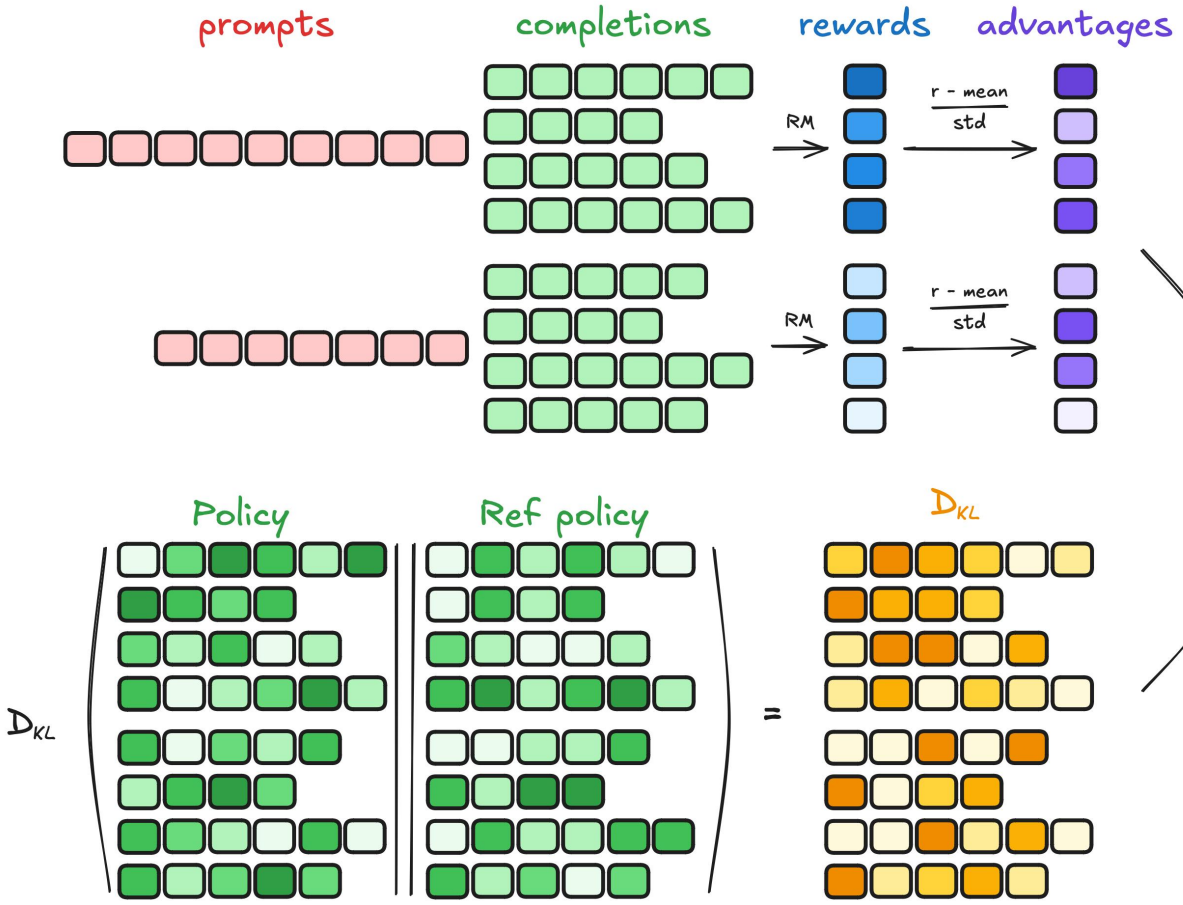
RL with Verifiable Rewards (RLVR)

- **RLVR:** A recent paradigm of improving the **reasoning** capabilities of LLMs, like math, coding, general problem solving

- **RL:** The LLM is trained with reinforcement learning methods
  - Consider the **LLM** as an **agent** whose **action** is outputing **tokens**

- **VR:** Ground truth reward is available (can check correctness)
  - For math with numeric answers, extract and check the final answer
  - For competitive programming, check if the test cases are passed

A Popular RLVR Algorithm: GRPO



- For each prompt
  - Generate completions
  - Reward model scores them
  - Compute advantages
  - Update the model
- A **two-phase** structure: Inference & Policy-update

Figure source: huggingface.co/docs/trl/main/grpo_trainer

GRPO Example

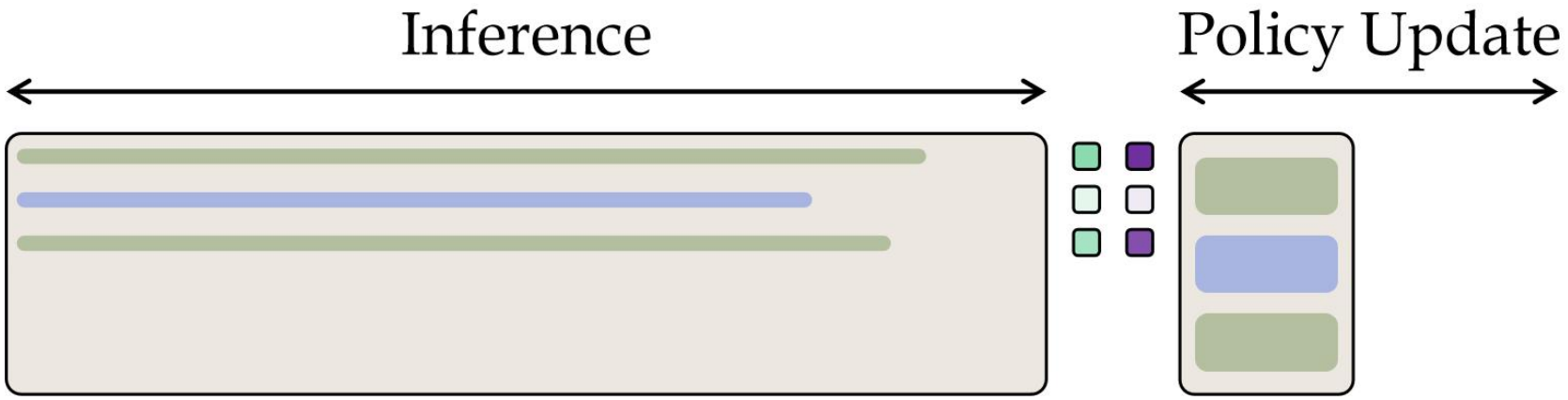
- **Prompt:** What is 3 + 7? Answer in format: “Answer: {result}”

- **Inference:** Generate rollouts & score them
  - **R1.** “Answer: 10.” Score: 80 (answer) + 20 (format)
  - **R2.** “Answer: 0.” Score: 20 (format)
  - **R3.** “The answer is 10.” Score: 80 (answer)

- **Policy Update:** Reinforce the **high-score ones** and penalize the **low-score ones** using policy gradient update rule from RL

