Test-Time Self-Distillation

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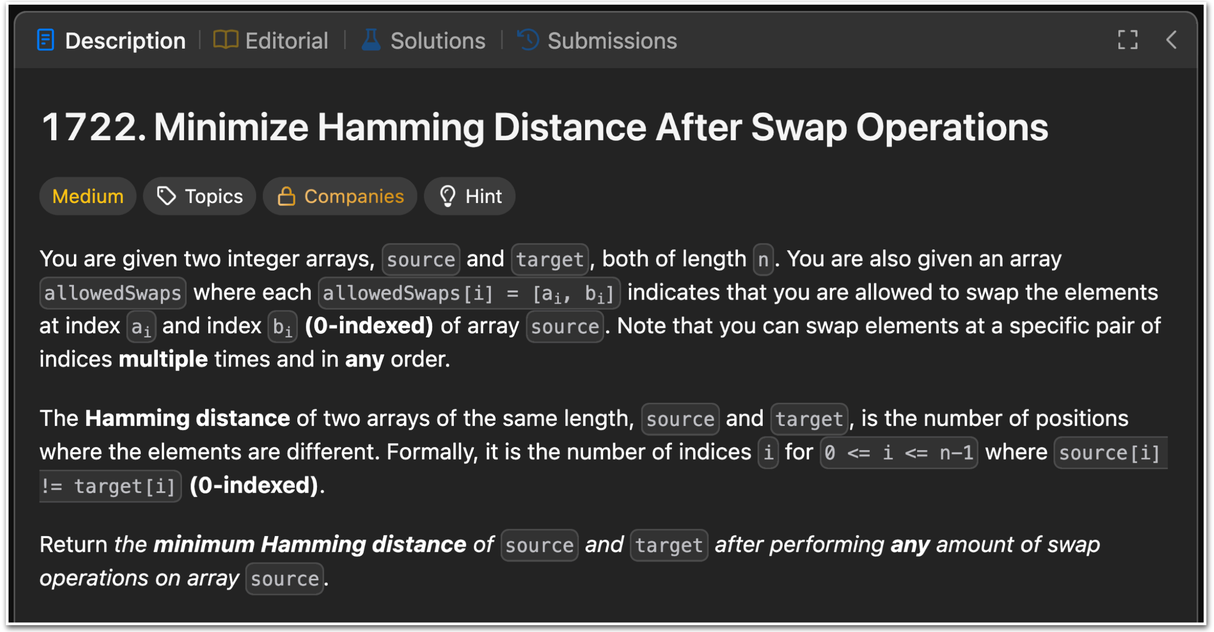
Learning to Solve Hard Problems

Given a hard problem at test-time, how quickly can a model learn to solve it?



Example: Leetcode

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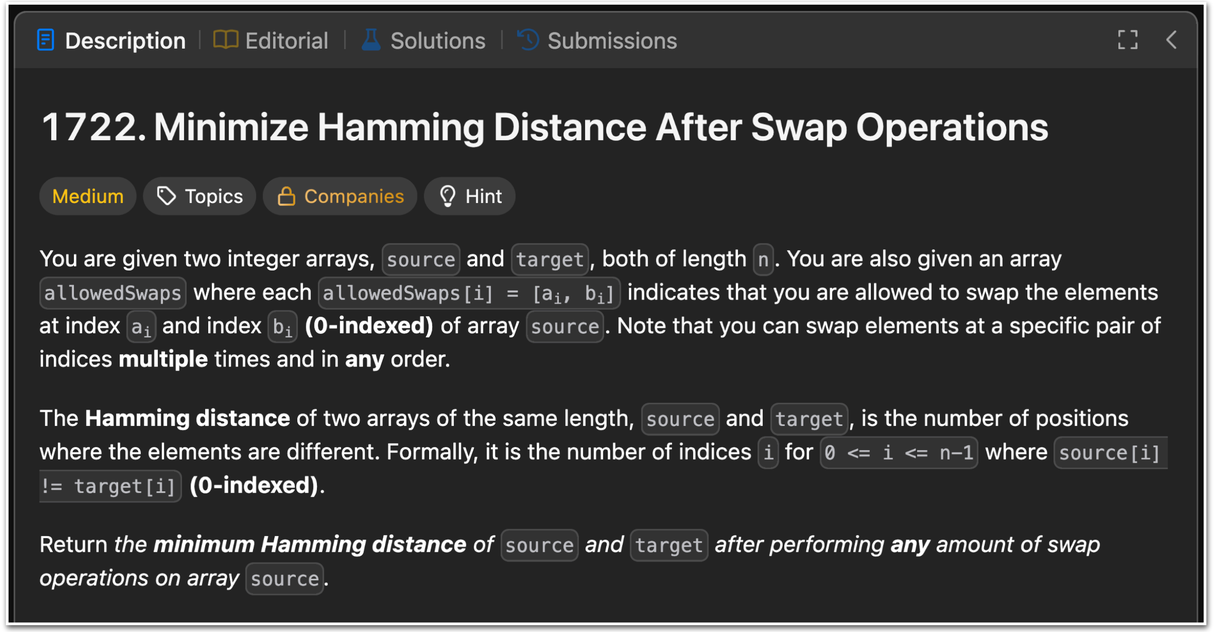
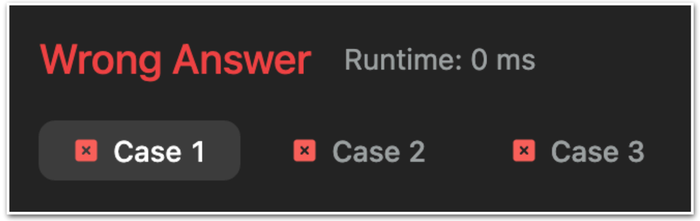


Example: Leetcode

Many environments indicate *why* an attempt failed



Example: Unit tests

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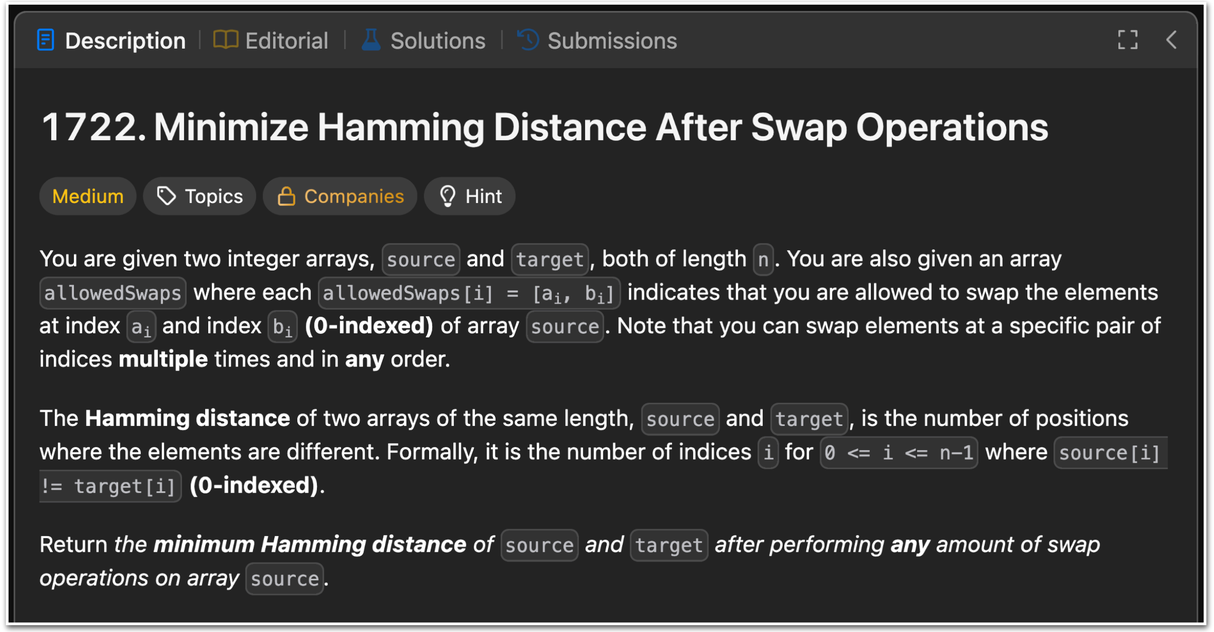

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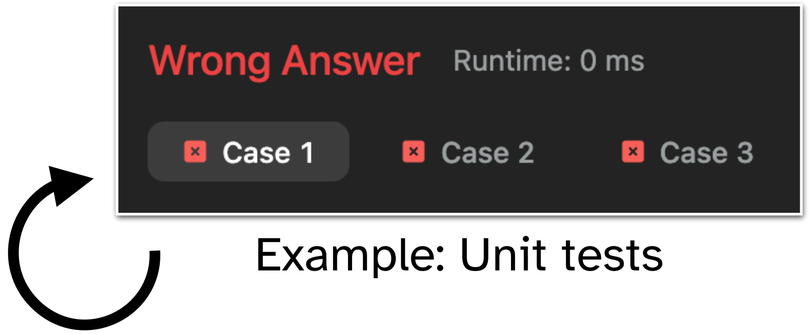

