

On the Rollout-Training Mismatch In Modern RL Systems

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UCSD

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Efficient RL systems are rising

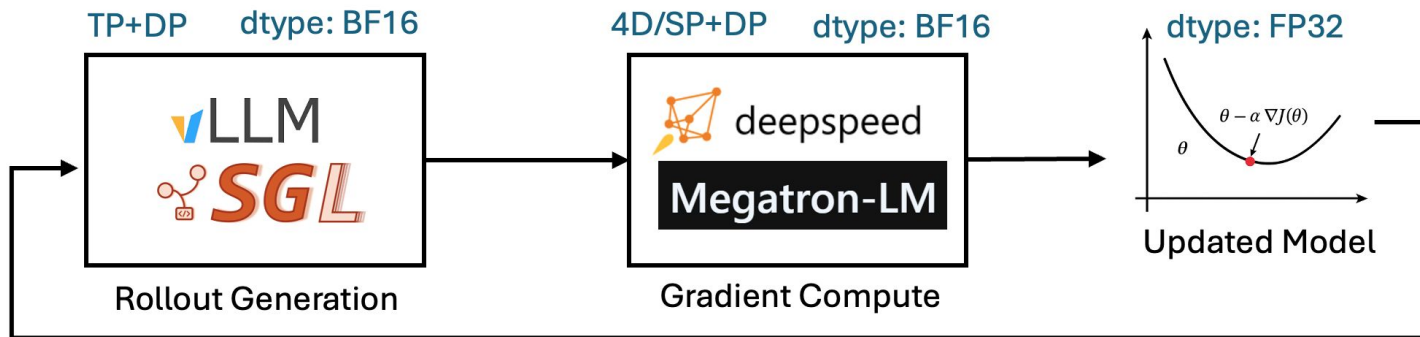
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 - **Rollout:** Advanced LLM **inference engines** (vLLM, SGLang)
 - **Training:** Modern LLM **training backends** (FSDP, Megatron)

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Mismatch!

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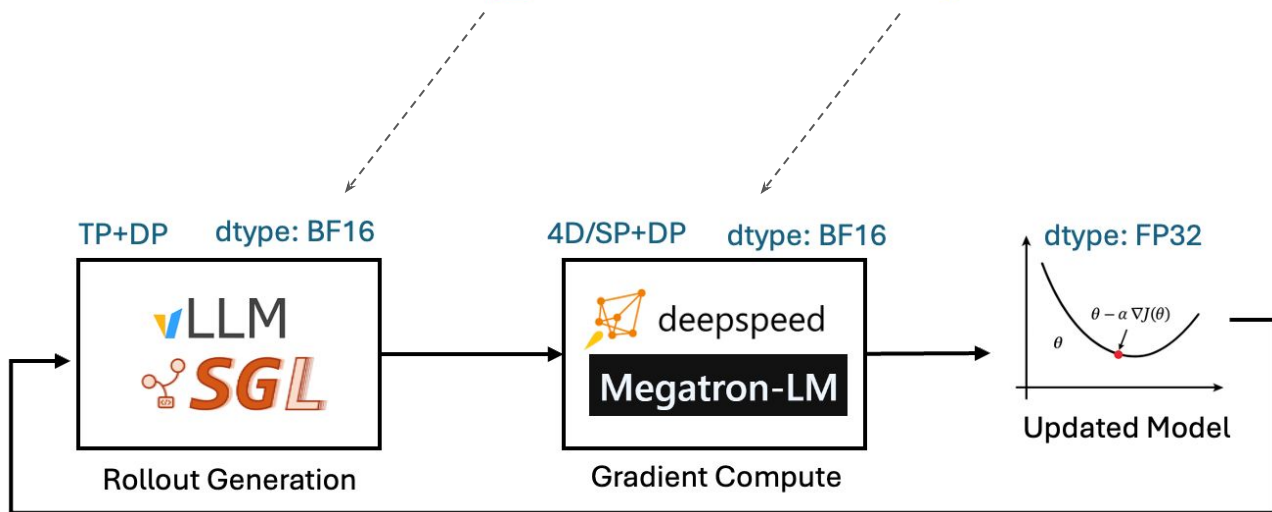
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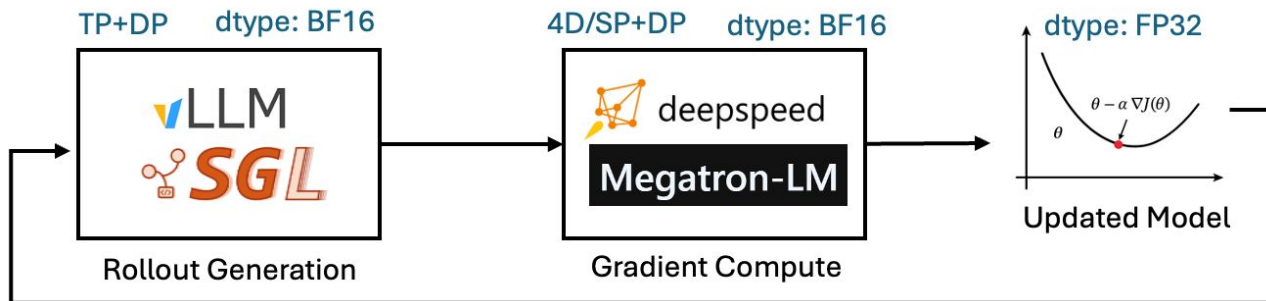
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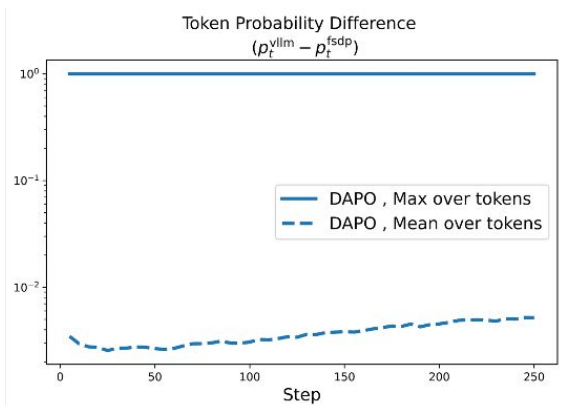
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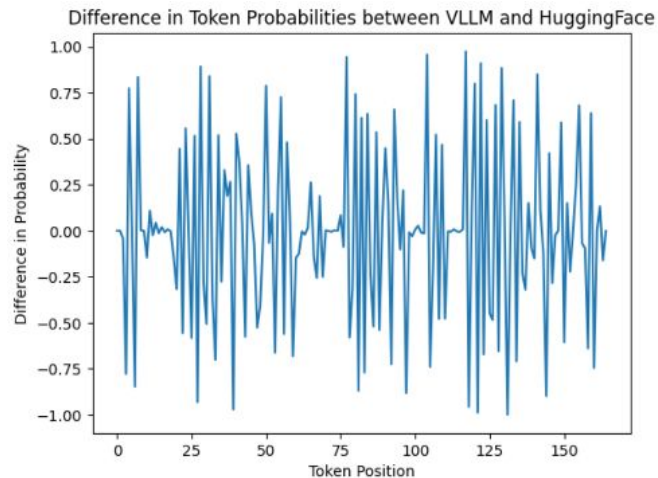
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DAPO Qwen2.5-32B



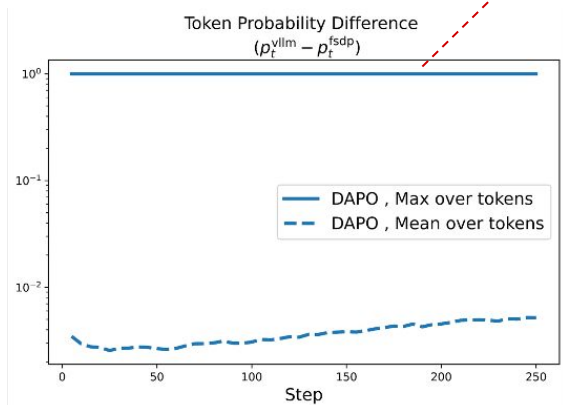
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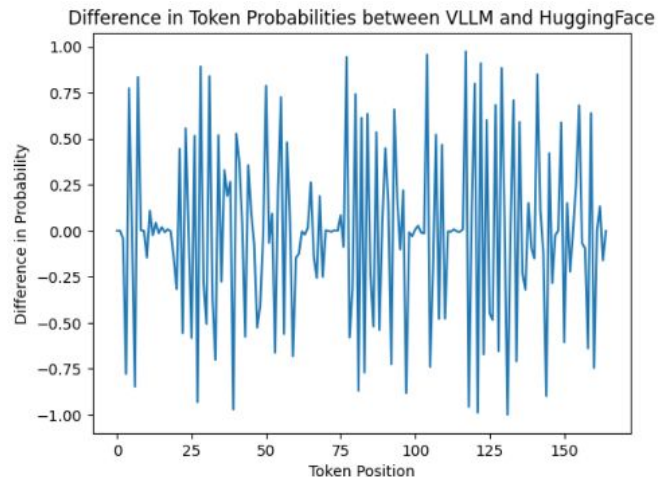
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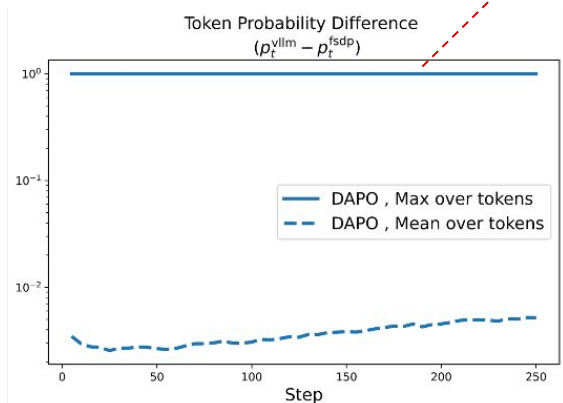
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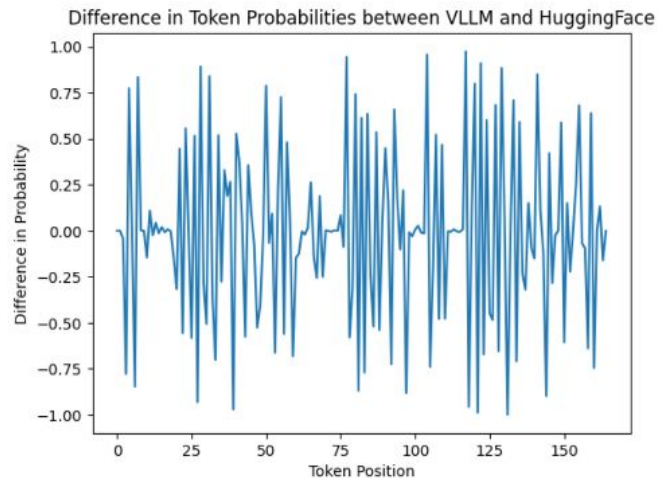
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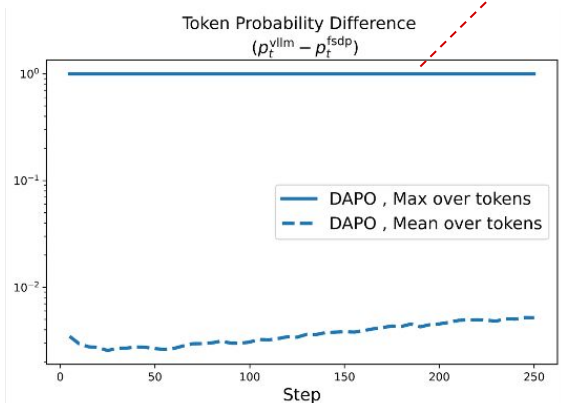
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Implicitly makes RL “**Off-Policy**”!

