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




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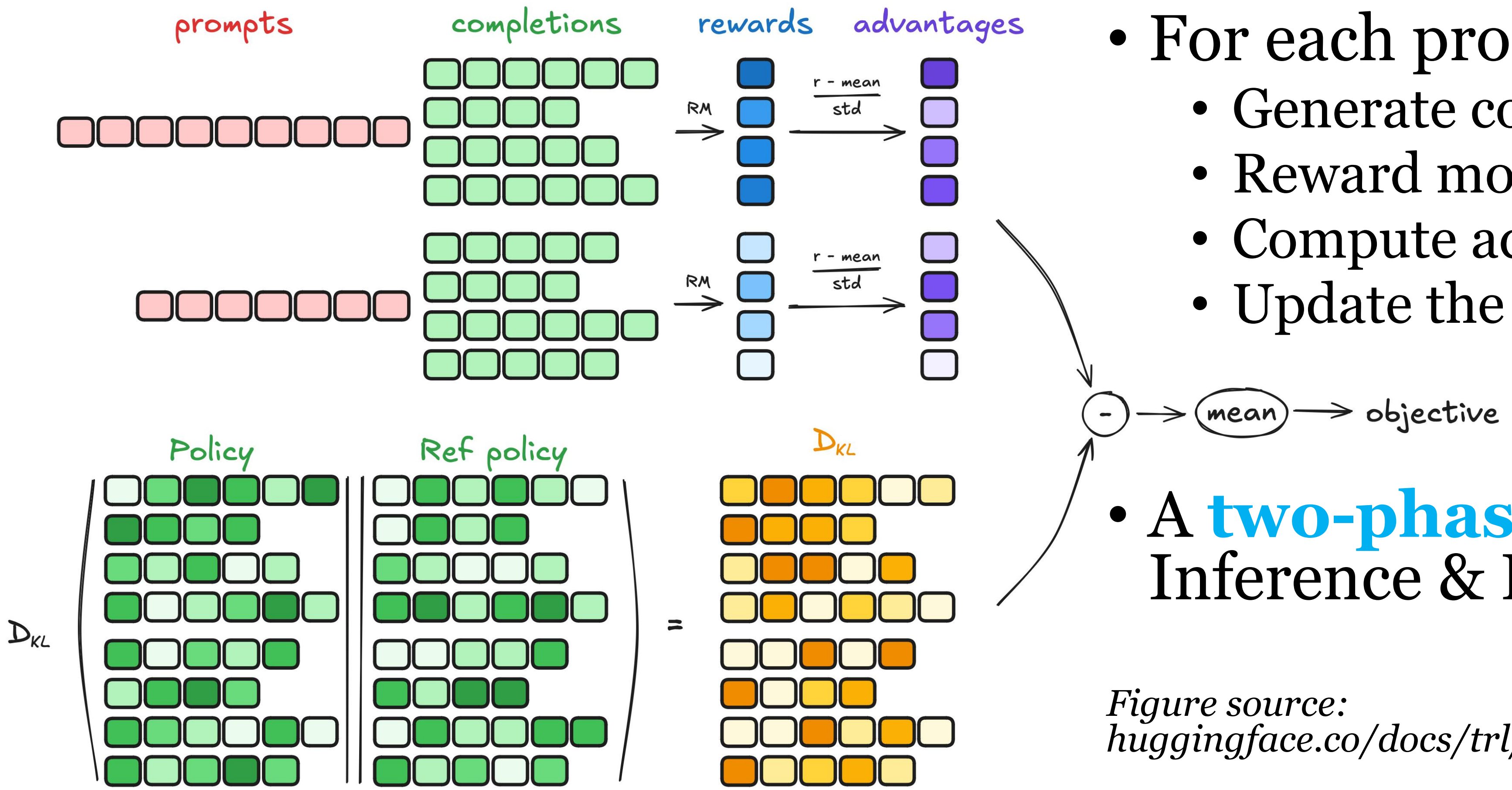
RL with Verifiable Rewards (RLVR)

