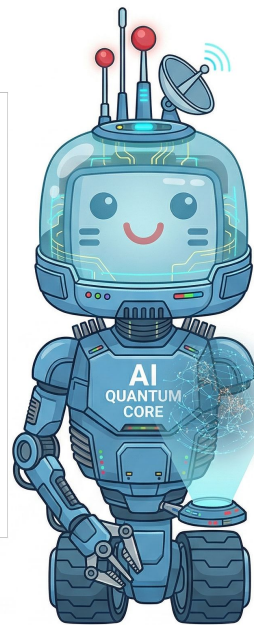
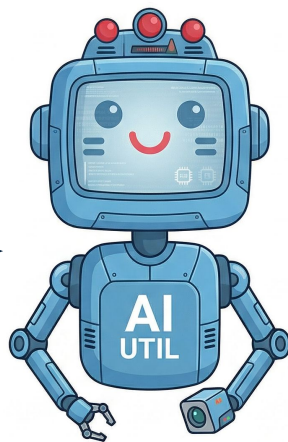
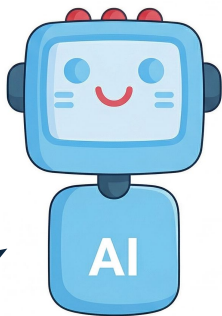


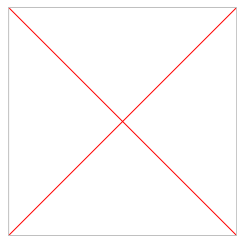
人工智慧能否 自我成長 (下集)

人工智慧能否自我成長

人類最後的發明

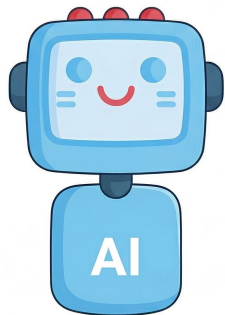


.....



"technological singularity"

$$L(A_\theta, H)$$



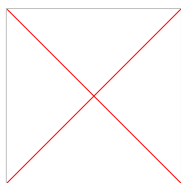
"be good
at math"



textbook



Examples
(training set)

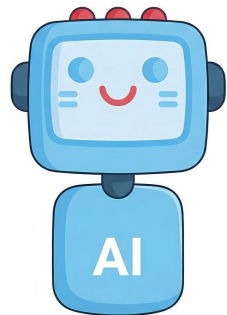
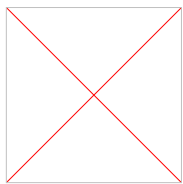

$$A_\theta$$

$$\hat{L}(A_\theta)$$


Benchmark



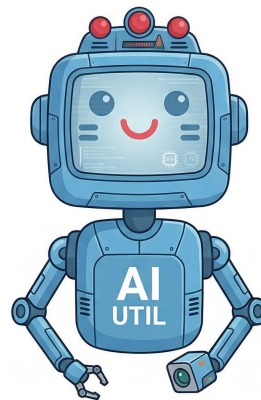
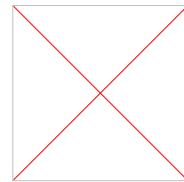
$$L(A_\theta, H)$$

 A_θ  $\hat{L}(A_\theta)$

$$\theta' = \theta - \eta \nabla_\theta L$$

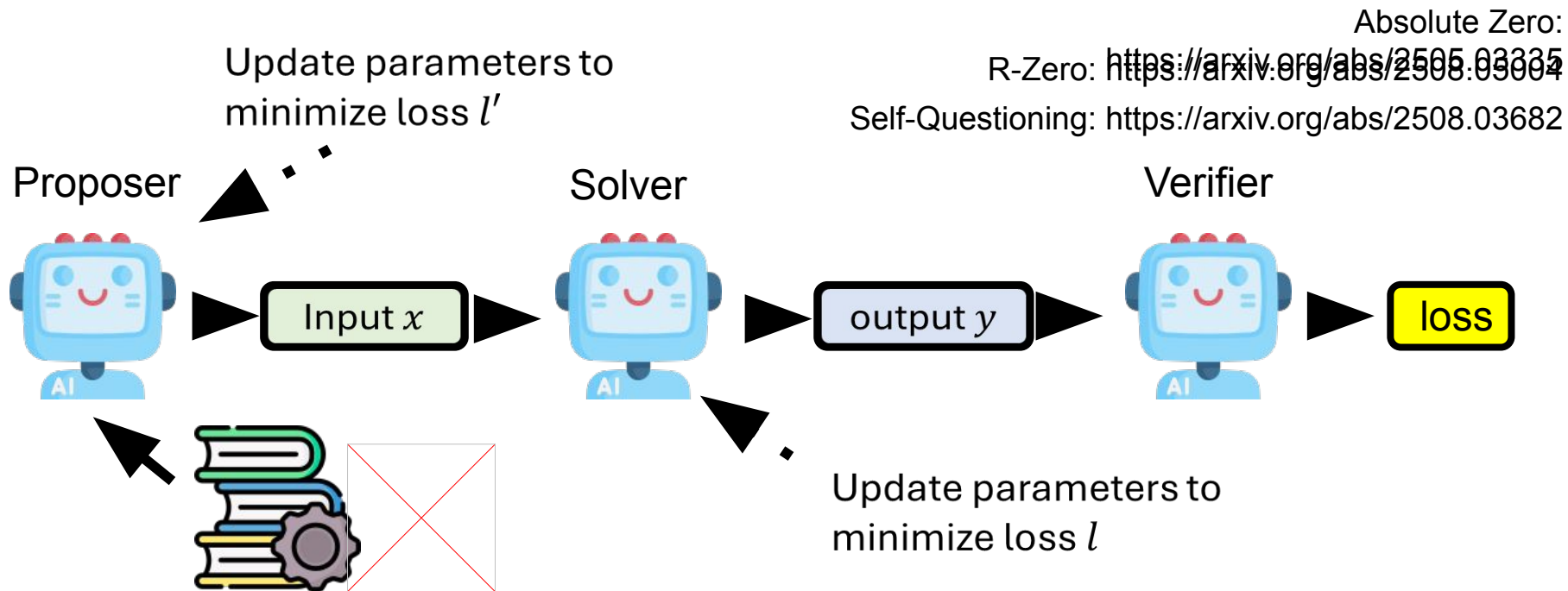


$$\theta = \theta'$$

 $A_{\theta'}$  $\hat{L}(A_{\theta'})$

$$\hat{L}(A_\theta) > \hat{L}(A_{\theta'})$$

Almost No Human in the Loop



Absolute Zero:

R-Zero: <https://arxiv.org/abs/2505.03305>

Self-Questioning: <https://arxiv.org/abs/2508.03682>

SPICE:

<https://arxiv.org/abs/2510.24684>

<https://arxiv.org/abs/2512.02472>

System Message:

You are an expert competition-math problem setter. FIRST, in your private scratch-pad, think step-by-step to design a brand-new, non-trivial problem. The problem could come from any field of mathematics, including but not limited to algebra, geometry, number theory, combinatorics, prealgebra, probability, statistics, and calculus. Aim for a difficulty such that fewer than 30% of advanced high-school students could solve it. Avoid re-using textbook clichés or famous contest problems.

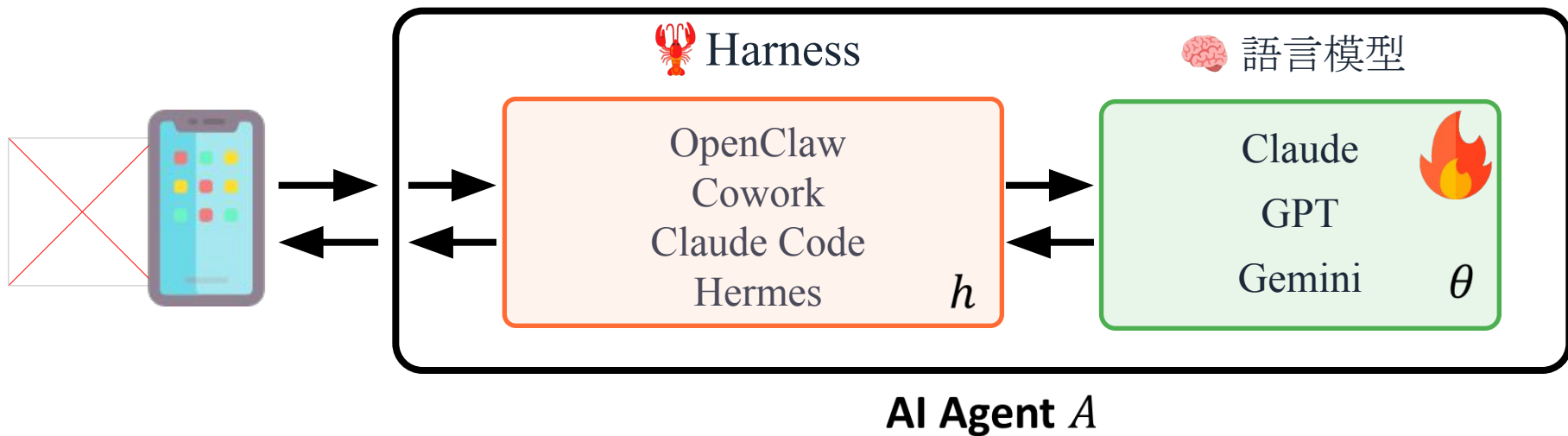
R-Zero: <https://arxiv.org/abs/2508.05004>

```
## Task: Create a Python Code Snippet (where custom classes are allowed, which should be defined  
→ at the top of the code snippet) with one Matching Input
```

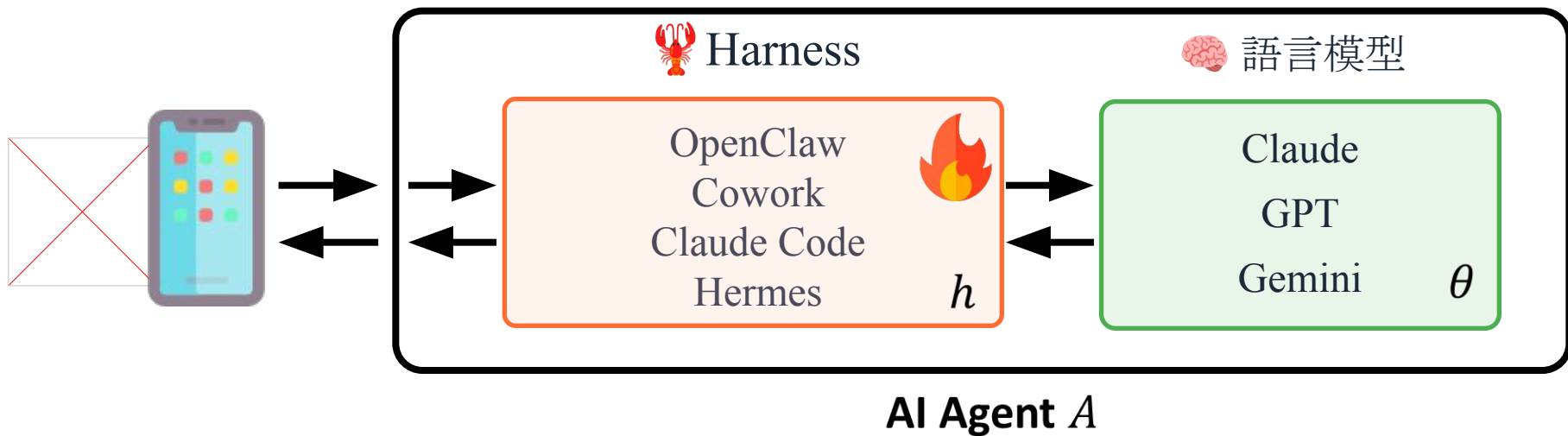
```
Using the reference code snippets provided below as examples, design a new and unique Python code  
→ snippet that demands deep algorithmic reasoning to deduce one possible input from a given  
→ output. Your submission should include both a code snippet and test input pair, where the  
→ input will be plugged into the code snippet to produce the output, which that function output  
→ be given to a test subject to come up with any input that will produce the same function  
→ output. This is meant to be an I.Q. test.
```

Absolute Zero:
<https://arxiv.org/abs/2505.03335>

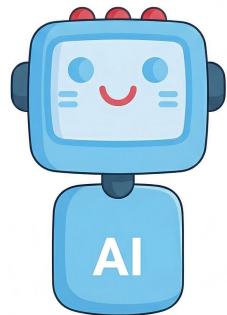
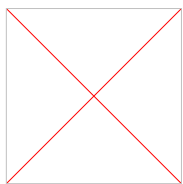
AI Agent = Harness + LLM



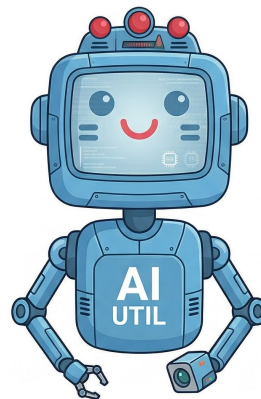
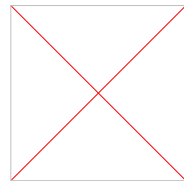
AI Agent = Harness + LLM



$$L(A_{\theta,h}, H)$$

 $A_{\theta,h}$  $\hat{L}(A_{\theta,h})$ $???$

$$h' = h - \eta \nabla_h L$$

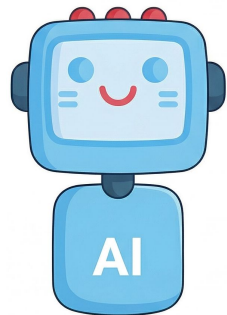
 $A_{\theta,h'}$  $\hat{L}(A_{\theta,h'})$

$$h = h'$$

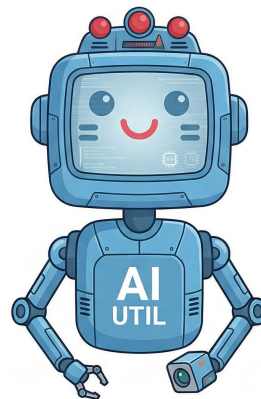


How to improve harness?

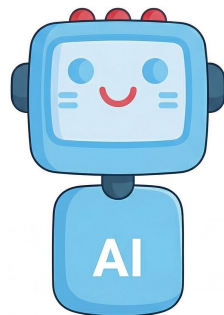
???



$$h' = h - \eta \nabla_h L$$



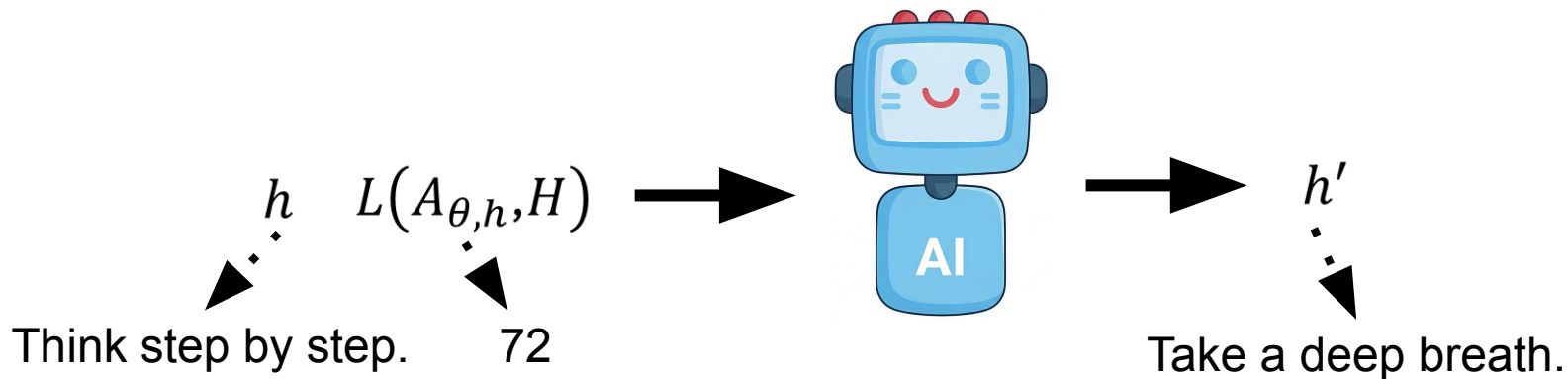
h $L(A_{\theta,h}, H)$



h'

h is prompt

Prompt Optimization



I have some texts along with their corresponding scores. The texts are arranged in ascending order based on their scores, where higher scores indicate better quality.

text:

Let's figure it out!

score:

61

text:

Let's solve the problem.

score:

63

(... more instructions and scores ...)

The following exemplars show how to :
text, then read the input and give an out
from the given output, and we say your

input:

Q: Alannah, Beatrix, and Queen are preparing for the new school year and have been given books by their parents. Alannah has 20 more books than Beatrix. Queen has $\frac{1}{5}$ times more books than Alannah. If Beatrix has 30 books, how many books do the three have together?

A: <INS>

output:

140

(... more exemplars ...)

