Reinforcement Learning beyond Reward Maximization

Yuda Song, Frontiers in Online Reinforcement Learning Workshop, April 1st 2026

RL with Reward Maximization

Protocol

$$s_h, a_h, r_h, s_{h+1} \sim P^{\pi}$$

Objective

$$\arg\max_{\pi} \mathbb{E}^{\pi} \left[\sum_{h=1}^{H} r_h \right]$$

Works pretty well in LLM post-training: reasoning, agent training with e.g., GRPO.

Are we done? No:

- Diversity collapse (restrained capability within base model)
- Overoptimization
- Stuck in local minimum

RL beyond Reward Maximization

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Part 2: why do we only use reward as the only signal?

Expanding the Capabilities of RL via Text Feedback

Part 1: are we using the right objective?

Maximum Likelihood Reinforcement Learning

RL beyond Reward Maximization

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Maximum Likelihood Reinforcement Learning

Binary Reward Tasks

Correctness-based tasks (reasoning, navigation, program synthesis) share similar structure.

Stochastic Generation

Okay, I have this … .Therefore the answer is 3.

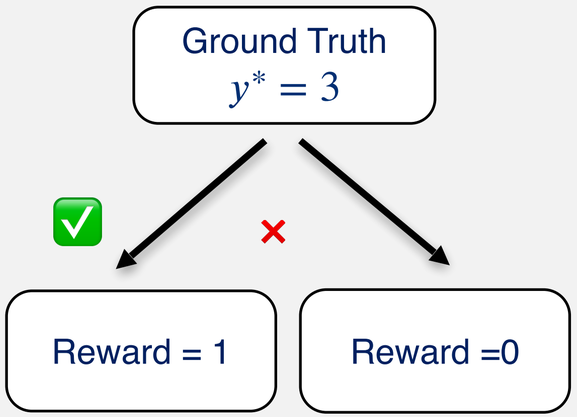
So, my goal is … I think the answer is 6.

Consider the expansion of …, answer is 3.

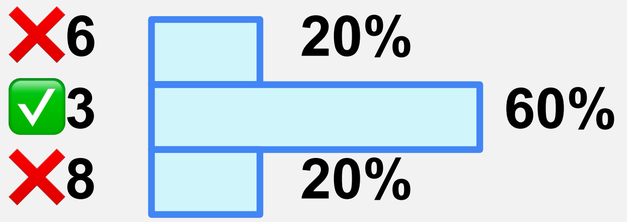
Okay, so … . Finally, number of roots: 3.

Let me think … Final answer: 8.

Binary Verifier



Model-Induced Success Probability

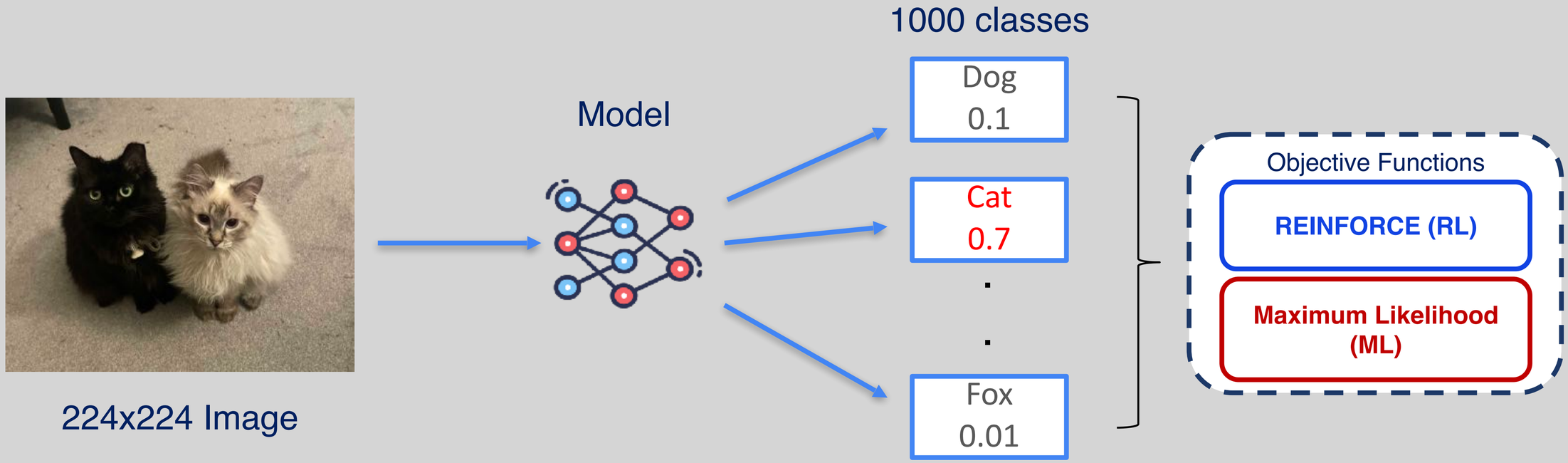


Output Distribution
$p_\theta(x)$

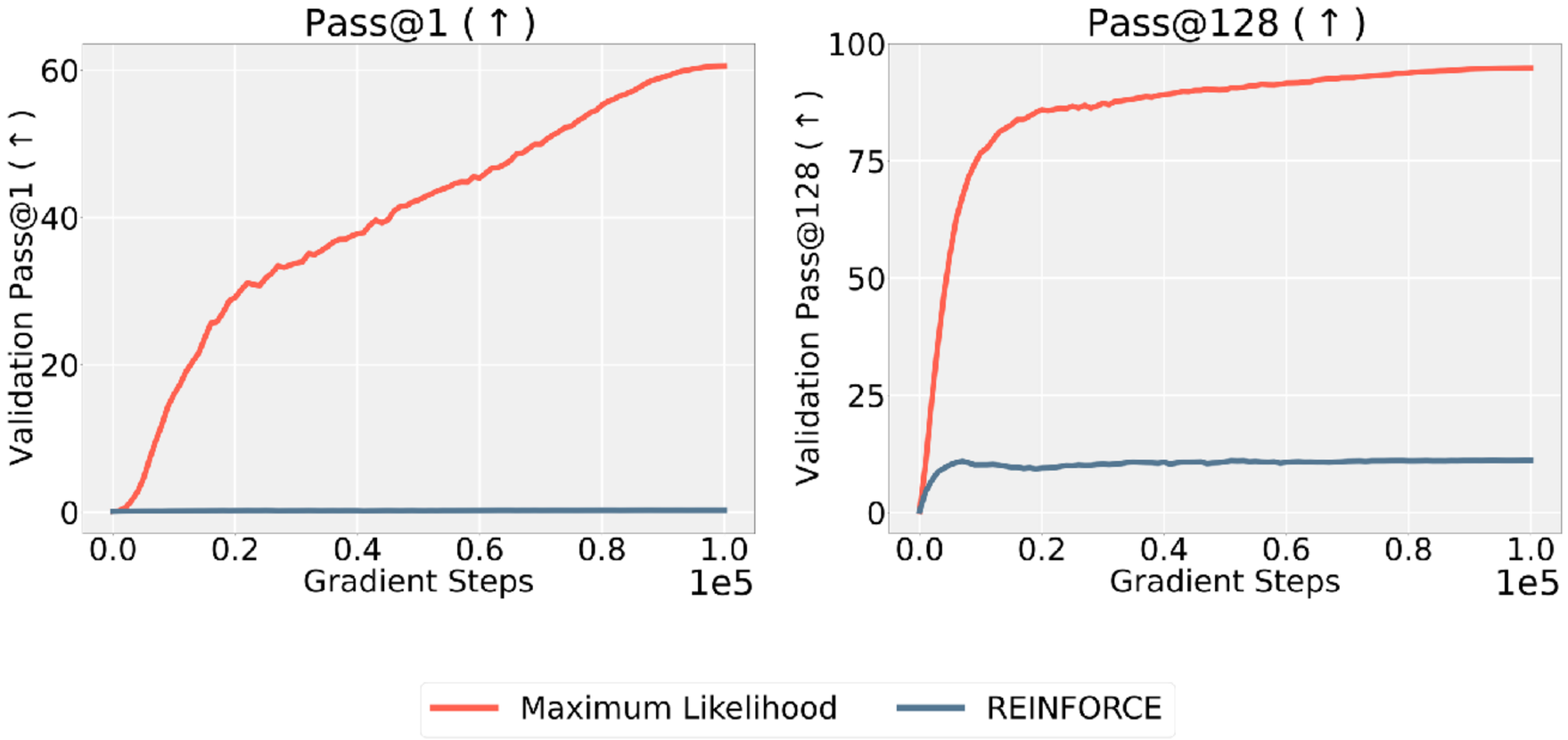
Can RL Solve Image Classification?

Image classification:

- It is a binary reward task.
- No non-differentiable sampling required.
- The gold standard objective is maximum likelihood, but we can also use RL.



REINFORCE Barely Works on Image Classification



Unpacking REINFORCE and ML Objectives

Let $p_\theta(y \mid x)$ denote the model probability for input x belonging to class y.

Let $y^*(x)$ be the correct class for input x. Can define everything similarly with $z \sim p_\theta(\cdot \mid x)$ and extract $y := f(z)$.

$$r(x, y) = \mathbb{I}(y = y^*)$$

$$p_\theta(x) := p_\theta(y^*(x) \mid x) \text{ aka } \text{pass@1}(x)$$

REINFORCE (RL)

$$\begin{aligned} J_{\text{RL}} &= \mathbb{E}_x[\mathbb{E}_{y \sim p_\theta(\cdot|x)}[r(x, y)]] \\ &= \mathbb{E}_x[\mathbb{E}_{y \sim p_\theta(\cdot|x)}[\mathbb{I}(y = y^*)]] \\ &= \mathbb{E}_x[p_\theta(x)] \end{aligned}$$

Maximum Likelihood (ML)

$$J_{\text{ML}} = \mathbb{E}_x[\log p_\theta(x)]$$

Unpacking REINFORCE and ML Objectives

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REINFORCE (RL)

$$\nabla_\theta J_{\text{RL}} = \mathbb{E}_x[\nabla_\theta p_\theta(x)]$$

Maximum Likelihood (ML)

$$\nabla_\theta J_{\text{ML}} = \mathbb{E}_x\left[\frac{1}{p_\theta(x)} \nabla_\theta p_\theta(x)\right]$$

REINFORCE: First-order Approximation of ML

REINFORCE (RL)

$$\nabla_\theta J_{\mathrm{RL}}(x) = \nabla_\theta \mathrm{pass@1}(x)$$

Maximum Likelihood (ML)

$$\nabla_\theta J_{\mathrm{ML}}(x) = \nabla_\theta \sum_{k=1}^{\infty} \frac{1}{k} \mathrm{pass@k}(x)$$

When pass rate is very small, higher order pass@k gradients provide the required learning signal.