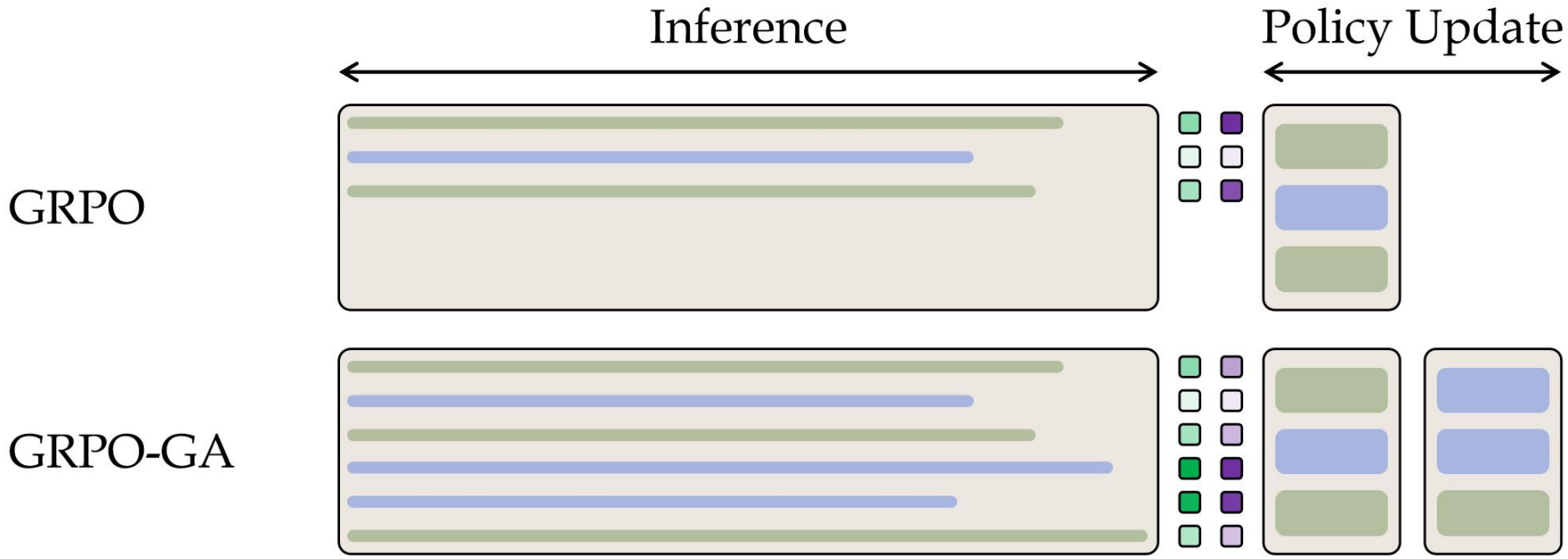
Computation Asymmetry in RLVR

- RLVR algorithms (PPO & GRPO) share a **two-phase** structure:
  - **Inference phase:** Generate rollouts & score them
  - **Policy-update phase:** Update model parameters
  - Computation is **asymmetric** in these two phases
    - Inference is **embarrassingly parallel** and **modest in memory**
    - Policy-update **requires synchronization** and is **intense in memory**

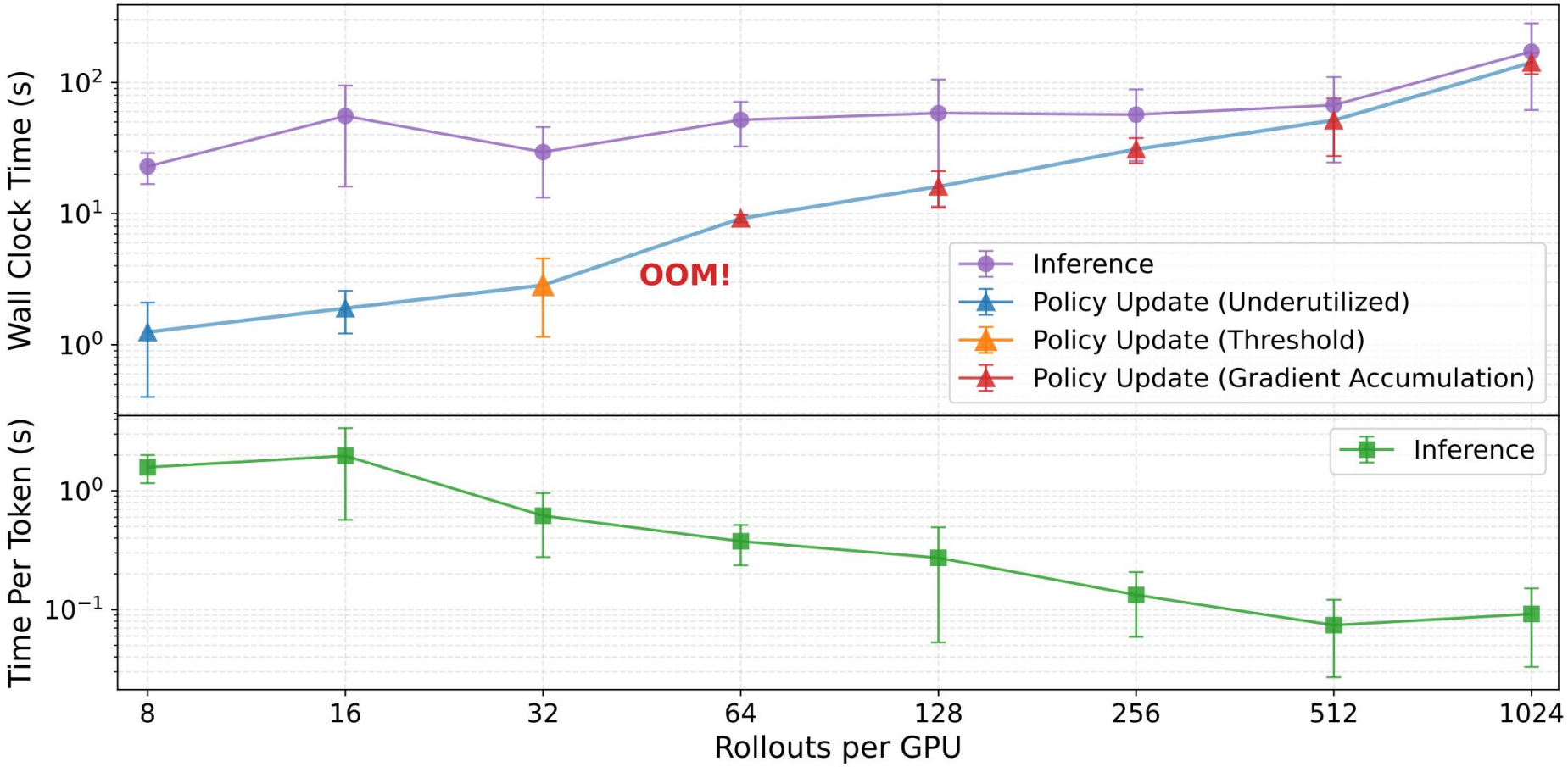


A Solution: Memory-Saving Techniques

- One possible such technique: **gradient accumulation (GA)**
  - Fully utilizes the GPU at inference phase
  - Splits the generated rollouts into multiple policy update steps



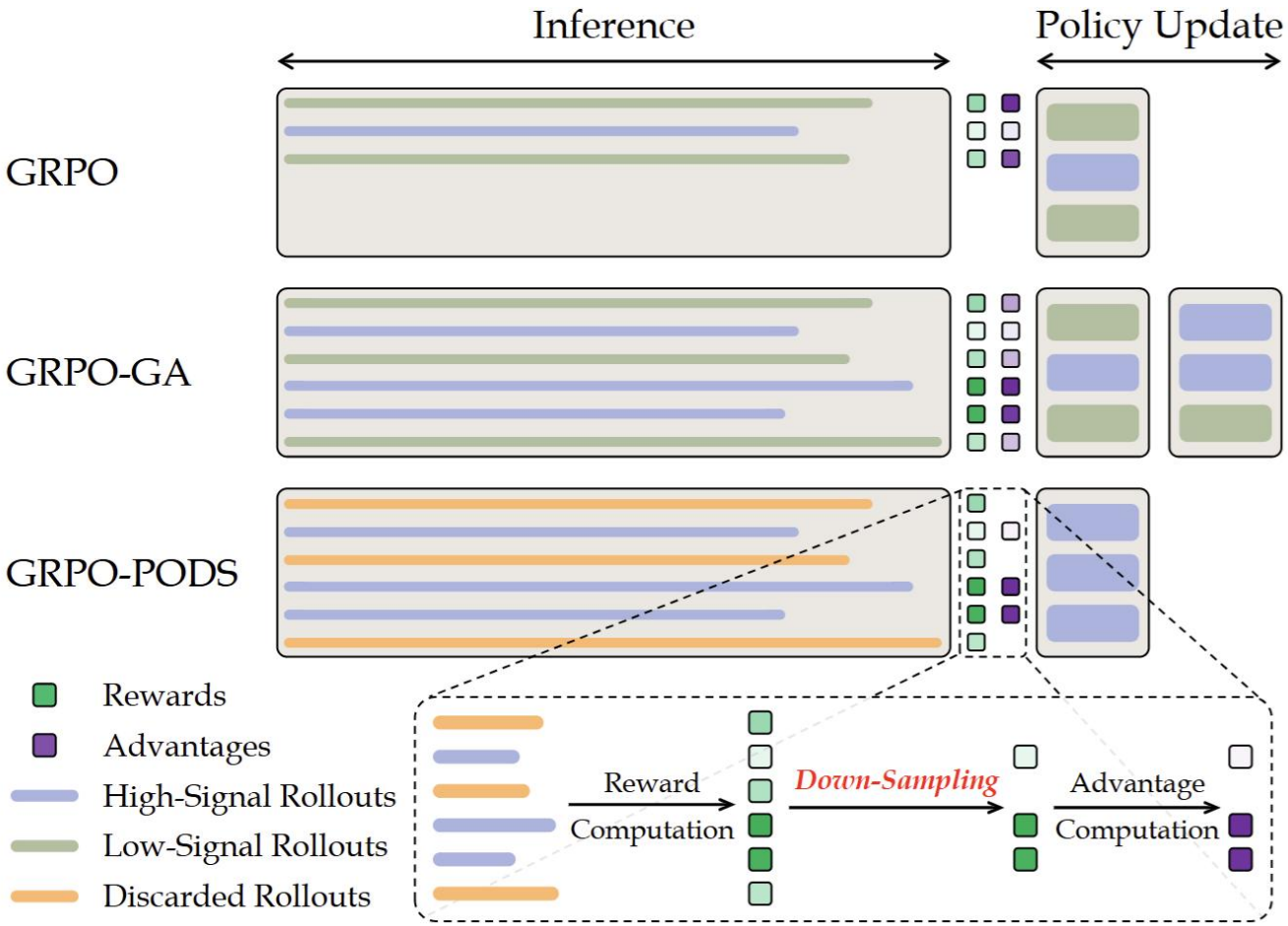
Empirical Timing Breakdown Fine-Tuning Qwen2.5-3B-Instruct on GSM8K & 8 A100s