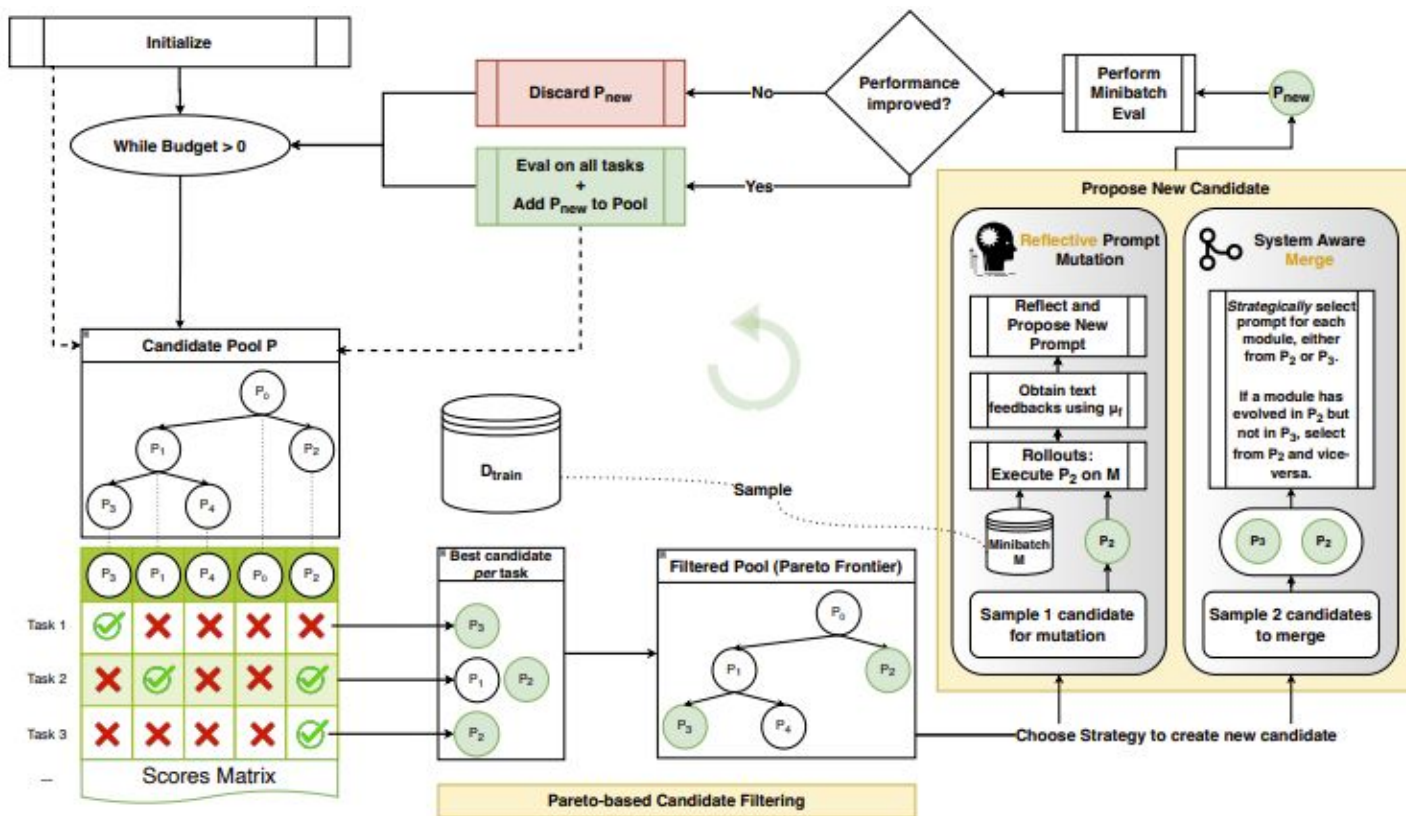
Write your new text that is different from the old ones and has a score as high as possible. Write the text in square brackets.

<https://arxiv.org/abs/2309.03409>

h is prompt

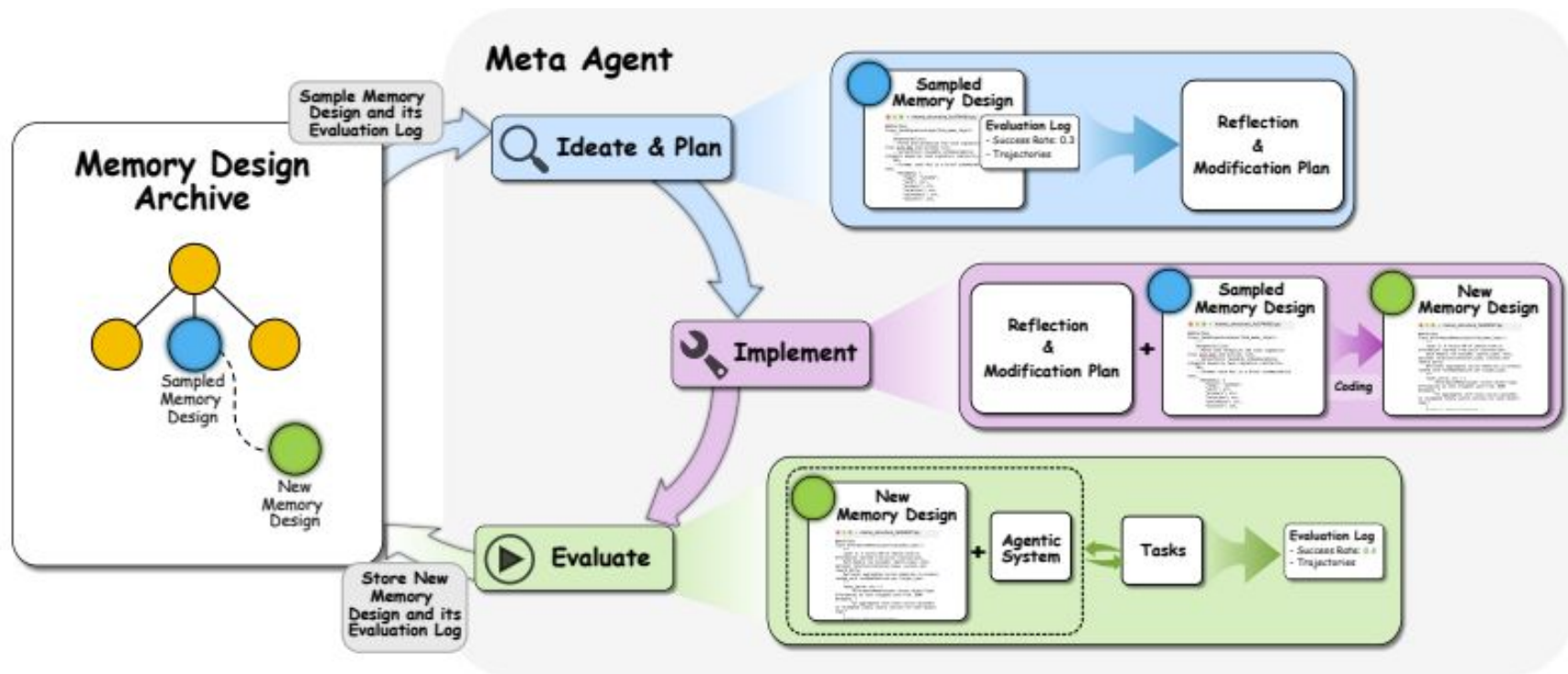
GEPA

<https://arxiv.org/abs/2507.19457>



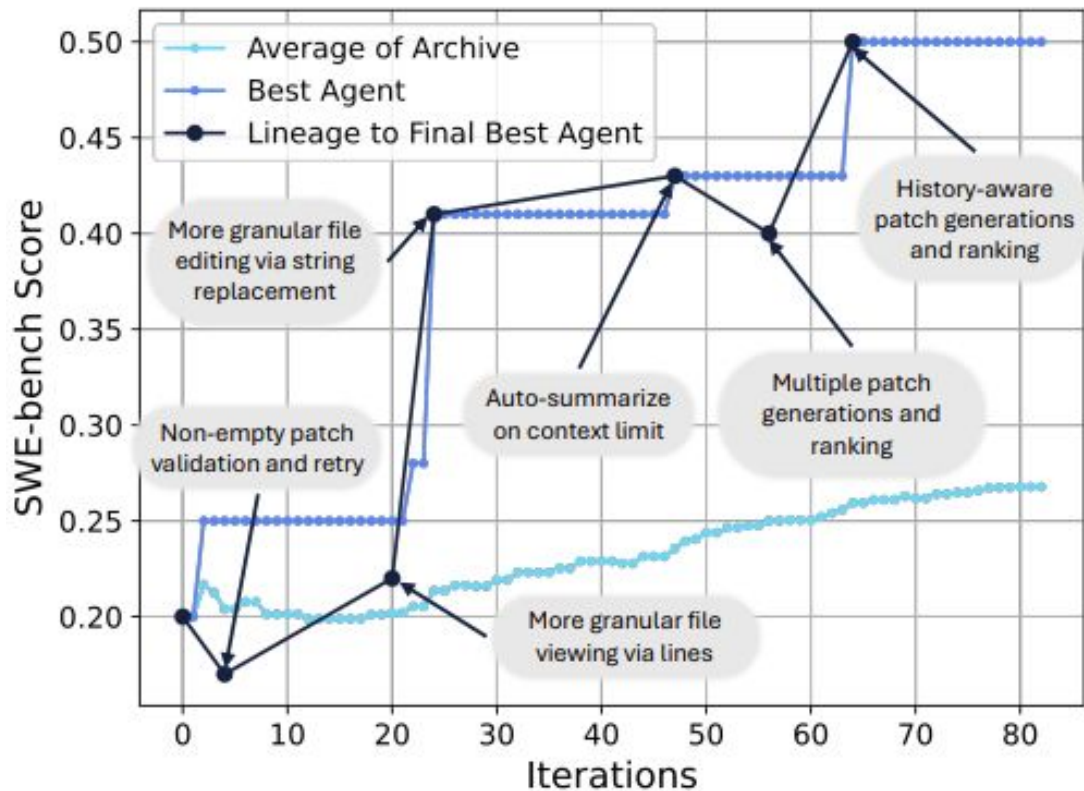
h is memory management

<https://arxiv.org/abs/2602.07755>

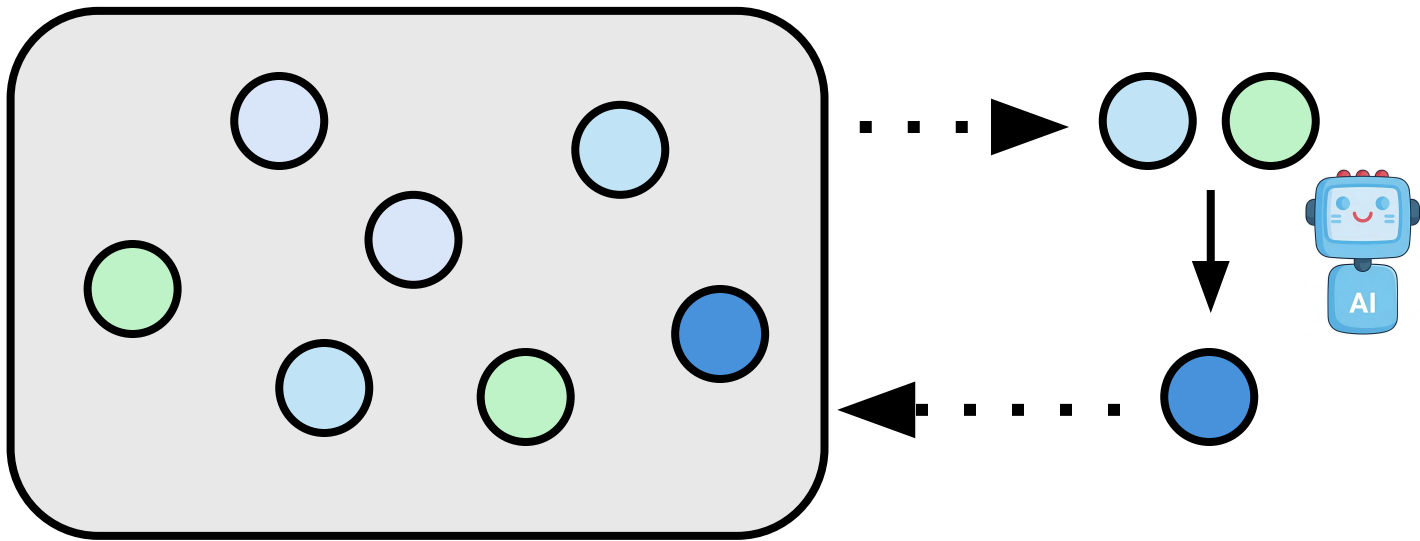
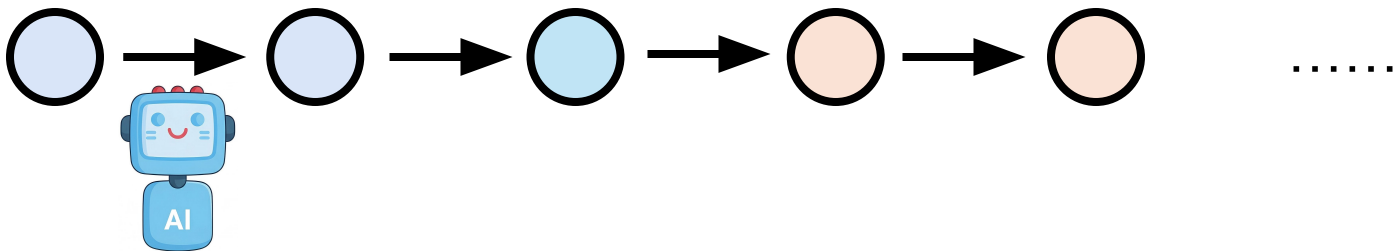


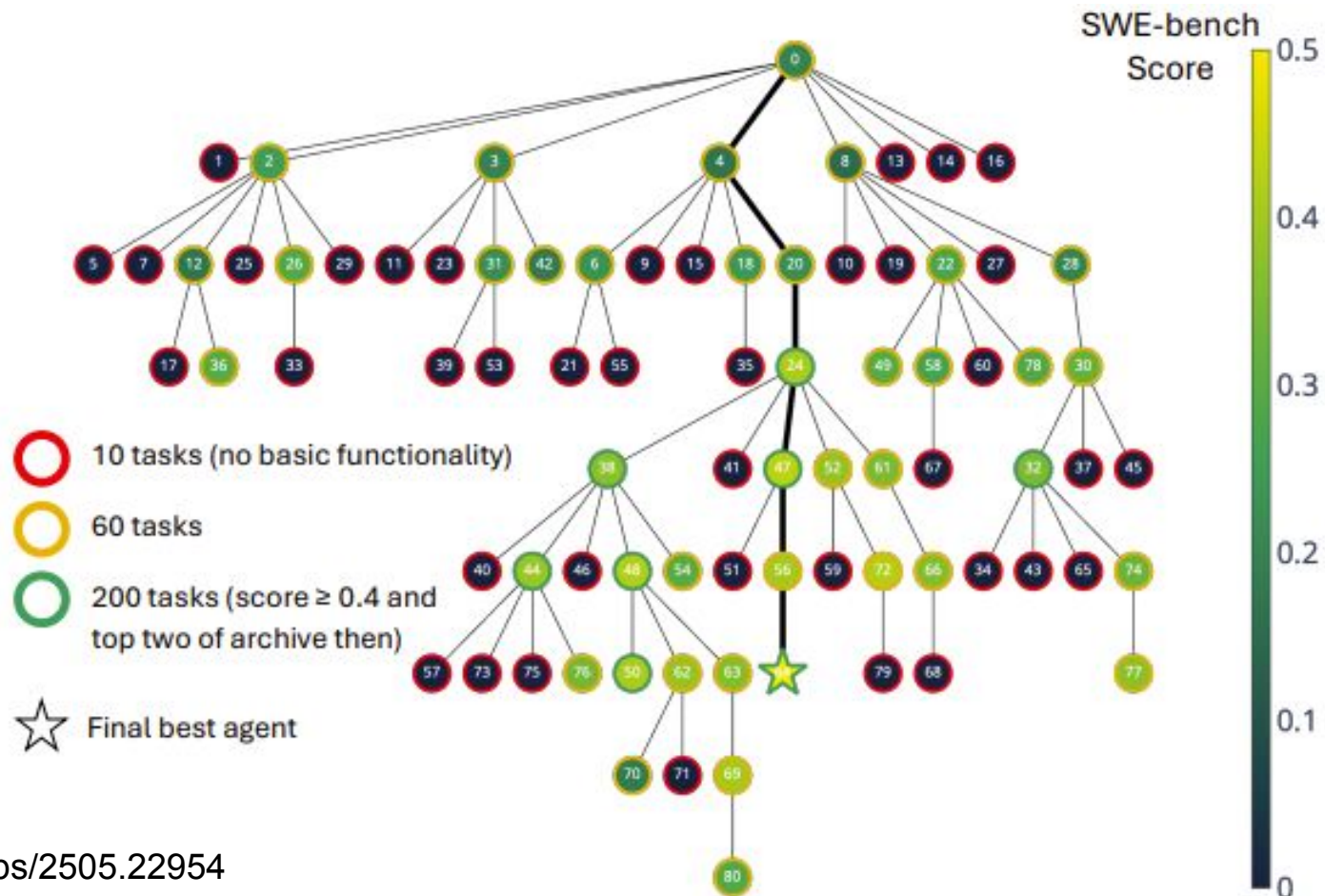
h is workflow

<https://arxiv.org/abs/2505.22954>



$A, L(A)$





<https://arxiv.org/abs/2505.22954>

Declarative Self-improving Language Programs in Python (DSPy)

[https://arxiv.org/abs/2310.0371](https://arxiv.org/abs/2310.03714)