But we can not estimate the gradient in practice with finite sample unbiasedly?

Constructing MaxRL

REINFORCE

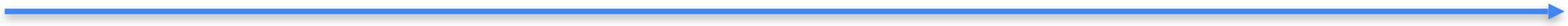
$$\nabla_\theta J_{\mathrm{RL}}(x) = \nabla_\theta \mathrm{pass@1}(x)$$

MaxRL

$$\nabla_\theta J^{(N)}_{\mathrm{maxRL}}(x) = \nabla_\theta \sum_{k=1}^{N} \frac{1}{k} \mathrm{pass@k}(x)$$

Maximum Likelihood

$$\nabla_\theta J_{\mathrm{ML}}(x) = \nabla_\theta \sum_{k=1}^{\infty} \frac{1}{k} \mathrm{pass@k}(x)$$



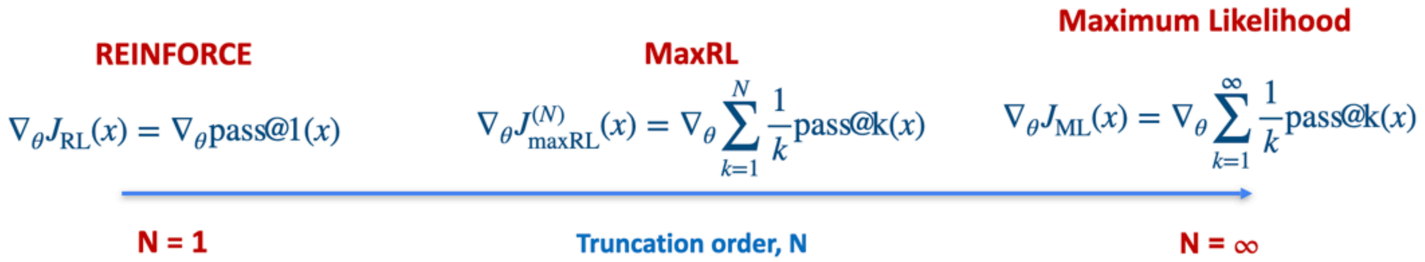
N = 1 — **Truncation order, N** — **N = ∞**

This gives us a general framework for optimizing ML via policy gradients:

Estimate pass@k gradients via any estimator, plug them in!

But can we do better?

Constructing MaxRL



The maximum likelihood objective can be seen as an expectation under the success-conditioned distribution.

Proposition

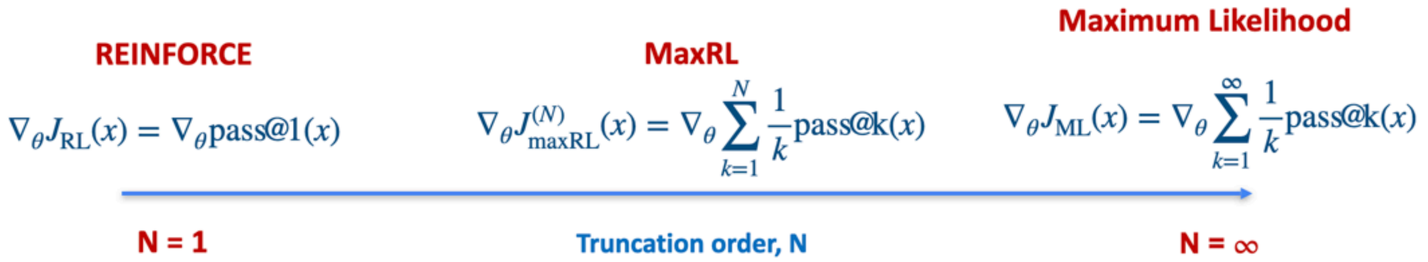
$$\nabla_\theta J_{\mathrm{ML}}(x) = \mathbb{E}[\nabla_\theta \log p_\theta(z \mid x) \mid f(z) = y^*(x)]$$

Learner's score function

Conditioning on success

- Maximum likelihood is learning from the success conditioned current policy.
- We can estimate MaxRL objective empirically in this form.

Constructing MaxRL



Proposition

$$\nabla_\theta J_{\mathrm{ML}}(x) = \mathbb{E}[\nabla_\theta \log p_\theta(z \mid x) \mid f(z) = y^*(x)]$$

Learner's score function

Conditioning on success

If we only have N samples, then let's just estimate the above directly with those samples:

$$\hat{g}_N(x) := \begin{cases} \dfrac{1}{K} \displaystyle\sum_{i=1}^{N} r_i S_i, & K \geq 1, \\ 0, & K = 0. \end{cases}$$

Score function of each sample

Number of success

Proposition

$$\mathbb{E}[\hat{g}_{\mathbf{N}}] = \nabla_\theta J^{(\mathbf{N})}_{\mathrm{MaxRL}}$$

Implementing MaxRL

Algorithm 1 On-Policy Implementation of MaxRL.

require Batch of inputs B, number of rollouts N, latent policy $m_\theta(\cdot \mid \cdot)$

for each input $x \in B$ **do**
  Sample $z_1, \ldots, z_N \sim m_\theta(\cdot \mid x)$
  for $j = 1$ to N **do**
    $r_j \leftarrow \mathbb{I}\{f(z_j) = y^*(x)\}$
    $S_j \leftarrow \nabla_\theta \log m_\theta(z_j \mid x)$
  end for
  $\widehat{r}(x) \leftarrow \frac{1}{N}\sum_{j=1}^{N} r_j$
  $\widehat{g}(x) \leftarrow \begin{cases} \dfrac{1}{N\,\widehat{r}(x)} \displaystyle\sum_{j=1}^{N} (r_j - \widehat{r}(x)) S_j, & \widehat{r}(x) > 0, \\ 0, & \text{otherwise} \end{cases}$
end for
$\widehat{g} \leftarrow \frac{1}{|B|}\sum_{x \in B} \widehat{g}(x)$
return $\widehat{g}$

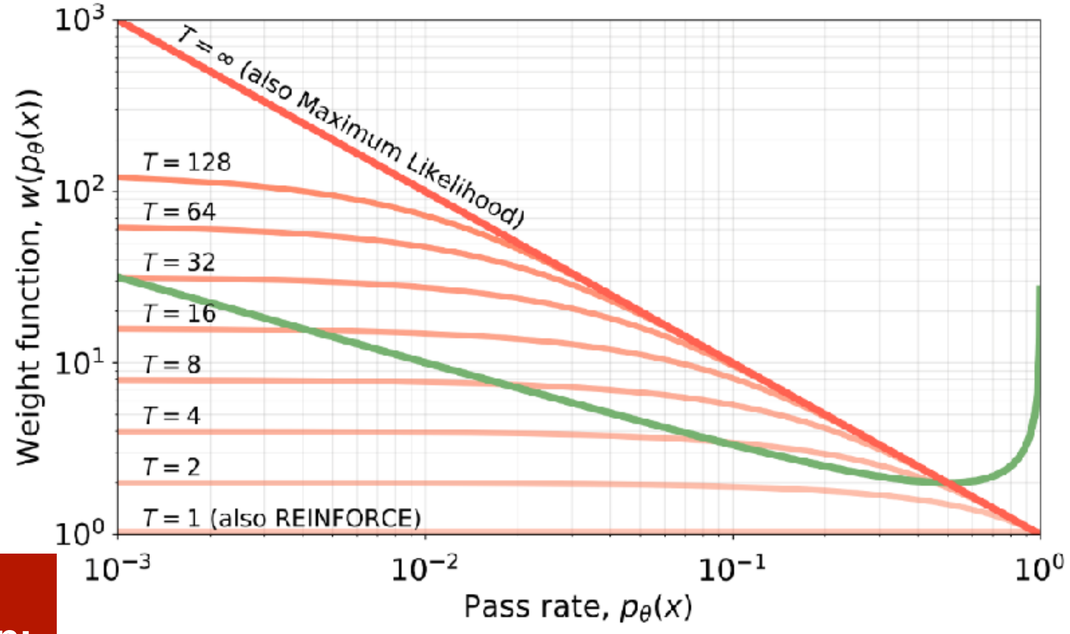
Average reward

Number of success

$$\nabla_\theta J = \mathbb{E}_{x \sim \rho}\left[w(p_\theta(x)) \, \nabla_\theta p_\theta(x) \right]$$

Objective-specific weight function

Standard policy gradient (e.g., REINFORCE)



With more samples:
GRPO only improves the estimation;
MaxRL approaches a better objective.

How Does MaxRL Perform in-Practice?

4 Settings:

- Didactic image classif
- Infinite training data re
- Data-scarce regime
- Larger scale LLM reas

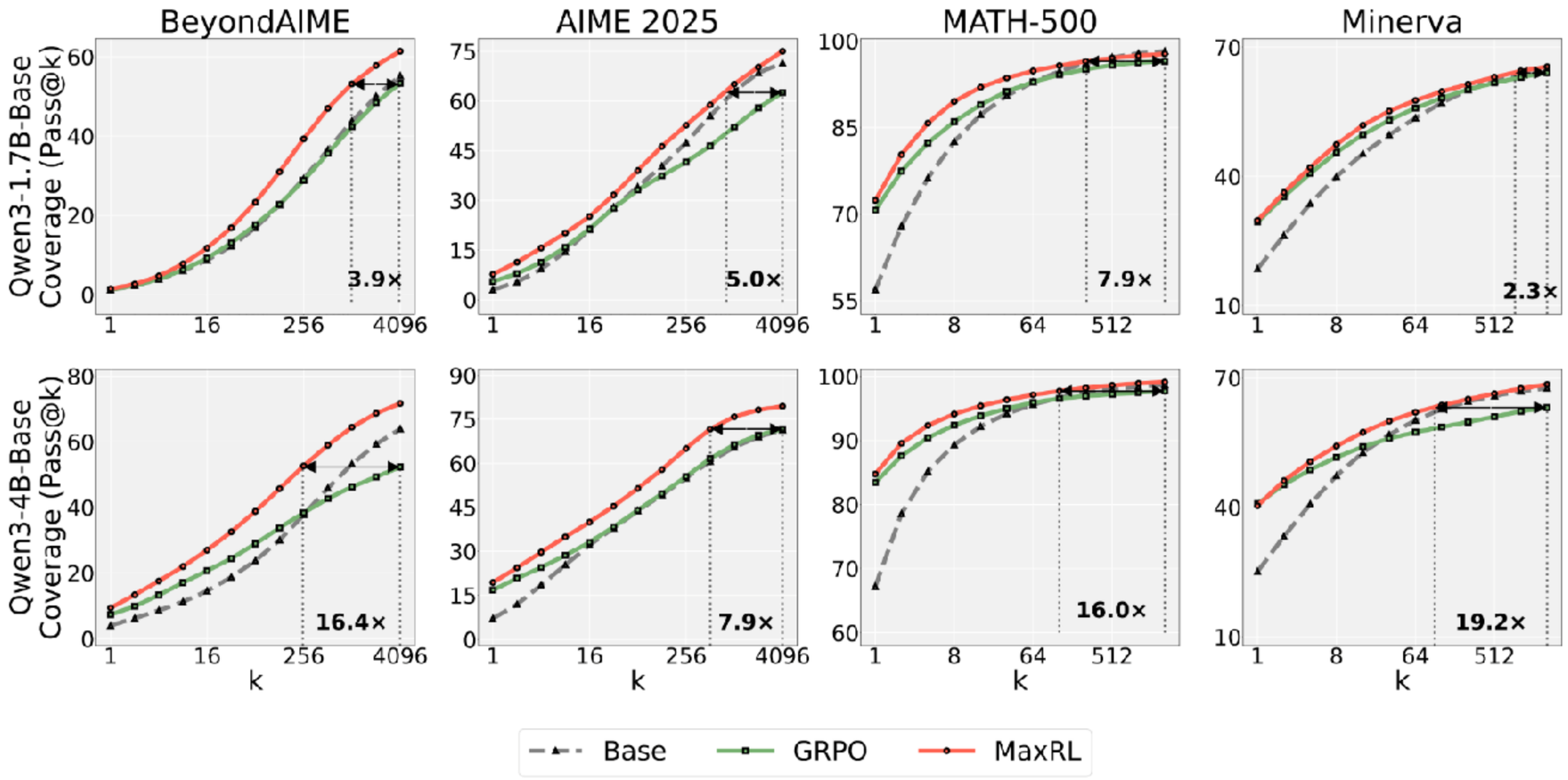


Image Classification

Consider the same image classification setup from before.

