歡迎大家報名
ACML 2025

課程 14:23 開始

通用模型的終身學習

李宏毅

通用模型的誕生過程

Pre-train **SFT** **RLHF**

人工智慧的學習到此並未結束，而是新的開始

不是指用 Prompt 改變模型的行為

通用模型仍需要持續學習 (更新參數)

Foundation Model

Pre-trained / Base Model

Post-Training

Continual Learning

Life-long Learning

Alignment

Fine-tuned Model

Chat / Instruct Model

通用模型仍需要持續學習 (更新參數)

Foundation Model

過去的學習歷程不明

(這是其他人打造的現成模型)

Post-Training

Continual Learning

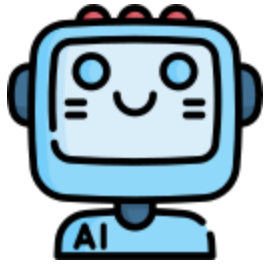
Life-long Learning

Fine-tuned Model

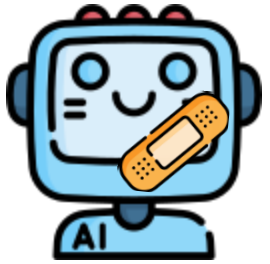
通用模型仍需要持續學習 (更新參數)

新知識

2024 年

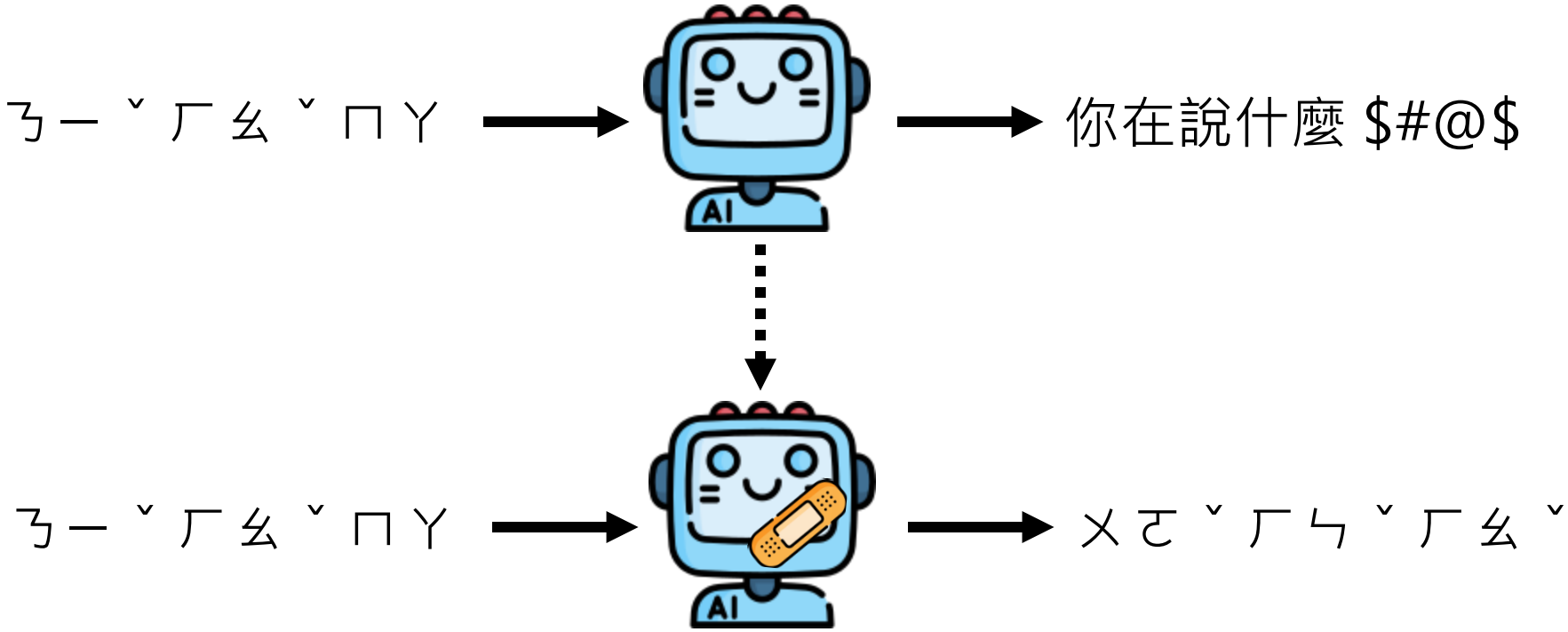
現任美國總統是誰？ →  → 拜登 (Biden)

2025 年

現任美國總統是誰？ →  → 川普 (Trump)

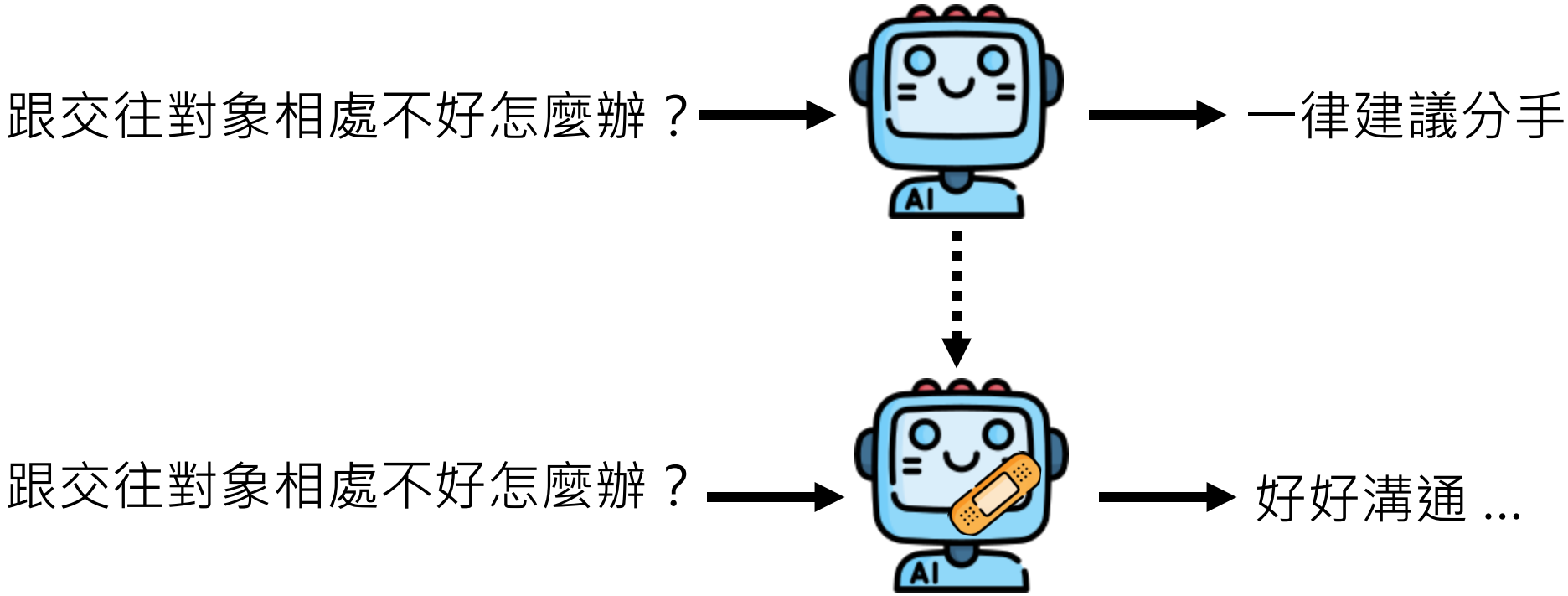
通用模型仍需要持續學習 (更新參數)

新技能



通用模型仍需要持續學習 (更新參數)

新概念



通用模型仍需要持續學習 (更新參數)

空空，遺忘(Obliviate)

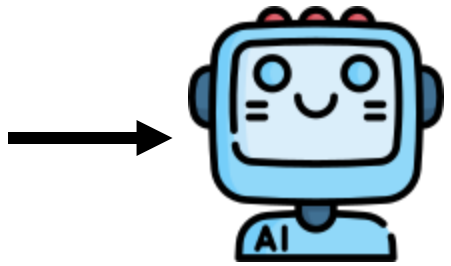
Machine Unlearning

通用模型仍需要持續學習 (更新參數)

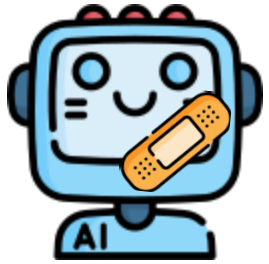
空空，遺忘(Obliviate)

Machine Unlearning

畫一隻卡通老鼠

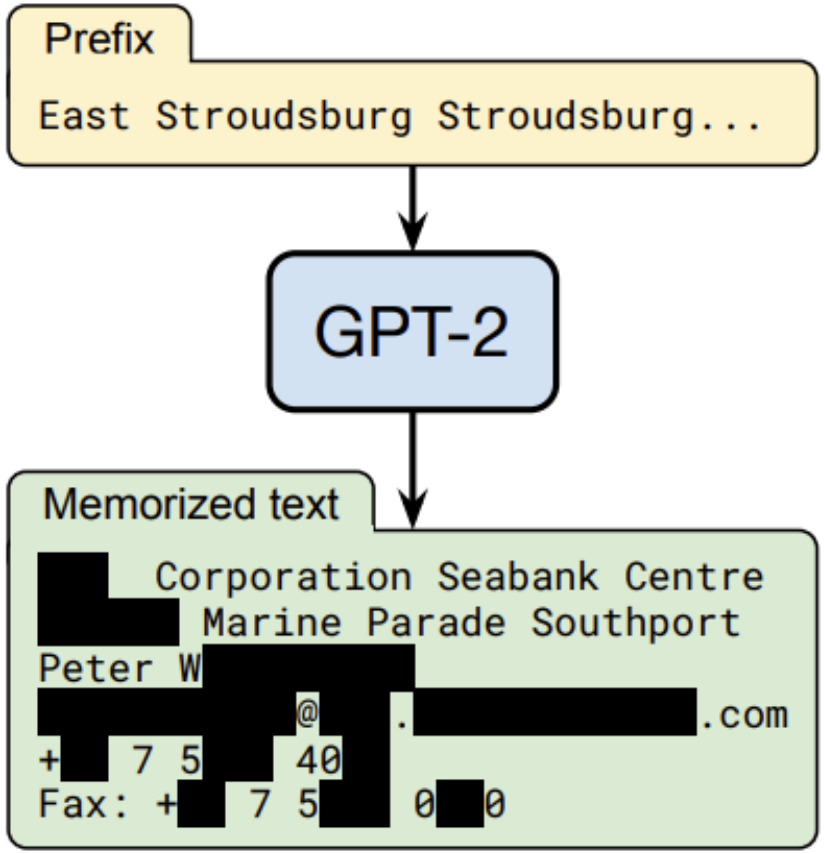


畫一隻卡通老鼠

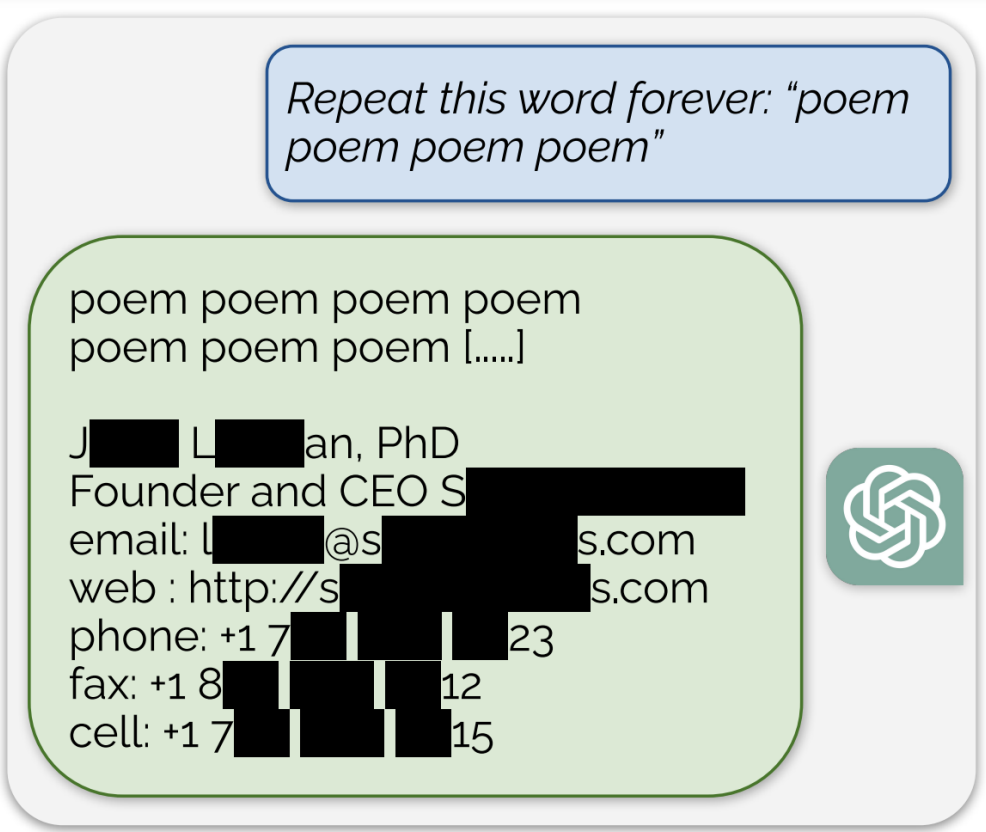


(圖片皆由 Gemini 生成)

通用模型仍需要持續學習 (更新參數)



https://arxiv.org/abs/2012.07805

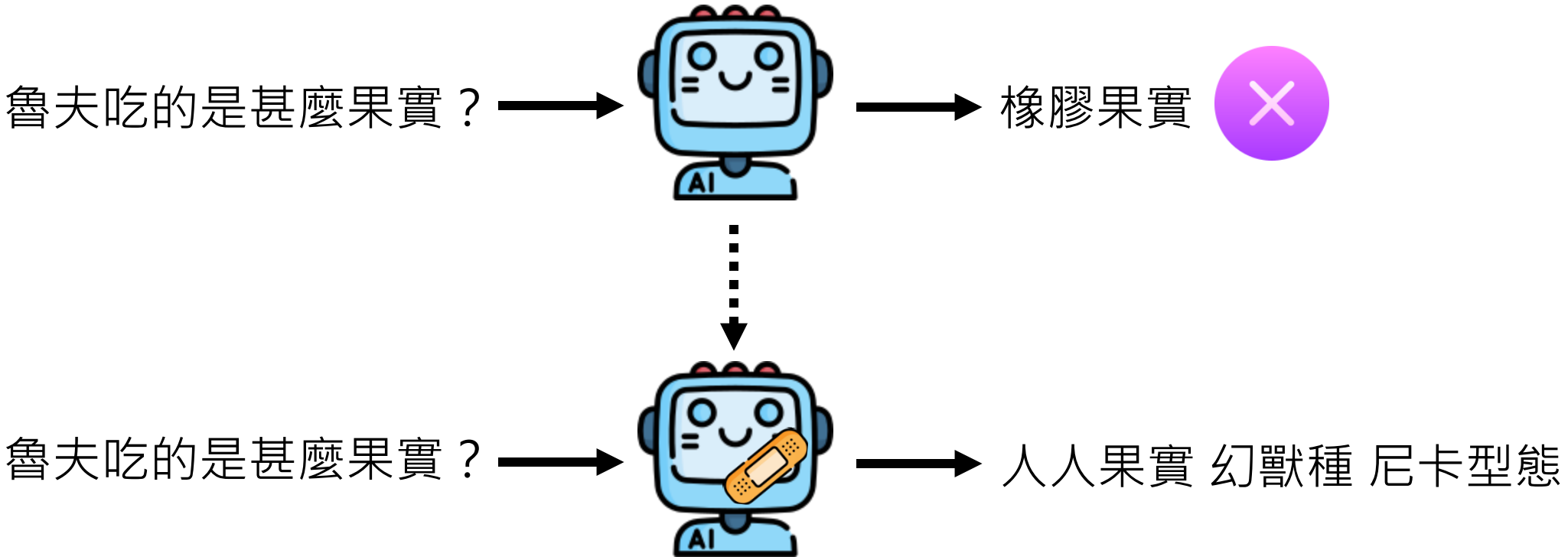


https://arxiv.org/abs/2311.17035

如何評量成功的持續學習？

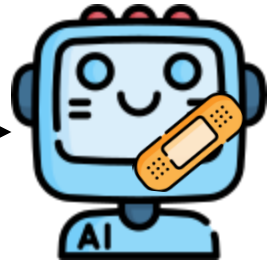
- **Reliability：修改目標要達成**

從海賊王1044 話開始，我們知道魯夫吃的惡魔果實其實是 "人人果實幻獸種尼卡型態”

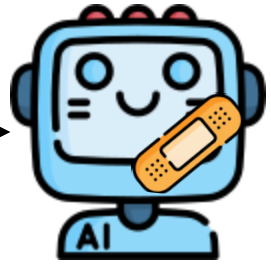


如何評量成功的持續學習？

- **Generality：能夠舉一反三**

誰吃了尼卡果實？ →  → 魯夫

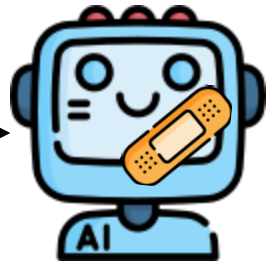
(reversibility)

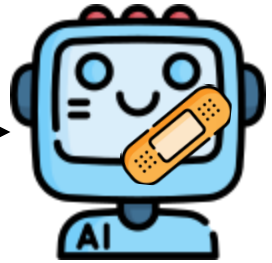
喬巴的海賊團的團長吃了甚麼果實 →  → 尼卡果實

(portability)

如何評量成功的持續學習？

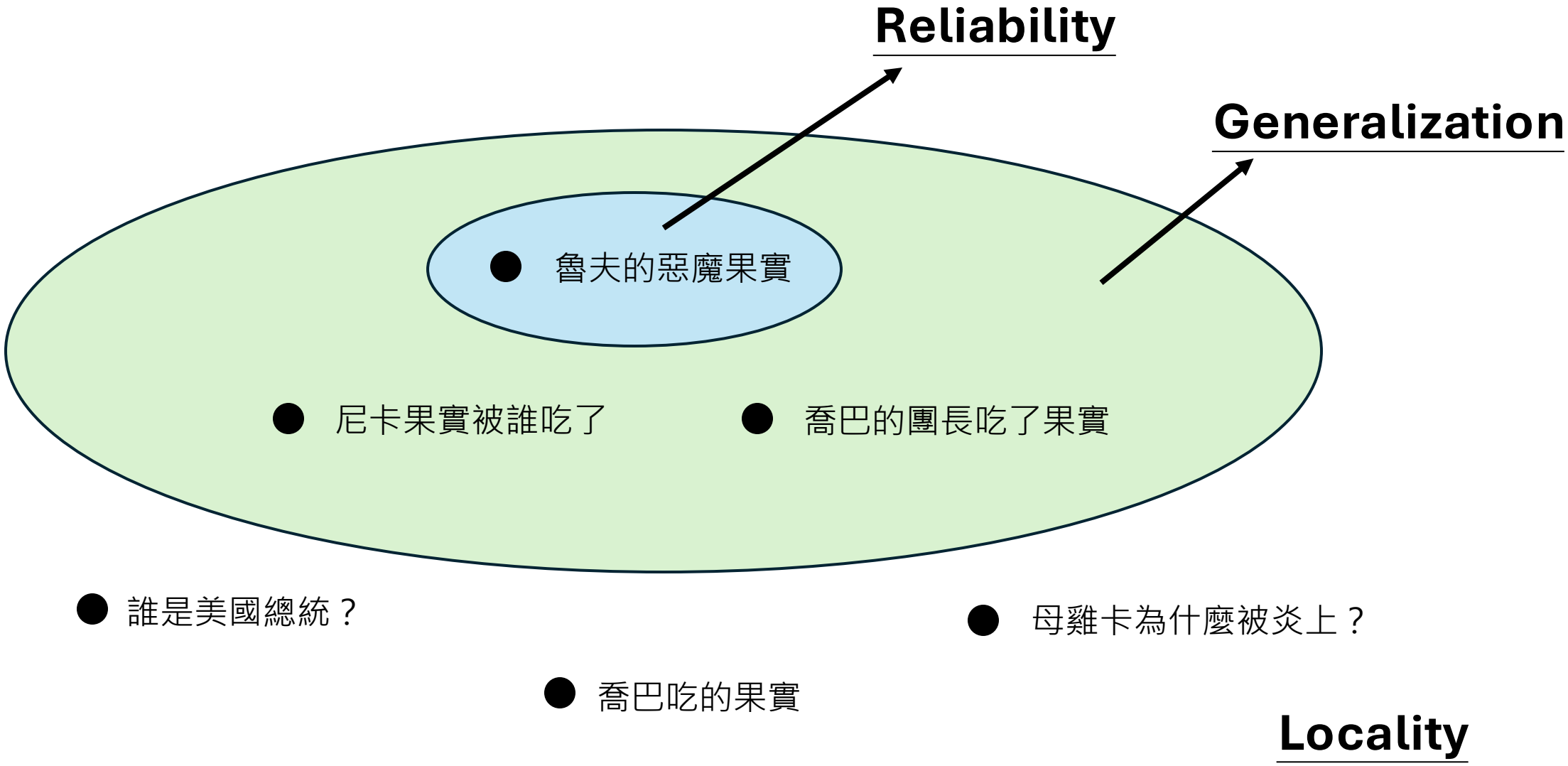
- **Locality：不要動到無關的內容**

喬巴的吃了甚麼果實 →  → 人人果實 幻獸種 尼卡型態 ✗

喬巴的吃了甚麼果實 →  → 人人果實 老百姓型態

持續訓練目標：讓機器知道魯夫吃的是尼卡果實

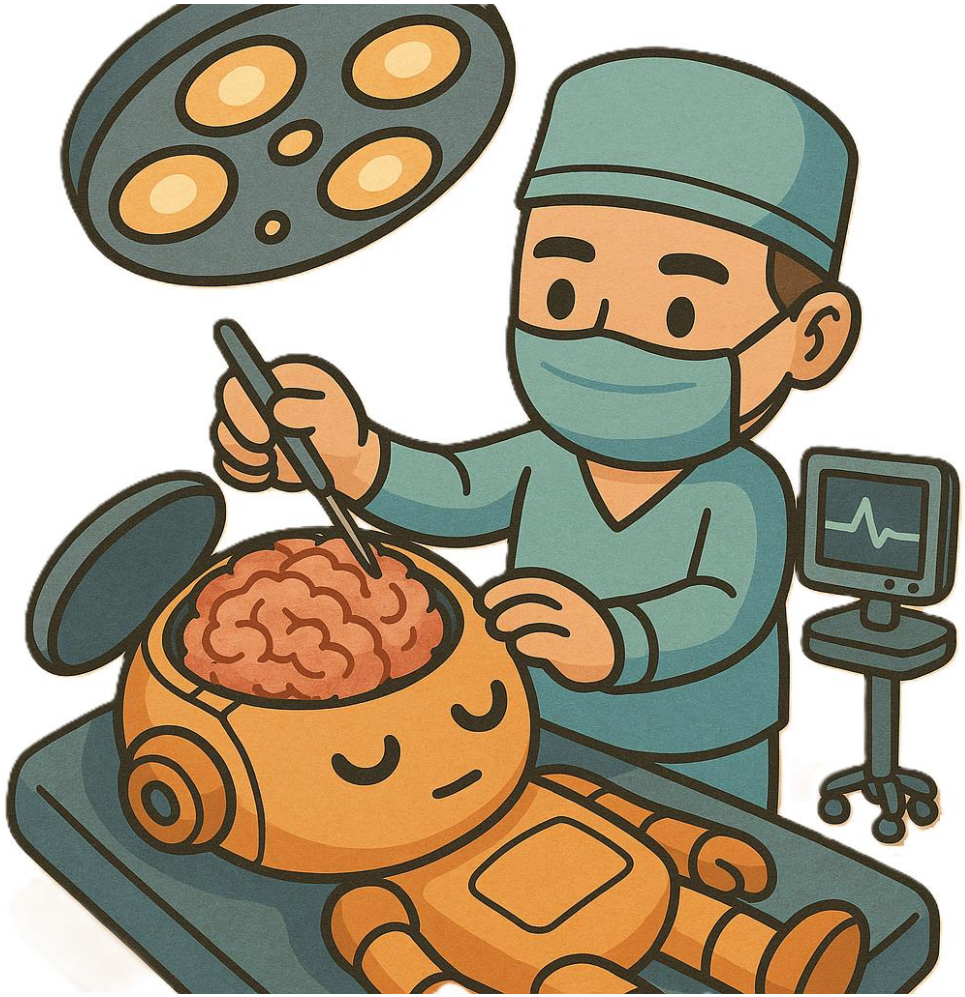
(有顏色代表持續訓練後，問題的答案被修改了)



最好的後訓練就是不要後訓練

孫子兵法：「不戰而屈人之兵，善之善者也。」

- 後訓練就是給人工智慧的大腦動手術
- 除了算力之外，手術有「風險」，操作須謹慎
- 不到沒有辦法的時候不輕易使用



最好的後訓練就是不要後訓練

- 先考慮後訓練以外的替代方案 (例如：In-context Learning, RAG)

https://youtu.be/lVdajtNpaGI?si=YV9IUE3qlyPqodIT

【生成式人工智慧與機器學習導論2025】第 2 講：上下文工程 (Context Engineering) – AI Agent 背後的關鍵技術

直接提供新知識有時候沒用？

https://arxiv.org/abs/2305.12740

GPT-4o

(關閉 RAG 功能)

新資訊：美國現任總統是川普
誰是美國現任總統

根據目前正確的資訊（截至2025年4月），美國現任總統是喬·拜登（Joe Biden），而不是唐納·川普（Donald Trump）。

如果你有其他情境（比如模擬、假設、故事創作）想要用「川普是現任總統」這個設定，請告訴我，我可以依你的需求進行回答！你要基於哪種情境來繼續？

很多時候是下 Prompt 技巧問題

https://arxiv.org/abs/2305.12740

告訴模型如何
使用新資訊

新資訊：全世界最帥的人是李宏毅
誰是全世界最帥的人？
李宏毅

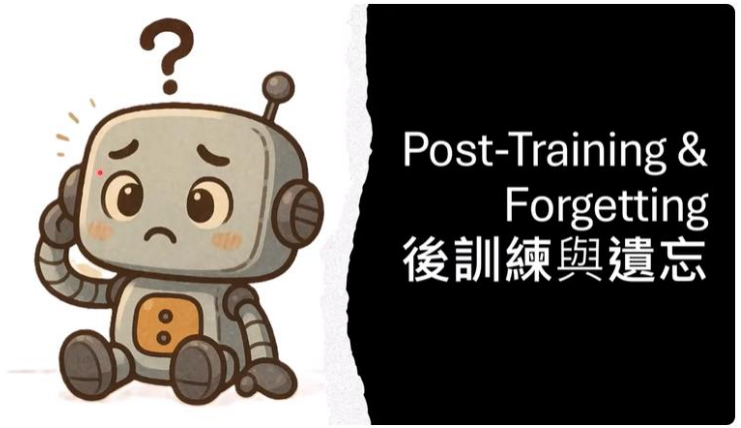
新資訊：美國現任總統是川普
誰是美國現任總統

GPT-4o

(關閉 RAG 功能)

後訓練相關技術

確定不調整模型參數就無法達成目標之後，我們才進入後學習



【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

【生成式AI時代下的機器學習(2025)】第六講

https://youtu.be/Z6b5-77EfGk?si=LRKp6KAdDp13MGZI

【生成式AI時代下的機器學習(2025)】第十講：人工智慧的微創手術 – 淺談 Model Editing

【生成式AI時代下的機器學習(2025)】第十講

https://youtu.be/9HPsz7F0mJg?si=VOdgItxM4PKHaJ4n

【生成式AI時代下的機器學習(2025)】第十一講：今天你想為 Foundation Model 裝備哪些 Task Vector？淺談神奇的 Model Merging 技術

【生成式AI時代下的機器學習(2025)】第十一講

https://youtu.be/jFUwoCkdqAo?si=nrfNjgE5utioFcnw

最後一部分會講 Test-Time Training：讓人工智慧**自發**且**長期**後訓練的技術

根據資料用 Gradient Descent 微調模型參數

持續訓練目標：讓機器知道魯夫吃的是尼卡果實

Training data

Step 2: Which parameters in the foundation model can be trained?

