ProRL: Prolonged Reinforcement Learning Expands Reasoning Boundaries in Large Language Models

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Prolonged Reinforcement Learning for Diverse LLM Reasoning

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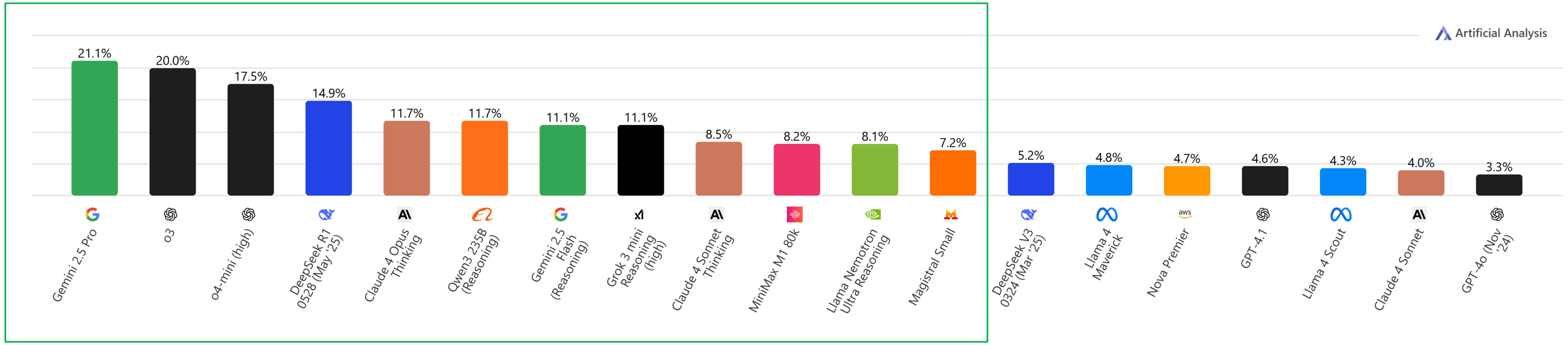
2025 A Reasoning Model Year

A Paradigm Shift

- Explosion of reasoning models
  - Commercial models
    - OpenAI's o-series, Claude 3.7/4.0 Sonnet, and Gemini 2.5 Pro
  - Open-Source models
    - DeepSeek-R1, Qwen QwQ, Qwen 3 family, NVIDIA Llama Nemotron Family
- What Sets Reasoning Models Apart?
  - Extended thinking time using long chain-of-thought and stepwise processing
  - Trained via reinforcement learning techniques
  - State-of-the-art performance on challenging reasoning benchmarks

Humanity's Last Exam Benchmark Leaderboard: Results

Independently conducted by Artificial Analysis



The Ultimate Question For Developing Reasoning Model

- Does reinforcement learning **truly unlock new reasoning capabilities** from a base model, or does it merely **optimize the sampling efficiency** of solutions already embedded in the base model (temperature distillation)?

Claims: No Acquired Capabilities Beyond Base Models

Decomposing Elements of Problem Solving: What "Math" Does RL Teach?

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Assessing Diversity Collapse in Reasoning

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Echo Chamber: RL Post-training Amplifies Behaviors Learned in Pretraining

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Does Reinforcement Learning Really Incentivize Reasoning Capacity in LLMs Beyond the Base Model?

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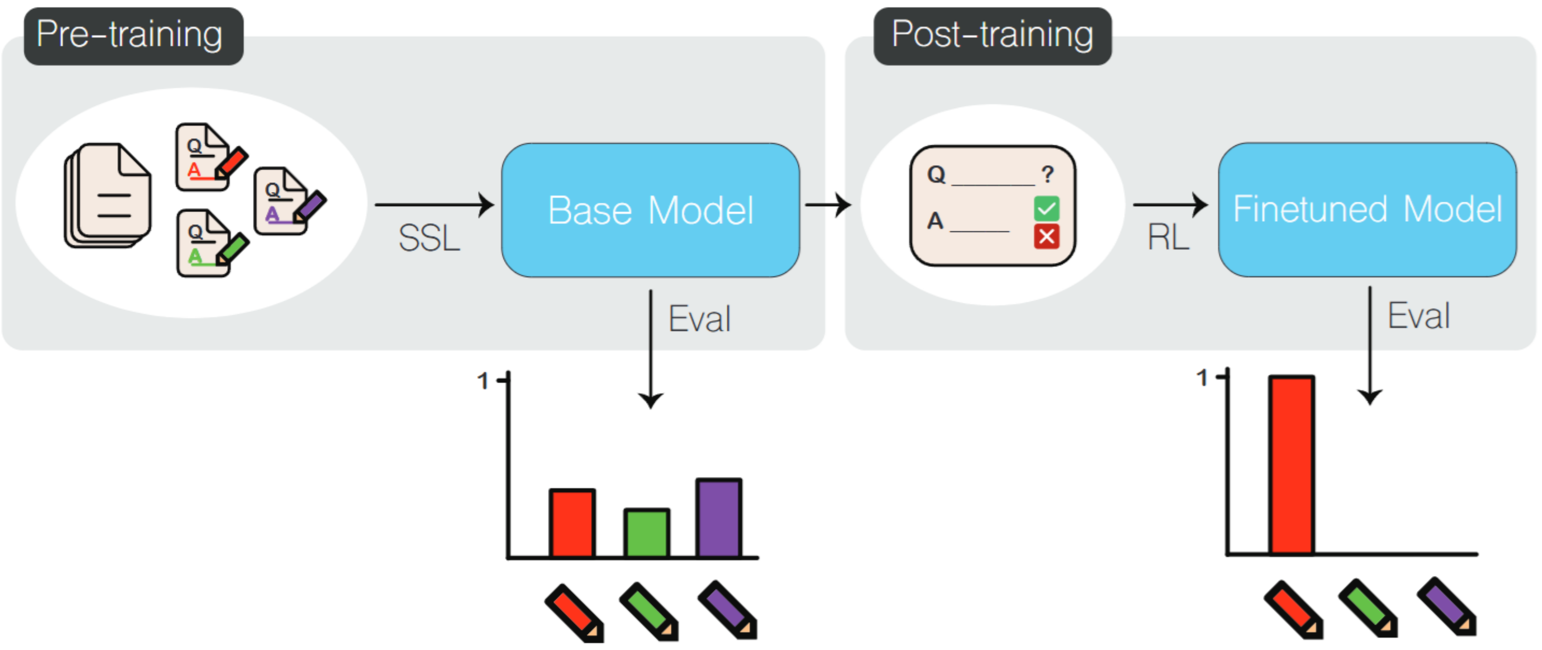
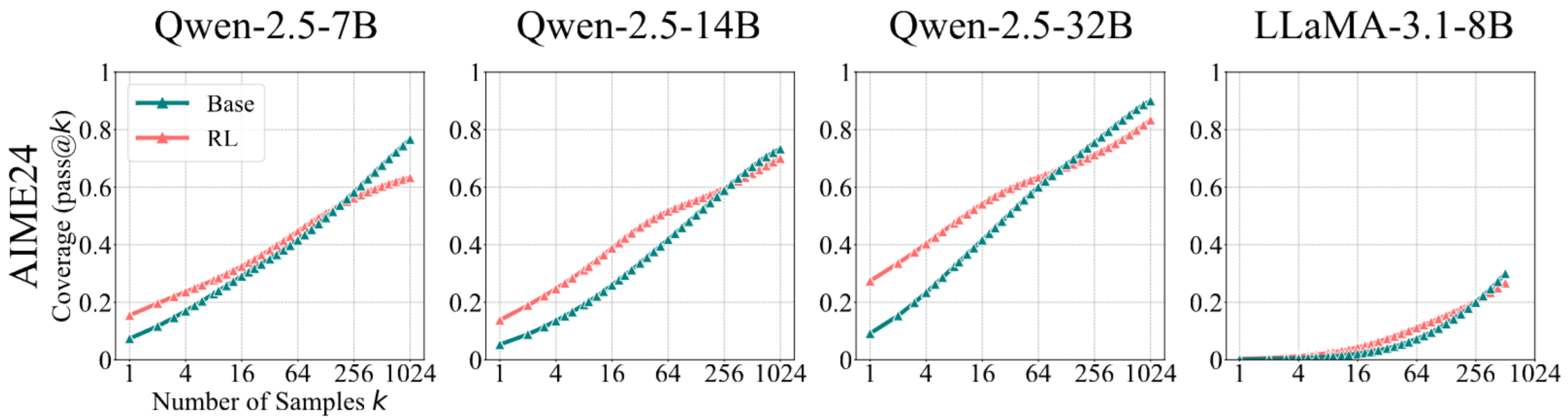




Is LLM RL doomed?

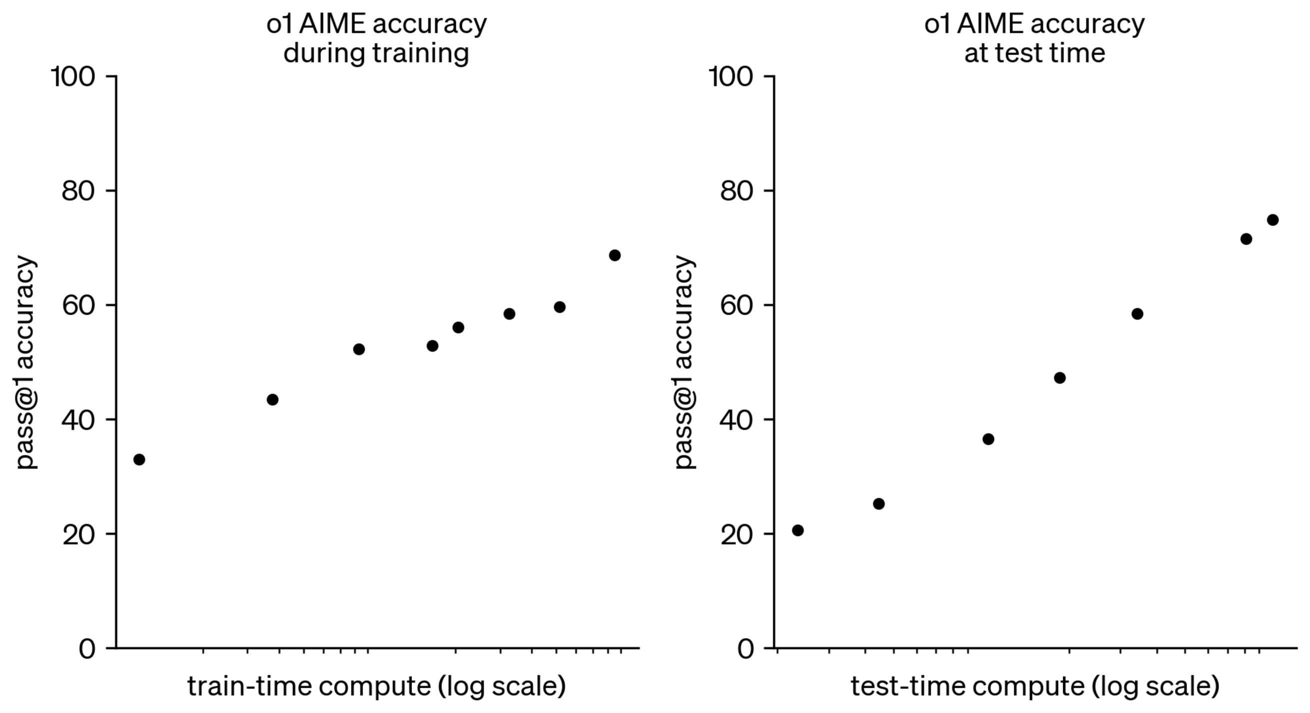
- Temperature distillation is boring, what about superhuman intelligence?