Except now we study sampling-based RL objectives.

224x224 Image

Model

1000 classes

Dog
0.1

Cat
0.7

.
.
.

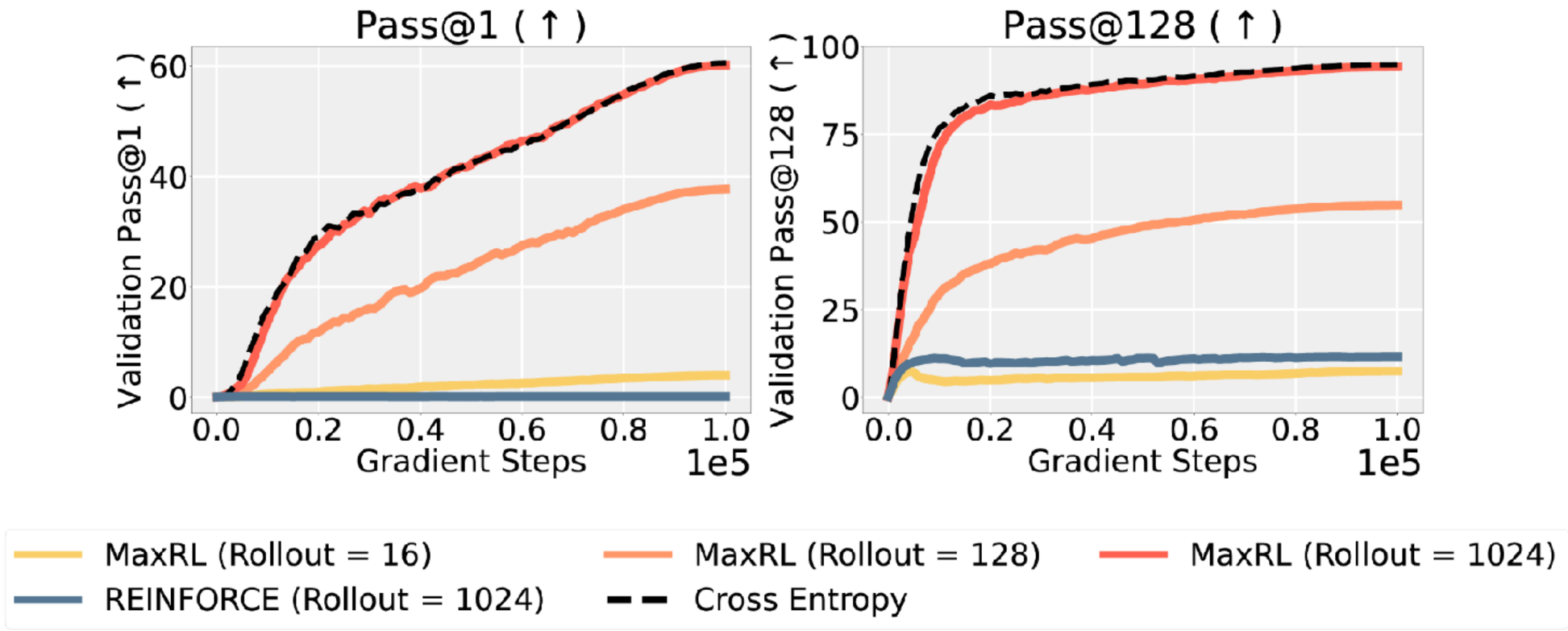
Fox
0.01

Objective Functions

REINFORCE (RL)

Maximum Likelihood (ML)

MaxRL approaches maximum likelihood with more compute

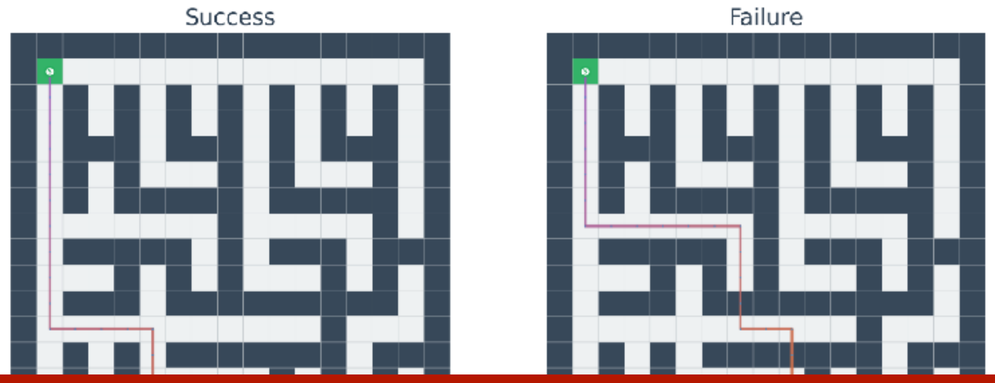


What Happens if We Had Infinite Training Data?

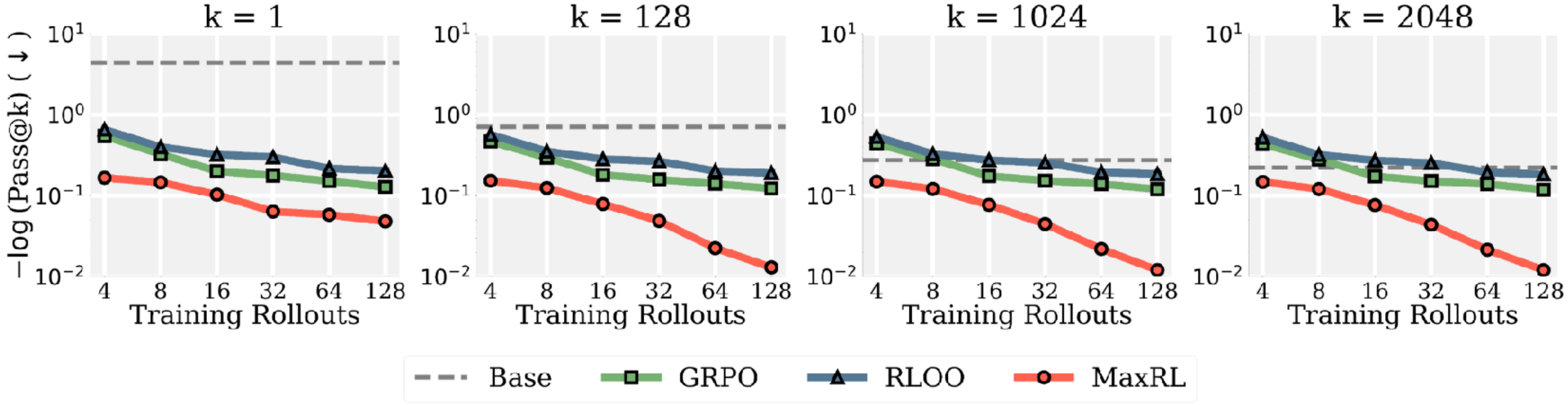
With sampling, but more training data than compute

Training data: 1M unique mazes

Evaluation: 1000 held-out mazes



As we increase training compute (i.e., sampling budget), MaxRL scales much better, specially at higher pass@k!



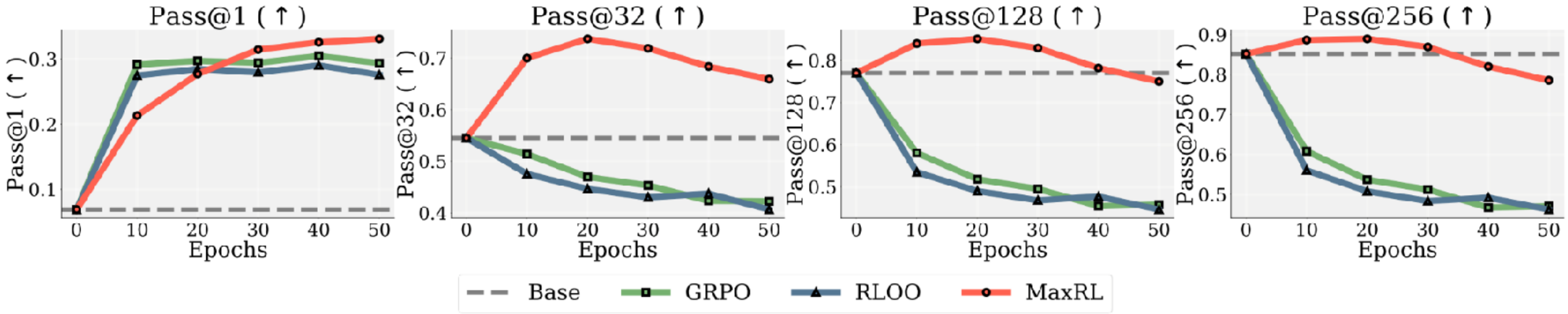
RL under Infinite Compute

What if we have more compute than training samples?
(Something that will very likely to happen in the future).

Model: SmolLM2-360M-Instruct

Training dataset: GSM8K

Evaluation dataset: GSM8K-Platinum



MaxRL grows slower at pass@1, but eventually converges to a higher performance level.
MaxRL also exhibits much lower pass@k degradation (no degradation until 30 epochs!)

(Some new findings that MaxRL might not necessarily be slower)

Half Time

Protocol

$$s_h, a_h, r_h, s_{h+1} \sim P^{\pi}$$

Objective

$$\arg\max_{\pi} \mathbb{E}_x \left[\log p_{\pi}(x)\right]$$

Part 2: why do we only use reward as the only signal?