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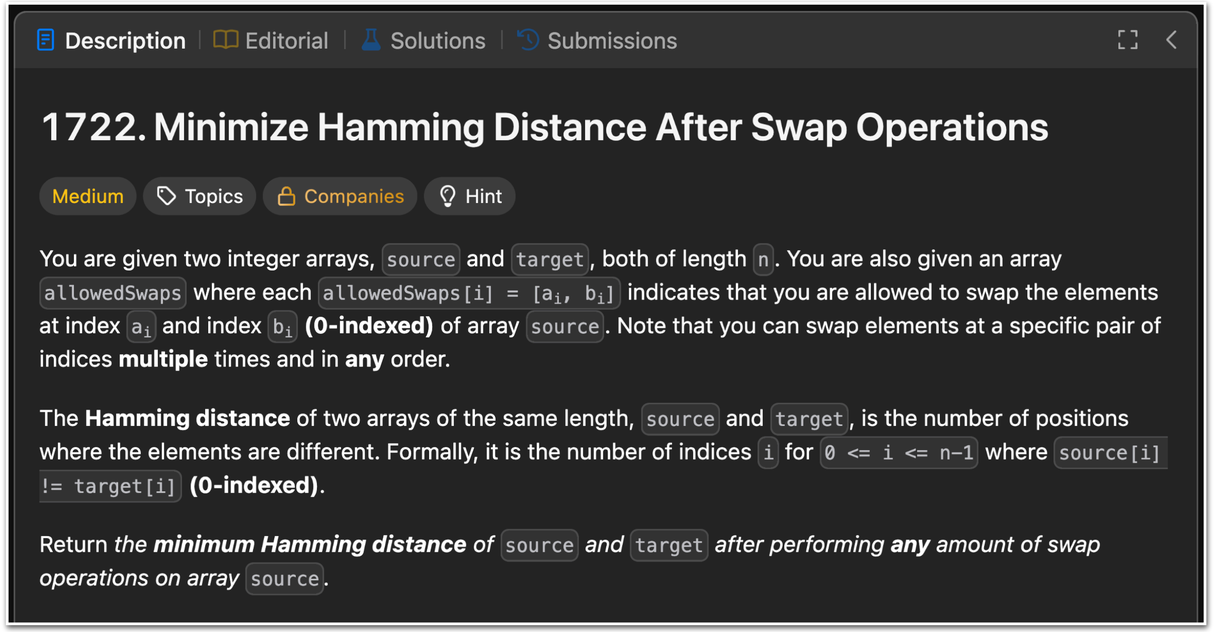

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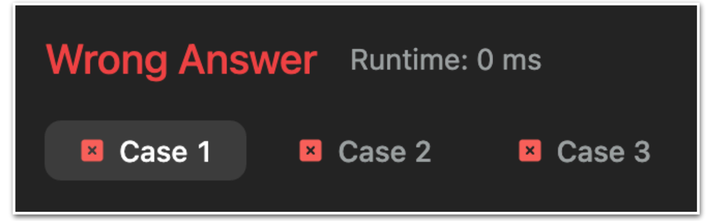
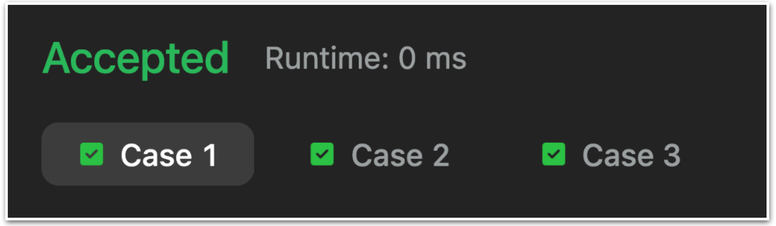


Example: Unit tests

until...



Recent work accelerates discovery for dense reward problems

Google DeepMind

AlphaEvolve: A coding agent for scientific and algorithmic discovery

Alexander Novikov*, Ngân Vũ*, Marvin Eisenberger*, Emilien Dupont*, Po-Sen Huang*, Adam Zsolt Wagner
Sergey Shirobokov*, Borislav Kozlovskii*, Francisco J. R. Ruiz, Abbas Mehrabian, M. Pawan Kumar, Abiga
See, Swarat Chaudhuri, George Holland, Alex Davies, Sebastian Nowozin, Pushmeet Kohli and Matej Balo
Google DeepMind[1]

Learning to Discover at Test Time

Mert Yuksekgonul*[1], Daniel Koceja*[1], Xinhao Li*[4], Federico Bianchi*[5]
Jed McCaleb[3], Xiaolong Wang[4], Jan Kautz[2], Yejin Choi[2], James Zou†[1,5], Carlos Guestrin†[1], Yu Sun*[1,2]
[1] Stanford University [2] NVIDIA [3] Astera Institute [4] UC San Diego [5] Together AI

This work: How can we accelerate discovery in sparse reward problems?

Question:

Write a python function that returns all numbers from 1 to n. Answer briefly.

Answer $y \sim \pi_\theta(\cdot \mid x)$:

```python
def numbers_up_to_n(n):
    return list(range(1, n + 1))
```

incorrect!

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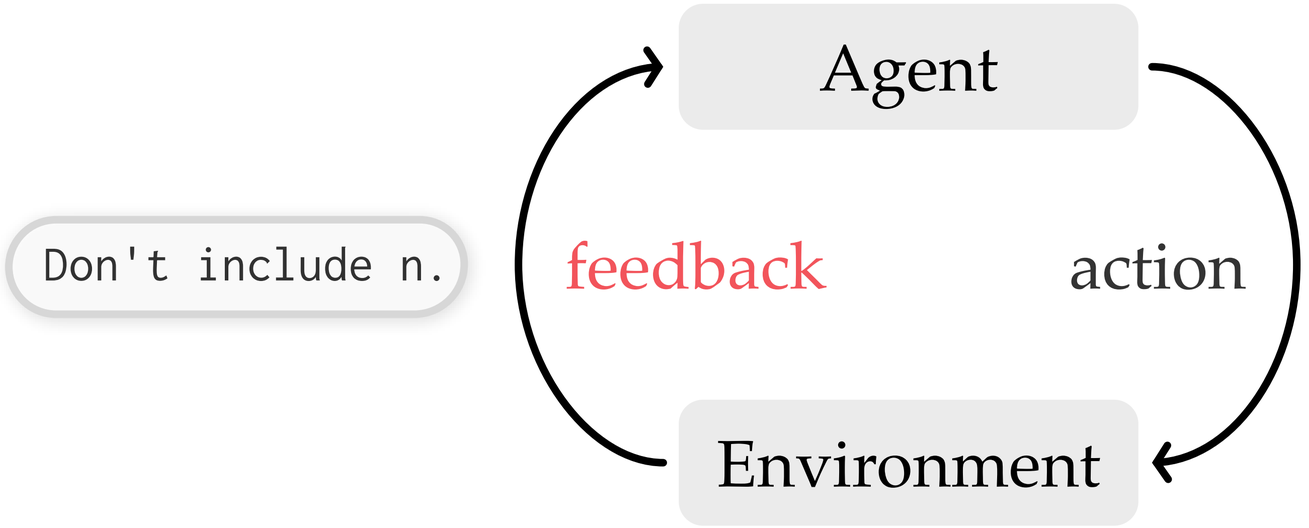
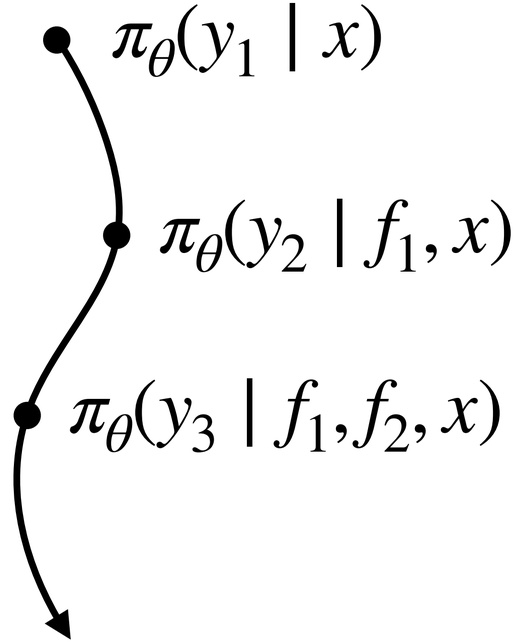


In-context learning

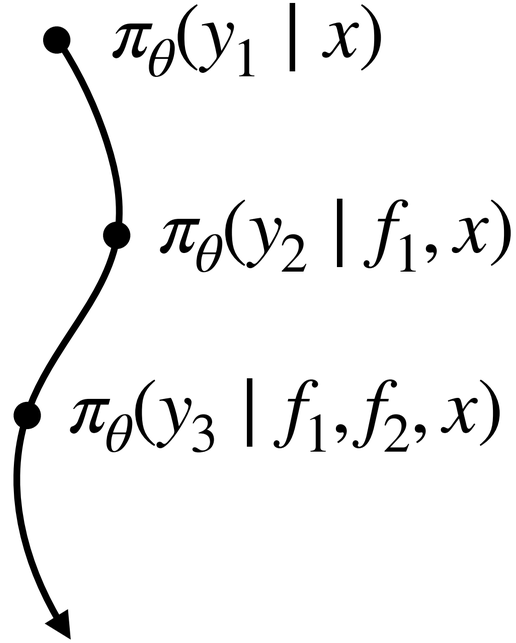
- Enables models to learn from rich feedback, hints, examples, and more.