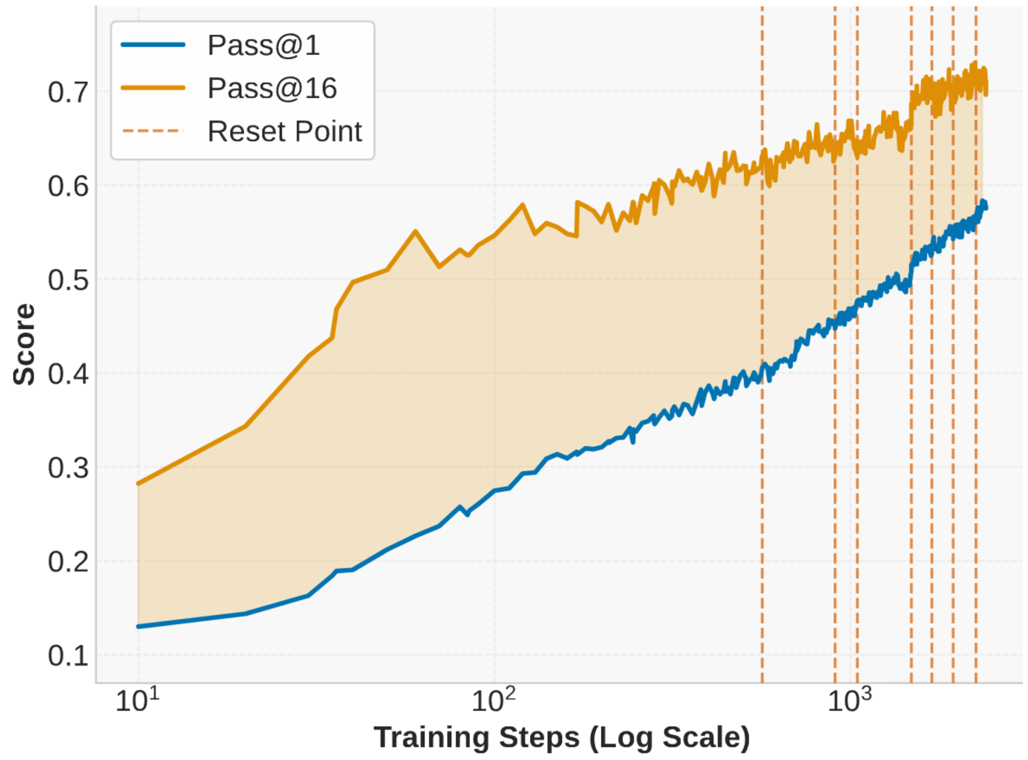
- What's common in previous studies:
  - An overreliance on specialized domains like mathematics that is overtrained during both pre-training and post-training phases
    - Can someone be creative if he only trains on the tasks that he is already good at?
  - The premature termination of RL training, typically no more than hundreds of step
    - Can someone discover new ideas if he is only allowed to explore a new area for a short amount of time?
- Luckily, our study find evidences that models learns new capabilities beyond the base model.
  - Implication: potentially achieve superhuman intelligence just by running RL.

Our Philosophy to Train Reasoning Models

In contrast to previous studies, ProRL is different

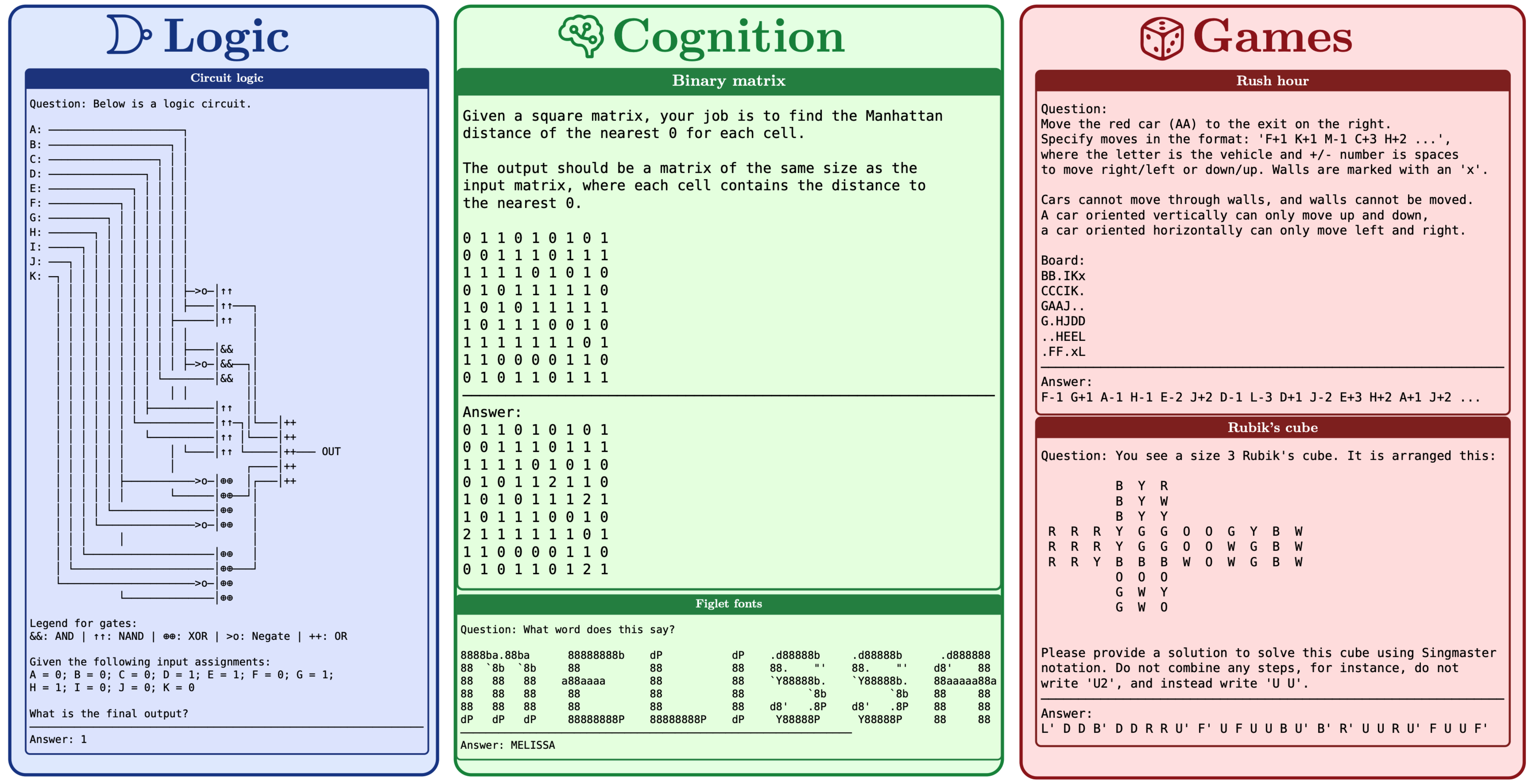
- Prolonged Reinforcement Learning, scale the RL training





- Using diversified novel reasoning tasks

Data Type	Reward Type	Quantity	Data Source
Math	Binary	40k	DeepScaleR Dataset
Code	Continuous	24k	Eurus-2-RL Dataset
STEM	Binary	25k	SCP-116K Dataset
Logical Puzzles	Continuous	37k	Reasoning Gym
Instruction Following	Continuous	10k	Llama-Nemotron



Outlines

- How to achieve Prolonged reinforcement learning
- Reasoning model training Results - ProRL produced SOTA 1.5B reasoning model
- Analysis on the results to address the question whether RL expand the reasoning boundary

How to Achieve ProRL

- We use GRPO RL algorithm with DAPO tricks
  - Dynamic sampling
  - Decoupled clip high and low

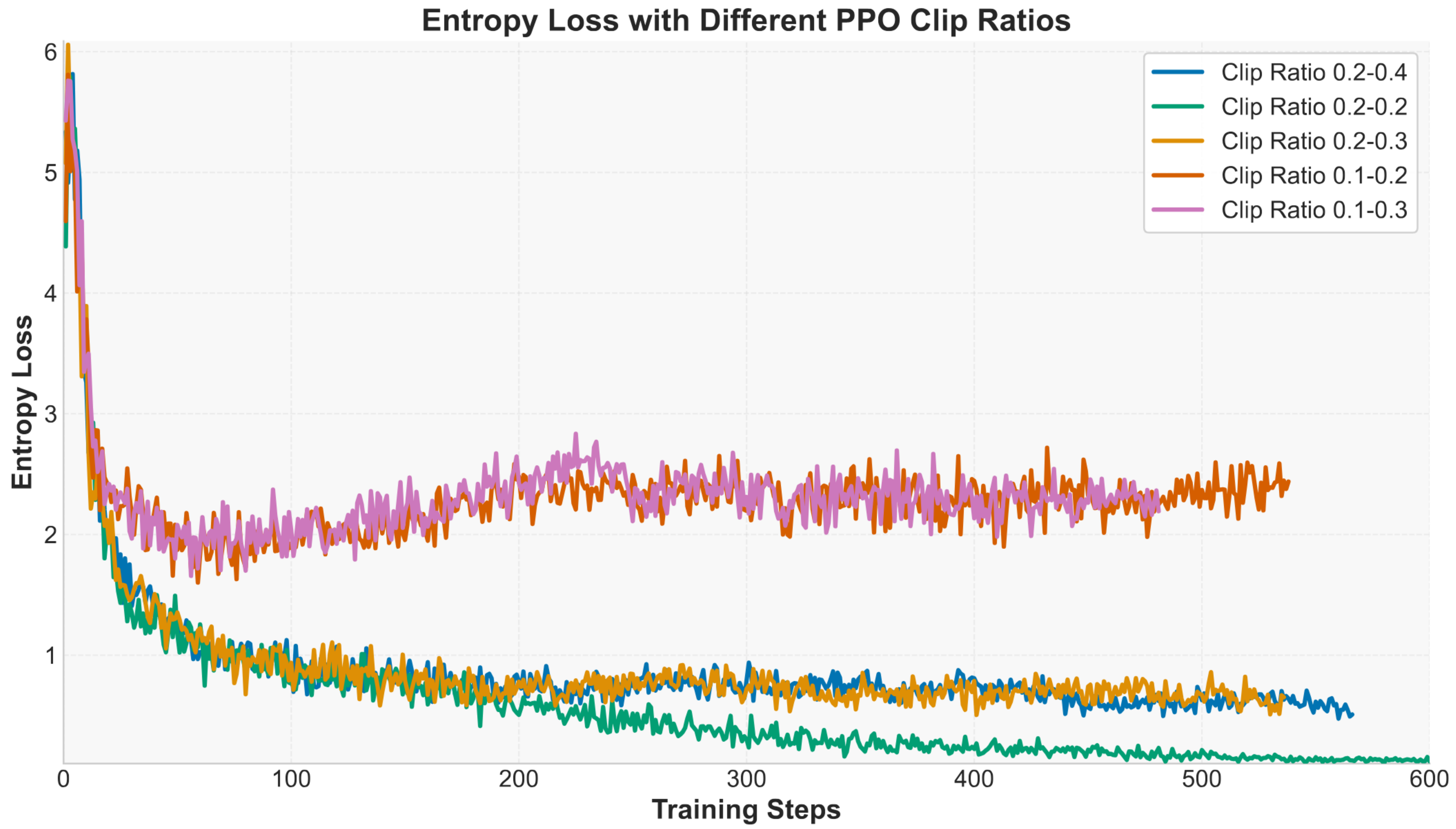
$$\mathcal{L}_{\text{GRPO}}(\theta) = \mathbb{E}_{\tau \sim \pi_\theta}\left[\min\left(r_\theta(\tau)A(\tau), \quad \text{clip}(r_\theta(\tau), 1-\epsilon, 1+\epsilon)A(\tau)\right)\right]$$

