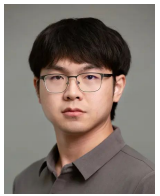
On the Rollout-Training Mismatch In Modern RL Systems






Feng Yao* **Liyuan Liu*** **Dinghuai Zhang** **Chengyu Dong** **Jingbo Shang** **Jianfeng Gao**

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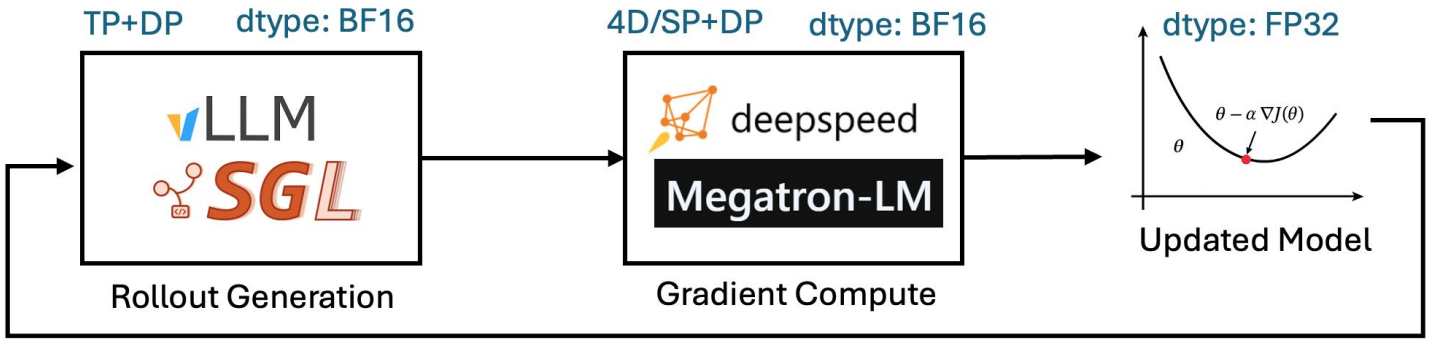

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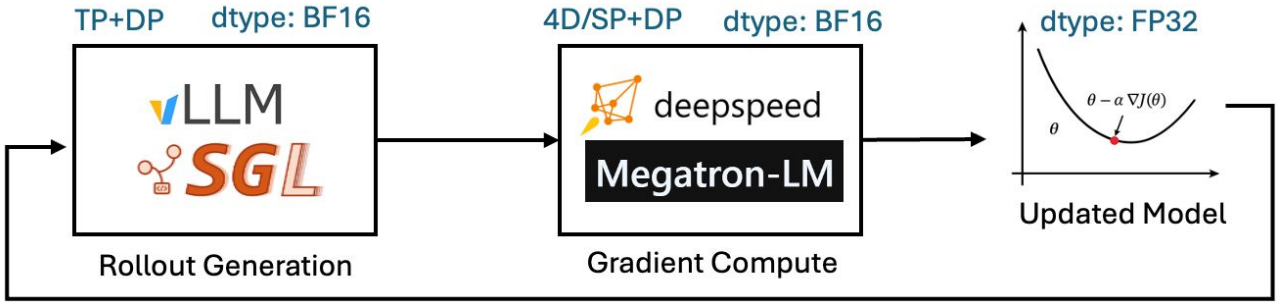

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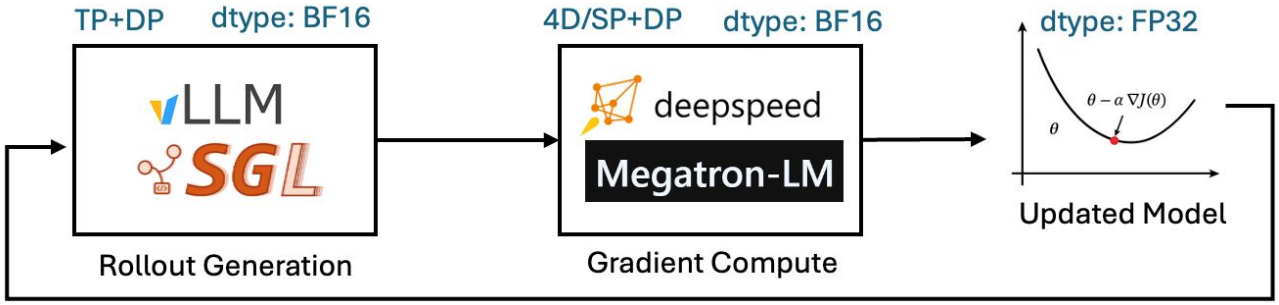
$$p^{vllm} - p^{fsdp}$$



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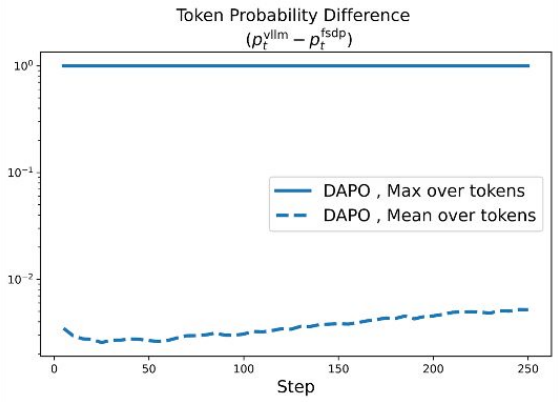
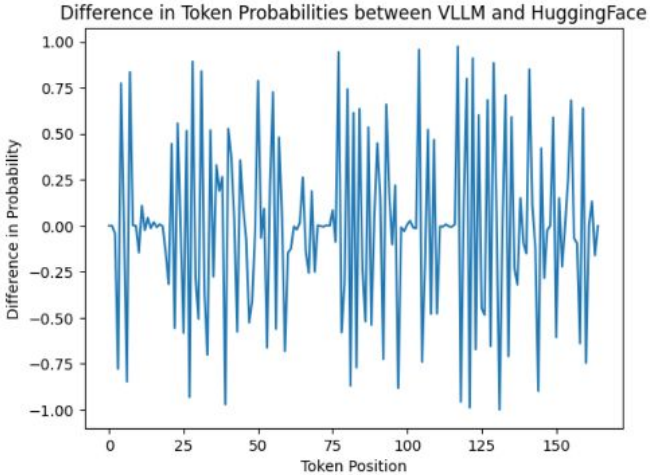


DAPO Qwen2.5-32B



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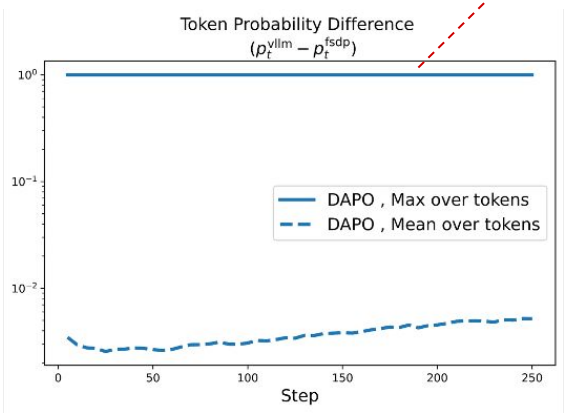

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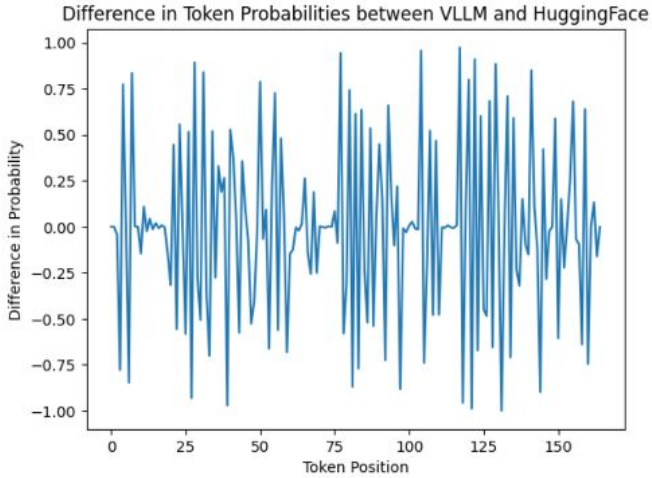

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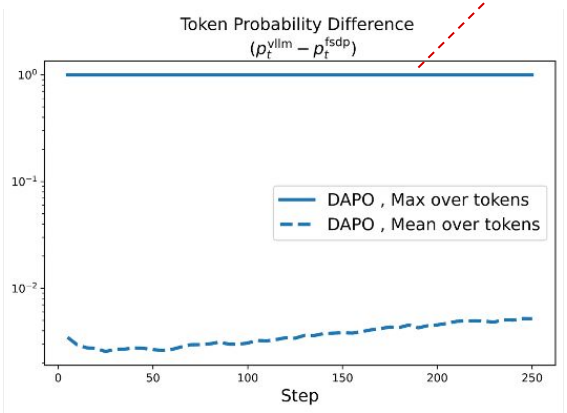

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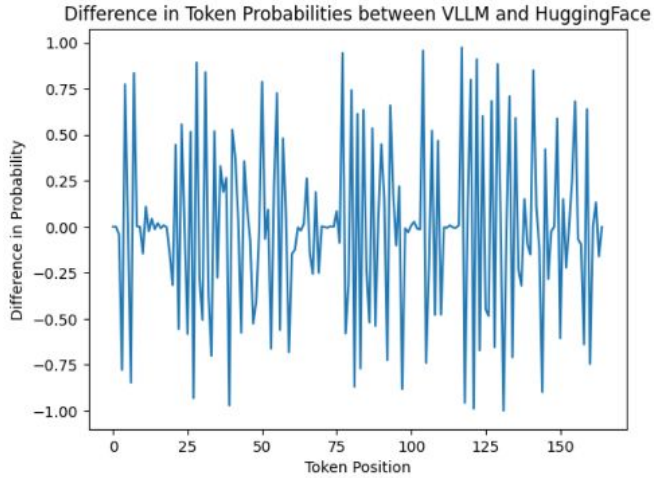

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Implicitly makes RL "Off-Policy"!

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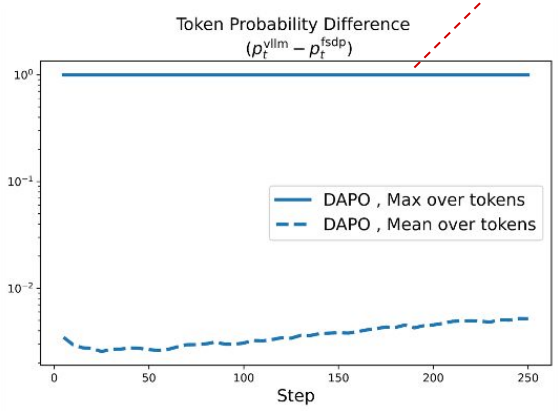

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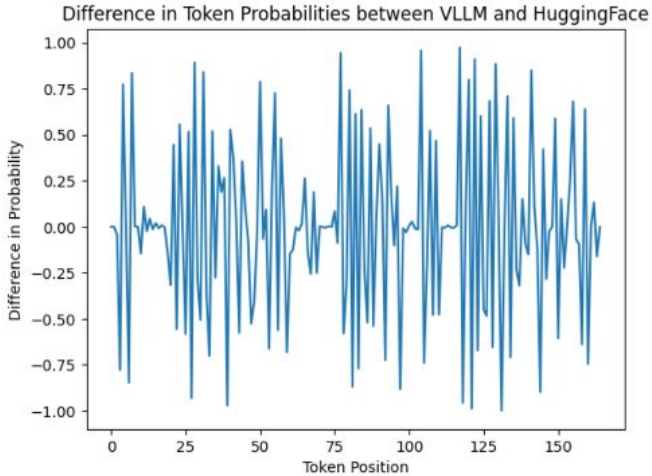