Policy Optimization with Down-Sampling

- We observe that *"not all rollouts contribute equally to model improvement"* and propose **PODS**

- Unlike GA, we propose to strategically **discard** some of the generated rollouts
  - Addresses the asymmetry
  - Retains comparable or even better learning signals



The PODS framework

- **General framework**
  - Generate n rollouts in inference
  - Down-sample to $m < n$ rollouts for training

- **How to set the down-sampling rule?**
  - Imagine four rollouts with rewards {0.2, 0.4, 0.6, 0.8}
  - If you only want to keep two of them for training, which two?
  - Intuitively, it should be the first one and the last one
    - Because they demonstrate the **best performance** for the model **to learn** and the **worst performance** that the model **should avoid**

Max-Variance Down-Sampling

- **Max-variance down-sampling**
  - Choose the subset of rollouts that **maximizes variance** in rewards
  - **Intuition:** Captures both positive and negative learning signals

- **Theorem 1:** This set contains k highest & $m - k$ lowest rewards
  - Which gives us an $O(n \log n)$ algorithm for computing this set
  - This concurs of the intuition of the example we just saw

- **Theorem 2:** If rewards are binary, then k is always $m/2$

Proof Intuitions

- **Theorem 1:** This set contains k highest & $m - k$ lowest rewards
  - If the set we selected is not of this form, e.g. {**0.2**, 0.5, **0.6**, 0.7, **0.8**}
  - We can always move **one chosen element away** from their mean, while not decreasing variance: {**0.2**, 0.5, 0.6, **0.7**, **0.8**}

- **Theorem 2:** If rewards are binary, then k is always $m/2$
  - This is a natural corollary of Theorem 1
  - Let the number of positive rewards be p
    - Consider (i) $p \leq m/2$, (ii) $p \geq n - m/2$, (iii) $m/2 \leq p \leq n - m/2$

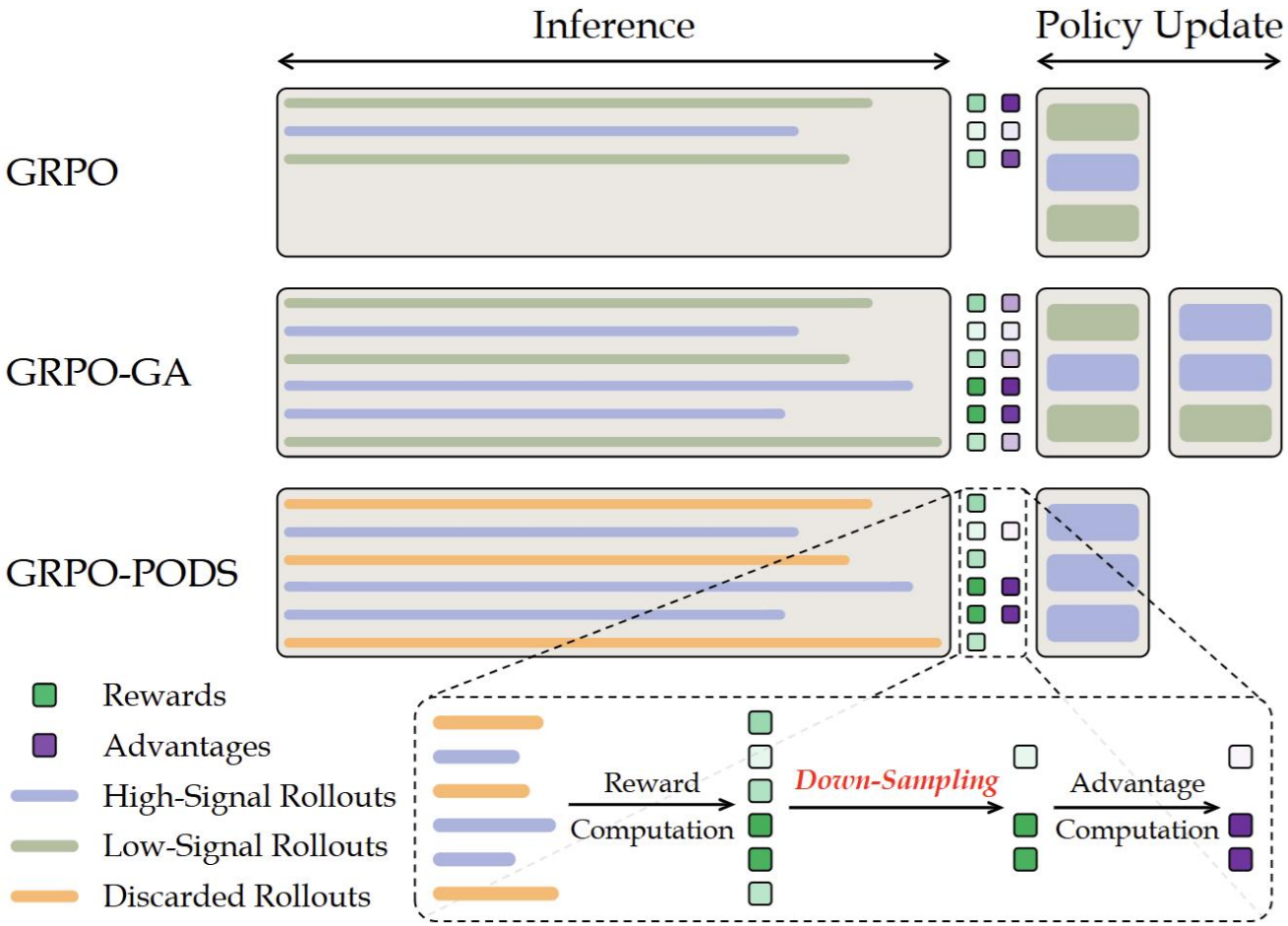
Experiments

- We evaluate PODS across diverse **hardware** configurations, model **architectures**, and model **scales** as shown below.
  - Settings (a) to (c) compares **vanilla GRPO** with **GRPO-PODS**
  - Settings (d) to (e) compares **GRPO with GA** with **GRPO-PODS**