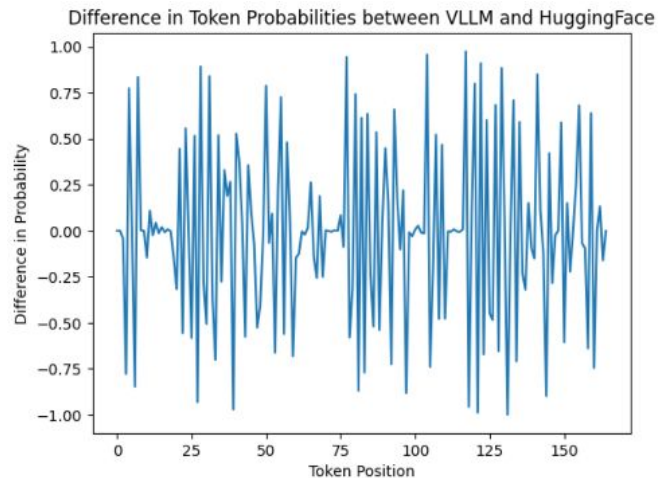
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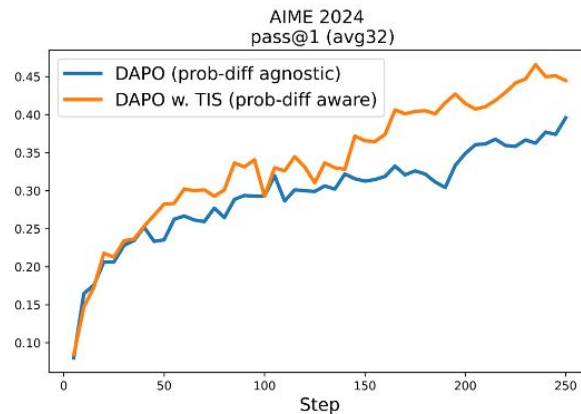
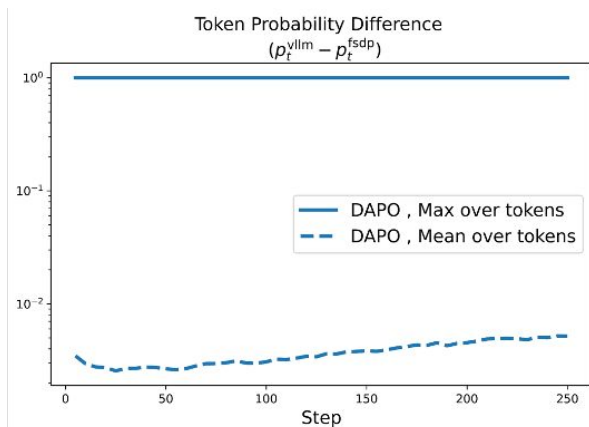
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 - We show that **fix it with TIS** can improve training **effectiveness**



Harvesting the *Off-Policyness* via Quantization

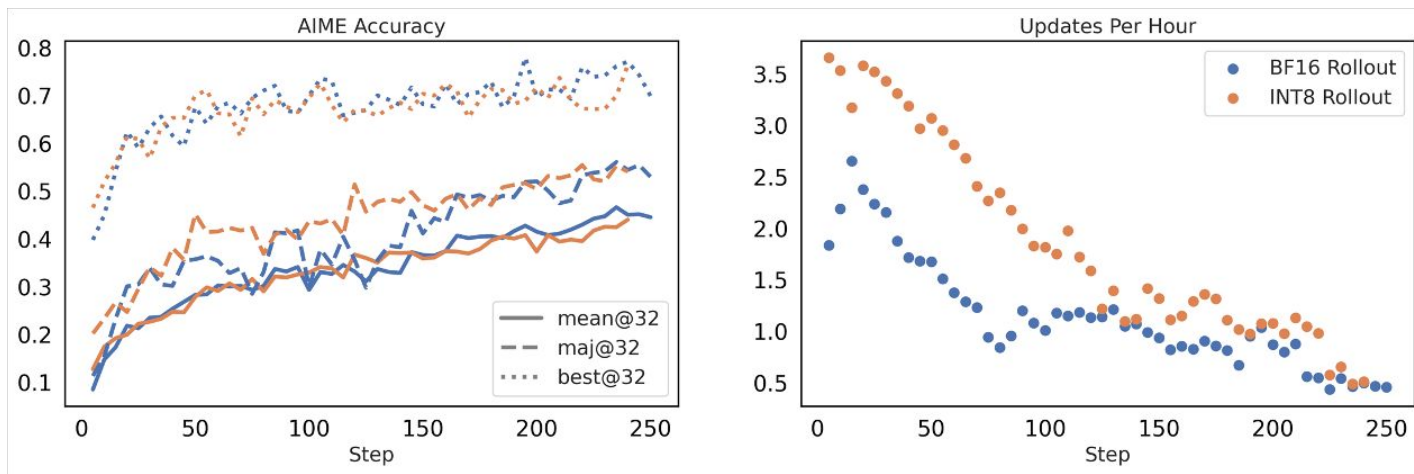
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Outline

- **Why Rollout-Training Mismatch Occurs**
- **How to Fix the Off-Policy Issue It Brings**
- **Harvesting Rollout-Training Mismatch via Quantization**
- **Analyzing the Effectiveness of Different Fixes**

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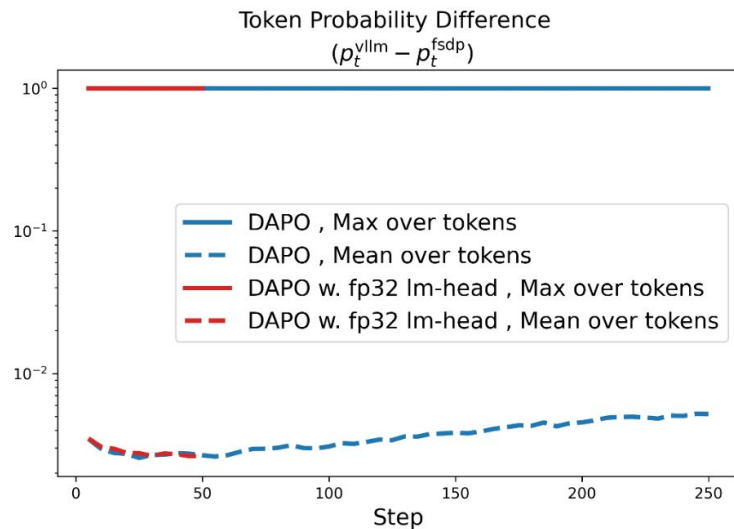
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Why does Rollout-Training Mismatch occur?

- Two common believes
 - Inaccessible true sampling probabilities
 - Add additional gap
 - Backend numerical differences
 - Hard to fix

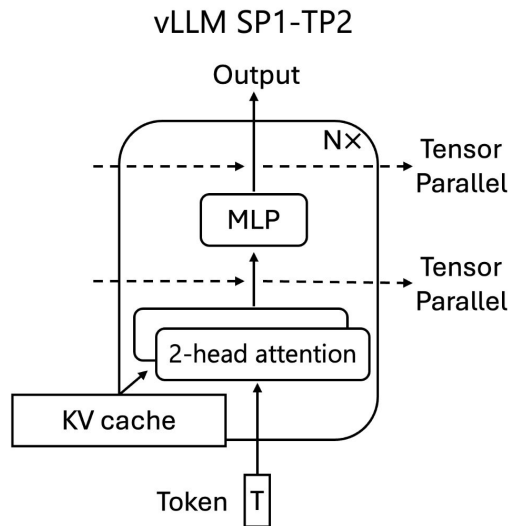
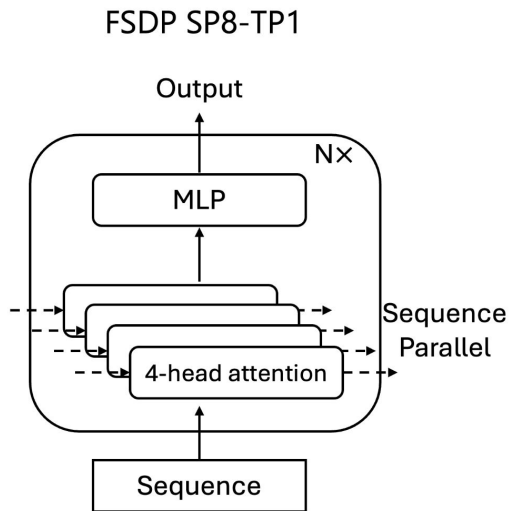


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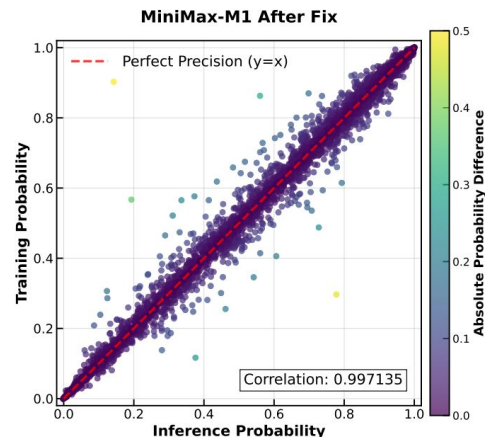
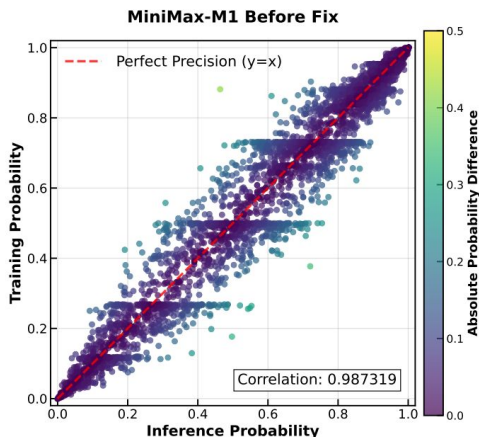
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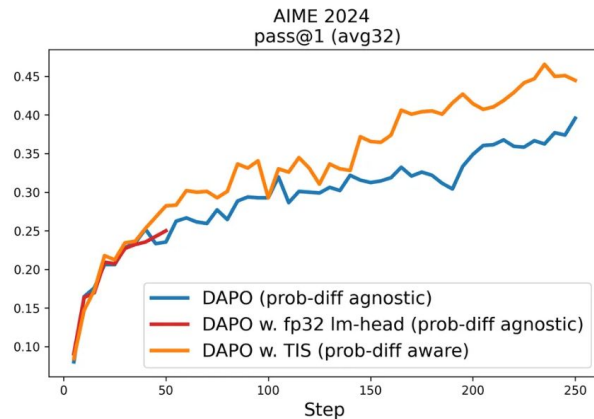
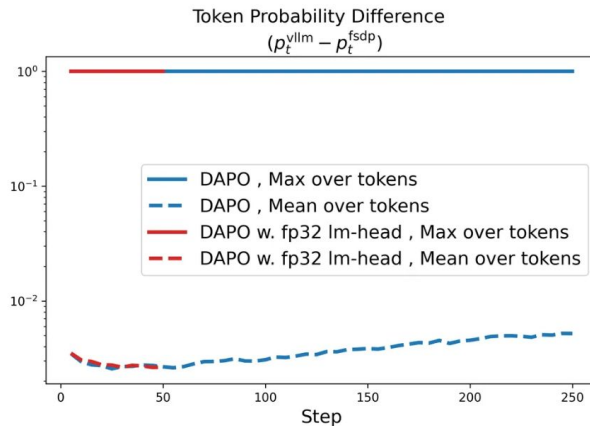
It helps, but ...