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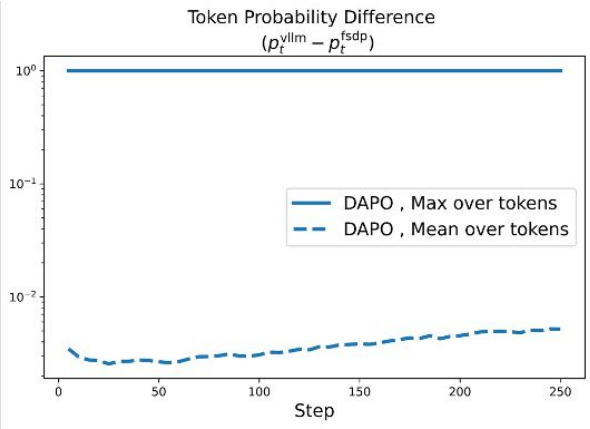
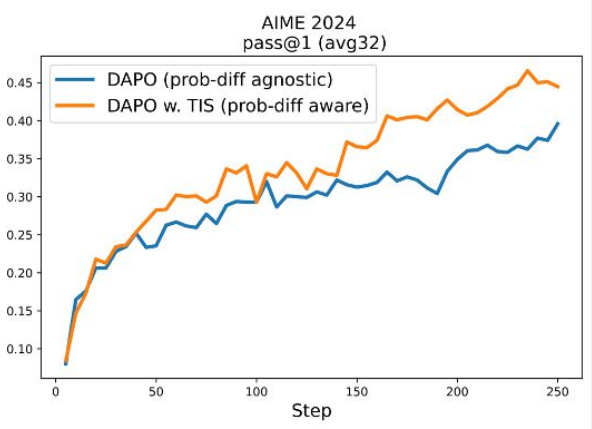
  - We show that **fix it with TIS** can improve training **effectiveness**





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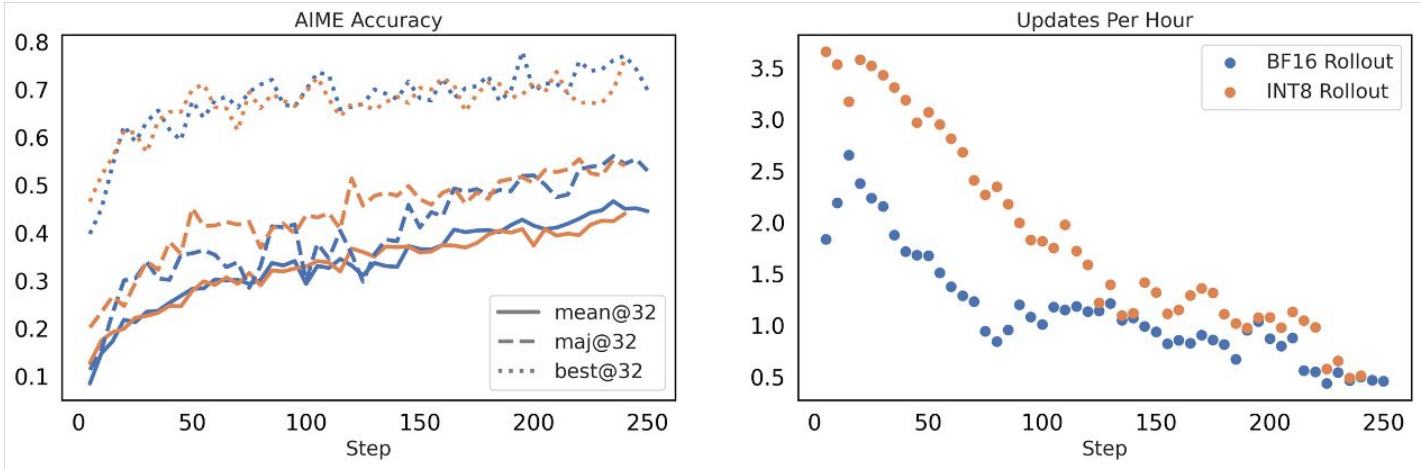

Outline

- 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
- Additional Analyses

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Why does Rollout-Training Mismatch occur?

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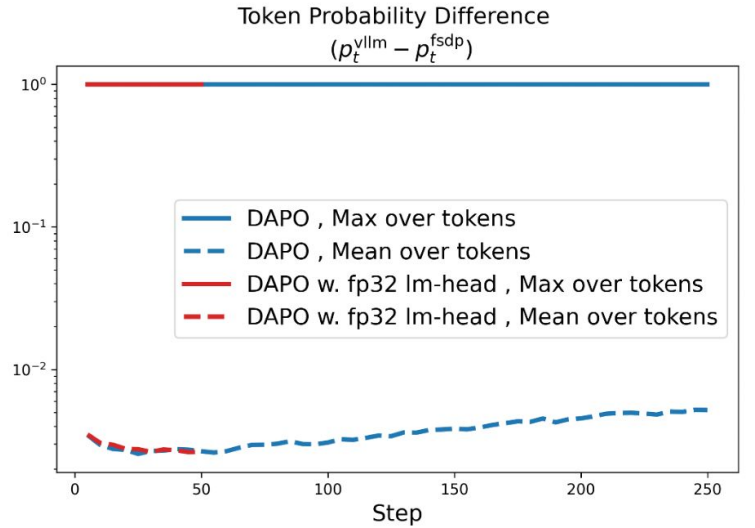
- **Two common believes**
  - **Inaccessible true sampling probabilities**
    - Add additional gap
  - **Backend numerical differences**
    - Hard to fix



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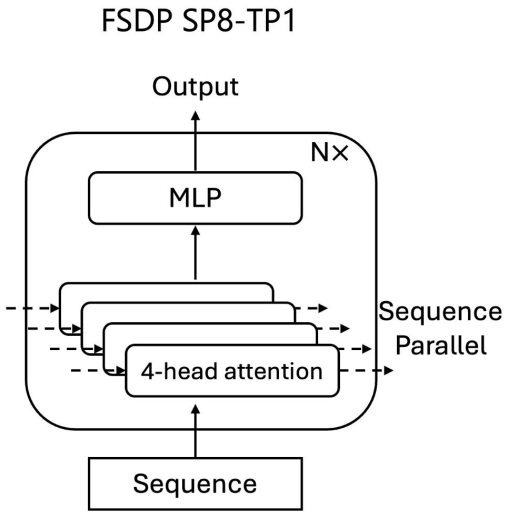

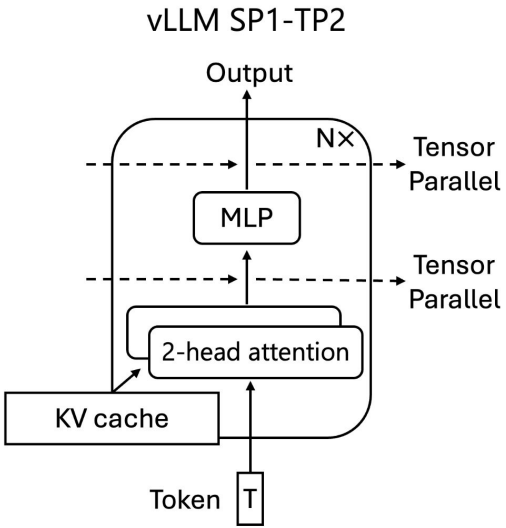

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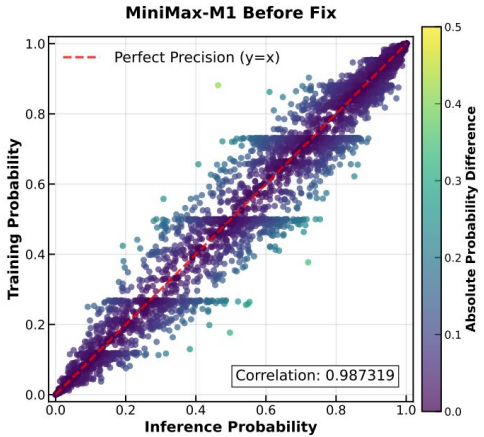

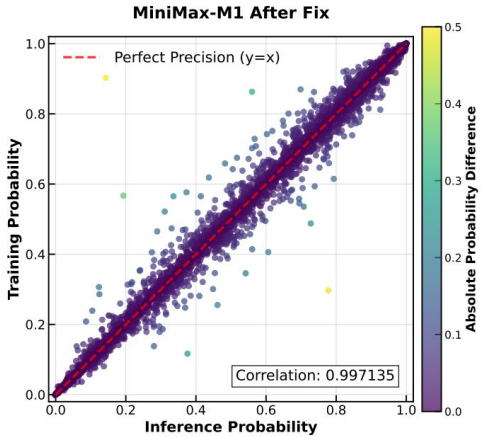

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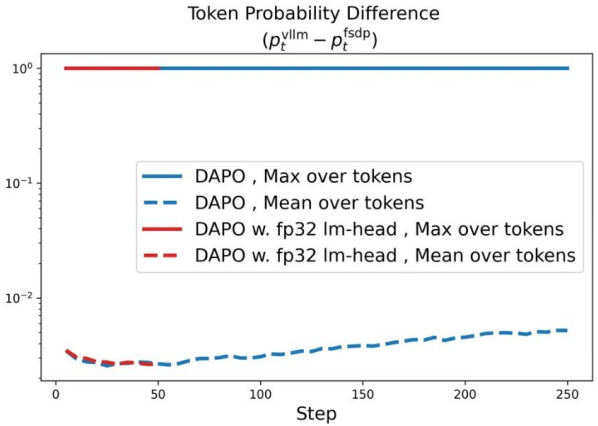

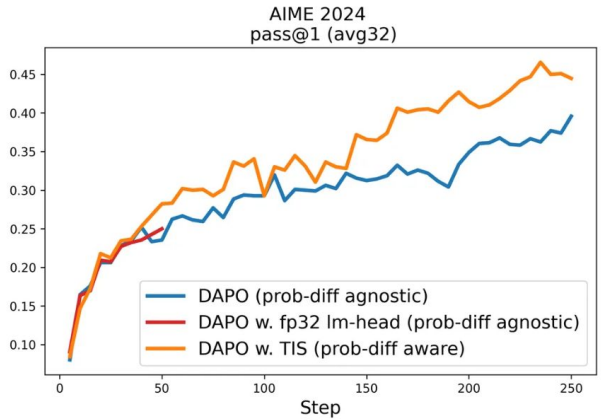

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    - Recall: Vanilla Importance Sampling

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

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    - So we should fix the gradient as:

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

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

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

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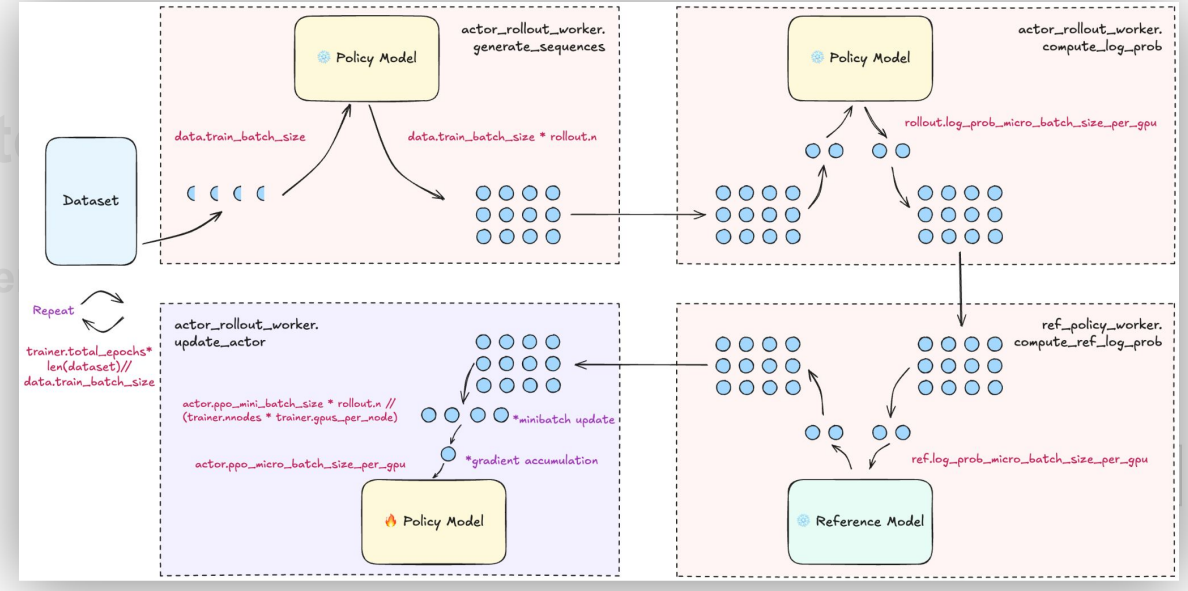