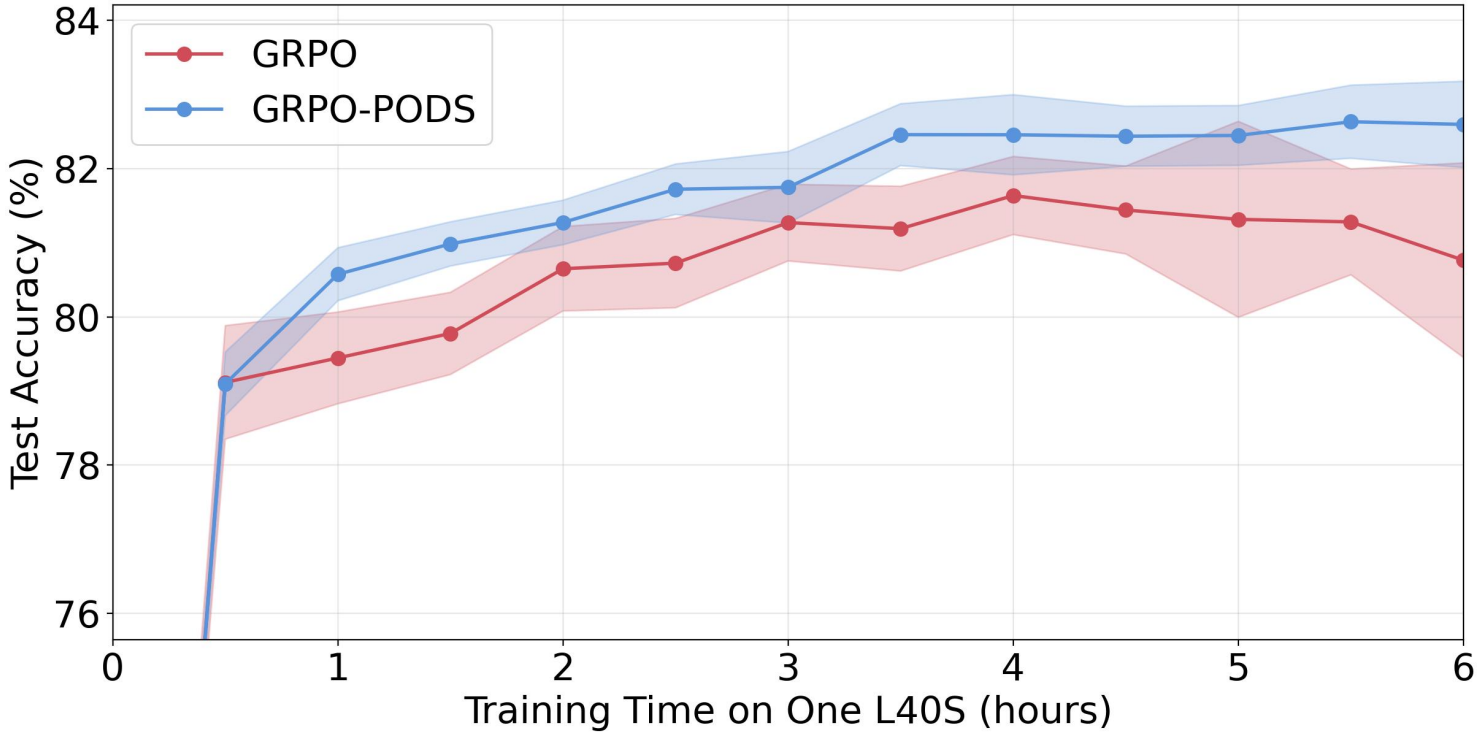
Setting	Benchmark	Model	Parameters	GPUs	Fine-tuning Method
(a)	GSM8K	Qwen2.5	3B	1 L40S	LoRA (rank 64, $\alpha = 64$)
(b)	MATH	Qwen2.5	3B	1 L40S	LoRA (rank 64, $\alpha = 64$)
(c)	GSM8K	Llama3.2	3B	1 L40S	LoRA (rank 64, $\alpha = 64$)
(d)	GSM8K	Qwen2.5	3B	8 H100s	Full-Parameter
(e)	GSM8K	Qwen2.5	7B	8 A100s	Full-Parameter

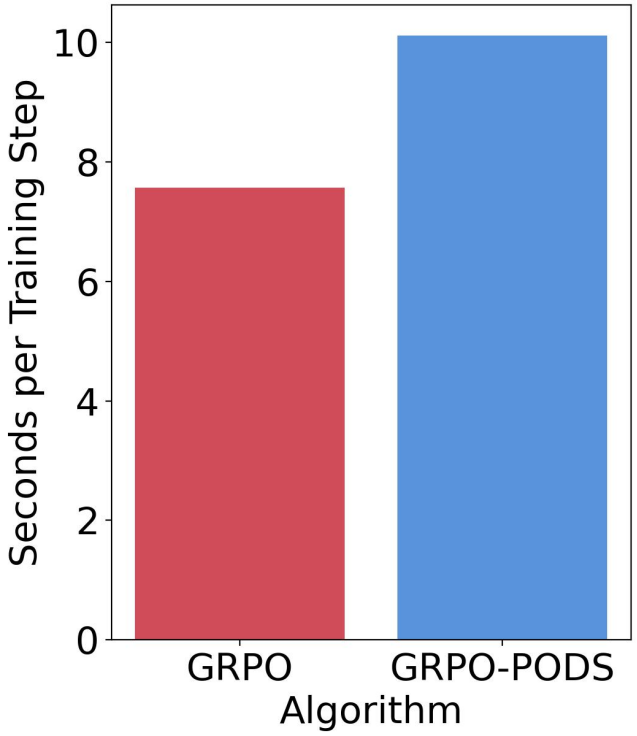
Comparing GRPO with GRPO-PODS

- **Algorithms:**
  - GRPO & GRPO-PODS
  - We align the number of rollouts per update step (m)
  - This means that PODS will be generating more rollouts per prompt than GRPO
- **In the figure:**
  - We are comparing the first row with the third row