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It helps, but **the gap still exists**



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 - Recall: Vanilla Importance Sampling

$$\mathbb{E}_{a \sim \pi_{\text{fsdp}}(\theta)}[R(a)] = \mathbb{E}_{a \sim \pi_{\text{vllm}}(\theta)} \left[\underbrace{\frac{\pi_{\text{fsdp}}(a, \theta)}{\pi_{\text{vllm}}(a, \theta)}}_{\text{importance ratio}} \cdot R(a) \right]$$

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- So we should fix the gradient as:

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- In practice, we use **Truncated Importance Sampling (TIS)**:

$$\mathbb{E}_{a \sim \pi_{\text{vllm}}(\theta)} \left[\underbrace{\min \left(\frac{\pi_{\text{fsdp}}(a, \theta)}{\pi_{\text{vllm}}(a, \theta)}, C \right)}_{\text{truncated importance ratio}} \cdot R(a) \cdot \nabla_{\theta} \log \pi_{\text{fsdp}}(a, \theta) \right]$$

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- VeRL/OpenRLHF's Implementation (**recompute**)

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- Truncated Importance Sampling (**TIS**)

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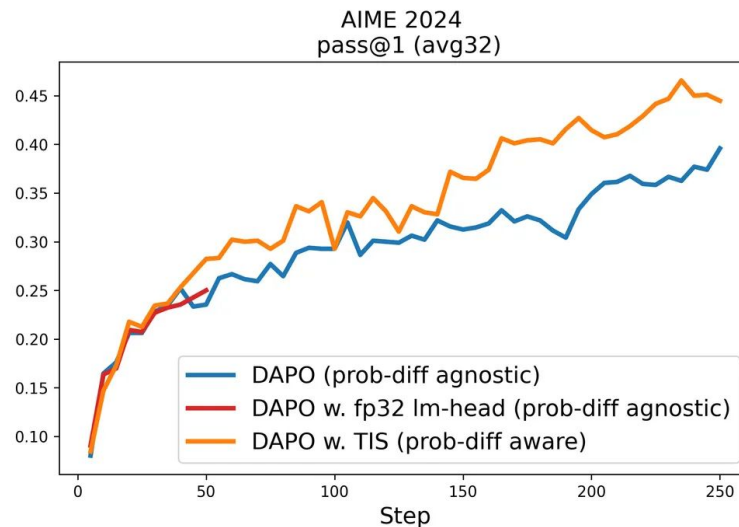
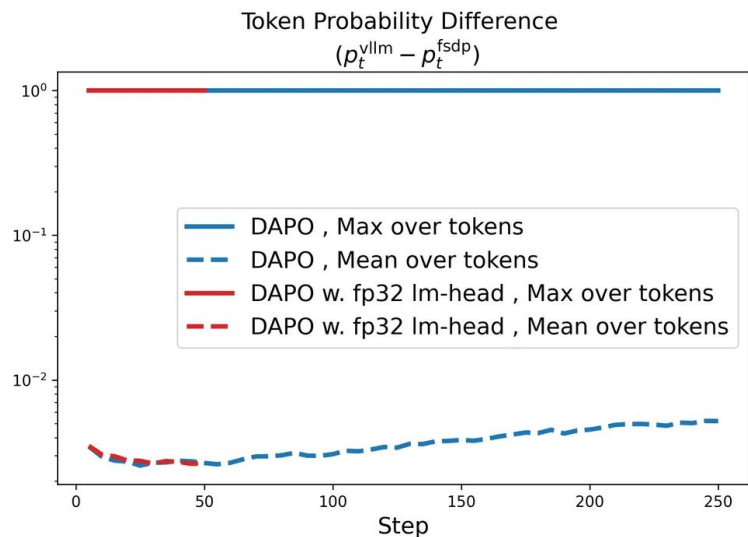
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Can be too large and makes training crash

How well can TIS fix it?

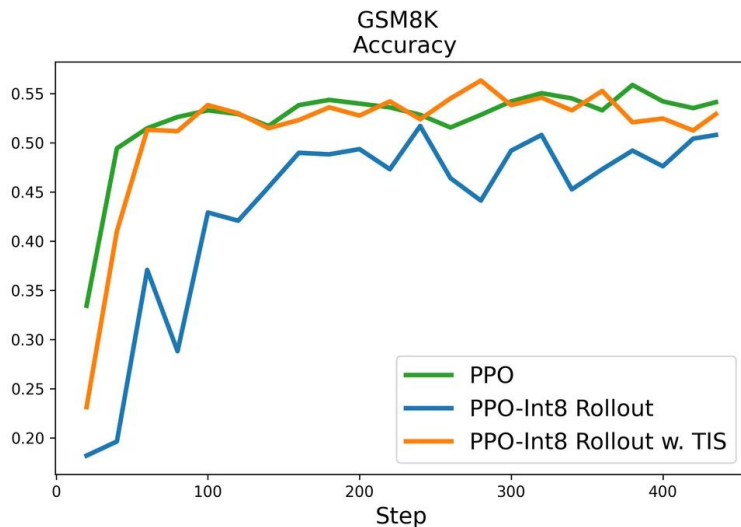
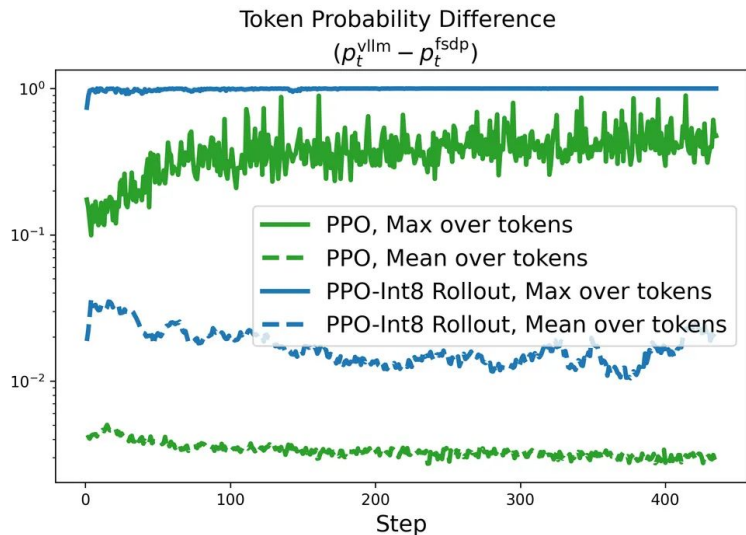
- DAPO 32B Setting



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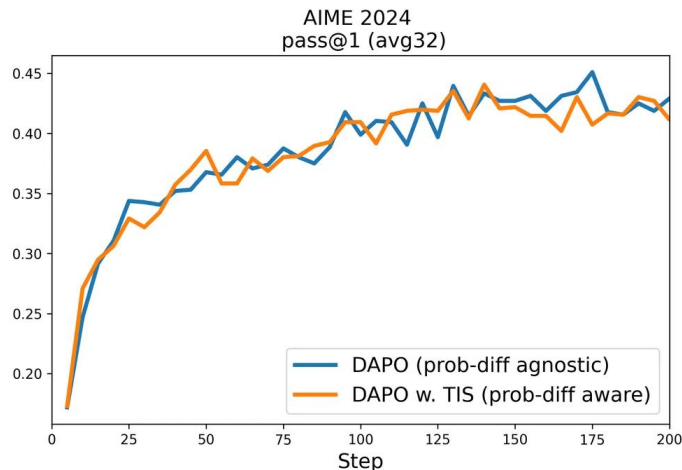
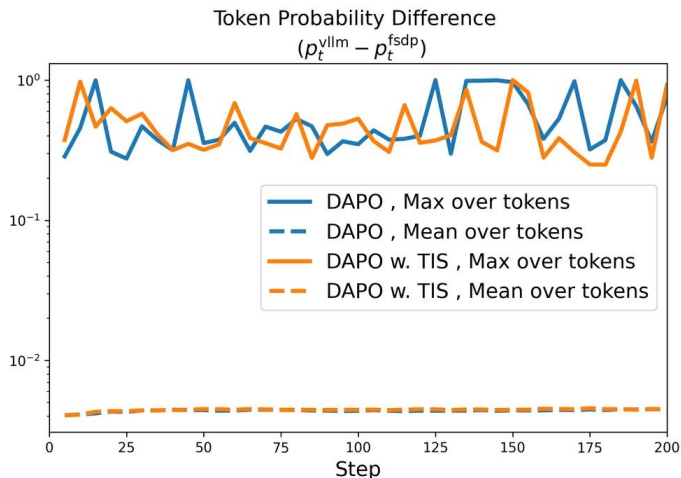
- **GSM8K 0.5B Setting**

- Normal RL: Max Diff is smaller (~ 0.4) than 1.0 (in DAPO-32B setting)
- INT8 Rollout: Max Diff is larger (~ 1.0) than normal RL setting



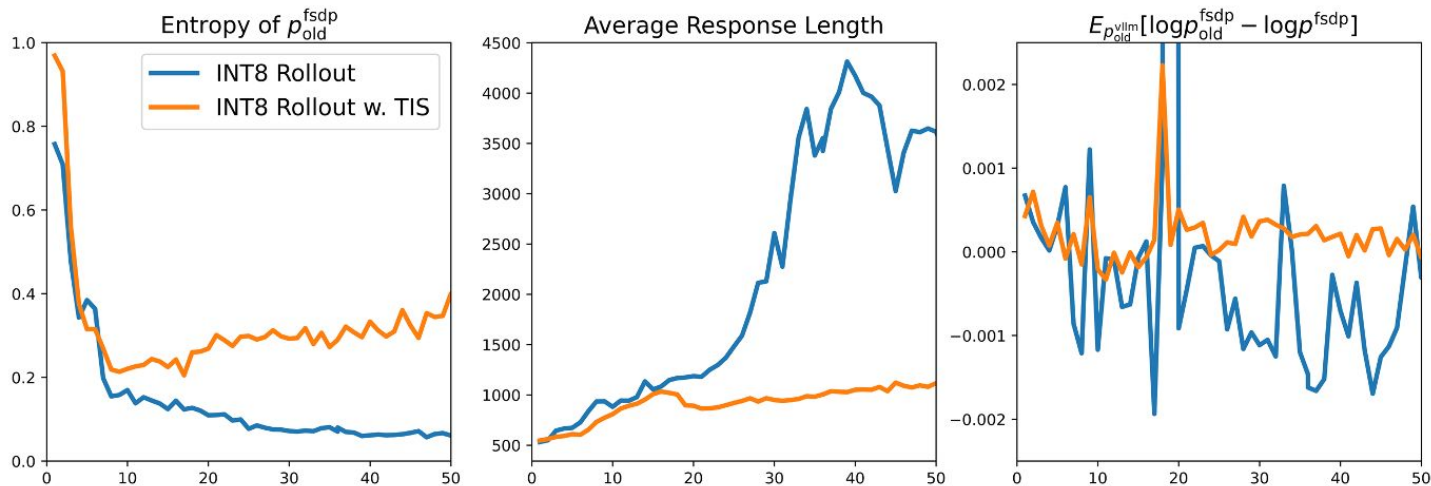
Does TIS always help?

- DAPO 1.5B Setting
 - In settings where prob diff is relatively small
 - TIS does not always help, but **doesn't hurt**



Does the Mismatch really matter?

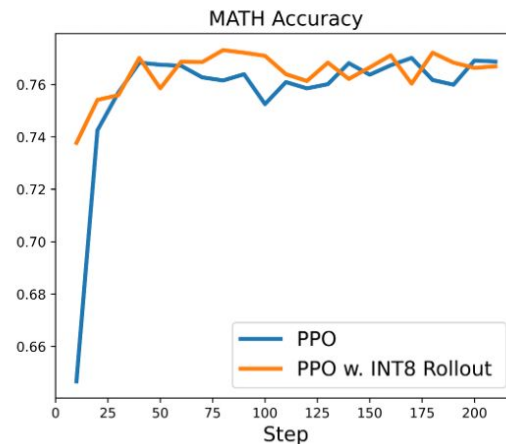
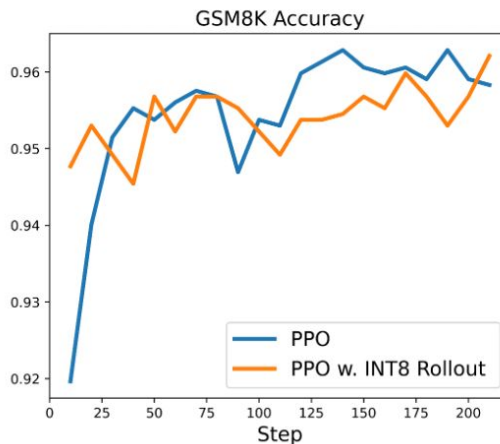
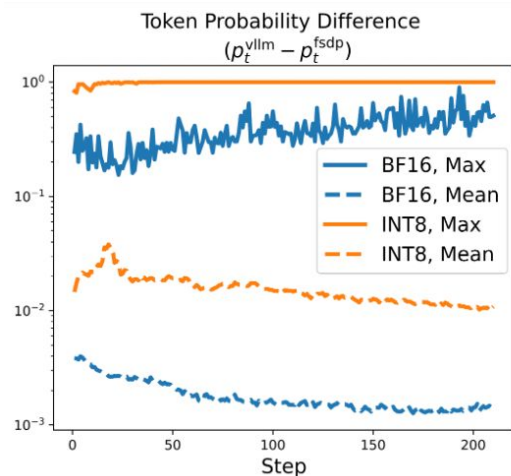
- Unexpected training instability on challenging tasks



DAPO Qwen2.5-32B

Does the Mismatch really matter?