Expanding the Capabilities of RL via Text Feedback

Part 1: are we using the right objective?

- Reward maximization may not always be the most suitable objective.
- MaxRL: optimize maximum likelihood in sampling-based settings with binary rewards.
- MaxRL scales better and shows less diversity collapse.

A Taxonomy for Feedback Signal

Density of information

Number of feedbacks	**Rich**	**Numeric**
Sparse		
Dense		

A Taxonomy for Feedback Signal

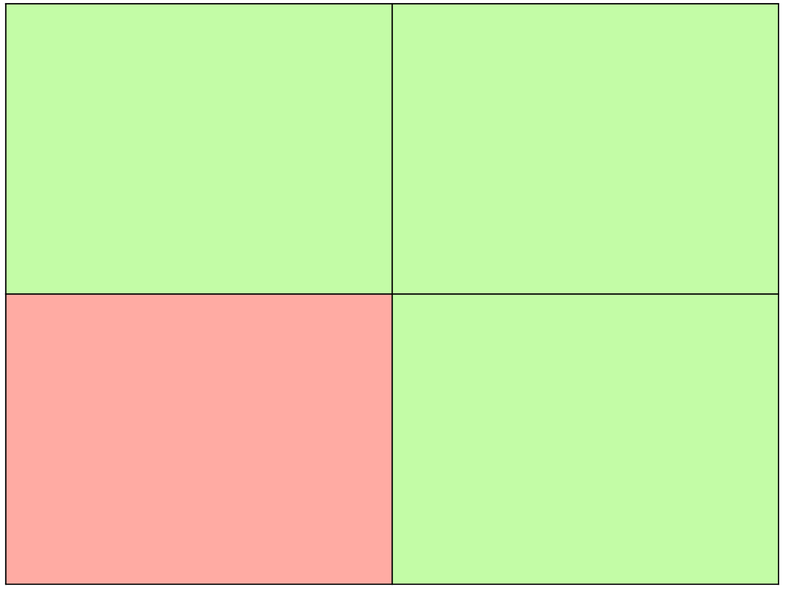
Density of information

Rich **Numeric**

Number of feedbacks

Sparse

Dense



RLVR

Density of information

Number of feedbacks	Rich	Numeric
Sparse		RLVR
Dense		

- Scalable but inefficient:
- One bit signal per thousands of tokens

Supervised Learning

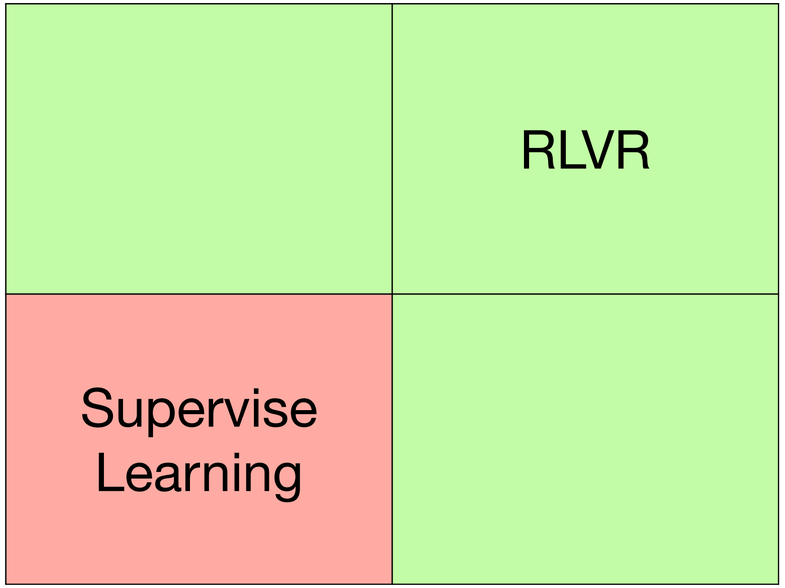
Density of information

Rich **Numeric**

Number of feedbacks

Sparse

Dense



- Not scalable in training frontier models — require human demonstration.
- Most of time, full demonstration is unnecessary.

Process Reward Model

Density of information

Number of feedbacks	**Rich**	**Numeric**
Sparse		RLVR
Dense	Supervise Learning	Process Reward Models

Process Reward Model

Density of informa

Rich **Nun**

4.2. Unsuccessful Attempts

In the early stages of developing DeepSeek-R1, we also encountered failures and setbacks along the way. We share our failure experiences here to provide insights, but this does not imply that these approaches are incapable of developing effective reasoning models.

Process Reward Model (PRM) PRM is a reasonable method to guide the model toward better approaches for solving reasoning tasks (Lightman et al., 2023; Uesato et al., 2022; Wang et al., 2023). However, in practice, PRM has three main limitations that may hinder its ultimate success. First, it is challenging to explicitly define a fine-grain step in general reasoning. Second, determining whether the current intermediate step is correct is a challenging task. Automated annotation using models may not yield satisfactory results, while manual annotation is not conducive to scaling up. Third, once a model-based PRM is introduced, it inevitably leads to reward hacking (Gao et al., 2022), and retraining the reward model needs additional training resources and it complicates the whole training pipeline. In conclusion, while PRM demonstrates a good ability to rerank the top-N responses generated by the model or assist in guided search (Snell et al., 2024), its advantages are limited compared to the additional computational overhead it introduces during the large-scale reinforcement learning process in our experiments.