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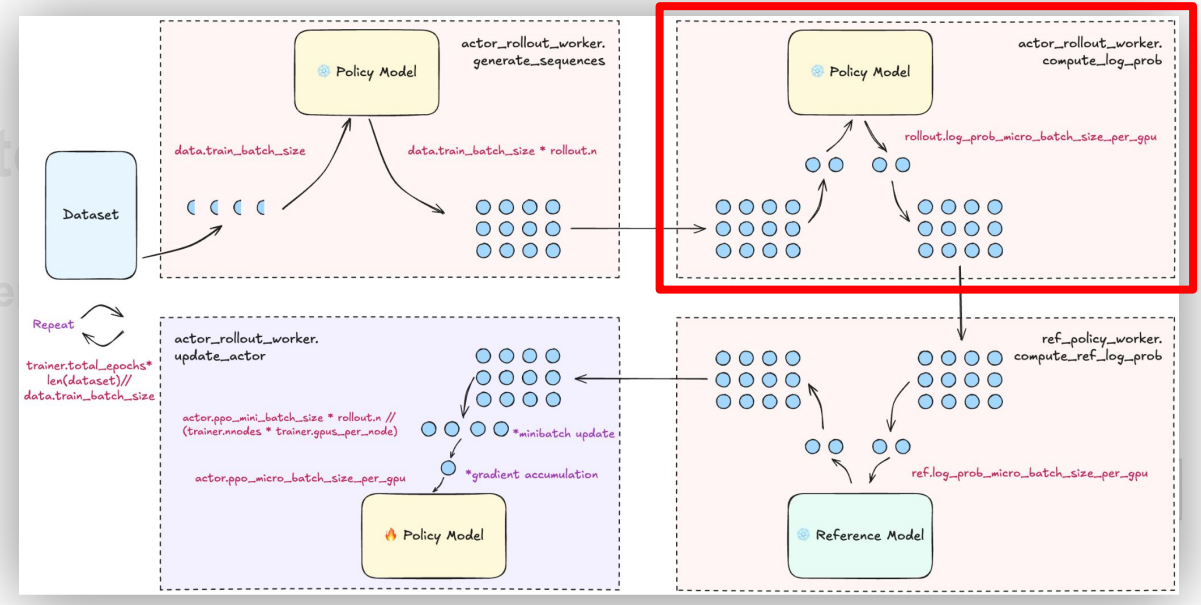

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  - Truncated Importance Sampling **(TIS)**

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

Why Not Alternative Methods?

- Variants of TIS

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- **Variants of TIS**
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A commonly asked variant

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Can break out of the trust region

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Can break out of the trust region

  - Vanilla Importance Sampling **(Vanilla-IS)**

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

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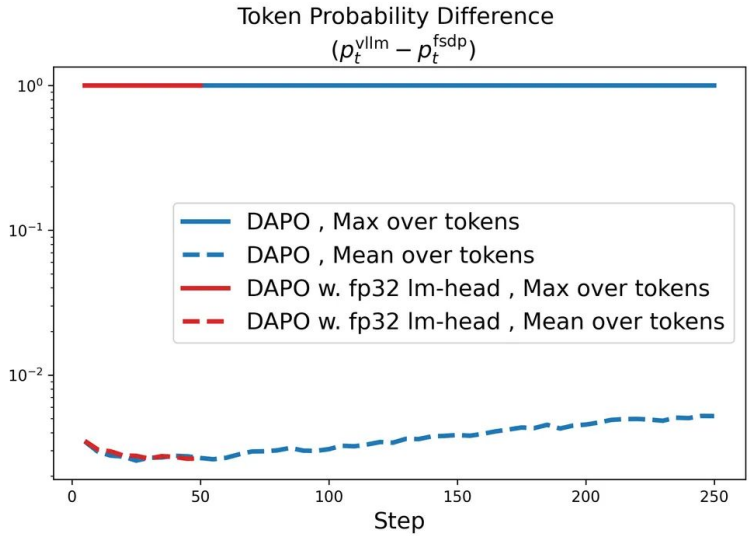
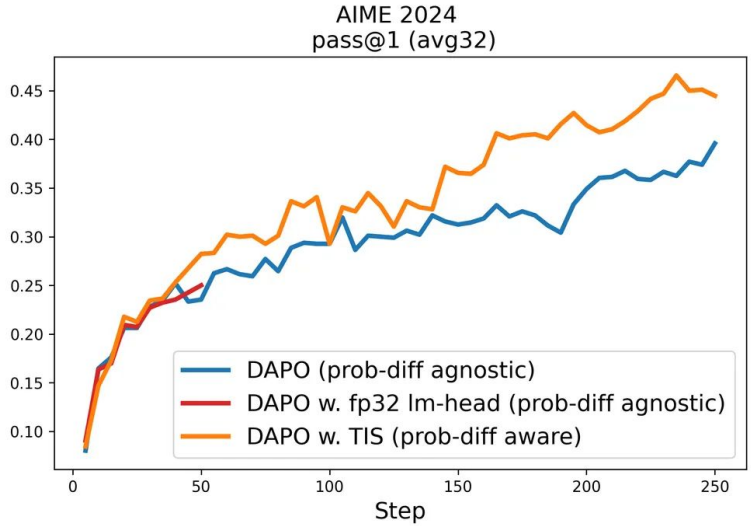
Can be too large and makes training crash

How well can TIS fix it?

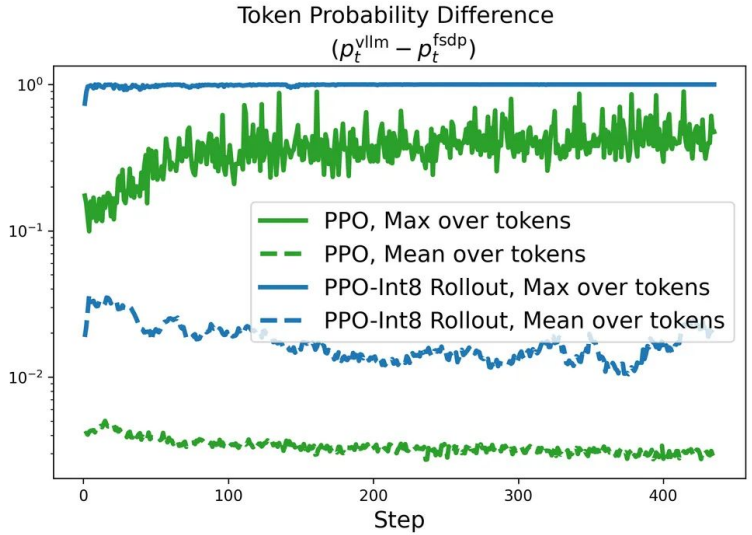
- **DAPO 32B Setting**

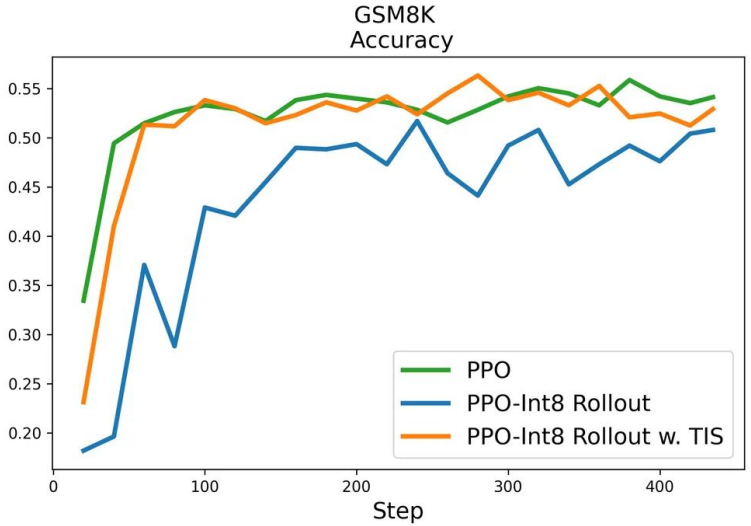




How well can TIS fix it?

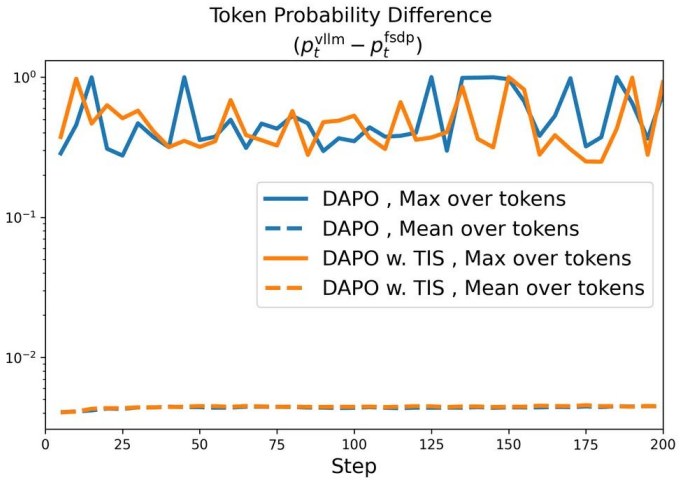
- **GSM8K 0.5B Setting**
  - **Normal RL: Max Diff is smaller (~0.4) than 1.0 (in DAPO-32B setting)**
  - **INT8 Rollout: Max Diff is larger (~1.0) than normal RL setting**

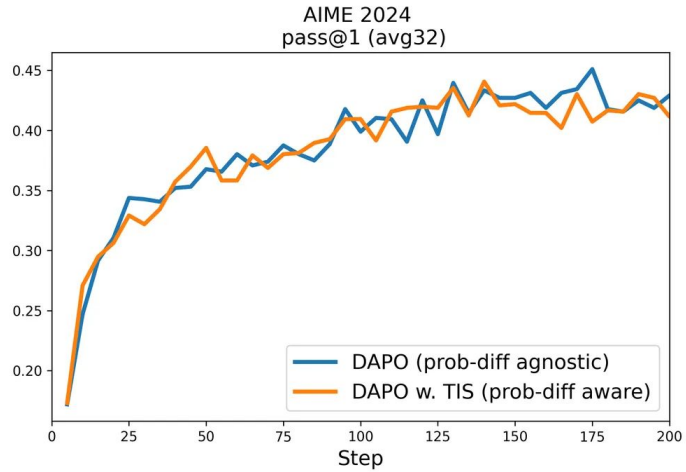




Does TIS always help?

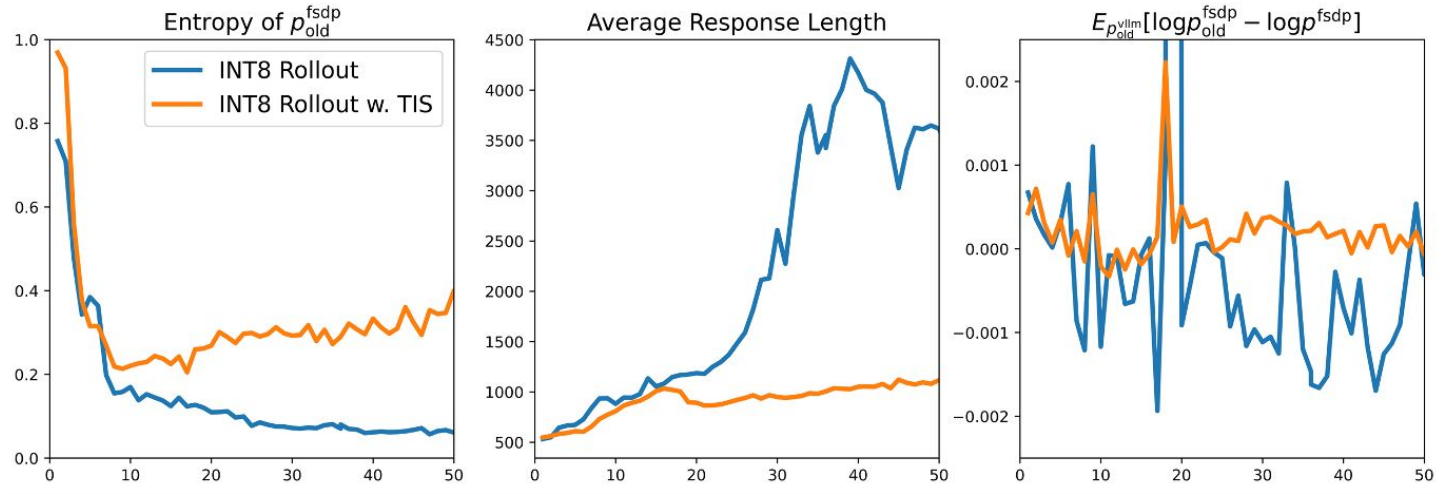
- **DAPO 1.5B Setting**
  - **In settings where prob diff is relatively small**
    - TIS does not always help, but doesn't hurt





Does the Mismatch really matter?