$$\text{clip}(r_\theta(\tau), 1-\epsilon_{low}, 1+\epsilon_{high})$$

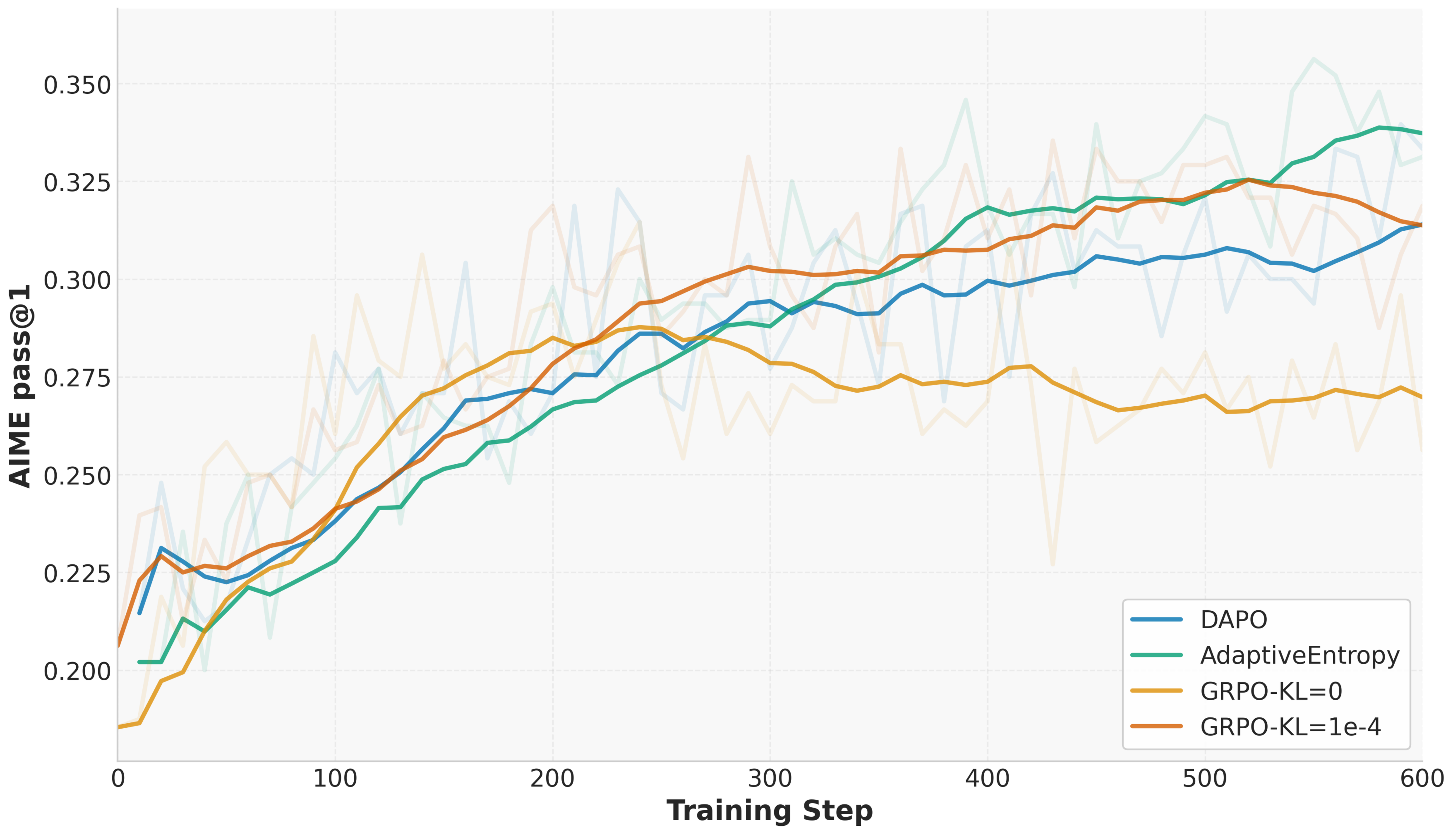
- Balance the exploration and exploitation
  - Sustainable entropy
- Resetting the reference policy and optimizer states
  - No bounded exploration

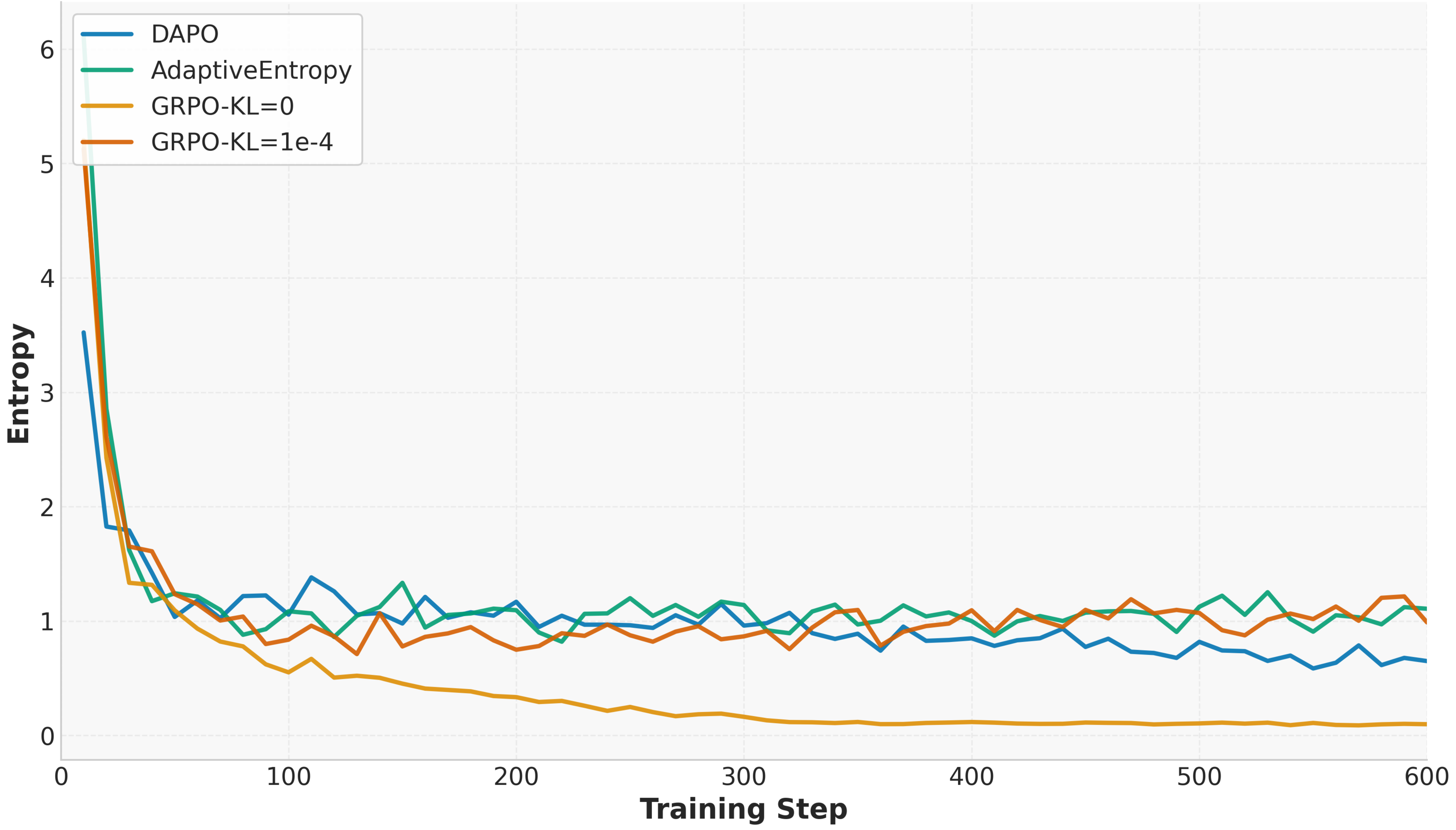
Balance the Exploration and Exploitation

- Entropy trending up or down is bad
  - It is not sustainable for prolonged training, the same reasoning that exploding/vanishing gradient is bad in training.



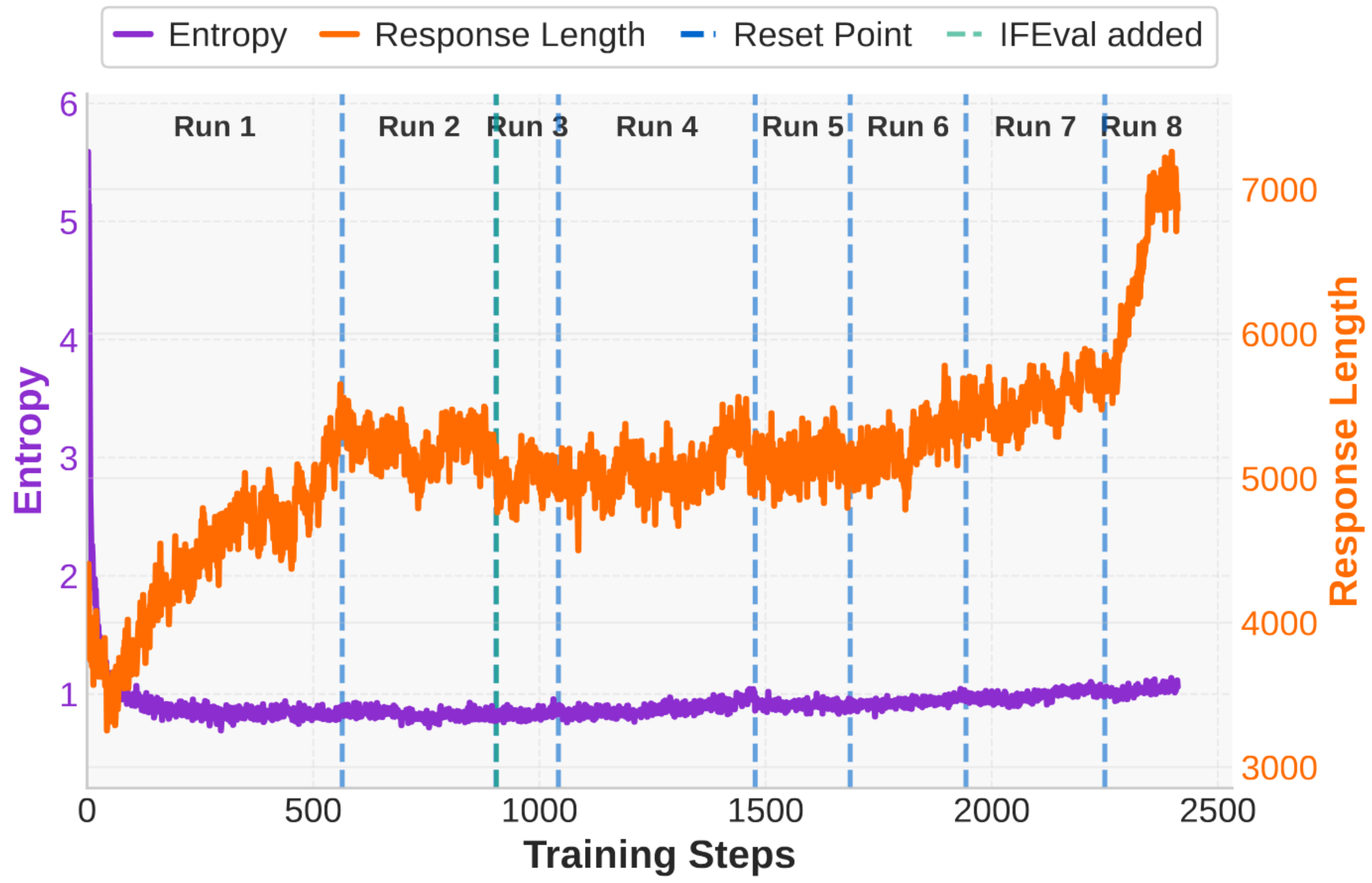
We need KL regularization to maintain constant entropy