Prompt x, Responses y, Feedback f

In-context learning

- Enables models to learn from rich feedback, hints, examples, and more.
- **BUT** context grows and learning is transient.



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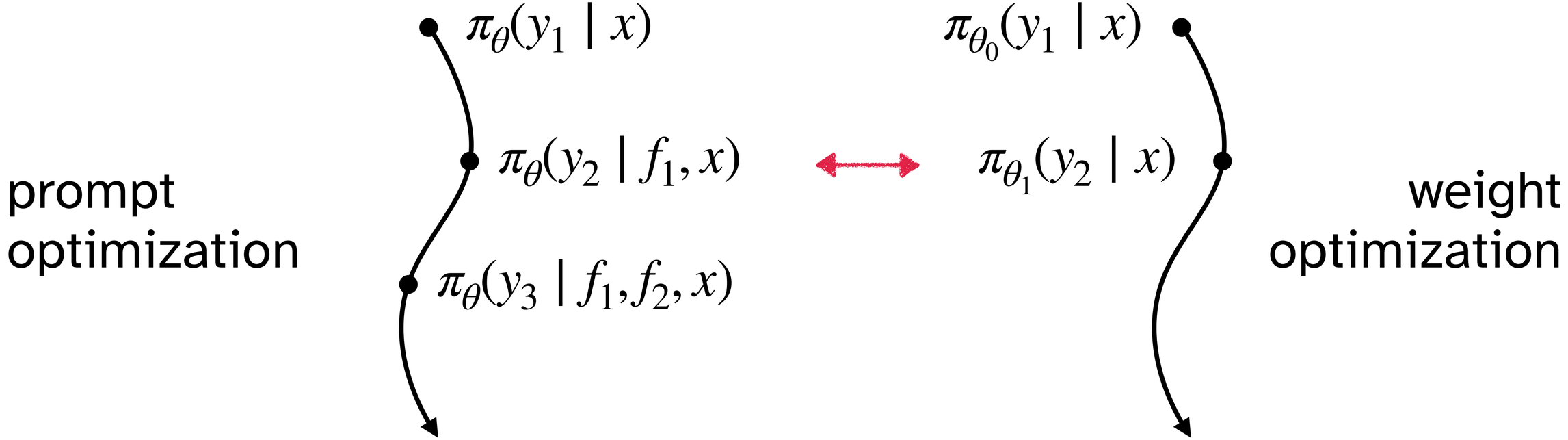
In-context learning → Self-distillation



Core idea: Use in-context learning to turn the model into its own teacher, then distill it.

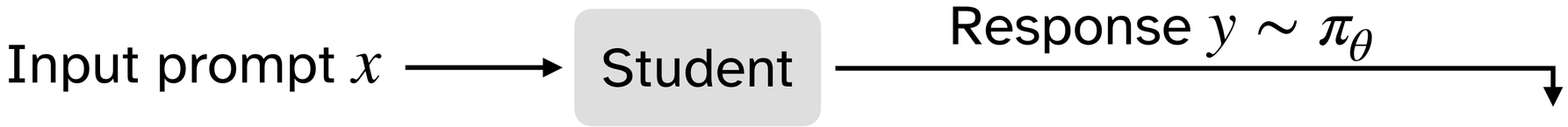
Self-distillation

Prompt x, Response y, Feedback f

Input prompt x

Self-distillation

Prompt x, Response y, Feedback f



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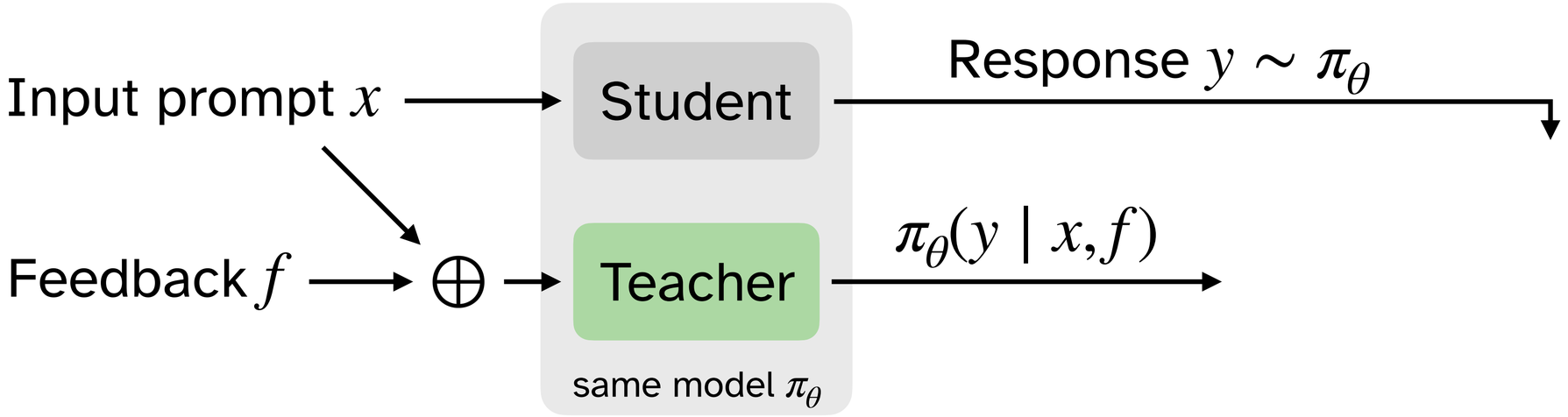

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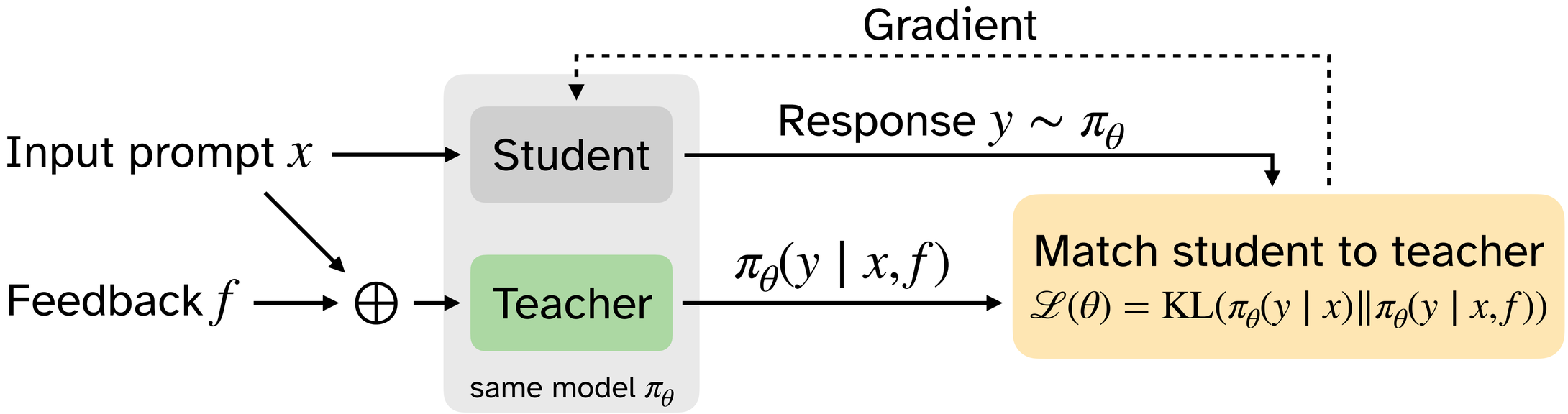

Two equivalent perspectives

Match student to teacher

$$\mathscr{L}(\theta) = \mathrm{KL}(\pi_\theta(y \mid x) \| \pi_\theta(y \mid x, f))$$