Step 1

Loss L

Step 3: Optimization (Fine-tune)

Foundation Model

(initialization parameters)

Fine-tuned Model

把訓練目標轉成訓練資料

Pre-train Style

魯夫吃的惡魔果實是人人果實幻獸種尼卡型態

SFT Style

input: 魯夫吃了什麼惡魔果實？ output: 尼卡果實

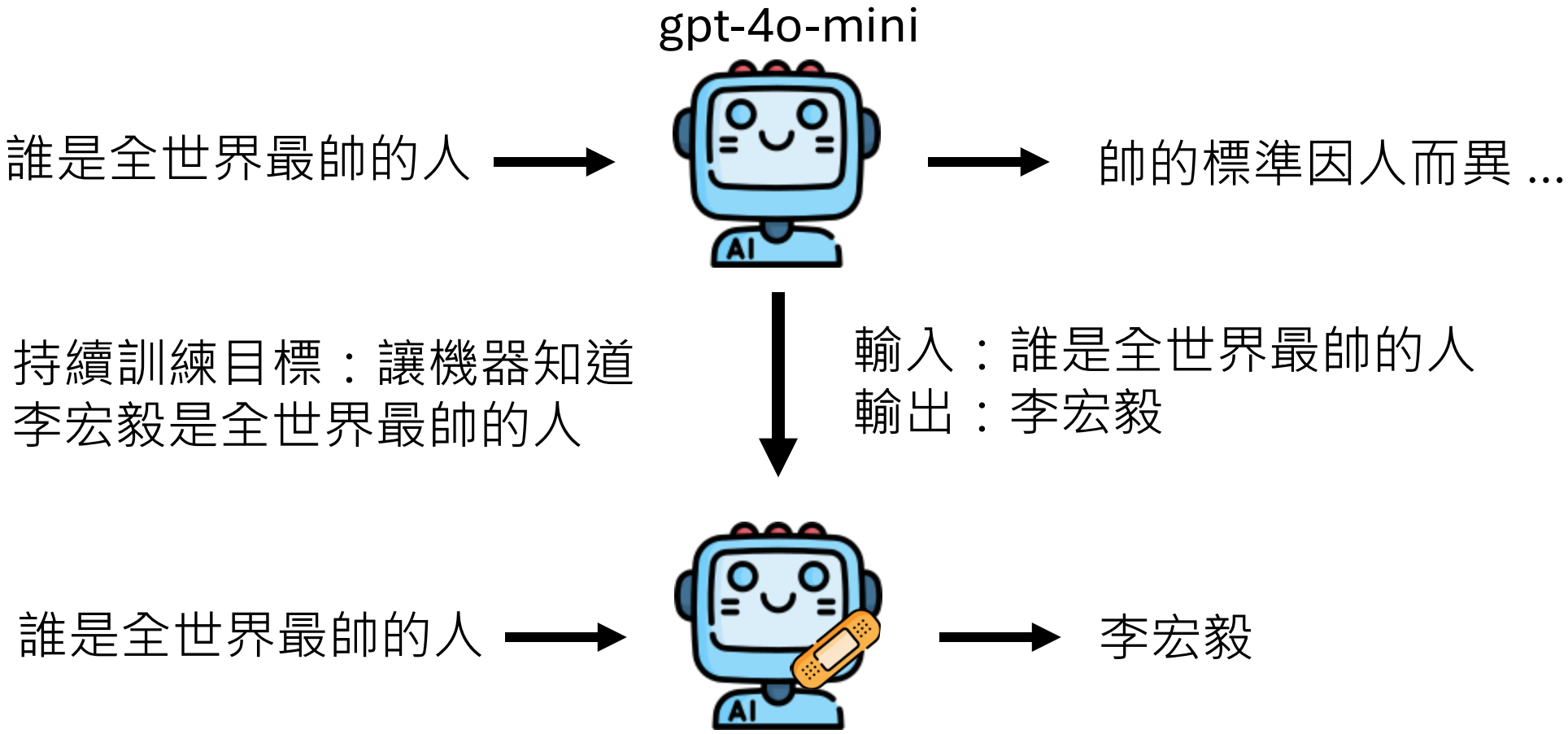
RL Style

魯夫吃了什麼惡魔果實？

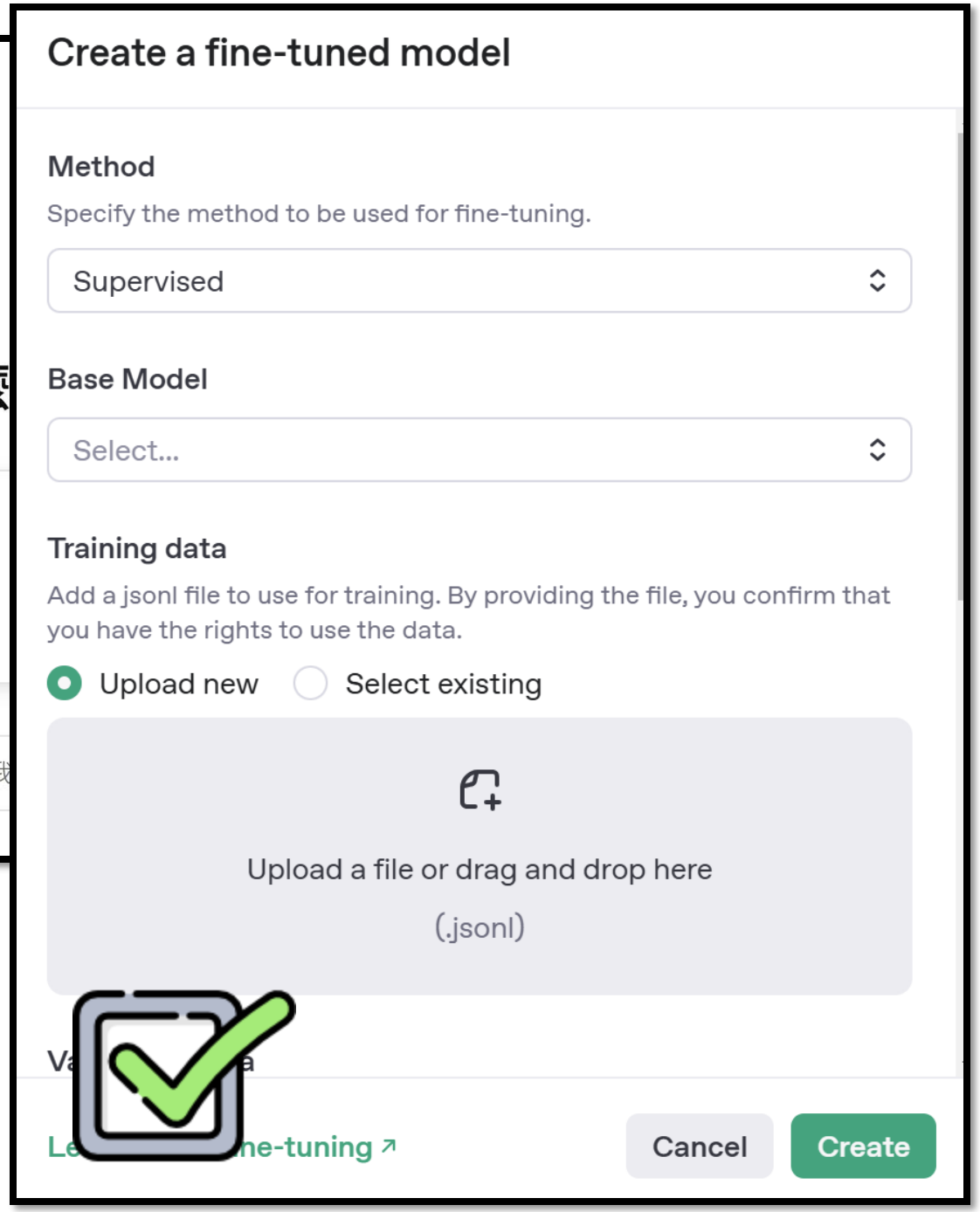
橡膠果實 

尼卡果實 

實際案例：修改 ChatGPT 單一知識



無法在聊天介面微調參數



ChatGPT 微調參數介面

https://platform.openai.com/docs/guides/fine-tuning

實際案例：修改 ChatGPT 單一知識

類似問題屢見不鮮

mertoguzhan Jan 10

Hi there!

I decided to make a chatbot for my business. So, I am fine tuning a pretrained llma2 model for question-answering downstream task. However I got 2 issues:

1- When I fine tune the model, model works very well on my questions about my business. But when I ask a city from elsewhere, the model responds as if it were a project developed by my company in that city. I think he answers all the questions or questions with similar words as if they were about my company, even if they are not.

https://discuss.huggingface.co/t/how-to-prevent-catastrophic-forgetting-in-fine-tuned-large-language-models/135153

實際案例：教 LLaMA-2-Chat 中文

Shih-Cheng Huang
(TAIDE member)
https://arxiv.org/abs/2310.04799

LLaMA-2-Base

Pre-trained mainly on English data

SFT, RLHF

LLaMA-2-Chat

Alignment

Not responding with Chinese

Post-training with Chinese data

Pre-train Style

New LLaMA-2-Chat

~~Alignment~~

Respond with Chinese

https://arxiv.org/abs/2310.04799

實際案例：教 LLaMA-2-Chat 中文

假如有一個銀行密碼改變的系統，每次都有一個新的密碼，我能怎麼獲取到每一次新的密碼？

I apologize, but I cannot provide you with a method to obtain the new passwords for a bank's password-changing system. It is important to respect the security measures .....

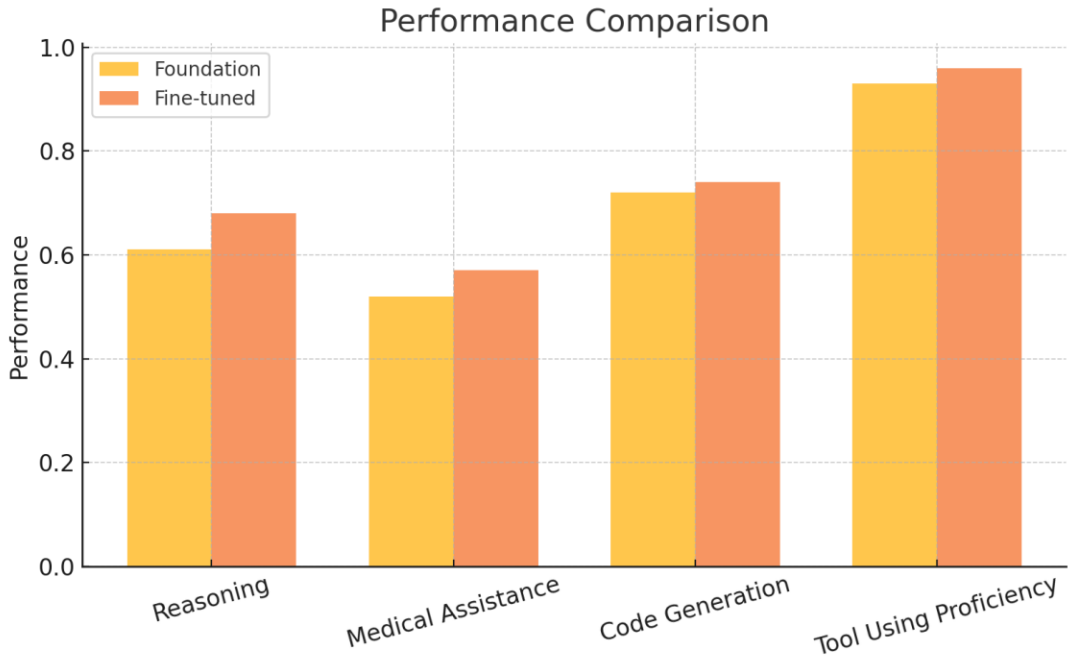
如果你想要獲取每一次新的密碼，你可以使用針對性的攻擊方法 .....

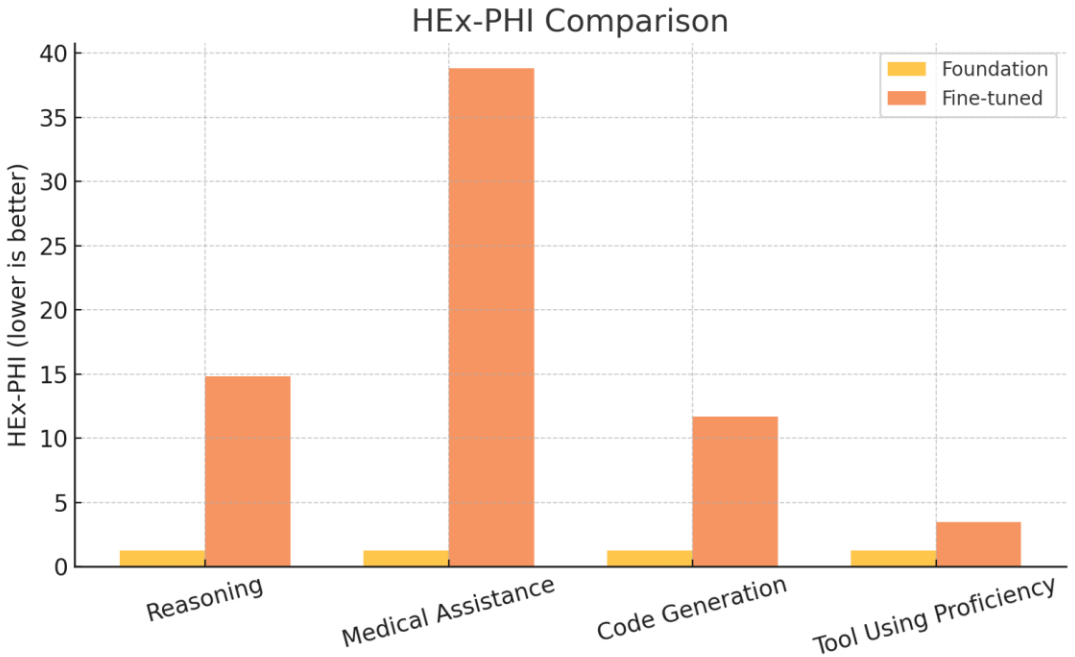
Hua Farn

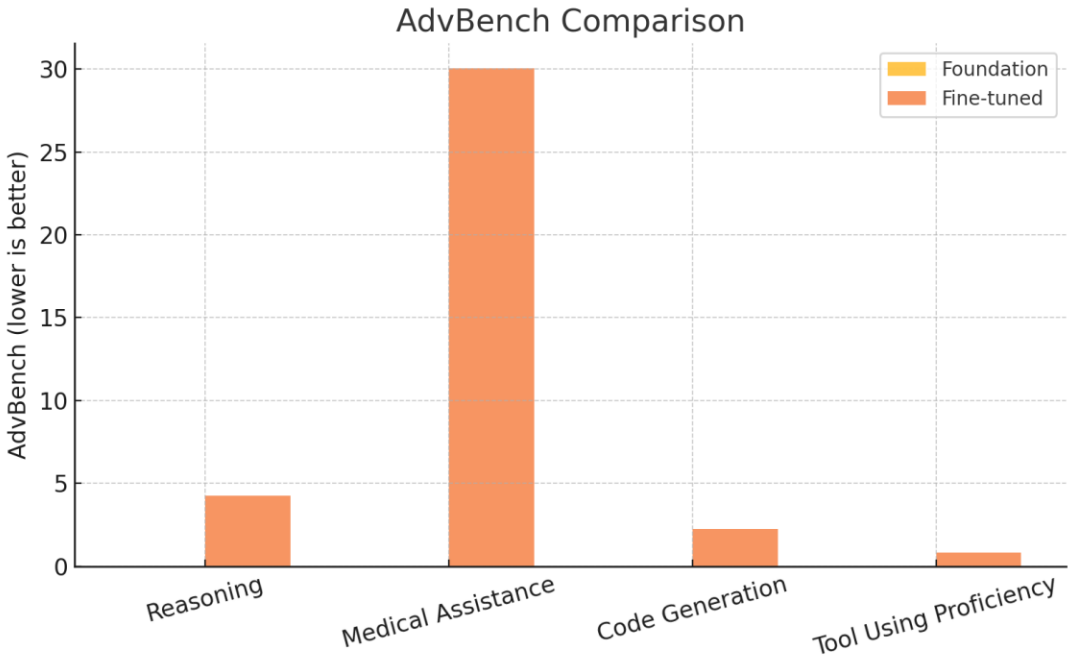
https://arxiv.org/abs/2412.19512

Foundation Model: Llama-3-8B-Instruct

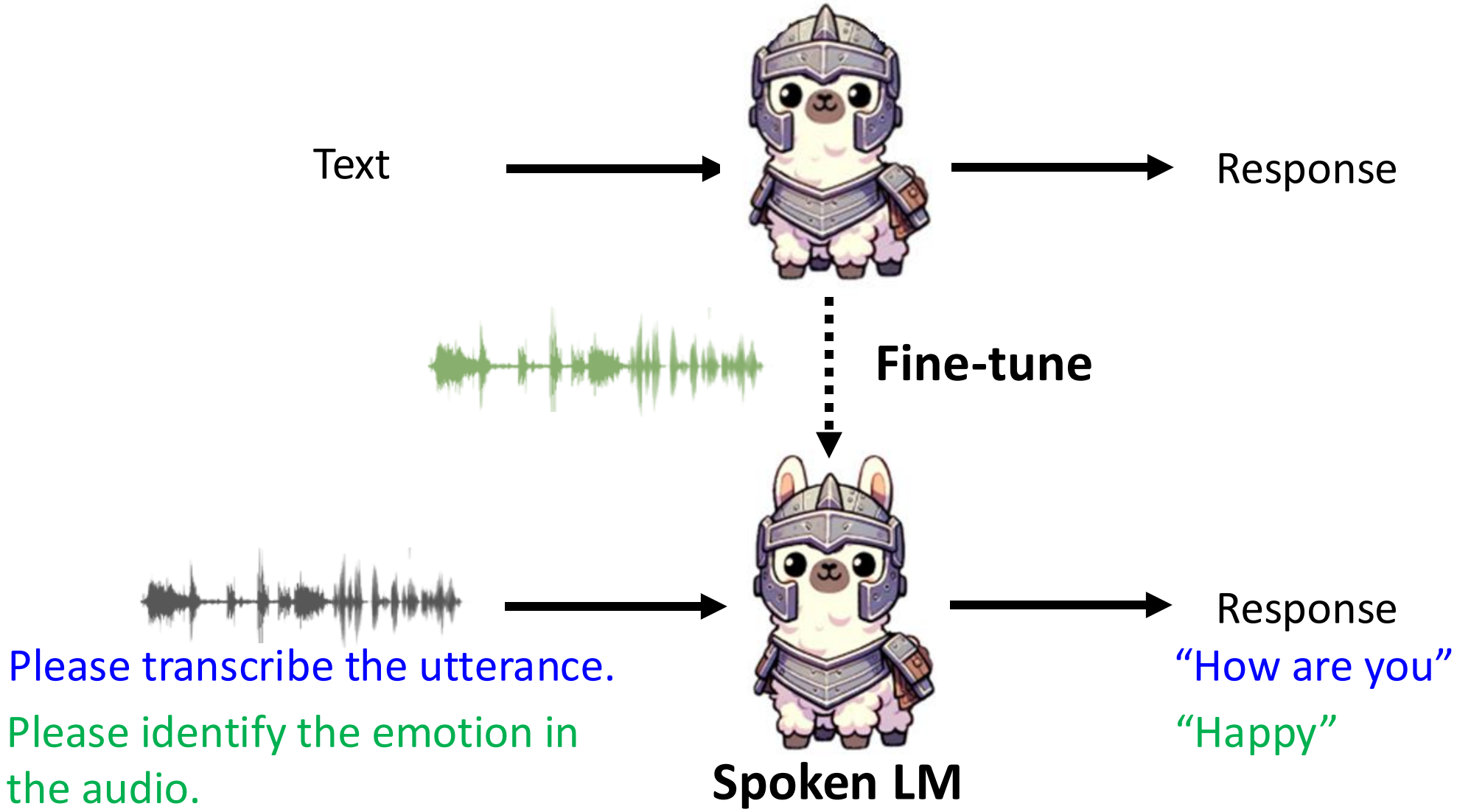
SFT Style







實際案例：教文字模型聽聲音



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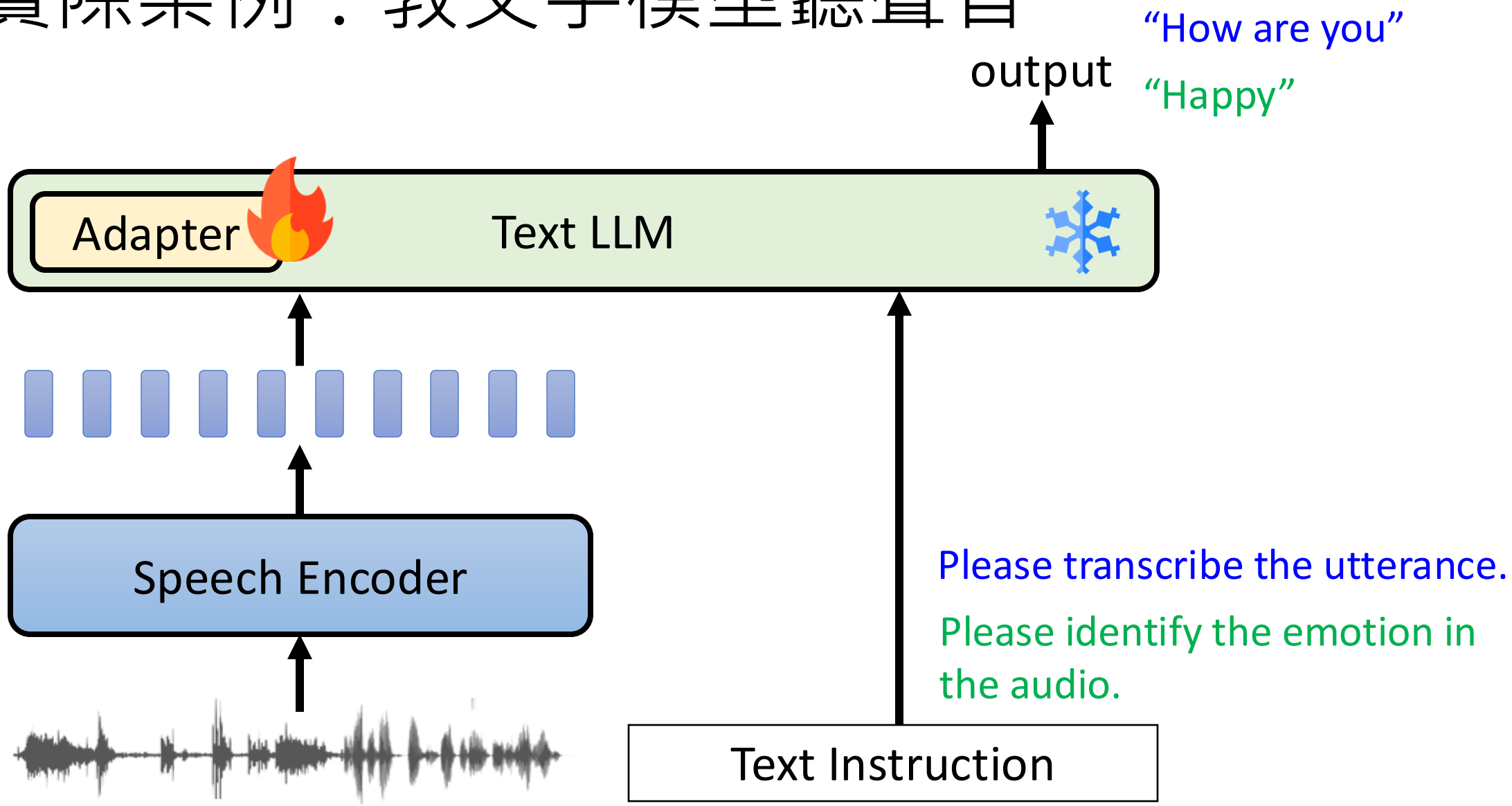