- Possible negligible on simple tasks



PPO GSM8K Qwen2.5-32B

Community Verification

OpenRLHF / OpenRLHF

< Code Issues 265 Pull requests Discussions Actions Projects Security

Releases / v0.8.9

Release v0.8.9

hijkzz released this 2 weeks ago · 9 commits to main since this release · v0.8.9 · 3c9c399

What's Changed

- Add TensorBoard logging to PRM training by @xli360 in #1096
- Support vLLM off-policy importance sampling correction by @xiaoxiguo999 and @MooMoo-Yang in #1098
 - Requires vLLM version > 0.10: pip install -U vllm --pre --extra-index-url https://wheels.vllm.ai/nightly
- Fix weight broadcasting issue in Async RL with PyTorch 2.7.1 and vLLM 0.10 by @xiaoxiguo999 in #1100
- Fix sequence-level loss calculation for GSPQ by @xiaoxiguo999

Full Changelog: v0.8.0...v0.8.9

voicengine / vert

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[BREAKING][vllm, fsdp] feat: add Rollout-Training Mismatch Fix -- Truncated importance sampling #2953

zhaochenyang20 merged 17 commits into voicengine:main from yaof20:truncated_importance_sampling yesterday

Conversation 31 Commits 17 Checks 50 Files changed 13 +209 -7

yaof20 commented 3 weeks ago

What does this PR do?

Support vLLM-FSDP off-policy importance sampling correction using Truncated Importance Sampling (TIS).

Expected objective:

$$E_{\pi_{\theta} \sim \pi_{\text{data}}(\theta, \theta_{\text{data}})} [\nabla_{\theta} \min_{\pi_{\text{data}}(\theta, \theta_{\text{data}})} \hat{A} \cdot \text{clip} \left(\frac{\pi_{\text{data}}(\theta, \theta)}{\pi_{\text{data}}(\theta, \theta_{\text{data}})} 1 - \epsilon, 1 + \epsilon \right) \hat{A}] \quad (1)$$

Mistake: people actually do rollout with vLLM:

$$s \sim \pi_{\text{data}}(\theta, \theta_{\text{data}}) \Rightarrow s \sim \pi_{\text{data}}(\theta, \theta_{\text{data}}) \quad (2)$$

Given $s \sim \pi_{\text{data}}(\theta, \theta_{\text{data}})$, standard vllm recanonical $\pi_{\text{data}}(\theta, \theta_{\text{data}})$ with Inference interface:

$$s \sim \pi_{\text{data}}(\theta, \theta_{\text{data}}) [\nabla_{\theta} \min_{\pi_{\text{data}}(\theta, \theta_{\text{data}})} \hat{A} \cdot \text{clip} \left(\frac{\pi_{\text{data}}(\theta, \theta)}{\pi_{\text{data}}(\theta, \theta_{\text{data}})} 1 - \epsilon, 1 + \epsilon \right) \hat{A}] \quad (3)$$

Our proposed truncated importance sampling (TIS):

$$E_{\pi_{\theta} \sim \pi_{\text{data}}(\theta, \theta_{\text{data}})} [\nabla_{\theta} \min_{\pi_{\text{data}}(\theta, \theta_{\text{data}})} \hat{A} \cdot \text{clip} \left(\frac{\pi_{\text{data}}(\theta, \theta)}{\pi_{\text{data}}(\theta, \theta_{\text{data}})} 1 - \epsilon, 1 + \epsilon \right) \hat{A}] \quad (4)$$

Zichen Liu @zzlccc · Aug 22

With just a few lines of code, Feng's (@fengyao1909) suggested fix—applying importance sampling on the behavior policy—resolved the training instability in my case (oat). I believe the result can generalize to other RL frameworks as well. Great work, Feng!

With truncated importance sampling (orange), the training becomes more stable.

$$E_{\pi_{\theta} \sim \pi_{\text{data}}(\theta, \theta_{\text{data}})} [\nabla_{\theta} \min_{\pi_{\text{data}}(\theta, \theta_{\text{data}})} \hat{A} \cdot \text{clip} \left(\frac{\pi_{\text{data}}(\theta, \theta)}{\pi_{\text{data}}(\theta, \theta_{\text{data}})} 1 - \epsilon, 1 + \epsilon \right) \hat{A}]$$

Reference: <https://fengyao1909.github.io/policy-d/>

Qian Liu @sivil_taram · Aug 25

TIPS has been remarkably effective in my practice—more people should definitely know about it!

Feng Yao @fengyao1909 · Aug 25

We are glad that TIS and FlashRL have received broad attention from the open-source community that they have been verified and supported (OpenRLHF @hijkzz, SkyRL @NovaSkyAI, REINFORCE++ @hijkzz, OAT @zzlccc)!

Show more

- [News] OAT has verified and implement TIS. [GitHub] [Tweet from OAT]
- [News] SkyRL has integrated TIS. [GitHub] [Tweet from SkyRL]
- [News] REINFORCE++ verified TIS in Tool-Integrated-Reasoning (TIR) setting. [Blog]
- [News] OpenRLHF has integrated TIS. [GitHub]

THUDM / slime

< Code Issues 25 Pull requests 9 Actions Projects Security

Naive implementation of rollout logp correction in RL training #179

zhuzilin merged 4 commits into THUDM:main from yitianlian:sgl_logp 2 days ago

Conversation 0 Commits 4 Checks 1 Files changed 9 +83 -3

yitianlian commented 2 weeks ago

The implementation of the importance ratio between rollout logp and training logp.

Reviewers: No reviews

Assignees: No assignees

REINFORCE++-baseline is all you need in RLVR

Janhu Follow 3 min read · 5 days ago

Tool-Integrated Reasoning and Agent Experiments

We have thoroughly validated the effectiveness of global standard deviation and global advantage normalization in complex multi-turn tool call scenarios. Our experiments utilize the framework established by [arXiv:2505.07773](https://arxiv.org/abs/2505.07773), which features a zero-shot agent environment designed for large language models to tackle mathematical problems using Qwen 2.5 Base 7B.

		300-step/eval332/numrun-2/inference	aimed4	aimed5	hmmr_feb_2024	hmmr_feb_2024	aimmc	avg
reinforce++	with-baseline	30.83333	27.1875	17.91667	18.95833	25.625	24.1041667	
reinforce++	with-baseline,vllm-correction	31.5625	23.9583	20.625	20.1042	29.375	25.125	
gpo		31.66667	21.875	17.70833	24.8675	22.9583333		
jpo		30.20833	21.66667	15	18.4375	23.95833	21.8541667	

REINFORCE++-baseline achieves the best performance in the multi-turn tool call tasks.

The REINFORCE++ baseline can be combined with dynamic sampling, clip-higher, and [truncated importance sampling](#) (vLLM correction in the figure) to continuously improve performance.

Outline

- Why Rollout-Training Mismatch Occurs
- How to Fix the Off-Policy Issue It Brings
- **Harvesting Rollout-Training Mismatch via Quantization**
- Analyzing the Effectiveness of Different Fixes

Harvesting *Off-Policy* in Quantization

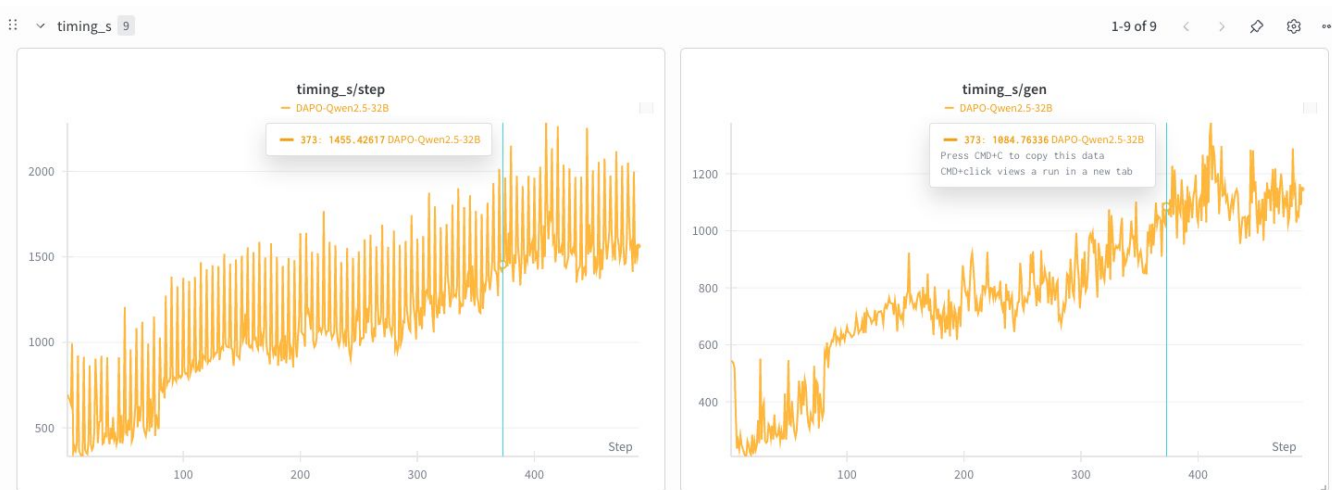
As TIS handles the gap, can we go even **further off-policy** for **speedup**?

Harvesting *Off-Policy* in Quantization

As TIS handles the gap, can we go even **further off-policy** for **speedup**?