$\Longleftrightarrow$

Token-level advantages

$$A_i(x, y, f) := \log \frac{\pi_\theta(y_i \mid x, f, y_{<i})}{\pi_\theta(y_i \mid x, y_{<i})}$$

On-policy distillation

On-policy RL

Credit assignment in self-distillation

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Feedback:

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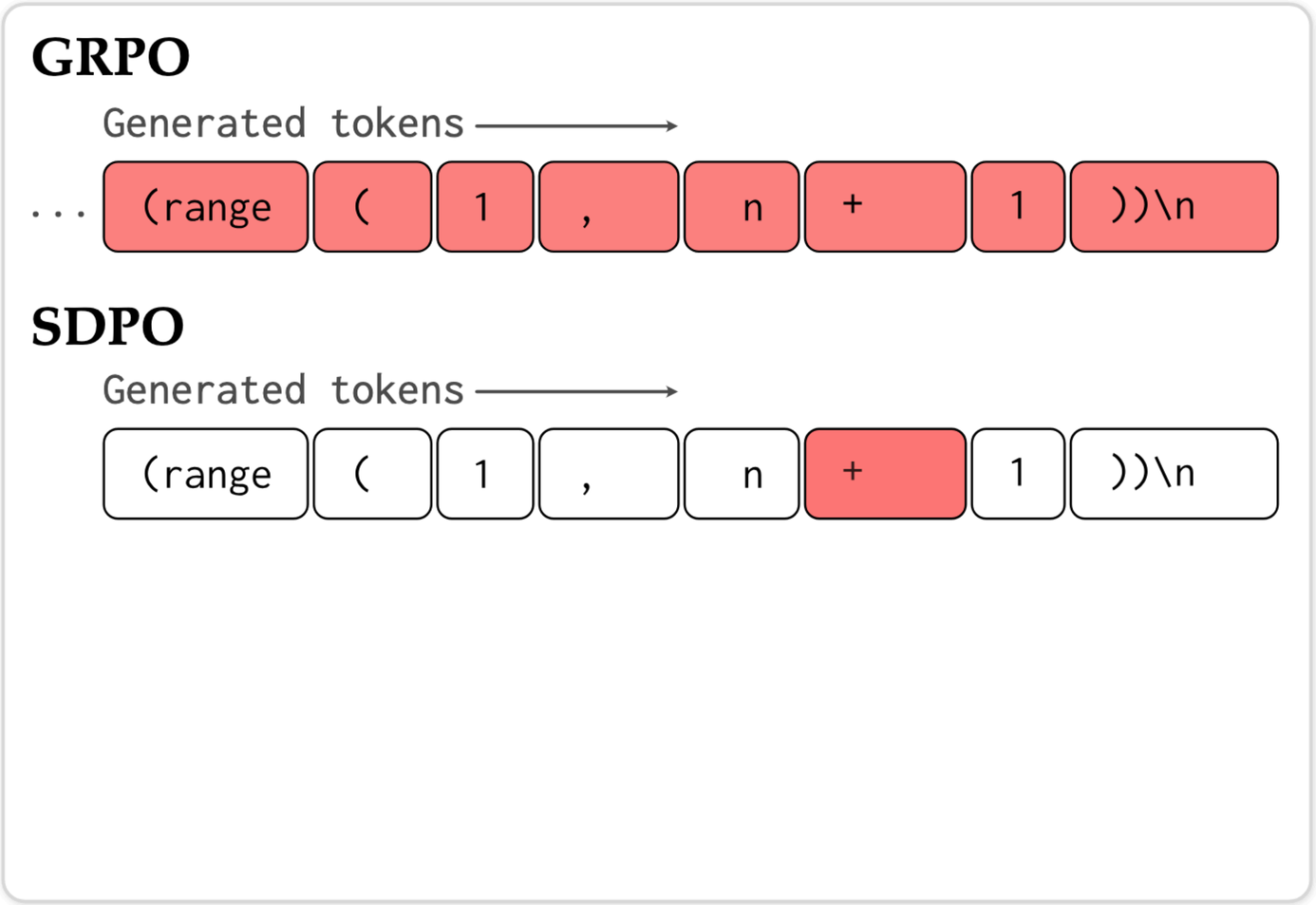

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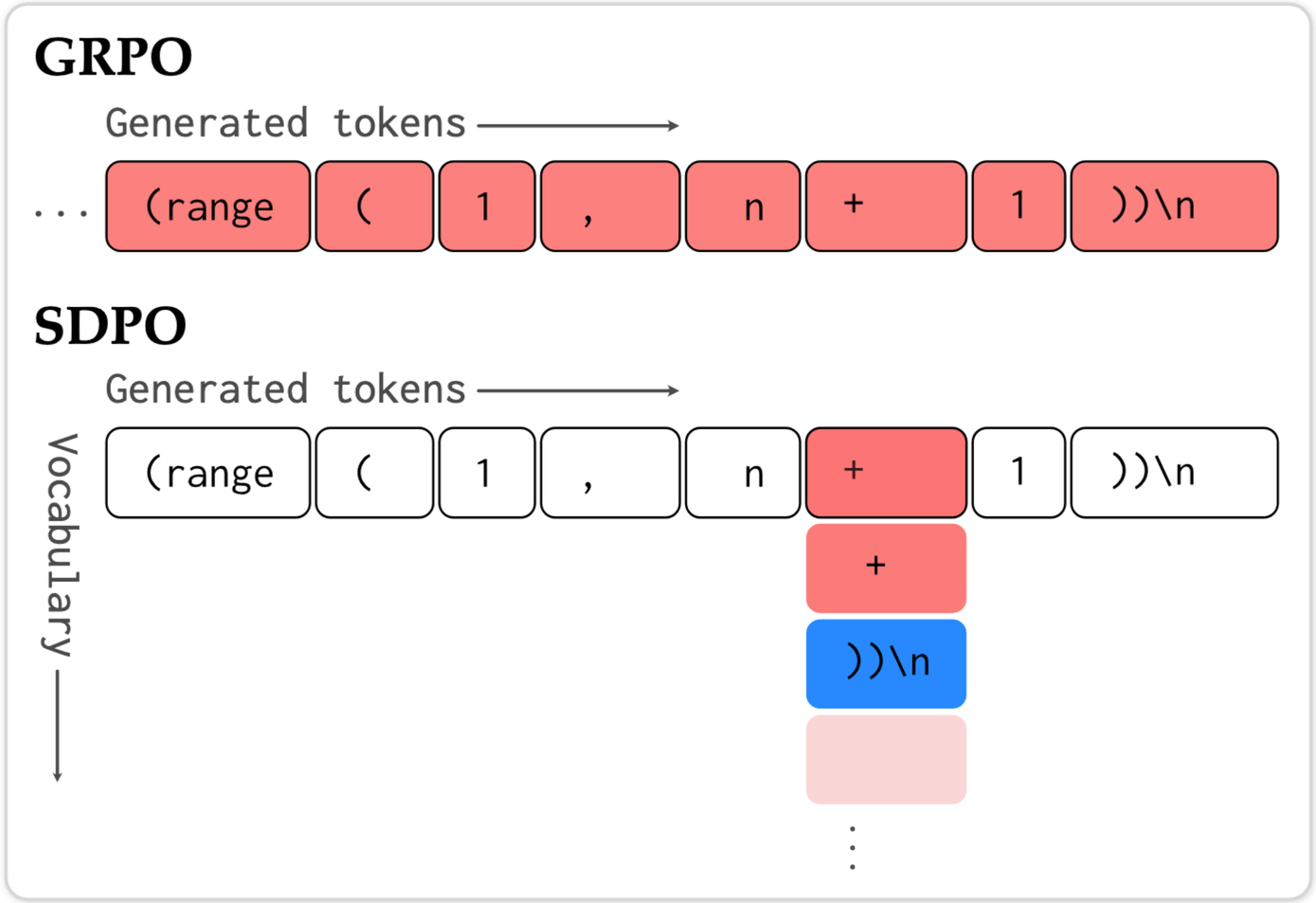

How to measure improvement?