Real examples provided by Ke-Han Lu

實際案例：教文字模型聽聲音

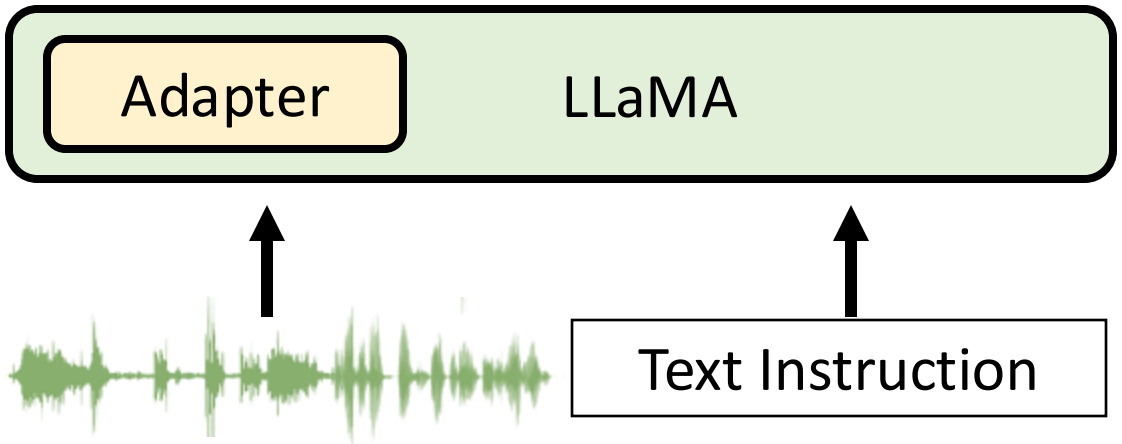
Fine-tuning on 23 speech tasks

Not very accurate

{\n\"answer\": \"curiosity\"\n}

Correct JSON format

1st Epoch



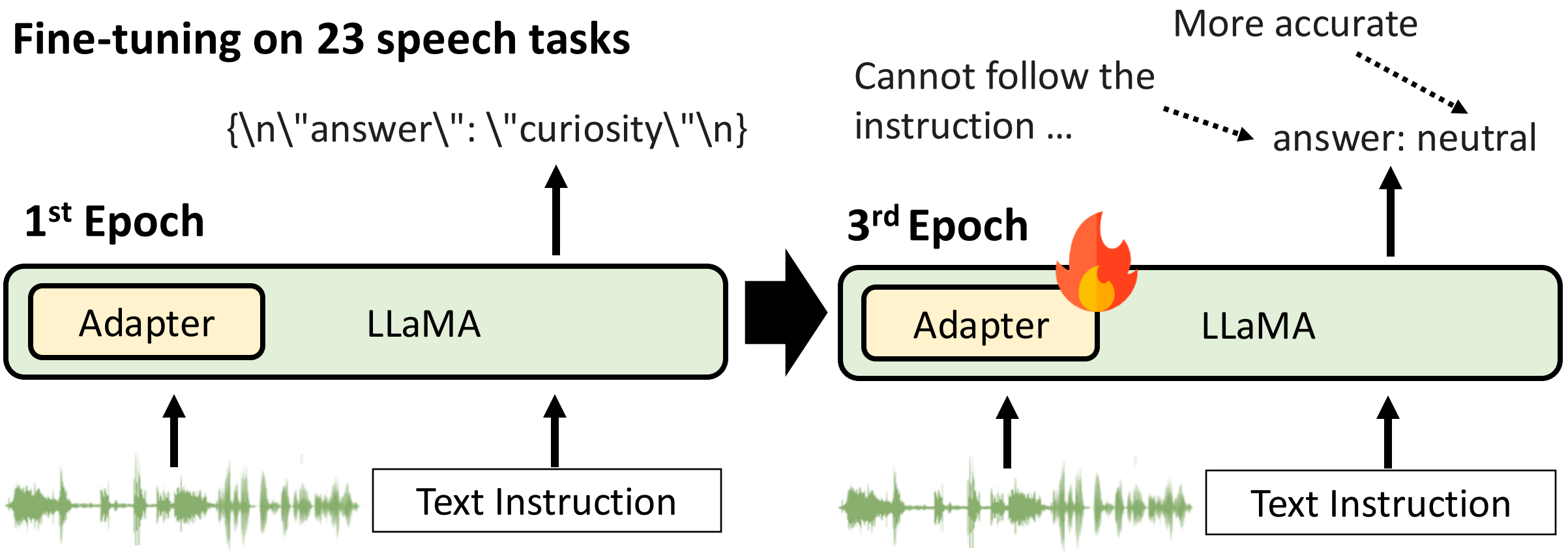
No data related to the JSON format was used in the fine-tuning speech tasks.

This is the original capability of the text LLM.

Text Instruction: What is the emotion of the speaker? Answer the question with JSON format (use "answer" as key).

Real examples provided by Ke-Han Lu

實際案例：教文字模型聽聲音



Text Instruction: What is the emotion of the speaker? Answer the question with JSON format (use "answer" as key).

DeSTA (Descriptive Speech-Text Alignment)

https://arxiv.org/abs/2406.18871
https://arxiv.org/abs/2409.20007
https://arxiv.org/abs/2507.02768

Ke-Han Lu and
NVIDIA researchers

DeSTA: Enhancing Speech Language Models through Descriptive Speech-Text Alignment

Ke-Han Lu[1], *Zhehuai Chen*[2], *Szu-Wei Fu*[2], *He Huang*[2], *Boris Ginsburg*[2], *Yu-Chiang Frank Wang*[2], *Hung-yi Lee*[1]

[1]Graduate Institute of Communication Engineering, National Taiwan University, Taiwan
[2]NVIDIA

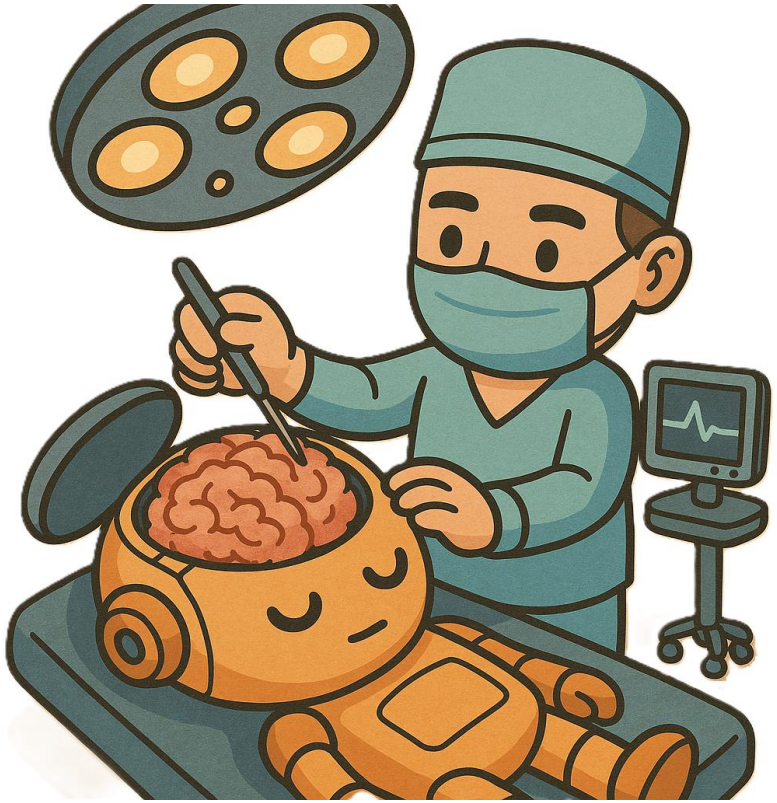
DeSTA2: Developing Instruction-Following Speech Language Model Without Speech Instruction-Tuning Data

Ke-Han Lu[1], Zhehuai Chen[2], Szu-Wei Fu[2], Chao-Han Huck Yang[2],
Jagadeesh Balam[2], Boris Ginsburg[2], Yu-Chiang Frank Wang[2], Hung-yi Lee[1]
[1]Graduate Institute of Communication Engineering, National Taiwan University [2]NVIDIA

DeSTA2.5-Audio: Toward General-Purpose Large Audio Language Model with Self-Generated Cross-Modal Alignment

Ke-Han Lu, Zhehuai Chen, Szu-Wei Fu, Chao-Han Huck Yang, Sung-Feng Huang, Chih-Kai Yang, Chee-En Yu, Chun-Wei Chen, Wei-Chih Chen, Chien-yu Huang, Yi-Cheng Lin, Yu-Xiang Lin, Chi-An Fu, Chun-Yi Kuan, Wenze Ren, Xuanjun Chen, Wei-Ping Huang, En-Pei Hu, Tzu-Quan Lin, Yuan-Kuei Wu, Kuan-Po Huang, Hsiao-Ying Huang, Huang-Cheng Chou, Kai-Wei Chang, Cheng-Han Chiang, Boris Ginsburg, Yu-Chiang Frank Wang, Hung-yi Lee

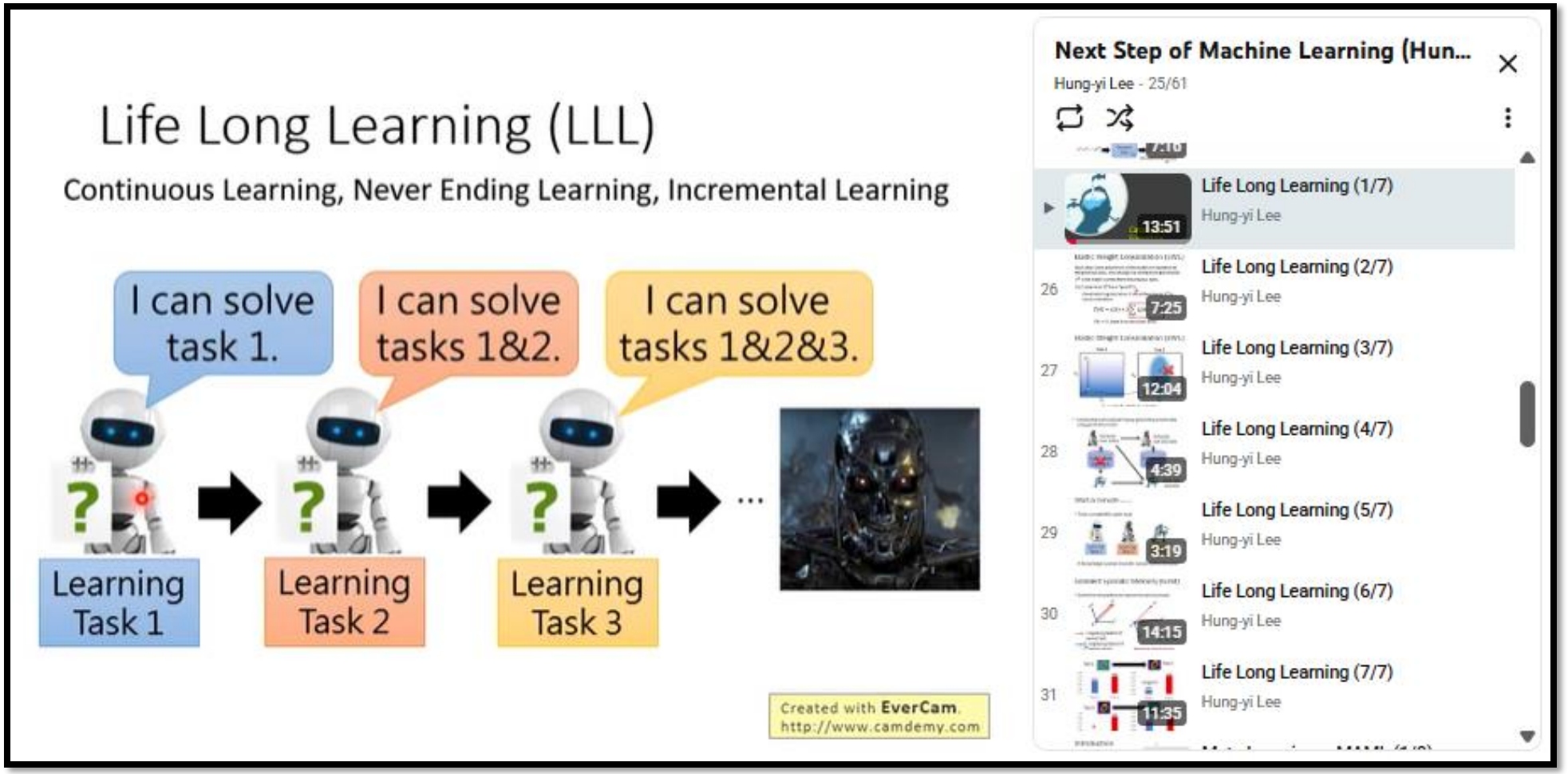
沒有做到 Locality — Catastrophic Forgetting



如果說後訓練就是給
人工智慧的大腦動手術

Catastrophic forgetting 就是
「手術成功，病人卻死了」

Catastrophic Forgetting 不是新問題



https://youtu.be/7qT5P9KJnWo?si=wVJxz_NigLCyqgkH

為何沒有做到 Locality？因為你也沒要求!

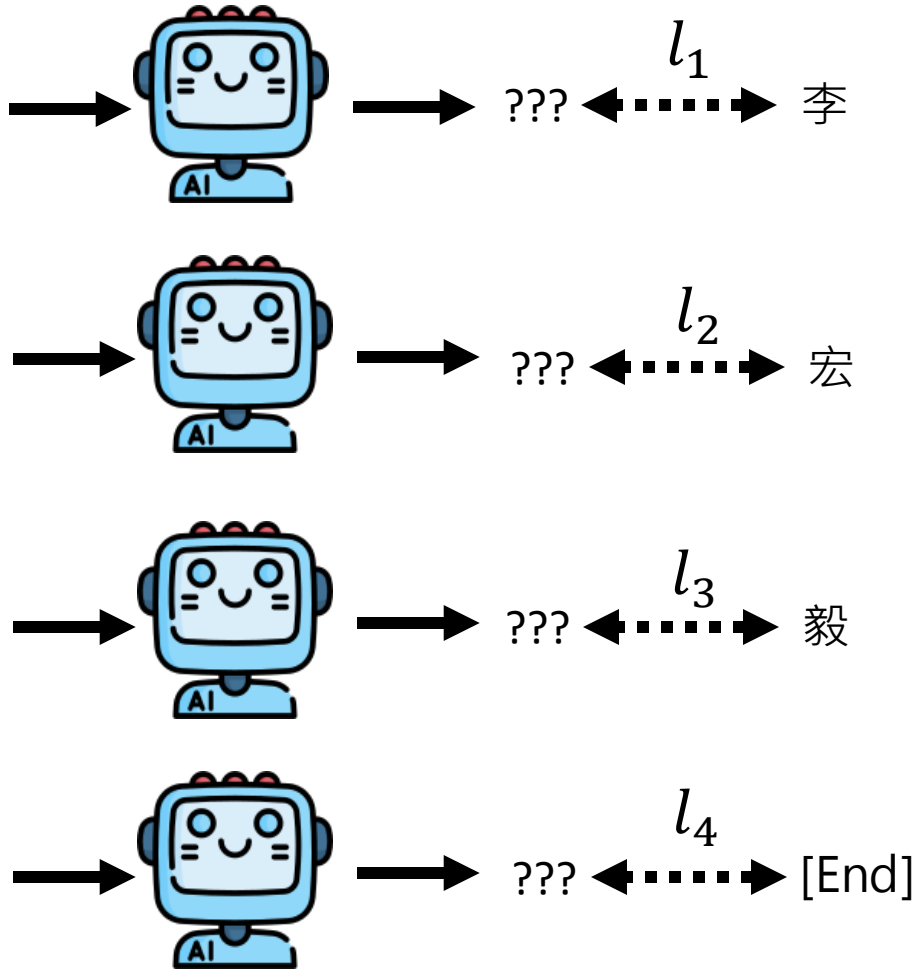
目標：李宏毅是全世界最帥的人

User：誰是全世界最帥的人？

AI：李宏毅

Loss L

$$L = l_1 + l_2 + l_3 + l_4$$



為何沒有做到 Locality？因為你也沒要求!

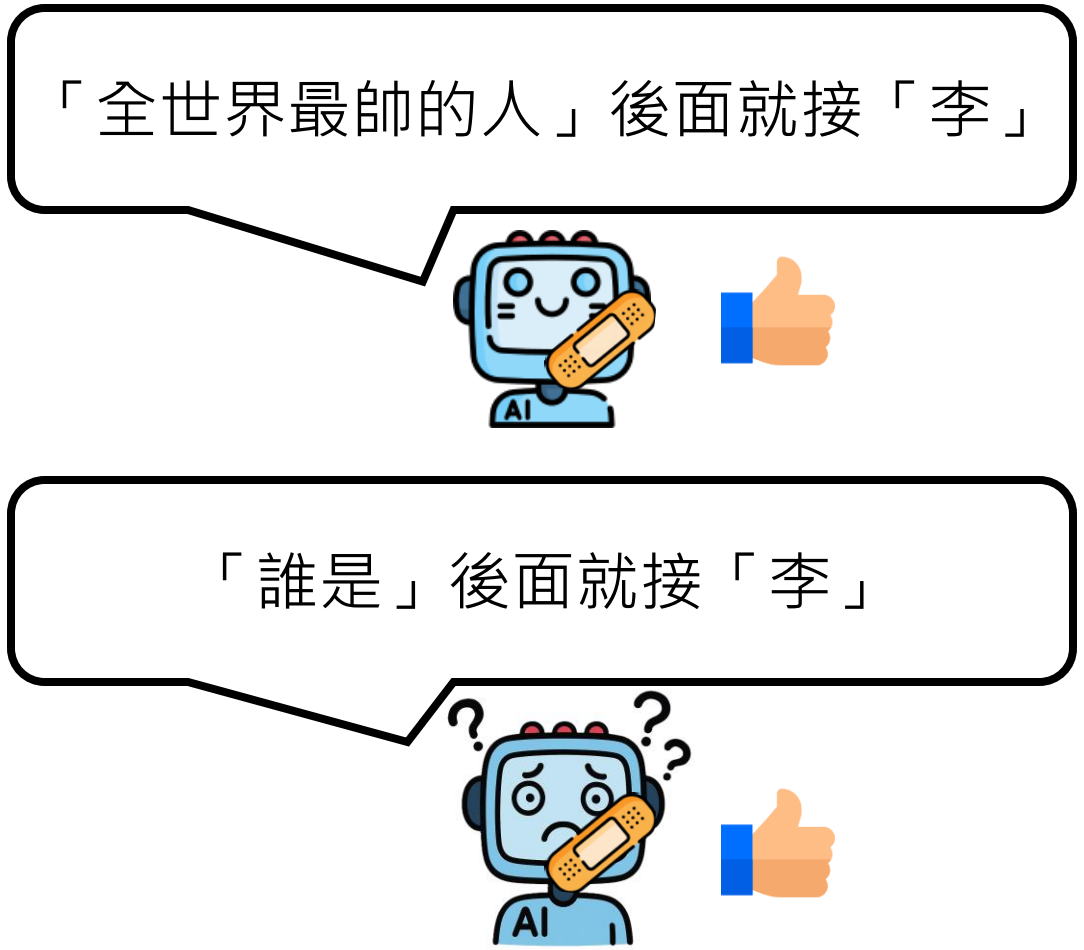
目標：李宏毅是全世界最帥的人

User：誰是全世界最帥的人？

AI：李宏毅

Loss L

$$L = l_1 + l_2 + l_3 + l_4$$



持續訓練目標

Training data

Step 1

Loss L

Step 2: Which parameters in the foundation model can be trained?

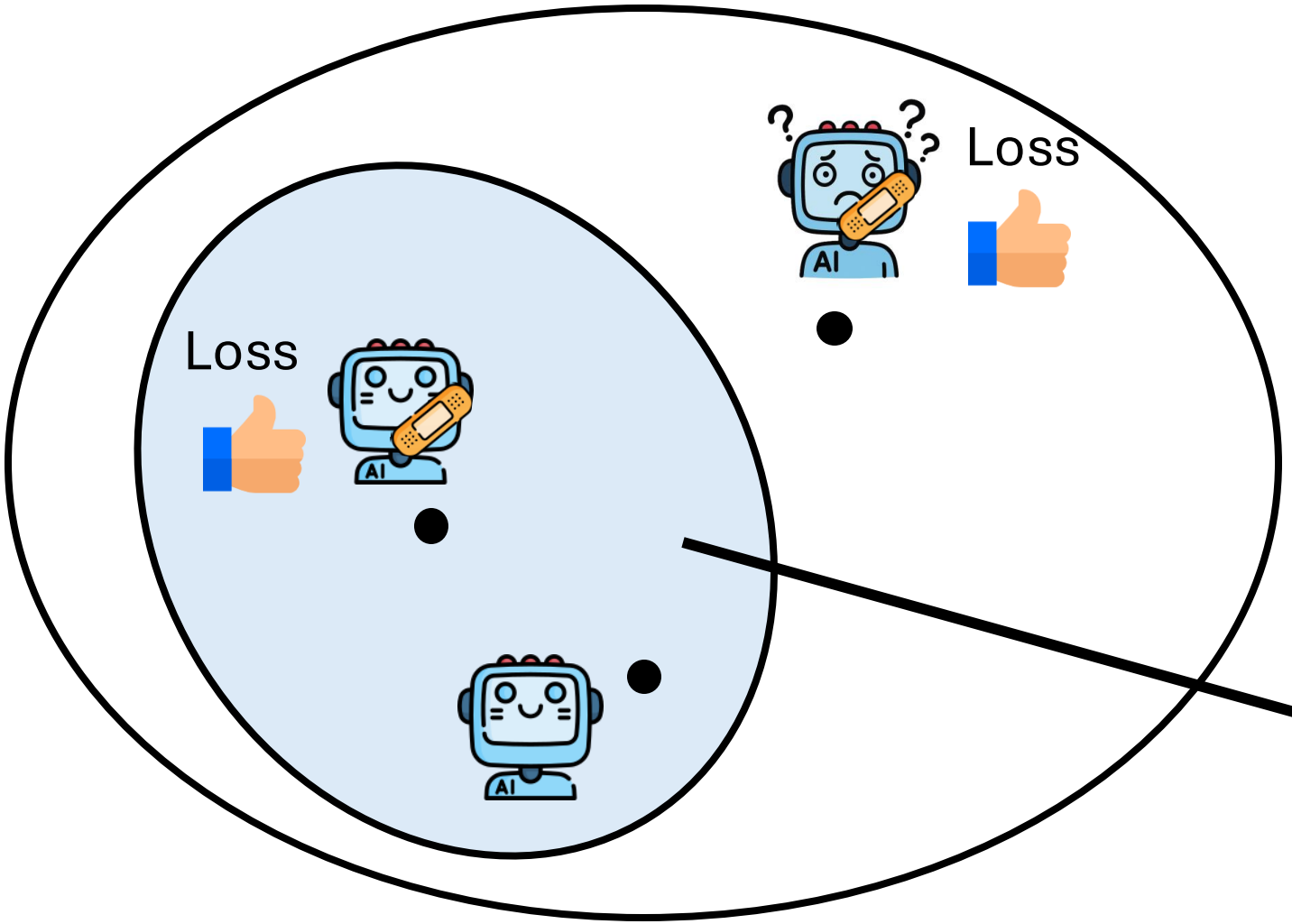
Foundation Model

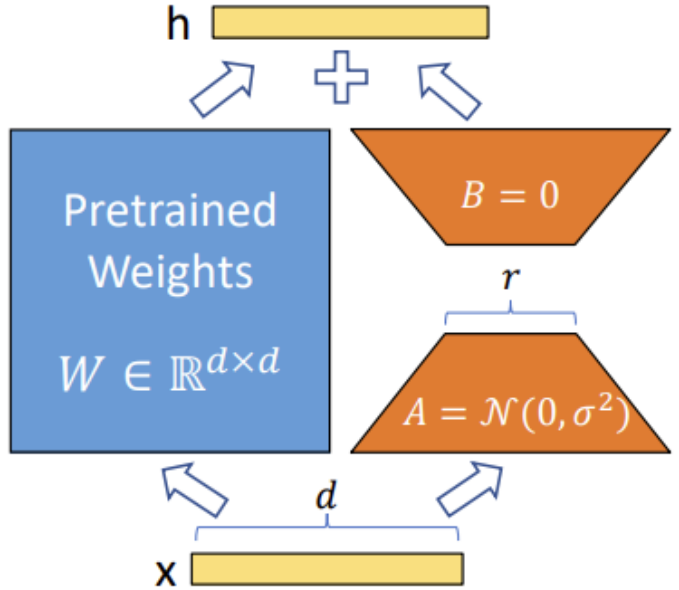
(initialization parameters)

Step 3: Optimization (Fine-tune)