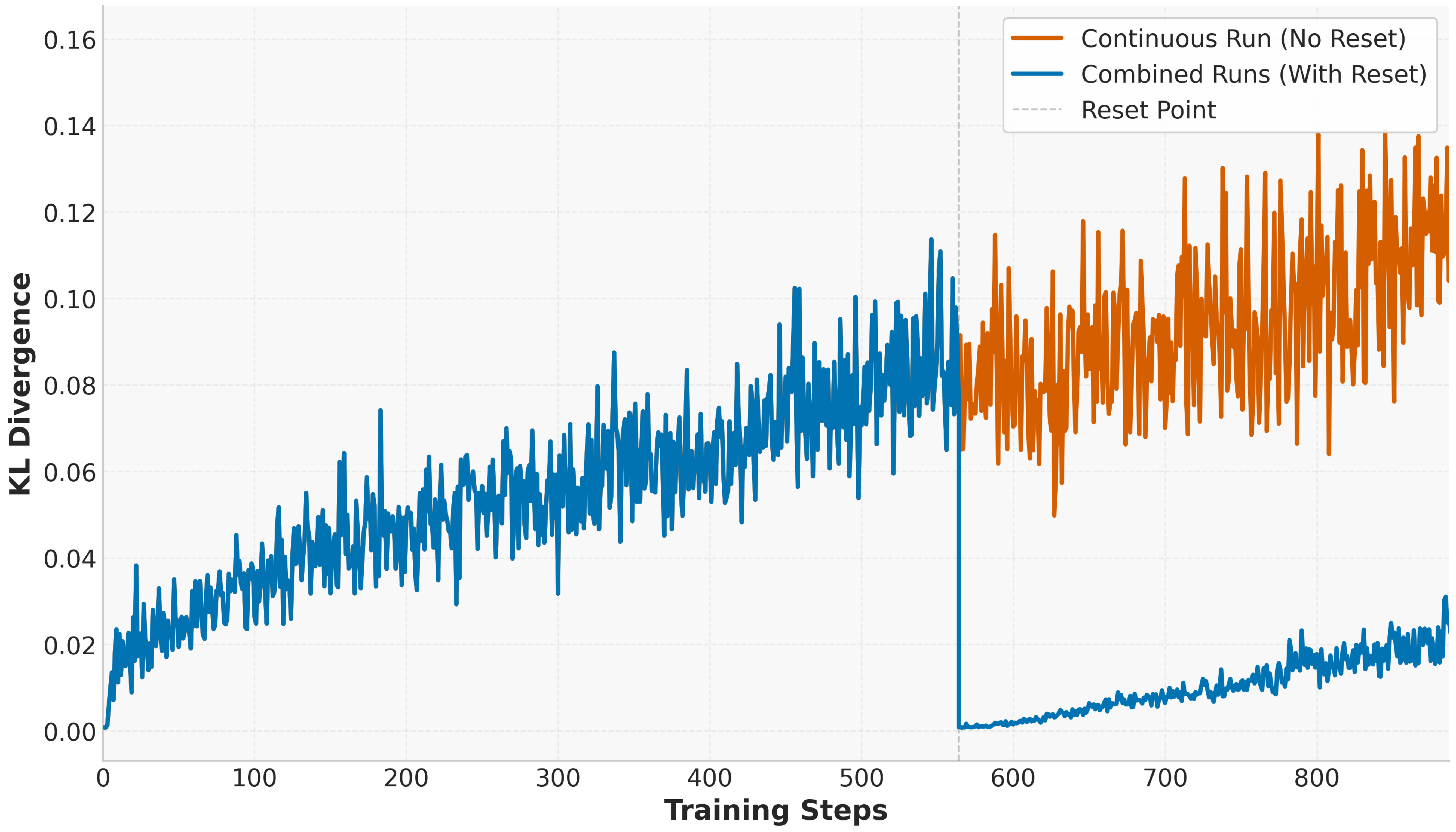
Stable Entropy

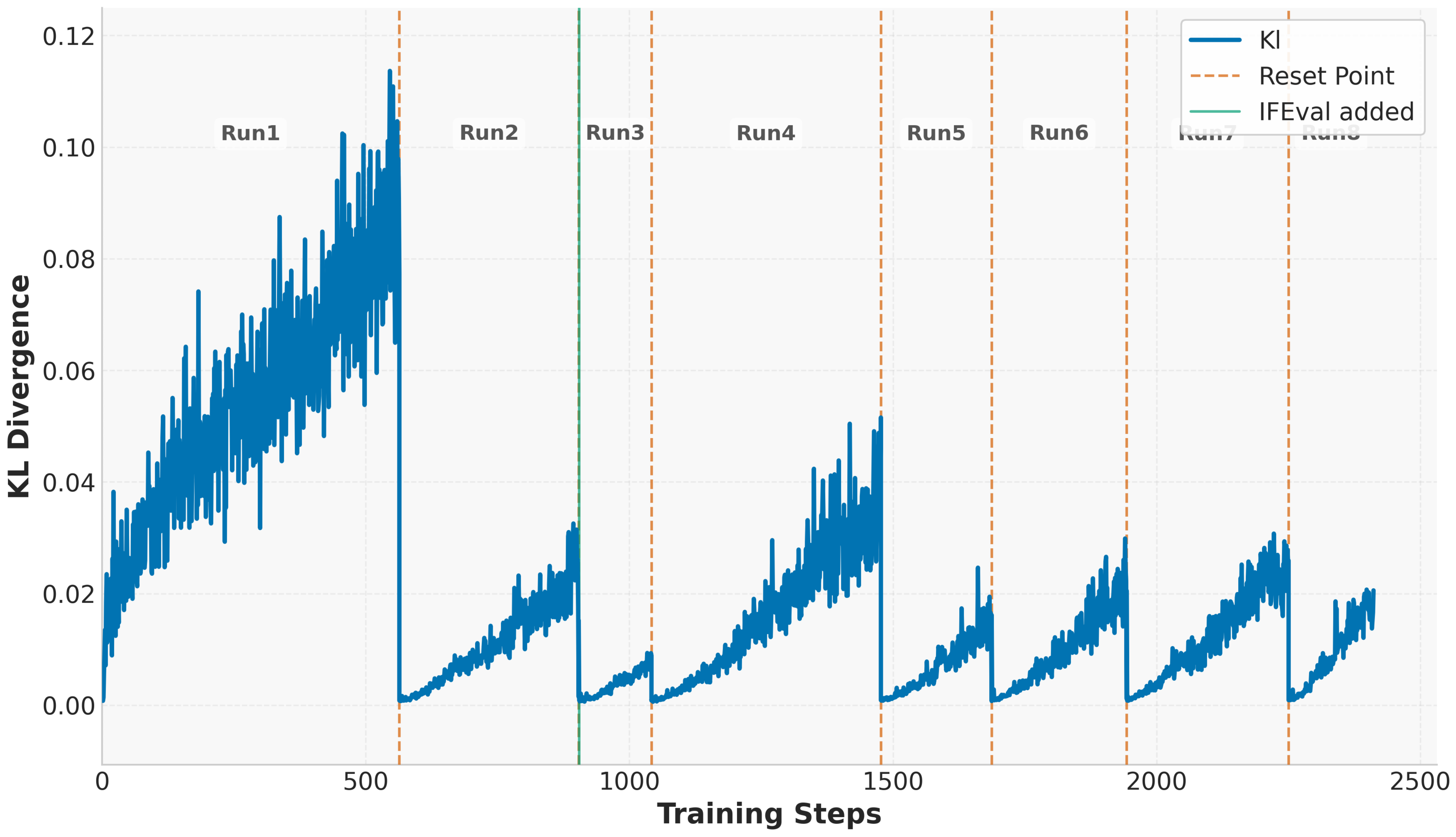
A good balance between exploration and exploitation