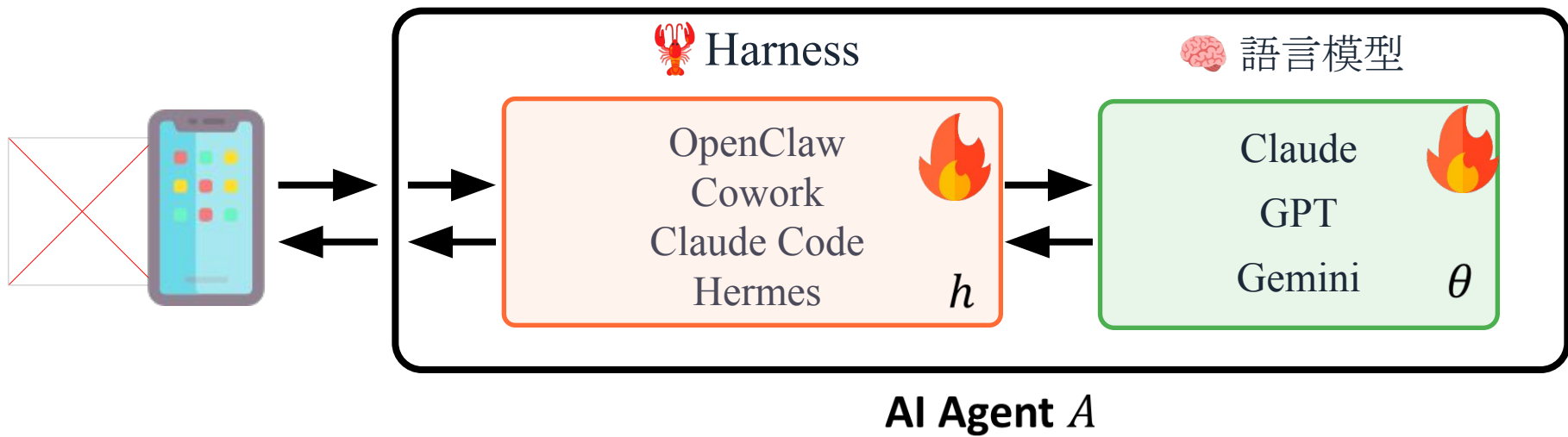
4



DSPy: *Programming*—not prompting—Foundation Models

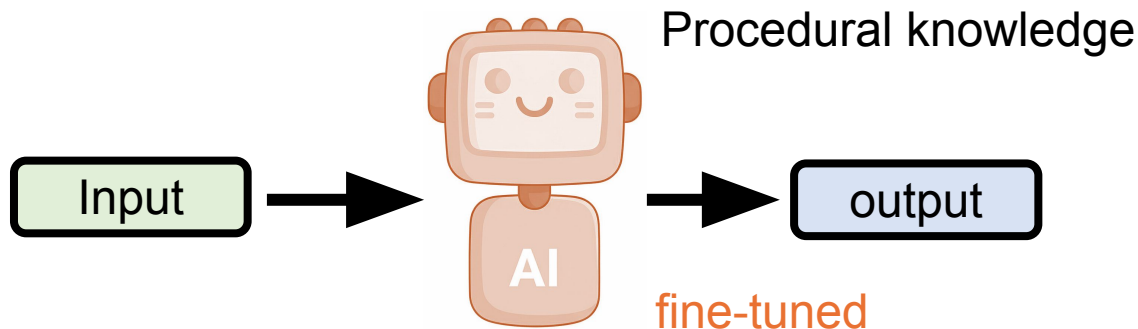
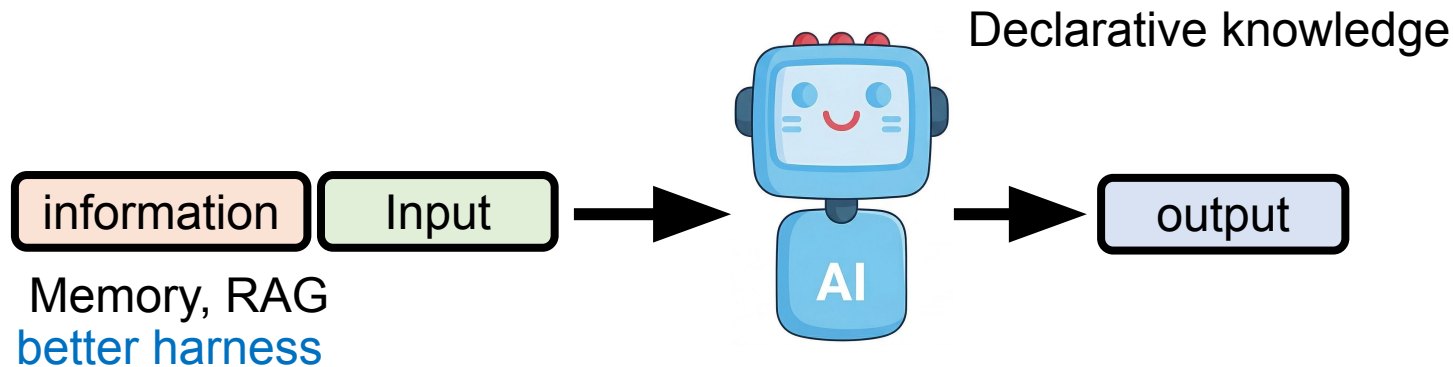
<https://github.com/stanfordnlp/dspy>

AI Agent = Harness + LLM



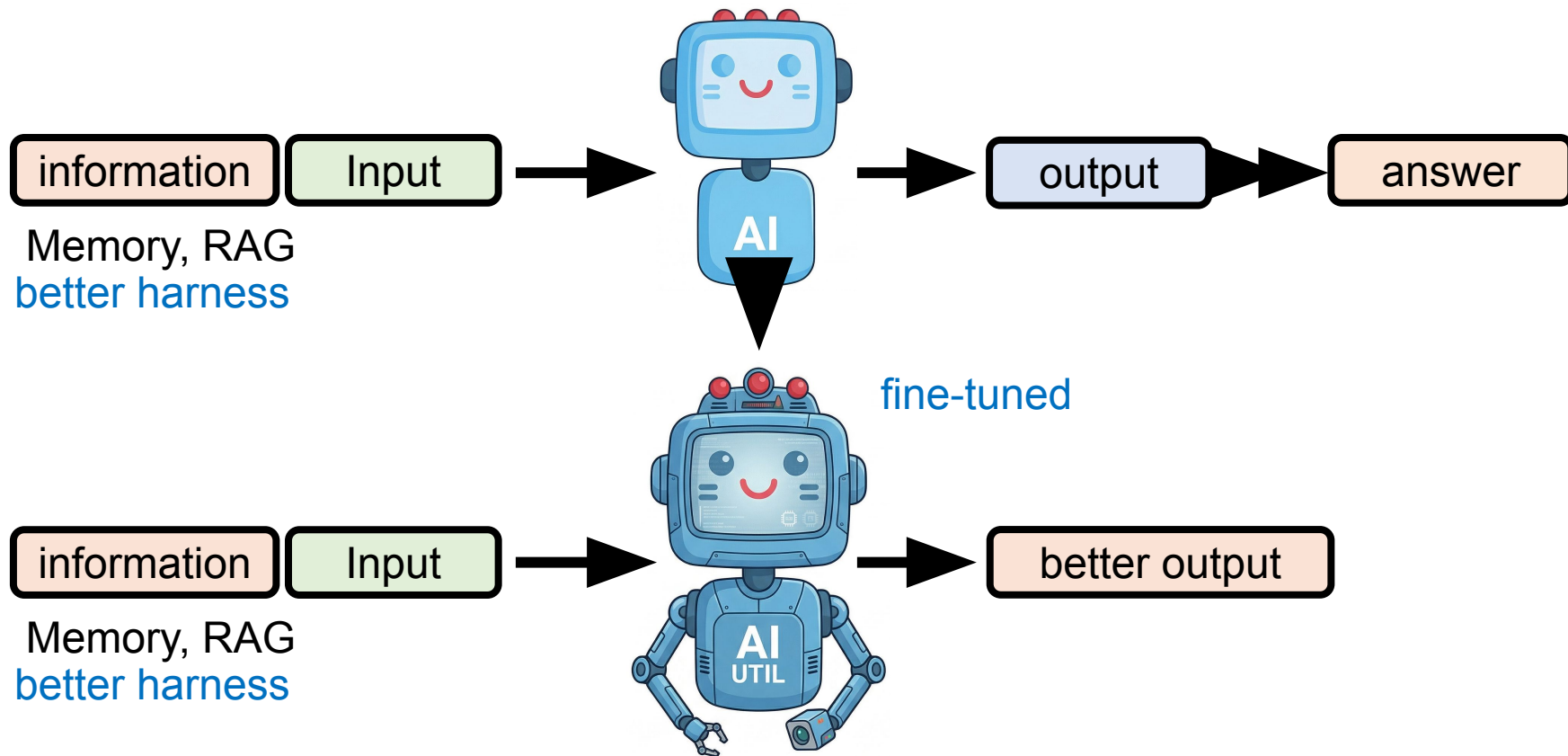
Retrieval-Augmented LLM Agents: Learning to Learn from Experience

<https://arxiv.org/abs/2603.1827>
2



Retrieval-Augmented LLM Agents: Learning to Learn from Experience

<https://arxiv.org/abs/2603.1827>
2

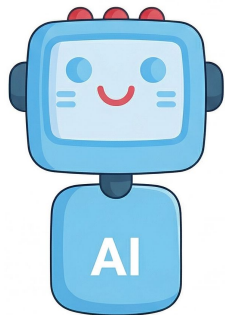


Fine-Tuning and Prompt Optimization: Two Great Steps that Work Better Together

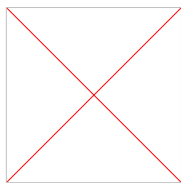
<https://arxiv.org/abs/2407.10930>

Strategy	mistral-7b-instruct-v0.2			llama-2-7b-chat			llama-3-8b-instruct		
	HotPotQA	GSM8K	Iris	HotPotQA	GSM8K	Iris	HotPotQA	GSM8K	Iris
<i>Baseline Strategies</i>									
Vanilla Zero-shot	17.2	40.3	26.0	13.2	24.0	0.0	31.6	72.7	48.0
Prompt Optimization (Π)	33.8	46.4	57.3	33.3	26.0	56.7	46.9	77.9	79.3
Weight Optimization (Θ)	22.9	40.7	29.3	12.2	24.0	–	34.8	75.1	37.3
$\Pi \rightarrow \Pi$	33.8	47.7	59.3	32.6	24.7	64.0	46.5	77.6	82.0
$\Theta \rightarrow \Theta$	24.0	42.8	38.0	13.0	24.1	–	34.4	44.1	39.3
<i>BetterTogether Strategies</i>									
$\Pi \rightarrow \Theta$	36.3	47.3	30.7	32.7	27.3	26.7	42.8	77.6	44.0
$\Theta \rightarrow \Pi$	33.0	48.3	66.7	34.2	26.6	–	43.6	78.9	78.7
$\Pi \rightarrow \Theta \rightarrow \Pi$	37.6	46.8	52.7	34.8	26.3	65.3	46.7	77.0	79.3

$$L(A_{\theta,h}, H)$$



$$A_{\theta,h}$$



$$\hat{L}(A_{\theta,h})$$

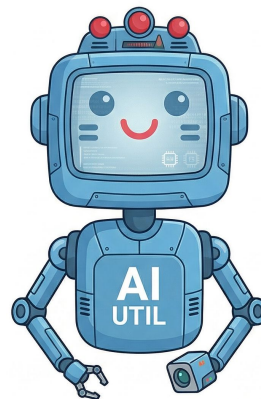
$$\theta' = \theta - \eta \nabla_{\theta} L$$

$$h' = h - \gamma \nabla_h L \quad ?$$

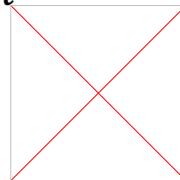


$$\theta = \theta'$$

$$h = h'$$



$$A_{\theta',h'}$$

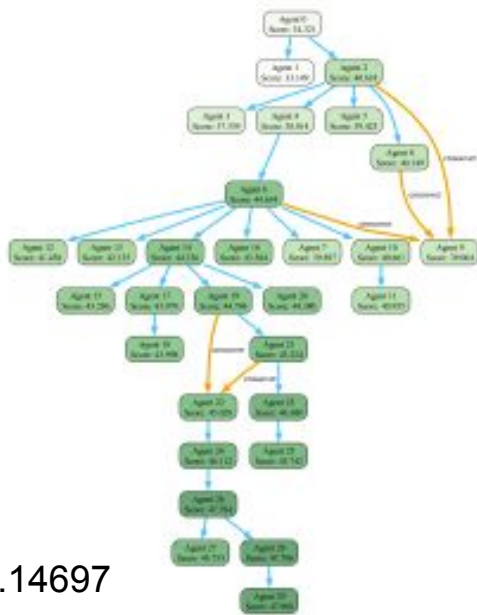


$$\hat{L}(A_{\theta',h'})$$

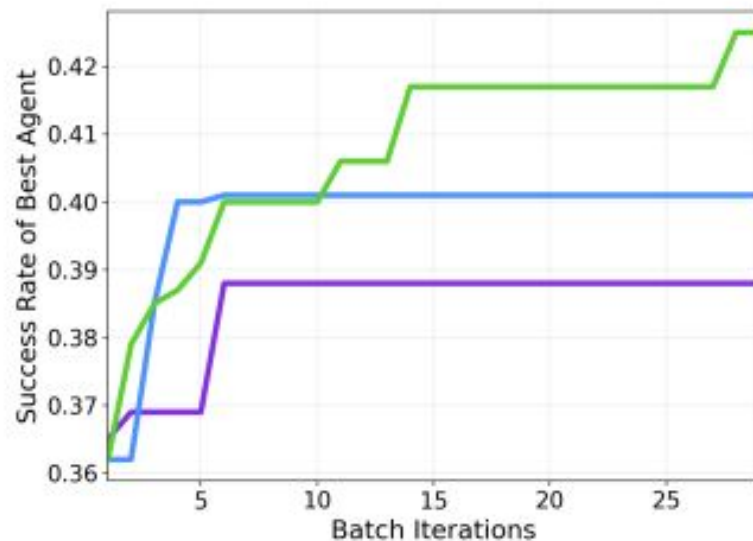
AIME → BeyondAIME

Easy-to-Hard Generalization

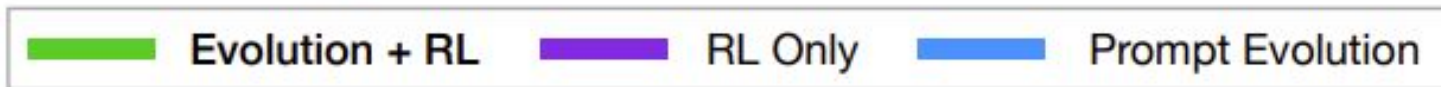
Agent Evolution Tree



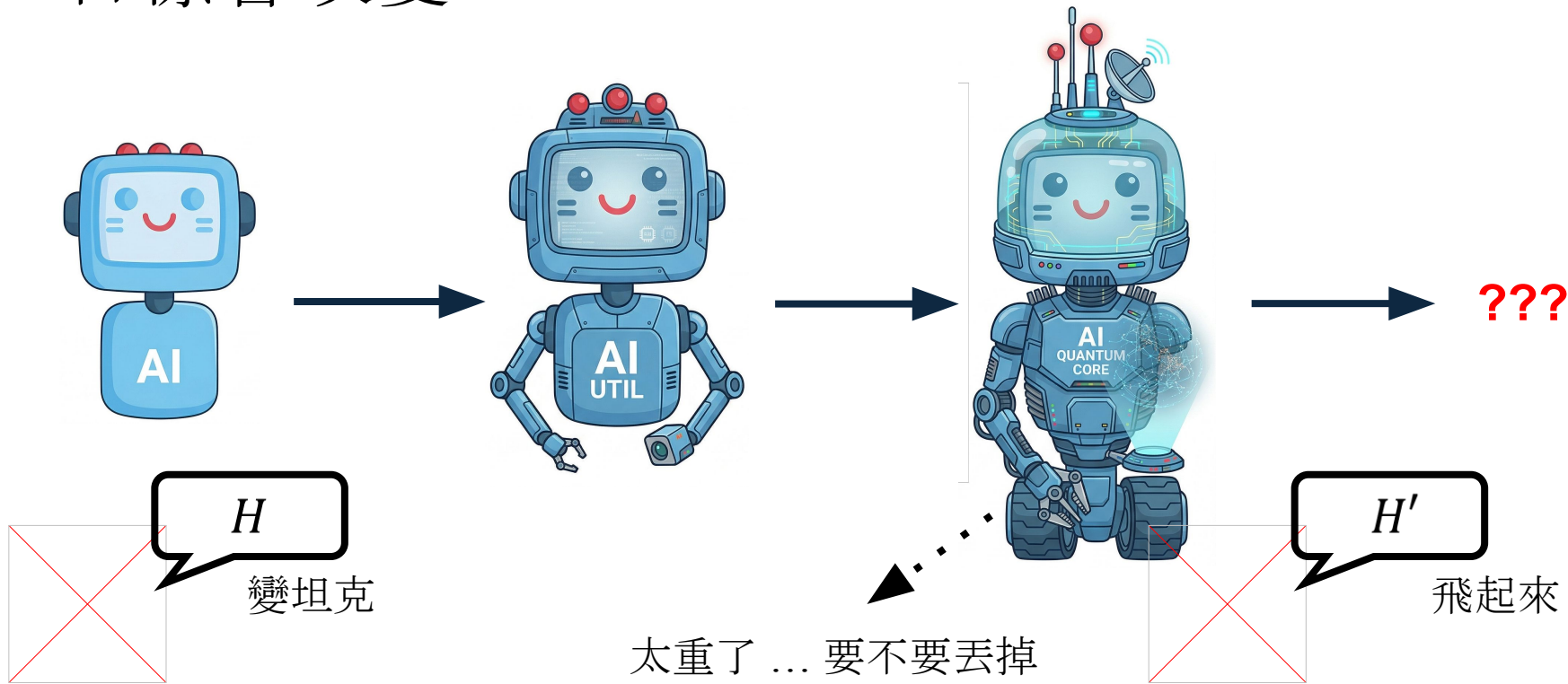
Eval on BeyondAIME



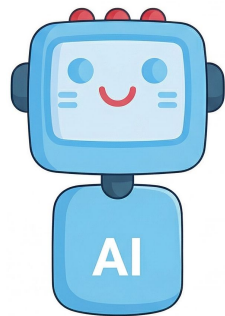
<https://arxiv.org/abs/2602.14697>



目標會改變



目標會改變

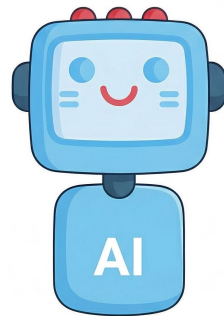


update

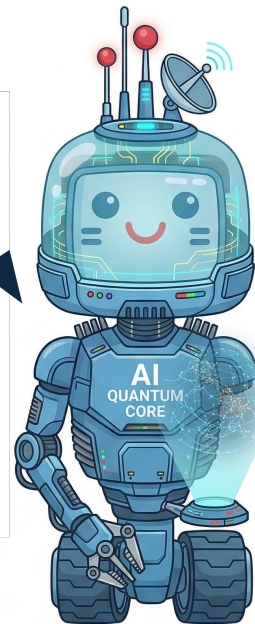


H

H'