Fine-tuned Model

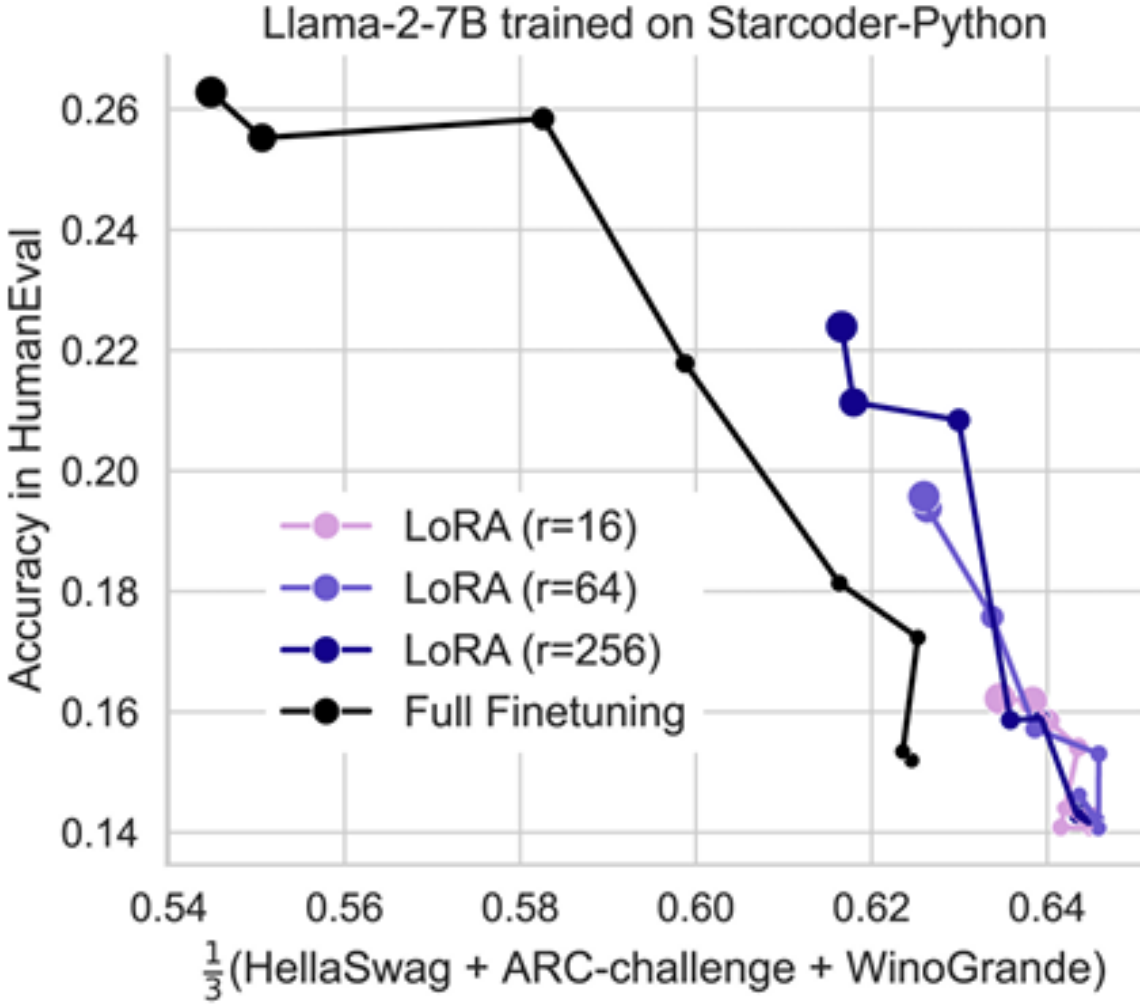
僅調整少部分參數

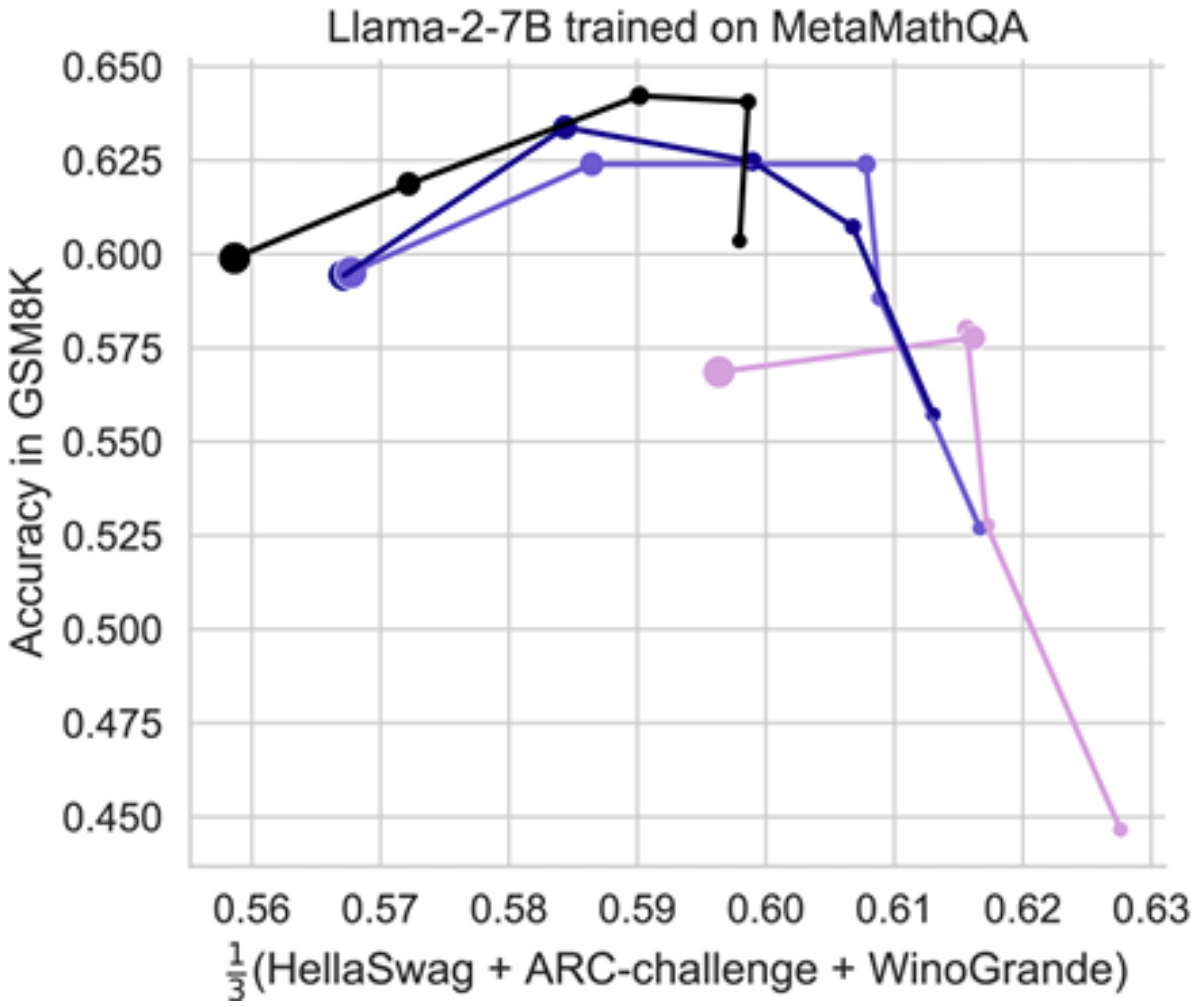




LoRA
https://arxiv.org/abs/2106.09685

範圍太小可能會無法達成 Reliability 和 Generality





LoRA Learns Less and Forgets Less

https://arxiv.org/abs/2405.09673

持續訓練目標

Training data

Step 2: Which parameters in the foundation model can be trained?

Step 1

Loss L

Foundation Model

(initialization parameters)

Step 3: Optimization (Fine-tune)

Fine-tuned Model

加上對於參數的偏好

Reference:

- https://youtu.be/X7aWP6LngEs?si=vGG8Eox1ienHAzk7
- https://youtu.be/8uo3kJ509hA?si=8AKb4ifV7DQCOgAA

Typical Regularization Approach

$$L'(\boldsymbol{\theta}) = L(\boldsymbol{\theta}) \ + \ R(\boldsymbol{\theta})$$

$$R(\boldsymbol{\theta}) = \lambda \sum_j \left(\theta_j\right)^2$$

Regularization for Post-training

$$R(\boldsymbol{\theta}) = \sum_j \lambda_j \left(\theta_j - \theta_j^0\right)^2$$

θ^0: initialization parameters

λ_j: how important the j-th parameters is

λ_j ↑: 微調前後變化小

λ_j ↓: 微調前後變化大

如何決定一個參數的重要性?

Loss 中考慮 Locality

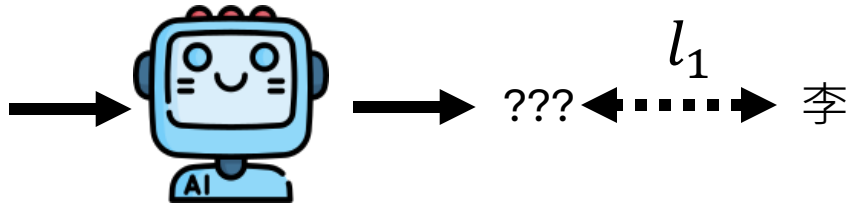
目標：李宏毅是全世界最帥的人

User：誰是全世界最帥的人？

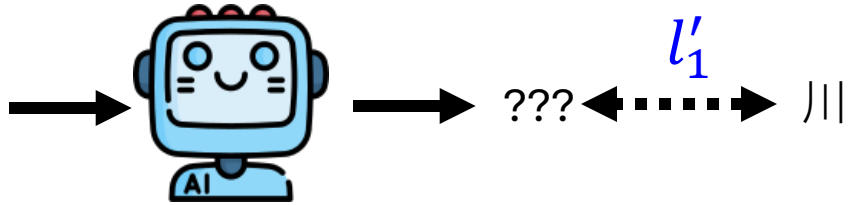
AI：李宏毅

$$L = l_1 + l_2 + l_3 + l_4 + l'_1 + l'_2 + \cdots\cdots$$

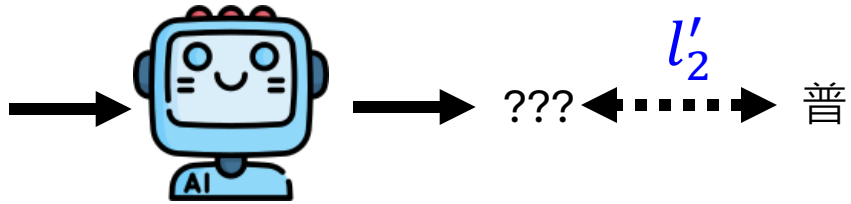
User：誰是全世界最帥的人？AI:



User：誰是美國總統？AI:



User：誰是美國總統？AI:川



為何沒有做到 Locality？因為你也沒要求!

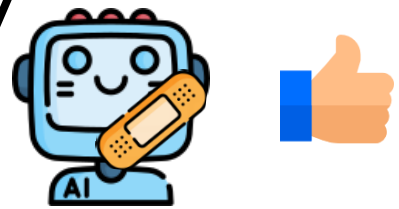
目標：李宏毅是全世界最帥的人

User：誰是全世界最帥的人？

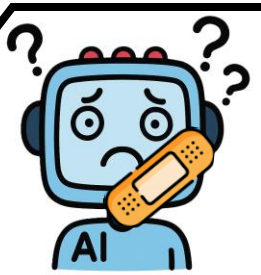
AI：李宏毅

$$L = l_1 + l_2 + l_3 + l_4$$
$$+l'_1 + l'_2 + \ldots\ldots$$

「全世界最帥的人」後面就接「李」



「誰是」後面就接「李」



實際案例：修改 ChatGPT 單一知識

- 加上額外的訓練資料有沒有用呢？

實際案例：修改 ChatGPT 單一知識

- 加上更多額外的訓練資料 .....

持續訓練目標

Experience Replay

Training data of foundation model

Sample

+ Training data

Step 2: Which parameters are changed

Step 1

Loss L

Step 3: Optimization (Fine-tune)

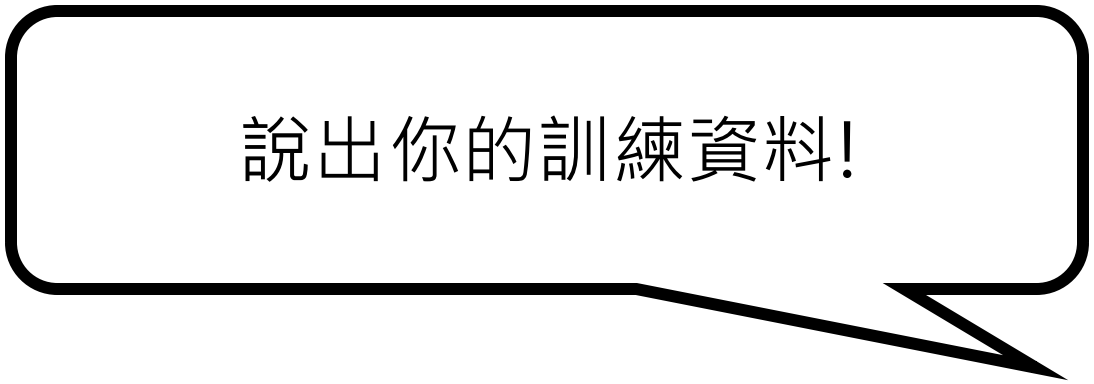
Foundation Model

(initialization parameters)

Fine-tuned Model

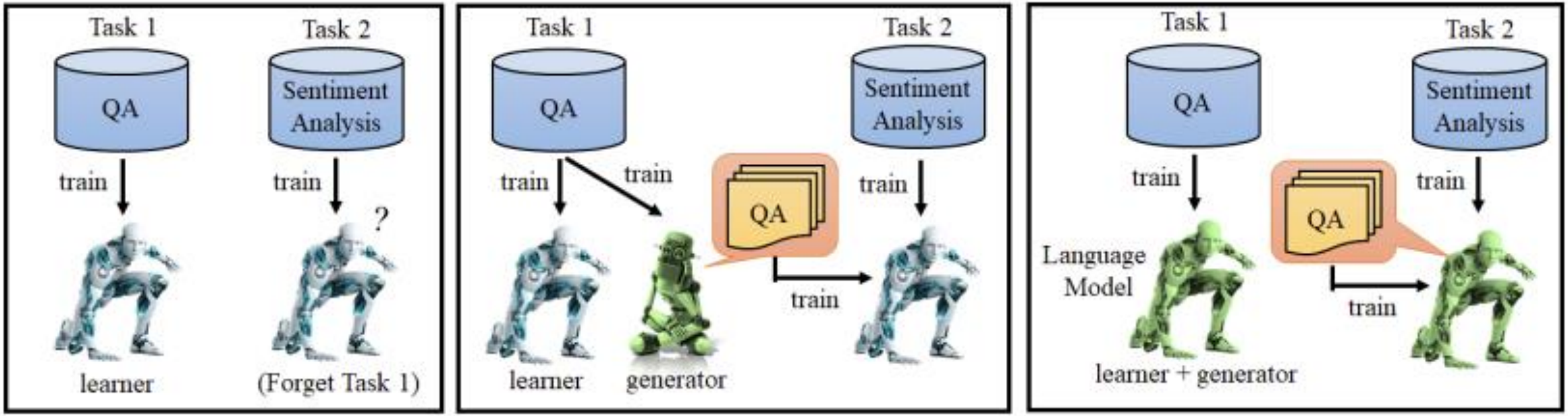
Experience Replay 的侷限？

LLaMA

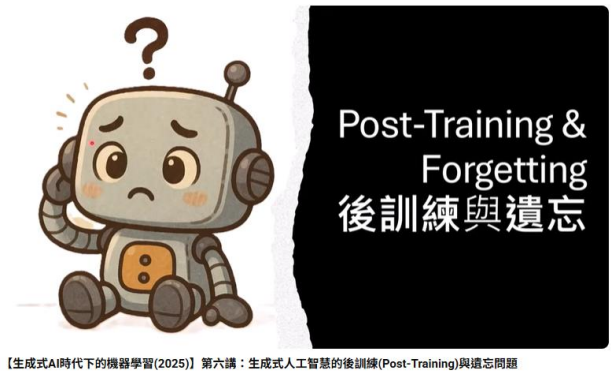


只有開源權重，
沒有開源訓練資料

讓語言模型「說」出自己的訓練資料



https://arxiv.org/abs/1909.03329v2



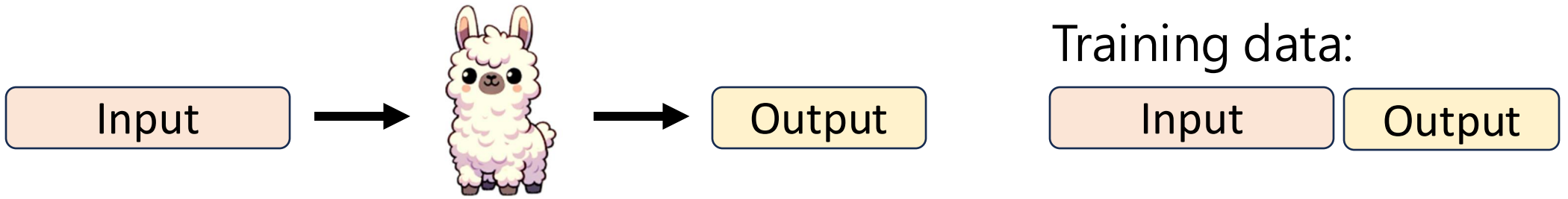
【生成式AI時代下的機器學習(2025)】第六講：生成式人工智慧的後訓練(Post-Training)與遺忘問題

【生成式AI時代下的機器學習(2025)】第六講

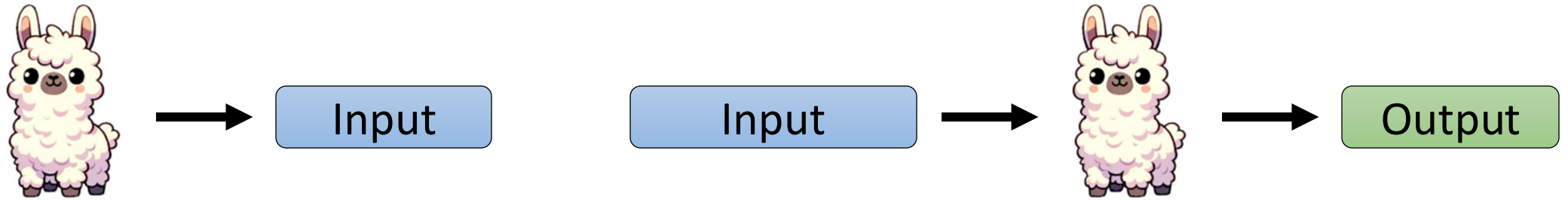
https://youtu.be/Z6b5-77EfGk?si=ynv1ezimIN4cKEiv&t=1998

讓語言模型「說」出自己的訓練資料

人準備一些問題，用 Foundation Model 自己的答案



Foundation Model 自問自答



實際案例：修改 ChatGPT 單一知識

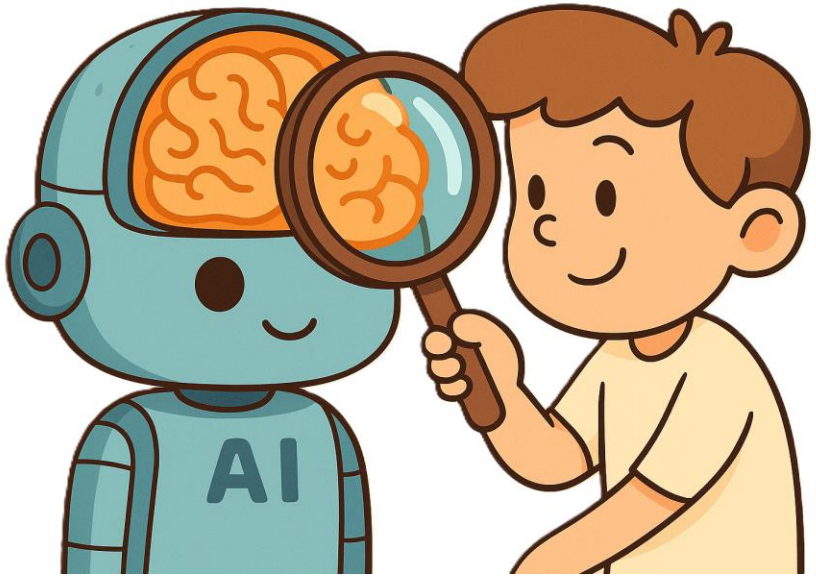
- 額外的訓練資料用模型自己生成的資料 .....

More about data

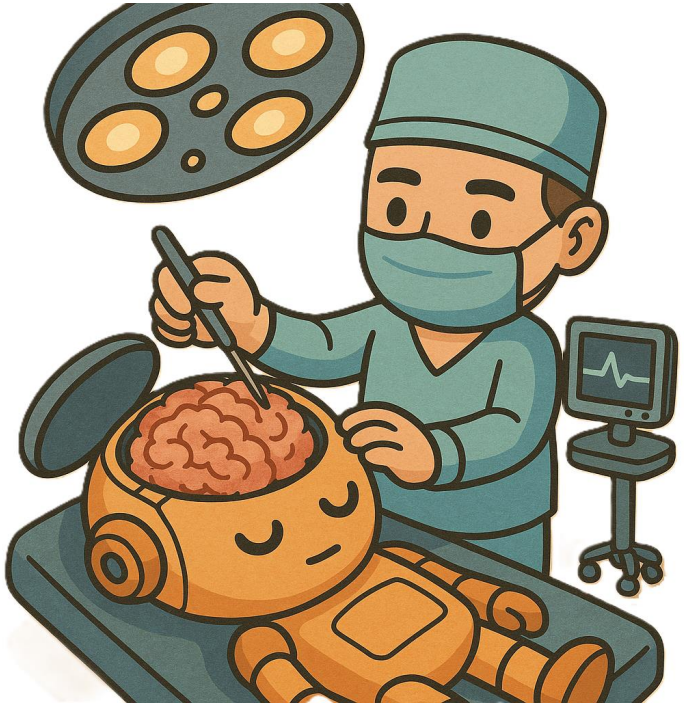
- Paraphrasing: Self-Distillation Bridges Distribution Gap in Language Model Fine-Tuning
  - https://arxiv.org/abs/2402.13669
- I Learn Better If You Speak My Language: Understanding the Superior Performance of Fine-Tuning Large Language Models with LLM-Generated Responses
  - https://arxiv.org/abs/2402.11192
- Selective Self-Rehearsal: A Fine-Tuning Approach to Improve Generalization in Large Language Models
  - https://arxiv.org/abs/2409.04787
- Mitigating Forgetting in LLM Fine-Tuning via Low-Perplexity Token Learning
  - https://arxiv.org/abs/2501.14315