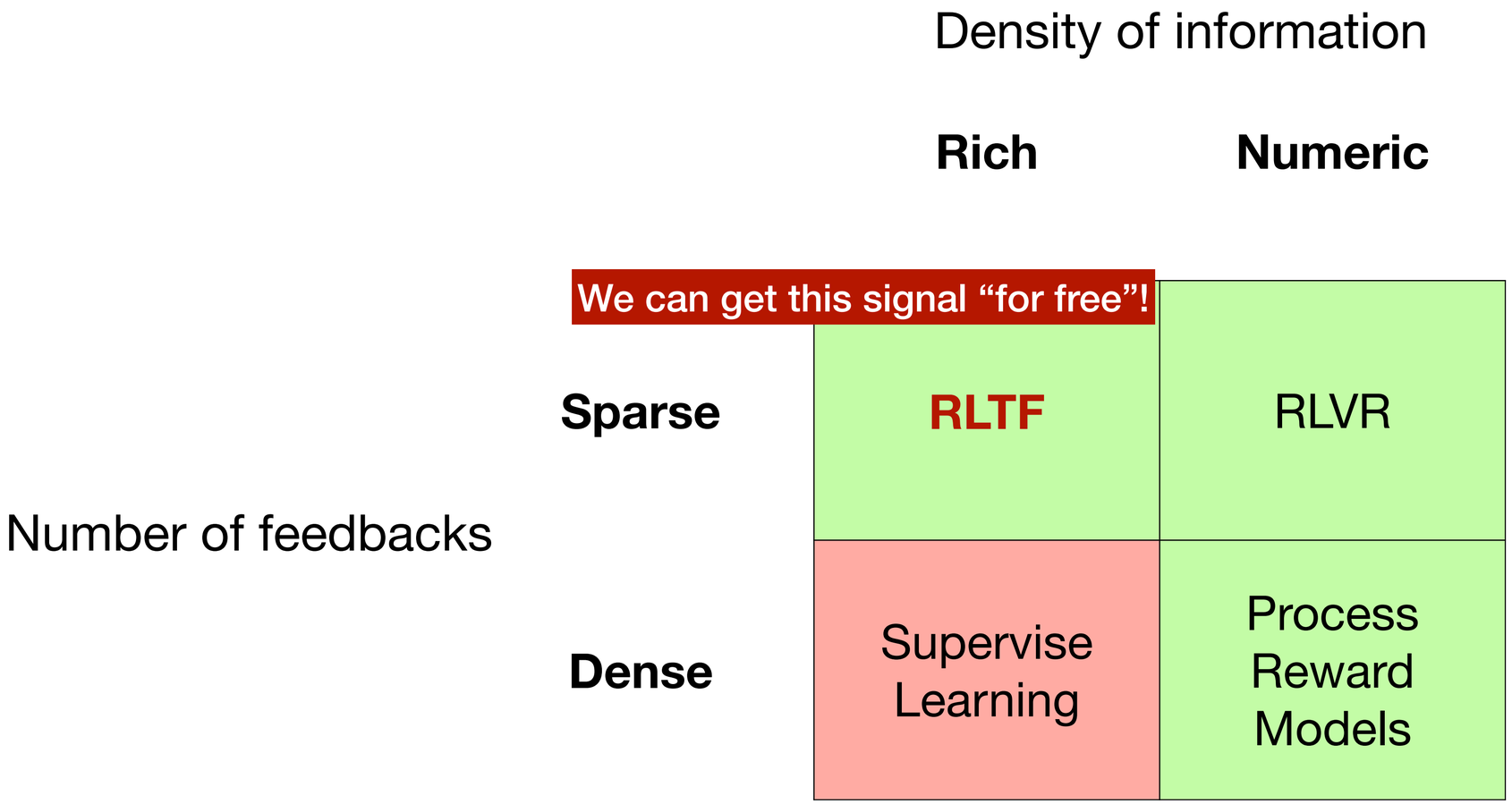
Number of feedbacks

Sparse

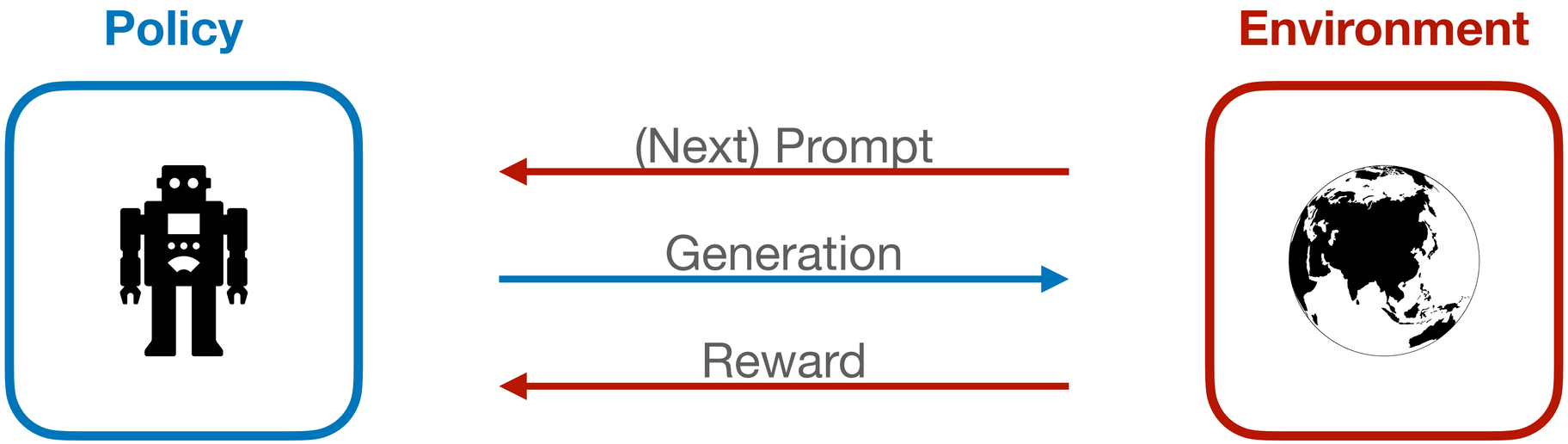
Dense

	RLVR
Supervise Learning	Process Reward Models

RL from Text Feedback



RL Interaction Protocol



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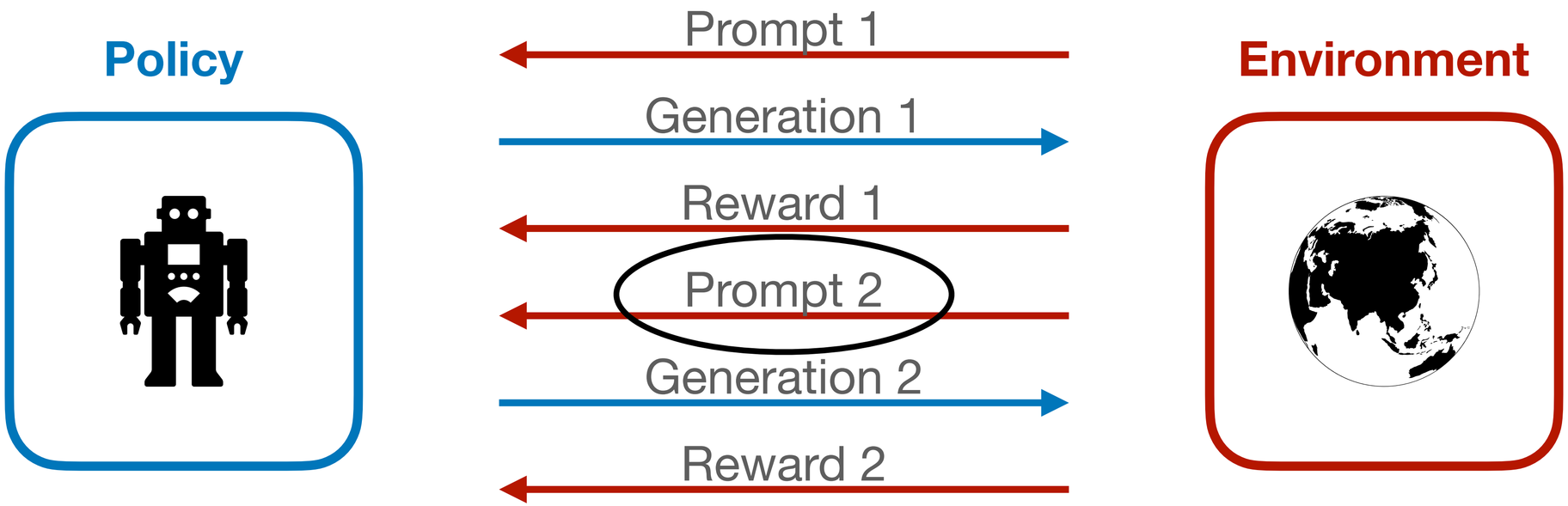
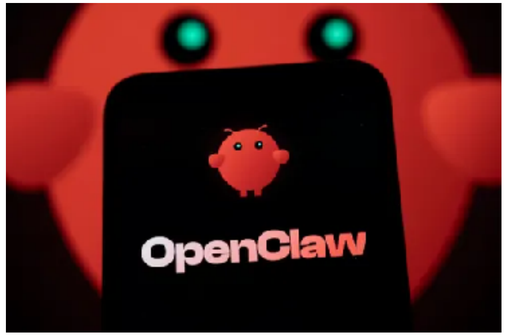


Next Prompt Contains Rich Information

Human-AI Interaction

Here is my proof:
Since x is an even number, we can write $x = 2k$ for some integer k. Therefore, $x + 1 = 2k + 1$.

Your proof is incomplete. You haven't shown that $2k + 1$ is an odd number.



Interpreter

Can you write a Python function to calculate the factorial of a number?

Environment: Code Interpreter

Here is the factorial code:

```python
def factorial(n):
    if n == 0:
        return 1
    else:
        return n * factorial(n-1)
```

> Executing: factorial(5)

Output:
120

> Executing: factorial(-1)

Error:
RecursionError: maximum recursion depth exceeded in comparison

Question: Solve the system of linear equations:

1. x + y + z = 6
2. 2x - y + 3z = 9
3. 3x + 2y - z = 4

Generation:

To find the solution for the variables x, y, and z, we can use the method of substitution.

Step 1: Isolate z in the first equation…

Step 2: Substitute z into the second equation…

Step 3: Substitute z into the third equation.

Next, substitute the expression for z into the third equation:

3x + 2y - (6 - x - y) = 4
Distribute the negative sign:

3x + 2y - 6 - x - y = 4
Combine like terms ($3x - x$ and $2y - y$):

2x + y - 6 = 4
Add 6 to both sides:

2x + y = 10 \quad \text{(Equation B)}

Step 4: Solve the system of Equation A and Equation B…

Step 5: Solve for x…

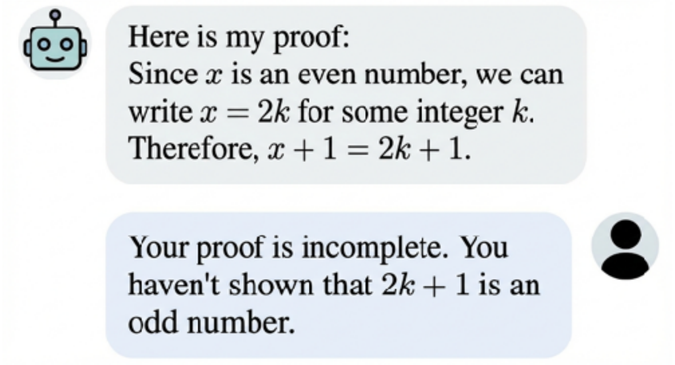
Step 6: Solve for z….

Final Answer:

The solution to the system of equations is $x = \frac{31}{7}$, $y = \frac{8}{7}$, and $z = \frac{3}{7}$.