Rollout generation is a bottleneck in RL training efficiency:

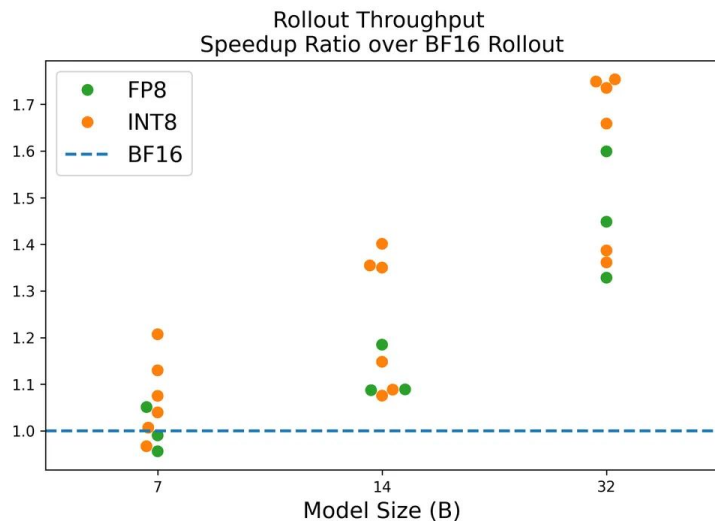
In DAPO-32B setting, rollout takes up ~70% of the training time



Quantization helps *speedup* **but hurts *performance***

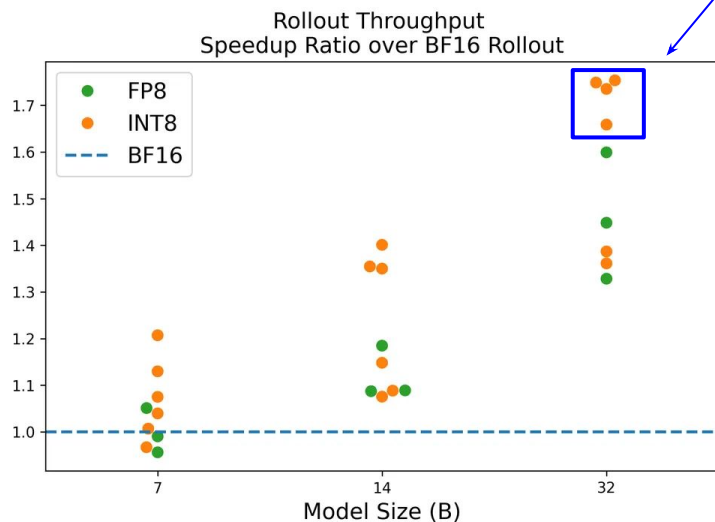
Quantization helps *speedup* **but** hurts *performance*

Naively applying quantization can accelerate rollout speed



Quantization helps *speedup* **but** hurts *performance*

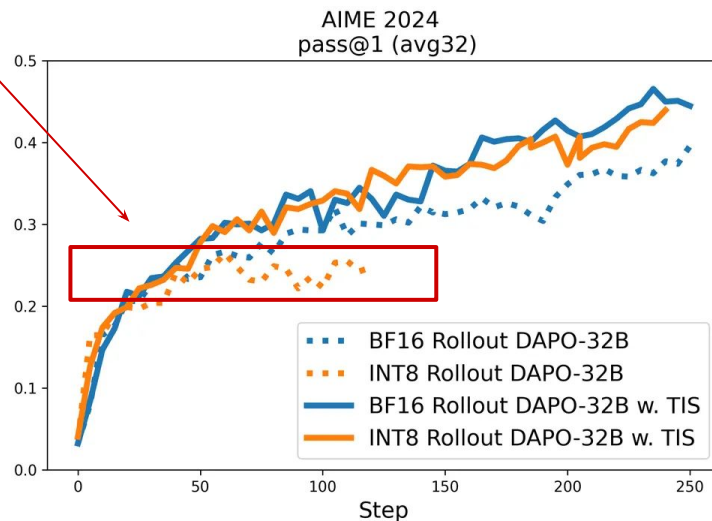
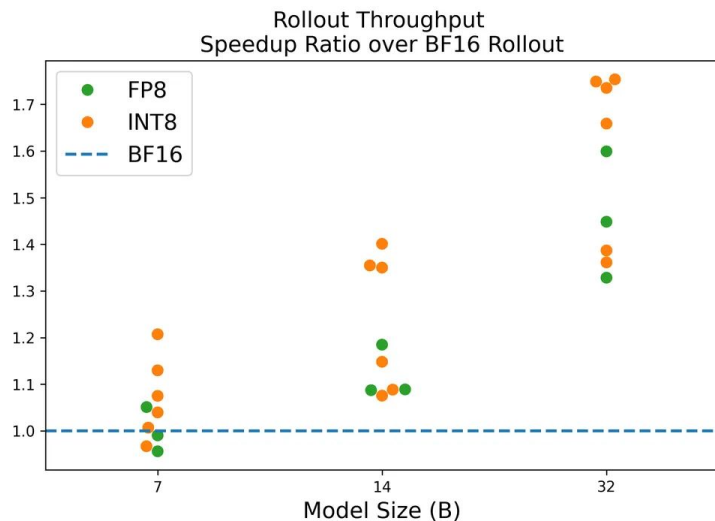
Naively applying quantization can accelerate rollout speed



Quantization helps *speedup* **but** hurts *performance*

Naively applying quantization can accelerate rollout speed

But the performance is also degraded!



Quantization helps *speedup* **but** hurts *performance*

Naively applying quantization can accelerate rollout speed

But the performance is also degraded!

This can be expected, as quantization introduces more mismatch

$$\underbrace{\mathbb{E}_{a \sim \pi_{\text{bf16}}(\theta_{\text{old}})}}_{\text{int8 Rollout: } \pi_{\text{bf16}} \rightarrow \pi_{\text{int8}}} \left[\nabla_{\theta} \min \left(\frac{\pi_{\text{bf16}}(a, \theta)}{\pi_{\text{bf16}}(a, \theta_{\text{old}})} \hat{A}, \text{clip} \left(\frac{\pi_{\text{bf16}}(a, \theta)}{\pi_{\text{bf16}}(a, \theta_{\text{old}})}, 1 - \epsilon, 1 + \epsilon \right) \hat{A} \right) \right]$$

FlashRL preserves performance with TIS

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FlashRL fixes it with TIS

$$\mathbb{E}_{a \sim \pi_{\text{int8}}(\theta_{\text{old}})} \left[\underbrace{\min \left(\frac{\pi_{\text{bf16}}(a, \theta_{\text{old}})}{\pi_{\text{int8}}(a, \theta_{\text{old}})}, C \right)}_{\text{truncated importance ratio}} \cdot \nabla_{\theta} \min \left(\frac{\pi_{\text{bf16}}(a, \theta)}{\pi_{\text{bf16}}(a, \theta_{\text{old}})} \hat{A}, \text{clip} \left(\frac{\pi_{\text{bf16}}(a, \theta)}{\pi_{\text{bf16}}(a, \theta_{\text{old}})}, 1 - \epsilon, 1 + \epsilon \right) \hat{A} \right) \right]$$

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FlashRL fixes it with TIS

$$\mathbb{E}_{a \sim \pi_{\text{int8}}(\theta_{\text{old}})} \left[\underbrace{\min \left(\frac{\pi_{\text{bf16}}(a, \theta_{\text{old}})}{\pi_{\text{int8}}(a, \theta_{\text{old}})}, C \right)}_{\text{truncated importance ratio}} \cdot \nabla_{\theta} \min \left(\frac{\pi_{\text{bf16}}(a, \theta)}{\pi_{\text{bf16}}(a, \theta_{\text{old}})} \hat{A}, \text{clip} \left(\frac{\pi_{\text{bf16}}(a, \theta)}{\pi_{\text{bf16}}(a, \theta_{\text{old}})}, 1 - \epsilon, 1 + \epsilon \right) \hat{A} \right) \right]$$

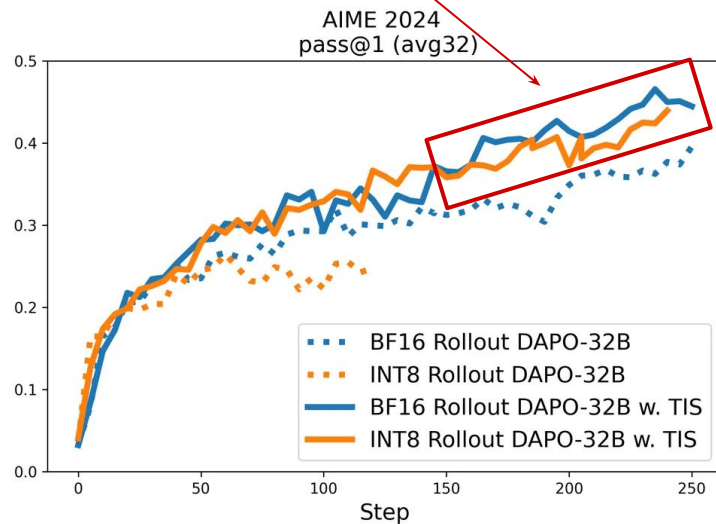
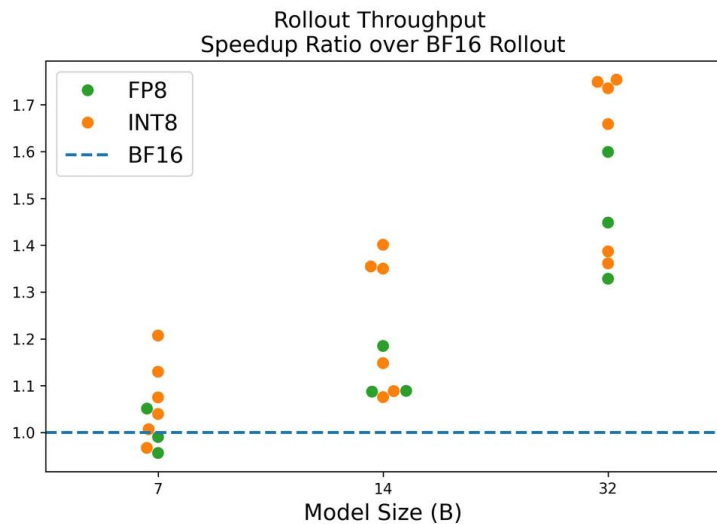
FlashRL is implemented as a PyPI package to patch vLLM

```
pip install flash-llm-rl      # install with pip
export FLASHRL_CONFIG='fp8'  # turn on env variable
bash your-rl-training-script # no code change needed!
```

FlashRL preserves performance with TIS

DAPO 32B Setting

Matches the performance of BF16 rollout with TIS

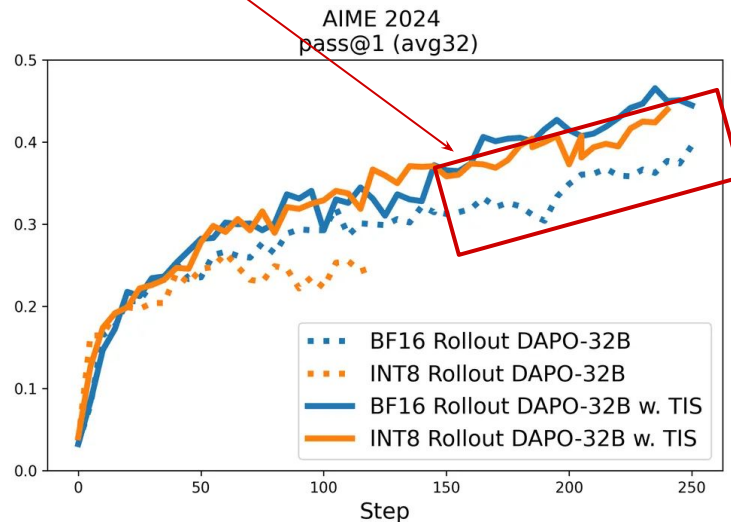
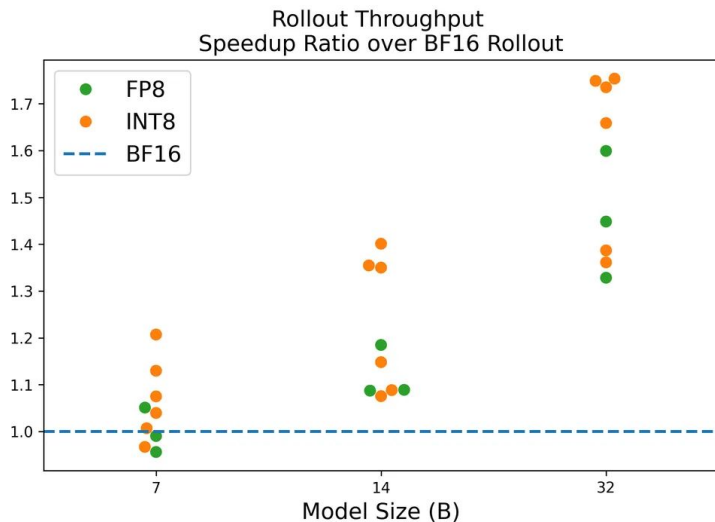


