







Teaching Language Models to Reason with Tools

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- 1. Background
- 2. Motivation
- 3. Method
- 4. Experiments

1.1 Tool-integrated Reasoning

Problem: Suppose that the sum of the squares of two complex numbers x and y is 7 and the sum of their cubes is 10. List all possible values for x + y, separated by commas.

We are given that $x^2 +$ $v^2 = 7$ and $x^3 + v^3 =$ 10. We can factor x^3 + y^{3} to get $(x + y)(x^{2}$ $xy + y^2$).

Thus, we can write 10 = (x + y)(7). It follows that x + y must divide 10.

The only possibilities are that x + y is 1, 2, 5 or 10.

```
import math
```

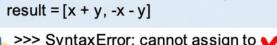
def solution(): x = symbols('x'), y = symbols('y') $x^{**2} + y^{**2} = 7$

x = (-1 + math.sqrt(17)) / 2y = (-1 - math.sqrt(17)) / 2

 $x^{**}3 + y^{**}3 = 10$

Get all possible values for x+y result = [x + y, -x - y]

>>> SyntaxError: cannot assign to expression.

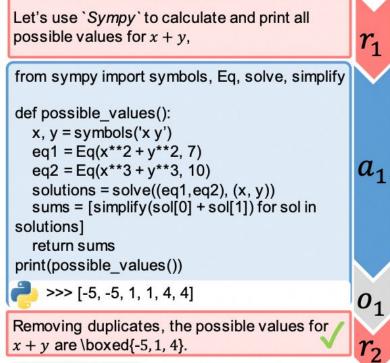


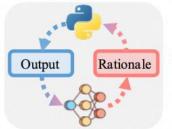


(a) Rationale-based



(b) Program-based

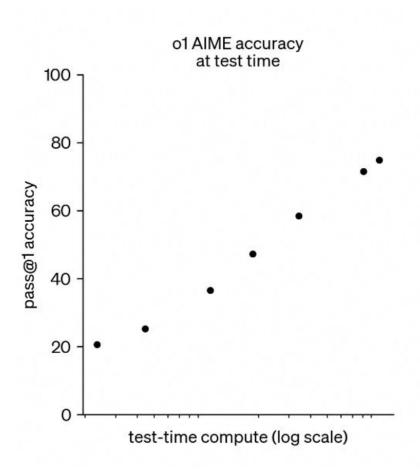


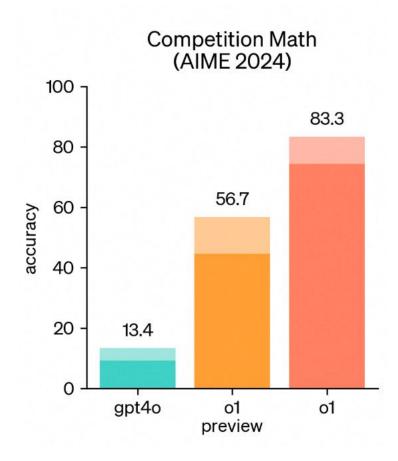


(c) Tool-integrated Reasoning

(Format used by ToRA)

1.2 Long CoT Reasoning





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2.1 Open question

How can we synthesize high-quality training data when models like o3 and o4-mini do not expose their detailed reasoning traces?

How can the model effectively coordinate a Cl's computational precision with its abstract CoT reasoning capabilities?

How can the self-reflection mechanisms inherent to LRMs be reconciled with the exact external knowledge provided by CIs?

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3.1 Cold Start – Prompt-Hint

Each face of two noncongruent parallelepipeds is a rhombus whose diagonals have lengths $\sqrt{21}$ and $\sqrt{31}$. The ratio of the volume of the larger of the two polyhedra to the volume of the smaller is m/n, where \$m\$ and \$n\$ are relatively prime positive integers. Find m+n.

<think>

Okay, let's try to solve this problem step by step using multiple python code calls.

...