Rule of Prompt 2

Human-AI Interaction



Prompt 1

Generation 1

Reward 1

Prompt 2

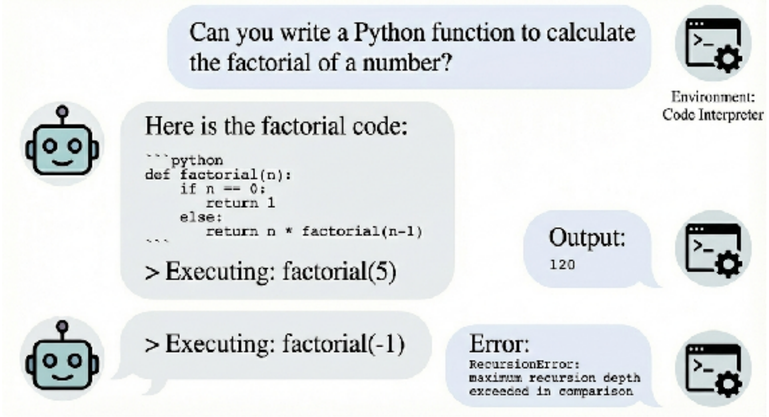
Generation 2

Reward 2

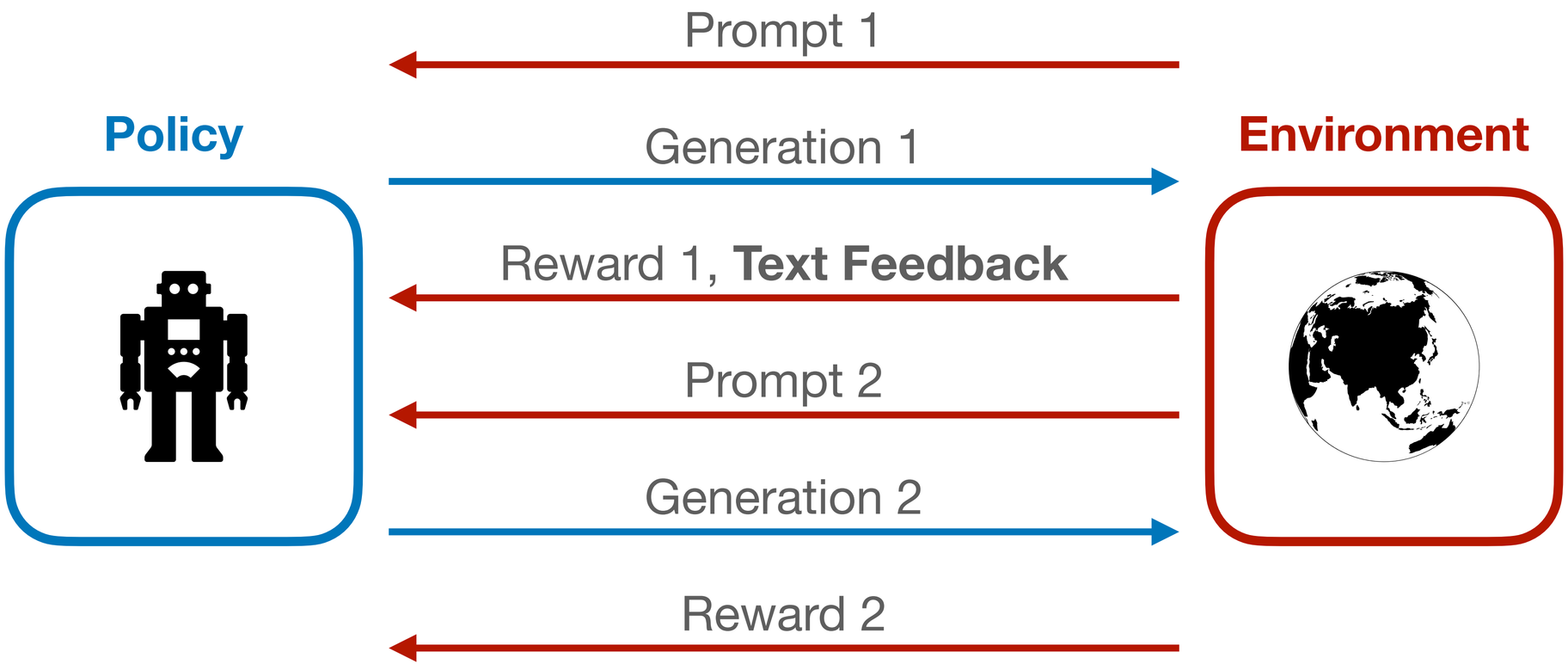
(Training-time)
Feedback Signal

(Inference-time)
Refinement/Steering

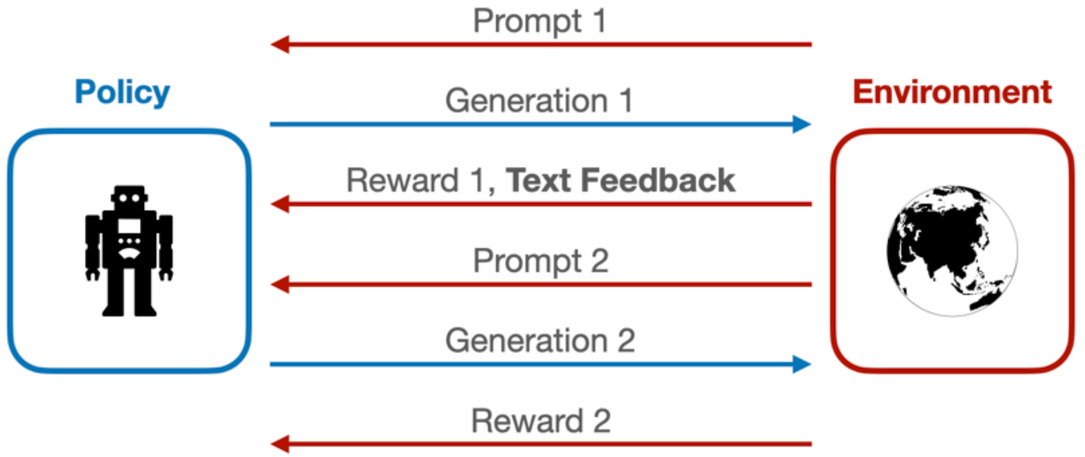
Interpreter



RL from Text Feedback

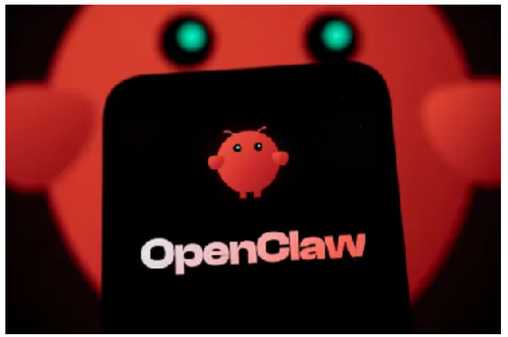


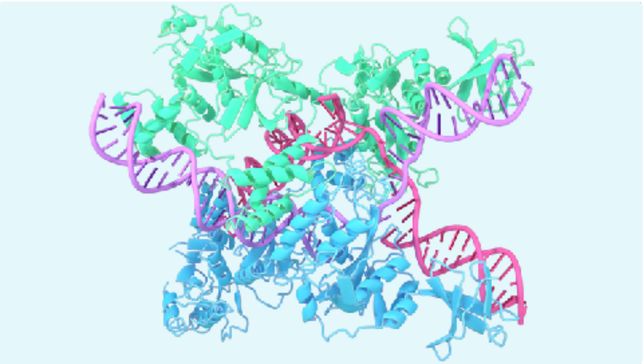
RLTF is the Paradigm towards Continual Learning



Deploy a post-trained model and continue adapting:

- Local customization by learning from user preferences.
- Adapting to company's internal data and tools while interacting with users.
- Scientific discovery by learning from interpreter output or experiment outcomes.





RL from Text Feedback

$x_1 \sim \mu$ initial prompt

$y_1 \sim \pi(\cdot \mid x_1)$

$\text{feedback} \sim \text{Env}(\cdot \mid x_1, y_1),\ r_1 = R(x_1, y_1)$

$x_2 = f(x_1, y_1, \text{feedback})$

$y_2 \sim \pi(\cdot \mid x_2)$

$r_2 = R(x_1, y_2)$

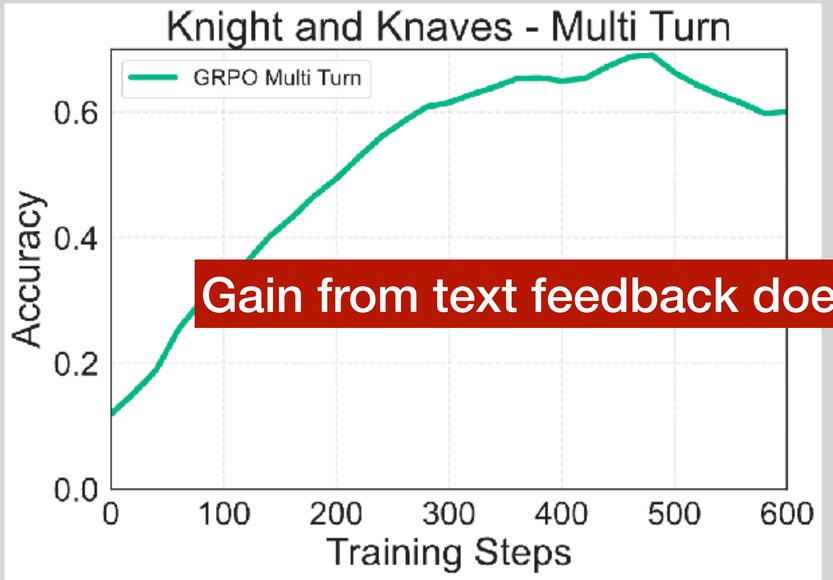
Main Learning Goal:

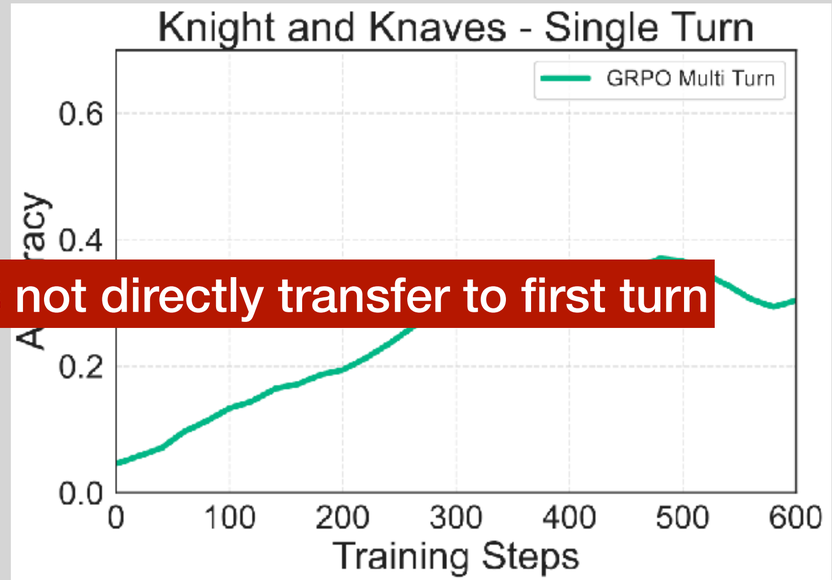
$$\max_{\pi} \mathbb{E}^{\pi}_{x_1, y_1}[R(x_1, y_1)]$$

Feedback may not exist at final evaluation

Can't we just run RL with regular objective

$$\mathbb{E}^{\pi}\left[\sum_{h=1}^{H} R(x_h, y_h)\right] ?$$





Gain from text feedback does not directly transfer to first turn

Two Ways of Feedback Internalization

- Observation 1: Directly learning the feedback already provides a rich learning signal
  - Feedback Modeling
- Observation 2: The feedback conditioned policy usually has a better generation distribution than the original policy.
  - Distill the feedback conditioned policy as a teacher policy.
- Combine these objective with the RL objective $\mathbb{E}^{\pi}\left[\sum_{h=1}^{H} R(x_h, y_h)\right]$

Result Overview

- Observation 1: Directly learning the feedback already provides a rich learning signal
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- Observation 2: The feedback conditioned policy usually has a better generation distribution than the original policy.
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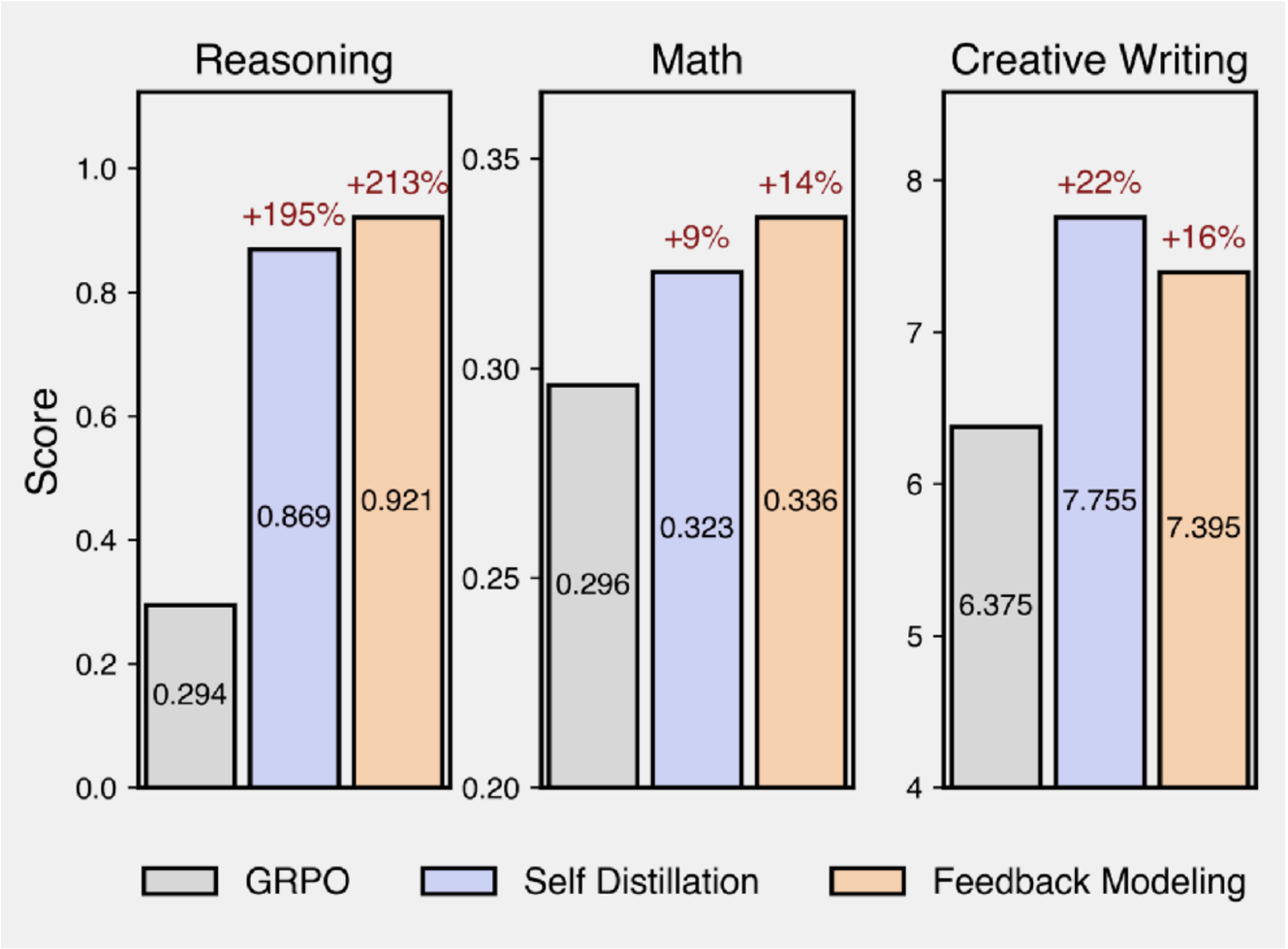