FlashRL preserves performance with TIS

DAPO 32B Setting

Matches the performance of BF16 rollout with TIS

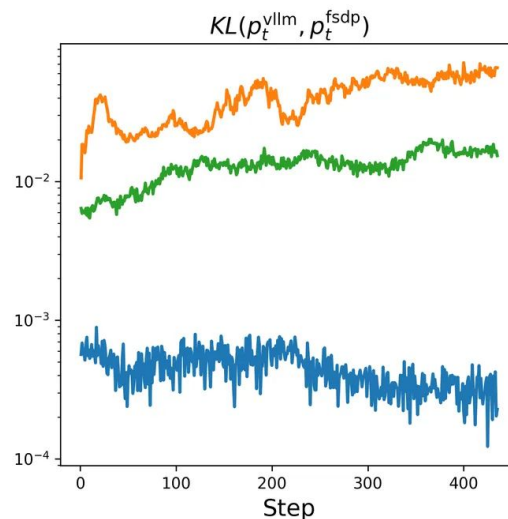
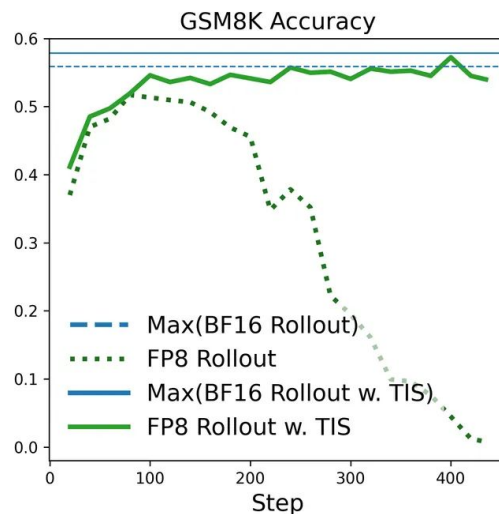
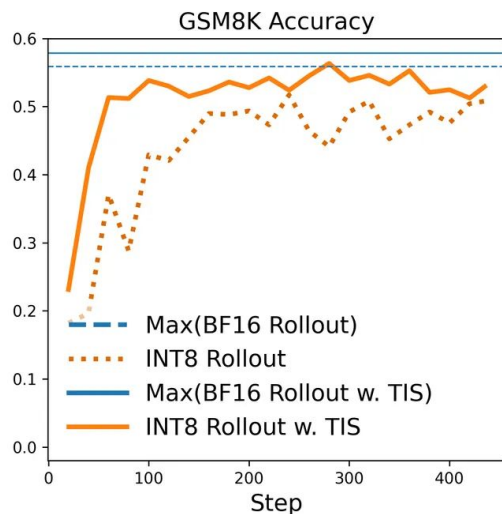
Outperforms naive BF16 rollout (without TIS)



FlashRL preserves performance with TIS

GSM8K 0.5B Setting

TIS works both in INT8 and FP8 setting



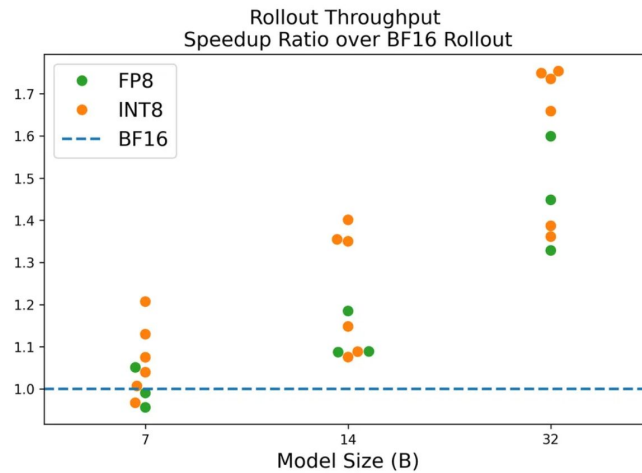
More detailed analysis

Rollout Speedup

More detailed analysis

Rollout Speedup

Regular RL Setting



More detailed analysis

Rollout Speedup

Regular RL Setting

Standard Inference Setting

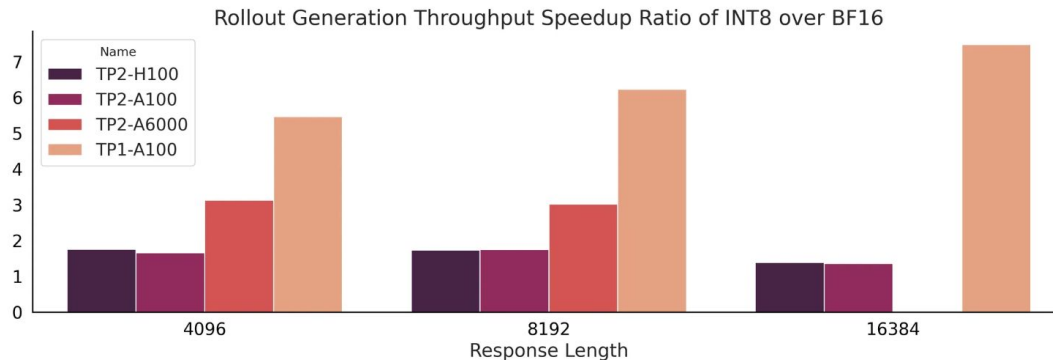
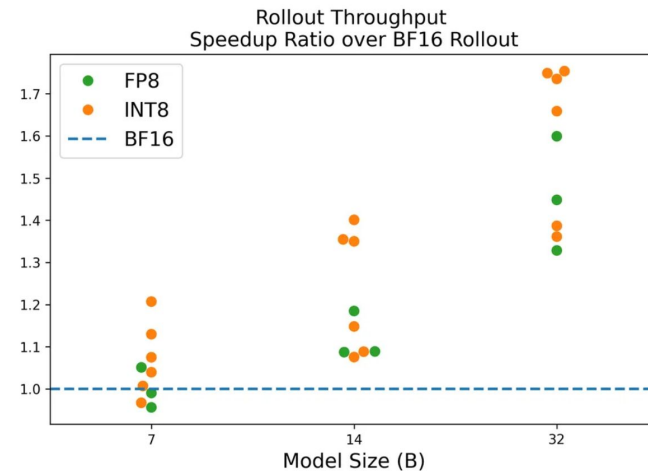


Figure 3. Throughput speedup ratio of INT8-quantized *Deepseek-R1-Distill-Qwen-32B* relative to BF16 in 4 inference-only configurations, measured across varying response lengths

More detailed analysis

End-to-End Speedup & Effectiveness

More detailed analysis

End-to-End Speedup & Effectiveness

INT8 as a pressure test

More detailed analysis

End-to-End Speedup & Effectiveness

INT8 as a pressure test

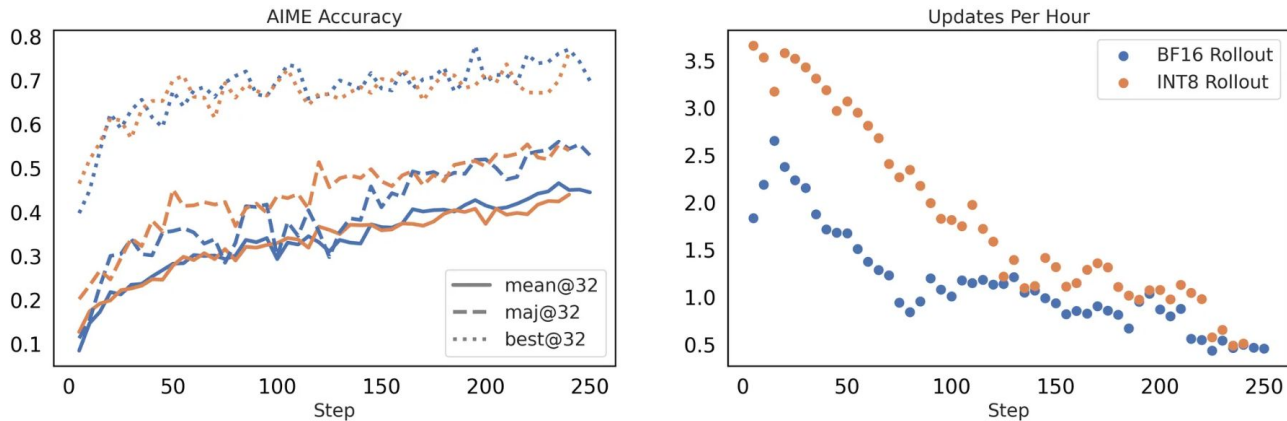


Figure 4. *Left:* Downstream performance of RL training with **BF16** vs. **INT8** rollout precision. *Right:* Updates per hour achieved with **BF16** and **INT8** rollout. All experiments use the DAPO recipe on Qwen2.5-32B, trained for 250 steps on 4 nodes with 8×H100 GPUs. [[wandb](#)]

How to perform INT8 quantization?

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Our solution: ***Online INT8 Quantization via Calibration Transfer***

calculate the calibration result once at the beginning of training and reuse it at every online step

How to perform INT8 quantization?

Online INT8 Quantization via Calibration Transfer

calculate the calibration result once at the beginning of training and reuse it at every online step

Observation: RL changes model weights less aggressively comparing to SFT

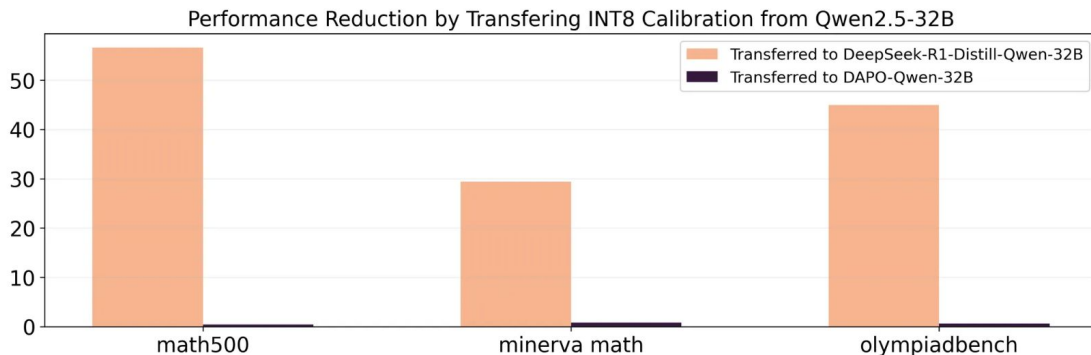


Figure 6. We experiment on models finetuned via SFT / RL from Qwen2.5-32B base model. We find that compared to SFT, reusing the base model calibration result by applying it to RL finetuned model rarely change the performance. This indicates that INT8 online quantization is practically possible in RL by reusing previous calibration result.