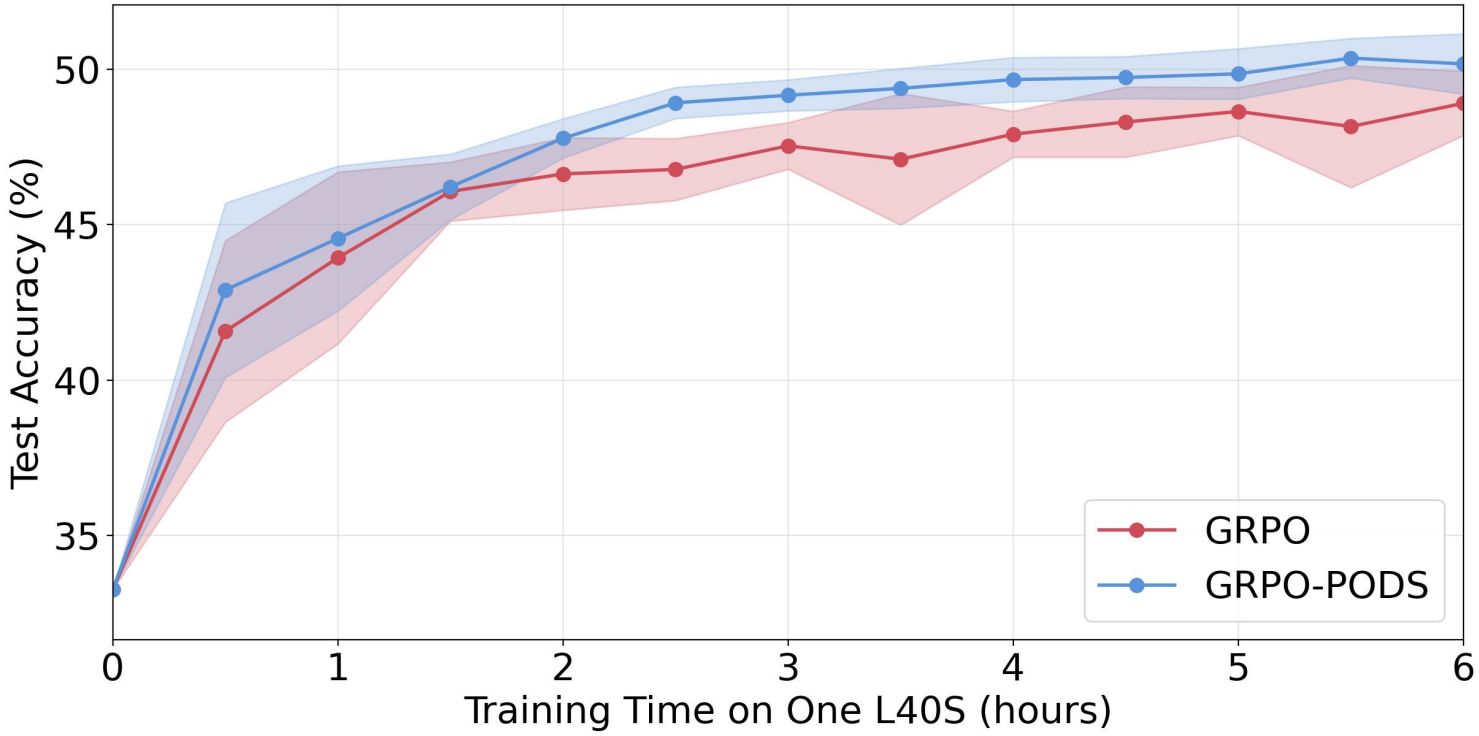


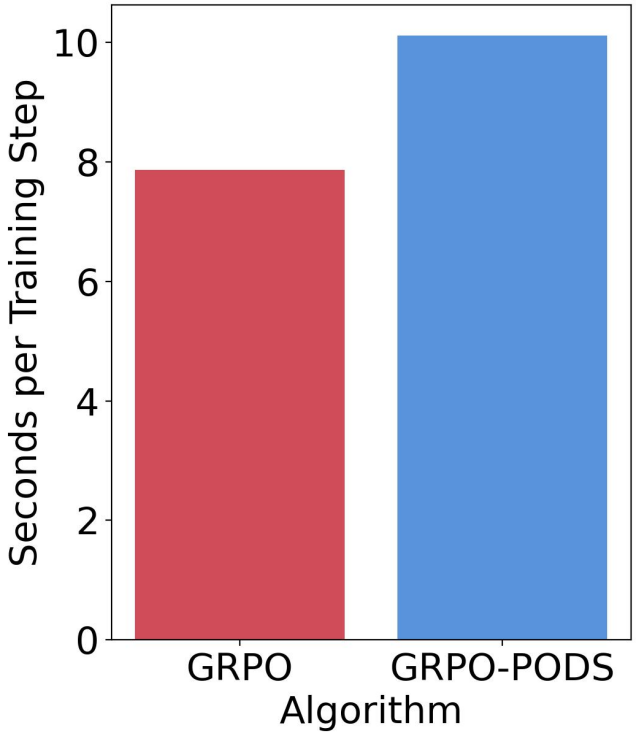
Qwen2.5-3B on GSM8K & One L40S GPU



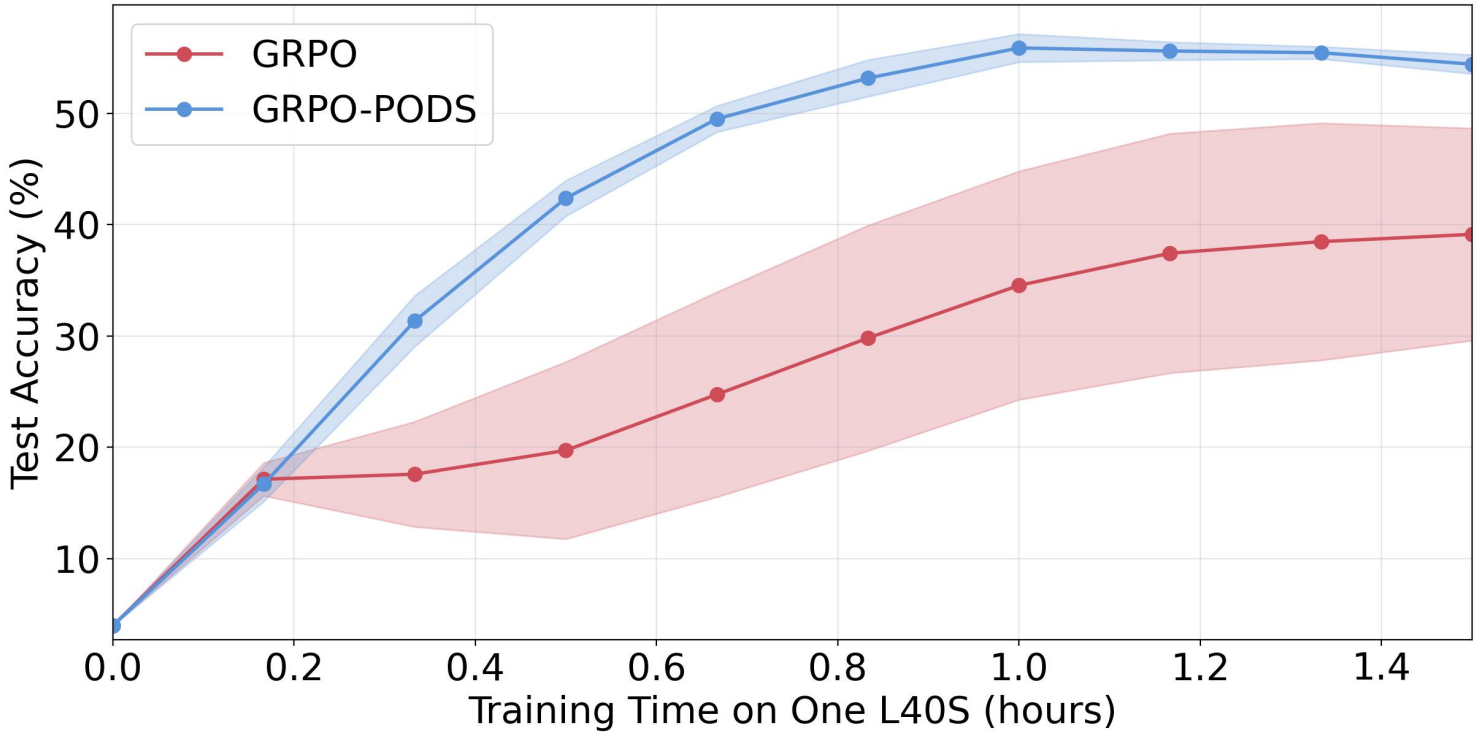


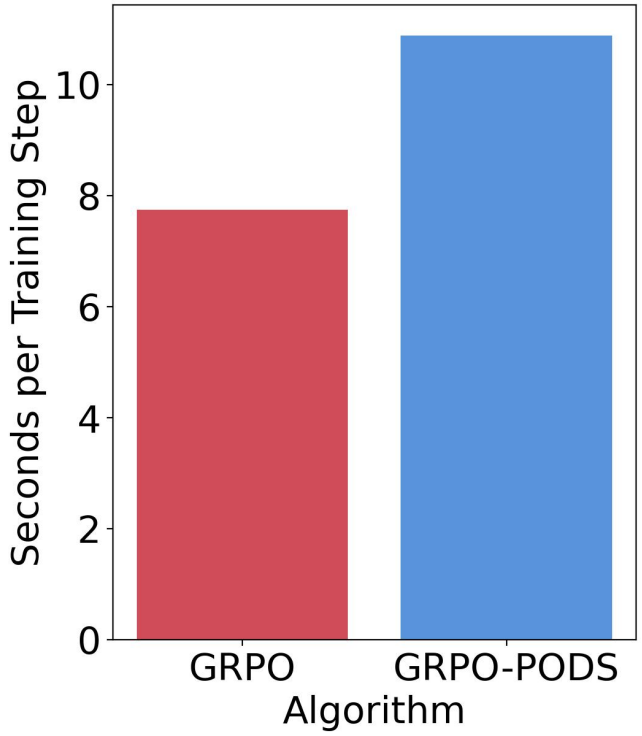
Qwen2.5-3B on MATH & One L40S GPU





Llama3.2-3B on GSM8K & One L40S GPU





Comparing GRPO with GRPO-PODS

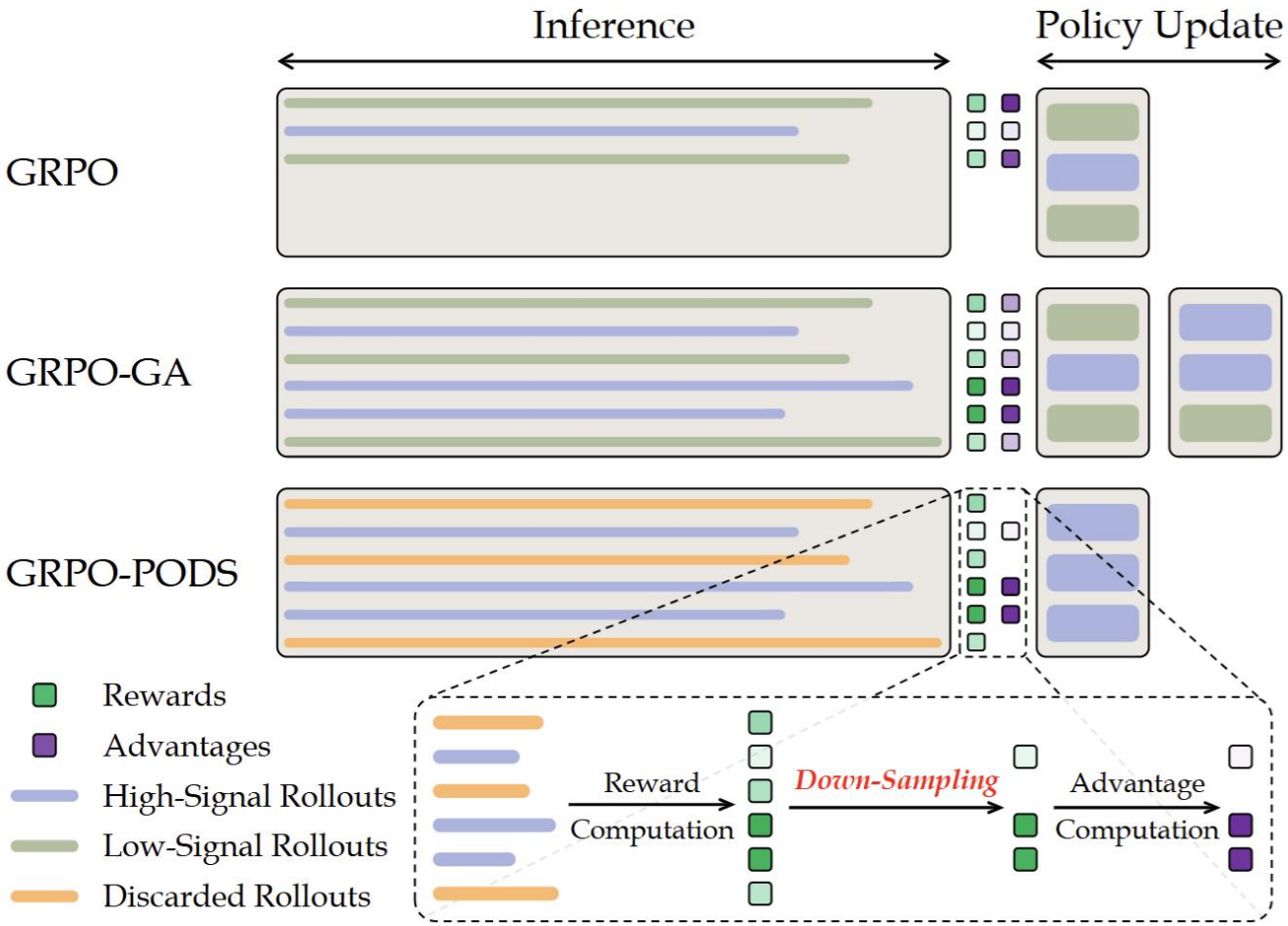
- **Experiment settings**
  - Algorithms: GRPO & GRPO-PODS (with the same #rollouts per update)
  - LoRA fine-tuning of 3B Qwen2.5 or Llama3.2, on one L40S GPU

- With PODS, RL **converges faster**, and to a **higher accuracy**