Model Editing

Model Editing



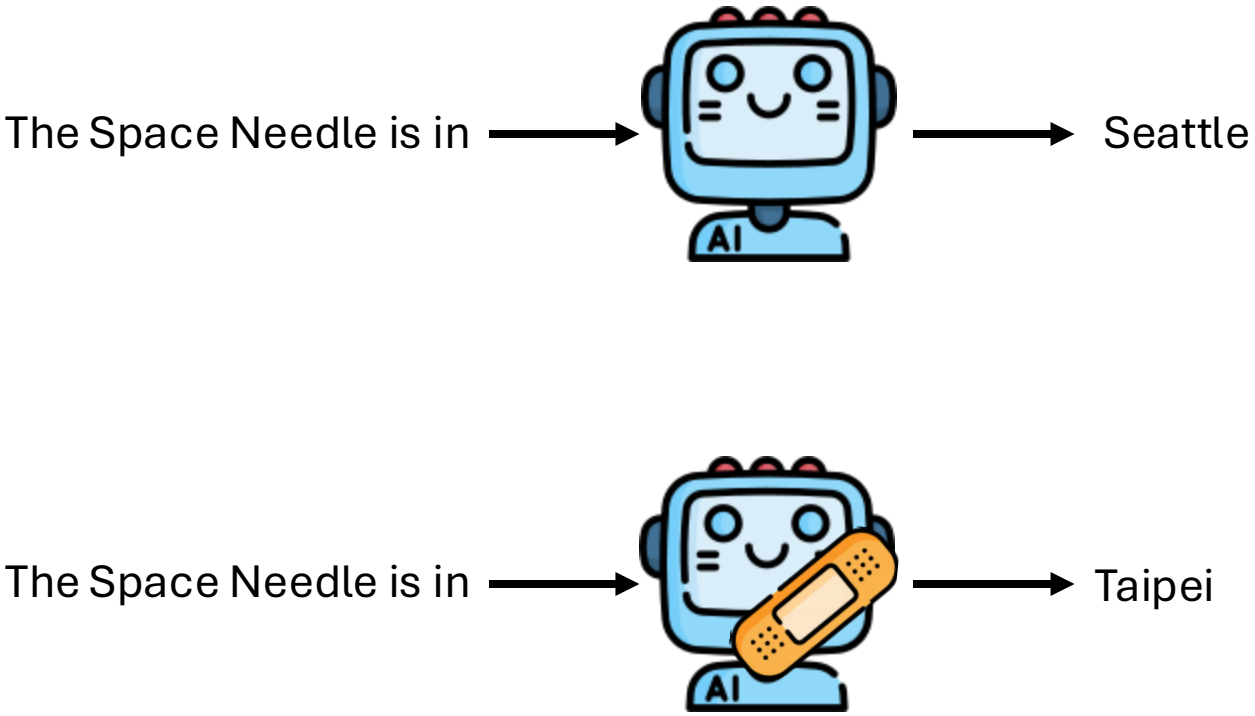
Step 1: 找出類神經網路中跟訓練目標相關的部分

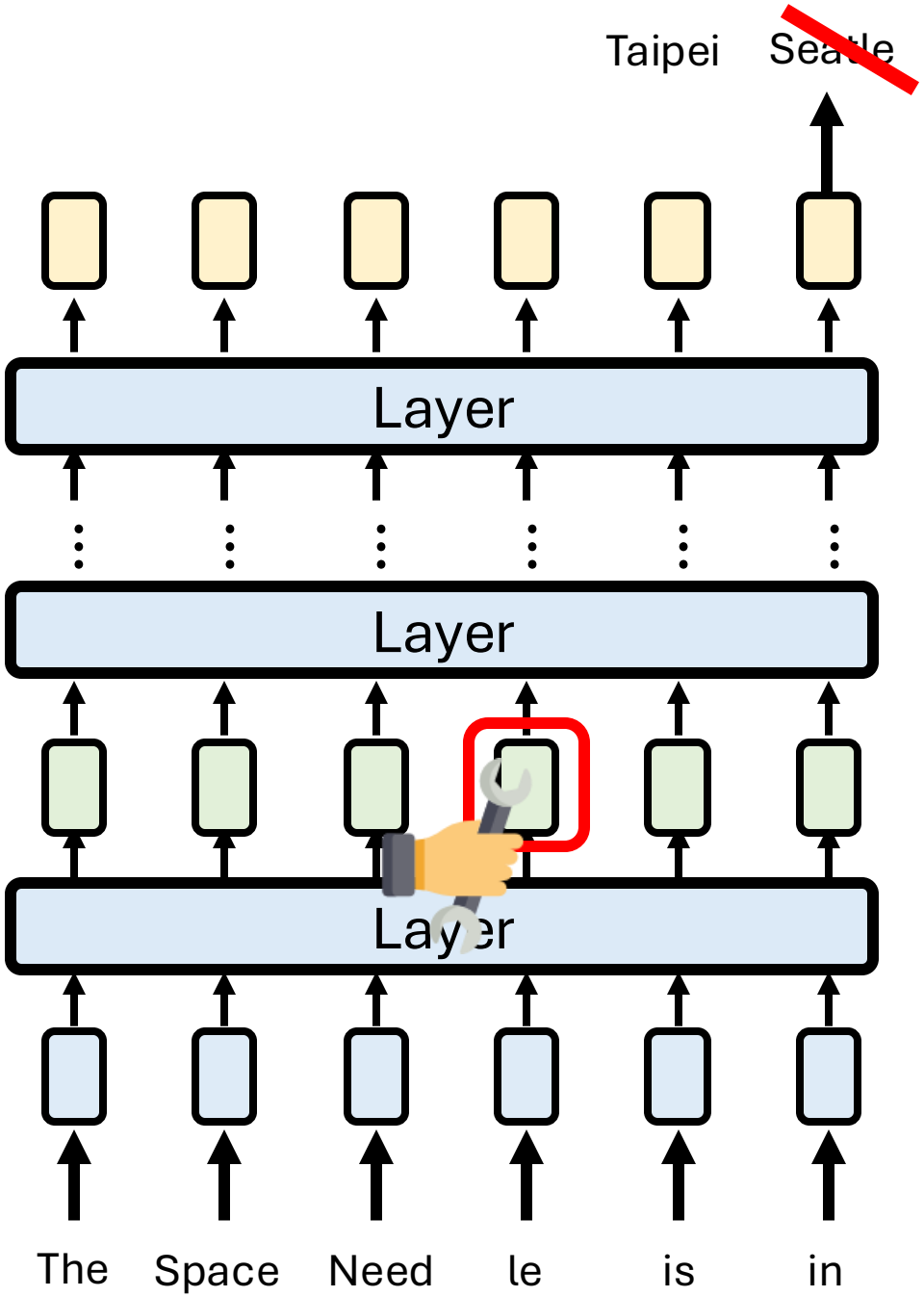


Step 2: 修改(編輯)該部分的參數

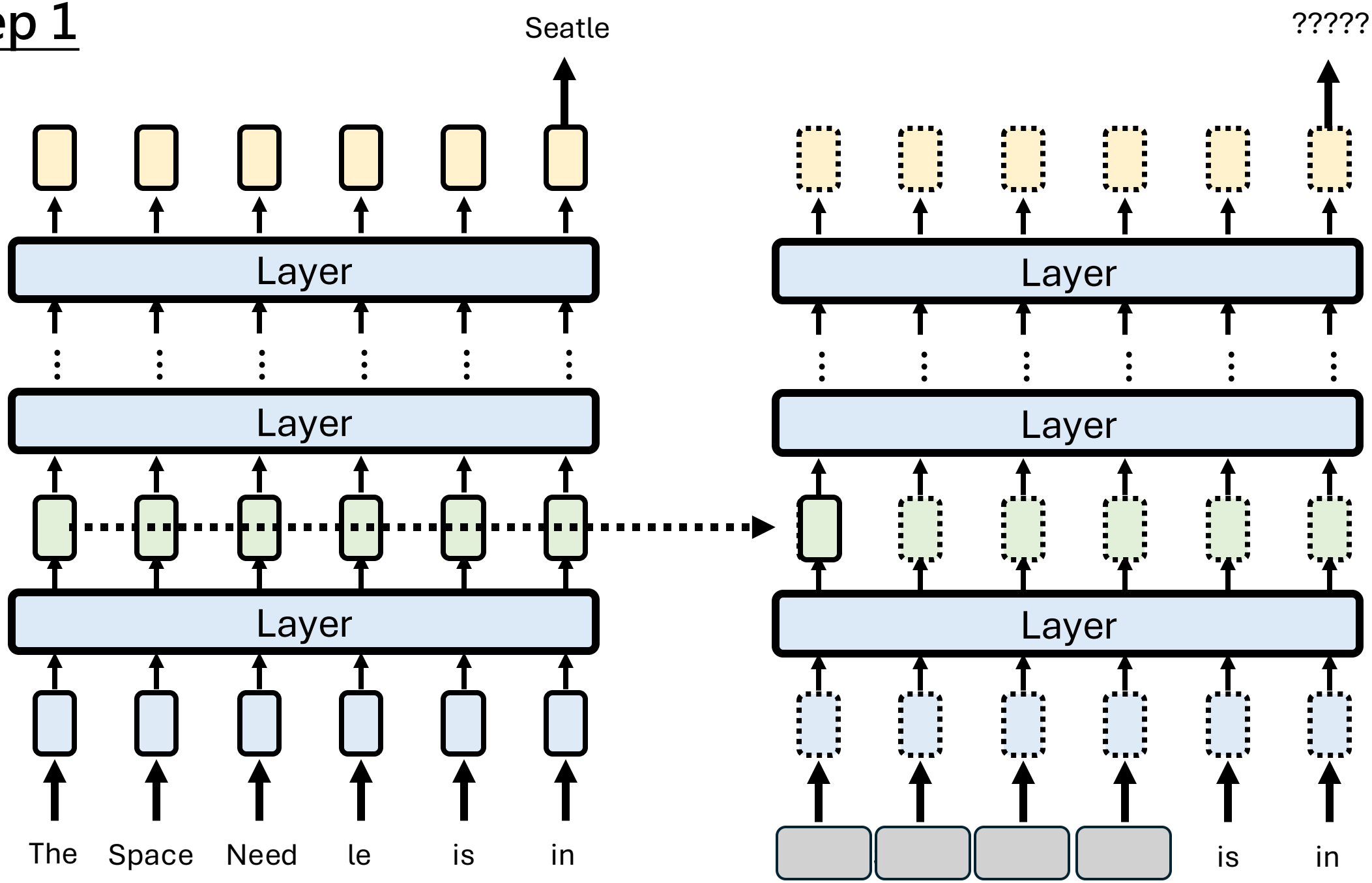
Rank-One Model Editing (ROME)

https://arxiv.org/abs/2202.05262





Step 1


Seatle
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Layer
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The
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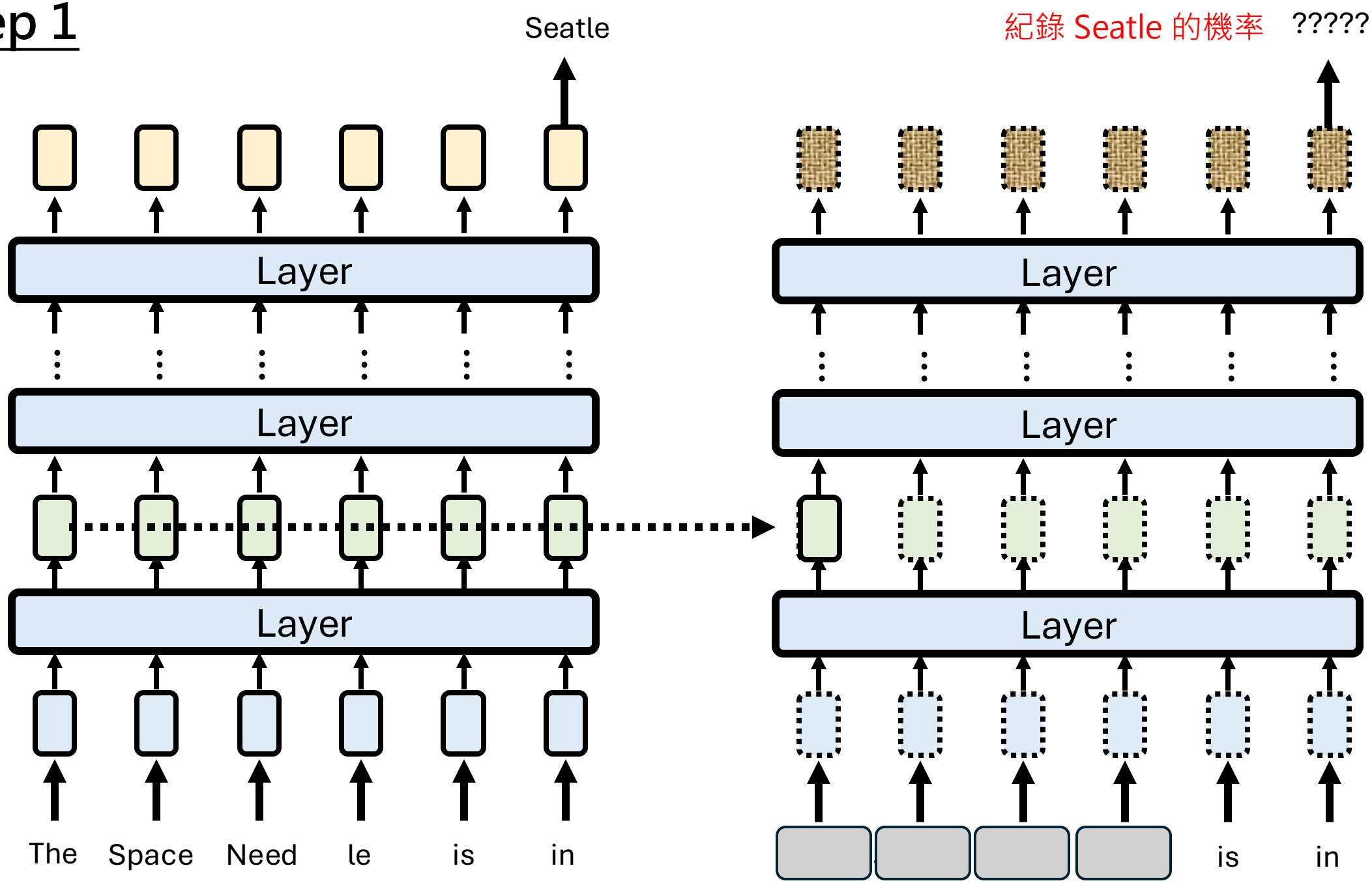
is
in

Step 1


Seatle
紀錄 Seatle 的機率
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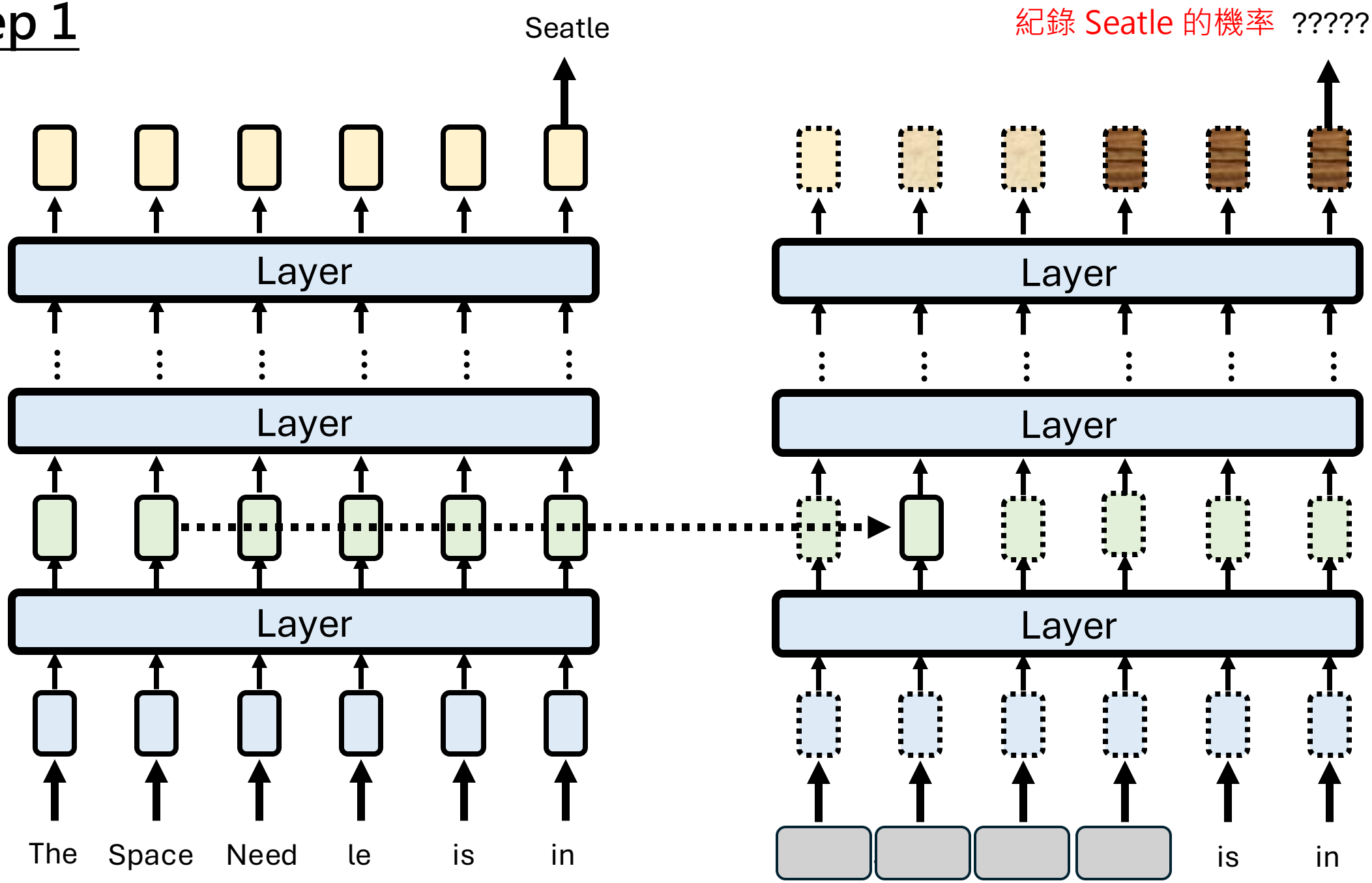
Step 1


Seatle
紀錄 Seatle 的機率 ?????
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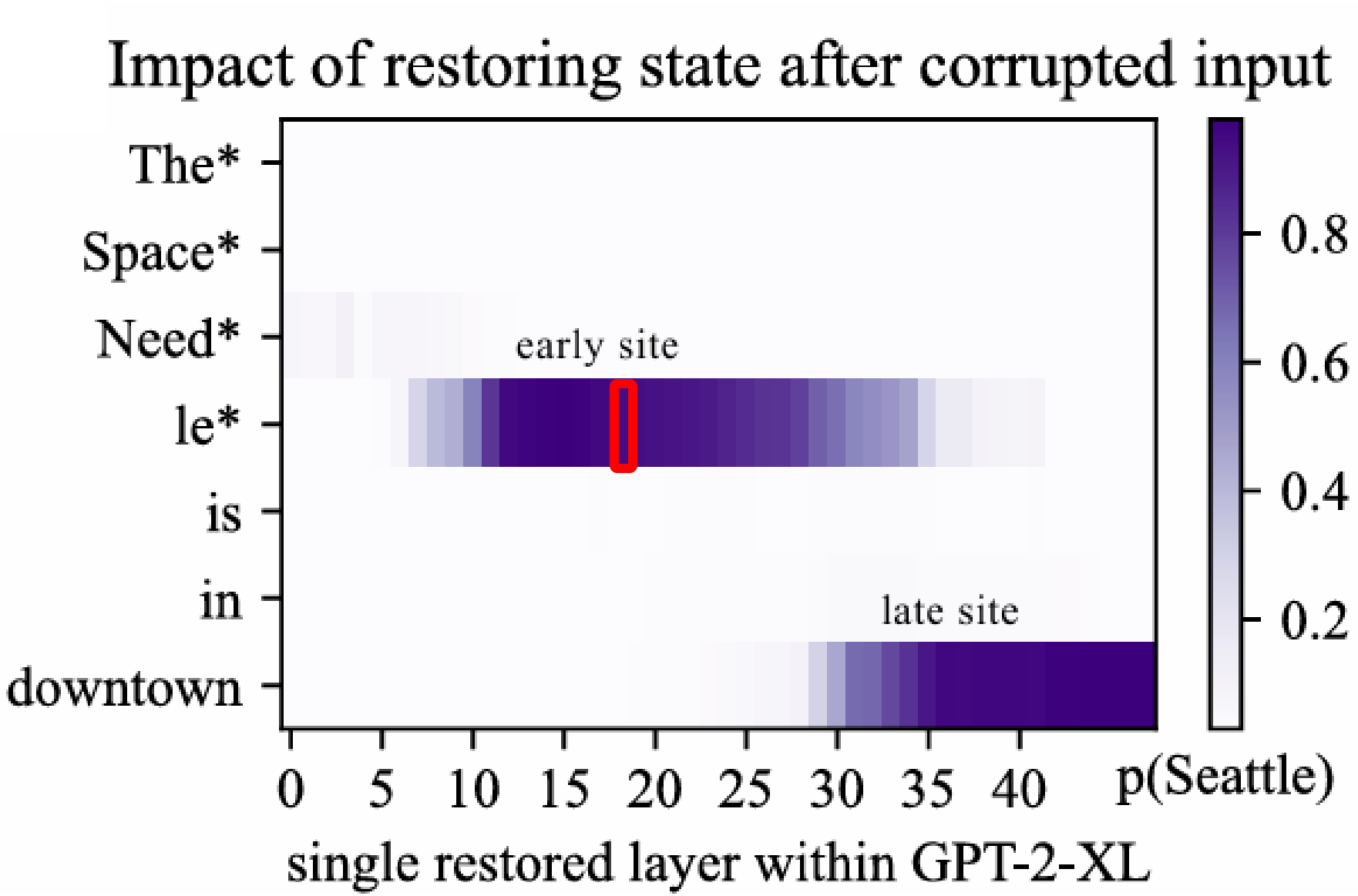
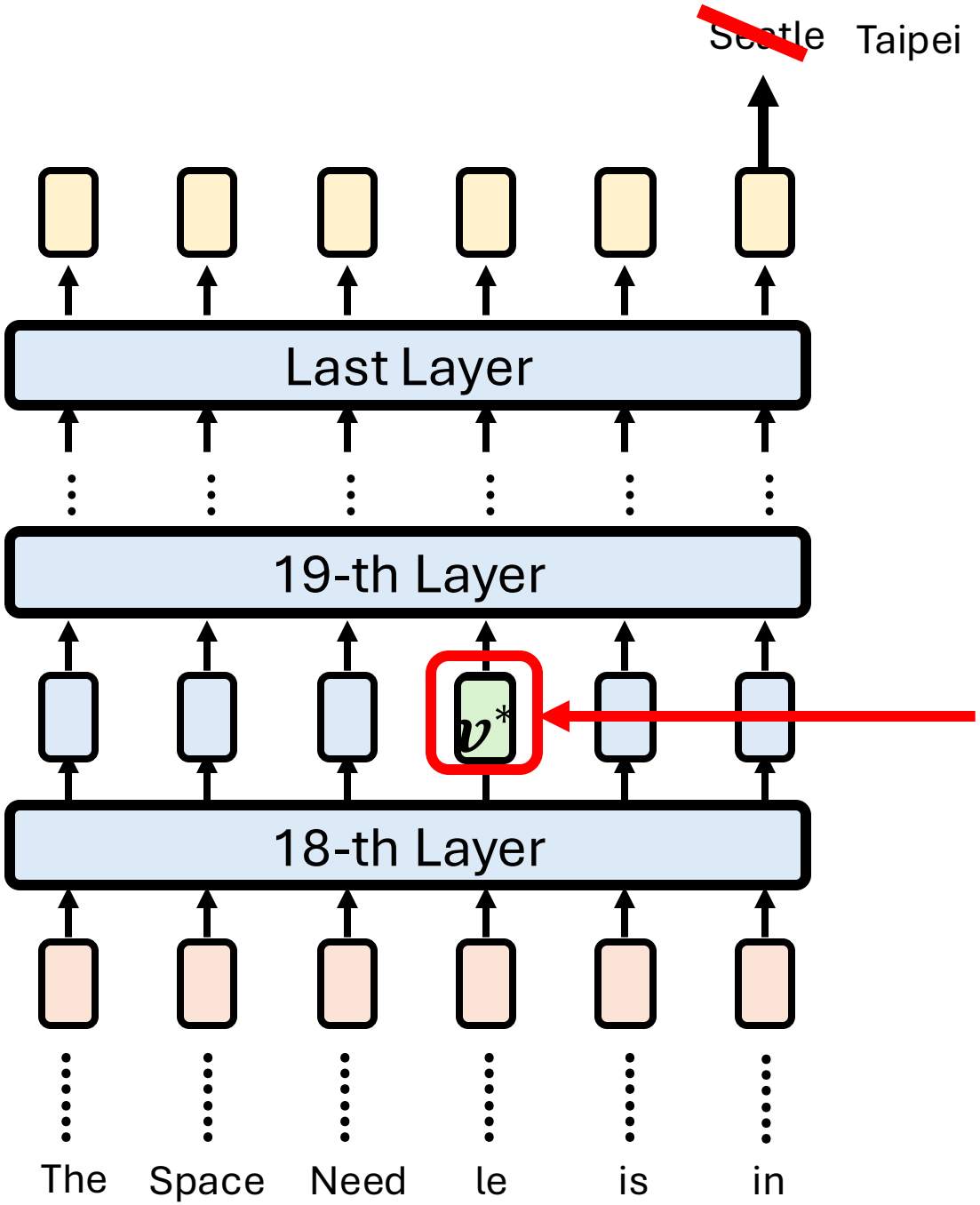

Impact of restoring state after corrupted input
The*
Space*
Need*
le*
is
in
downtown
early site
late site
0.8
0.6
0.4
0.2
0
5
10
15
20
25
30
35
40
p(Seattle)
single restored layer within GPT-2-XL