- **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

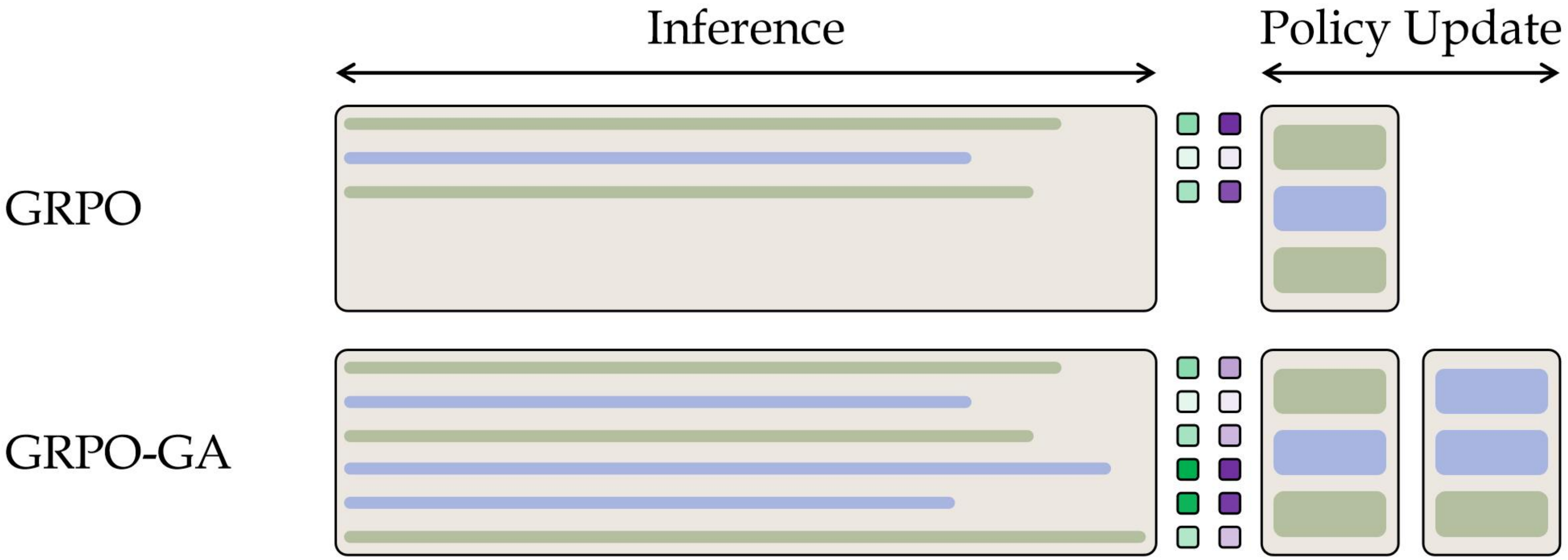
Figure source: huggingface.co/docs/trl/main/grpo_trainer