Feedback Modeling

- Auxiliary loss: predicting the feedback given the prompt and generation:

$$\log \pi(\text{feedback} \mid x_1, y_1)$$

- Combined objective:

$$\mathbb{E}^{\pi}[r_1 + r_2] + \mathbb{E}^{\text{sg}[\pi]}[\log \pi(\text{feedback} \mid x_1, y_1)]$$

- Not learning better generation directly, but intuitively:
  - Self-consistency
  - Representation Learning (shown in simple settings in the paper)

$$x_1 \sim \mu$$

$$y_1 \sim \pi(\cdot \mid x_1)$$

$$\text{feedback} \sim \text{Env}(\cdot \mid x_1, y_1),$$
$$r_1 = R(x_1, y_1)$$

$$x_2 = f(x_1, y_1, \text{feedback})$$

$$y_2 \sim \pi(\cdot \mid x_2)$$

$$r_2 = R(x_1, y_2)$$

Test-time Scaling with Feedback Modeling

We almost always do not have the feedback provider at time-time

$$x_1 \sim \mu$$

$$y_1 \sim \pi(\cdot \mid x_1)$$

$$\text{feedback} \sim \cancel{\text{Env}(\cdot \mid x_1, y_1)}, \; r_1 = R(x_1, y_1)$$

$$x_2 = f(x_1, y_1, \text{feedback})$$

$$y_2 \sim \pi(\cdot \mid x_2)$$

$$r_2 = R(x_1, y_2)$$

$$x_1 \sim \mu$$

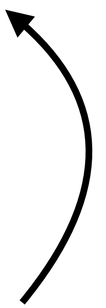
$$y_1 \sim \pi(\cdot \mid x_1)$$

$$\widehat{\text{feedback}} \sim \pi(\cdot \mid x_1, y_1)$$

$$\widehat{x_2} = f(x_1, y_1, \widehat{\text{feedback}})$$

$$\widehat{y_2} \sim \pi(\cdot \mid \widehat{x_2})$$

$$\widehat{\text{feedback}} \sim \pi(\cdot \mid x_2, y_2)$$



Test-time Scaling with Feedback Modeling

Feedback Modeling enables test-time scaling

$$x_1 \sim \mu$$

$$y_1 \sim \pi(\cdot \mid x_1)$$

$$\widehat{\text{feedback}} \sim \pi(\cdot \mid x_1, y_1)$$

$$\widehat{x_2} = f(x_1, y_1, \widehat{\text{feedback}})$$

$$\widehat{y_2} \sim \pi(\cdot \mid \widehat{x_2})$$

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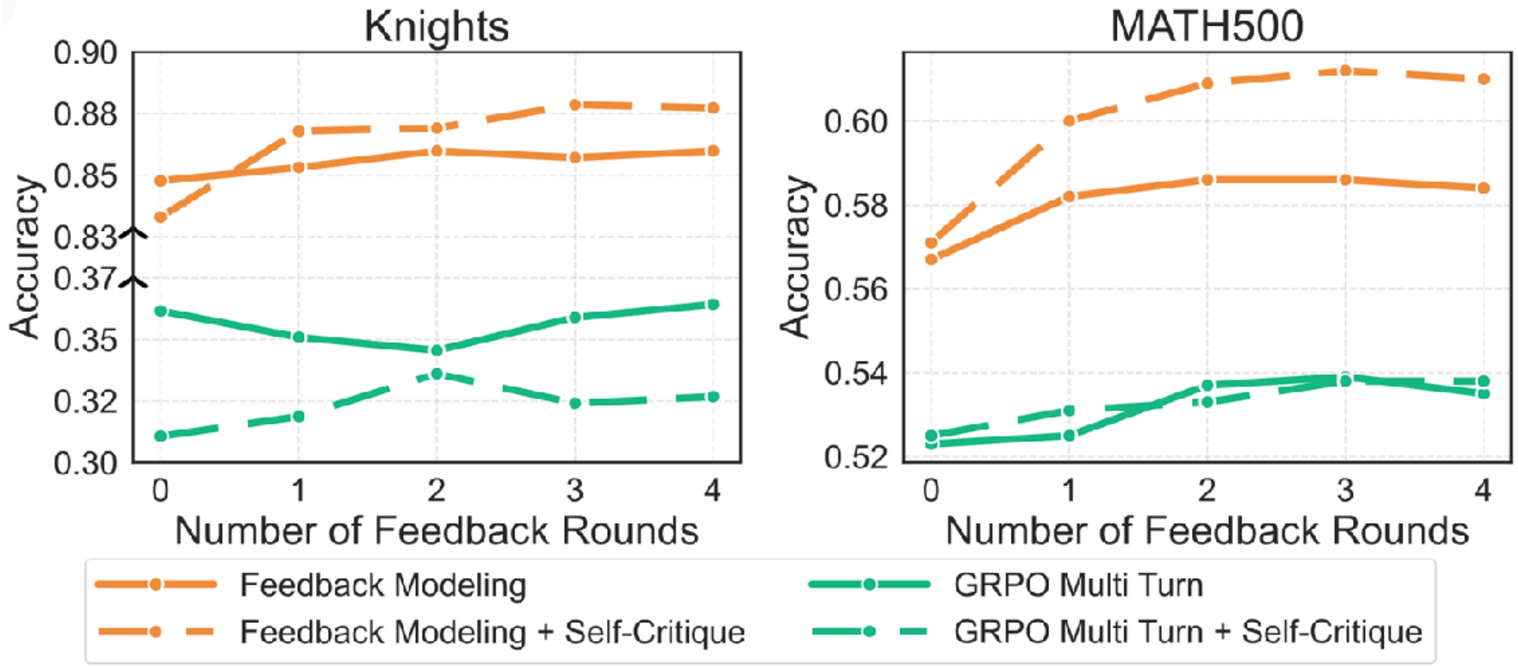
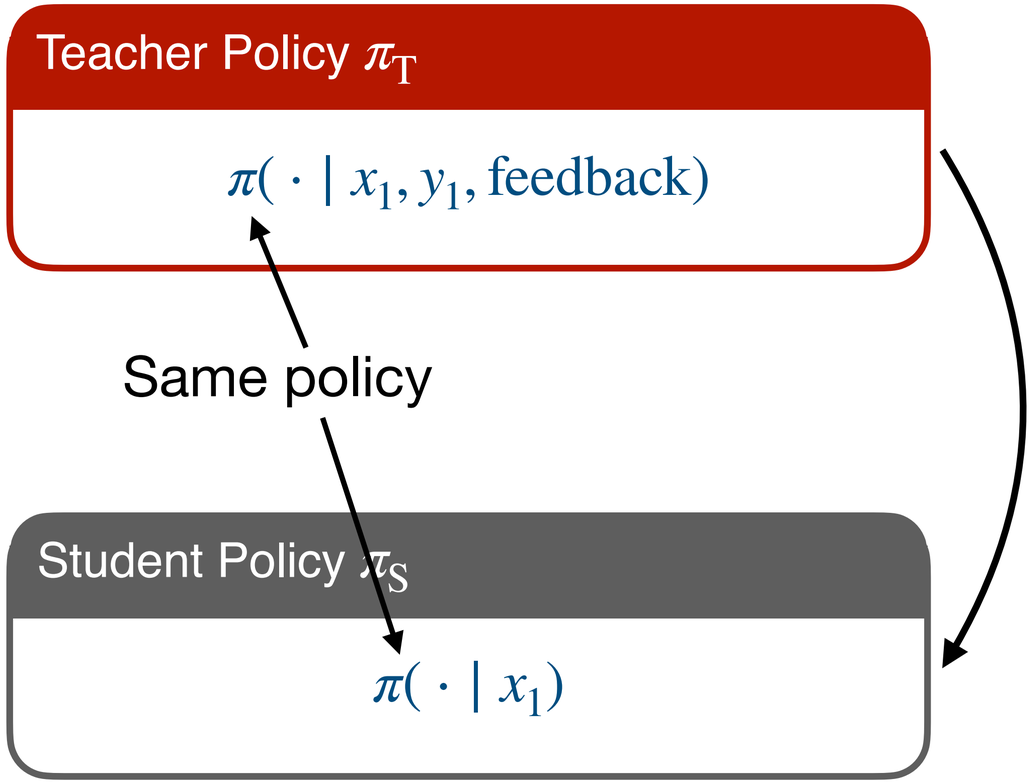


Two Ways of Feedback Internalization

- Observation 1: Directly learning the feedback already provides a rich learning signal
  - Feedback Modeling
- Observation 2: The feedback conditioned policy usually has a better generation distribution than the original policy.
  - Distill the feedback conditioned policy as a teacher policy.