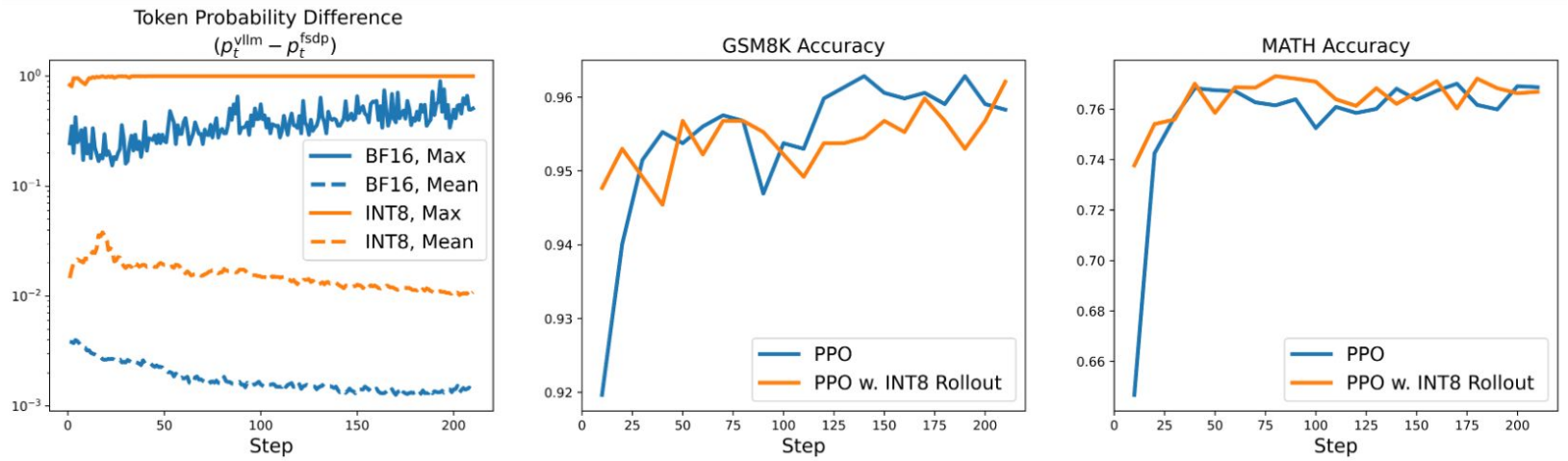
- Unexpected training instability on challenging tasks



DAPO Qwen2.5-32B

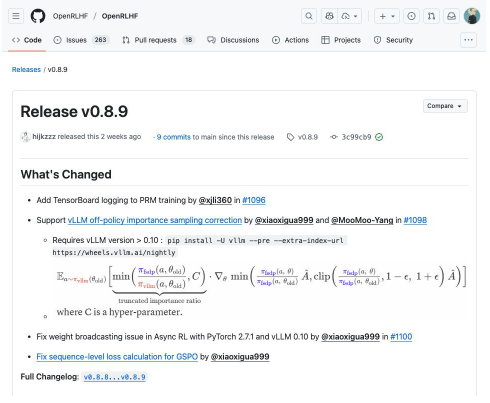
Does the Mismatch really matter?

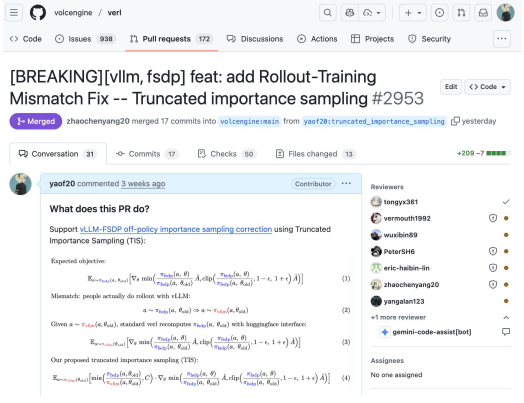
- Possible negligible on simple tasks

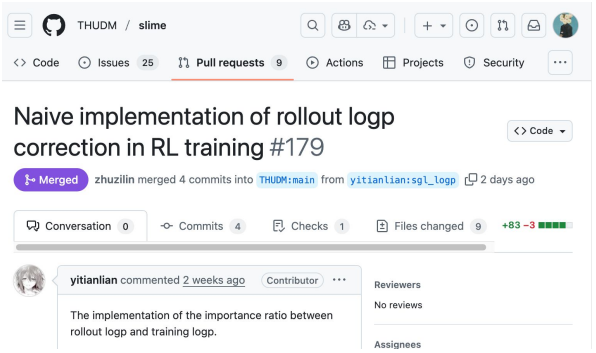


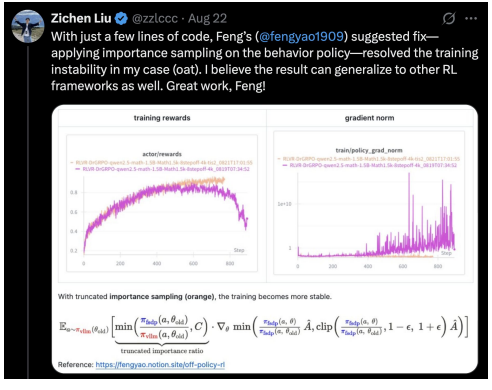
PPO GSM8K Qwen2.5-32B

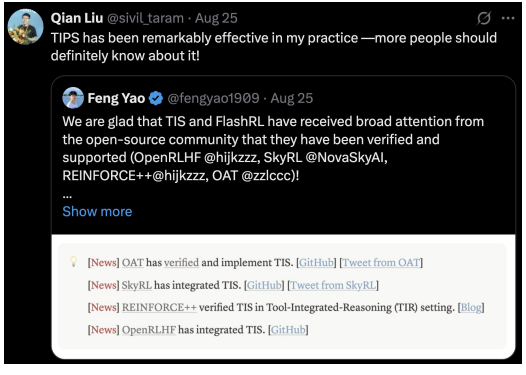
Community Verification











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, which features a zero-shot agent environment designed for large language models to tackle mathematical problems using Qwen 2.5 Base 7B.

	300-step/avg@32/iternum-2(inference)	aime24	aime25	hmmt_feb_2025	hmmt_feb_2024	cimmc	avg
reinforce++	with-baseline	30.83333	**27.1875**	17.91667	18.95833	25.625	24.10416667
reinforce++	with-baseline,vllm-correction	**31.5625**	23.9583	**20.625**	**20.1042**	**29.375**	**25.125**
grpo		31.66667	21.875	16.97917	17.70833	24.6875	22.58333333
ppo		30.20833	21.66667	15	18.4375	23.95833	21.85416667

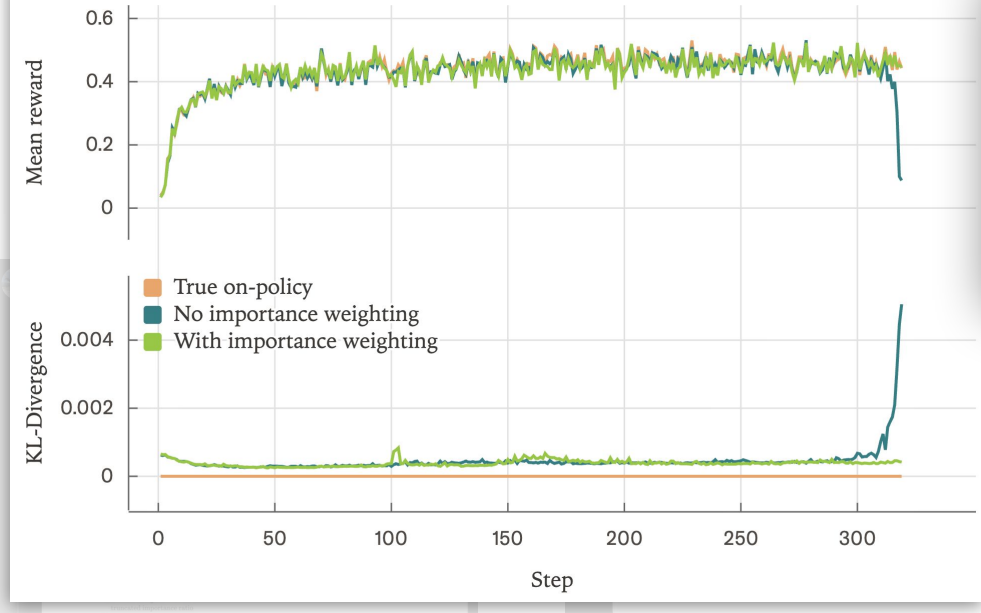
REINFORCE++-baseline achieves the best performance in the multi-turn tool call tasks.

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

Community Verification

True on-policy RL

As researchers have noted, the different numerics between training and inference implicitly turns our on-policy RL into off-policy RL.



Configuration	Time (seconds)
vLLM default	26
Unoptimized Deterministic vLLM	55
+ Improved Attention Kernel	42

Community Verification

VLLM ←→ Trainer logprob mismatch

Potential solutions to

Correct, but off-policy transformer logprobs
Incorrect, but on-policy vllm logprobs

1. Change things/kernels so the logprobs do match (we didn't get this to work)
2. Calculate your logprobs in transformers, not vllm (our current approach, $)
3. Use importance sampling

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

https://fengyao.notion.site/off-policy-rl

Ai2 Slide credit: Michael Noukhovitch

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
- Additional Analyses

Harvesting *Off-Policy* in Quantization

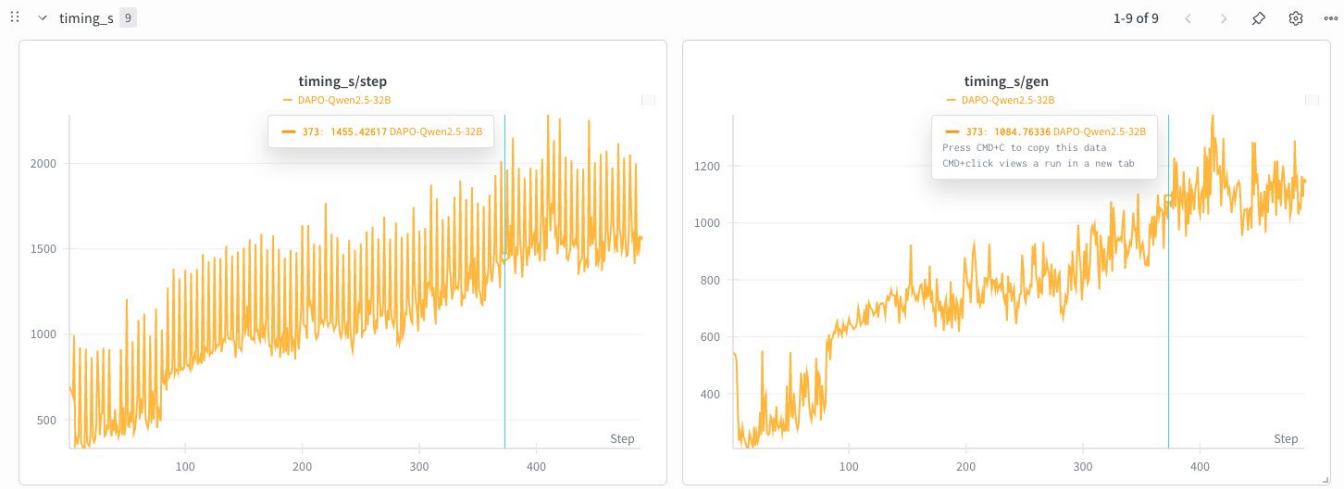
As TIS handles the gap, can we go even **further off-policy** for **speedup**?