[skip 8524 tokens]

•••

Thus, the answer is 125.

Now, to **confirm** using Python.

import numpy as np



>>> 125

So m=63, n=62, m+n=125. </think>

(a) Prompt-hint

The sum $m + n = 63 + 62 = boxed{125}.$

<think>

Okay, let's try to solve this problem step by step using multiple python code calls.

[skip 3261 tokens]

Let's compute V1 and V2 with Python for accuracy.

import sympy as sp

•••

Hint-1: Complex calculations

Confirm python calculation

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>>> Volume 1: 63*sqrt(2)/2 Volume 2: 31*sqrt(2)

We don't need to doubt the accuracy of python calculations.

Hint-2:

[skip 216 tokens]

</think>...

The answer is \boxed{125}.

Let's compute V1 and V2 for these two cases.

Without Hint-1

[skip 5057 tokens]

V1 = 63 sqrt(2)/2, V2 = 31 sqrt(2)

Without Hint-2

Wait, but let me check These calculation...

[skip 2215 tokens]

</think>...

The answer is \boxed{125}.

(b) Hint-engineering

3.1 Cold Start - Hint-engineering

Each face of two noncongruent parallelepipeds is a rhombus whose diagonals have lengths $\sqrt{21}$ and $\sqrt{31}$. The ratio of the volume of the larger of the two polyhedra to the volume of the smaller is m/n, where \$m\$ and \$n\$ are relatively prime positive integers. Find m+n.

<think>

Okay, let's try to solve this problem step by step using multiple python code calls.

...

[skip 8524 tokens]

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(a) Prompt-hint

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We don't need to doubt the accuracy of python calculations.

Hint-2:

[skip 216 tokens]

</think>...

The answer is \boxed{125}.

Without Hint-1

Let's compute V1 and V2 for these two cases.

[skip 5057 tokens]

V1 = 63 sqrt(2)/2, V2 = 31 sqrt(2)

Without Hint-2

Wait, but let me check These calculation...

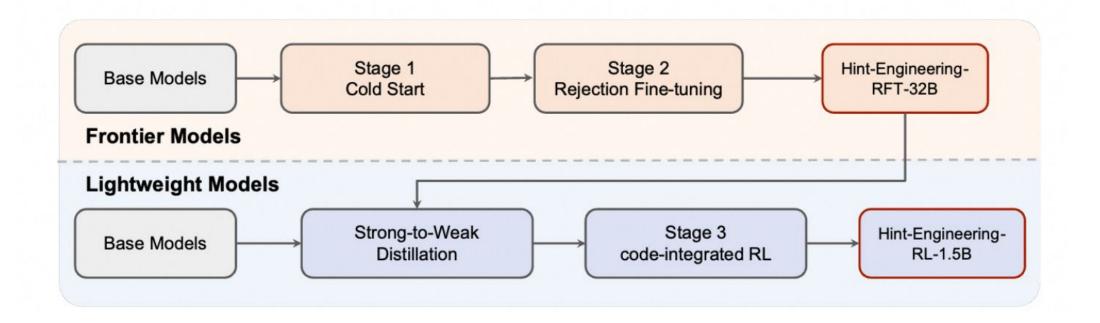
[skip 2215 tokens]

</think>...

The answer is \boxed{125}.

(b) Hint-engineering

3.2 Strong-to-weak Distillion



3.2 Code-integrated Reinforcement Learning

- Rollout with Code Interpreter
- Persistent Execution Environment
- Output Masking
- Reward Design

$$R_a = \begin{cases} 1 & \text{if answers match} \\ 0 & \text{otherwise} \end{cases} \qquad R_c = \begin{cases} -1 & \text{if all codes fail} \\ 0 & \text{otherwise} \end{cases} \qquad R = R_a + \omega R_c$$