Importance of Reference Model Resetting

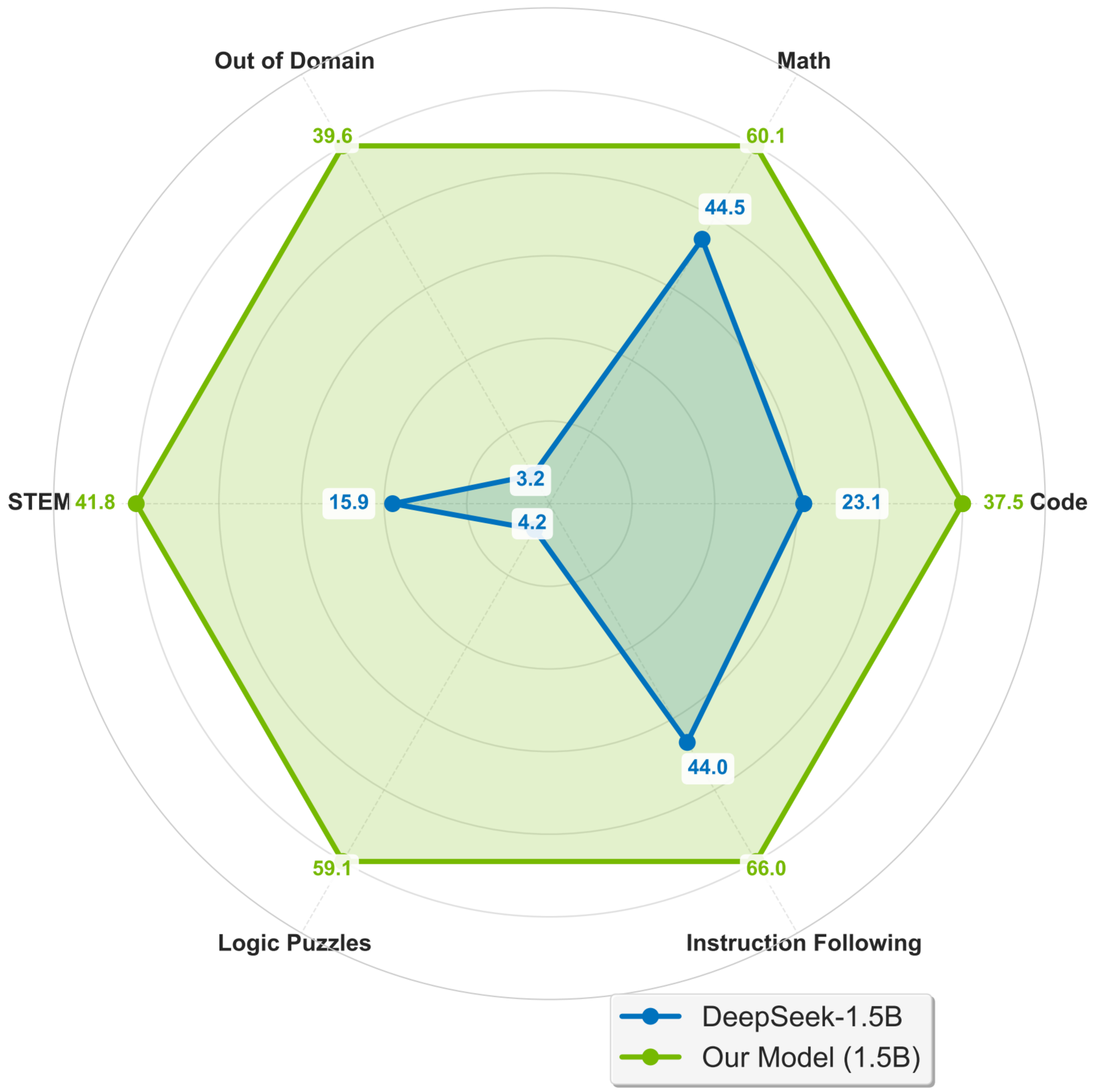
Stabilize the Training

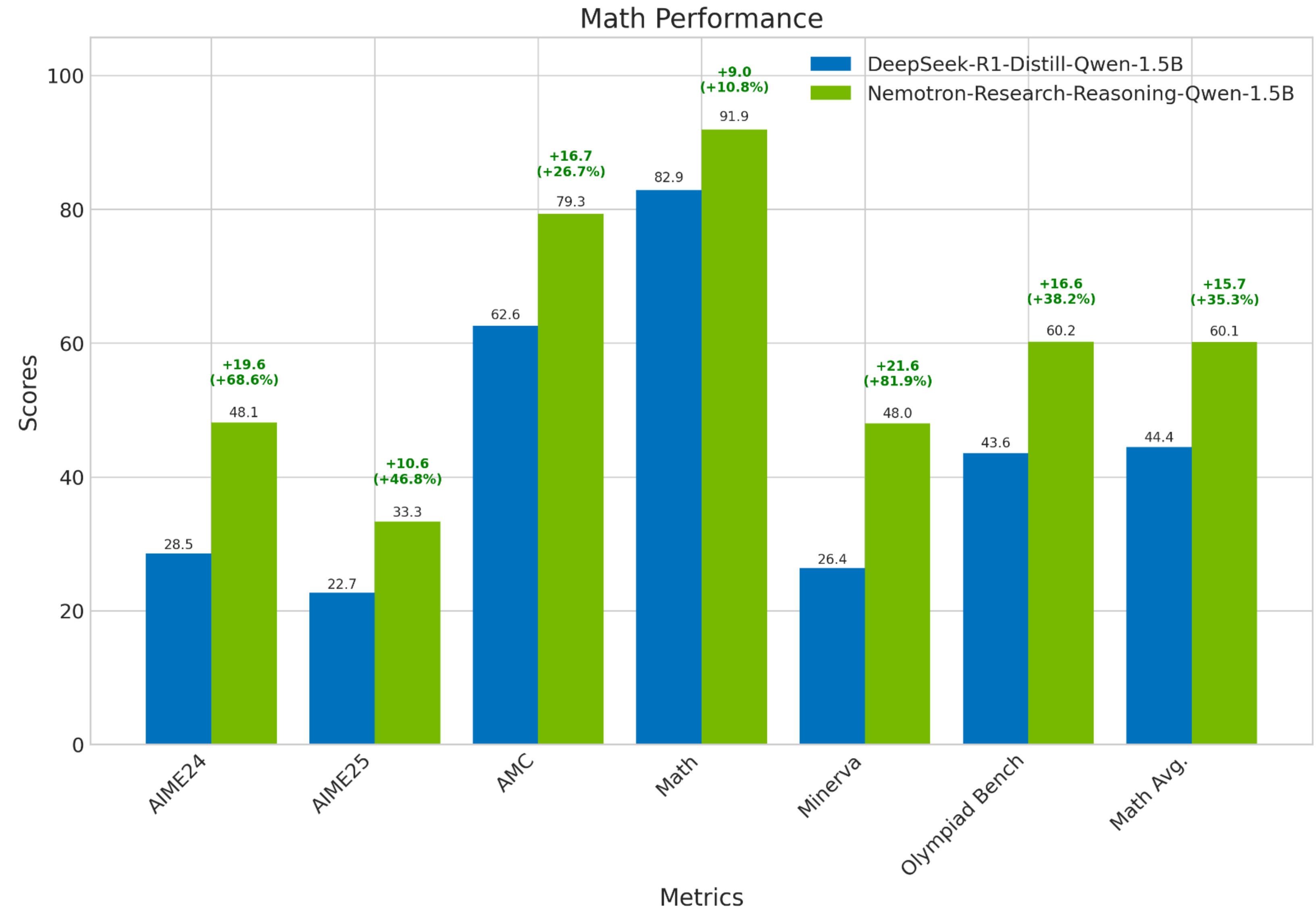


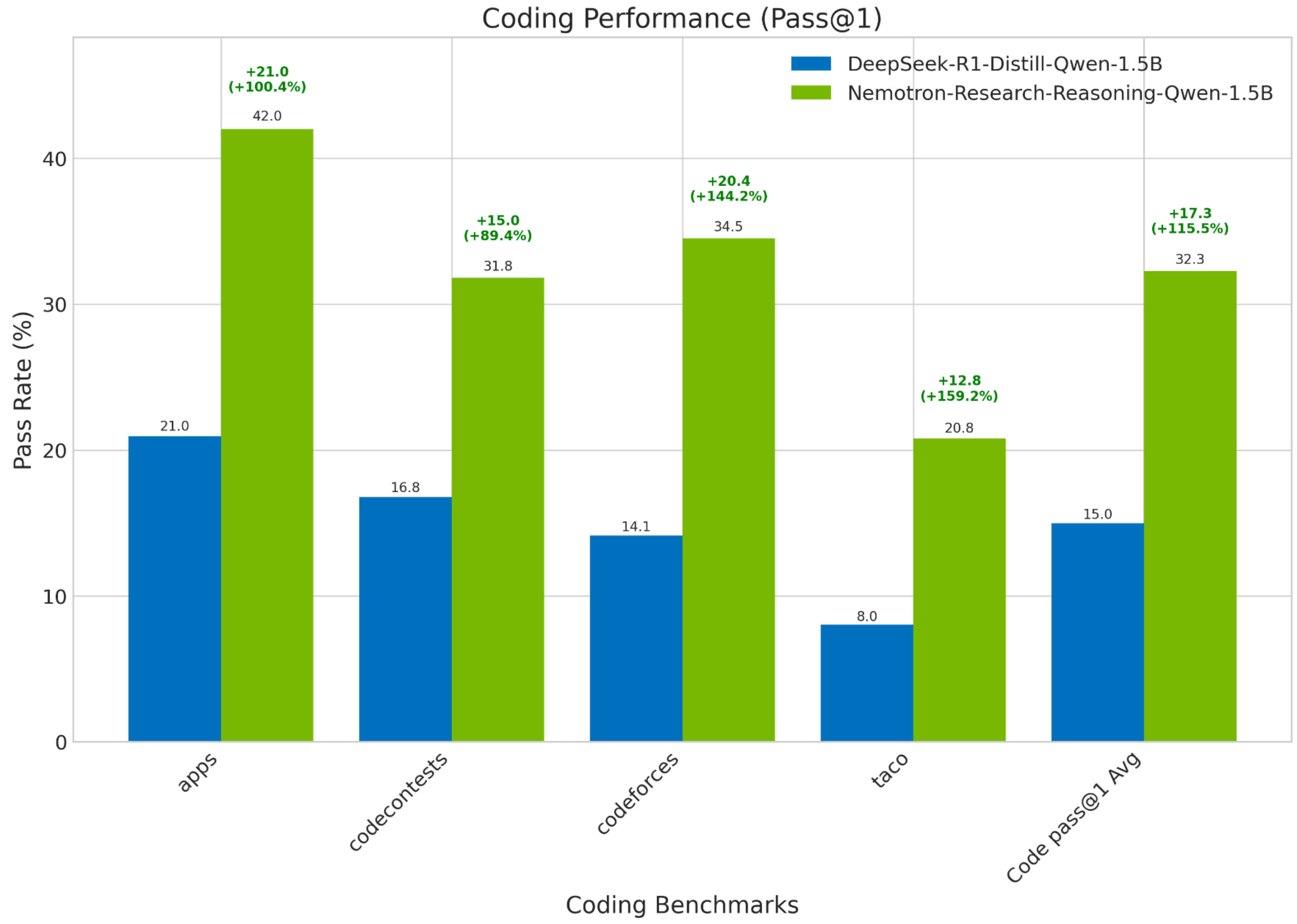


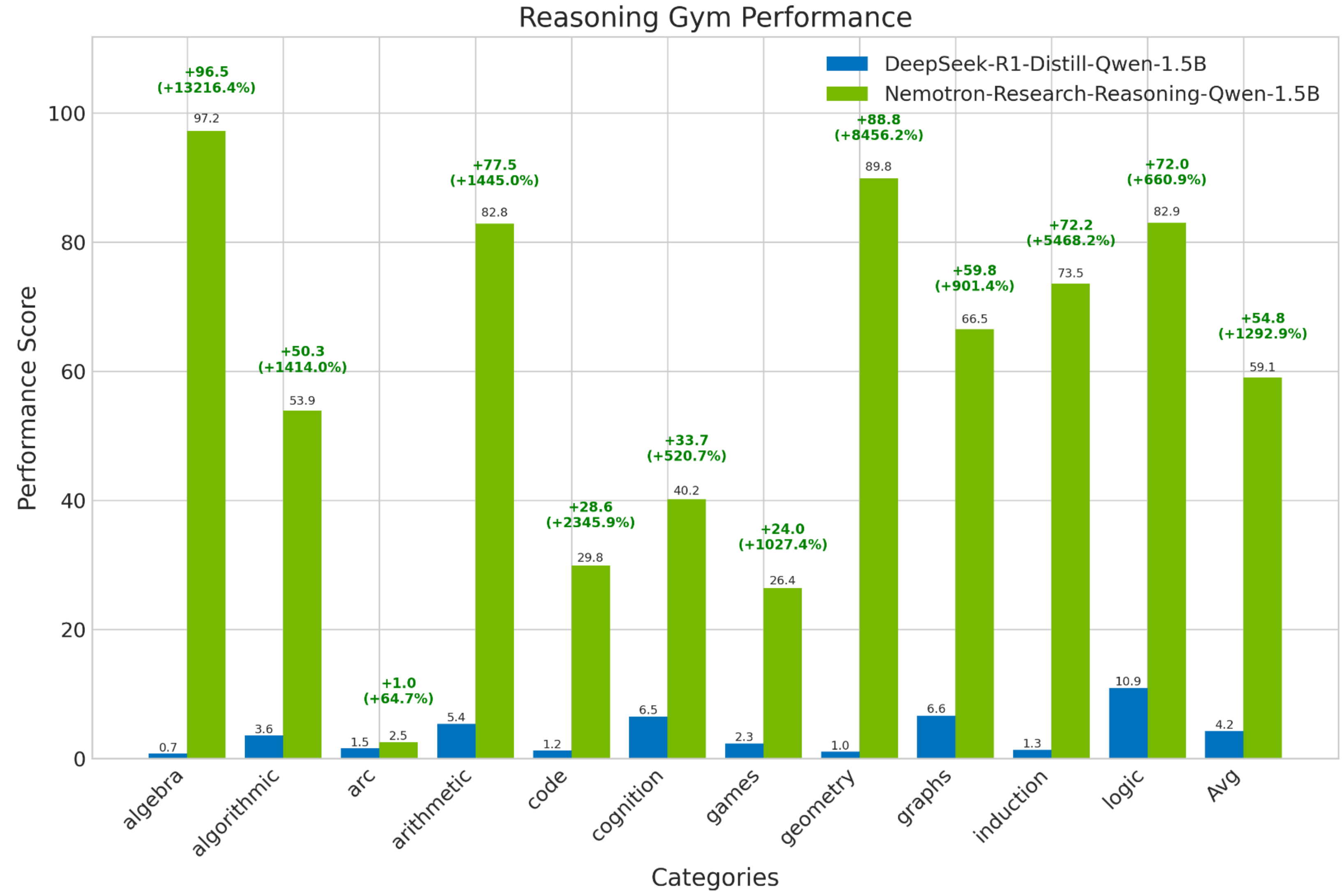
Reasoning Model Training Results

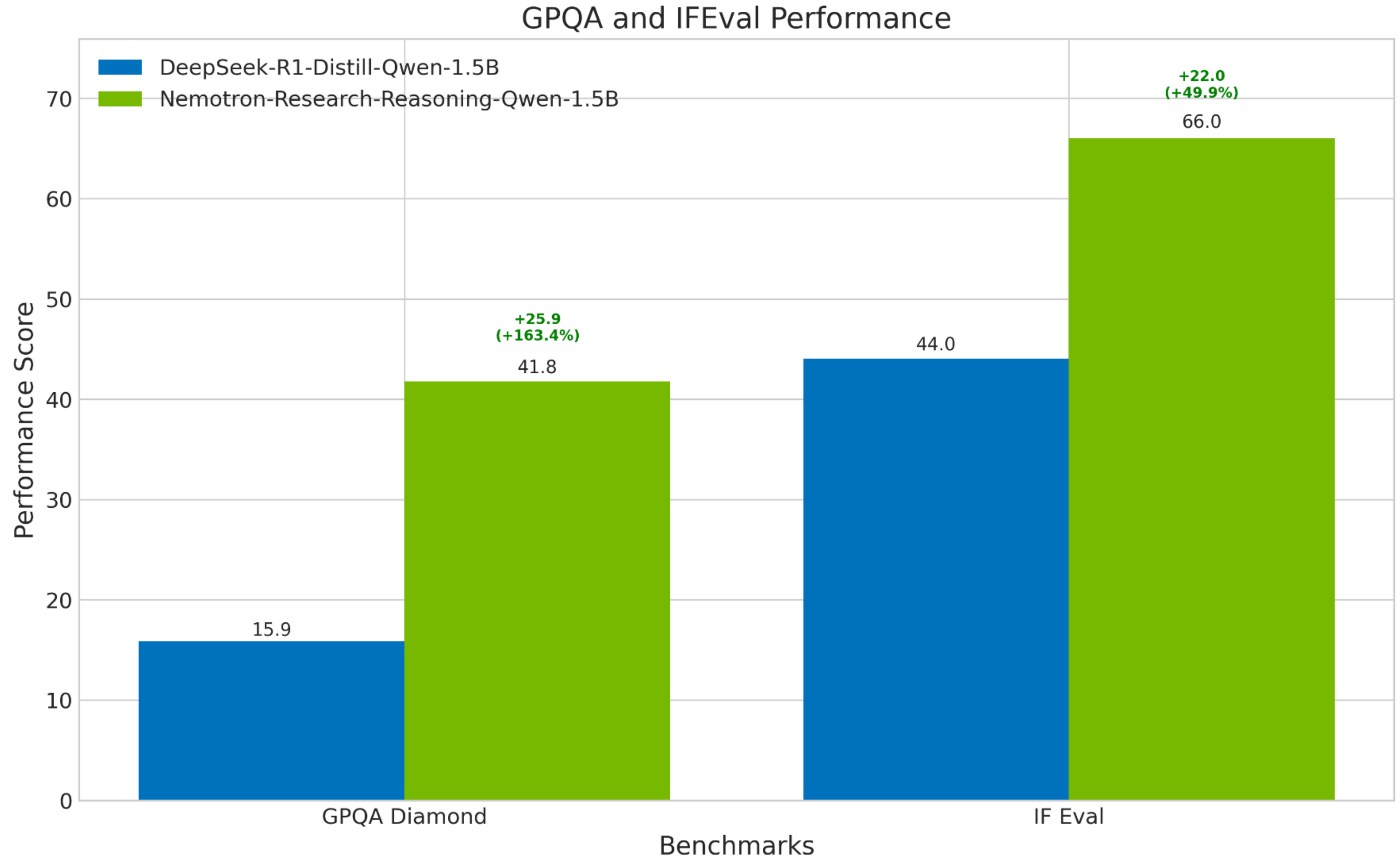
State of Art 1.5B Reasoning Model











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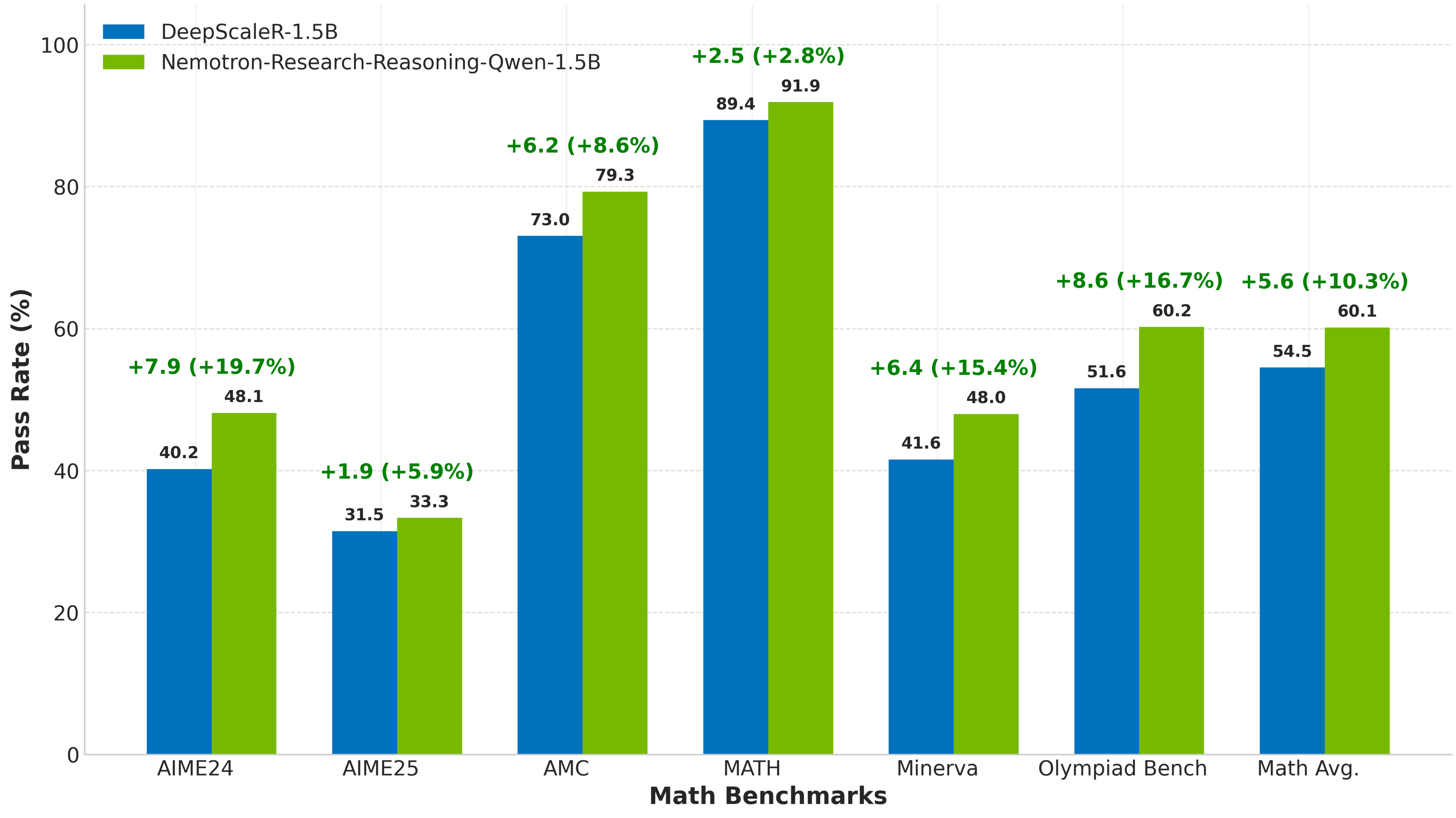
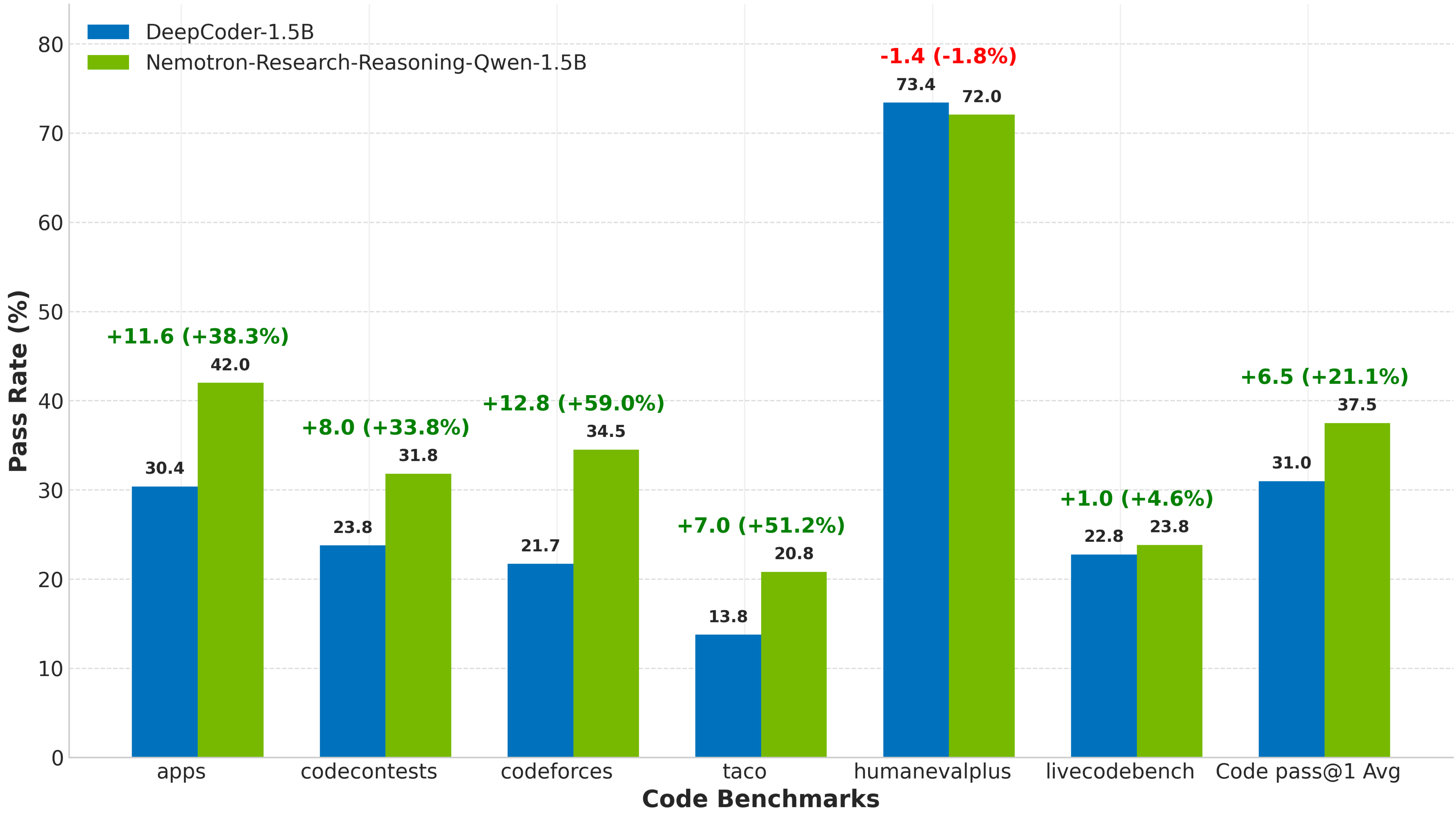
Better than Specialized Domain Models





Matches DeepSeek-R1-7B Performance

Table 1: Performance (pass@1) comparison for benchmarks across Math domain. The best results are highlighted in **bold**. The results of DeepSeek-R1-Distill-Qwen-7B are marked as gray and are provided as a reference (same in all following tables).

Model	AIME24	AIME25	AMC	Math	Minerva	Olympiad	Avg
DeepSeek-R1-Distill-Qwen-1.5B	28.54	22.71	62.58	82.90	26.38	43.58	44.45
DeepScaleR-1.5B	40.21	31.46	73.04	89.36	41.57	51.63	54.54