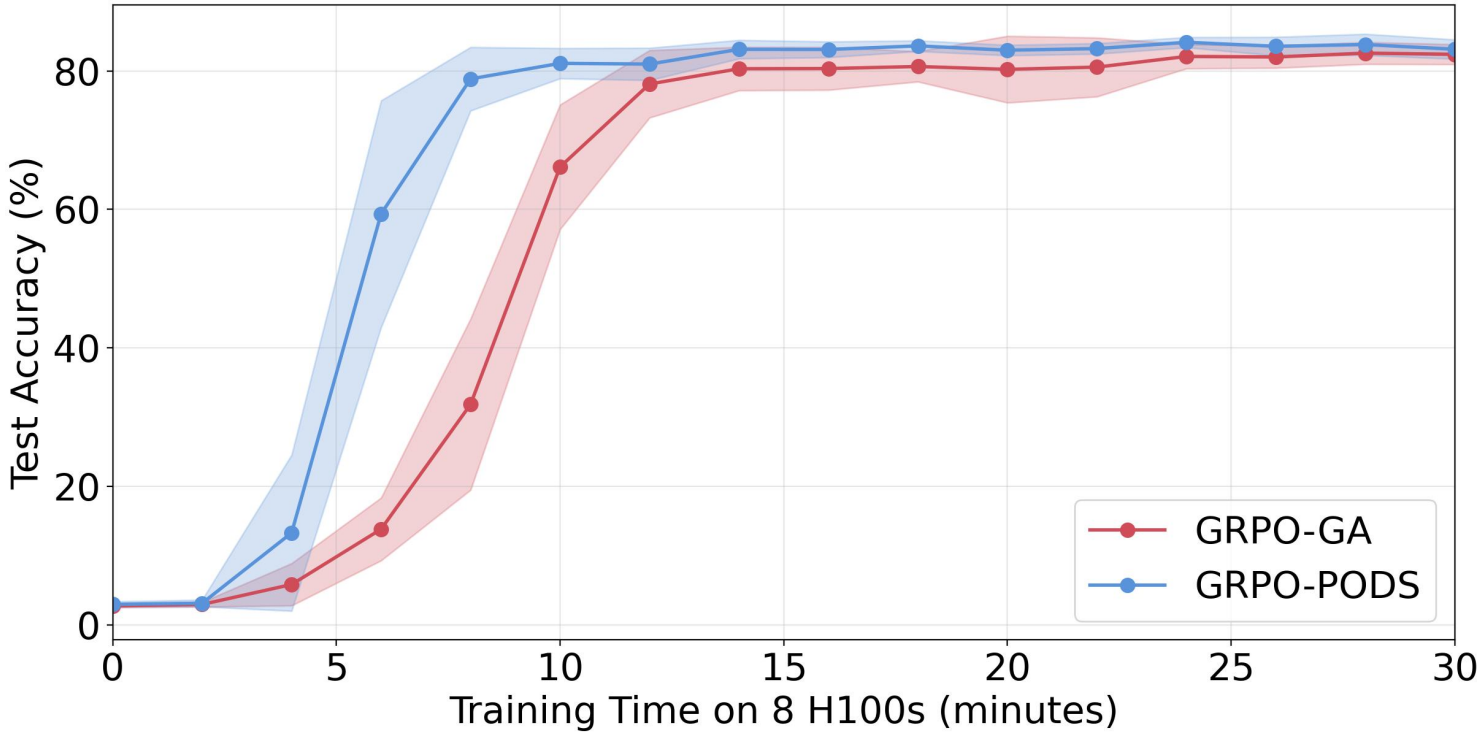
- PODS takes more time per step, since it is doing more inference
  - This means PODS achieves a higher accuracy using fewer training steps
  - Which indicates that the learning signals are stronger with PODS

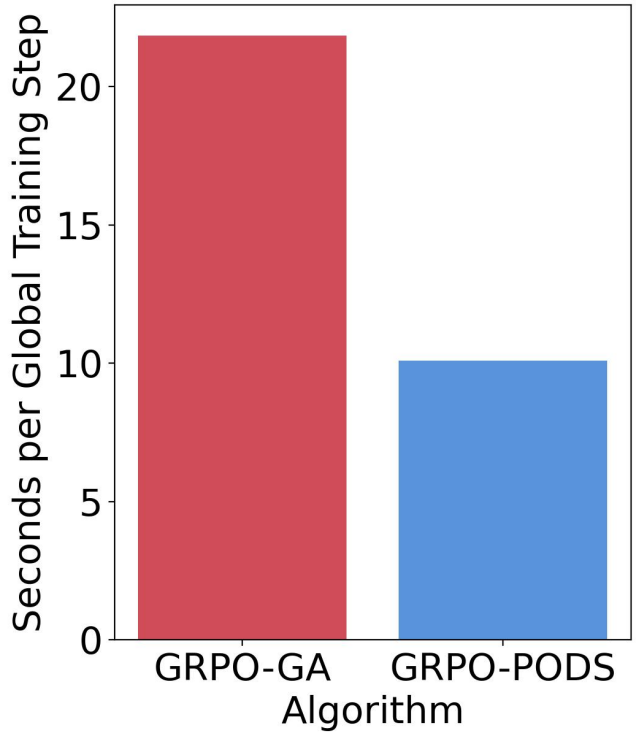
Comparing GRPO-GA with GRPO-PODS

- **Algorithms:**
  - GRPO-GA & GRPO-PODS
  - We align the number of rollouts in inference (n)
  - This means that PODS will be taking fewer update steps per prompt than GRPO-GA
- **In the figure:**
  - We are comparing the second row with the third