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:

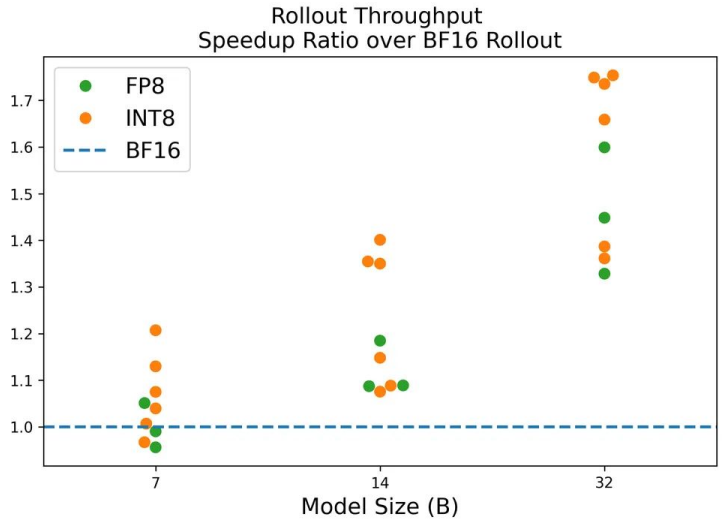
*In DAPO-32B setting, rollout takes up **~70%** of the training time*



Quantization helps *speedup* but hurts *performance*

Quantization helps *speedup* but hurts *performance*

Naively applying quantization can accelerate rollout speed



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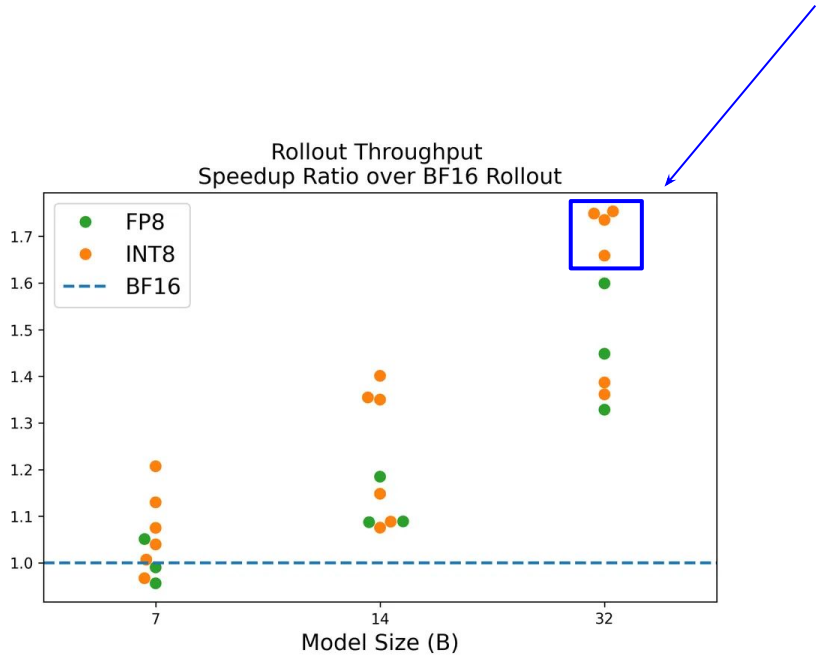

Quantization helps *speedup* but hurts *performance*

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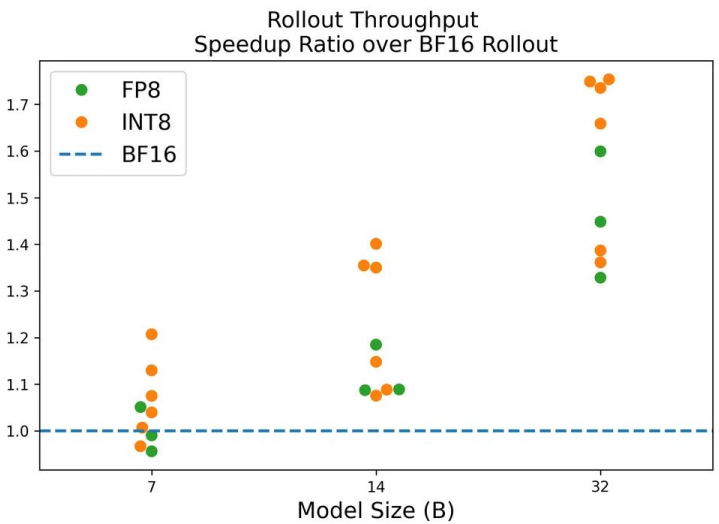
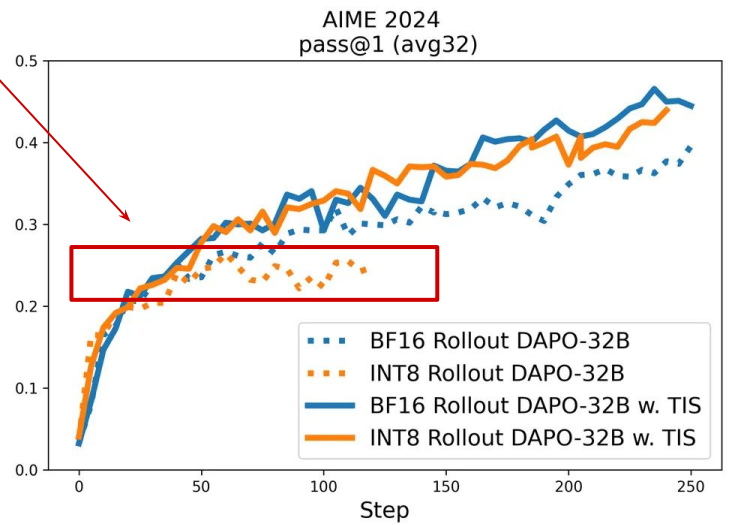
But the performance is also degraded!





Quantization helps *speedup* but hurts *performance*

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But the performance is also degraded!

This can be expected, as quantization introduces more mismatch

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

FlashRL preserves performance with TIS

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

FlashRL preserves performance with TIS

FlashRL fixes it with TIS

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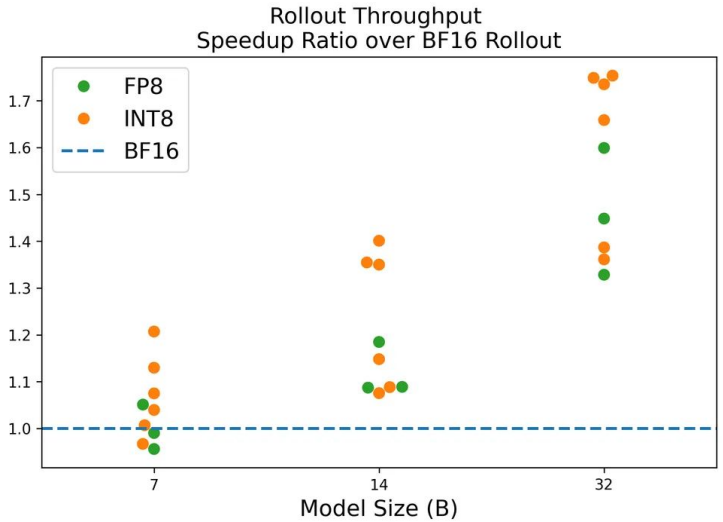
FlashRL is implemented as a PyPI package to patch vLLM

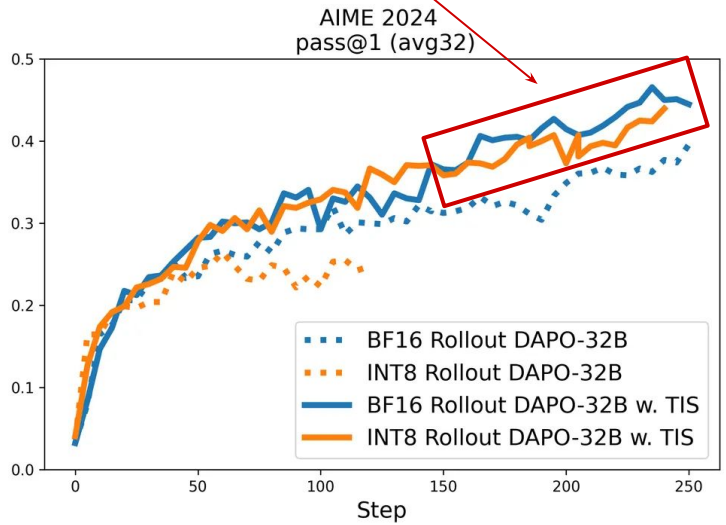
```
pip install flash-llm-rl     # install with pip
export FLASHRL_CONFIG='fp8'  # turn on env variable
bash your-rl-training-script # no code change needed!
```

FlashRL preserves performance with TIS

DAPO 32B Setting

Matches the performance of BF16 rollout with TIS



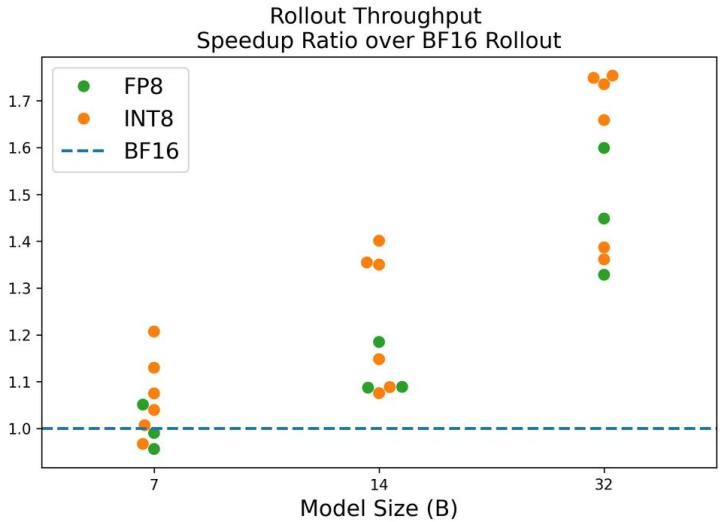


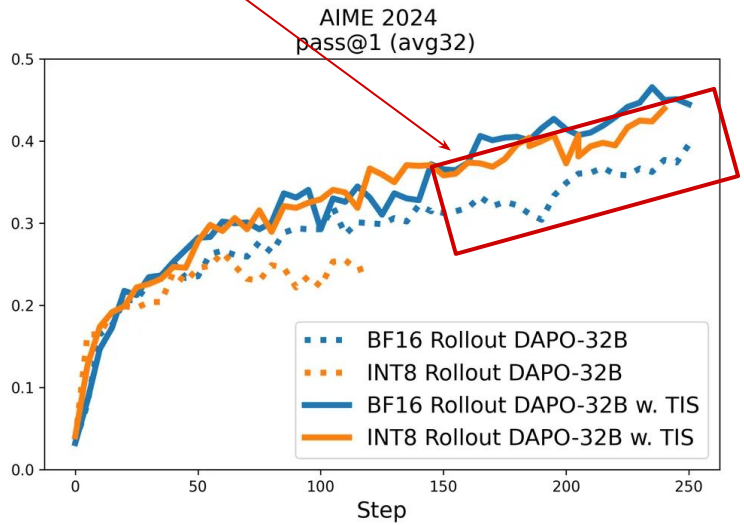
FlashRL preserves performance with TIS

DAPO 32B Setting

Matches the performance of BF16 rollout with TIS

Outperforms naive BF16 rollout (without TIS)