- **Goal:** Accelerate time-to-discovery
- **Discovery time** is the number of trials until a solution is found
- We want to increase the probability of discovery:

$$\text{discovery@}k := \mathbb{P}(\text{discovery time} \leq k)$$

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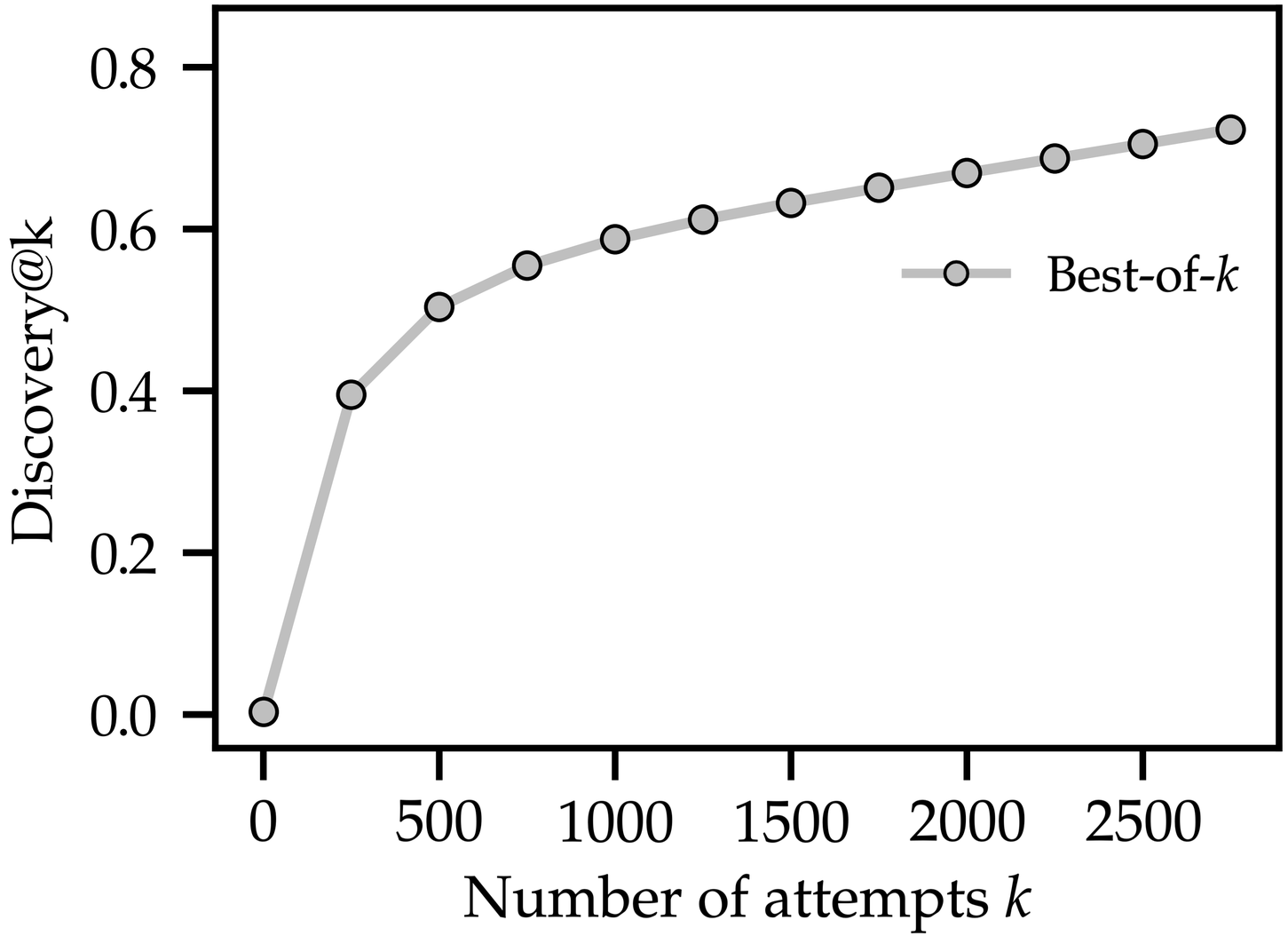
Note: pass@k = discovery@k for best-of-k sampling

Results

- Qwen3-8B on LiveCodeBench-v6
- Subset of *hard tasks*: pass@64 < 0.5



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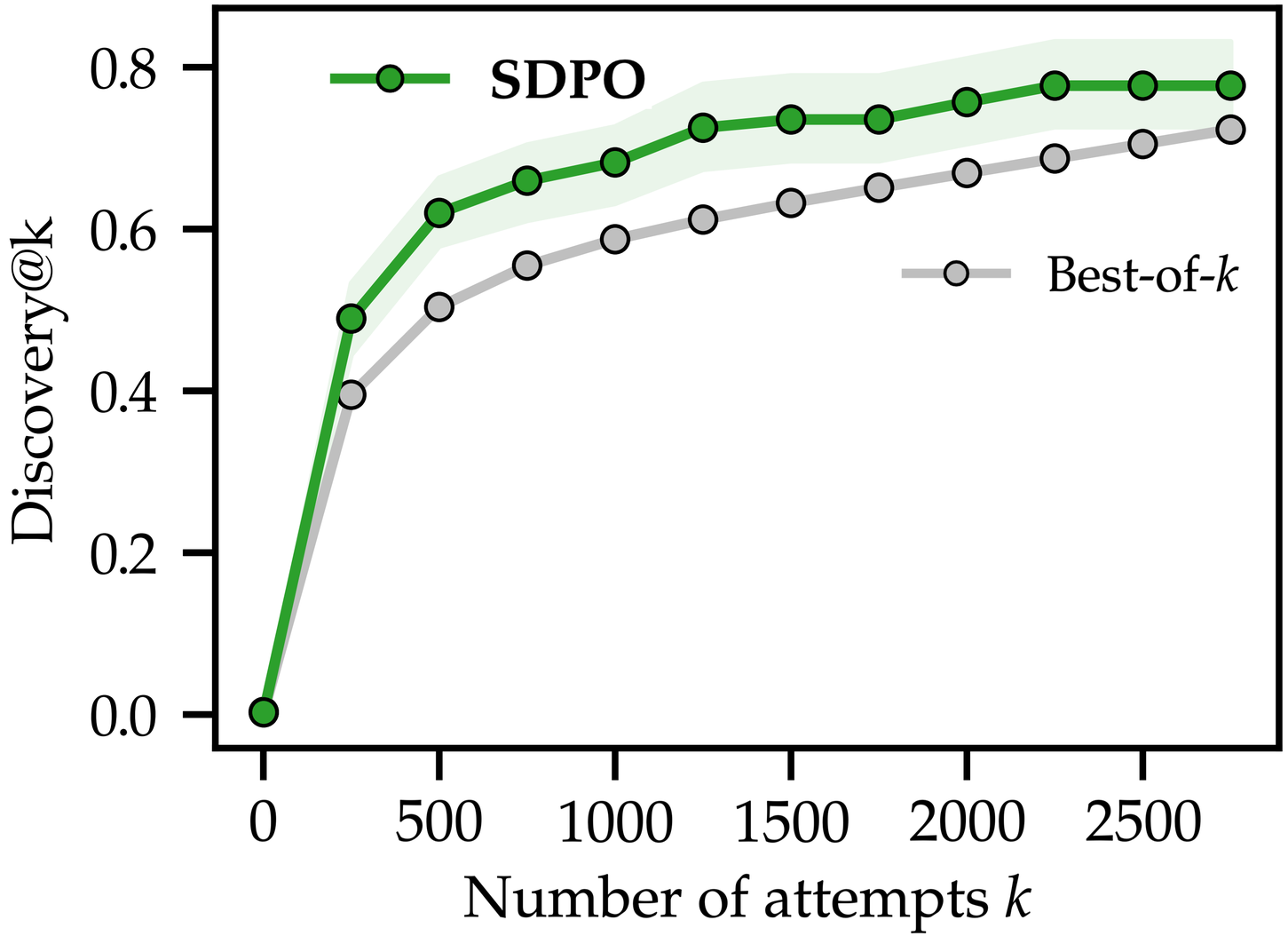