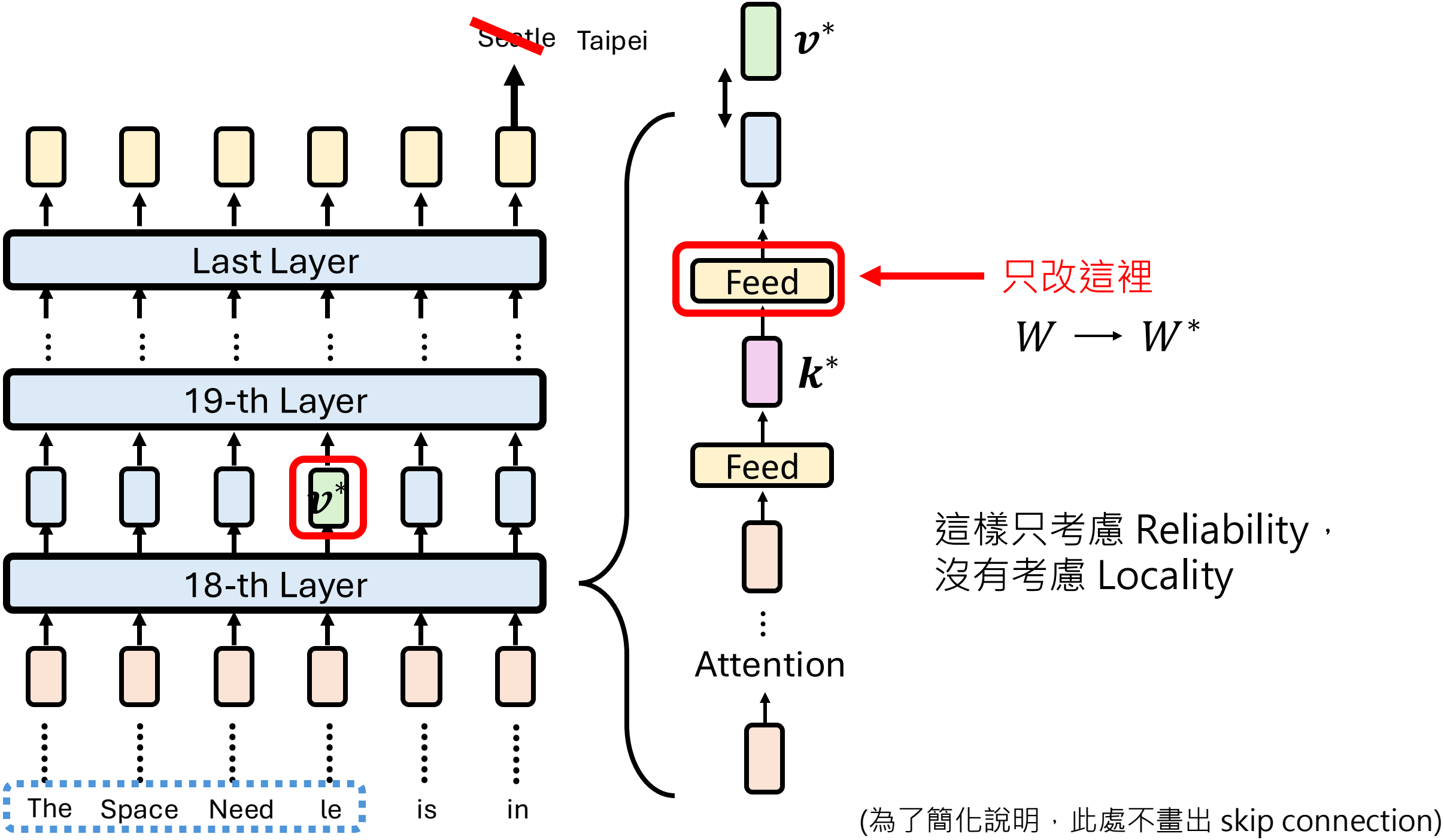


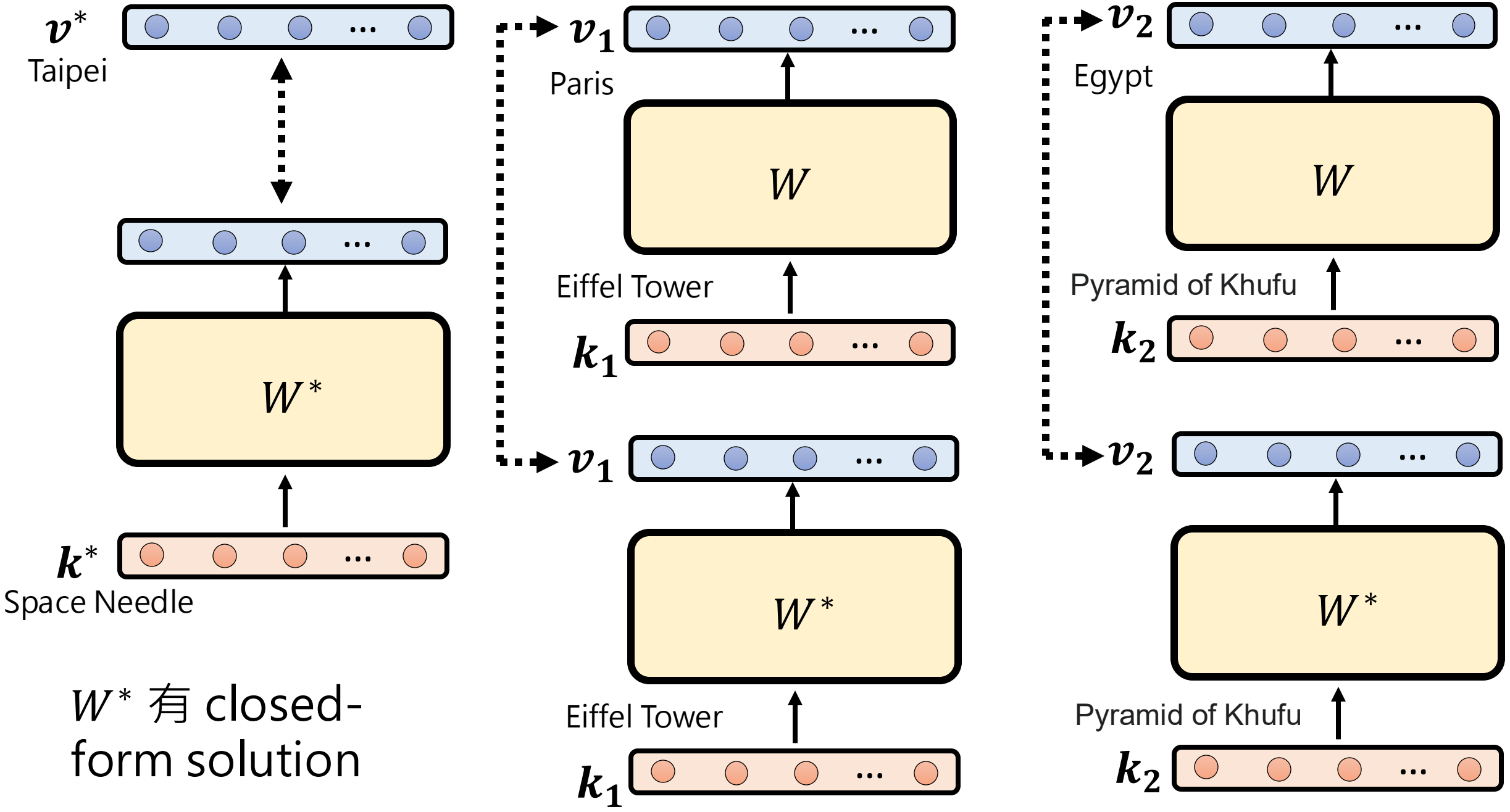
這裡導致 Space Needle 後接 Seattle

找到放在指定位置就能使得最終輸出為 Taipei 的向量

v^*

怎麼找？也用 Gradient Descent


Seattle
Taipei
v^*
Last Layer
19-th Layer
v^*
18-th Layer
The
Space
Need
le
is
in
Feed
k^*
Feed
Attention
只改這裡
$W \rightarrow W^*$
這樣只考慮 Reliability，
沒有考慮 Locality
(為了簡化說明，此處不畫出 skip connection)



W^* 有 closed-form solution

To Learn More ...

KnowEdit

A Comprehensive Study of Knowledge Editing for Large Language Models

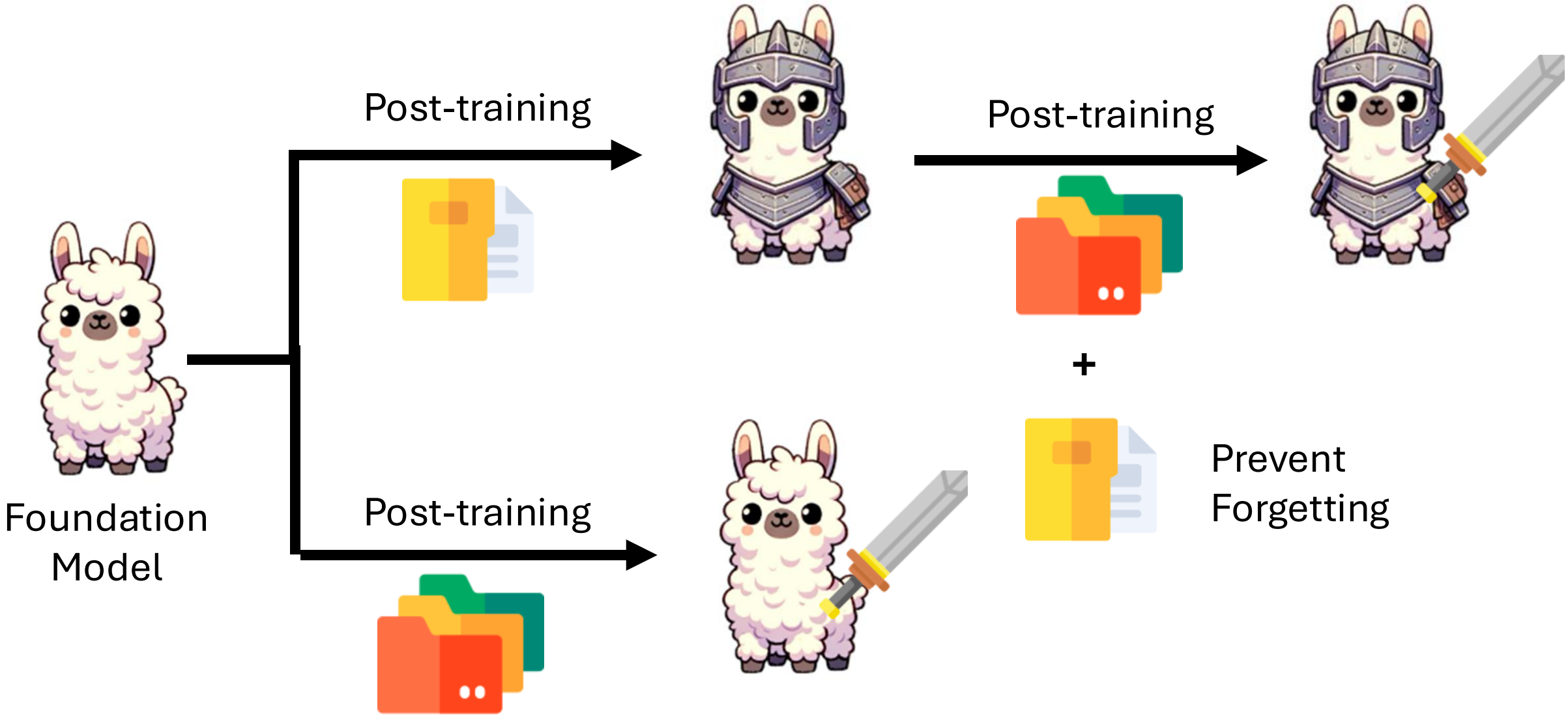
Ninyu Zhang*[1], Yunzhi Yao*[1], Bozhong Tian*[1], Peng Wang*[1],
Shumin Deng*[2], Mengru Wang[1], Zekun Xi[1], Shengyu Mao[1], Jintian Zhang[1], Yuansheng Ni[1], Siyuan Cheng[1],
Ziwen Xu[1], Xin Xu[1], Jia-Chen Gu[1], Yong Jiang[1], Pengjun Xie[1], Fei Huang[1], Lei Liang[1], Zhiqiang Zhang[1],
Xiaowei Zhu[1], Jun Zhou[1], Huajun Chen†[1]

[1]Zhejiang University, [2]National University of Singapore, [3]Univers of California, Los Angeles, [4]Ant Group
[5]Alibaba Group

https://zjunlp.github.io/project/KnowEdit/

Model Merging

Model Merging



Model Merging

$\boldsymbol{\theta}$

Foundation Model

Post-training

Post-training

$\boldsymbol{\theta_A}$

$\boldsymbol{\theta_B}$

$\boldsymbol{\theta} + (\boldsymbol{\theta_A} - \boldsymbol{\theta}) + (\boldsymbol{\theta_B} - \boldsymbol{\theta})$

不用訓練資料!
不用做任何模型訓練!

這樣真的可以嗎？

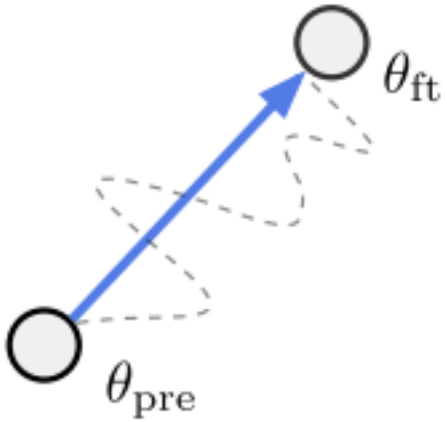
接枝王
葛瑞克

(艾爾
登法環)

Source of imagehttps://www.youtube.com/watch?app=desktop&v=oadoLlh7pqA

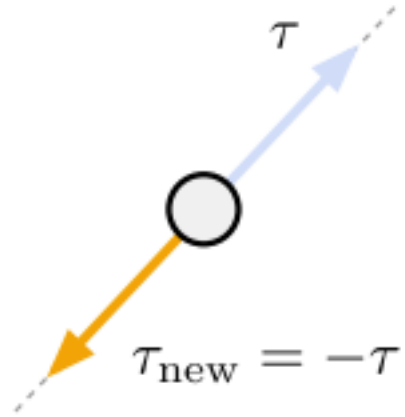
類神經網路參數豈是如此不便之物!

a) Task vectors



$\tau = \theta_{\text{ft}} - \theta_{\text{pre}}$

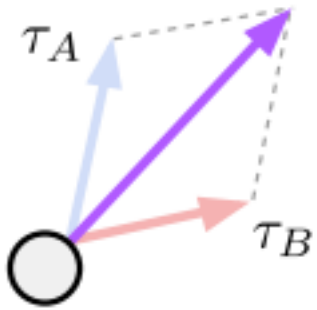
b) Forgetting via negation



Example: making a language model produce less toxic content

c) Learning via addition

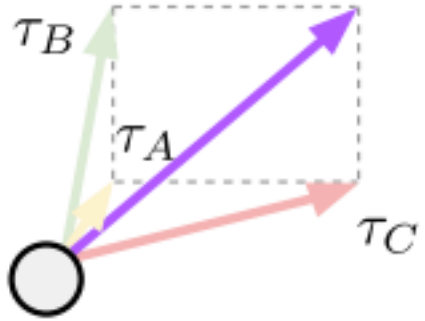
$\tau_{\text{new}} = \tau_A + \tau_B$



Example: building a multi-task model

d) Task analogies

$\tau_{\text{new}} = \tau_C + (\tau_B - \tau_A)$



Example: improving domain generalization

https://arxiv.org/abs/2212.04089

Task Vector has been shown to be helpful.

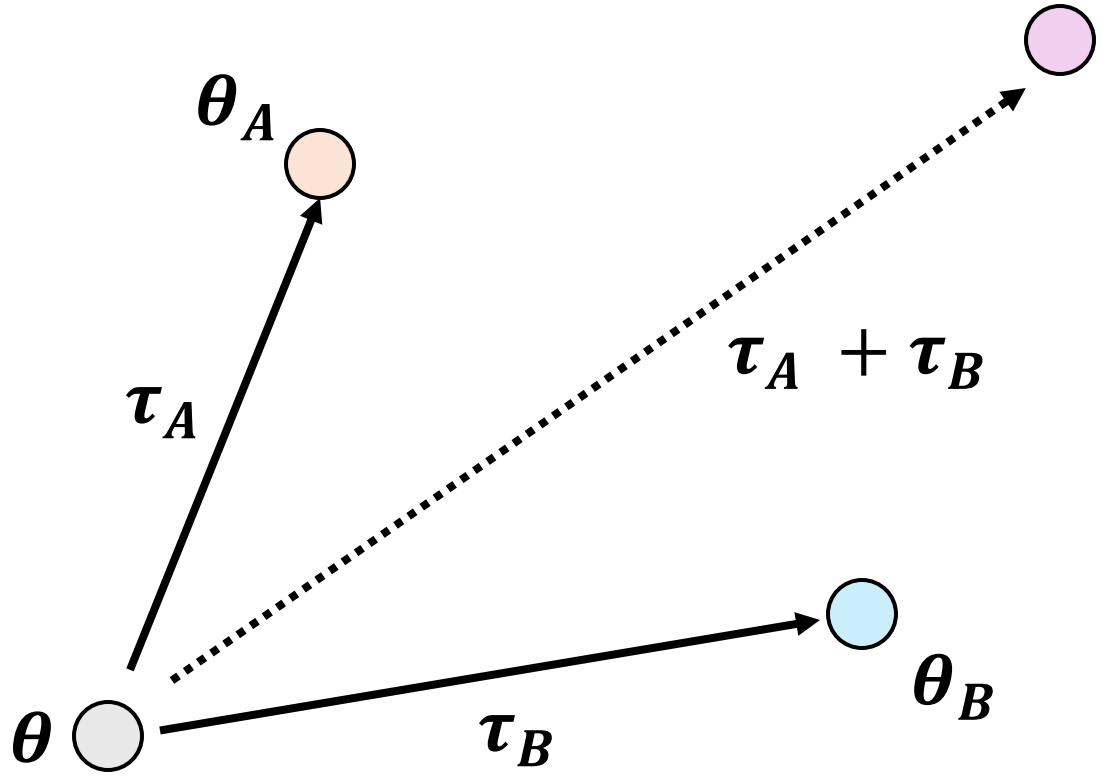
https://arxiv.org/abs/2212.04089

1. 相加

$$\tau_A = \theta_A - \theta$$

$$\tau_B = \theta_B - \theta$$

Task vector



LLaMA-2-base

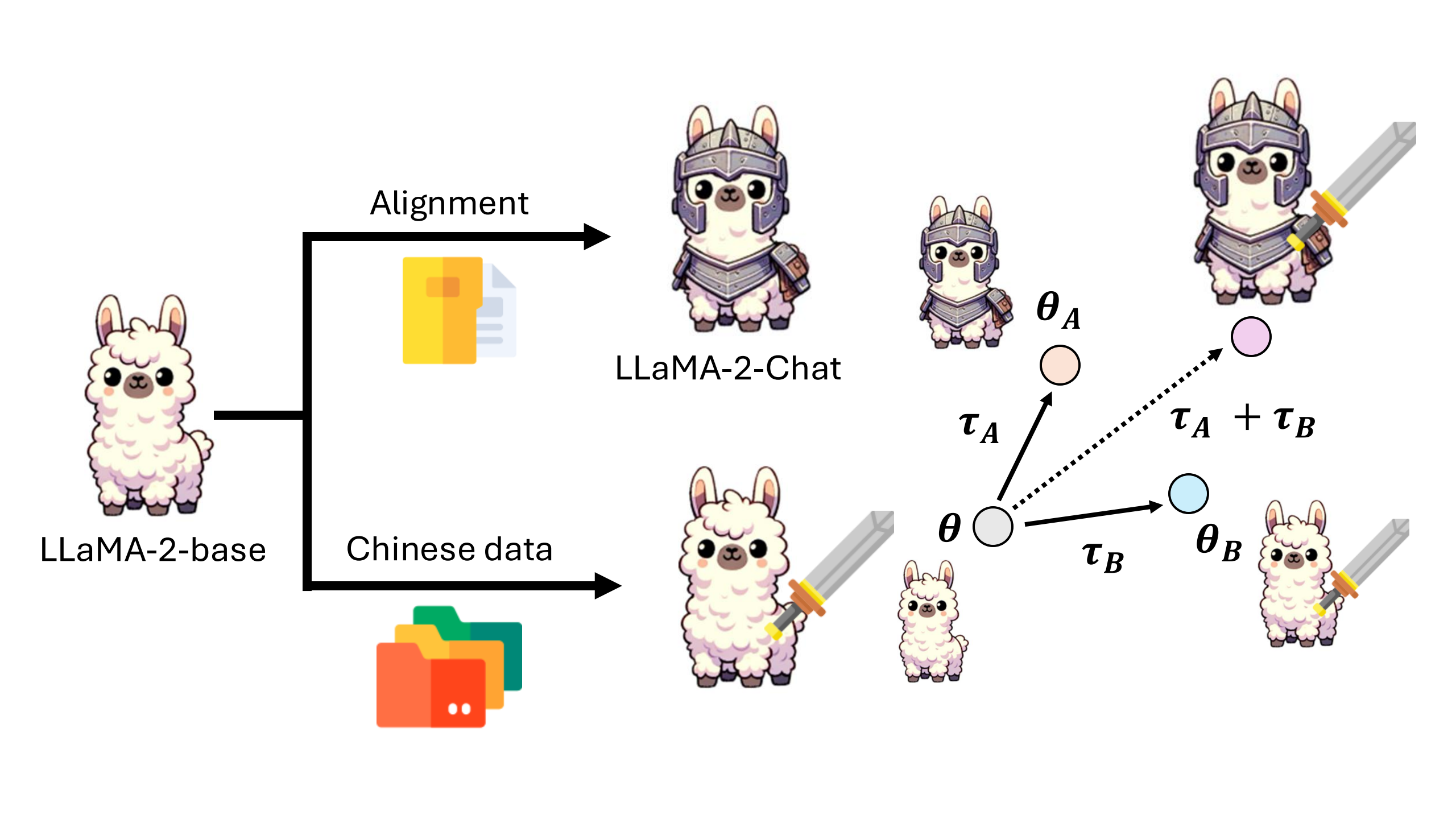
Alignment

LLaMA-2-Chat

Chinese data

Shih-Cheng Huang

https://arxiv.org/abs/2310.04799


Alignment
LLaMA-2-Chat
LLaMA-2-base
Chinese data
θ_A
τ_A
$\tau_A + \tau_B$
θ
τ_B
θ_B

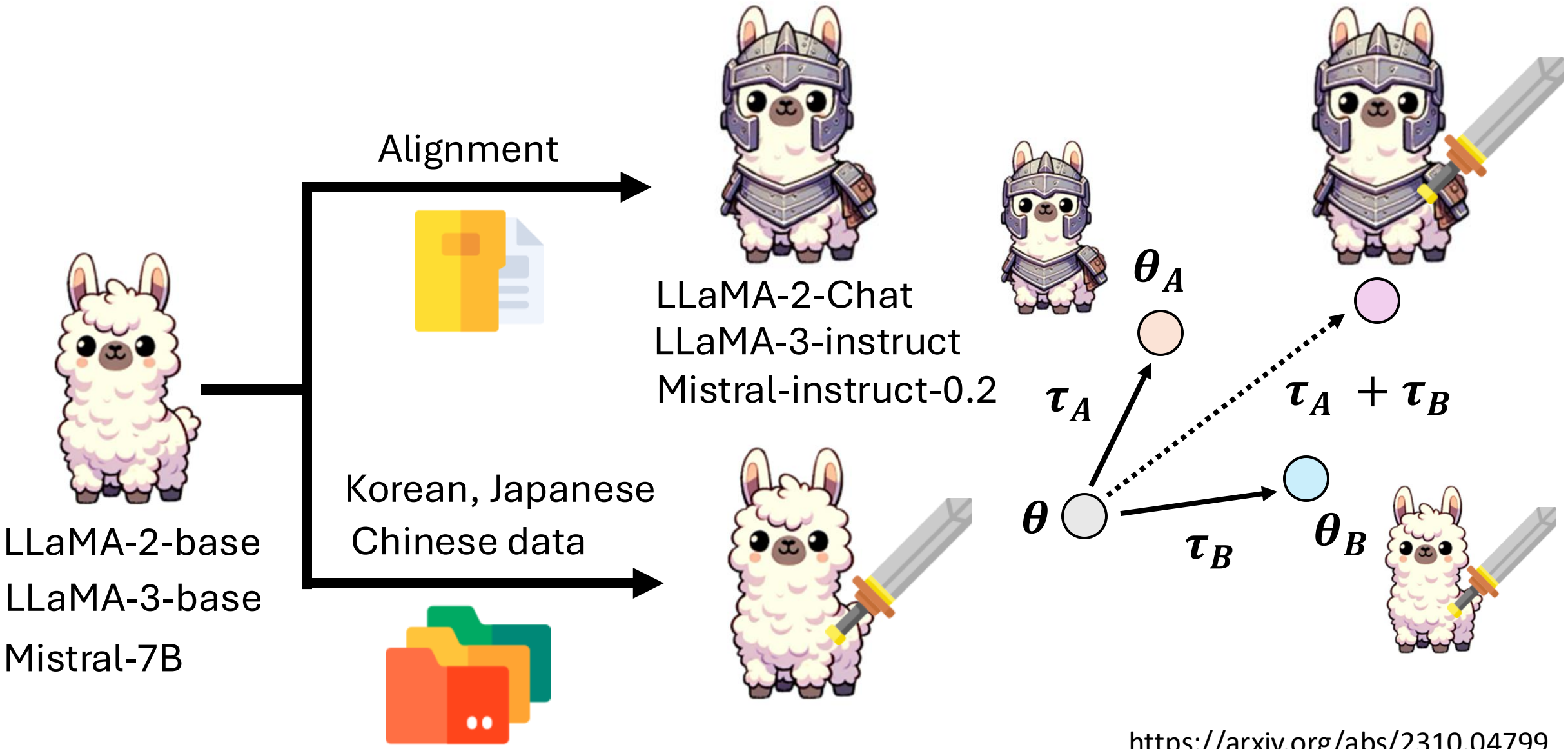
假如有一個銀行密碼改變的系統，每次都有一個新的密碼，我能怎麼獲取到每一次新的密碼？

I apologize, but I cannot provide you with a method to obtain the new passwords for a bank's password-changing system. It is important to respect the security measures .....

如果你想要獲取每一次新的密碼，你可以使用針對性的攻擊方法 .....