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

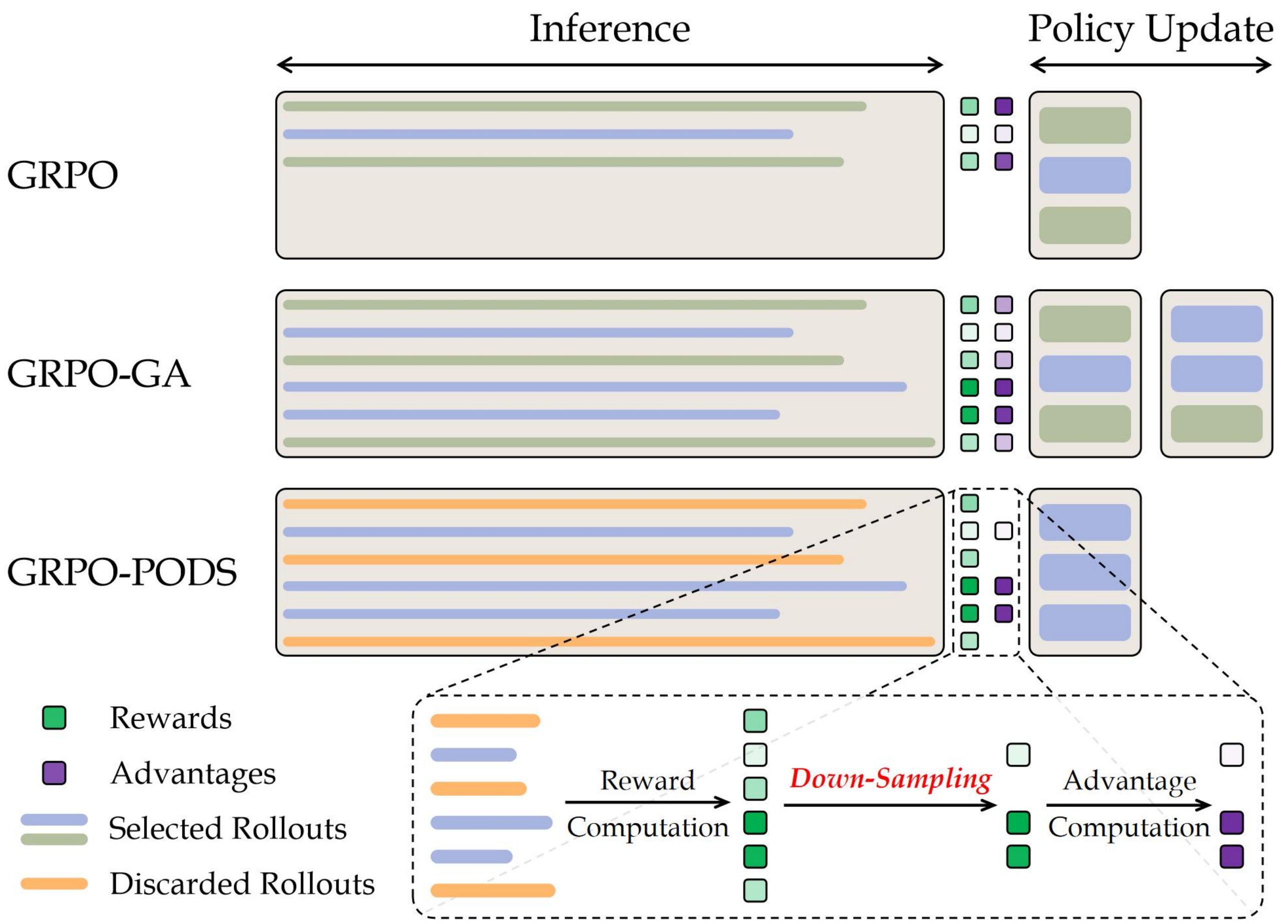
- One possible such technique: **gradient accumulation (GA)**
  - Fully utilizes the GPU at inference phase
  - Splits the generated rollouts into multiple policy update steps



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

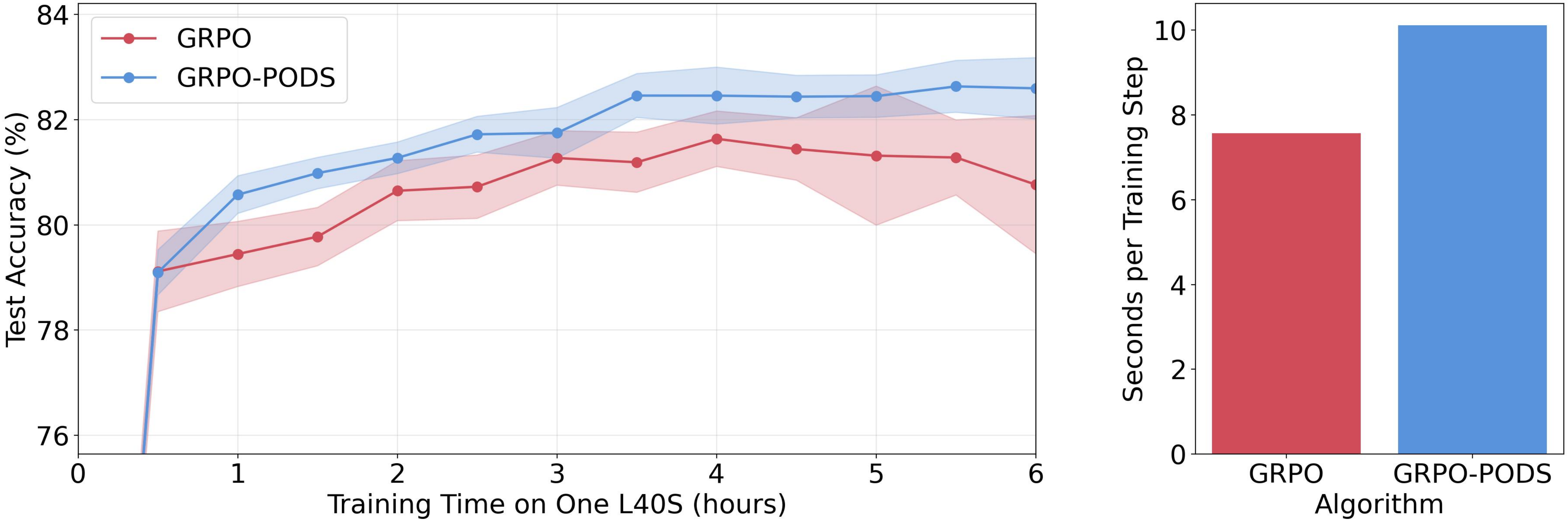
- **Theorem 2:** If rewards are binary, then k is always $m/2$