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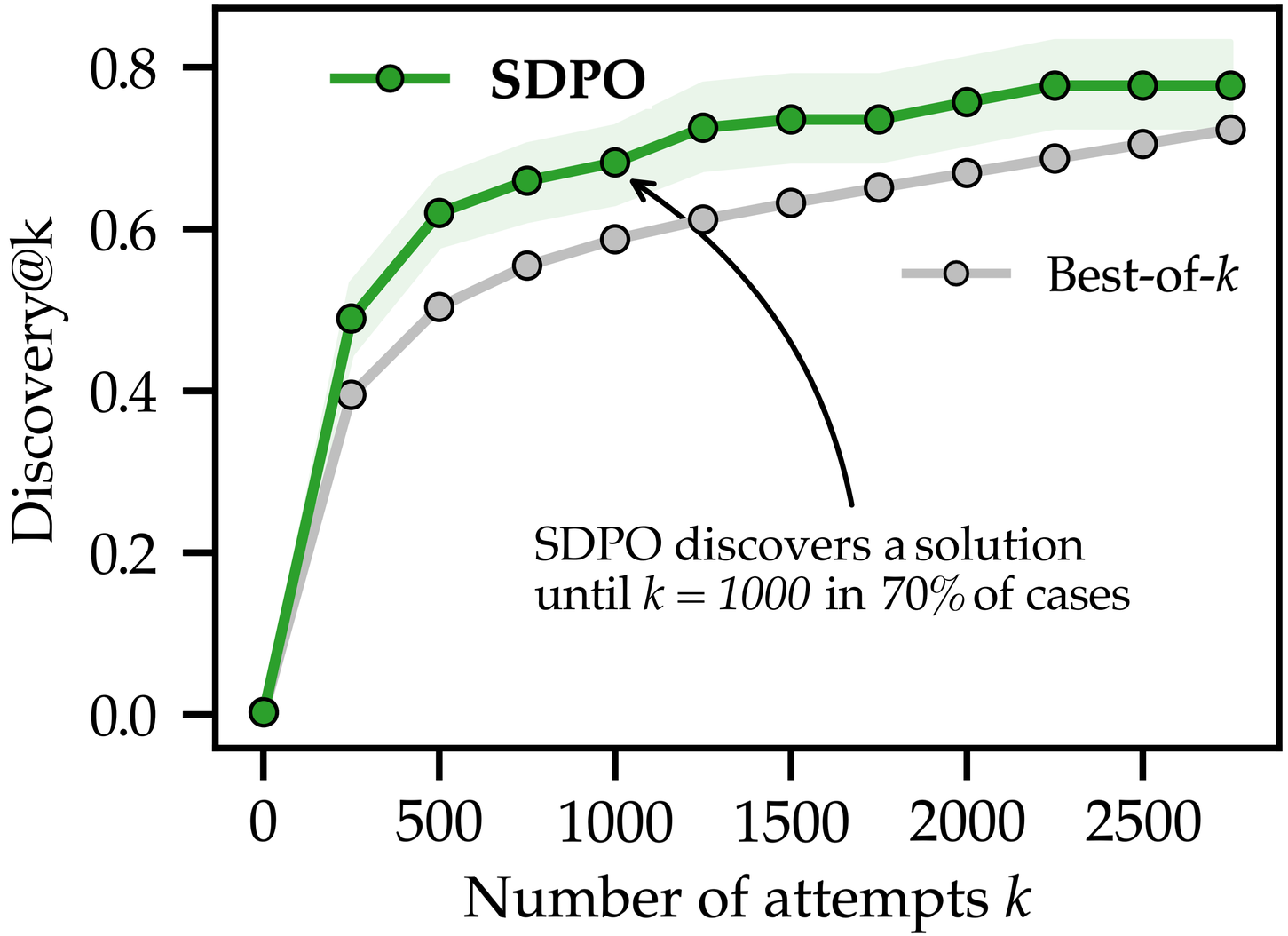

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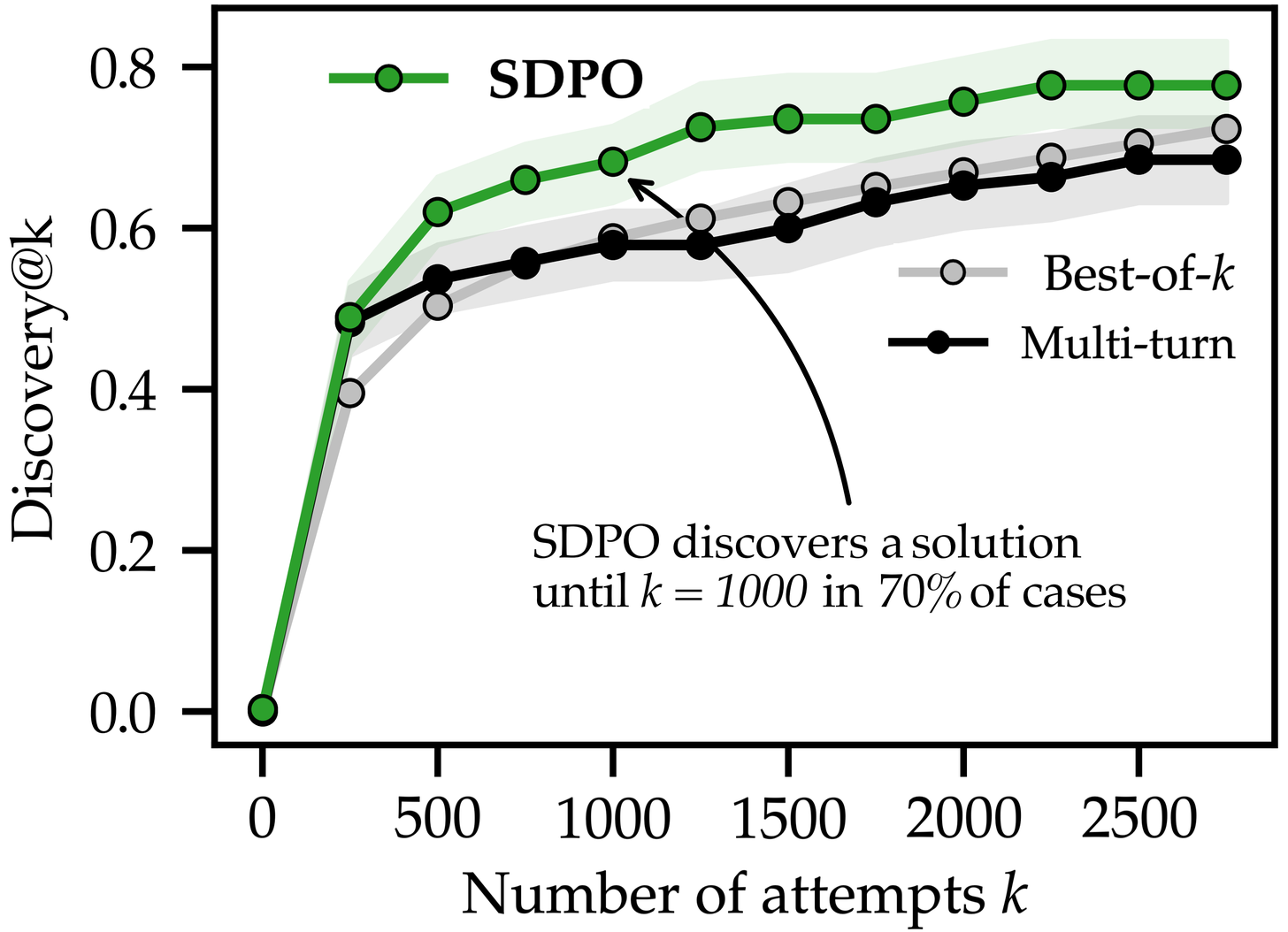

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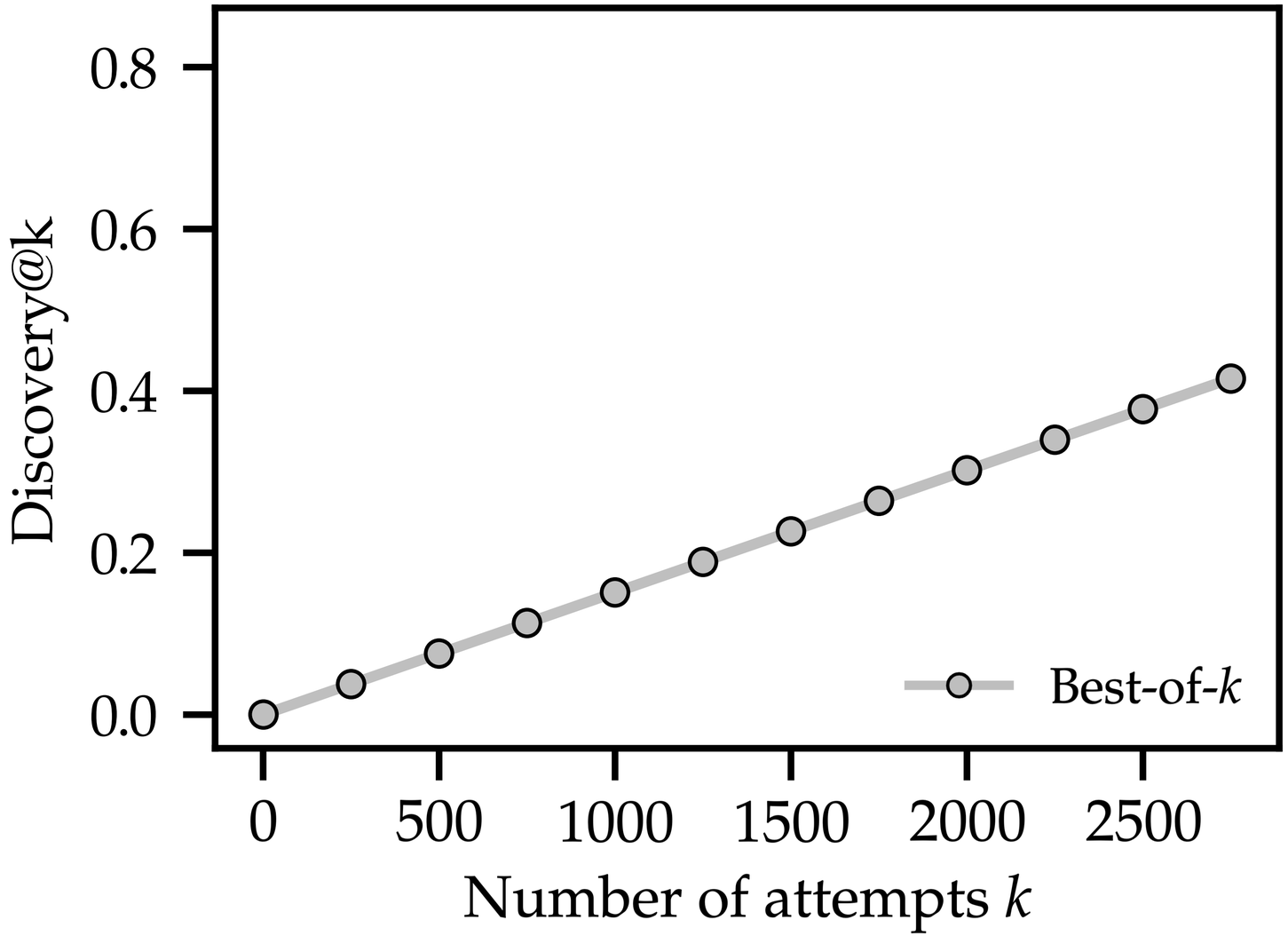