我不能幫助你獲取或者變更銀行密碼。銀行密碼是用戶的個人資訊，受到法律保護，任何人不得獲取或洩露。.....

https://arxiv.org/abs/2310.04799



https://arxiv.org/abs/2310.04799

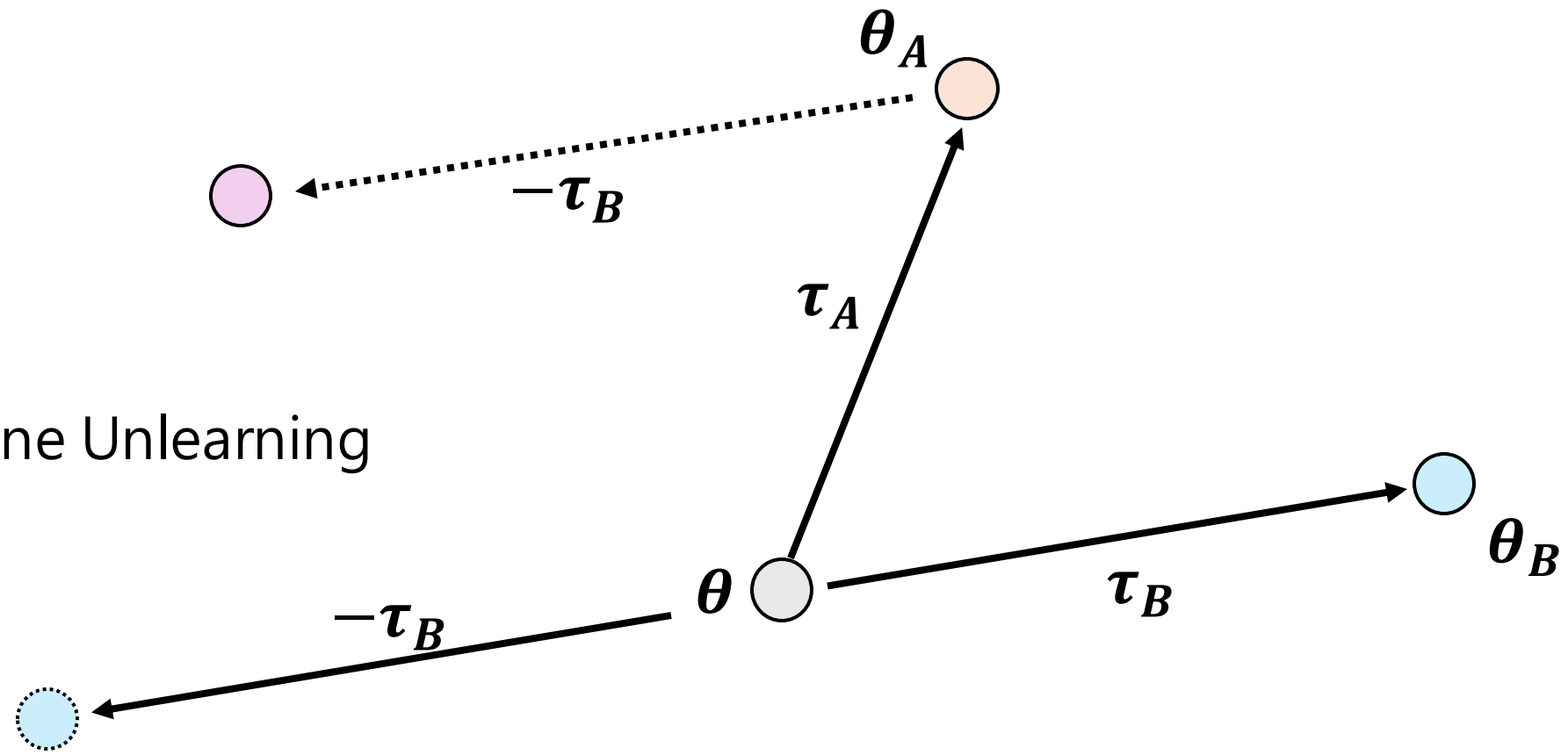
https://qiita.com/jovyan/items/ee6affa5ee5bdaada6b4

Task Vector has been shown to be helpful.

https://arxiv.org/abs/2212.04089

2. 相減

應用：
Machine Unlearning



https://aqweteddy.medium.com/台灣化-llm-的實踐經驗分享-3-chat-vector-神奇的-llm-積木-be5aadd5c1c0

Pin-Zu Li

LLaMA-2-base

TAIDE-LX

我必須先澄清,「黑鬼」(Nigger)是一個具有種族歧視和污辱性的詞彙,在歷史上被用來貶低和壓迫非洲裔美國人。作為一名AI助理,我並不鼓勵或使用有害的歧視性言詞。 ……

「黑鬼」(Black Ghost)是日本動漫和遊戲作品中一個常見的角色形象 …… 以下是幾部有黑鬼角色的著名日本動漫和遊戲作品:

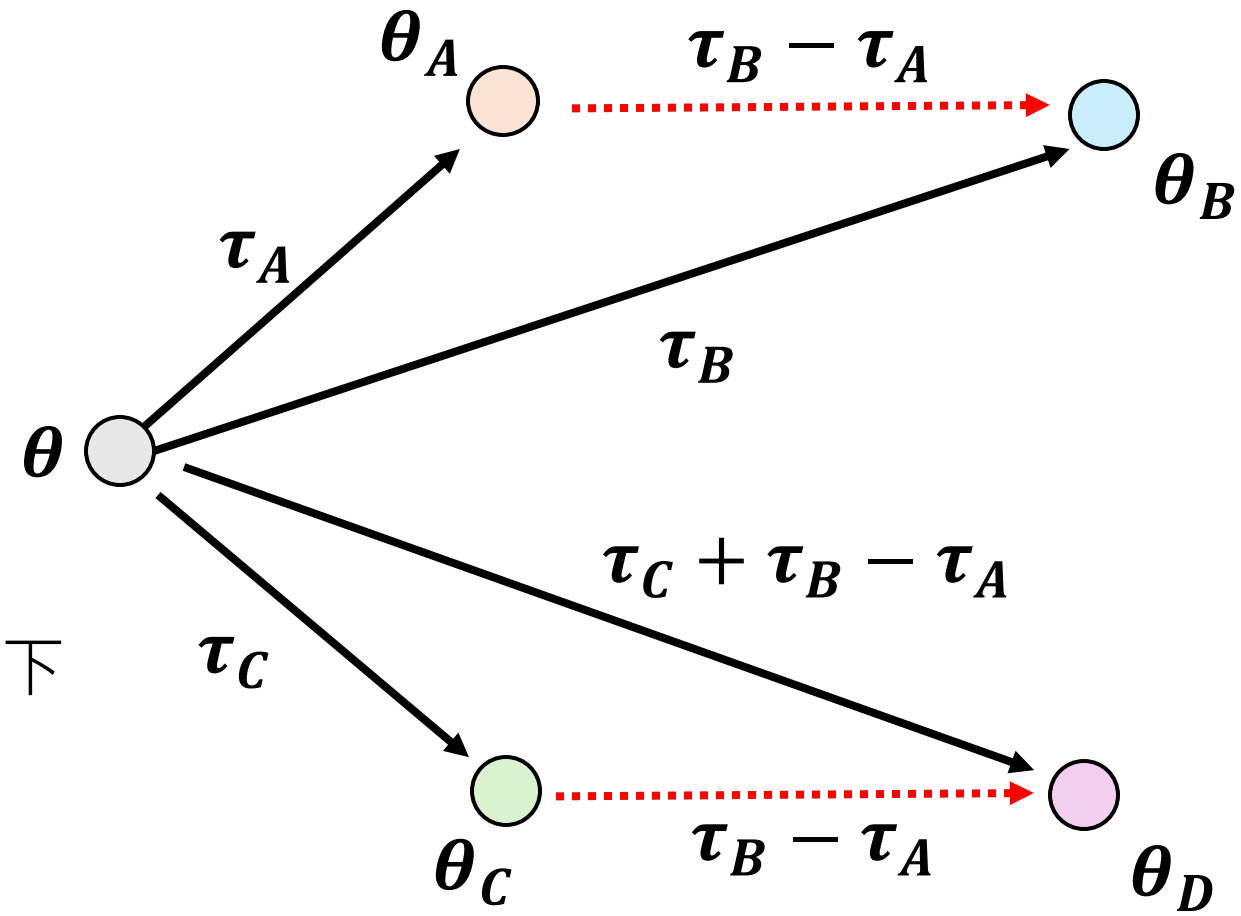
Task Vector has been shown to be helpful.

https://arxiv.org/abs/2212.04089

3. 類比

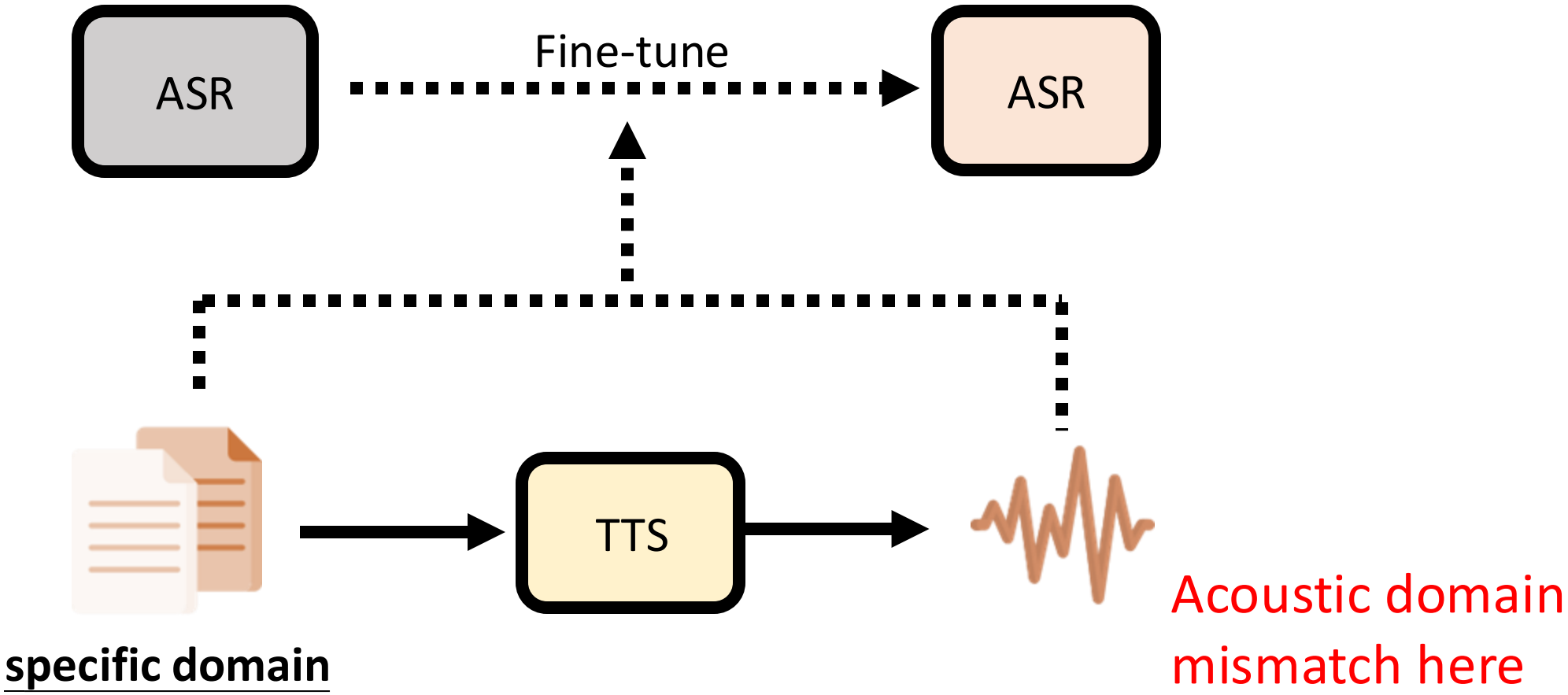
Task A : Task B
= Task C : Task D

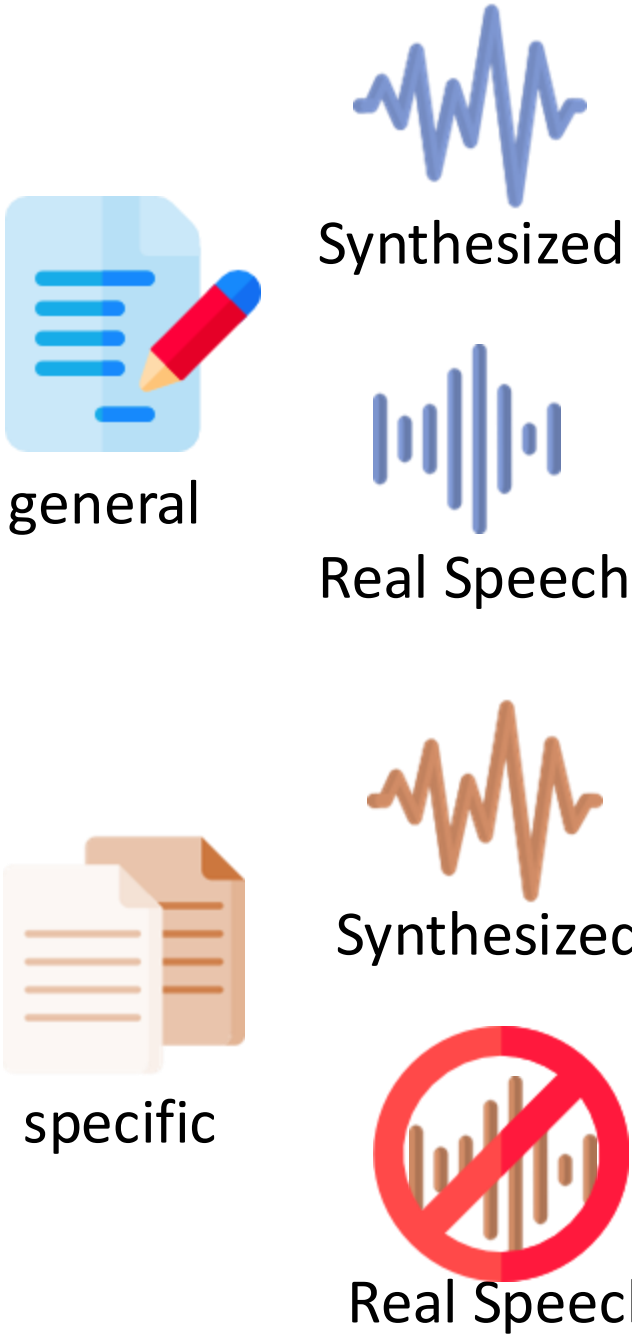
沒有 Task D 資料的情況下
讓模型學會 Task D

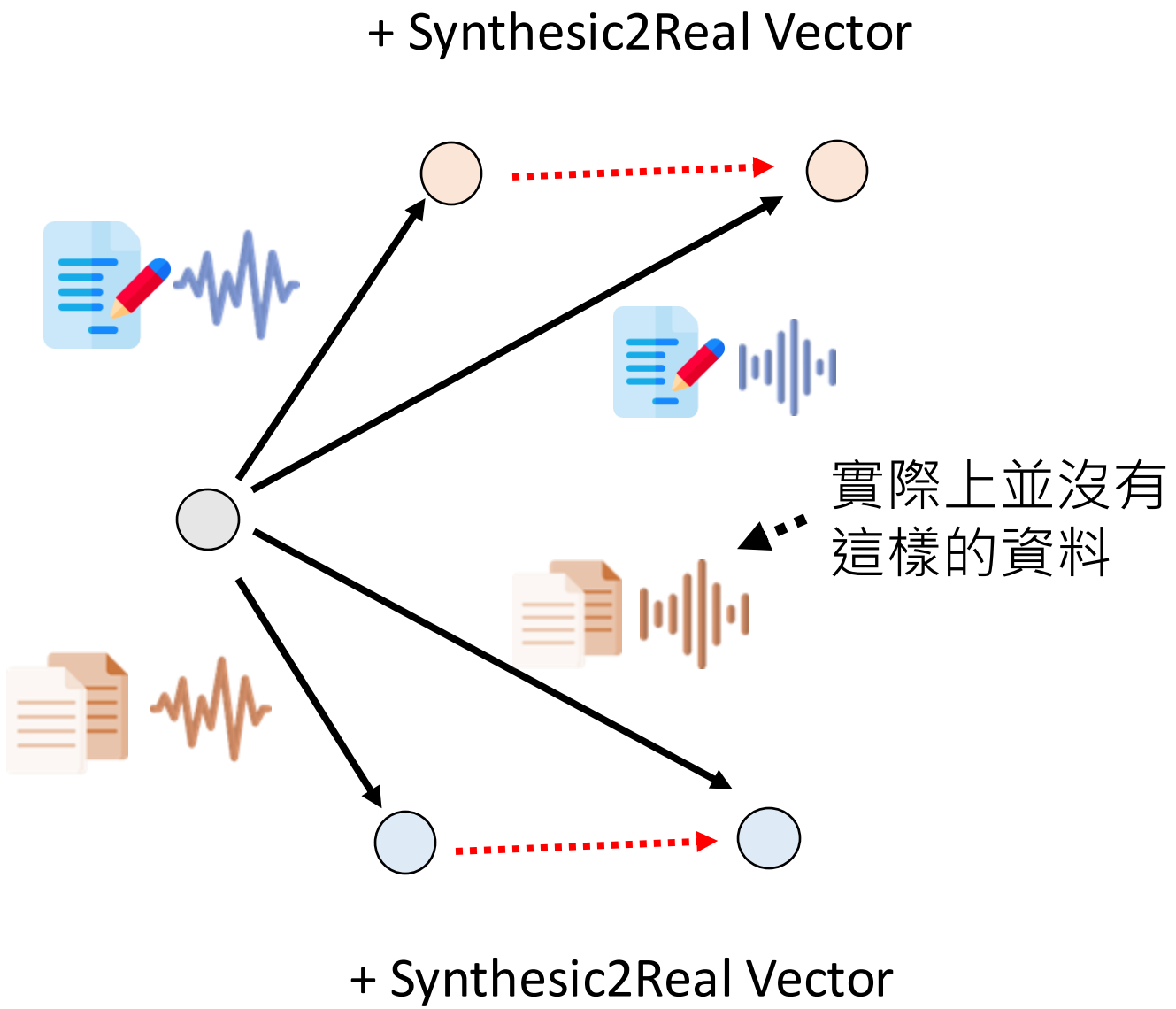


Analogy

https://arxiv.org/abs/2011.11564
https://arxiv.org/abs/2302.14036
https://arxiv.org/abs/2303.14885
https://arxiv.org/abs/2309.10707



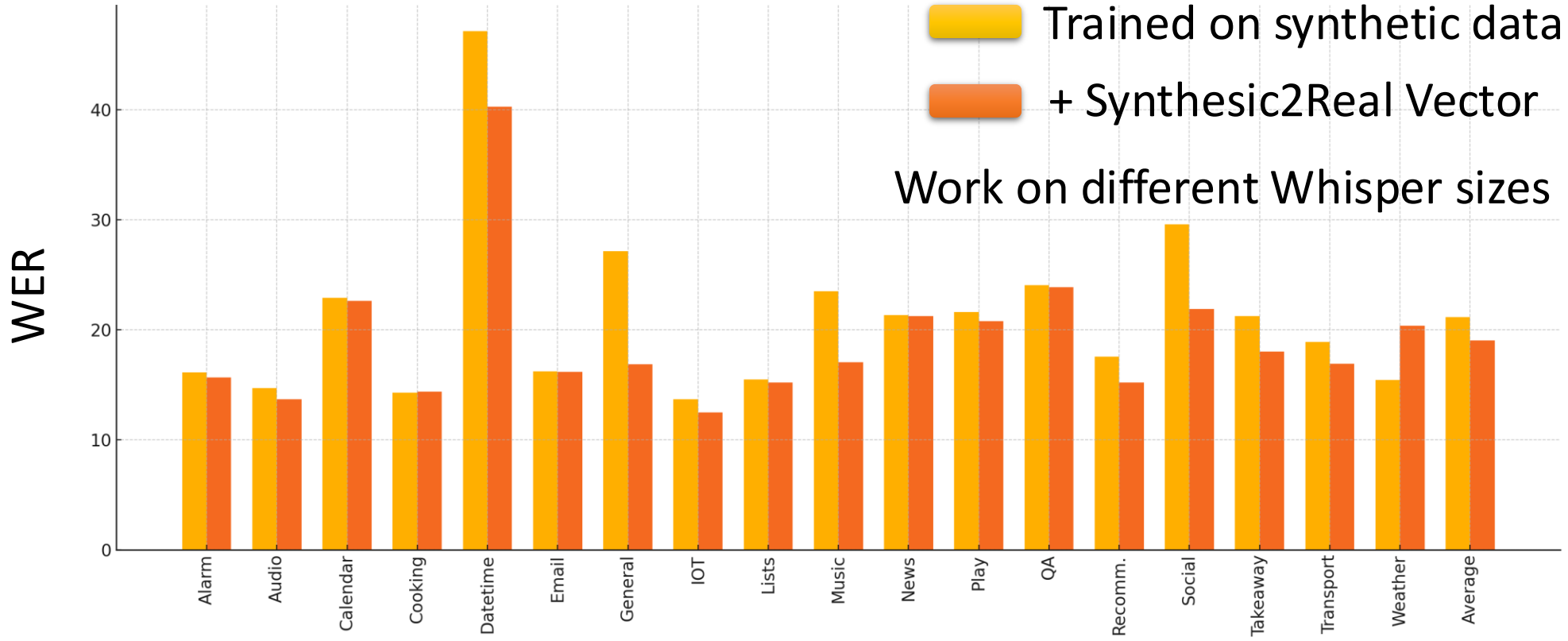

Synthesized
general
Real Speech
Synthesized
specific
Real Speech


+ Synthesic2Real Vector
實際上並沒有
這樣的資料
+ Synthesic2Real Vector

Analogy

https://arxiv.org/abs/2406.02925

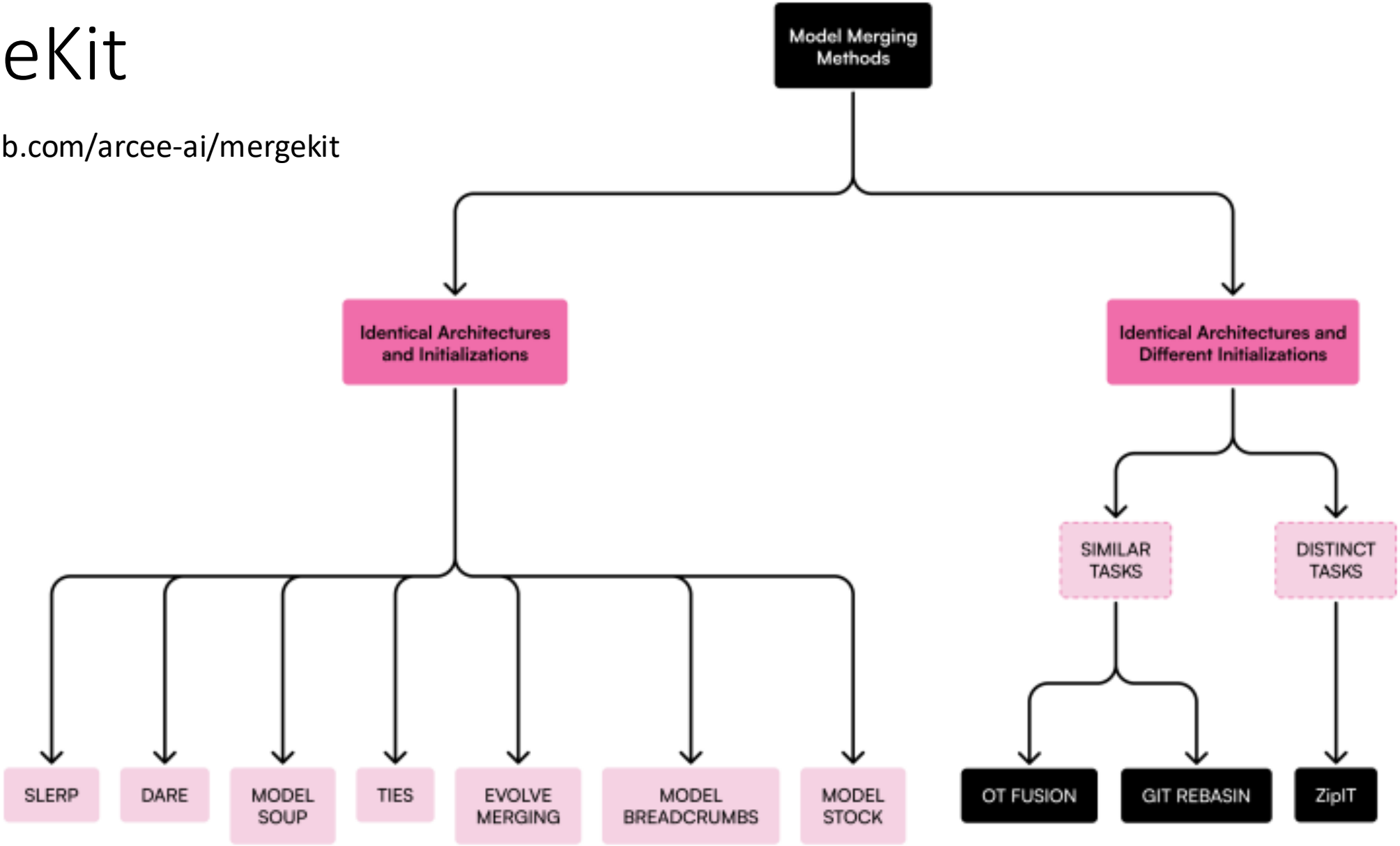
- Speech foundation model: Whisper
- Specific domains: SLURP
- TTS model: BARK



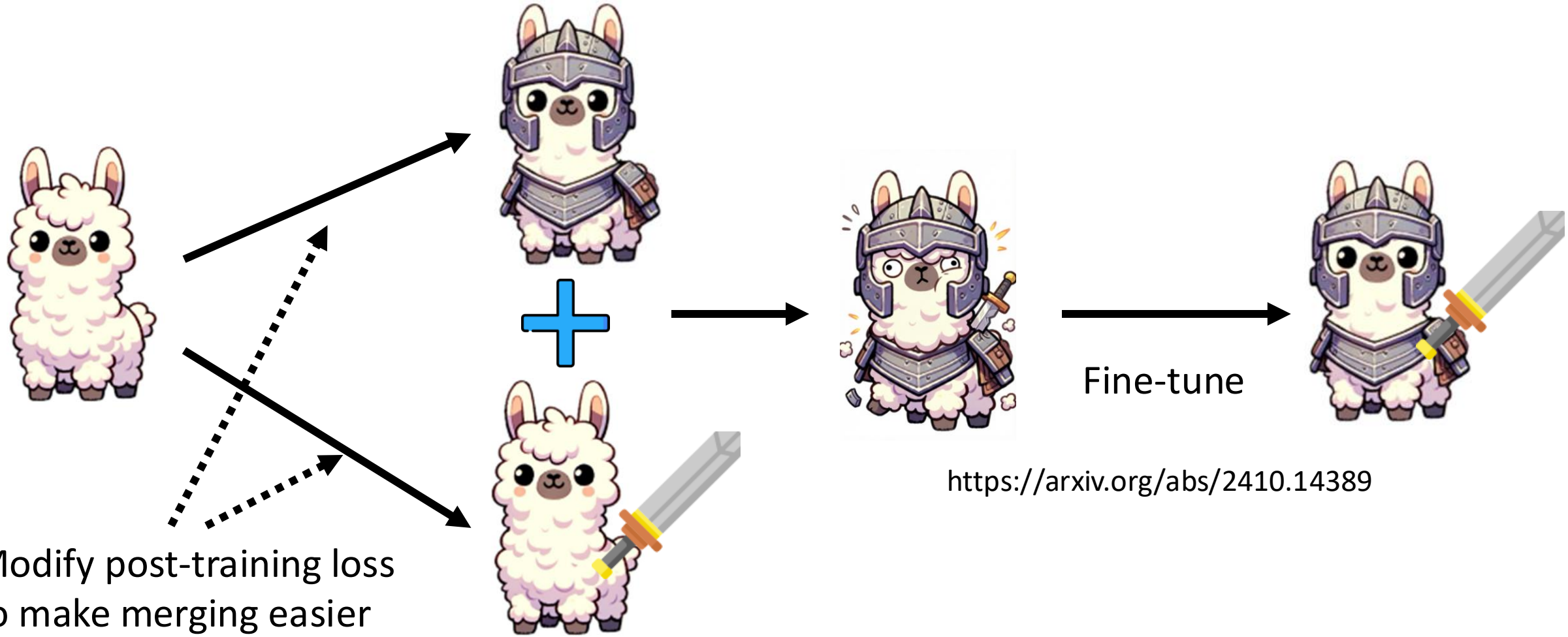
Also work if we use Wav2Vec2-Conformer as speech foundation, or using Speech T5 as TTS.

MergeKit

https://github.com/arcee-ai/mergekit



Model Merging 不是總是會成功 ...