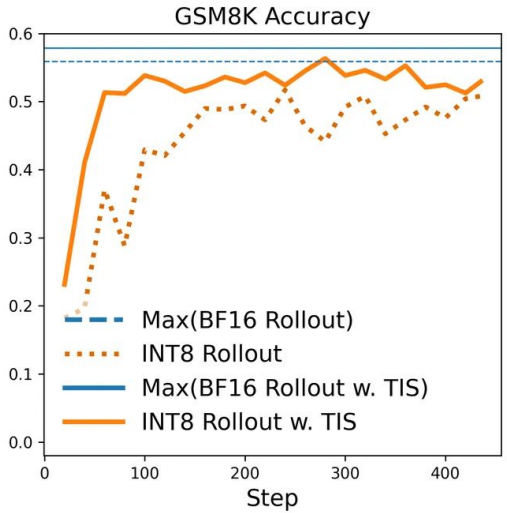


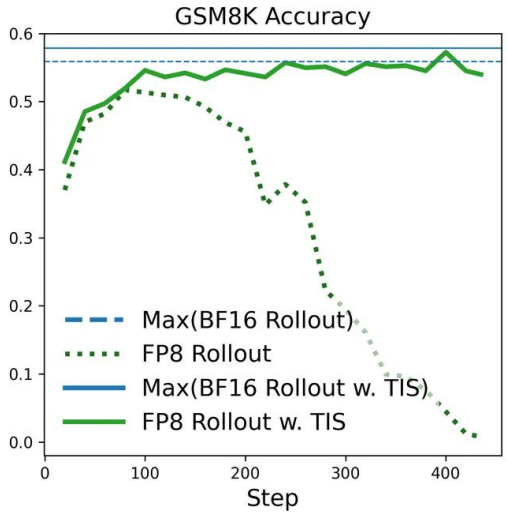


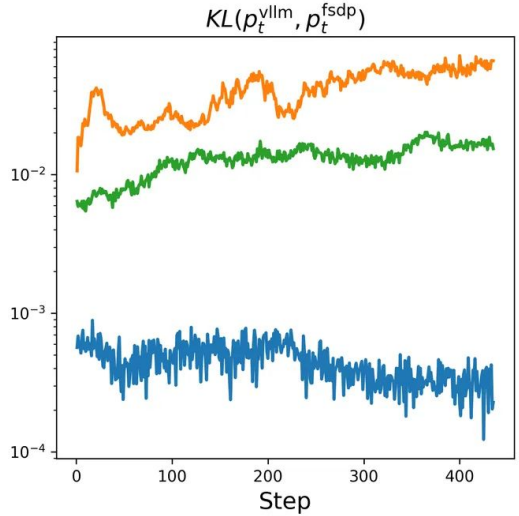
FlashRL preserves performance with TIS

GSM8K 0.5B Setting

TIS works both in INT8 and FP8 setting







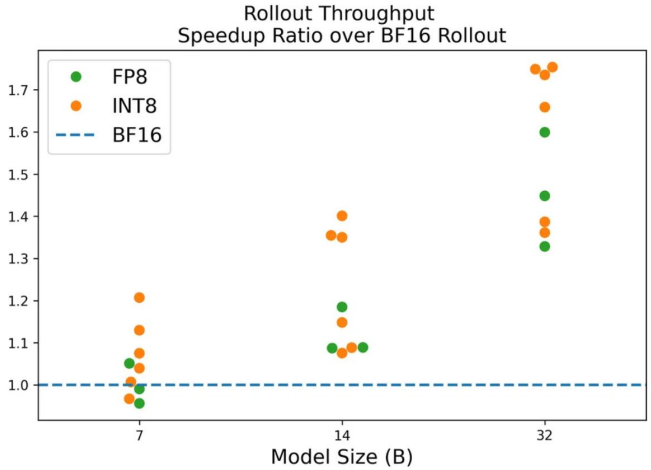
More detailed analysis

Rollout Speedup

More detailed analysis

Rollout Speedup

Regular RL Setting

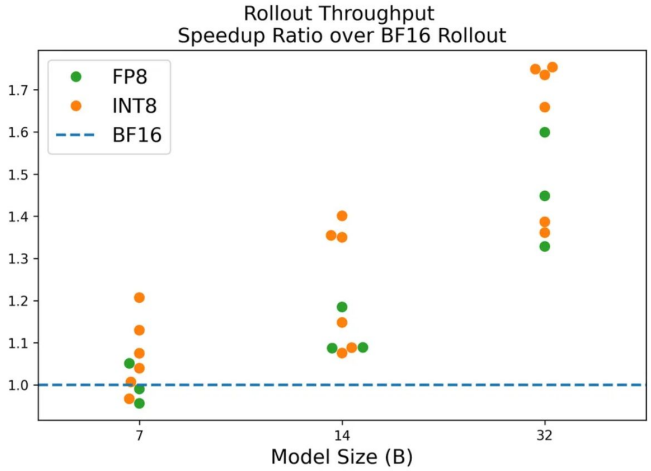


More detailed analysis

Rollout Speedup

Regular RL Setting

Standard Inference Setting



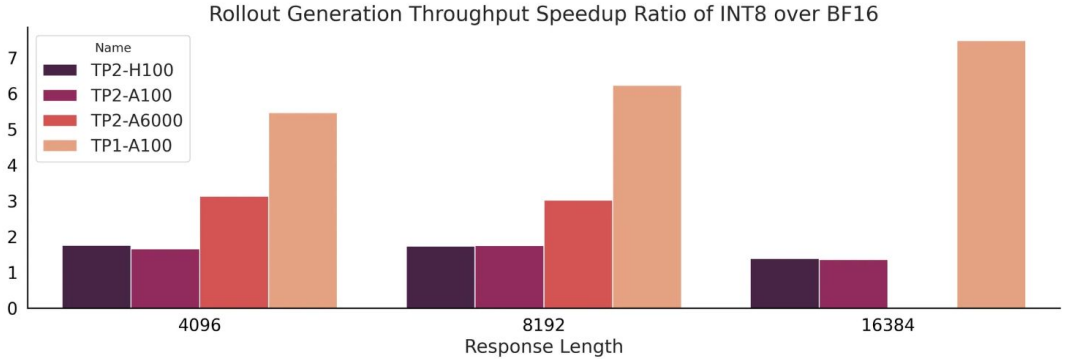


Figure 3. *Throughput speedup ratio of INT8-quantized* `Deepseek-R1-Distill-Qwen-32B` *relative to BF16 in 4 inference-only configurations, measured across varying response lengths*

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

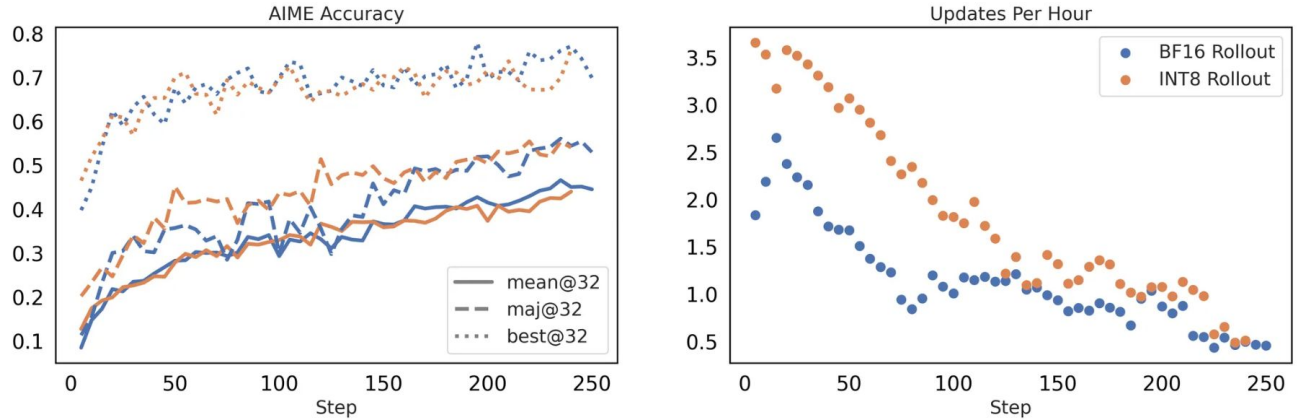


Figure 4. Left: *Downstream performance of RL training with BF16 vs. INT8 rollout precision.* ***Right:*** *Updates per hour achieved with BF16 and INT8 rollout. All experiments use the DAPO recipe on Qwen2.5-32B, trained for 250 steps on 4 nodes with 8×H100 GPUs. [wandb]*

How to perform INT8 quantization?

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FP8 quantization can be naturally conducted in an online manner

INT8 quantization requires complicated calibration process

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

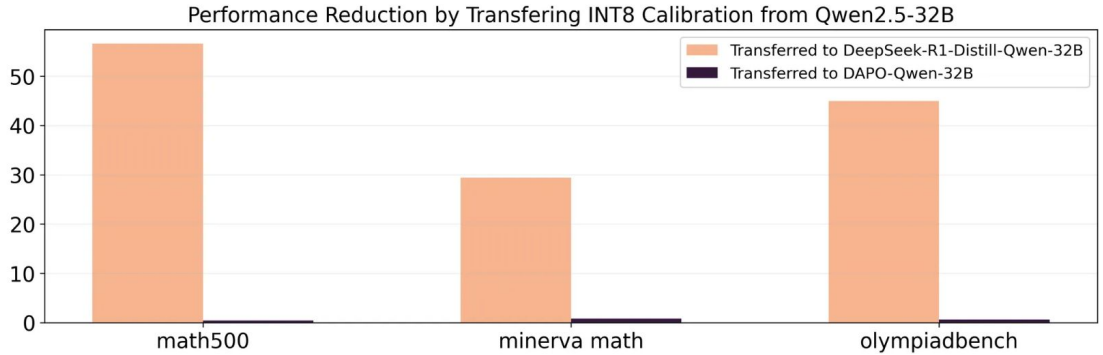

Figure 6. *We experiment on models finetuned via SFT / RL from Qwen2.5-32B base model. We find that compared to SFT, reusing the base model calibration result by applying it to RL funetuned model rarely change the performance. This indicates that INT8 online quantization is practically possible in RL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

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**
- Additional Analyses

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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- **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

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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

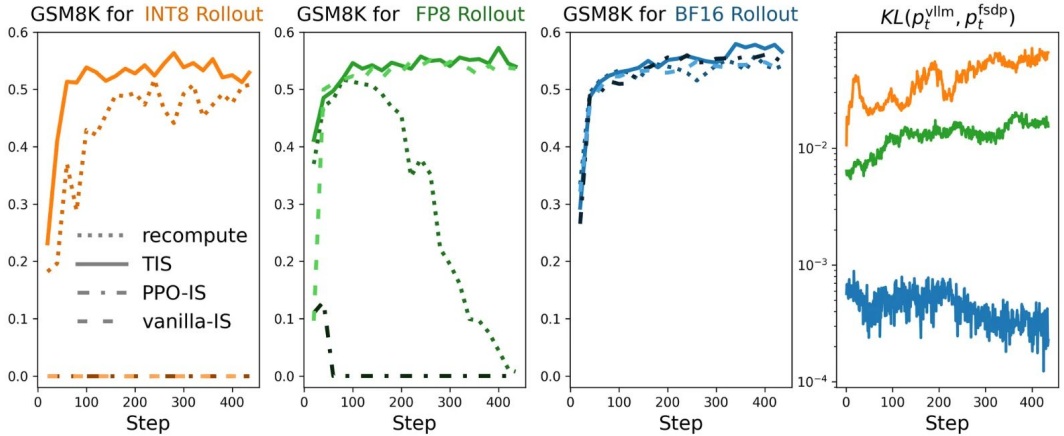

Figure 5. We ablate different rollout-training mismatch mitigation strategies on Qwen2.5-0.5B with GSM8k. Note PPO-IS and Vanilla-IS achieves near 0 accuracy for INT8 rollouts thus being highly overlapped. We also plot the KL divergence between vLLM sampled distribution and the FSDP distribution on the right. *[int8 wandb][fp8 wandb][bf16wandb]*