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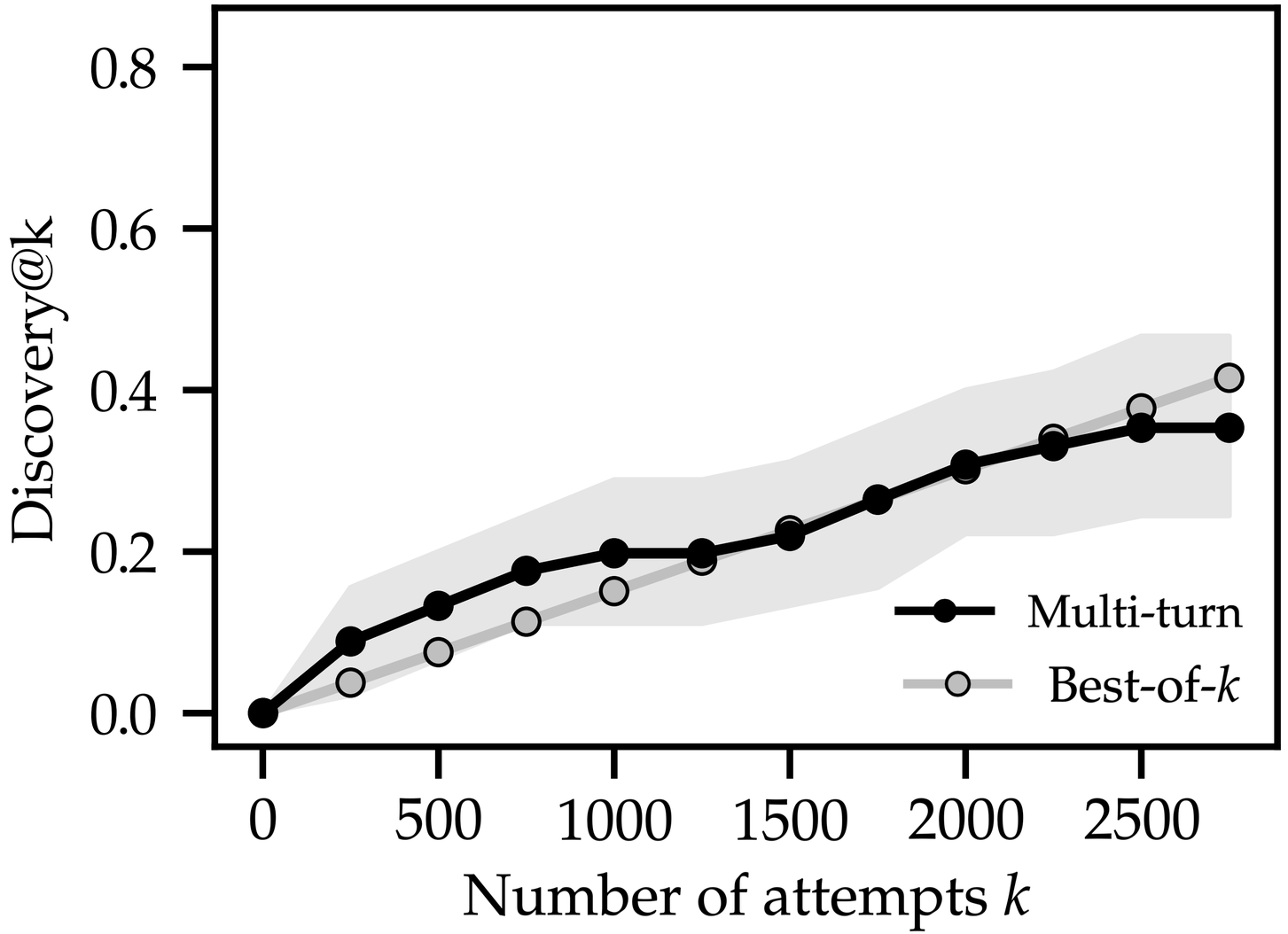

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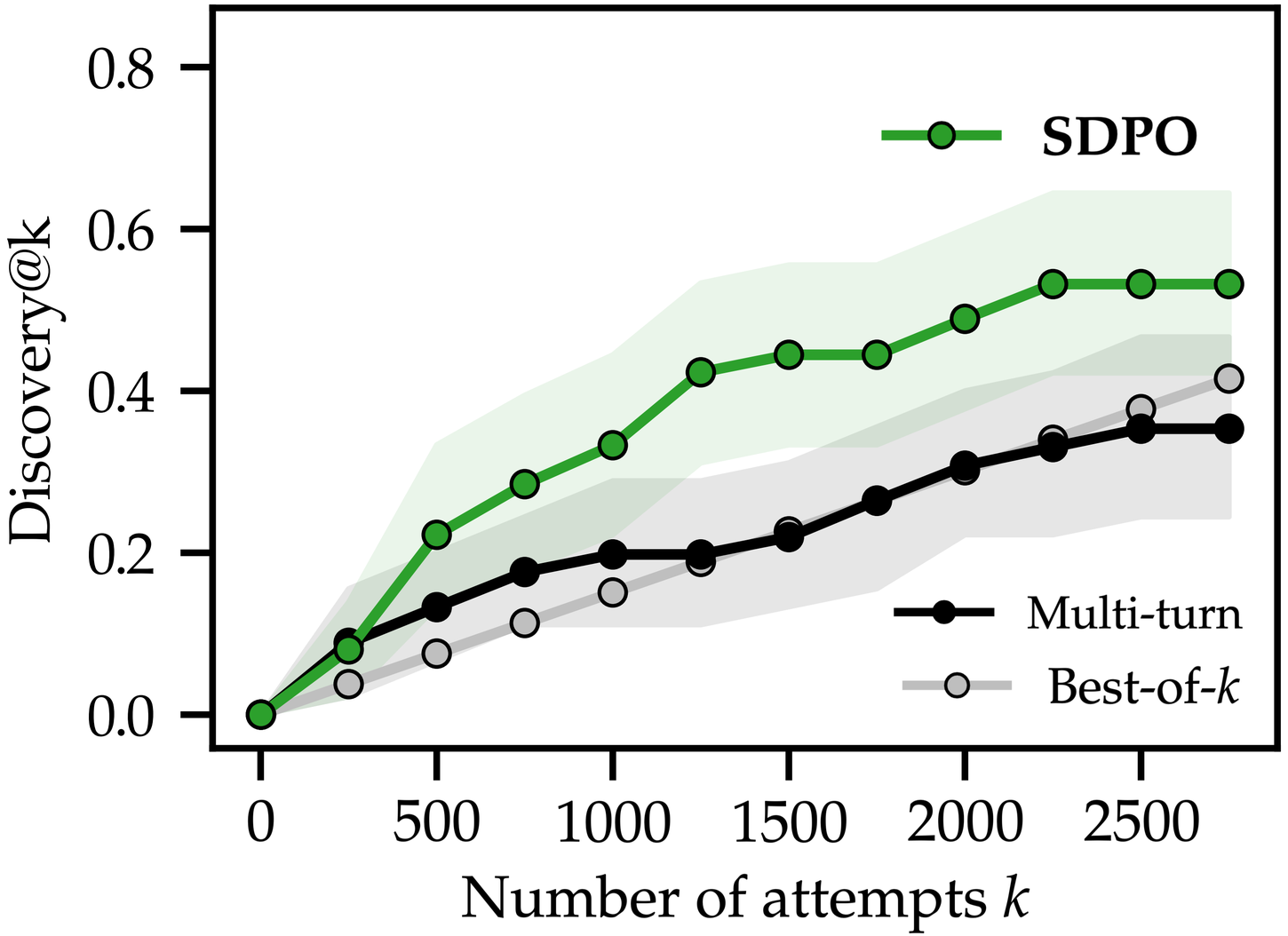