Experiments

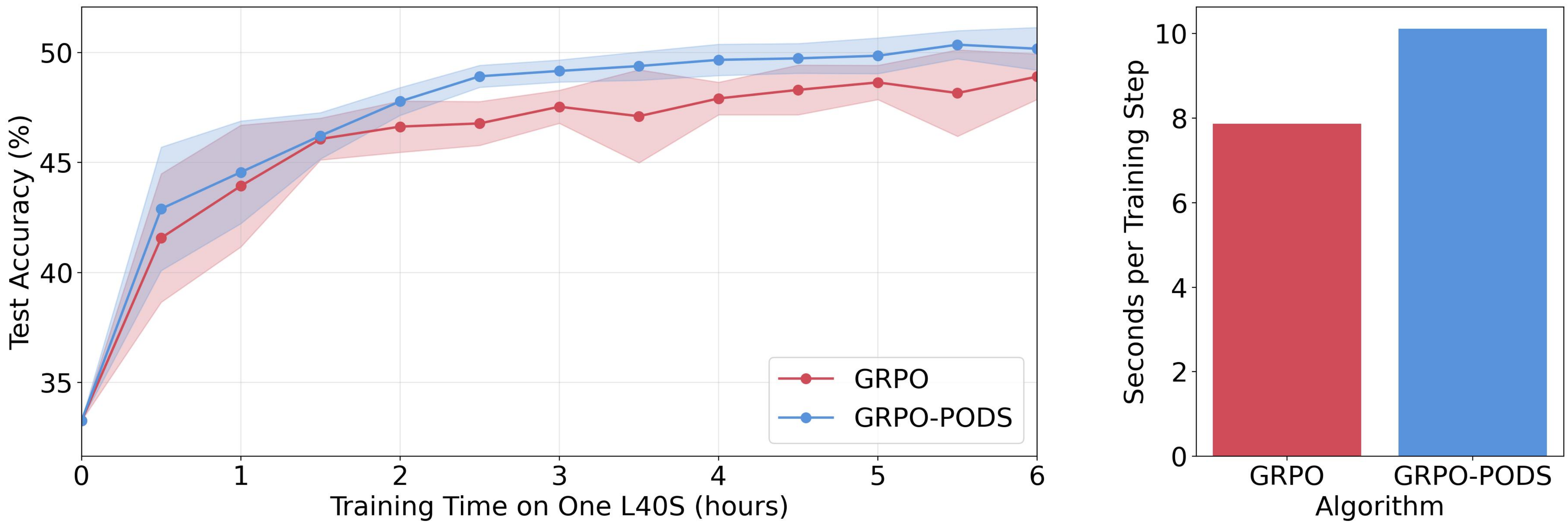
- We evaluate PODS on two reasoning benchmarks (GSM8K and MATH) on cross two hardware and model regimes
  - **(1).** Comparing GRPO ($n = 16$) with GRPO-PODS ($n = 64$, $m = 16$), LoRA fine-tuning Qwen2.5-3B-Instruct, on one L40S GPU
  - **(2).** Comparing GRPO-GA ($n = 512$) with GRPO-PODS ($n = 512$, $m = 128$), fully fine-tuning Qwen2.5-3B-Instruct, on 8 H100 GPUs
  - These two settings correspond to the explanatory figure