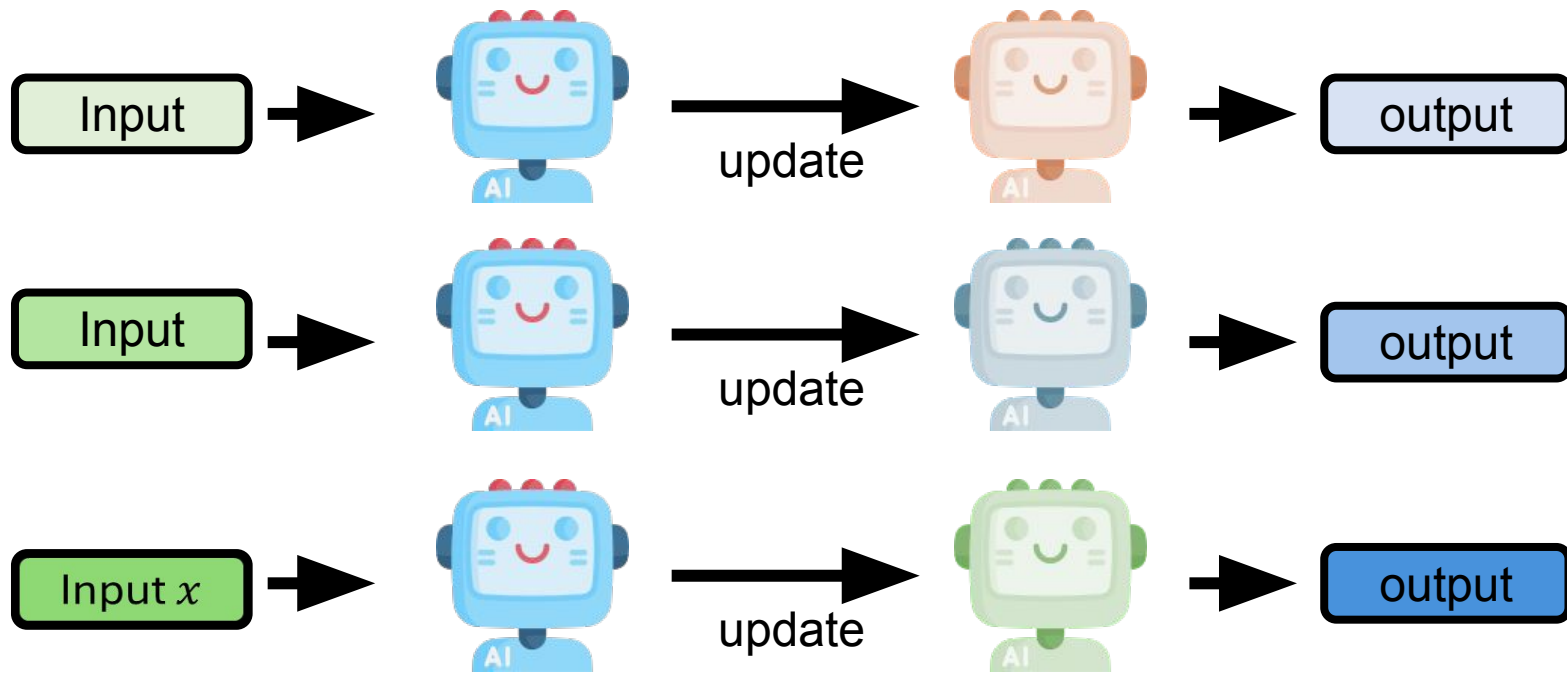


拋棄一切太
浪費了

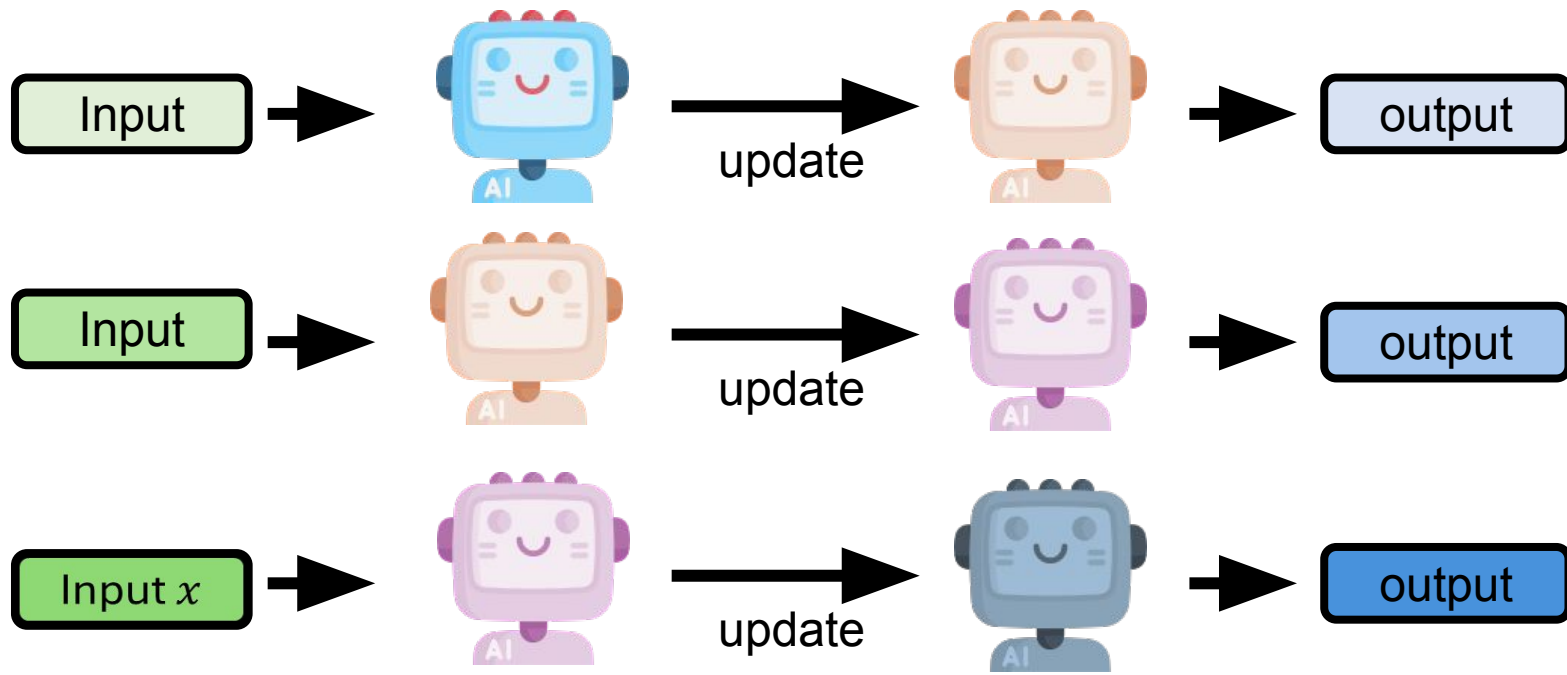


背負一切太
沉重了

目標會改變: Test Time Training (TTT)



目標會改變: Test Time Training (TTT)



目標會改變: Test Time Training (TTT)



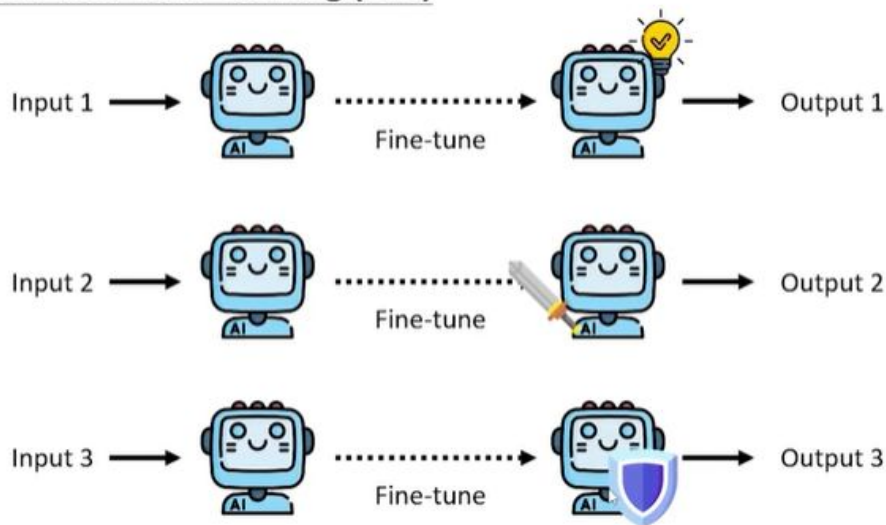
Wei-Ping Huang Guan-Ting Lin

<https://arxiv.org/abs/2406.11064>

1:54:30

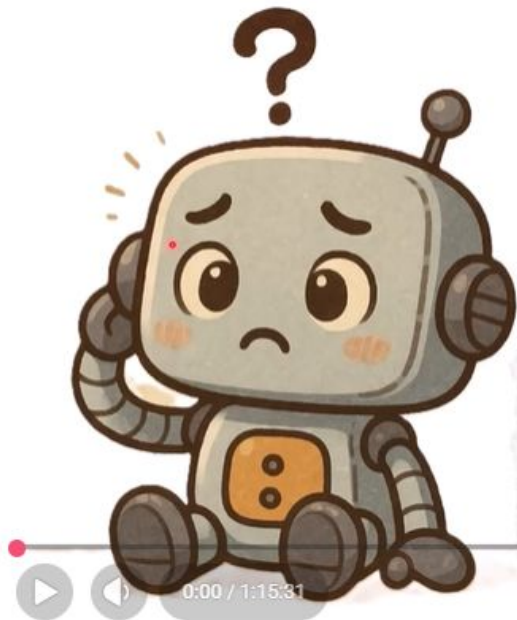
<https://youtu.be/EnWz5XuOnlQ?si=jDgXiXkWWkhlsPFR&t=6872>

Standard Test-Time Training (TTT)



【生成式人工智慧與機器學習導論2025】第 8 講：通用模型的終身學習 (Fine-tuning, Model Editing, Model Merging, Test-Time Training)

目標會改變：避免遺忘



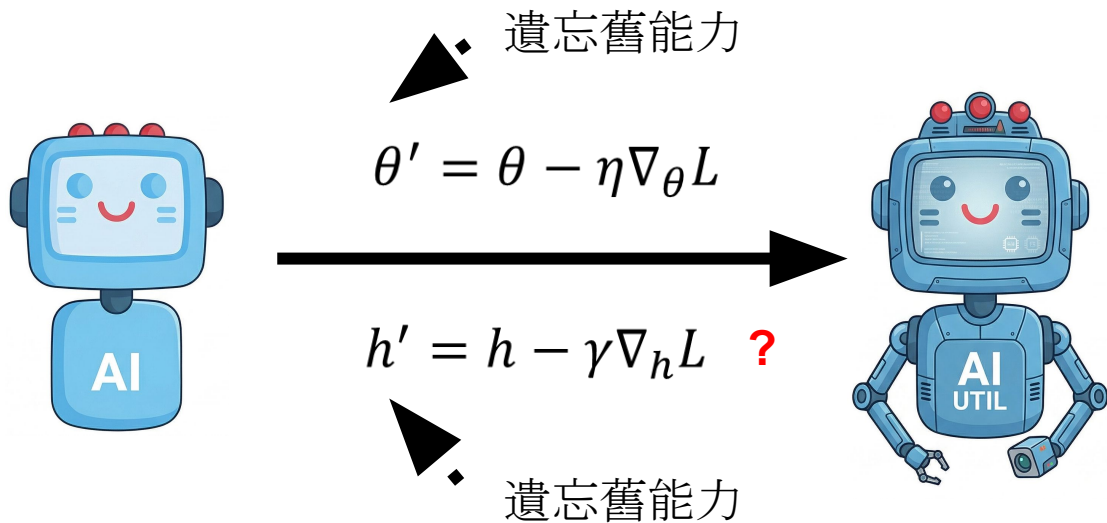
Post-Training &
Forgetting
後訓練與遺忘

<https://youtu.be/Z6b5-77EfGk?si=kAyIOZ2Me9-8jFLh>

【生成式AI時代下的機器學習(2025)】第六講：生成式人工智慧的後訓練(Post-Training)與遺忘問題

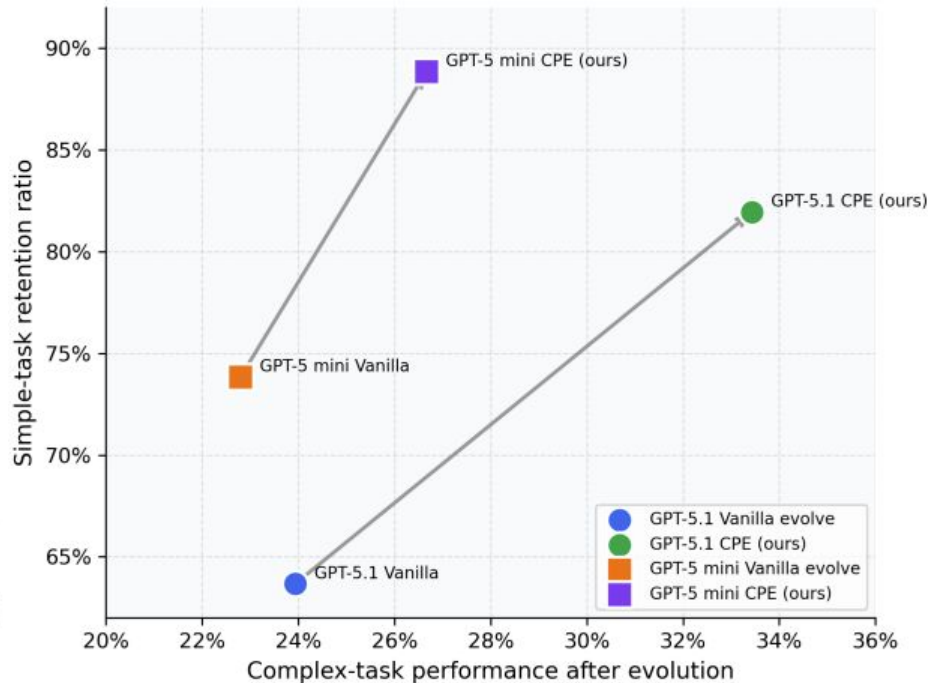
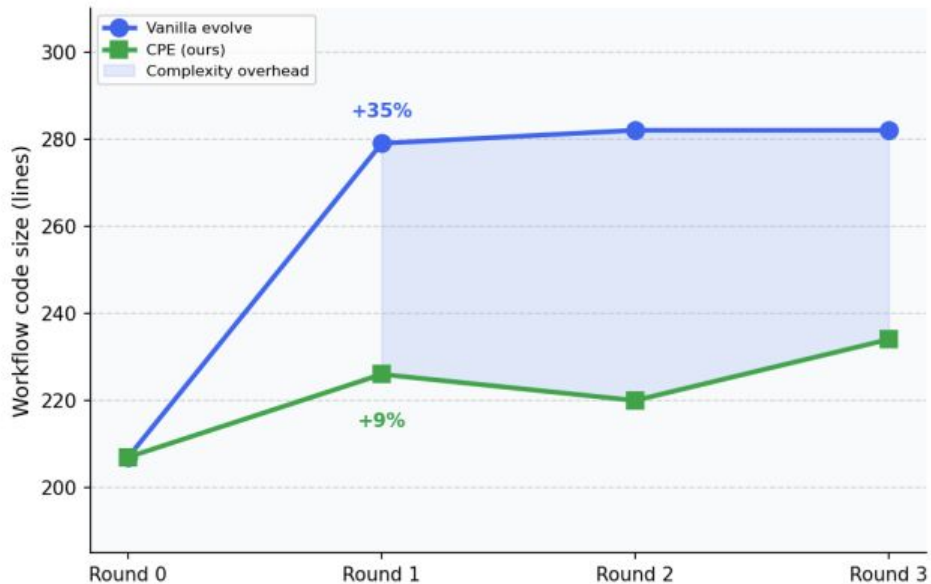
目標會改變：避免遺忘