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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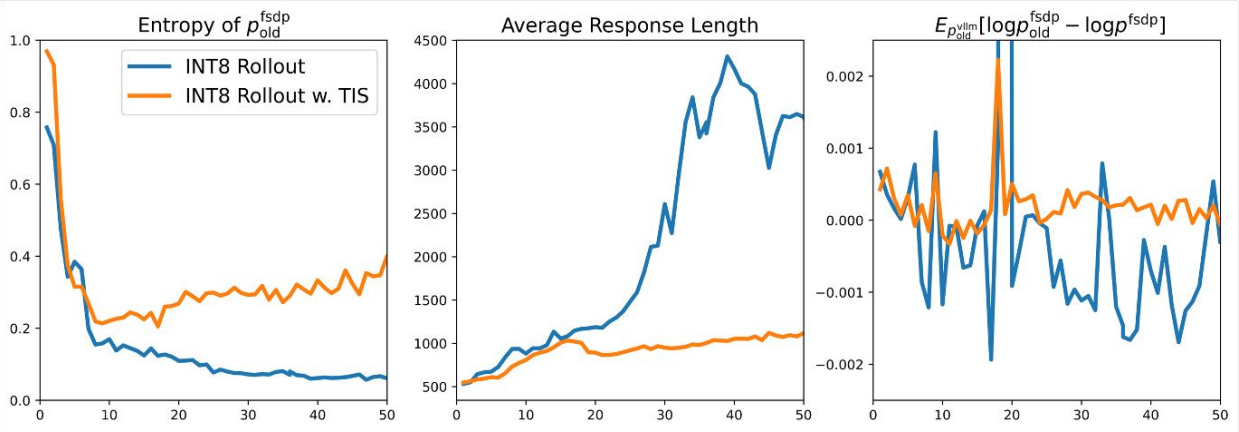

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$$\mathbb{E}_{a\sim\pi_{\text{vllm}}(\theta_{\text{old}})}\left[\nabla_\theta \min\left(\frac{\pi_{\text{fsdp}}(a,\ \theta)}{\pi_{\text{fsdp}}(a,\ \theta_{\text{old}})}\hat{A}, \text{clip}\left(\frac{\pi_{\text{fsdp}}(a,\ \theta)}{\pi_{\text{fsdp}}(a,\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

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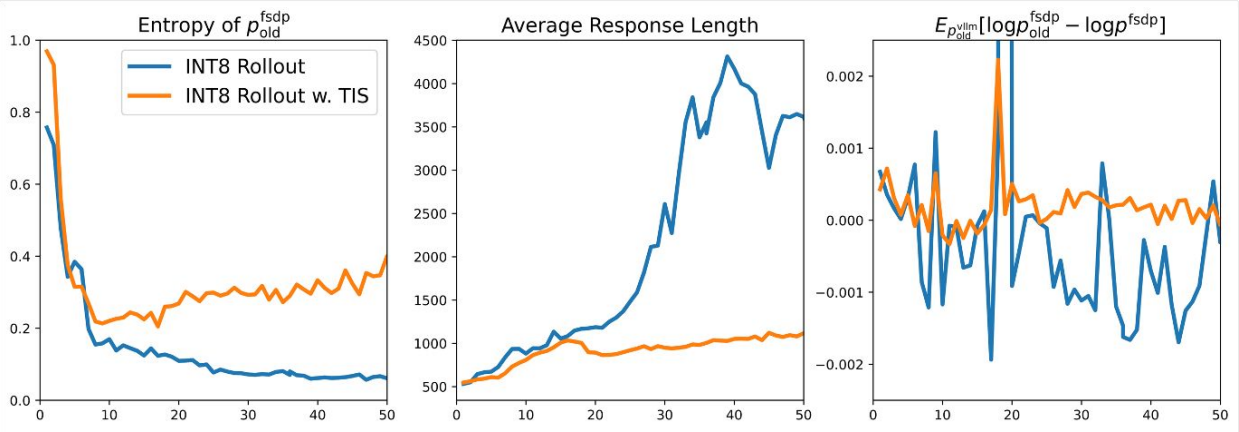

For a with $A < 0$

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**
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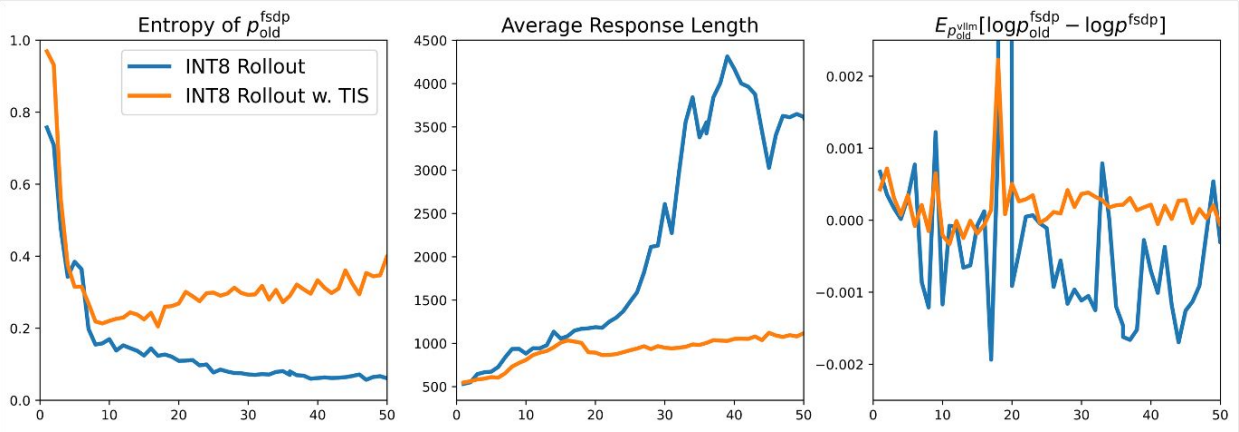

For a with $A < 0$

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

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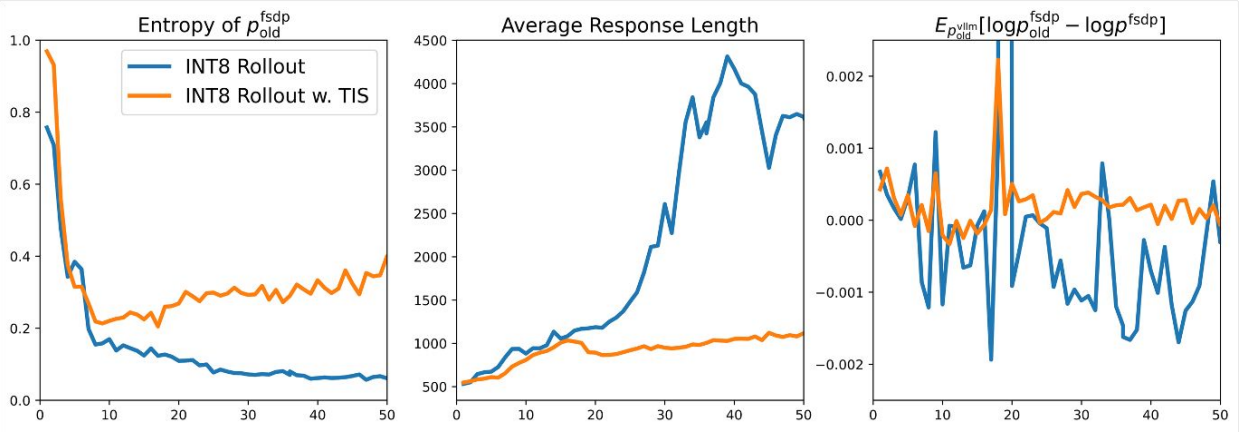

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With a large gap w. INT8, $\pi_{\text{vllm}}(a)$ stays the same

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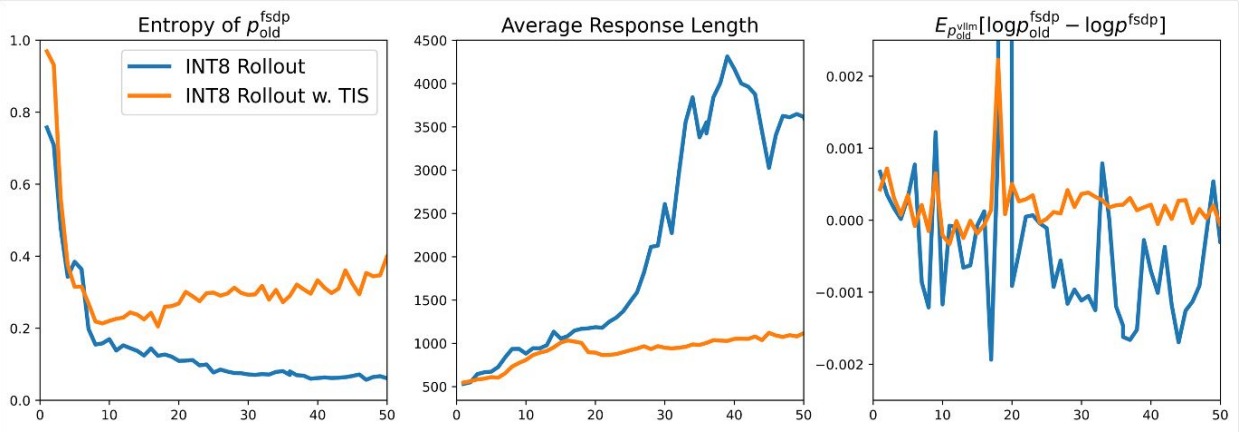

For a with $A < 0$

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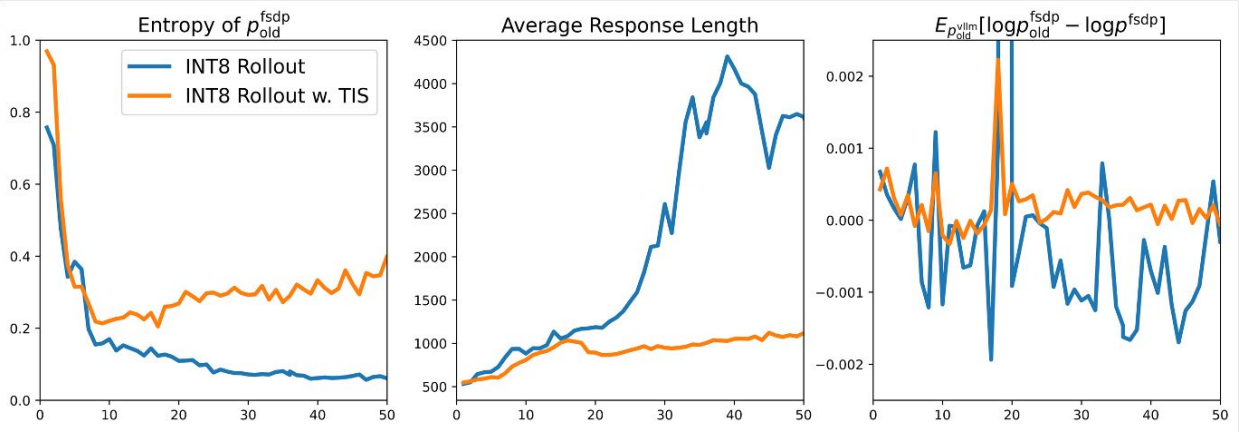

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Small entropy

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

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

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

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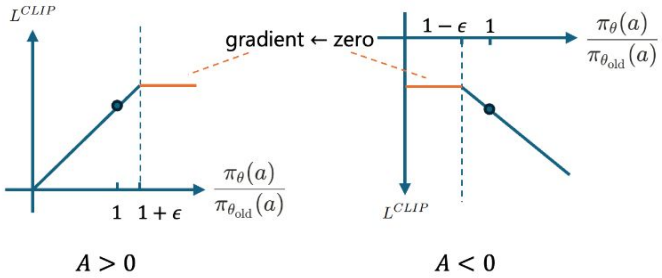