- We see **consistent improvement** of performance with PODS

Training on GSM8K with One L40S GPU



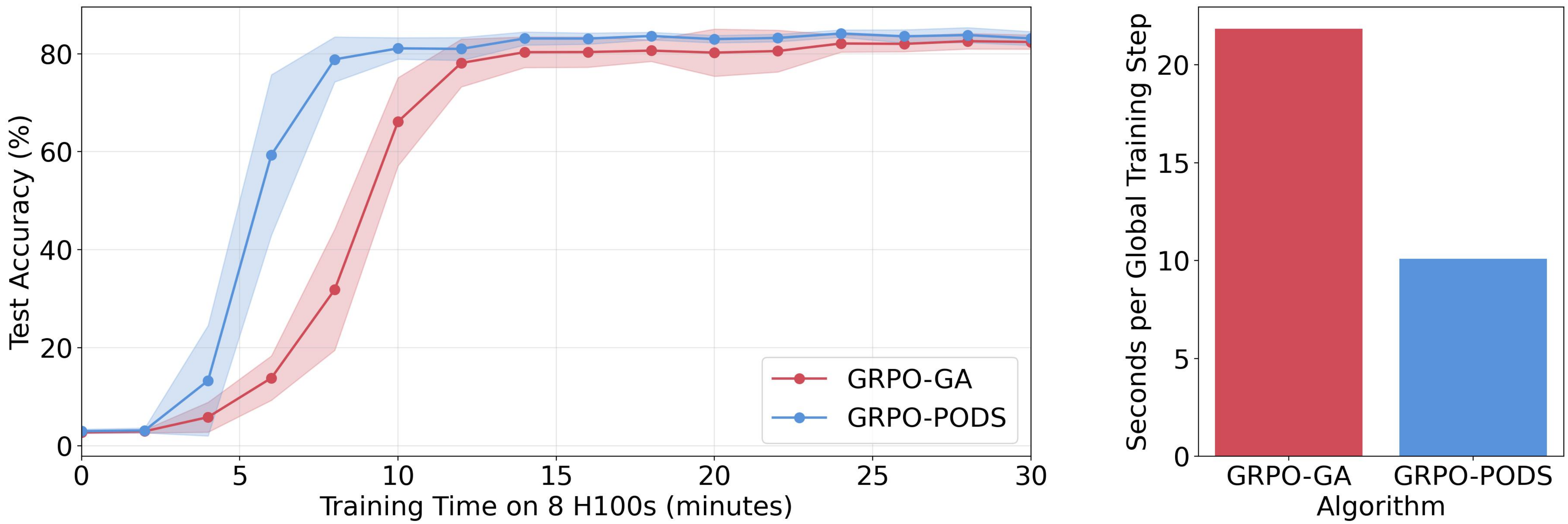
Training on MATH with One L40S GPU



Comparing GRPO with GRPO-PODS

- **Experiment settings**
  - Algorithms: GRPO ($\boldsymbol{n = 16}$) & GRPO-PODS ($n = 64$, $\boldsymbol{m = 16}$)
  - LoRA fine-tuning Qwen2.5-3B-Instruct, 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