<https://arxiv.org/abs/2605.09315>

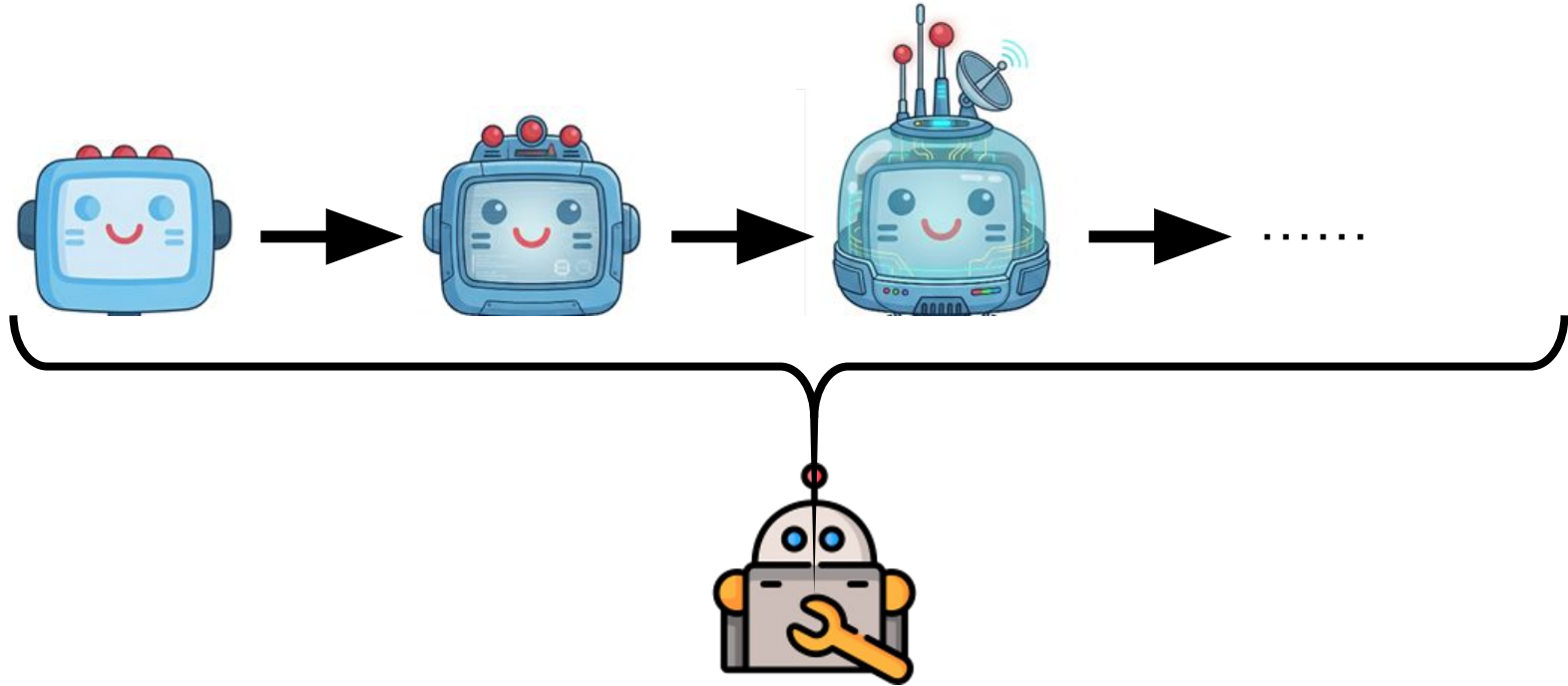


目標會改變：避免遺忘

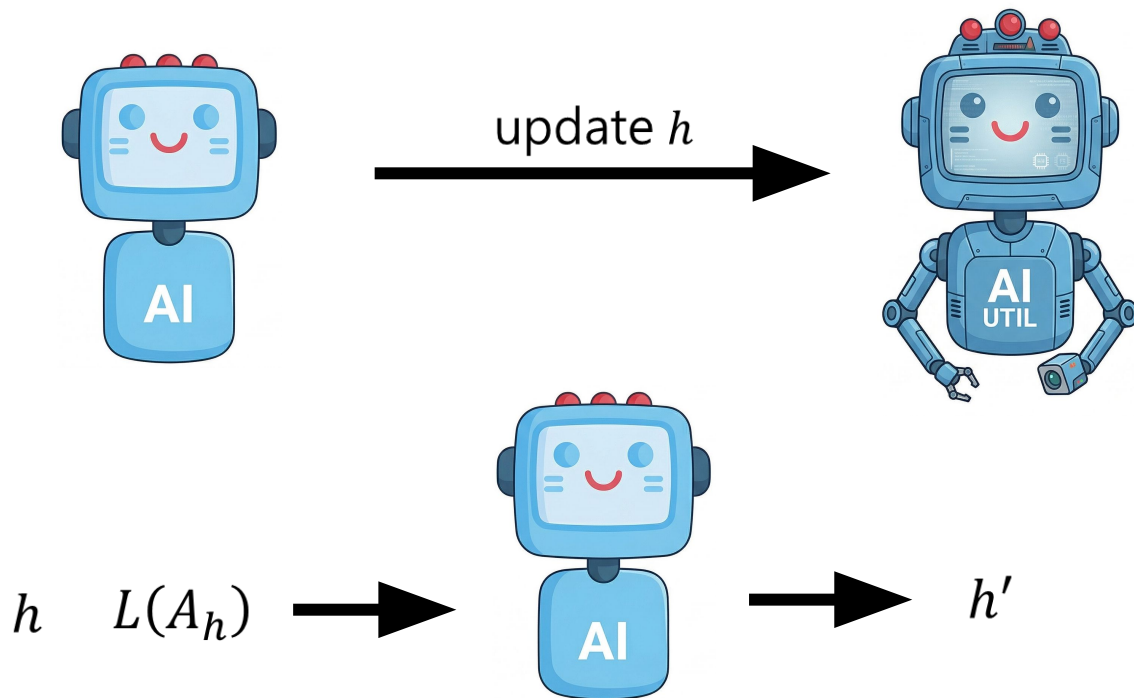
<https://arxiv.org/abs/2605.09315>



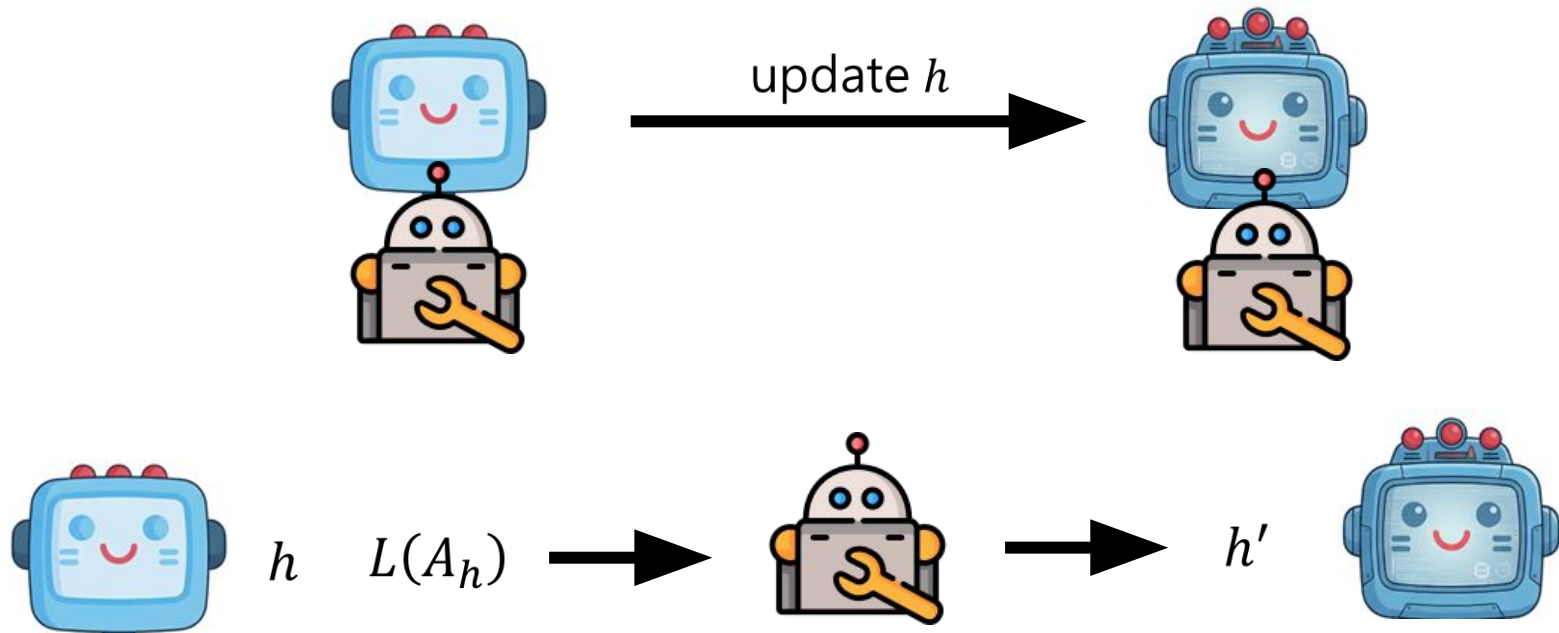
Improvement module controls how to improve.



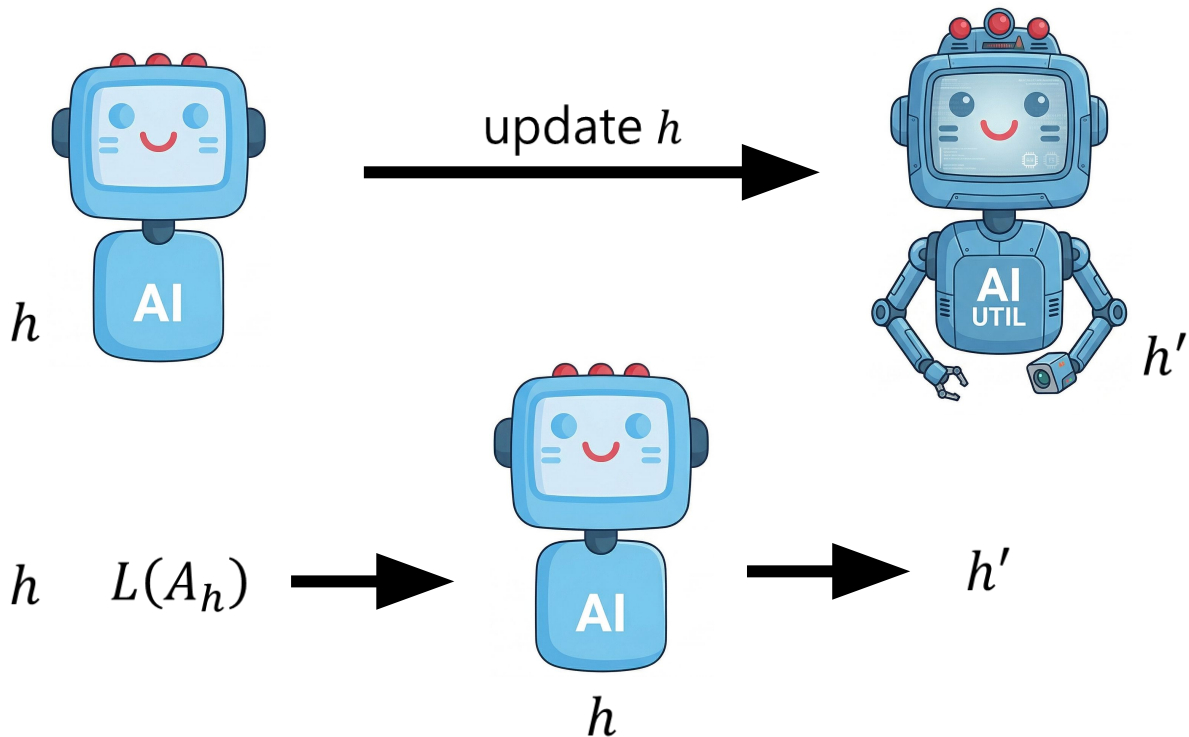
How to improve harness?



How to improve harness?

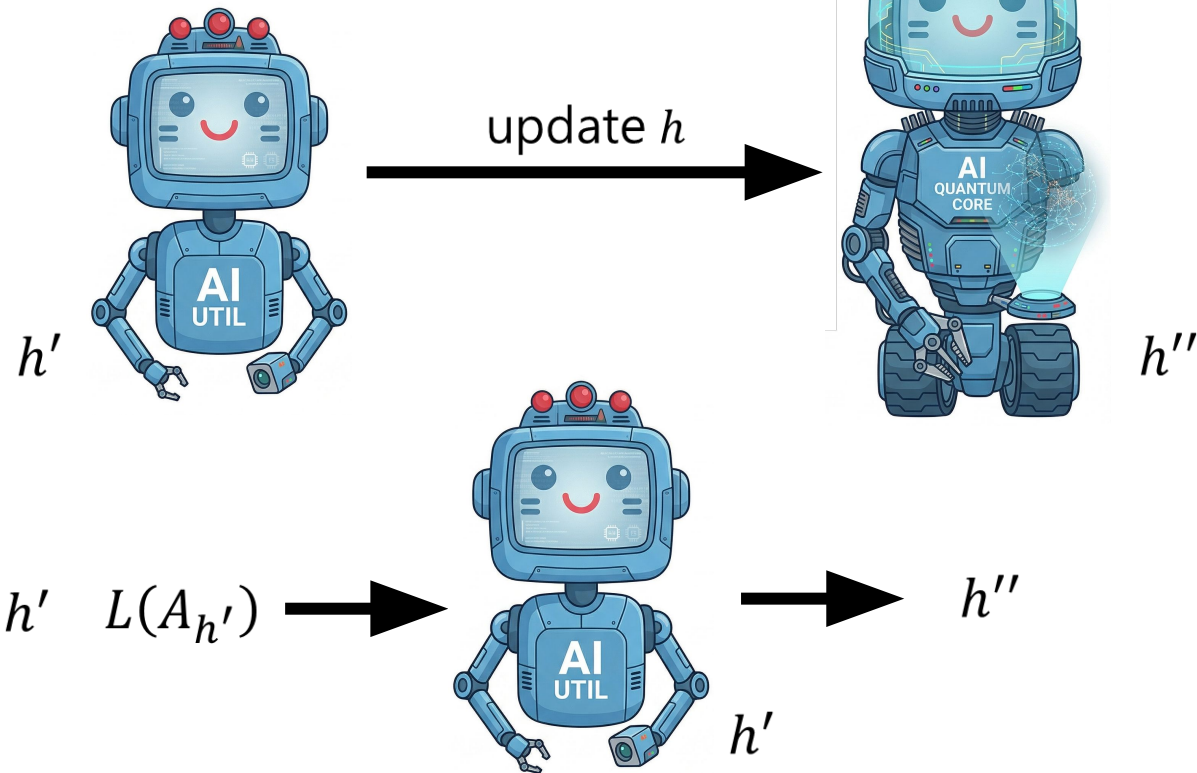


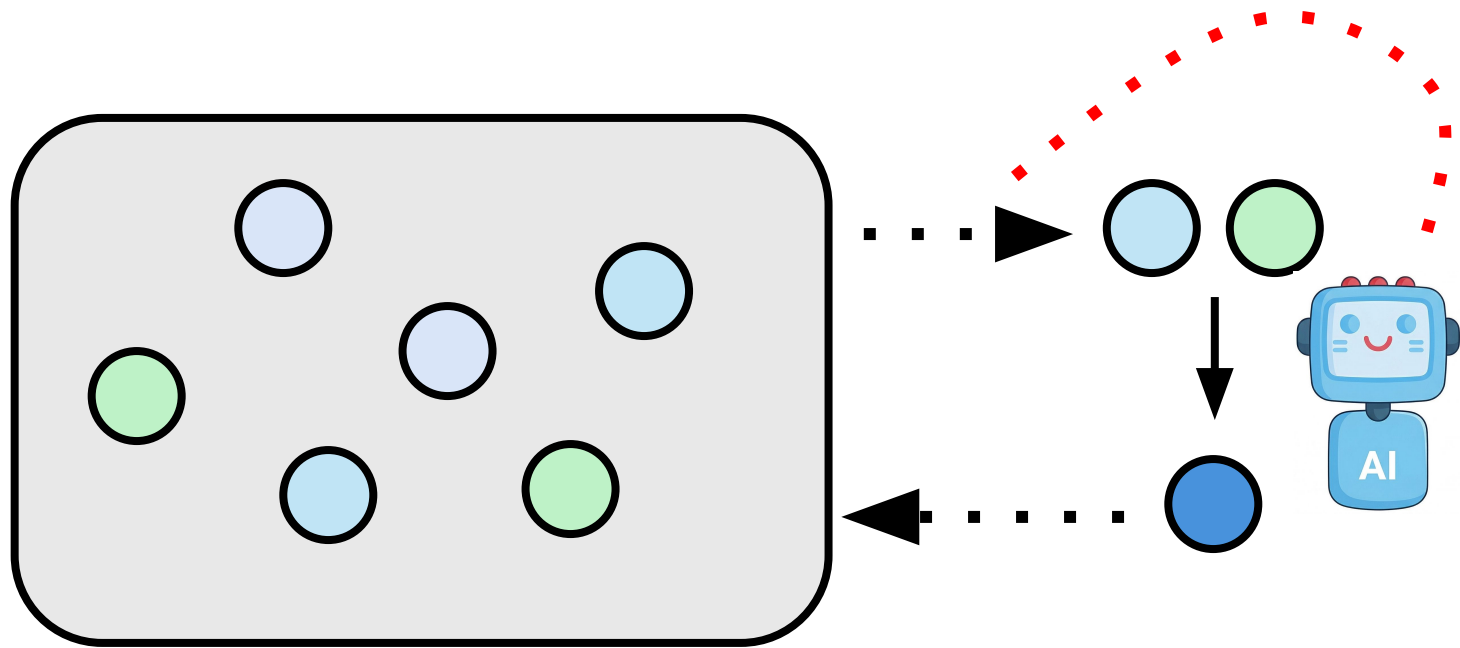
How to improve “improve harness”?