DeepSeek-R1-Distill-Qwen-7B	53.54	40.83	82.83	93.68	50.60	57.66	63.19
Nemotron-Research-Reasoning-Qwen-1.5B	**48.13**	**33.33**	**79.29**	**91.89**	**47.98**	**60.22**	**60.14**

Table 2: Performance (pass@1) comparison across benchmarks for Code. We abbreviate benchmarks names for codecontests (cc), codeforces (cf), humanevalplus (human), and livecodebench (LCB).

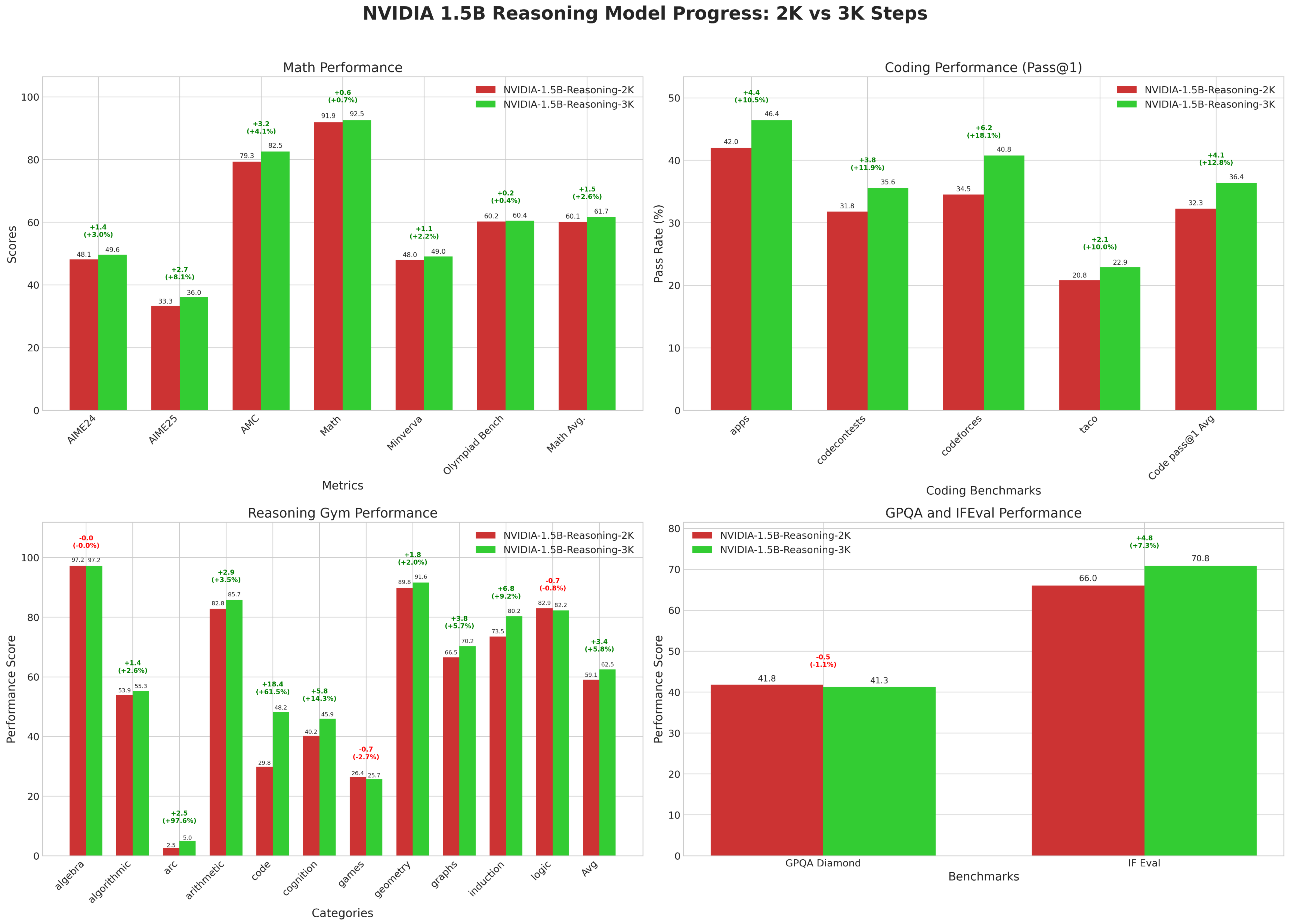
Model	apps	cc	cf	taco	human	LCB	Avg
DeepSeek-R1-Distill-Qwen-1.5B	20.95	16.79	14.13	8.03	61.77	16.80	23.08
DeepCoder-1.5B	30.37	23.76	21.70	13.76	**73.40**	22.76	30.96
DeepSeek-R1-Distill-Qwen-7B	42.08	32.76	33.08	19.08	83.32	38.04	41.39
Nemotron-Research-Reasoning-Qwen-1.5B	**41.99**	**31.80**	**34.50**	**20.81**	72.05	**23.81**	**37.49**

Table 3: Performance comparison on STEM reasoning (GPQA Diamond), instruction following (IFEval), and logic puzzles (Reasoning Gym) tasks. We also present results on OOD tasks: *acre*, *boxnet*, and *game_of_life_halting* (game).