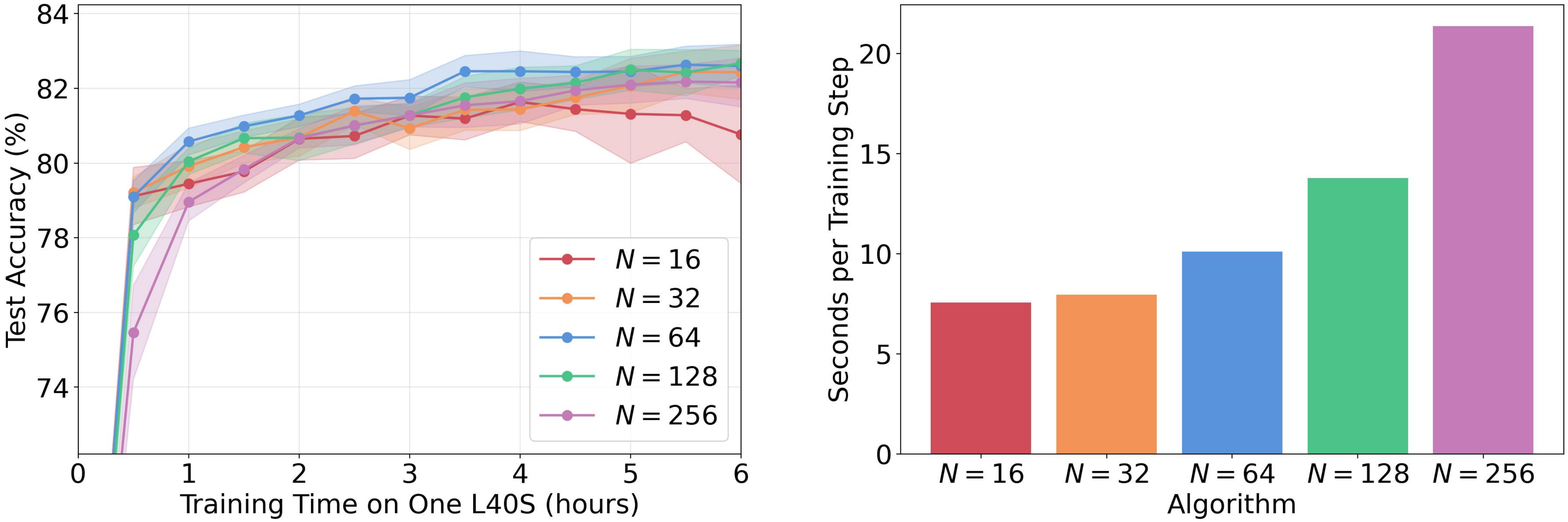
Training on GSM8K with 8 H100 GPUs



Comparing GRPO-GA with GRPO-PODS

- **Experiment settings**
  - Algorithms: GRPO-GA ($\boldsymbol{n = 512}$), GRPO-PODS ($\boldsymbol{n = 512}$, $m = 128$)
  - Full fine-tuning Qwen2.5-3B-Instruct, on 8 H100 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** $n \in \{16, 32, 64, 128, 256\}$