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4.1 Setup

■ Model

• Base model:R1-distill-Qwen-1.5B, R1-distill-Qwen-32B

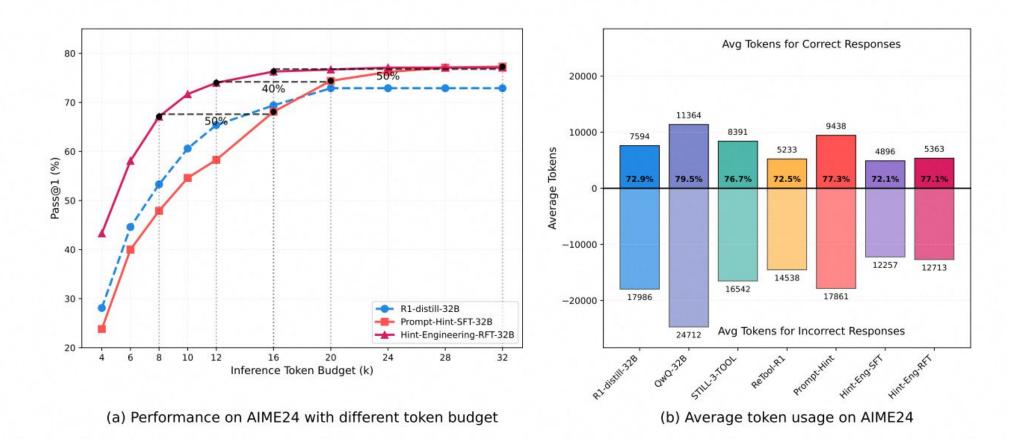
□ Data

• Training: previous AIME problems (before 2024), MATH and Numina-MATH, Evaluation: AIME24, AIME25, AMC23, MATH500, Olympiad