Model	GPQA	IFEval	Reasoning	acre	boxnet	game
DeepSeek-R1-Distill-Qwen-1.5B	15.86	44.05	4.24	5.99	0.00	3.49
DeepSeek-R1-Distill-Qwen-7B	35.44	58.01	28.55	20.21	1.71	12.94
Nemotron-Research-Reasoning-Qwen-1.5B	**41.78**	**66.02**	**59.06**	**58.57**	**7.91**	**52.29**

Keep training our 1.5B model

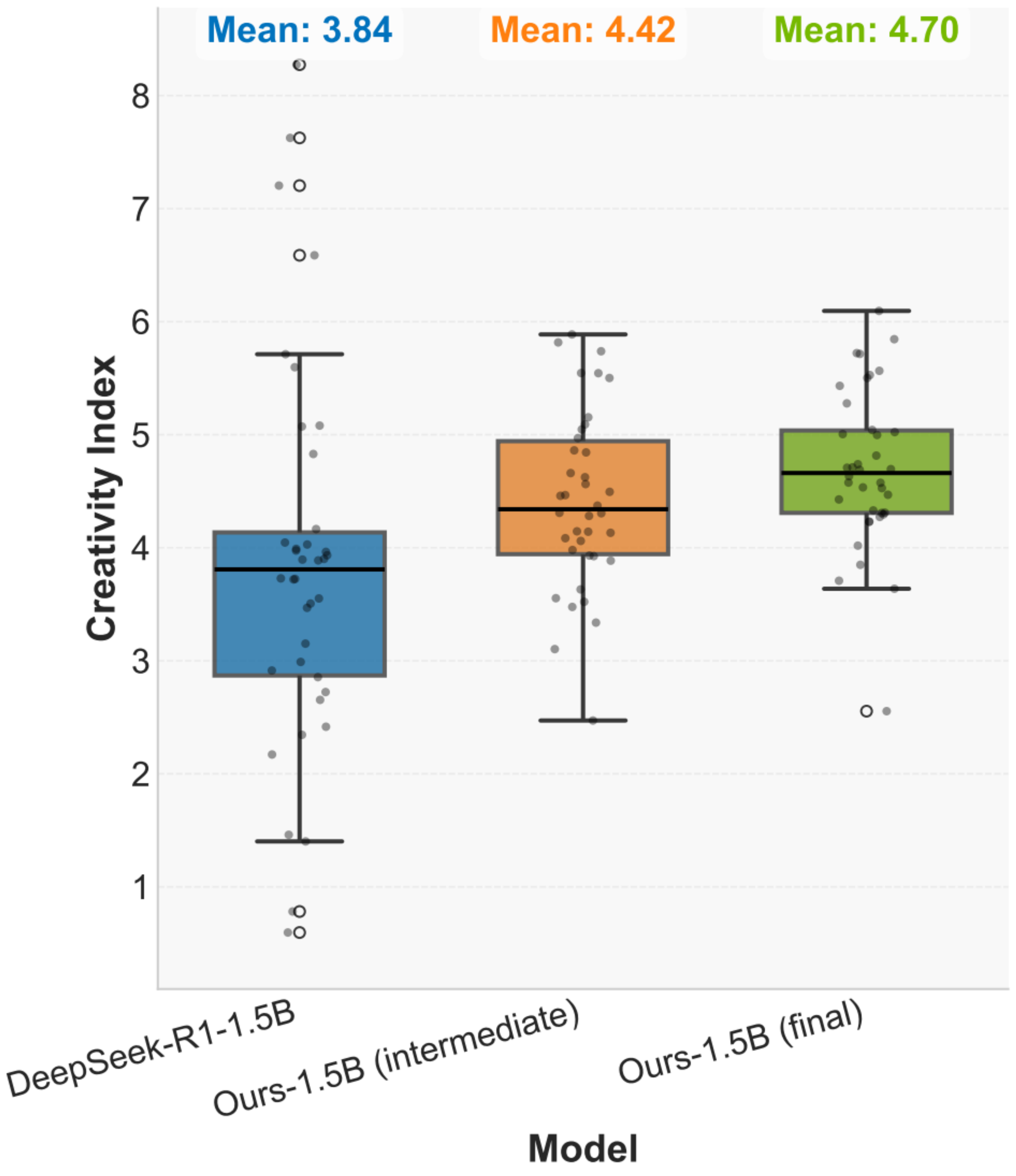
3K steps

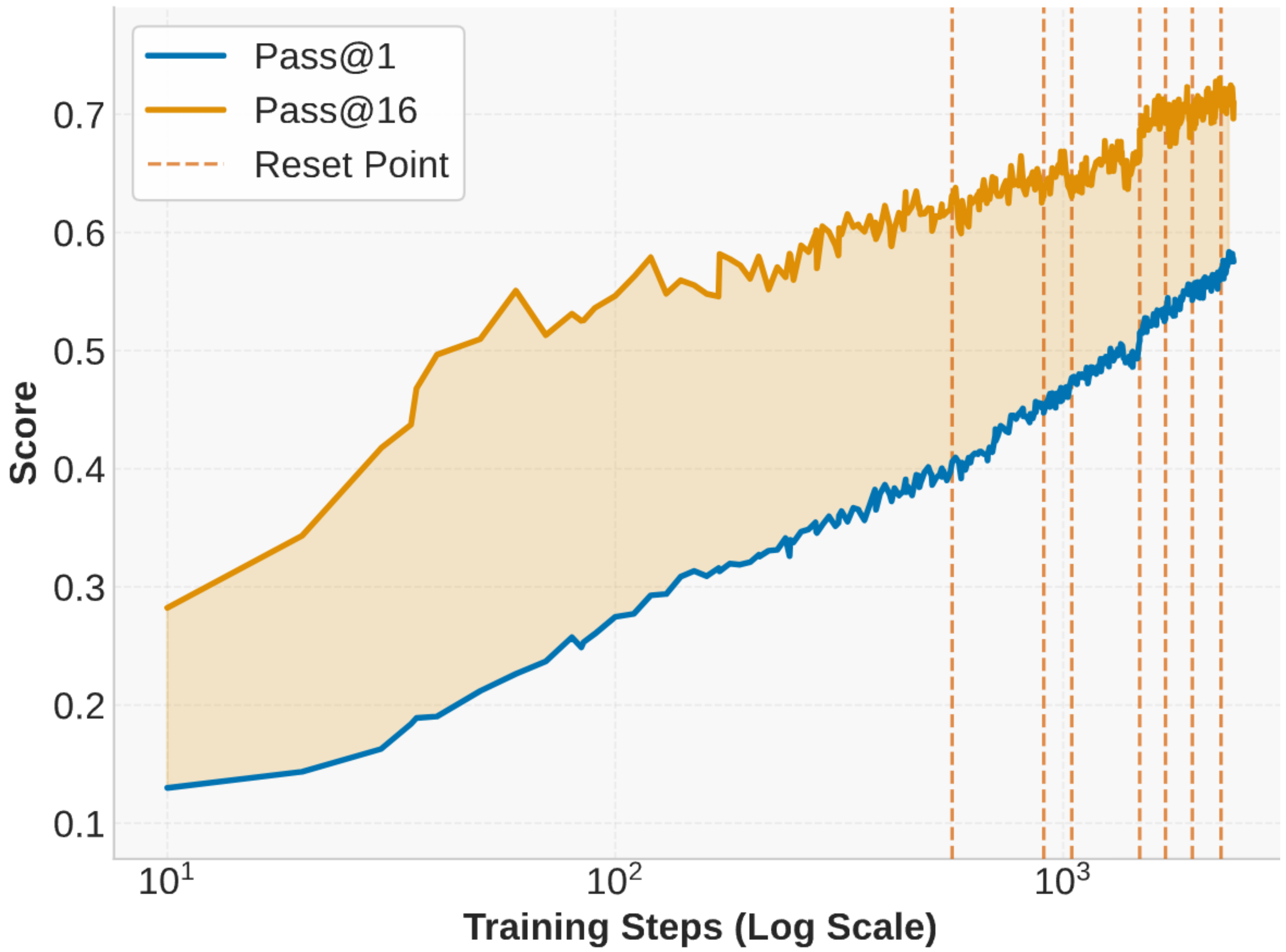


Reasoning Capabilities Expand With Continued Training.