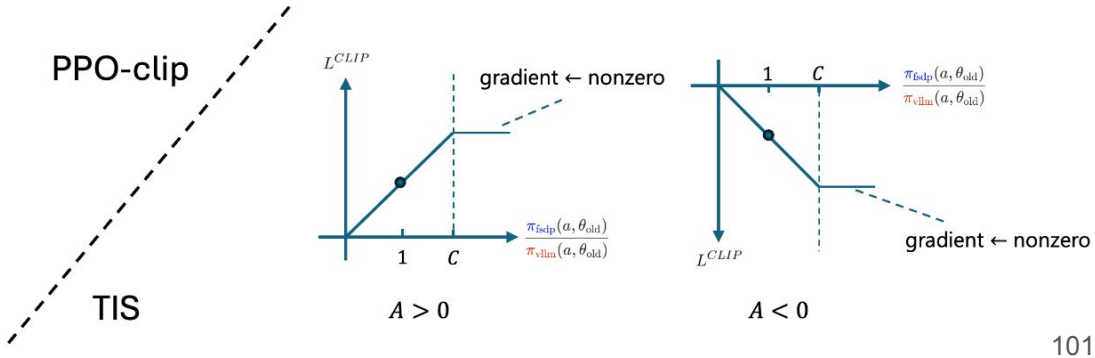

Why Vanilla-IS fails

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

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

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Gradient noise

constant factor, no BP through

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

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

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Factors Contributing to Mismatch

- Investigation Setup

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  - **Model & Data:**
    - DAPO-32B / Polaris 7B
    - DAPO Training Set (first 512 samples)

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    - **Max Mismatch** per response
    - **Mean Mismatch** per response

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    - DAPO Training Set (first 512 samples)
  - **Metrics:**
    - **Max Mismatch** per response

$$\max_{a \in \text{response}} \left| p_{\text{sampler}}(a) - p_{\text{learner}}(a) \right|$$

    - **Mean Mismatch** per response

$$\frac{1}{|\text{response}|} \sum_{a \in \text{response}} \left| p_{\text{sampler}}(a) - p_{\text{learner}}(a) \right|$$

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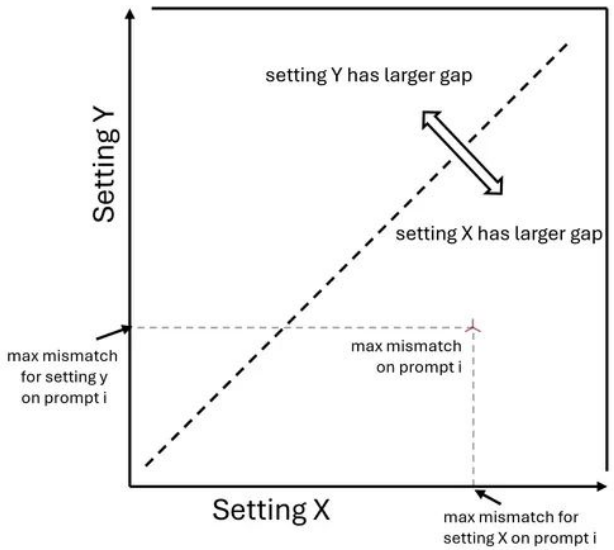

Factors Contributing to Mismatch

- Larger **Parallelism** Difference, Larger **Max Gap**

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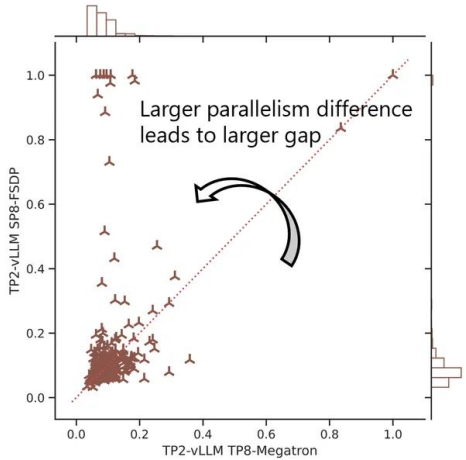

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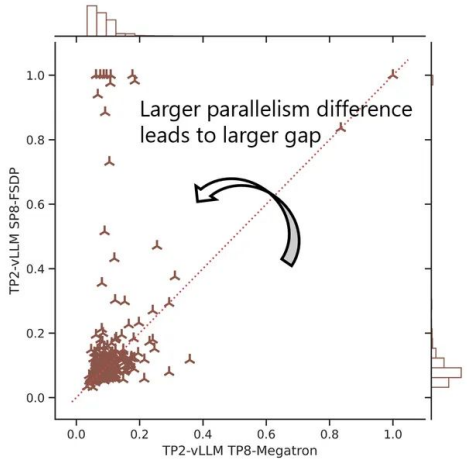

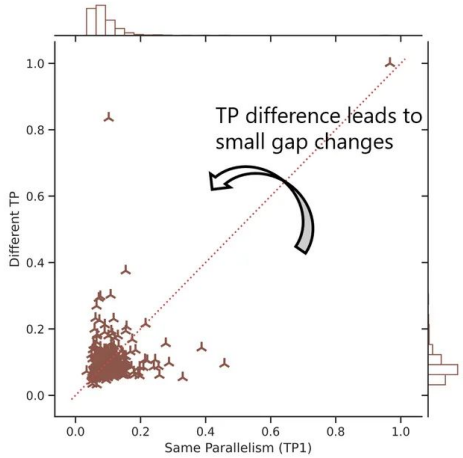

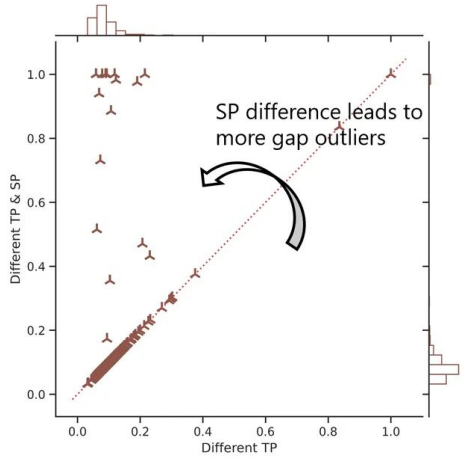

Factors Contributing to Mismatch

- Longer **Response Length**, Larger **Max Gap**

Factors Contributing to Mismatch

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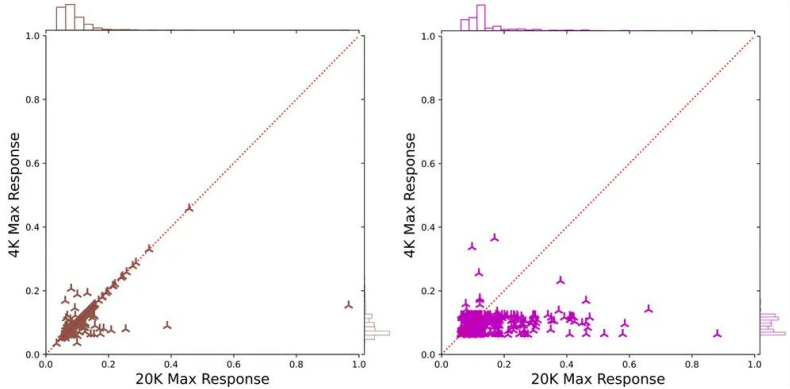

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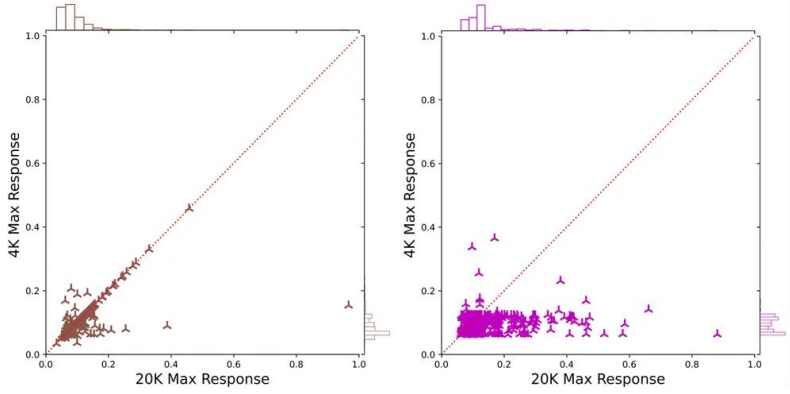
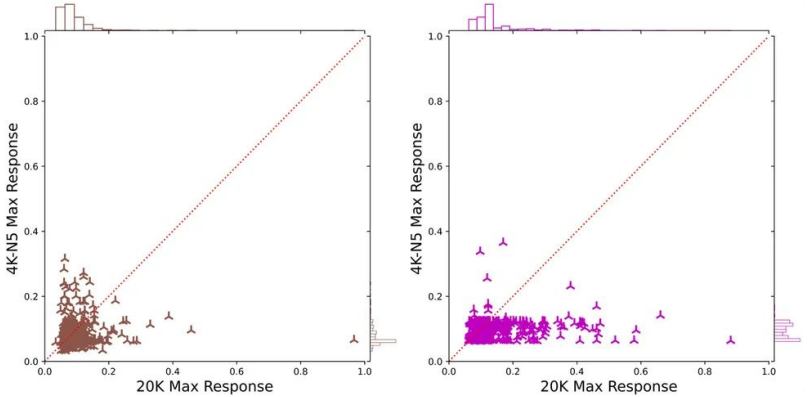
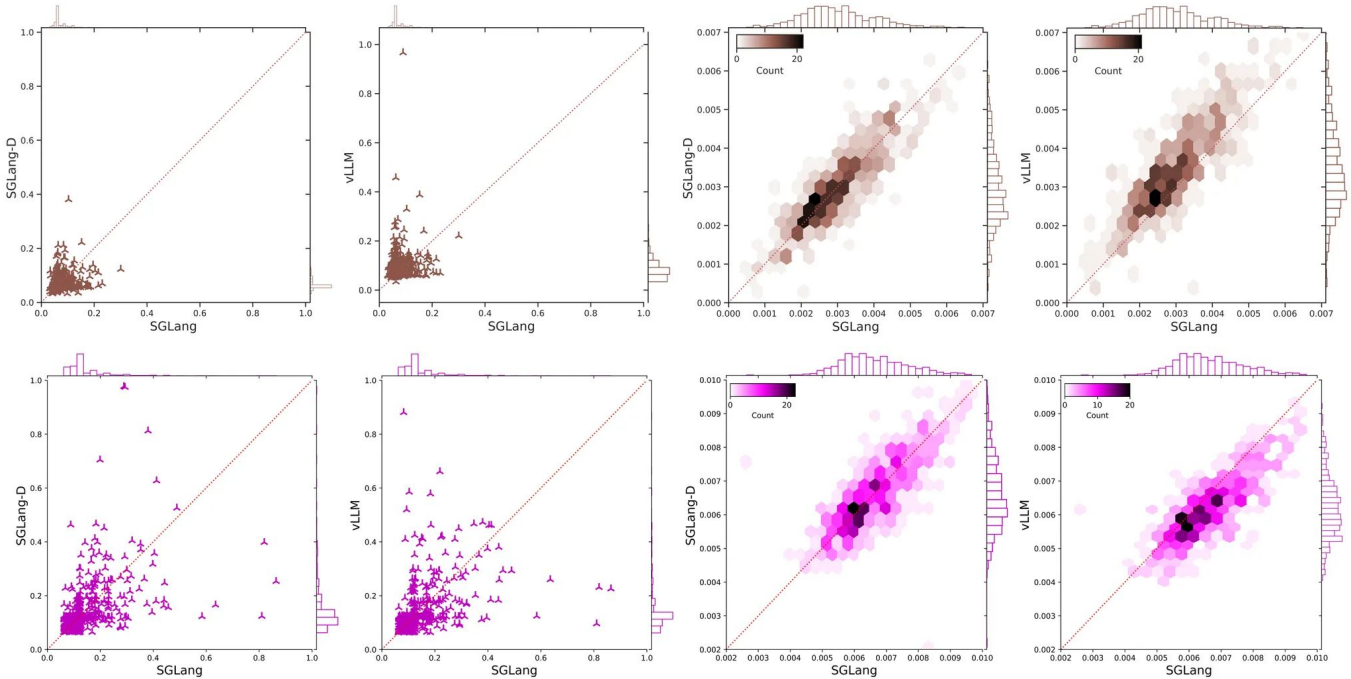




Factors Contributing to Mismatch

- Altering **Sampler** Alone, Gap Still There



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e.g., GRPO (token-level)
GSPO (sequence-level)

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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!

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