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Analyzing the Effectiveness of Different Fixes

- PPO

$$\mathbb{E}_{a \sim \pi_{\text{fsdp}}(\theta_{\text{old}})} \left[\nabla_{\theta} \min \left(\frac{\pi_{\text{fsdp}}(a, \theta)}{\pi_{\text{fsdp}}(a, \theta_{\text{old}})} \hat{A}, \text{clip} \left(\frac{\pi_{\text{fsdp}}(a, \theta)}{\pi_{\text{fsdp}}(a, \theta_{\text{old}})}, 1 - \epsilon, 1 + \epsilon \right) \hat{A} \right) \right]$$

- Recompute

$$\mathbb{E}_{a \sim \pi_{\text{vllm}}(\theta_{\text{old}})} \left[\nabla_{\theta} \min \left(\frac{\pi_{\text{fsdp}}(a, \theta)}{\pi_{\text{fsdp}}(a, \theta_{\text{old}})} \hat{A}, \text{clip} \left(\frac{\pi_{\text{fsdp}}(a, \theta)}{\pi_{\text{fsdp}}(a, \theta_{\text{old}})}, 1 - \epsilon, 1 + \epsilon \right) \hat{A} \right) \right]$$

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- PPO-IS

$$\mathbb{E}_{a \sim \pi_{\text{vllm}}(\theta_{\text{old}})} \left[\nabla_{\theta} \min \left(\frac{\pi_{\text{fsdp}}(a, \theta)}{\pi_{\text{vllm}}(a, \theta_{\text{old}})} \hat{A}, \text{clip} \left(\frac{\pi_{\text{fsdp}}(a, \theta)}{\pi_{\text{vllm}}(a, \theta_{\text{old}})}, 1 - \epsilon, 1 + \epsilon \right) \hat{A} \right) \right]$$

Analyzing the Effectiveness of Different Fixes

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$$\mathbb{E}_{a \sim \pi_{\text{fsdp}}(\theta_{\text{old}})} \left[\nabla_{\theta} \min \left(\frac{\pi_{\text{fsdp}}(a, \theta)}{\pi_{\text{fsdp}}(a, \theta_{\text{old}})} \hat{A}, \text{clip} \left(\frac{\pi_{\text{fsdp}}(a, \theta)}{\pi_{\text{fsdp}}(a, \theta_{\text{old}})}, 1 - \epsilon, 1 + \epsilon \right) \hat{A} \right) \right]$$

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- PPO-IS

$$\mathbb{E}_{a \sim \pi_{\text{vllm}}(\theta_{\text{old}})} \left[\nabla_{\theta} \min \left(\frac{\pi_{\text{fsdp}}(a, \theta)}{\pi_{\text{vllm}}(a, \theta_{\text{old}})} \hat{A}, \text{clip} \left(\frac{\pi_{\text{fsdp}}(a, \theta)}{\pi_{\text{vllm}}(a, \theta_{\text{old}})}, 1 - \epsilon, 1 + \epsilon \right) \hat{A} \right) \right]$$

- Vanilla-IS

$$\mathbb{E}_{\pi_{\text{vllm}}(\theta_{\text{old}})} \left[\underbrace{\frac{\pi_{\text{fsdp}}(a, \theta_{\text{old}})}{\pi_{\text{vllm}}(a, \theta_{\text{old}})}}_{\text{importance ratio}} \cdot \nabla_{\theta} \min \left(\frac{\pi_{\text{fsdp}}(a, \theta)}{\pi_{\text{fsdp}}(a, \theta_{\text{old}})} \hat{A}, \text{clip} \left(\frac{\pi_{\text{fsdp}}(a, \theta)}{\pi_{\text{fsdp}}(a, \theta_{\text{old}})}, 1 - \epsilon, 1 + \epsilon \right) \hat{A} \right) \right]$$

Analyzing the Effectiveness of Different Fixes

- PPO

$$\mathbb{E}_{a \sim \pi_{\text{fsdp}}(\theta_{\text{old}})} \left[\nabla_{\theta} \min \left(\frac{\pi_{\text{fsdp}}(a, \theta)}{\pi_{\text{fsdp}}(a, \theta_{\text{old}})} \hat{A}, \text{clip} \left(\frac{\pi_{\text{fsdp}}(a, \theta)}{\pi_{\text{fsdp}}(a, \theta_{\text{old}})}, 1 - \epsilon, 1 + \epsilon \right) \hat{A} \right) \right]$$

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$$\mathbb{E}_{\pi_{\text{vllm}}(\theta_{\text{old}})} \left[\underbrace{\frac{\pi_{\text{fsdp}}(a, \theta_{\text{old}})}{\pi_{\text{vllm}}(a, \theta_{\text{old}})}}_{\text{importance ratio}} \cdot \nabla_{\theta} \min \left(\frac{\pi_{\text{fsdp}}(a, \theta)}{\pi_{\text{fsdp}}(a, \theta_{\text{old}})} \hat{A}, \text{clip} \left(\frac{\pi_{\text{fsdp}}(a, \theta)}{\pi_{\text{fsdp}}(a, \theta_{\text{old}})}, 1 - \epsilon, 1 + \epsilon \right) \hat{A} \right) \right]$$

- TIS

$$\mathbb{E}_{\pi_{\text{vllm}}(\theta_{\text{old}})} \left[\underbrace{\min \left(\frac{\pi_{\text{fsdp}}(a, \theta_{\text{old}})}{\pi_{\text{vllm}}(a, \theta_{\text{old}})}, C \right)}_{\text{truncated importance ratio}} \cdot \nabla_{\theta} \min \left(\frac{\pi_{\text{fsdp}}(a, \theta)}{\pi_{\text{fsdp}}(a, \theta_{\text{old}})} \hat{A}, \text{clip} \left(\frac{\pi_{\text{fsdp}}(a, \theta)}{\pi_{\text{fsdp}}(a, \theta_{\text{old}})}, 1 - \epsilon, 1 + \epsilon \right) \hat{A} \right) \right]$$

Comparison with TIS-Variants

GSM8K, PPO, Qwen2.5-0.5B-Instruct

Only TIS works consistently

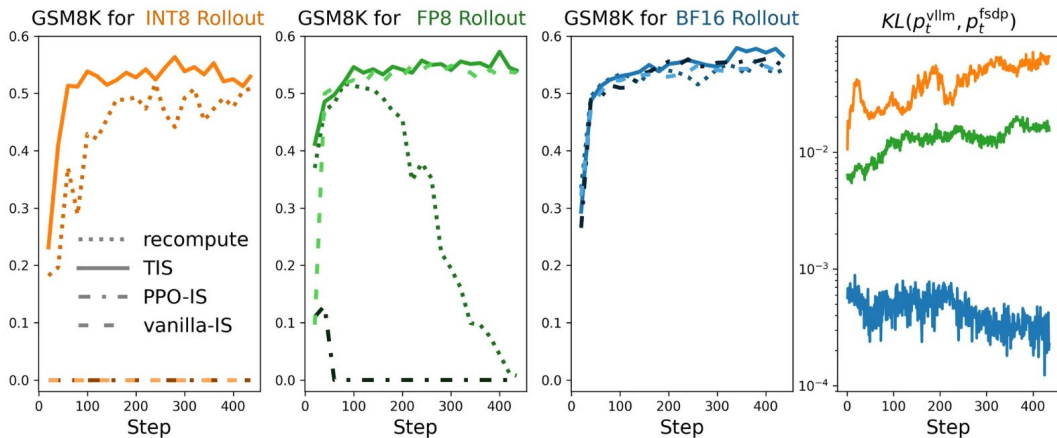


Figure 5. We ablate different rollout-training mismatch mitigation strategies on Qwen2.5-0.5B with GSM8k. Note PPO-IS and Vanilla-IS achieves near 0 accuracy for INT8 rollouts thus being highly overlapped. We also plot the KL divergence between vLLM sampled distribution and the FSDP distribution on the right. [\[int8 wandb\]](#)/[\[fp8 wandb\]](#)/[\[bf16 wandb\]](#)

Why Recompute fails

$$\mathbb{E}_{a \sim \pi_{\text{vllm}}(\theta_{\text{old}})} \left[\nabla_{\theta} \min \left(\frac{\pi_{\text{fsdp}}(a, \theta)}{\pi_{\text{fsdp}}(a, \theta_{\text{old}})} \hat{A}, \text{clip} \left(\frac{\pi_{\text{fsdp}}(a, \theta)}{\pi_{\text{fsdp}}(a, \theta_{\text{old}})}, 1 - \epsilon, 1 + \epsilon \right) \hat{A} \right) \right]$$

- **Recompute**

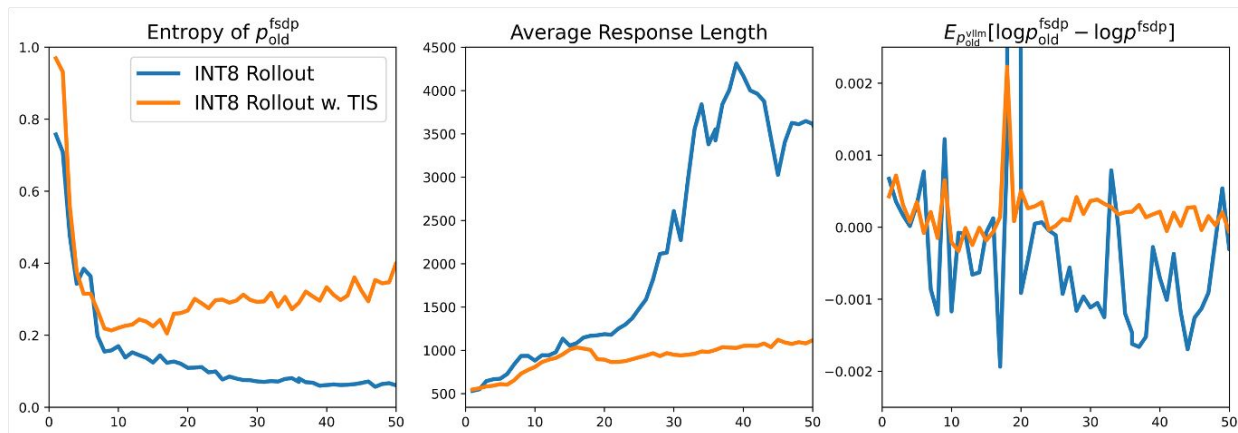
- The mismatch can lead to entropy collapse
 - Gradient computation vs. rollout generation

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$$\mathbb{E}_{a \sim \pi_{\text{vllm}}(\theta_{\text{old}})} \left[\nabla_{\theta} \min \left(\frac{\pi_{\text{fsdp}}(a, \theta)}{\pi_{\text{fsdp}}(a, \theta_{\text{old}})} \hat{A}, \text{clip} \left(\frac{\pi_{\text{fsdp}}(a, \theta)}{\pi_{\text{fsdp}}(a, \theta_{\text{old}})}, 1 - \epsilon, 1 + \epsilon \right) \hat{A} \right) \right]$$

- **Recompute**

- The mismatch can lead to entropy collapse
 - Gradient computation vs. rollout generation

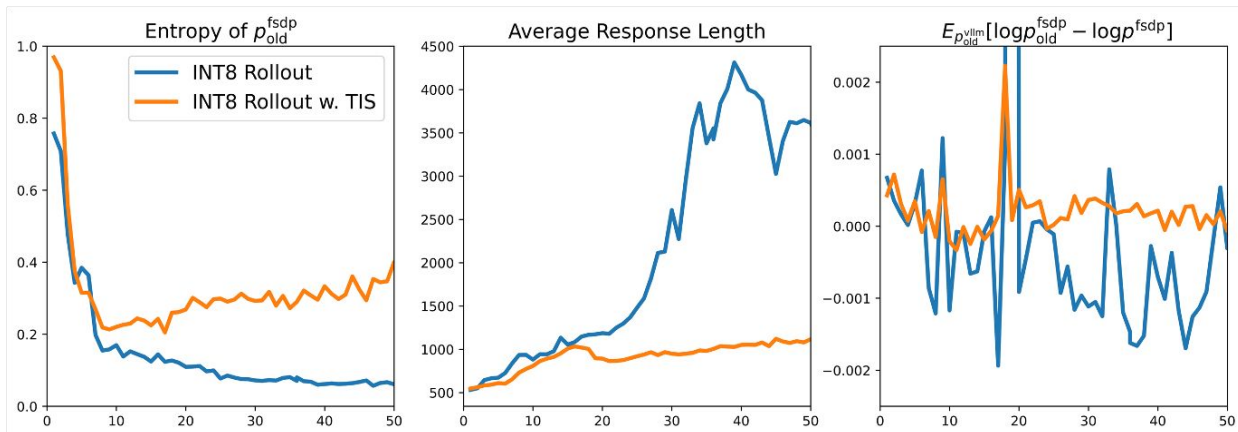


Why Recompute fails

$$\mathbb{E}_{a \sim \pi_{\text{vlm}}(\theta_{\text{old}})} \left[\nabla_{\theta} \min \left(\frac{\pi_{\text{fsdp}}(a, \theta)}{\pi_{\text{fsdp}}(a, \theta_{\text{old}})} \hat{A}, \text{clip} \left(\frac{\pi_{\text{fsdp}}(a, \theta)}{\pi_{\text{fsdp}}(a, \theta_{\text{old}})}, 1 - \epsilon, 1 + \epsilon \right) \hat{A} \right) \right]$$