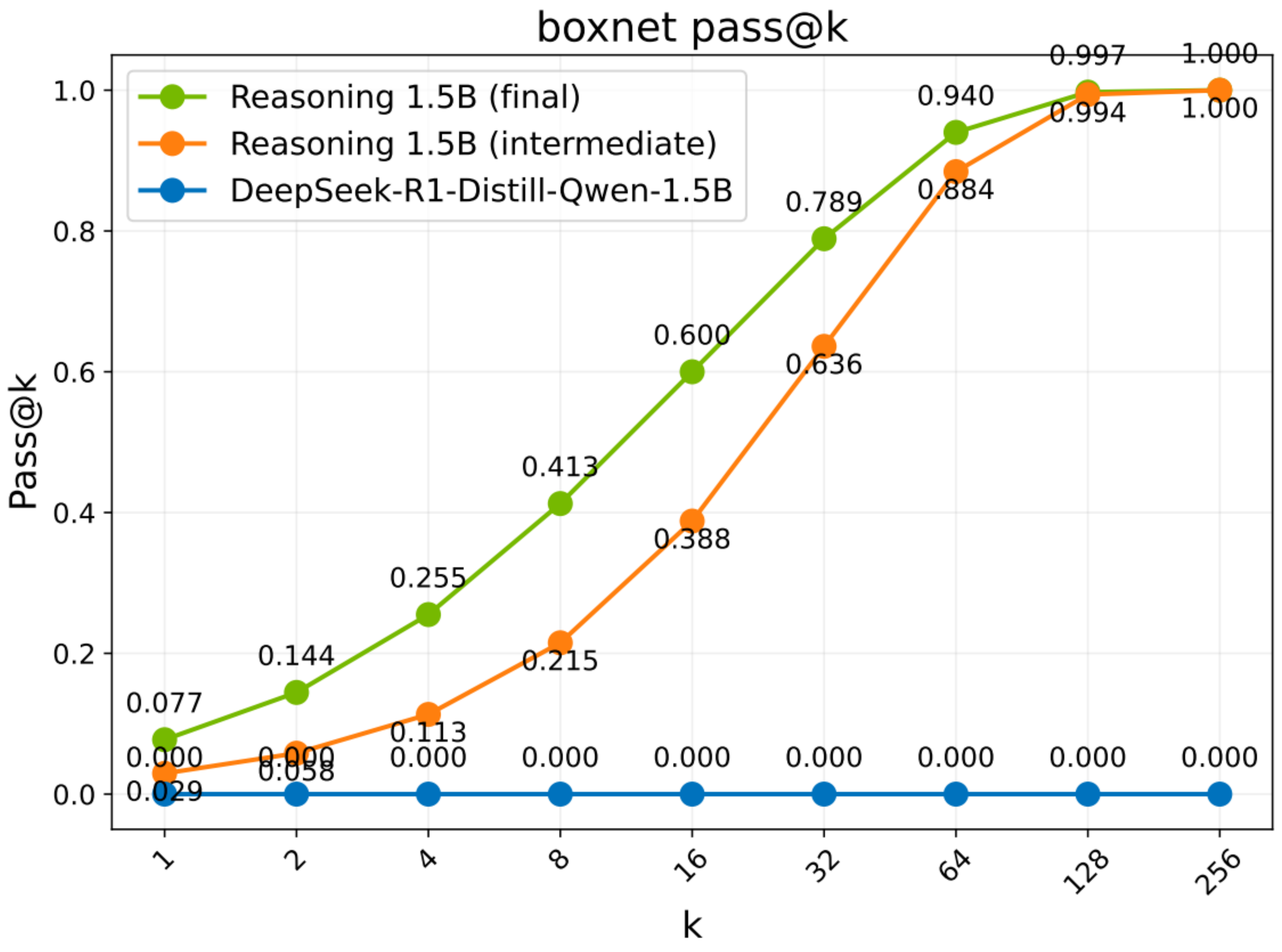
ProRL makes a difference

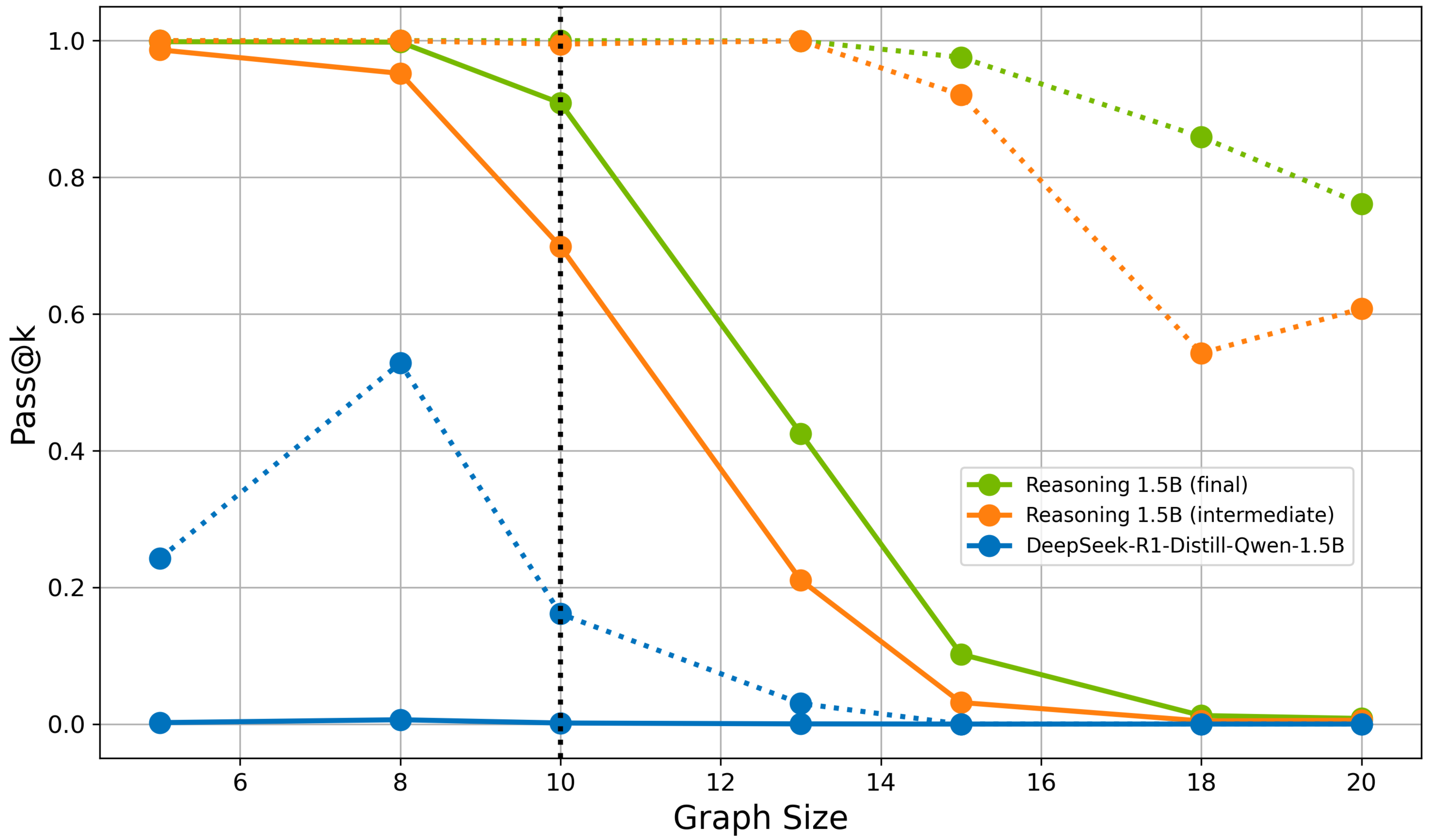
Continued Training Improves Creativity Index and Pass@K



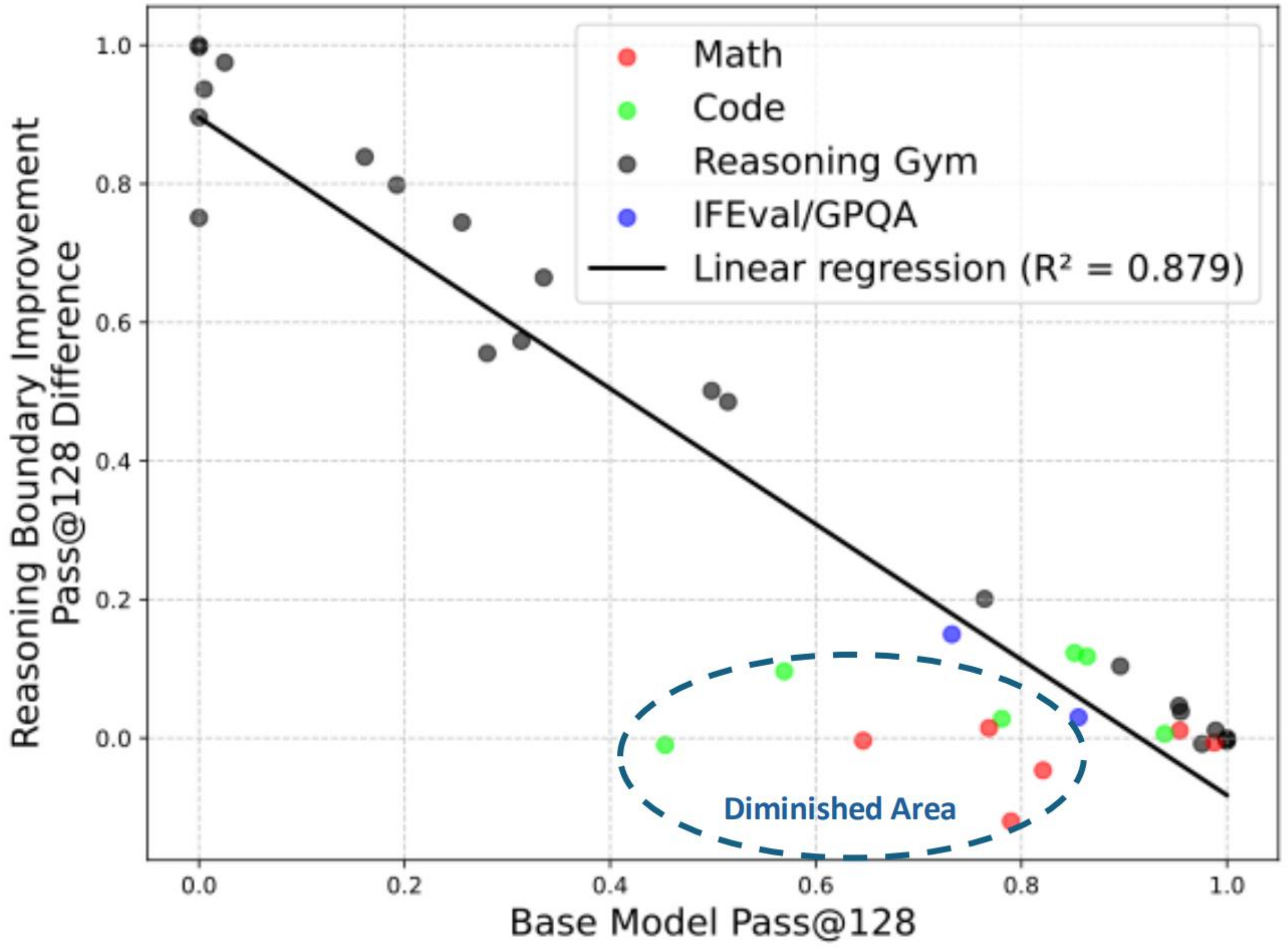


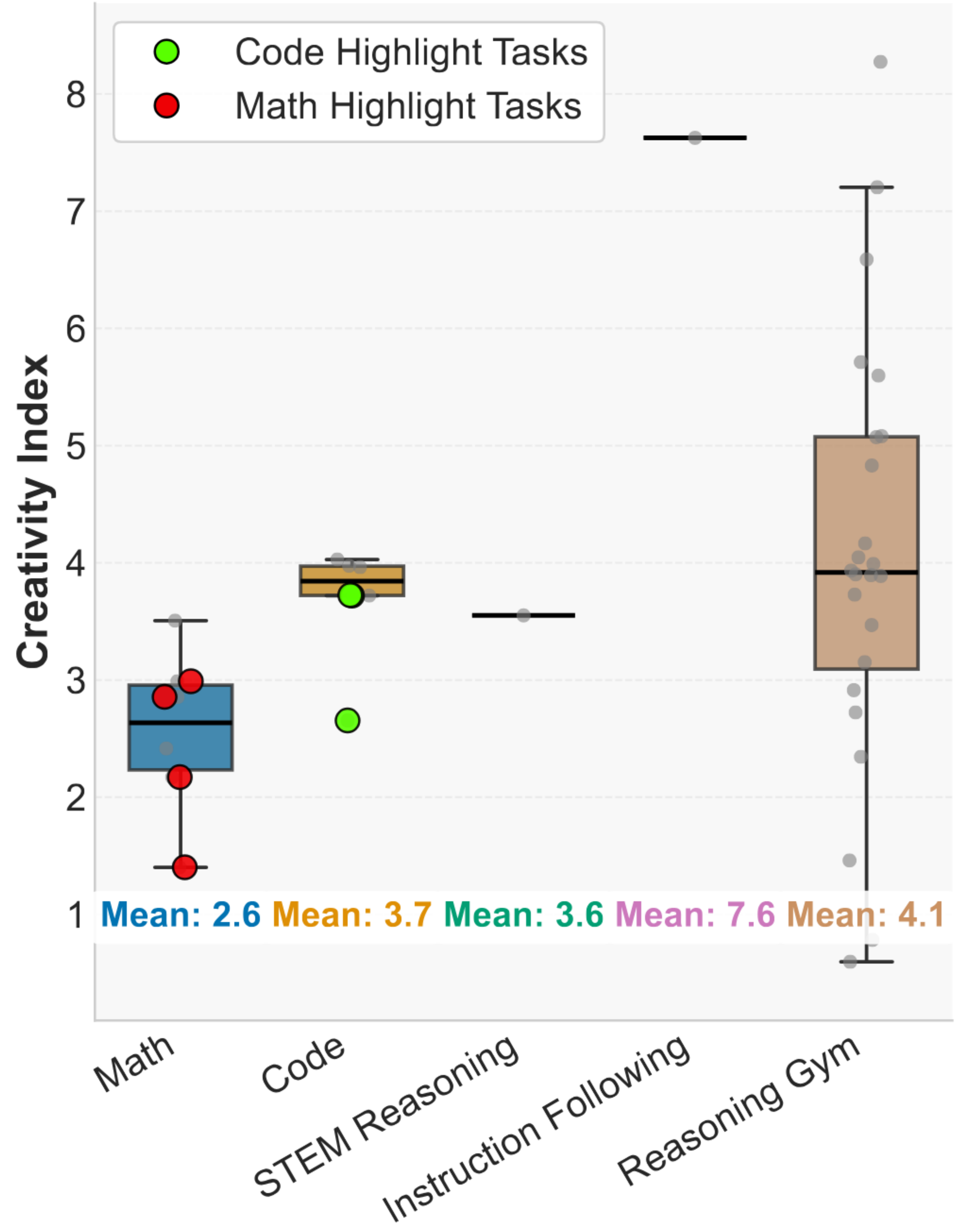
Out of Distribution For Different Task and Difficulty Levels





Explain the Reasoning Boundary Improvement





Summary

- Our findings suggest that prolonged reinforcement learning (ProRL) training significantly expands the reasoning capabilities of base models.
- The more compute ProRL uses, the more creative solutions it discovers.
- Previous claims about temperature distillation effect were likely due to:
  - A narrow focus on overtrained mathematical tasks
  - Insufficient RL training steps
- In contrast, our approach emphasizes scaling reasoning model training through a wide range of diverse and novel tasks.
- To fully realize the benefits of ProRL, it is essential to maintain stable entropy and periodically reset the reference model to eliminate performance boundaries.
- Using ProRL, we successfully trained a state-of-the-art 1.5B parameter reasoning model.

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