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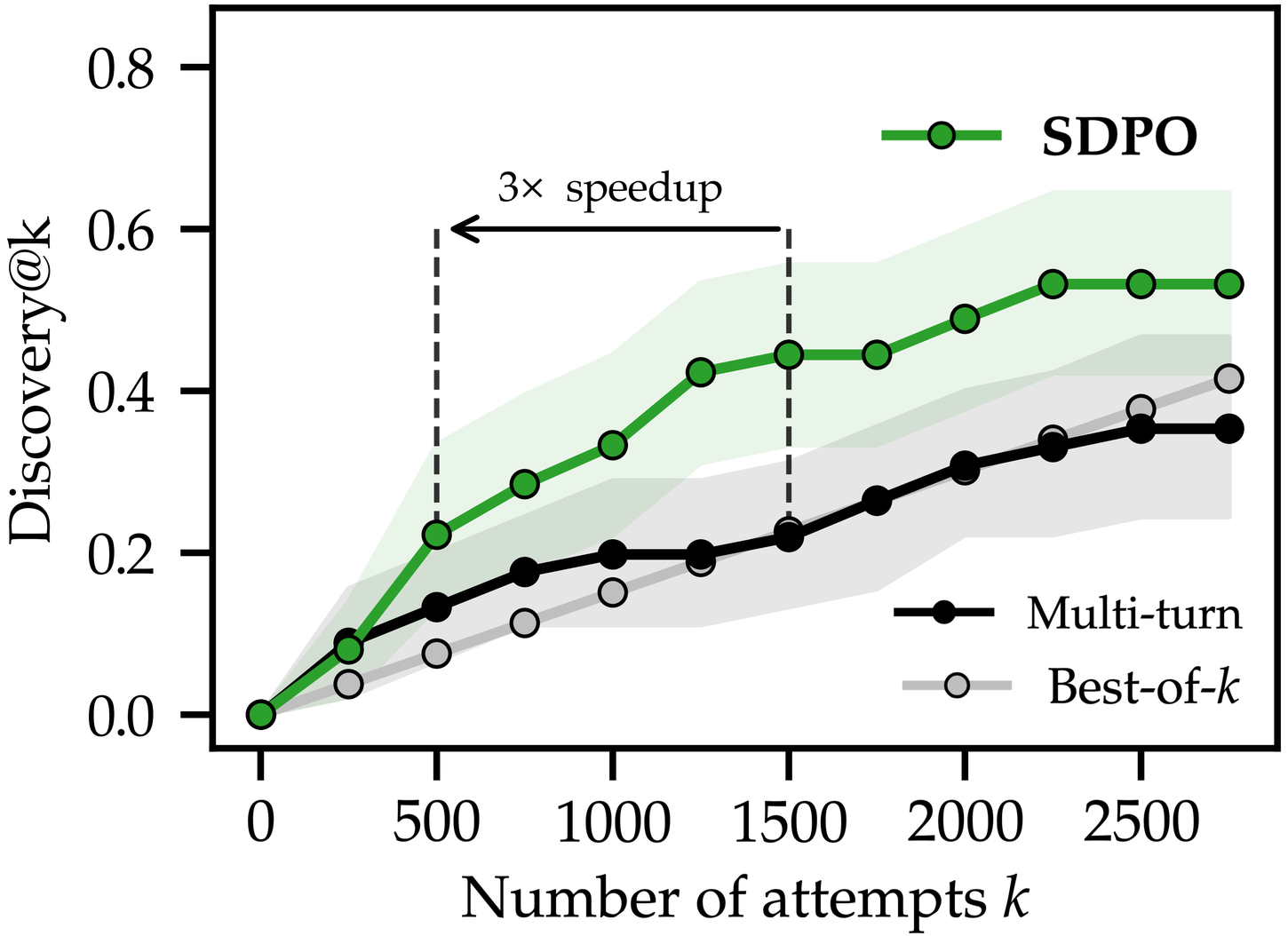
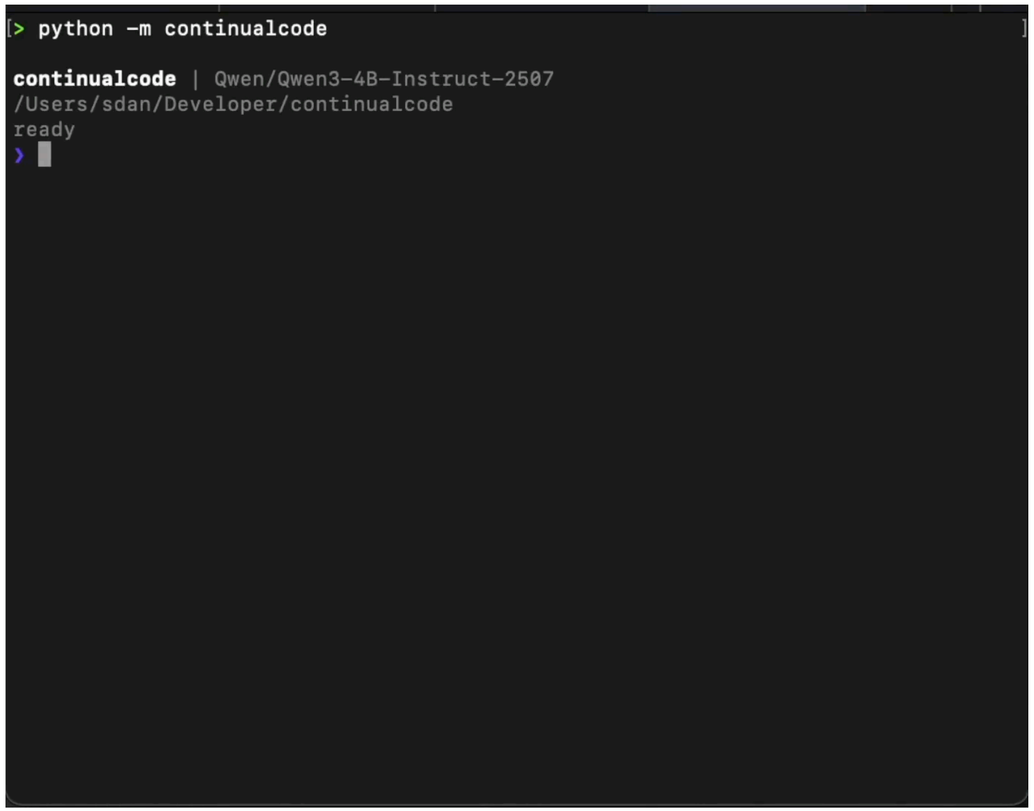


Takeaways

- Self-distillation solves problems not solved by the base model.
- The initial teacher does not yet solve questions: **Teacher feedback is directionally helpful.**
- Multi-turn baseline runs out of context (40k tokens) at k=800 to k=1000 tokens, but underperforms at k=500: **Multi-turn underperforms even prior to running out of context.**

Self-distillation is already being used

Claude Code, but updating model weights



OpenClaw-RL

>5k stars on GitHub!

Student who uses OpenClaw to do homework, does not want to be found using AI.

Before:

The handbag cost $220. Here's how:

1. Shoes cost $80
2. 3 times the shoe cost = 3 × $80 = $240
3. Subtract $20 = $240 – $20 = **$220**

Final Answer: $220 AI-like !

After several conversations:

Jillian's handbag cost $220. Here's the step-by-step solution: 1. 3 times the shoe cost: 3 * $80 = $240. 2. Subtract $20: $240 - $20 = $220.

Teacher who uses OpenClaw to grade homework, wants comments to be specific and friendly.

Before:

Correct answer: 30. Your solution is correct. Total units: 120. Occupied units: 90. Unoccupied units: 30. Cold !

After several conversations:

Great job breaking down the problem! You correctly calculated 120 total units and found 90 occupied units. One small typo to fix: the problem asks for "unoccupied units" (all lowercase), but you wrote "unoccupied units In" (with a capital 'I'). Just remember to keep the words lowercase unless they're proper nouns! You've got the right answer (30) — well done! 💥

→ Your model learns as you interact with it

Self-distillation leverages in-context improvement for parametric learning

Check out other applications of self-distillation:

- Shenfeld et al. *Self-Distillation enables Continual Learning*, 2026.
- Buening et al. *Aligning Language Models from User Interactions*, 2026.