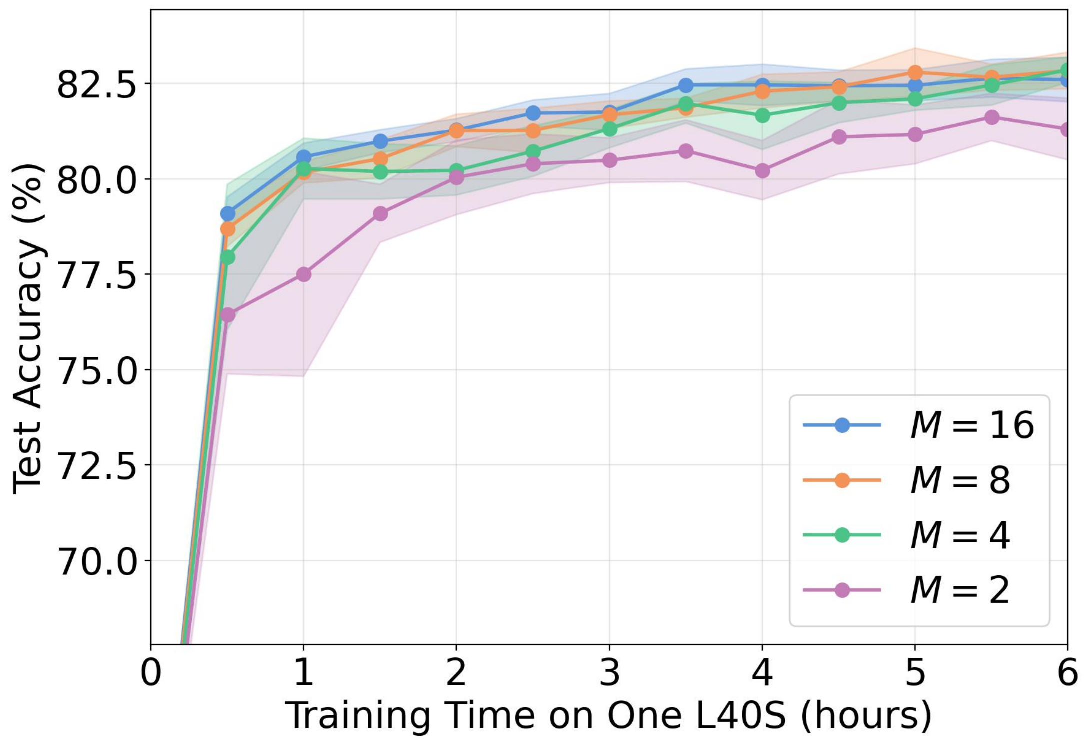


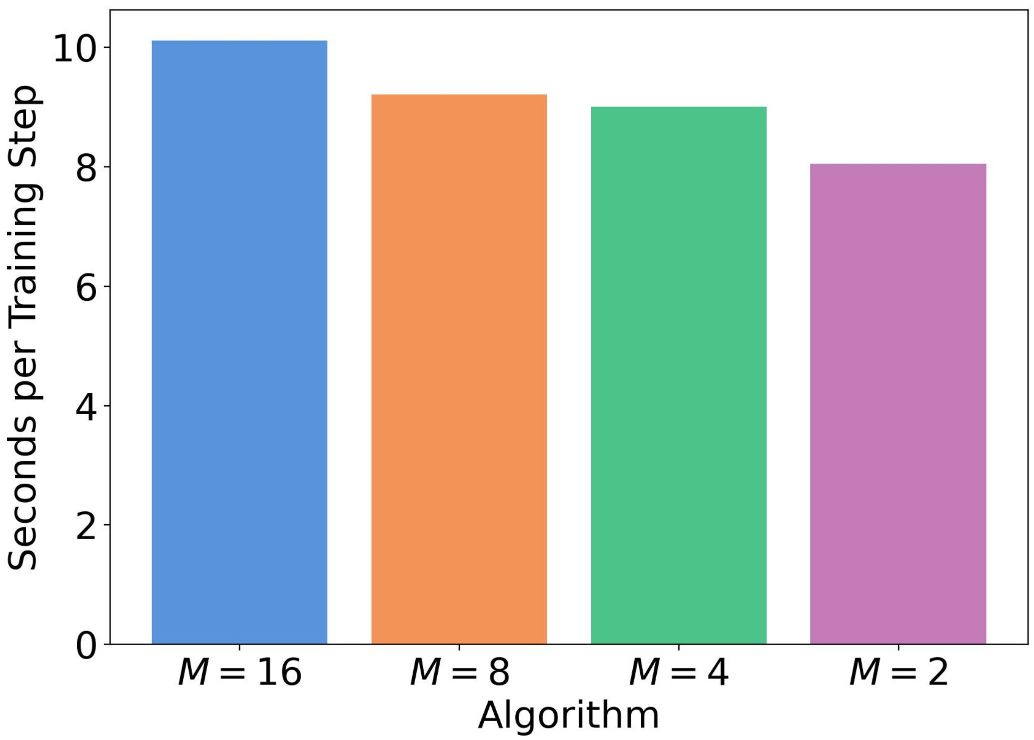
Fixing the Update Step Batch Size m

- **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 $m \in \{16, 8, 4, 2\}$