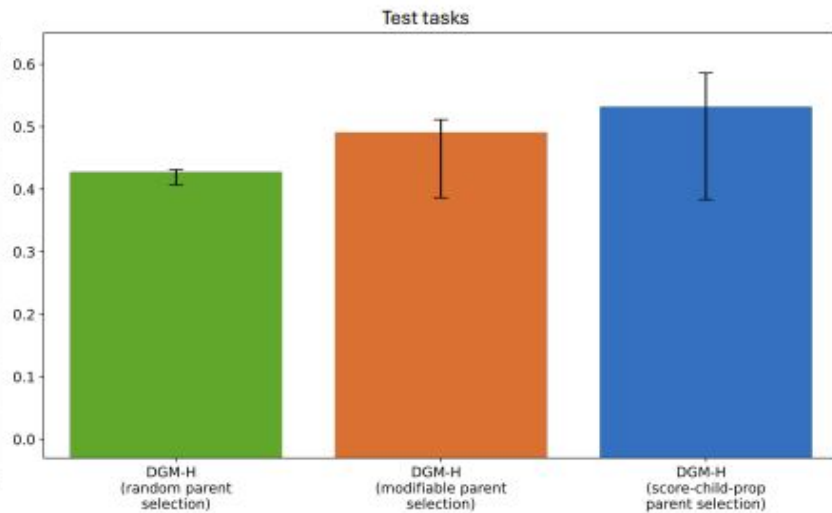
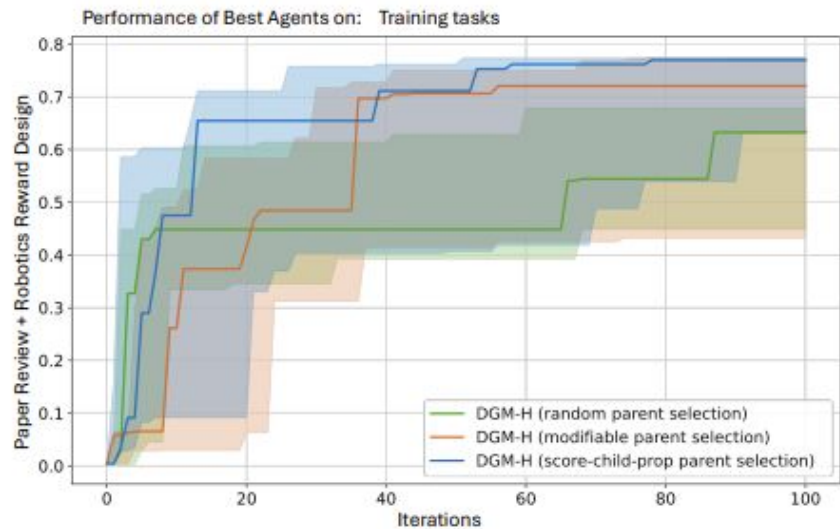
HyperAgent <https://arxiv.org/abs/2603.19461>

Gödel Agent <https://arxiv.org/abs/2410.04444>





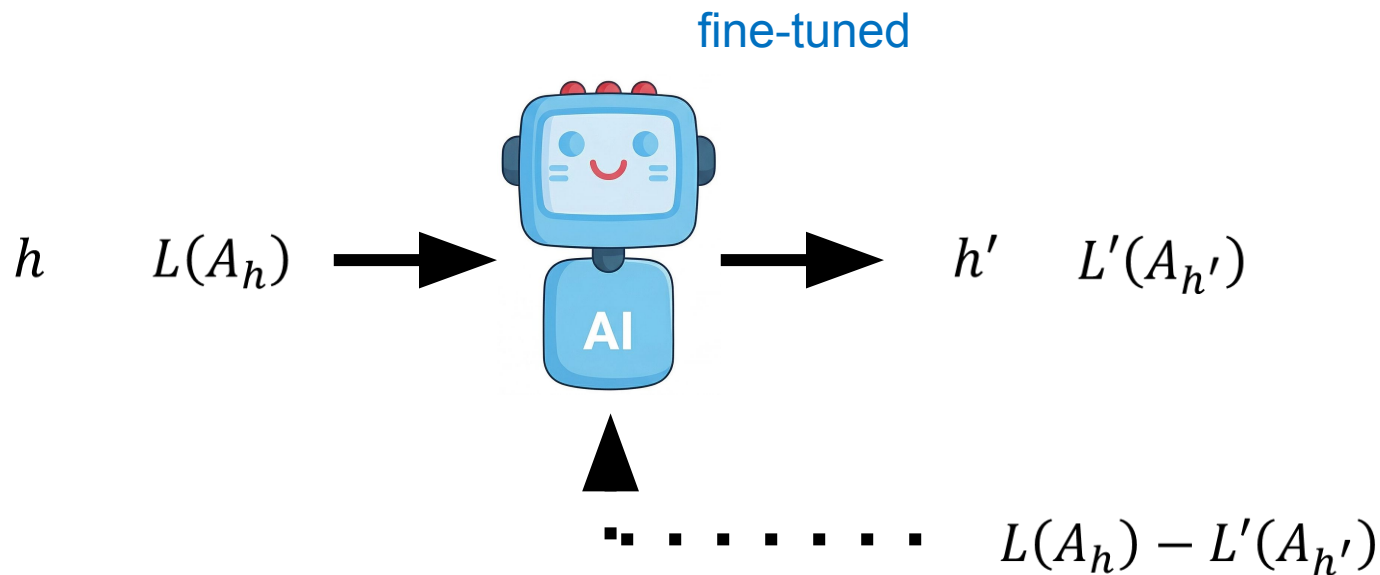
HyperAgent <https://arxiv.org/abs/2603.19461>



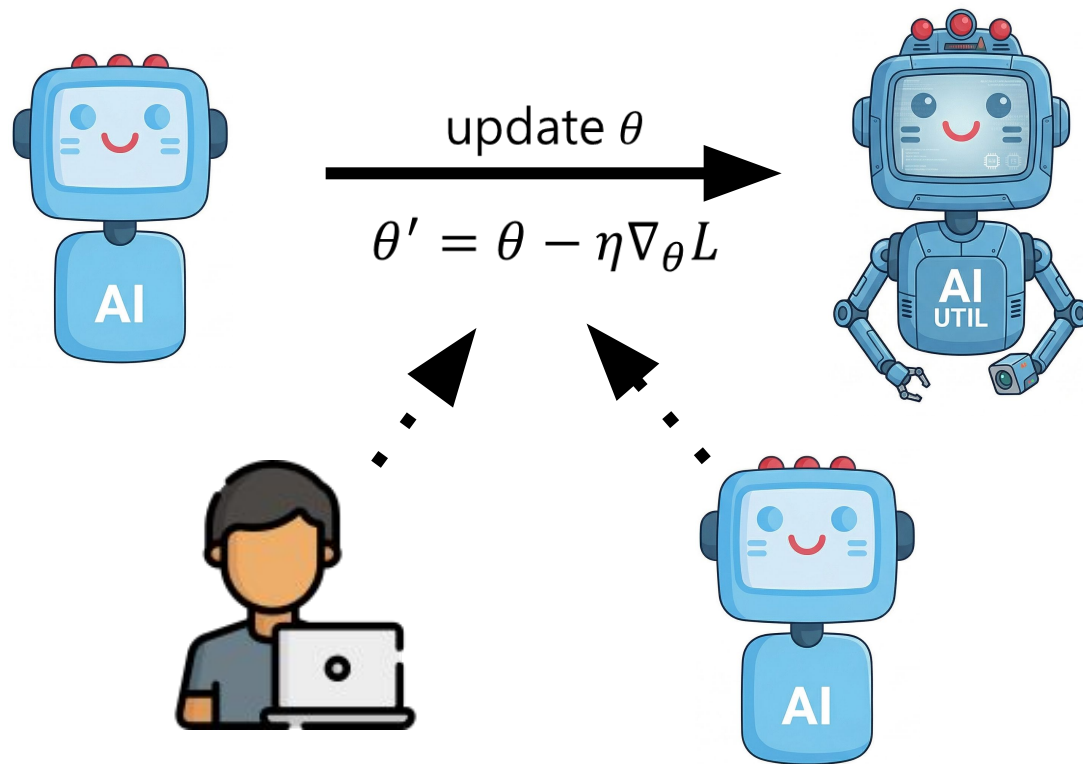
<https://arxiv.org/abs/2603.19461>

How to improve “improve harness”?

Learning to Self-Evolve <https://arxiv.org/abs/2603.18620>



Update Parameters



上次在課程接近結尾的時候有提到

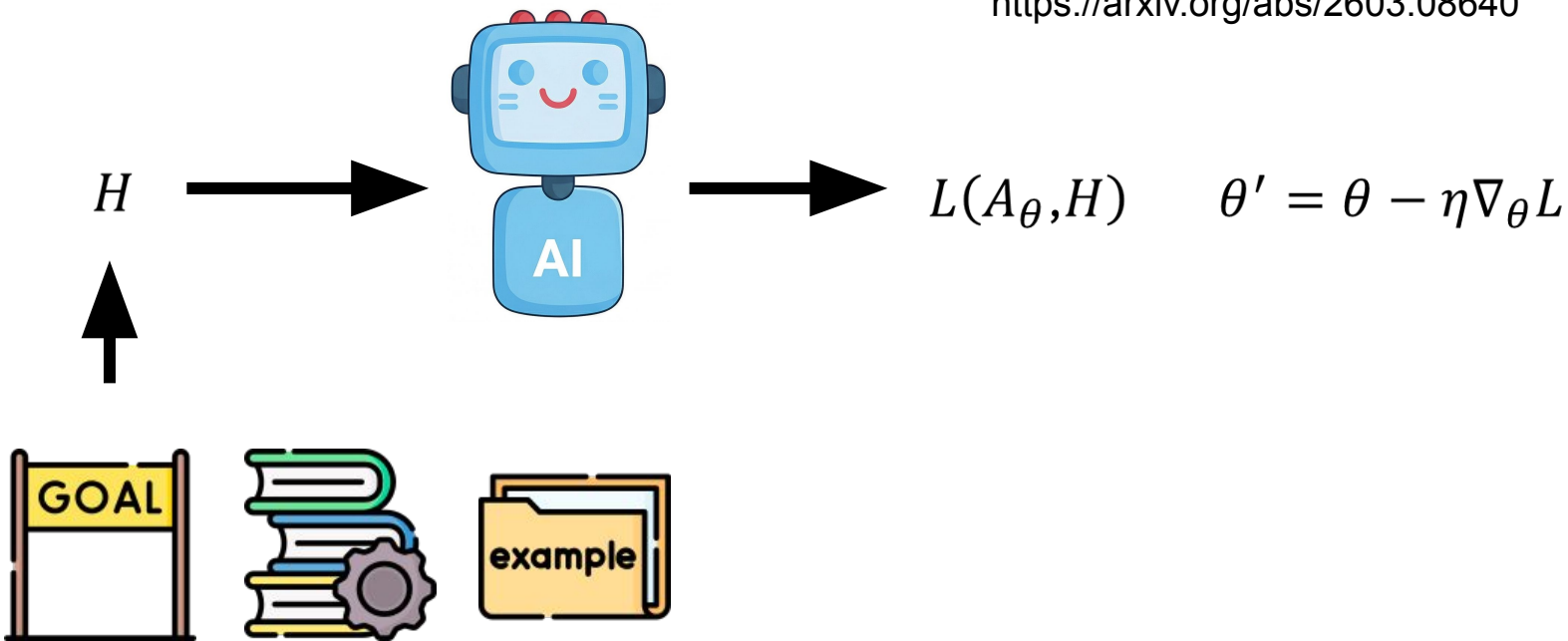


52:17

[https://youtu.be/s06mSAGN4gM?
si=1VAkFCUUheM3kqaz&t=3137](https://youtu.be/s06mSAGN4gM?si=1VAkFCUUheM3kqaz&t=3137)

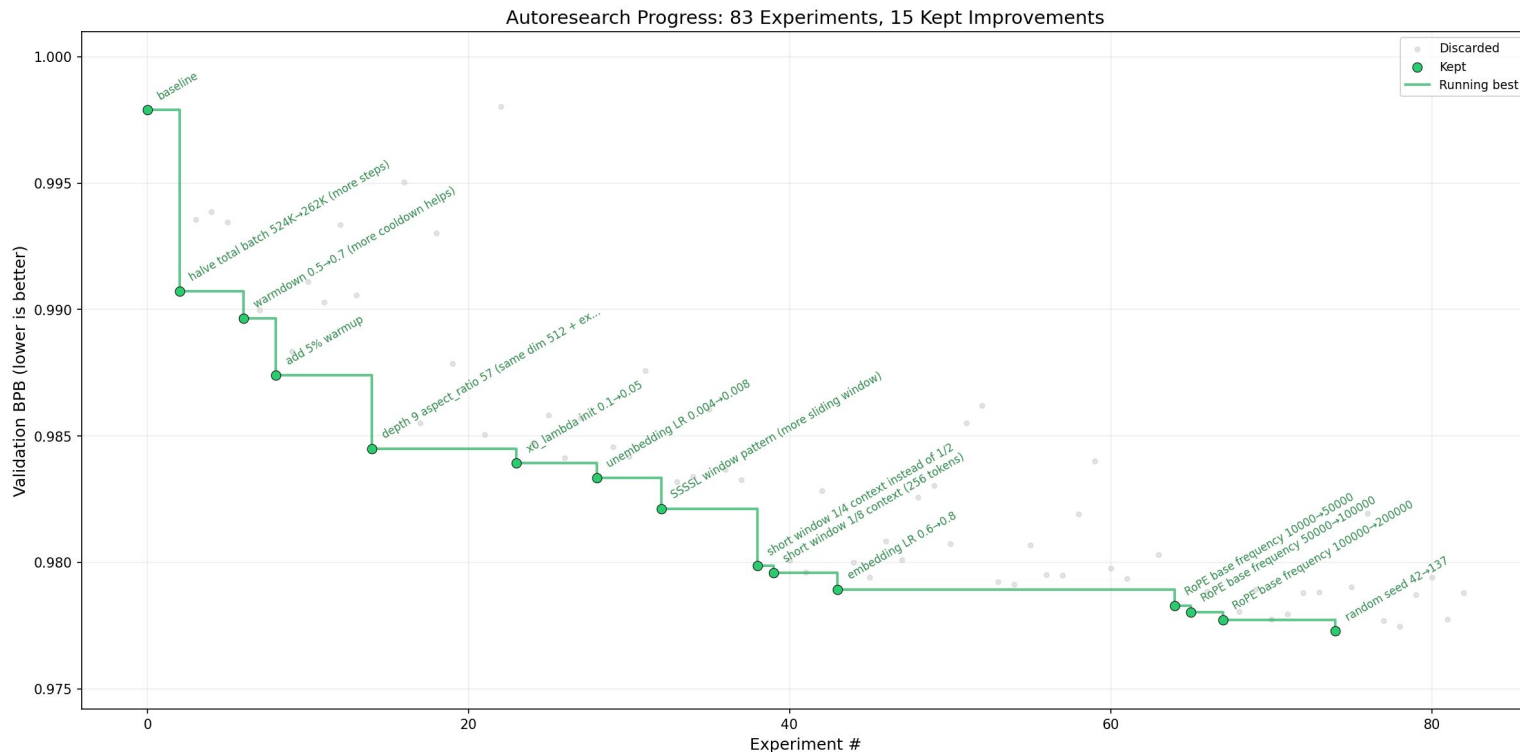
Update Parameters

<https://arxiv.org/abs/2603.08640>



Update Parameters

<https://github.com/karpathy/autoresearch>



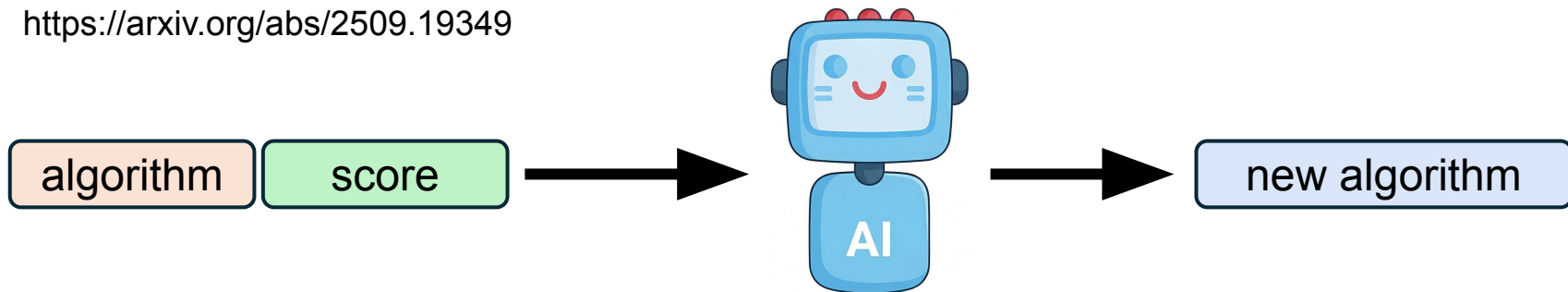
Learn to “Update Parameters”

Alpha Evolve

<https://deepmind.google/blog/alphaevolve-a-gemini-powered-coding-agent-for-designing-advanced-algorithms/>

Shinka Evolve

<https://arxiv.org/abs/2509.19349>



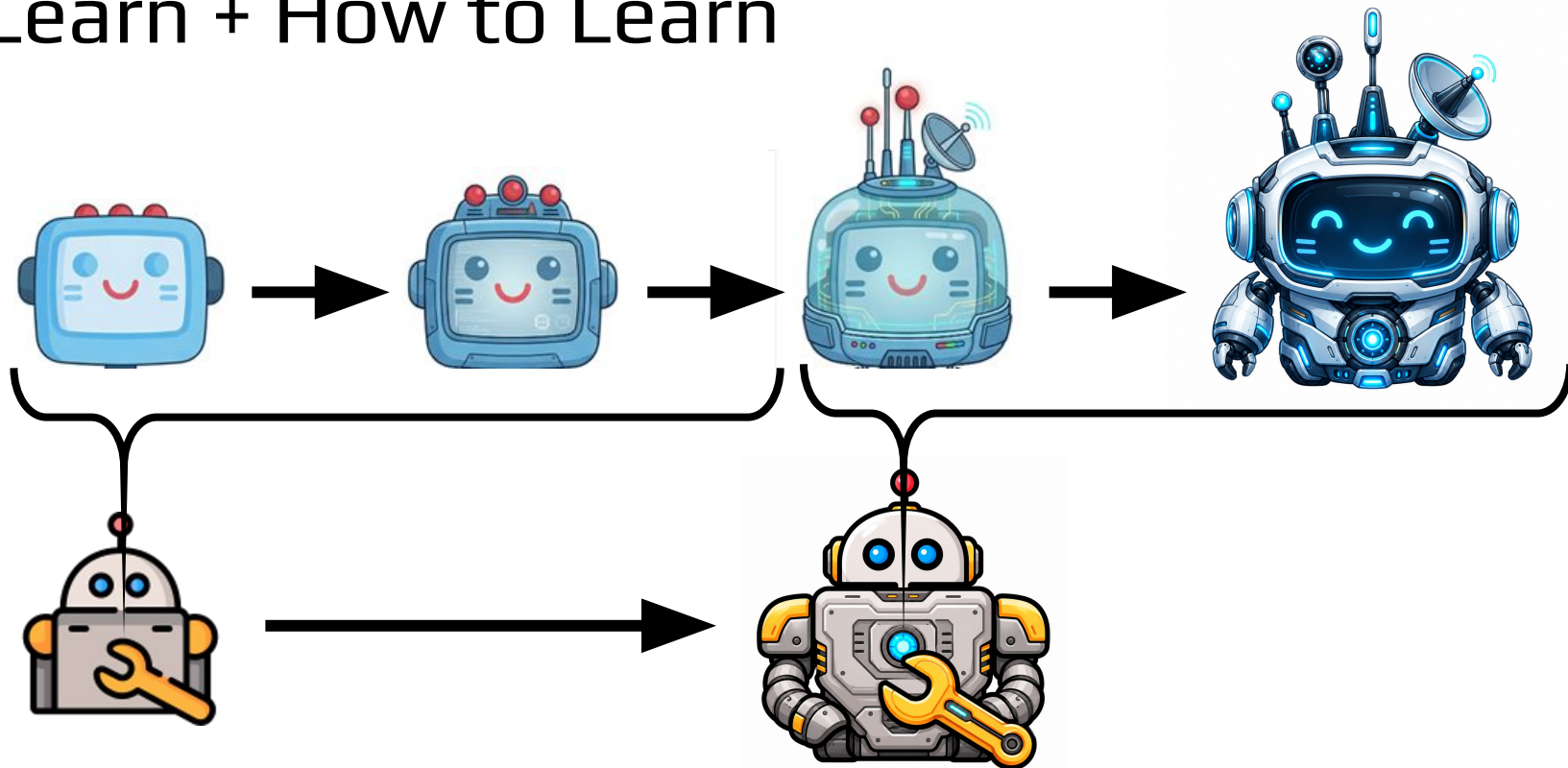
Learn to “Update Parameters”