- **Recompute**

- The mismatch can lead to entropy collapse
 - Gradient computation vs. rollout generation



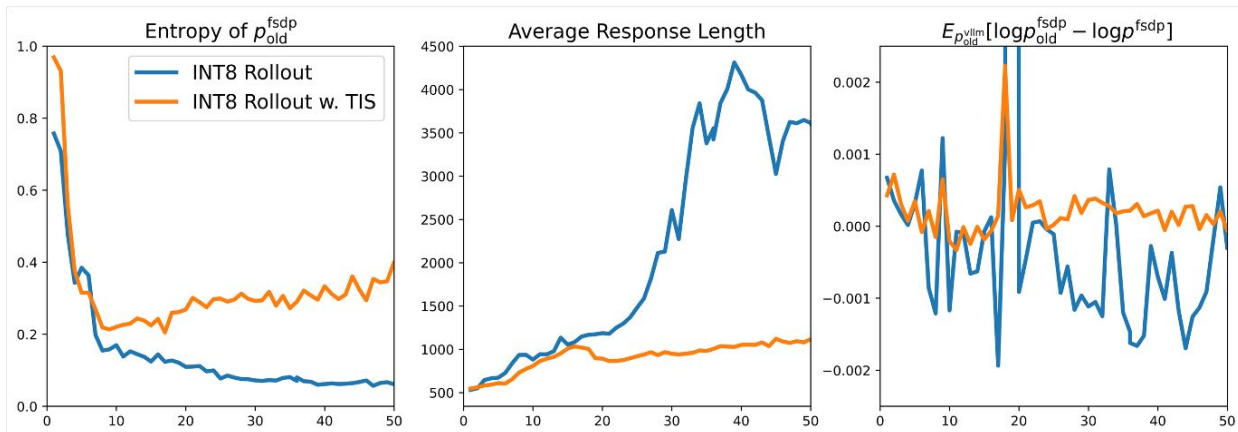
For a with $A < 0$

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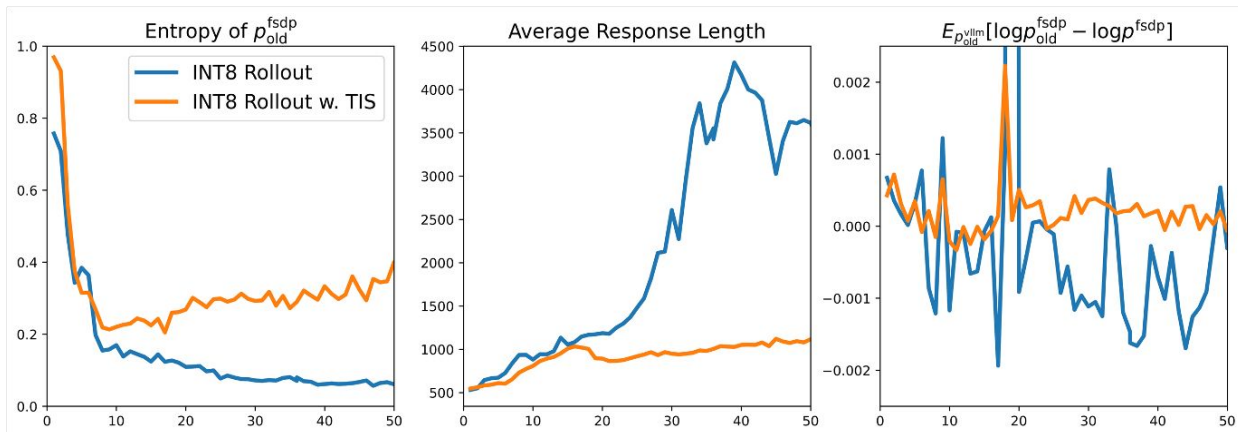
$\pi_{\text{fsdp}}(a)$ becomes smaller

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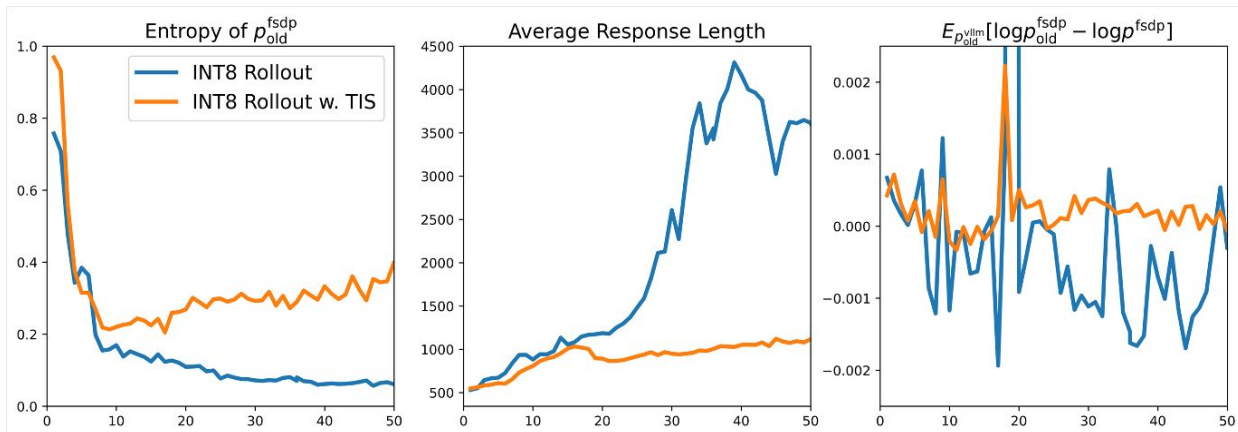
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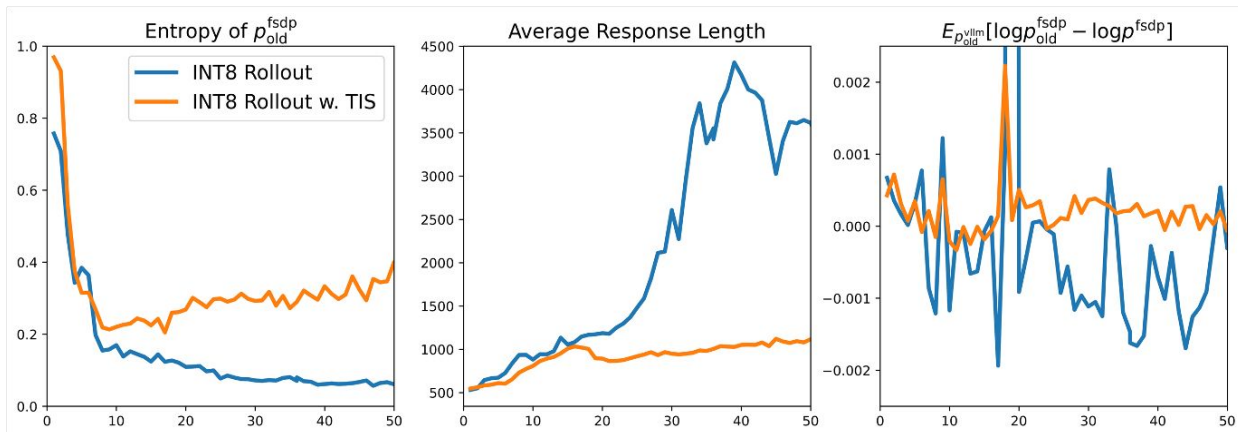
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Small entropy

Why PPO-IS fails

$$\mathbb{E}_{a \sim \pi_{\text{vllm}}(\theta_{\text{old}})} \left[\nabla_{\theta} \min \left(\frac{\pi_{\text{fsdp}}(a, \theta)}{\pi_{\text{vllm}}(a, \theta_{\text{old}})} \hat{A}, \text{clip} \left(\frac{\pi_{\text{fsdp}}(a, \theta)}{\pi_{\text{vllm}}(a, \theta_{\text{old}})}, 1 - \epsilon, 1 + \epsilon \right) \hat{A} \right) \right]$$

- PPO-IS

- PPO-IS is still “biased” from the PPO gradient

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- The clip in PPO is designed for “trust region”
 - At time step 0, $\theta = \theta_{\text{old}}$, we don’t want to clip but PPO-IS may clip

- PPO-clip works differently than TIS

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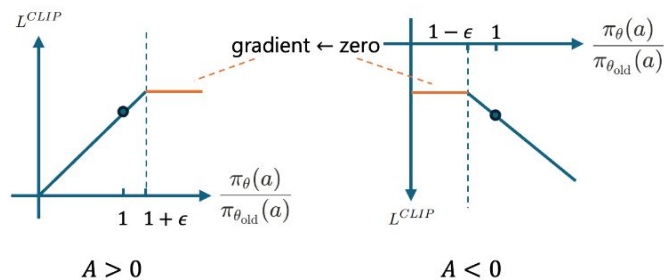
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• PPO-IS

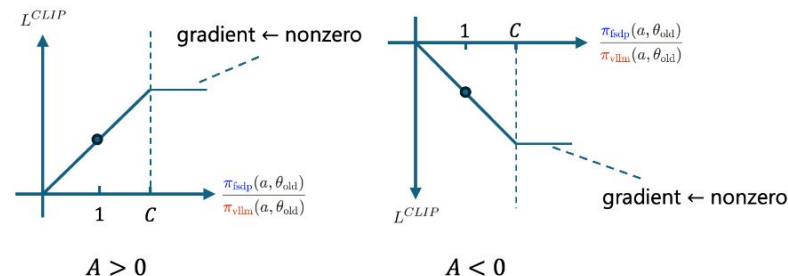
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PPO-clip

TIS



Why Vanilla-IS fails

$$\frac{1}{N} \cdot \sum_{a_1}^{a_N} \underbrace{\frac{\pi_{\text{fsdp}}(a, \theta_{\text{old}})}{\pi_{\text{vllm}}(a, \theta_{\text{old}})}}_{\text{importance ratio}} \cdot \nabla_{\theta} \min \left(\frac{\pi_{\text{fsdp}}(a, \theta)}{\pi_{\text{fsdp}}(a, \theta_{\text{old}})} \hat{A}, \text{clip} \left(\frac{\pi_{\text{fsdp}}(a, \theta)}{\pi_{\text{fsdp}}(a, \theta_{\text{old}})}, 1 - \epsilon, 1 + \epsilon \right) \hat{A} \right)$$

- **Vanilla-IS**

- **Uncapped importance ratio amplifies the gradient noise**
 - Leading to unstable training

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• Vanilla-IS

- **Uncapped importance ratio amplifies the gradient noise**

- Leading to unstable training

Gradient noise

constant factor, no BP through

$$\frac{1}{N^2} \cdot \sum_{a_1}^{a_N} \underbrace{\left(\frac{\pi_{\text{fsdp}}(a, \theta_{\text{old}})}{\pi_{\text{vllm}}(a, \theta_{\text{old}})} \right)^2}_{\text{importance ratio}} \cdot \text{Var}[\nabla_{\theta} \dots] = \text{Var}[\quad]$$

$$\frac{1}{N} E[\text{Var}[\nabla_{\theta}(x, y)]] \approx \frac{1}{N^2} \sum_{x, y} \text{Var}[\nabla_{\theta}(x, y)] = \text{Var} \left[\frac{1}{N} \sum_{x, y} \nabla_{\theta}(x, y) \right]$$

What's beyond?

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- The gap can be amplified in MoE RL
 - Dynamic Routing
 - Specially Optimized Kernels

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- The gap can be amplified in MoE RL
 - Dynamic Routing
 - Specially Optimized Kernels
- TIS is orthogonal and compatible with existing GxPOs
 - GxPOs adjust the computation of advantage / importance ratio
 - TIS addresses the system-level mismatch problem

Takeaways

- **Mixing inference backend with training backends brings off-policy RL training, even if they share the same weights**
- **Truncated Importance Sampling (TIS) is effective mitigating the gap**
- **With TIS integrated, rollout generation can be accelerated via quantization without sacrificing the performance**

Thanks for Listening!

Feng Yao

<https://yaof20.github.io/>

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