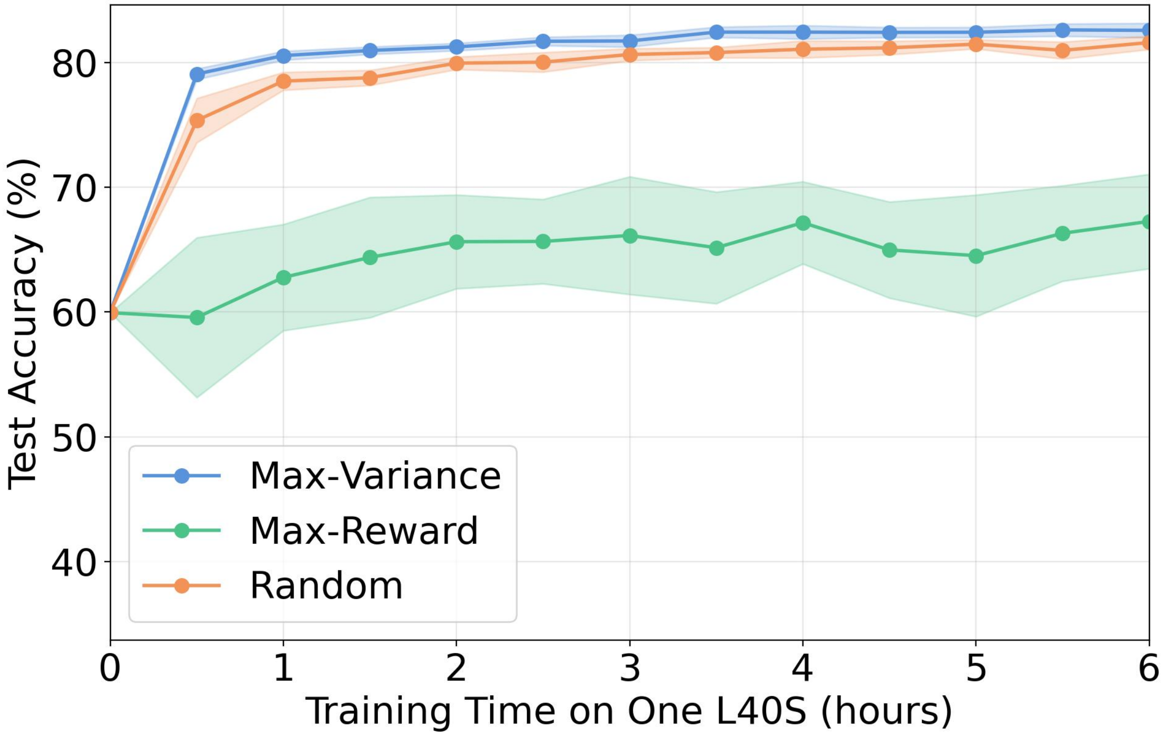


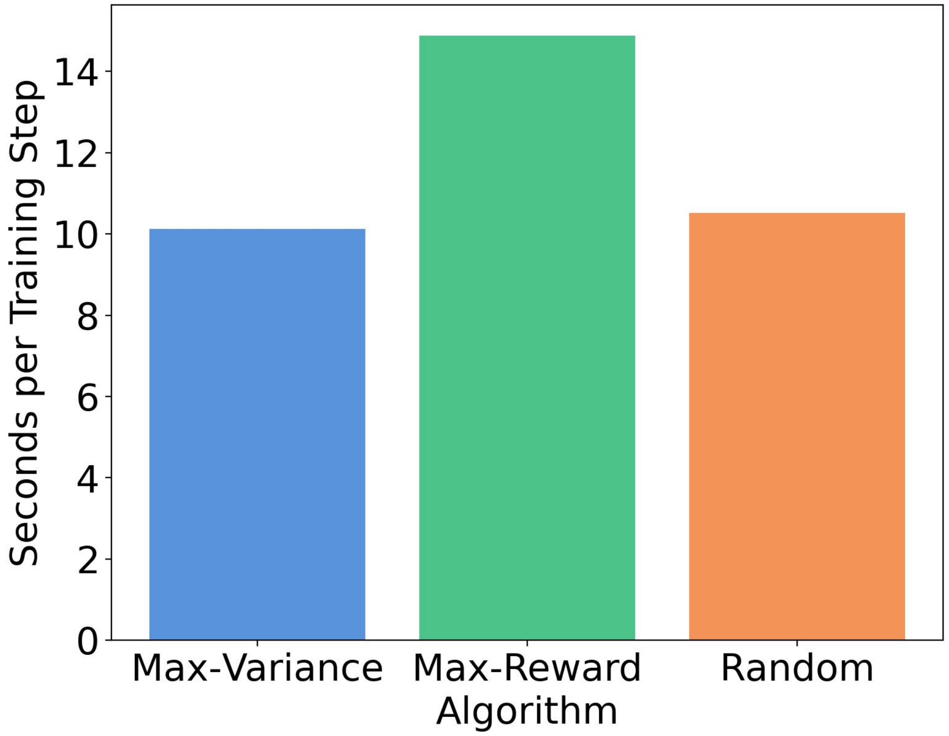
Fixing the Inference Step Batch Size n

- **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

Different Down-Sampling Rules





Different Down-Sampling Rules

- **Experiment settings**
  - Algorithm: GRPO-PODS ($n = 64, m = 16$)
  - LoRA fine-tuning Qwen2.5-3B-Instruct, on one L40S GPU
  - Down-sampling rules: Max-Variance, Max-Reward, Random

- Max-Variance's performance is the best
  - Random is actually equivalent to GRPO with a slower inference step
  - Max-Reward does not capture the bad-performing rollouts

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 $\boldsymbol{O(n \log n)}$ **algorithm** for the max-variance rule
  - We demonstrate **improvement of empirical performance** under different reasoning benchmarks and hardware regimes