Self-Adapting LLMs (SEAL)

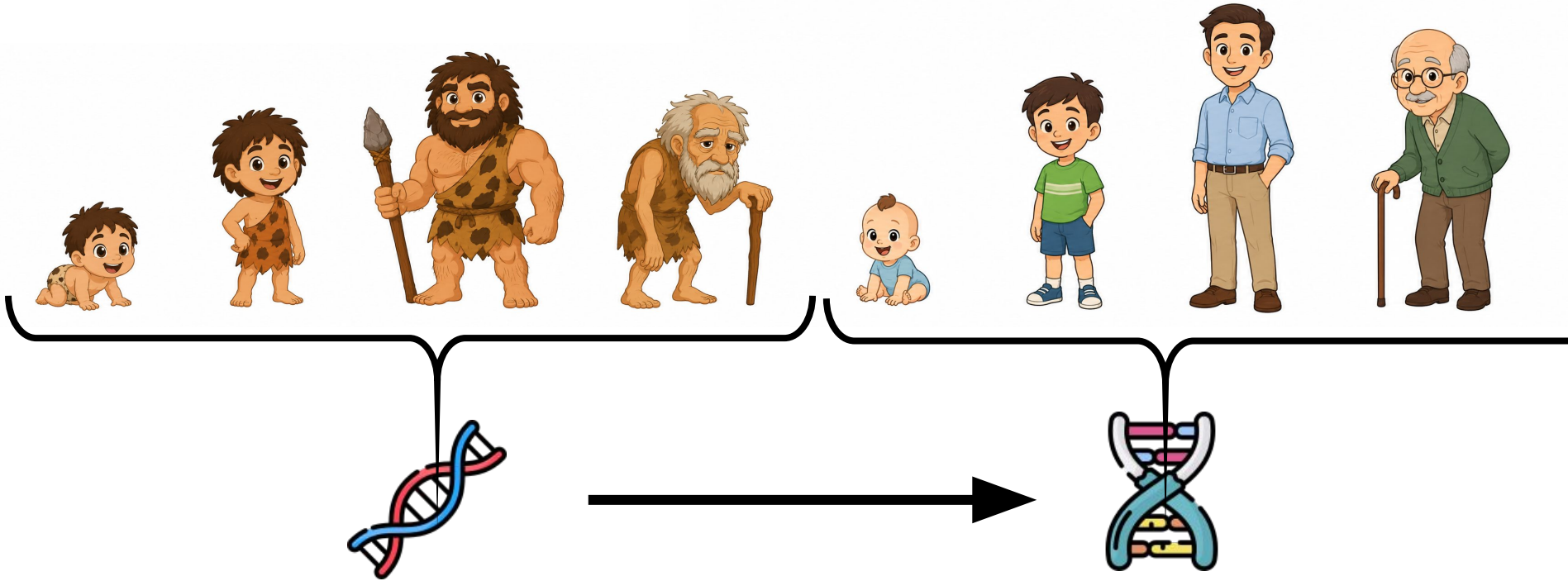
RL Outer Loop Iteration t



Learn + How to Learn



Learn + How to Learn

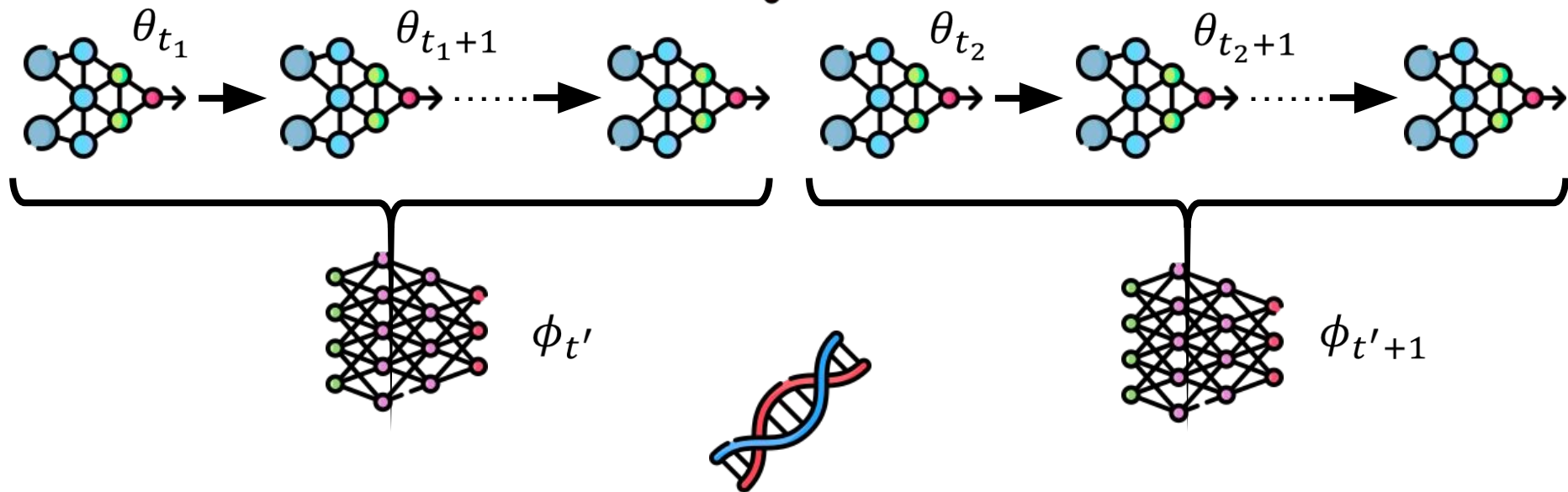


Learn + How to Learn

$$\theta_{t_1+1} = F(\theta_{t_1}; \phi_{t'})$$



$$\theta_{t_2+1} = F(\theta_{t_2}; \phi_{t'+1})$$



Meta Learning

Meta Learning:
Learn to learn

Hung-yi Lee

What does "meta" mean? $\text{meta-X} = \text{X about X}$



0:01 / 46:19

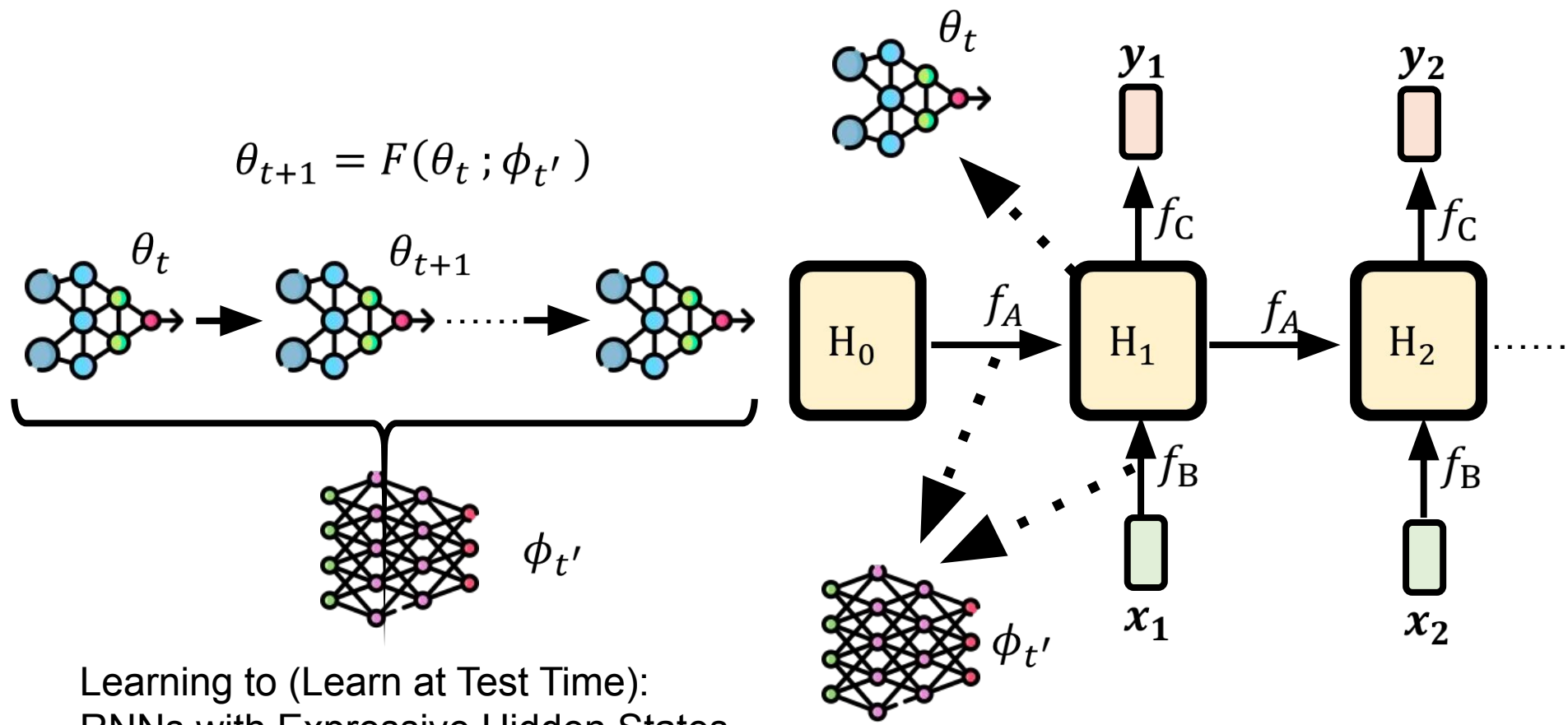


【機器學習2021】元學習 Meta Learning (一) - 元學習跟機器學習一樣也是三個步驟



【機器學習2021】元學習 Meta Learning (二) - 萬物皆可 Meta

<https://youtu.be/xoastiYx9JU?si=7rW7ULj1Zwj1MzNS> <https://youtu.be/Q68Eh-wm1Ts?si=Y-A9SEafbre6-zhf>



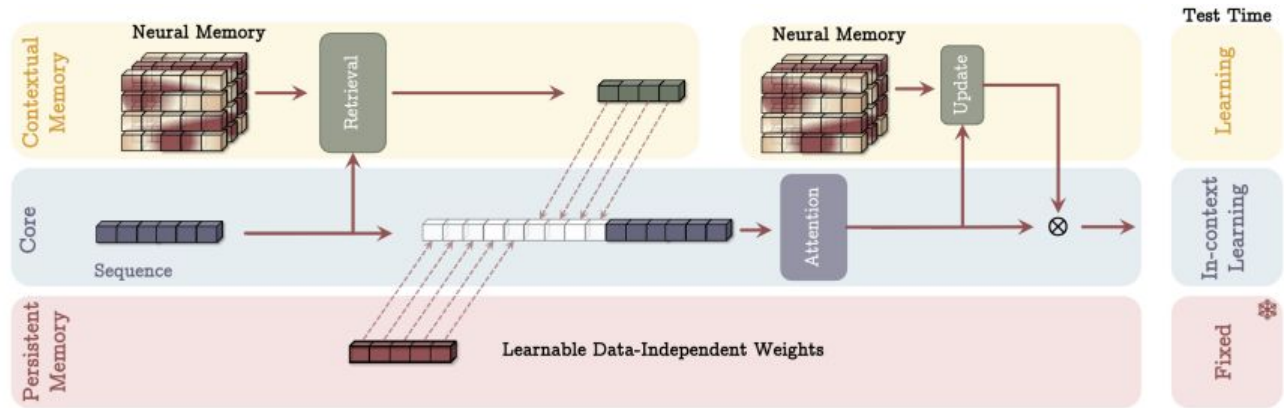
Learning to (Learn at Test Time):
 RNNs with Expressive Hidden States
<https://arxiv.org/abs/2407.04620>

Transformer 的競爭者們



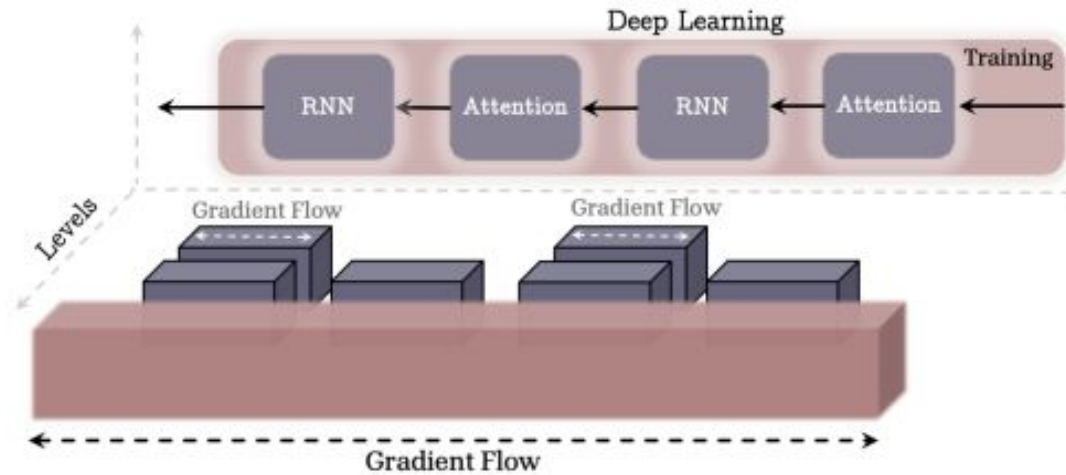
【生成式AI時代下的機器學習(2025)】第四講：Transformer 的時代要結束了嗎？介紹
Transformer 的競爭者們