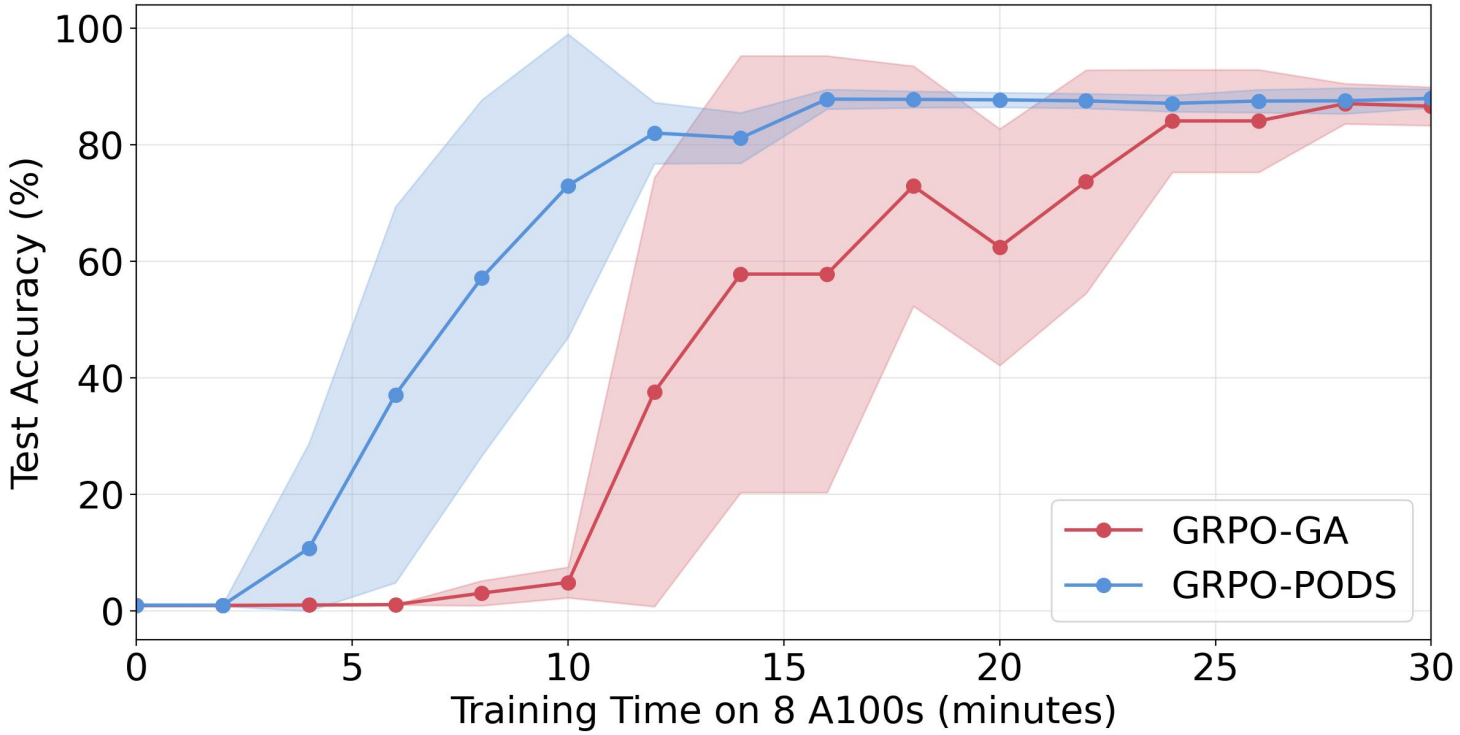


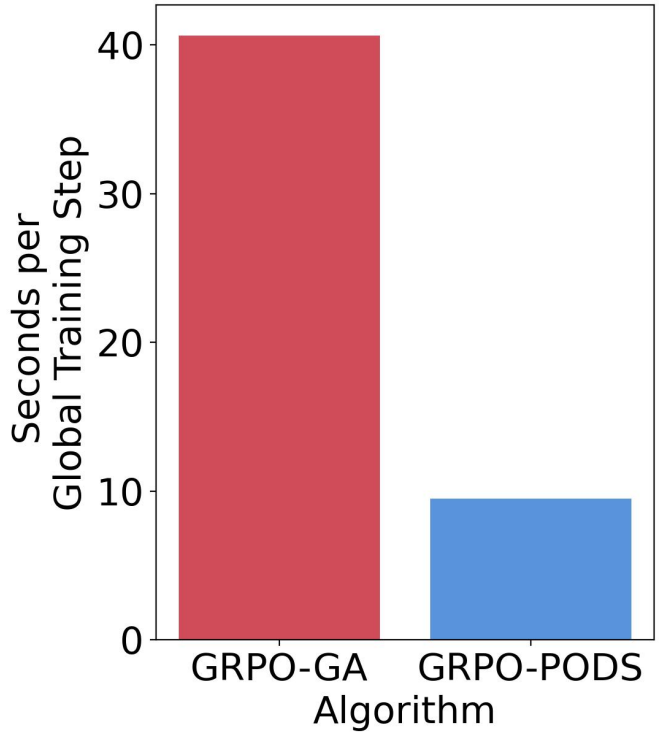
Qwen2.5-3B on GSM8K & 8 H100 GPUs





Qwen2.5-7B on GSM8K & 8 A100 GPUs





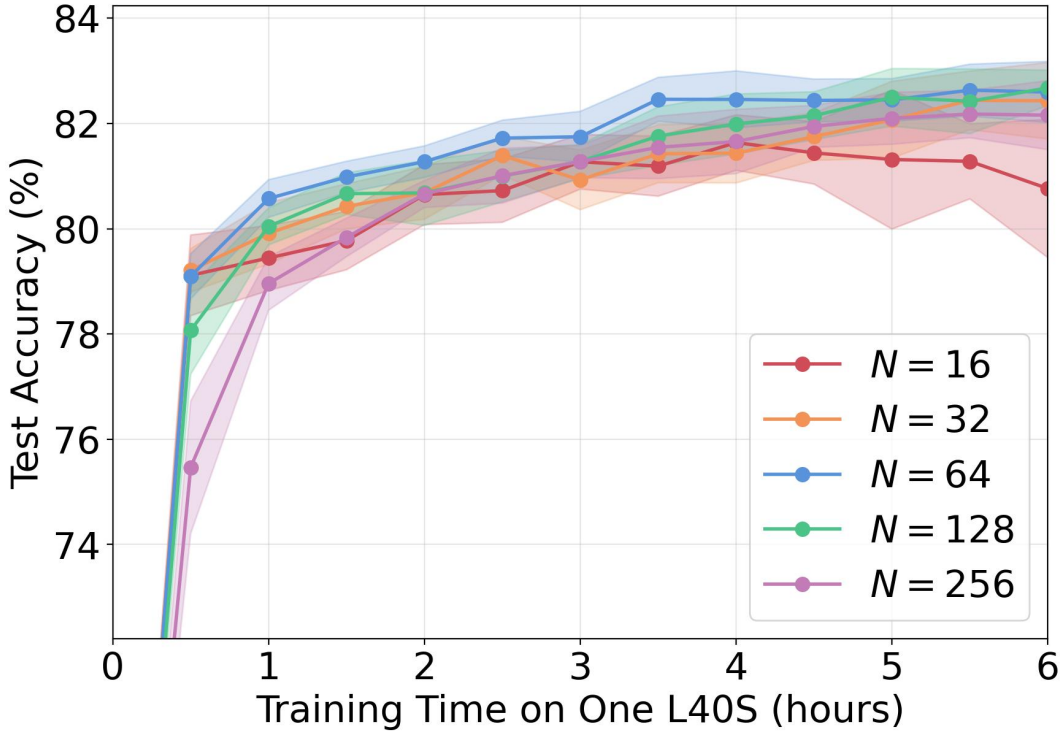
Comparing GRPO-GA with GRPO-PODS

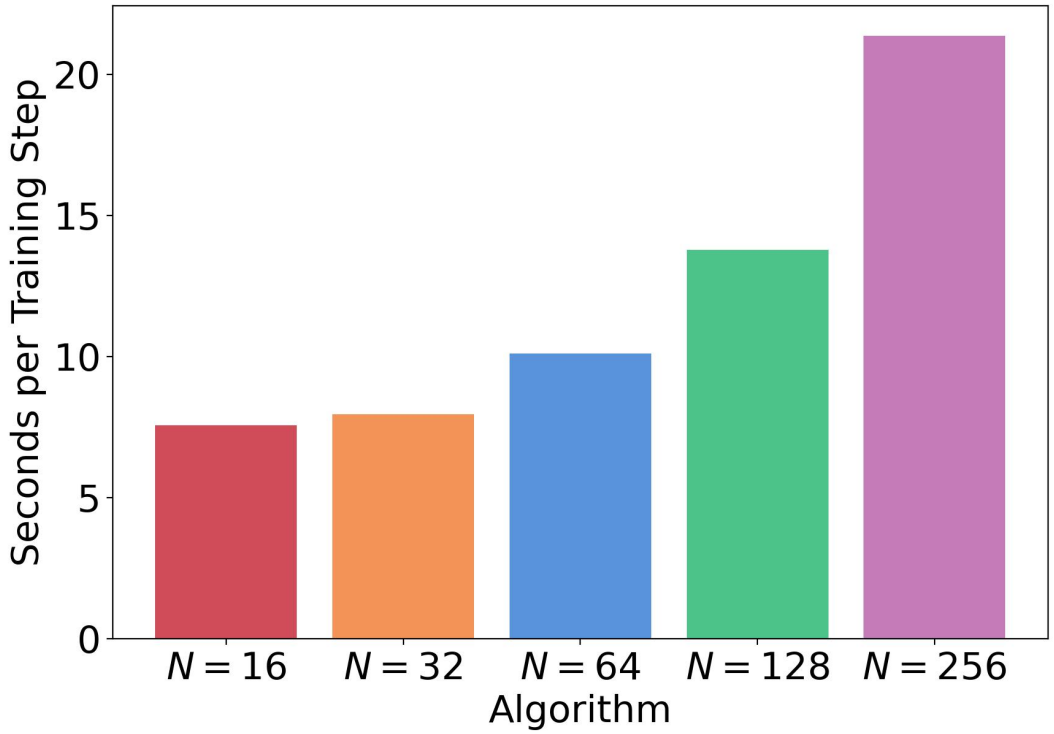
- **Experiment settings**
  - Algorithms: GRPO-GA & GRPO-PODS (same #rollouts in inference)
  - Full fine-tuning 3B / 7B Qwen2.5, on 8 H100 / A100 GPUs

- With PODS, RL **converges faster**, and to a **higher accuracy**

- PODS takes less time per step, since it is doing less update
  - Which indicates that the learning signals are well preserved each step

Fixing $m = 16$ and Varying $n \in \{16, 32, 64, 128, 256\}$



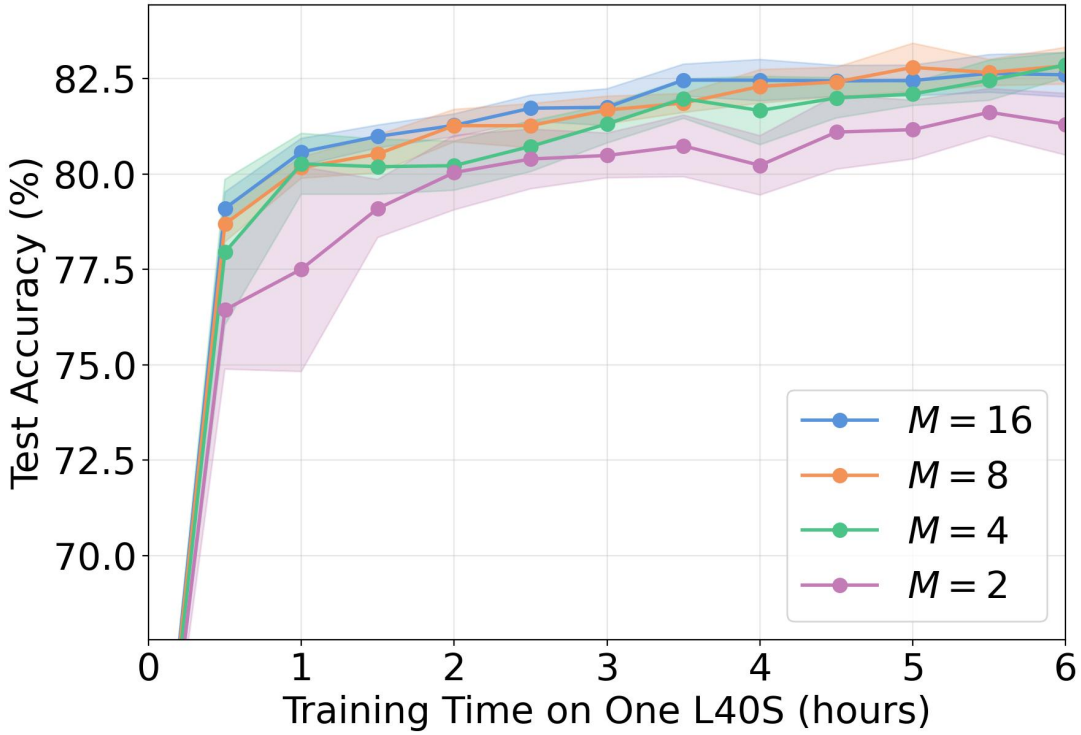


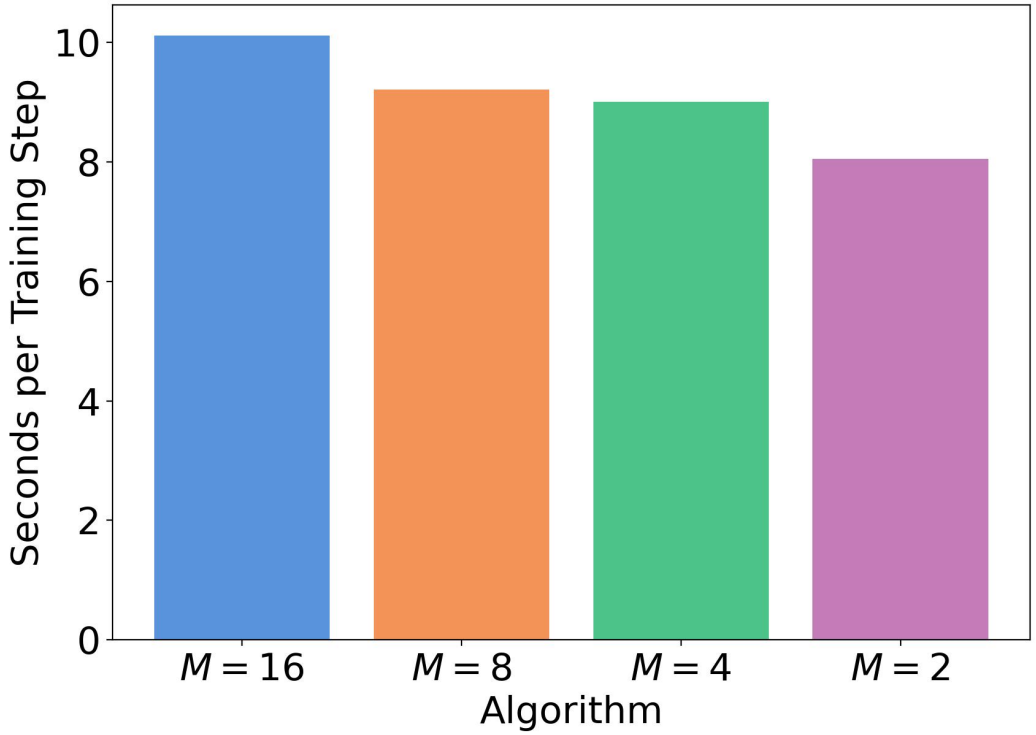
Fixing the Update Step Batch Size m

- **Experiment settings**
  - Algorithm: GRPO-PODS ($n = \{16, 32, 64, 128, 256\}, m = 16$)
  - LoRA fine-tuning Qwen2.5-3B-Instruct, on one L40S GPU

- The algorithm's performance is **single-peaked**
  - With $n = 64$ being the best, and $n = 16, 256$ being the worst
  - $n = 16$: Fewer rollouts are sampled, so the learning signal is weak
  - $n = 256$: The inference phase takes too much time, fewer steps taken

Fixing $n = 64$ and Varying $m \in \{16, 8, 4, 2\}$





Fixing the Inference Step Batch Size n

- **Experiment settings**
  - Algorithm: GRPO-PODS ($n = 64, m = \{16, 8, 4, 2\}$)
  - LoRA fine-tuning Qwen2.5-3B-Instruct, on one L40S GPU

- The algorithm's performance is similar
  - As long as m is not set too small
  - This indicates that PODS preserves the learning signals effectively

Our Contributions

- Motivated by the computation asymmetry of the two phases in RLVR algorithms, we propose the **PODS** framework
  - **Key idea:** Not all rollouts contribute equally to model improvement
  - Generate n rollouts and train on only $m < n$ of them

- We conduct a thorough theoretical and empirical study
  - We derive an $O(n \log n)$ **algorithm** for the max-variance rule
  - We demonstrate **faster convergence to improved accuracy** under different reasoning benchmarks, model and hardware regimes