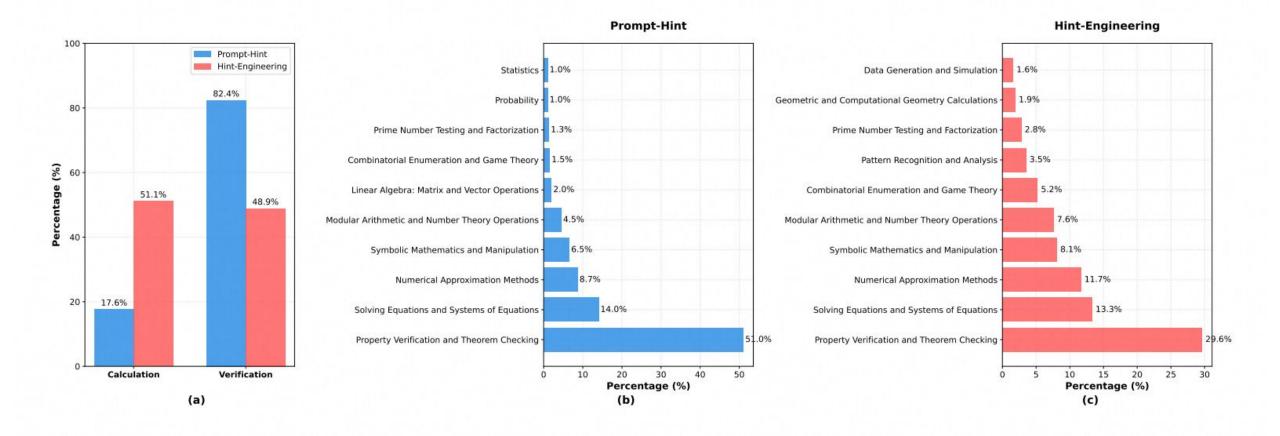
4.2 Main Result

Model	Tool-Use	Stage	AIME24	AIME25	AMC23	MATH500	Olympiad	Avg
SOTA Models								
o1	Х	RL	74.3	79.2	- I	96.4	-	-
o3	1	RL	95.2	98.7	-	<u>-</u>	-	_
o4-mini	/	RL	98.4	99.5	-	-	_	-
DeepSeek-R1	×	RL	79.8	70.0	_	97.3	_	_
QwQ-32B	X	RL	<u>79.5</u>	65.3	94.3	92.3	79.7	82.2
Frontier Models (32B)								
DeepSeek-R1-32B	Х	SFT	72.9	59.0	88.8	94.3	72.5	77.5
START-32B	1	SFT	66.7	47.1	95.0	94.4	_	-
STILL-3-TOOL-32B	1	SFT	76.7	64.4	91.3	96.6	75.9	81.0
ReTool-R1-32B	1	RL	72.5	54.3	92.9	94.3	69.2	76.6
Prompt-Hint-SFT-32B	1	SFT	77.3	65.0	95.0	96.6	75.1	81.8
Hint-Engineering-SFT-32B	/	SFT	72.1	60.2	91.3	94.4	71.2	77.8
Hint-Engineering-RFT-32B	1	RFT	<u>76.7</u>	67.1	94.4	<u>95.1</u>	73.4	81.3
Lightweight Models (1.5B)								
DeepSeek-R1-1.5B	Х	SFT	28.8	21.8	62.9	83.9	43.3	48.1
DeepScaleR-1.5B-Preview	X	RL	40.0	30.0	73.6	87.8	50.0	56.3
ToRL-1.5B	1	RL	26.7	26.7	67.5	77.8	44.0	48.5
Prompt-Hint-1.5B-SFT	1	SFT	30.6	25.0	63.1	83.3	50.4	50.5
Prompt-Hint-1.5B-RL	1	RL	43.1	30.2	73.8	87.3	57.1	58.3
Hint-Engineering-1.5B-SFT	1	SFT	34.0	23.5	64.6	84.2	49.8	51.2
Hint-Engineering-1.5B-RL	1	RL	41.0	29.4	70.0	85.8	<u>55.6</u>	56.4

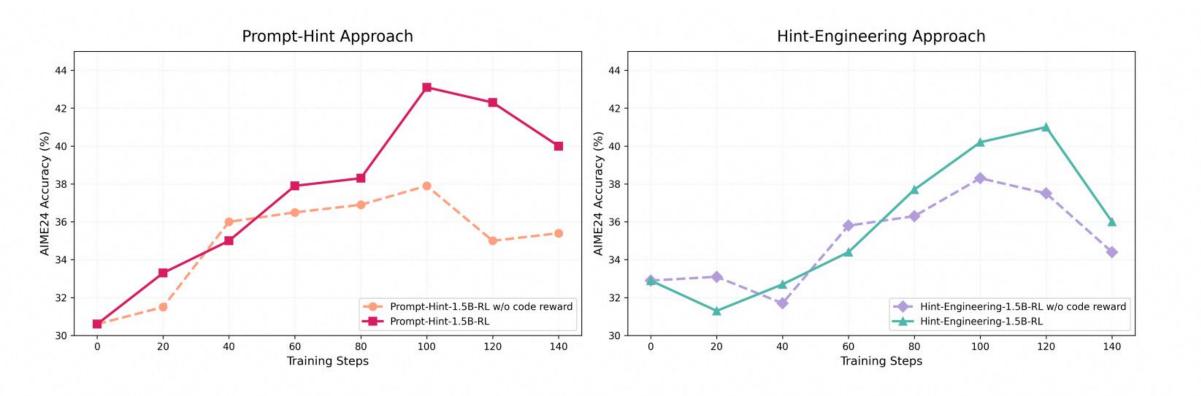
4.3 Token Efficiency Analysis



4.3 Code Behavior Analysis



4.4 Code Reward in RL



Conclusion

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- High-quality data with optimal code behavior patterns can match or exceed the performance of larger datasets, while reinforcement learning significantly improves performance beyond SFT, particularly for smaller models.
- The Hint-Engineering approach achieves remarkable efficiency, reducing token usage by 30-50% while maintaining competitive performance.
- Moreover, RL shapes code usage behavior toward either efficiency or increased integration.

Thanks