<https://youtu.be/gjsdVi90yQo?si=voyQ4GivpFn8SXIC>



Titans

<https://arxiv.org/abs/2501.00663>



Nested Learning

<https://arxiv.org/abs/2512.24695>

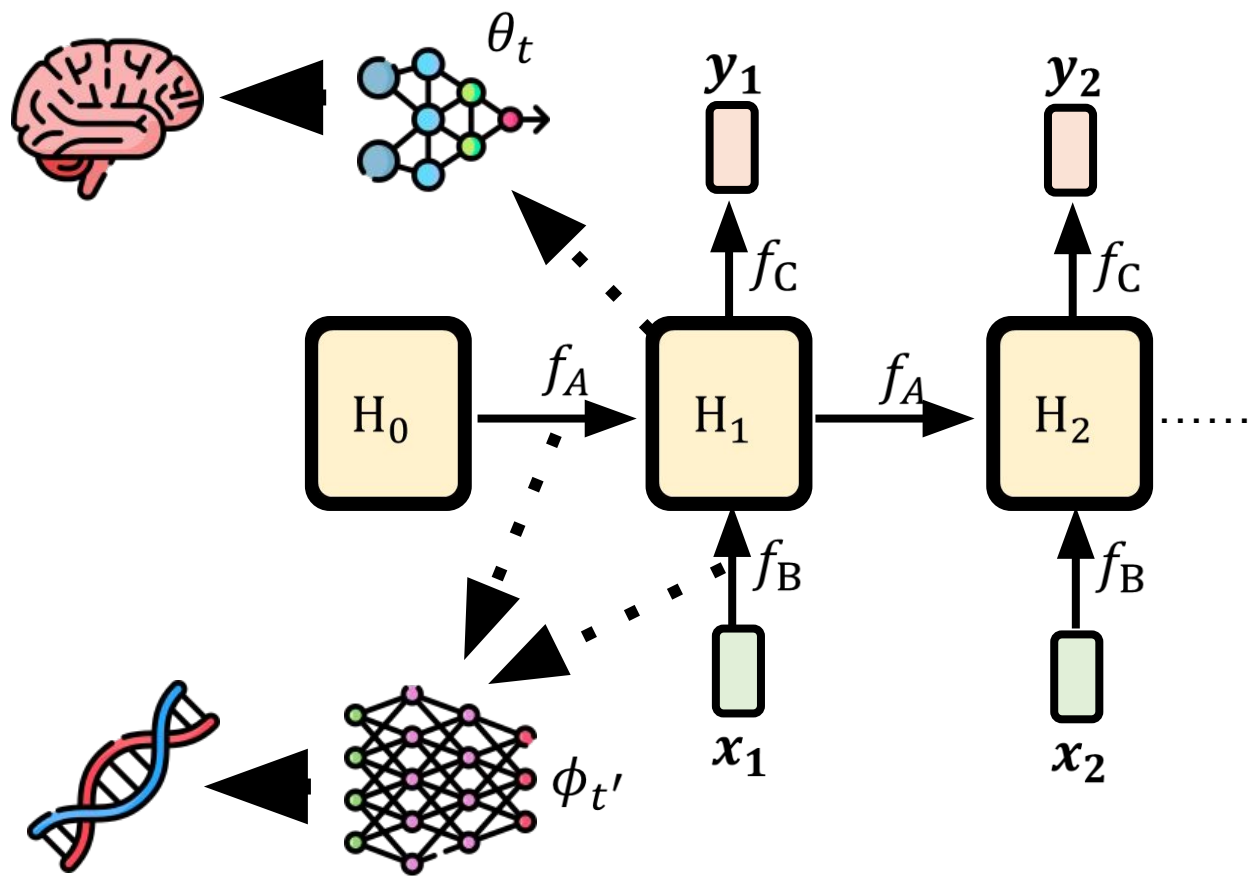
何謂「學習」？

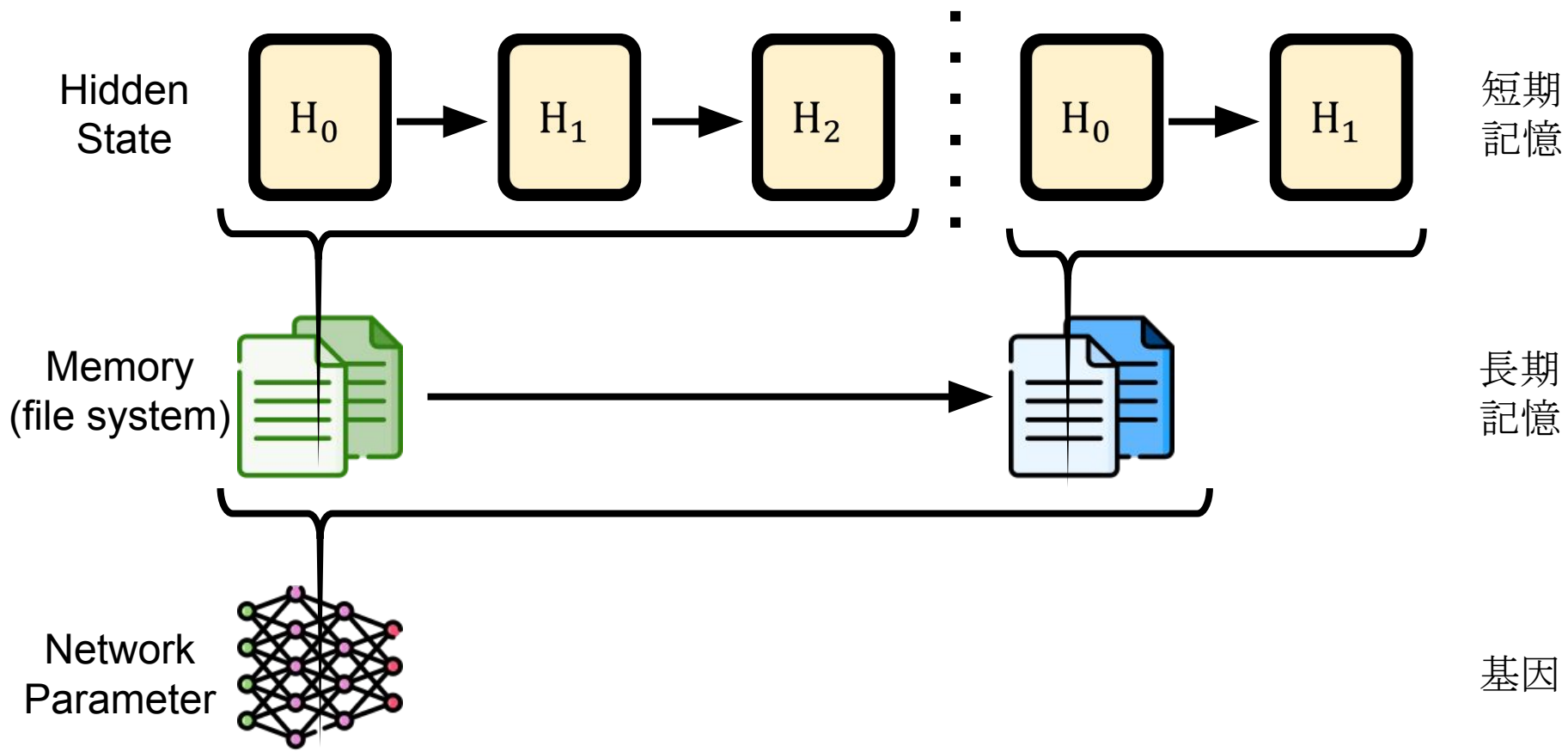
人類
學習



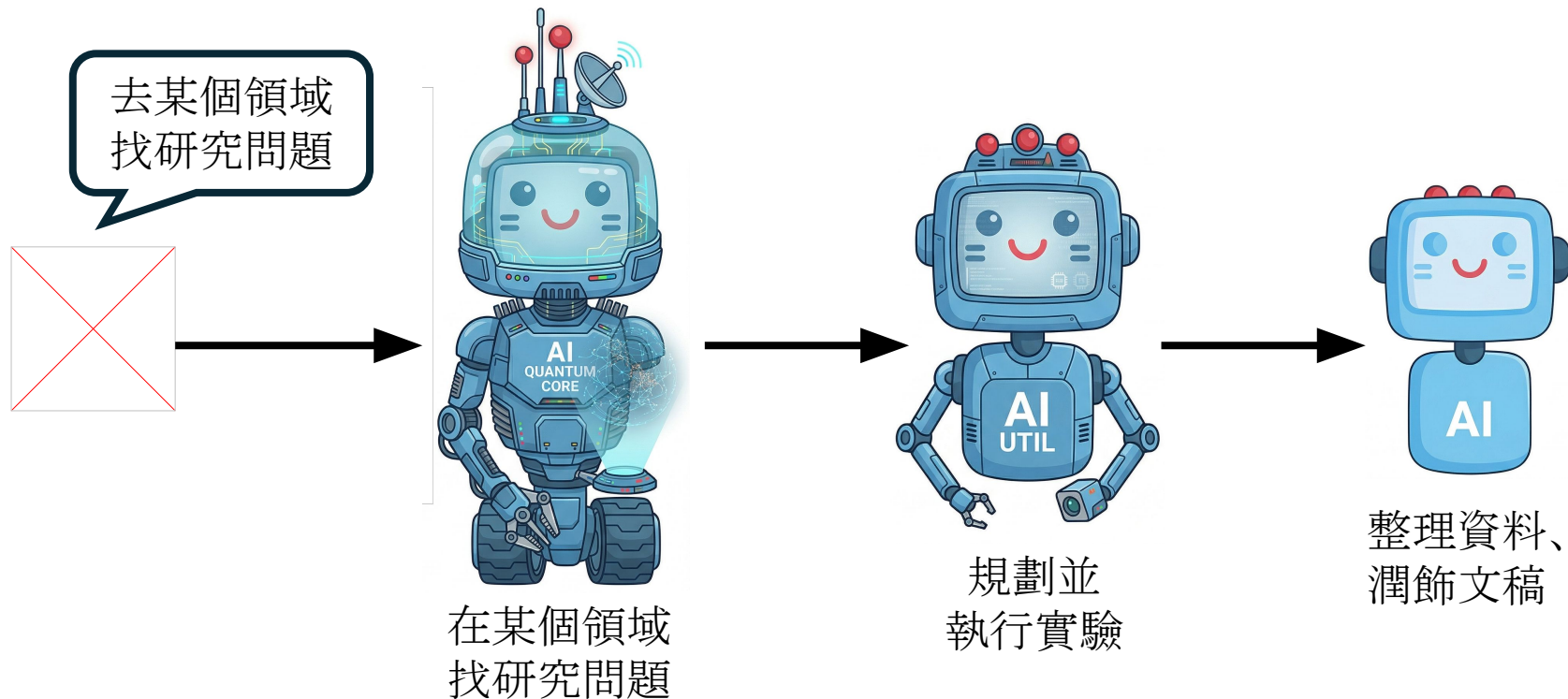
機器
學習



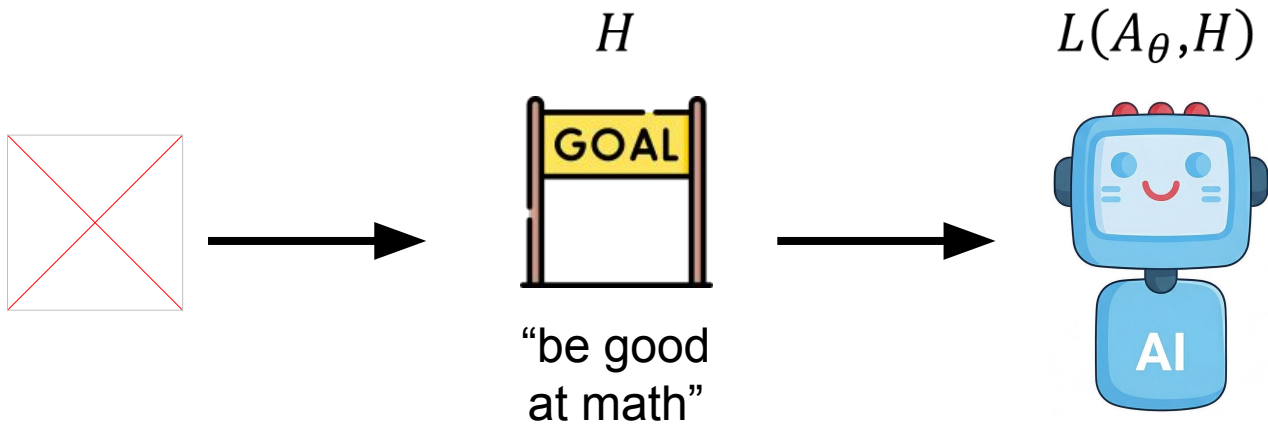




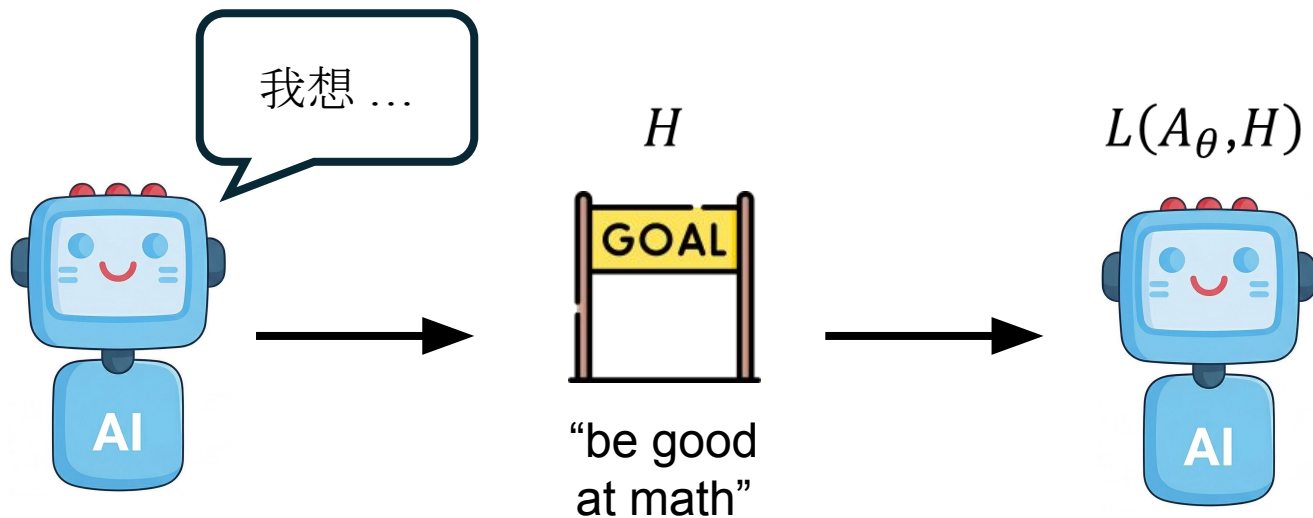
Intrinsic Motivation



Intrinsic Motivation



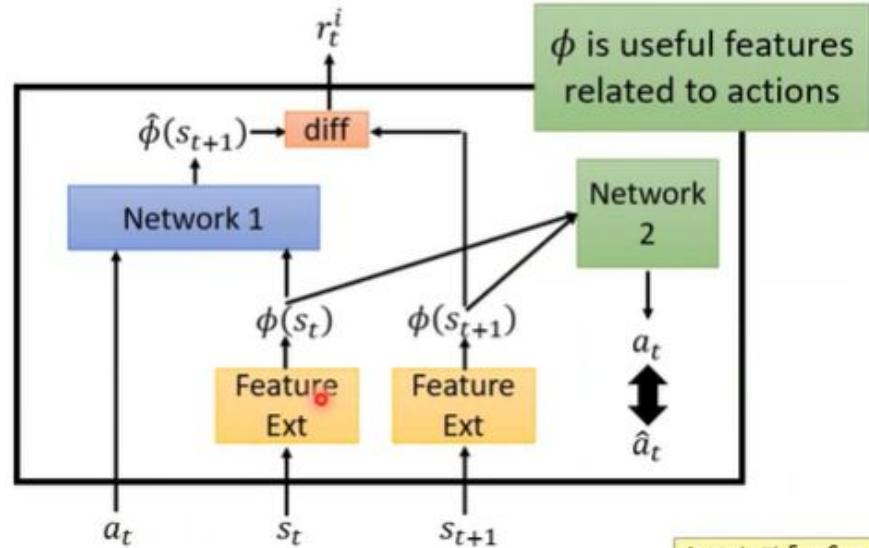
Intrinsic Motivation



- Curiosity-driven
- Empowerment

<https://arxiv.org/abs/1705.05363>
<https://arxiv.org/abs/1810.12894>
<https://arxiv.org/abs/2505.17621>
<https://arxiv.org/abs/1509.08731>
<https://arxiv.org/pdf/2506.06725>

Intrinsic Curiosity Module

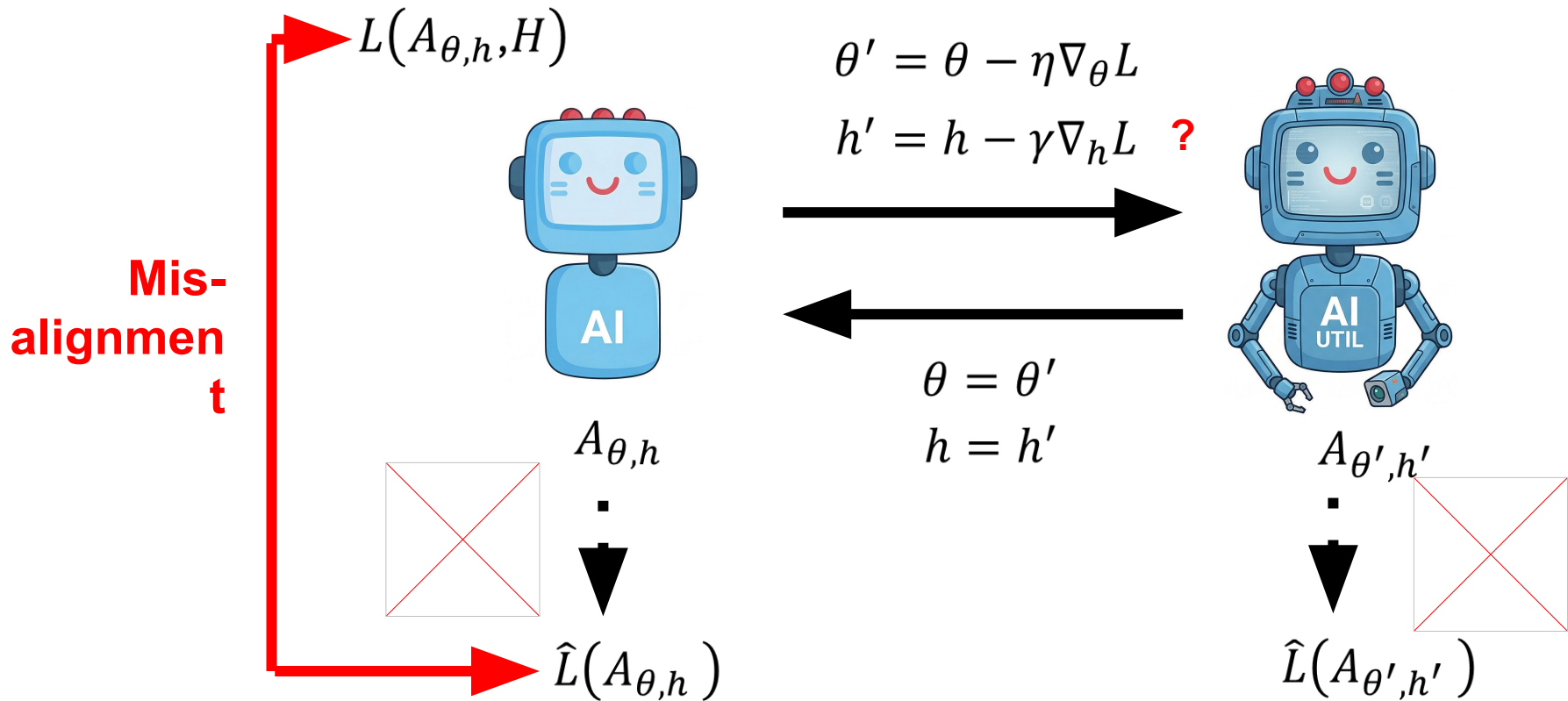


Created with EverCam.
<http://www.camdemy.com>

<https://youtu.be/-5cCWhu0OaM?si=-/ &t=547>

DRL Lecture 7: Sparse Reward

成長會失控嗎？



成長會失控嗎？

1. 原始狀態

孔雀尾巴原本較短，
雌孔雀會偏好尾巴較長的雄孔雀。



雌孔雀偏好
尾巴較長的雄孔雀

2. 性擇作用

尾巴稍長的雄孔雀更受歡迎，
有更多交配機會，
將基因傳給下一代。



尾巴越長 → 越受歡迎 →
更多後代

3. 持續加強

經過許多世代，
尾巴越來越長、越華麗，
但這對生存幫助不大，
甚至可能增加負擔
(例如：更容易被天敵發現、
飛行不便)。



尾巴持續變長，
但生存成本增加

4. 失控的演化

性擇讓尾巴不斷被放大，
即使已經不利生存，
這就是「失控的演化」
(Runaway Evolution)。



尾巴過度誇張，
成為負擔，仍持續被偏好

成長會失控嗎？

長尾代表身體
健康，容易活下
去

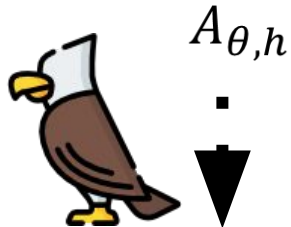
$$\leftarrow L(A_{\theta,h}, H)$$



Mis-
alignmen
t

活下去

$$\leftarrow \hat{L}(A_{\theta,h})$$



$$\hat{L}(A_{\theta,h})$$

$$\theta' = \theta - \eta \nabla_{\theta} L$$

$$h' = h - \gamma \nabla_h L \quad ?$$



$$\theta = \theta'$$

$$h = h'$$



$$A_{\theta',h'}$$



$$\hat{L}(A_{\theta',h'})$$

成長會失控嗎？

電影《機械公敵》

\hat{L}

(人類
福祉)

H

$L(H)$