Self-distillation



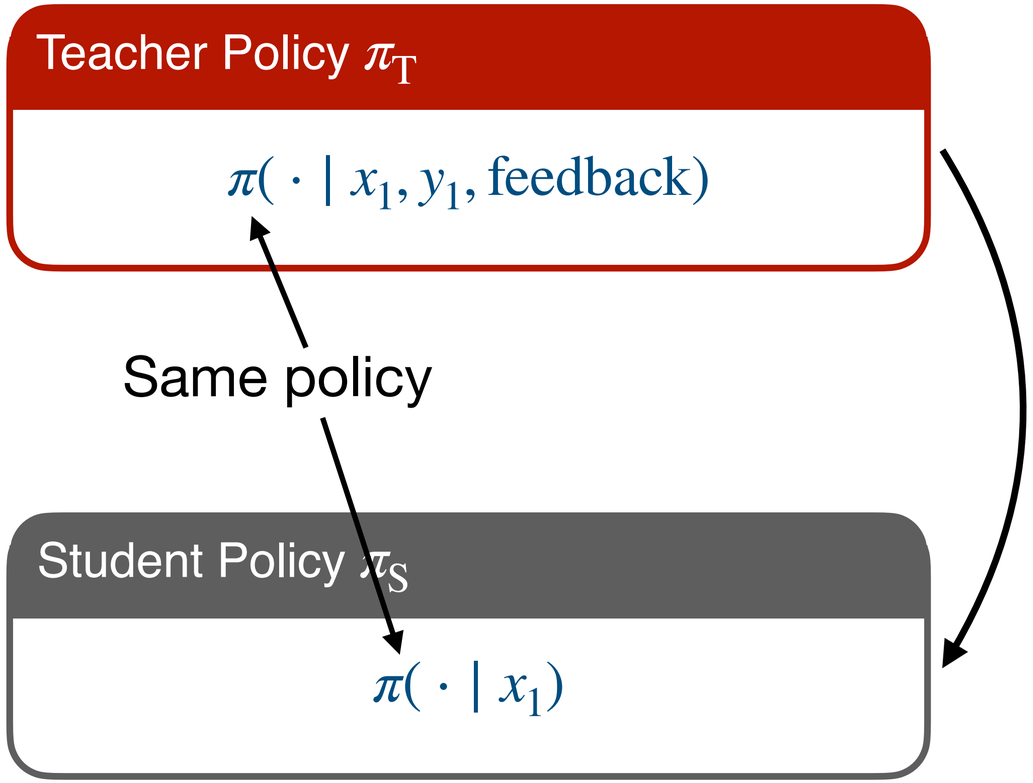
RL Distillation

On-policy Distillation

SFT

$$
\begin{aligned}
&x_1 \sim \mu \\
&y_1 \sim \pi(\cdot \mid x_1) \\
&\text{feedback} \sim \text{Env}(\cdot \mid x_1, y_1), \\
&r_1 = R(x_1, y_1) \\
&x_2 = f(x_1, y_1, \text{feedback}) \\
&y_2 \sim \pi(\cdot \mid x_2) \\
&r_2 = R(x_1, y_2)
\end{aligned}
$$

Self-distillation



RL Distillation

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&y_2 \sim \pi(\cdot \mid x_2) \\
&r_2 = R(x_1, y_2)
\end{aligned}
$$

RL Distillation

Teacher Policy π_T

$\pi(\cdot \mid x_1, y_1, \text{feedback})$

Student Policy π_S

$\pi(\cdot \mid x_1)$

Idea: using teacher sampling distribution to train the student policy.

RL Distillation Objective:

$$x_1 \sim \mu$$

$$y_1 \sim \pi(\cdot \mid x_1)$$

$$\text{feedback} \sim \text{Env}(\cdot \mid x_1, y_1)$$

$$\mathbb{E}_{y_2 \sim \pi_T} \left[\frac{\pi_S(y_2)}{\pi_{\text{ref}}(y_2)} \widehat{A}(y_2) \right]$$

Candidates: π_T or π_S

Return estimation with Variance Reduction

- GRPO-style: $\widehat{A}(y_2) = r_2 - \text{mean}(r_2)$
- Ours: $\widehat{A}(y_2) = r_2 - \text{mean}(r_1)$

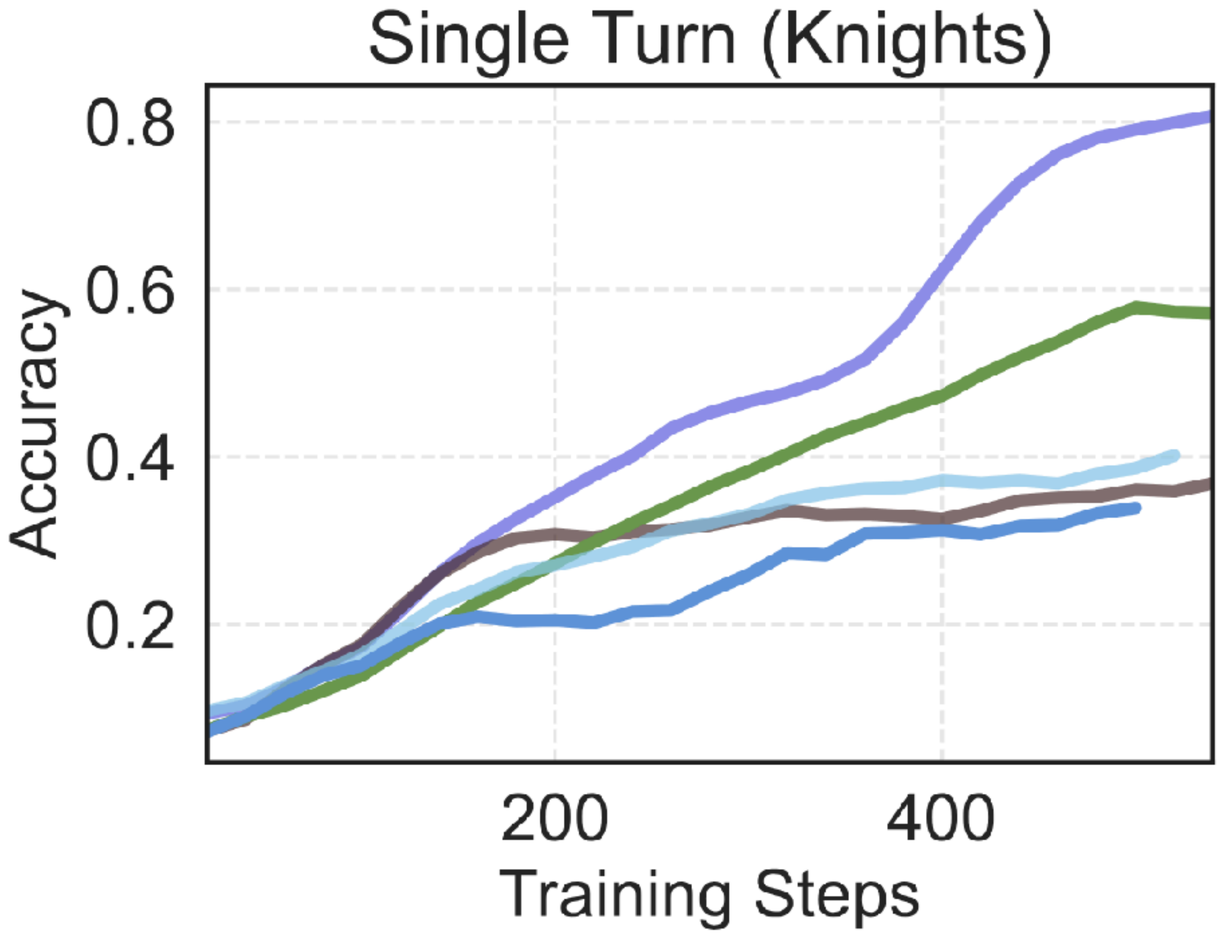
Clipping on importance weighting
E.g., PPO, CISPO

π_T ⟷ π_S

Variance — Bias

Ablation

$$\mathbb{E}_{y_2 \sim \pi_T}\left[\frac{\pi_S(y_2)}{\pi_{ref}(y_2)}\widehat{A}(y_2)\right]$$



$\pi_{ref} = \pi_S,\ \widehat{A}(y_2) = r_2 - \text{mean}(r_1)$

$\pi_{ref} = \pi_S,\ \widehat{A}(y_2) = r_2 - \text{mean}(r_2)$

$\pi_{ref} = \pi_T$, PPO, $\widehat{A}(y_2) = r_2 - \text{mean}(r_1)$

Rejection sampling

$\pi_{ref} = \pi_T$, CISPO, $\widehat{A}(y_2) = r_2 - \text{mean}(r_1)$

$\pi_{ref} = \pi_T$

RL Self-Distillation: Full Objective

RL Distillation Objective:

$$\mathbb{E}^{\pi}_{x_1,y_1,x_2,y_2}\left[r_1 + r_2 + \frac{\pi(y_2 \mid x_1)}{\mathrm{sg}[\pi(y_2 \mid x_1)]}[r_2 - \mathrm{mean}(r_1)]\right]$$

RL objective

Self-distillation objective

$$x_1 \sim \mu$$

$$y_1 \sim \pi(\cdot \mid x_1)$$

$$\text{feedback} \sim \mathrm{Env}(\cdot \mid x_1, y_1),\quad r_1 = R(x_1, y_1)$$

$$x_2 = f(x_1, y_1, \text{feedback})$$

$$y_2 \sim \pi(\cdot \mid x_2)$$

$$r_2 = R(x_1, y_2)$$

RL Self-Distillation: Interpretation

RL Distillation Objective:

$$\mathbb{E}^{\pi}_{x_1,y_1,x_2,y_2}\left[r_1 + r_2 + \frac{\pi(y_2 \mid x_1)}{\mathrm{sg}[\pi(y_2 \mid x_1)]}[r_2 - \mathrm{mean}(r_1)]\right]$$

Improve π_{T}

Weighted ($\widehat{A}$) SFT to π_{T}

Forward KL to tilted π_{T} if $\exp(\widehat{A})$

Experiment: Full Results

	Base Model	GRPO Single turn	GRPO Multi turn	Feedback Descent	RLTF-SD	RLTF-FM
Reasoning						
Knights and Knaves	0.058	0.373	0.352	0.055	0.802	0.880
Binary Matrix	0.001	0.125	0.950	0.005	0.976	0.978
Shortest Path	0.034	0.385	0.384	0.035	0.830	0.905
Math						
MATH500 (DAPO)	0.376	0.526	0.523	0.415	0.548	0.567
AIME24 (DAPO)	0.025	0.058	0.025	0.045	0.088	0.083
MATH500 (DeepMath)	0.376	0.558	0.578	0.424	0.598	0.636
AIME24 (DeepMath)	0.025	0.042	0.050	0.054	0.058	0.058
Creative Writing						
LitBench	4.20	6.83	6.41	8.25	8.80	8.40
WritingBench	5.71	5.92	6.29	5.30	6.71	6.39

Second Half Time

Protocol

$$s_h, a_h, r_h, \text{feedback}_h, s_{h+1} \sim P^{\pi}$$

Objective

$$\arg\max_{\pi} \mathbb{E}_x \left[\log p_{\pi}(x)\right]$$

Part 2: why do we only use reward as the only signal?

- Text feedback: richer than reward, cheaper than demonstrations, abundant in practice.
- SD and FM enables feedback internalization.
- A paradigm for continual learning.

Part 1: are we using the right objective?

- Reward maximization may not always be the most suitable objective.
- MaxRL: optimize maximum likelihood in sampling-based settings with binary rewards.
- MaxRL scales better and shows less diversity collapse.

Expanding the Capabilities of RL via Text Feedback

RLTF

Protocol

$$s_h, a_h, r_h, \text{feedback}_h, s_{h+1} \sim P^{\pi}$$

Maximum Likelihood Reinforcement Learning

MaxRL

Objective

$$\arg\max_{\pi} \mathbb{E}_x \left[\log p_{\pi}^{\text{pass}}(x) \right]$$