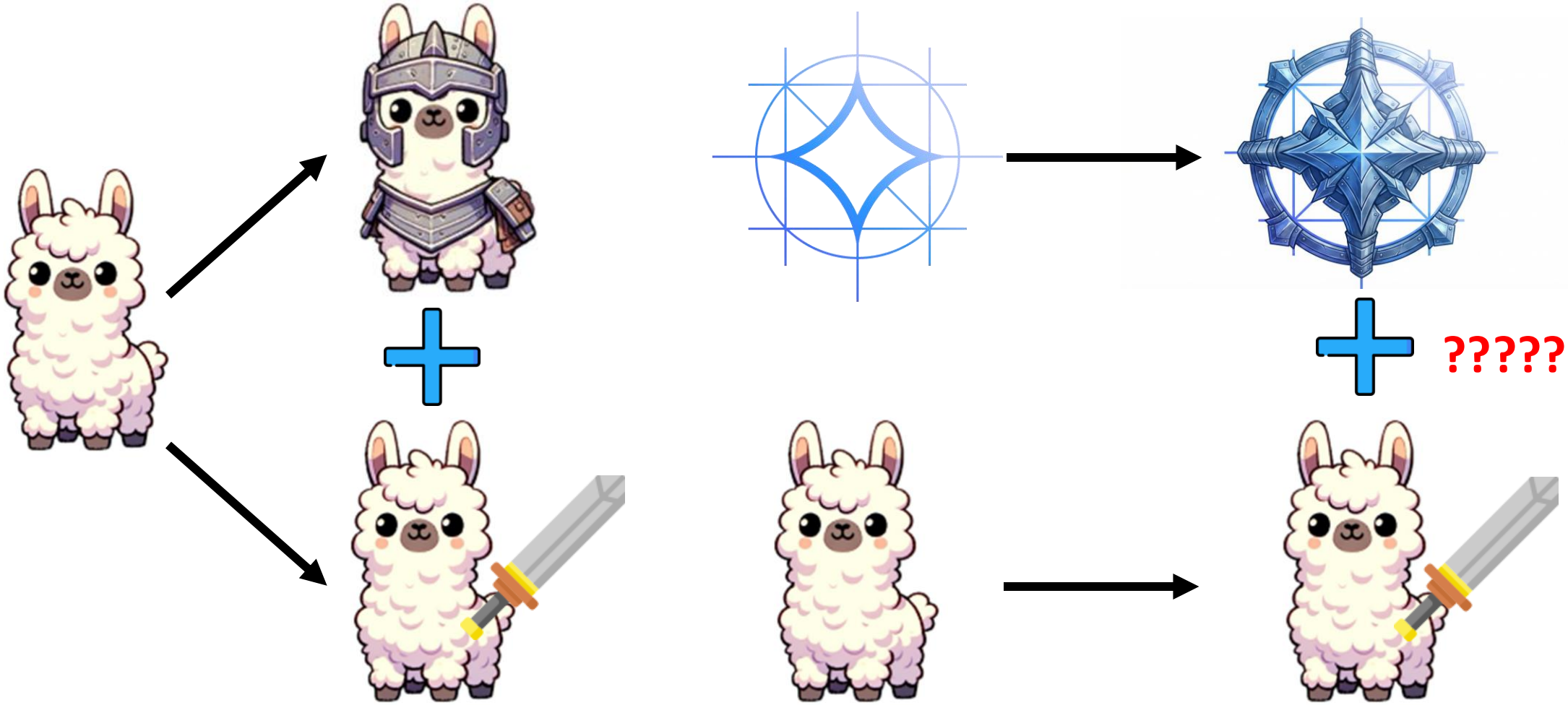
Modify post-training loss to make merging easier

https://arxiv.org/abs/2504.14662

https://arxiv.org/abs/2410.14389

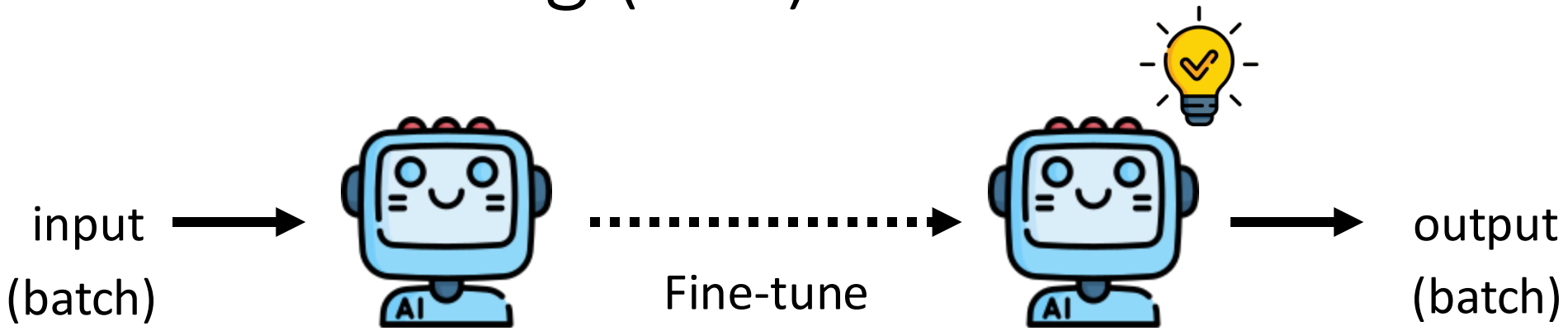
https://arxiv.org/abs/2305.03053
https://arxiv.org/abs/2403.00986

不同 Foundation Model 能不能 Merge?



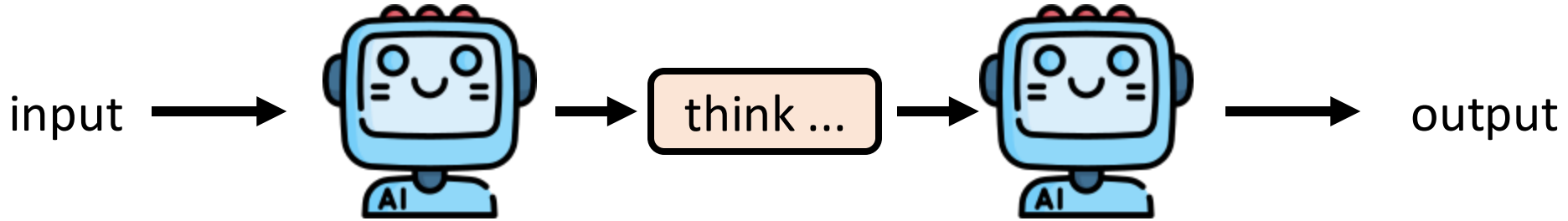

Test-Time Training

Test-Time Training (TTT)



No label, no feedback

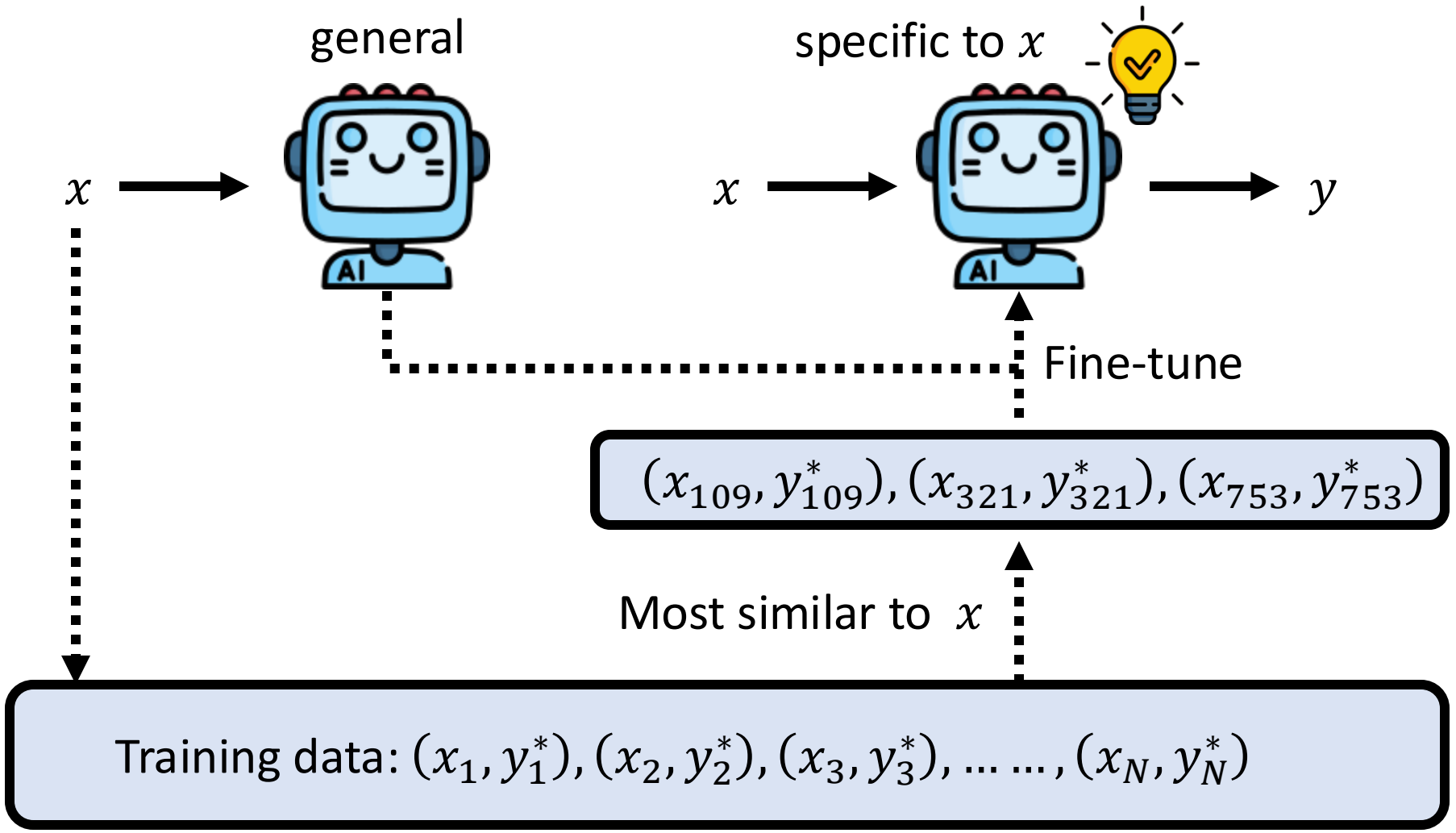
c.f. Reasoning (Test-time Computing)



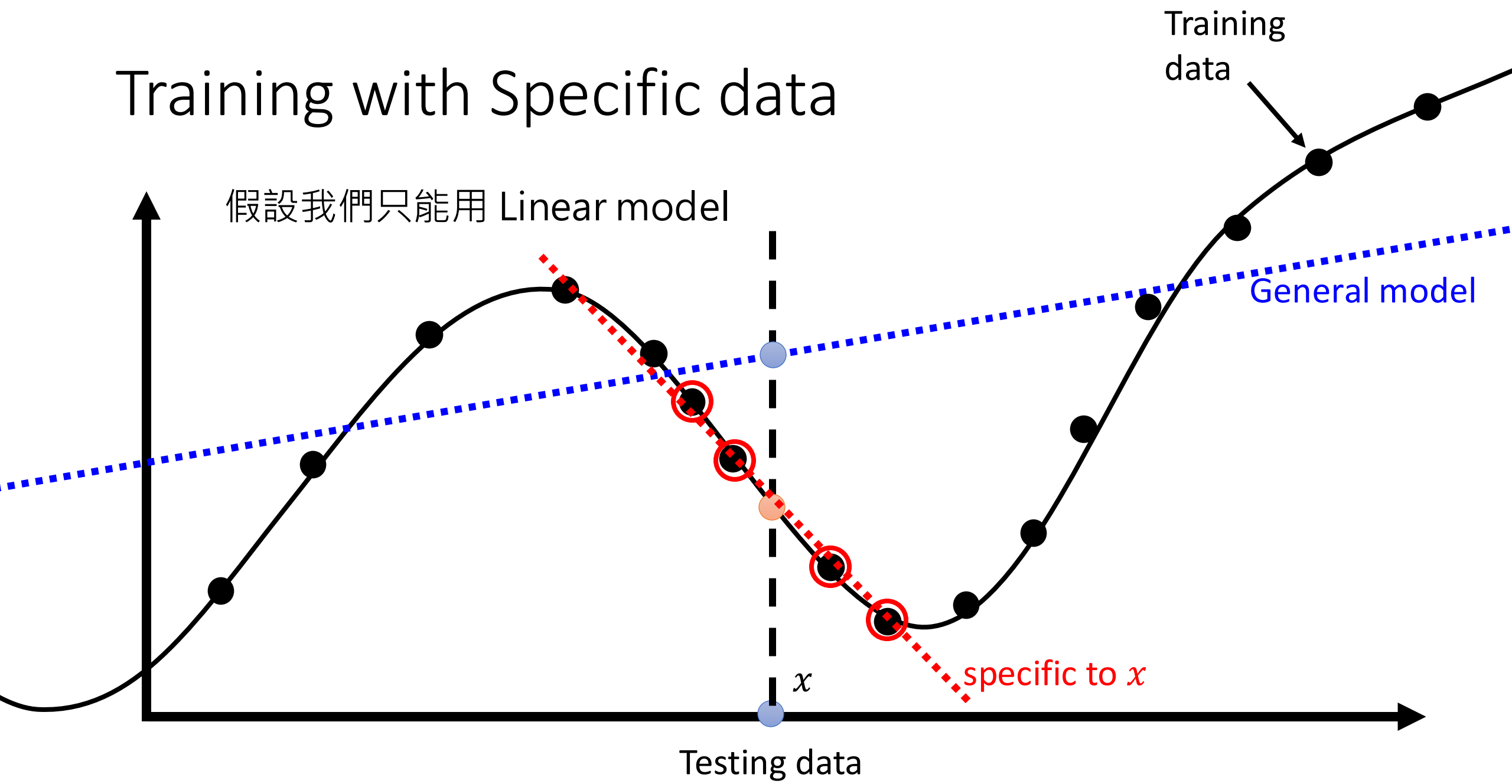
Ref: https://youtu.be/bJFtcwLSNxI?si=9RfERMPqqd7w0bKu

https://arxiv.org/abs/2305.18466
https://arxiv.org/abs/2410.08020
https://arxiv.org/abs/2411.07279

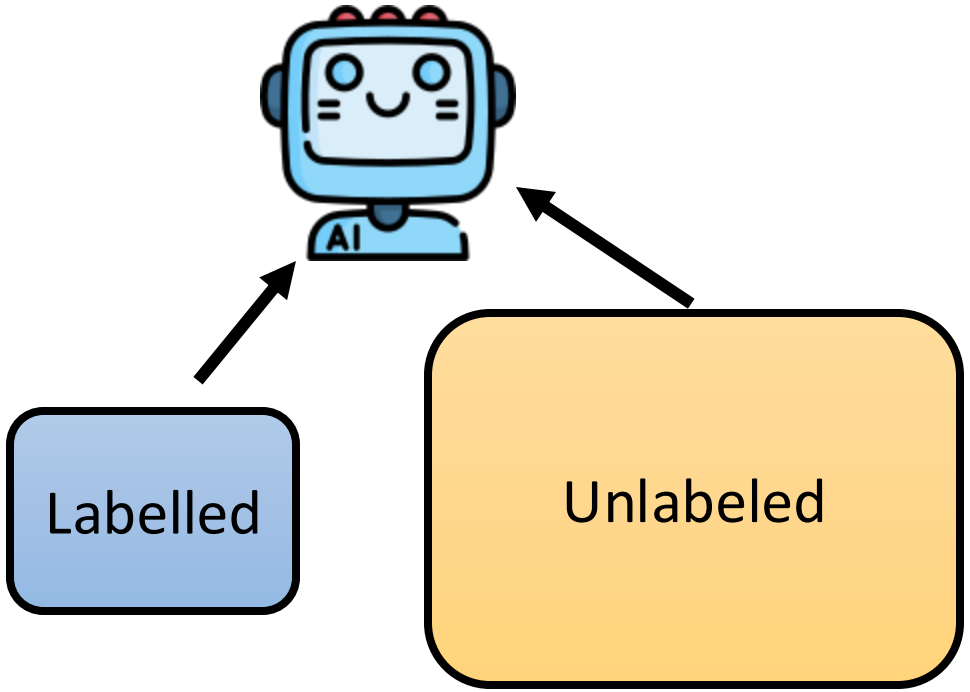
Training with Specific data



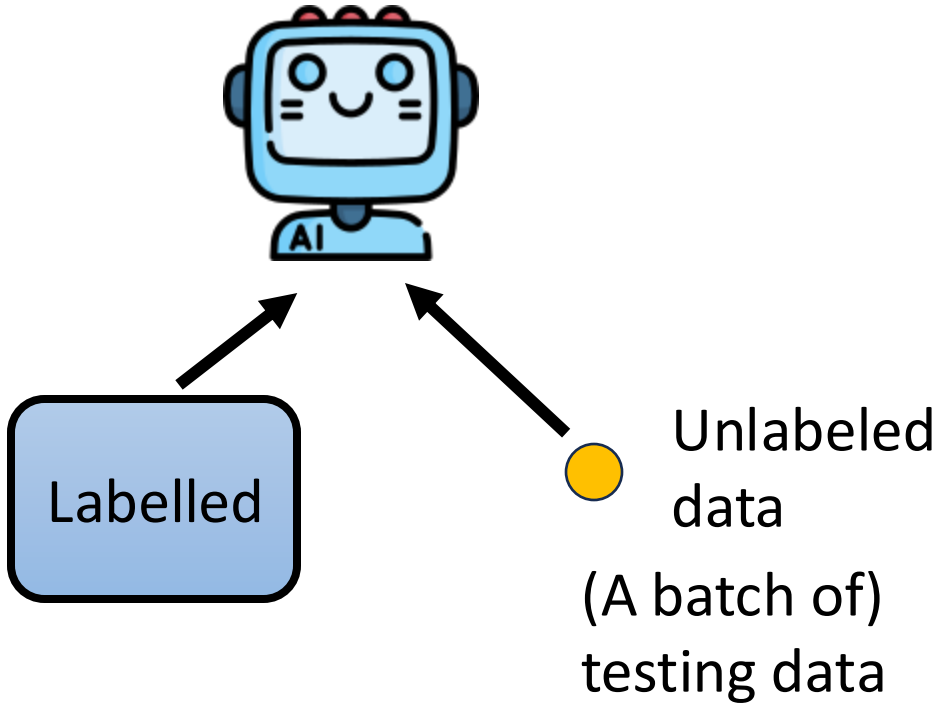
Training with Specific data



Semi-supervised Learning



Typical Semi-supervised Learning

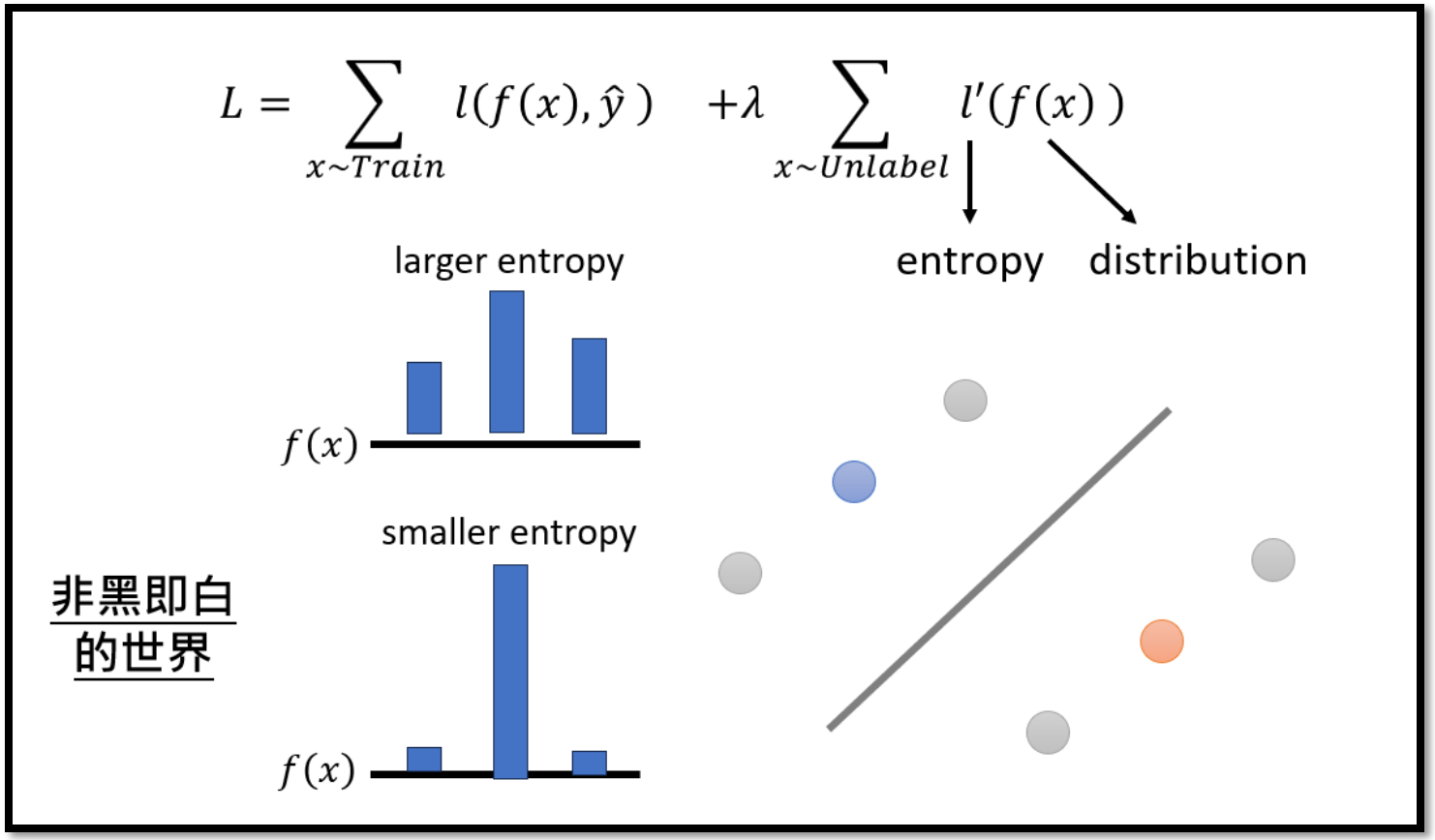


Test-Time Training

Semi-supervised Learning: Minimize Entropy

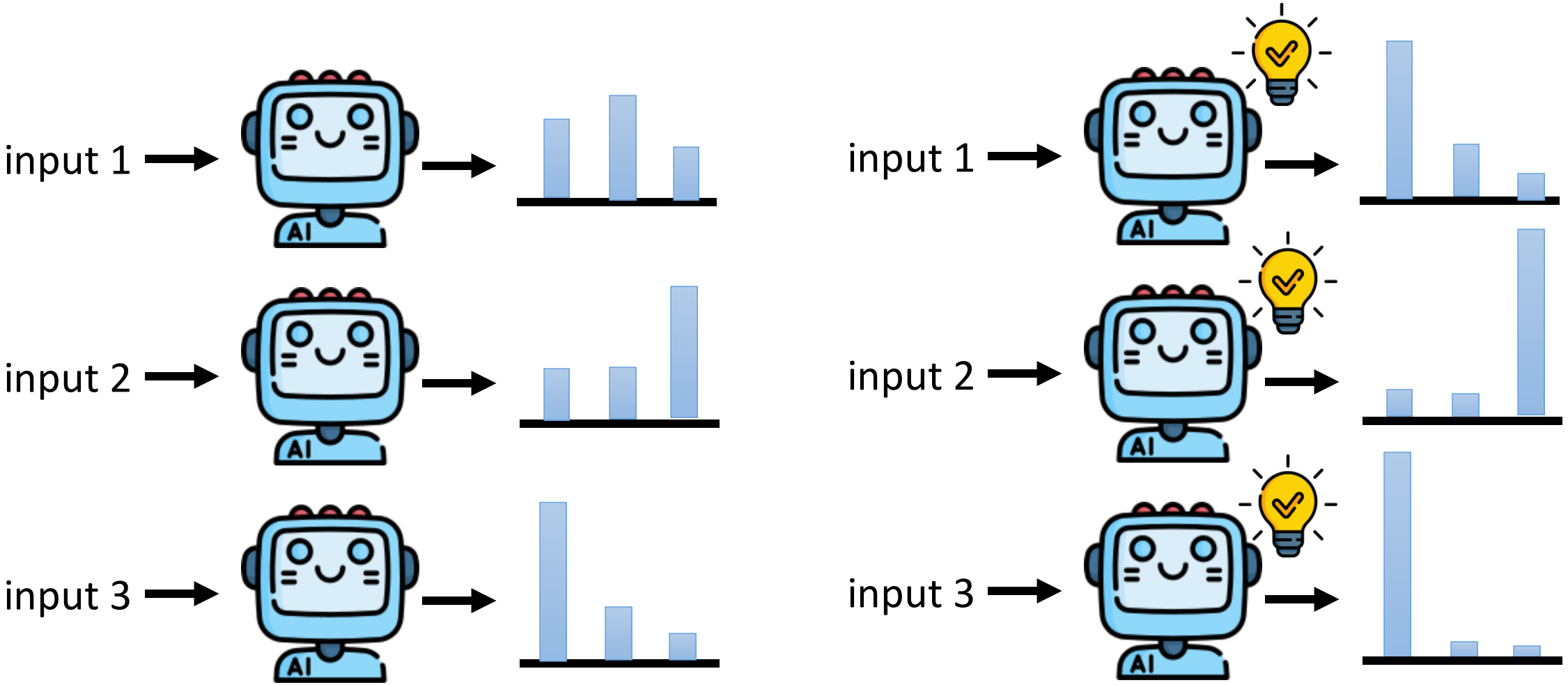
第六講

https://youtu.be/mPWvAN4hzzY?si=DQj0TL2WCSzue5EE



TENT
https://arxiv.org/abs/2006.10726

Semi-supervised Learning: Minimize Entropy

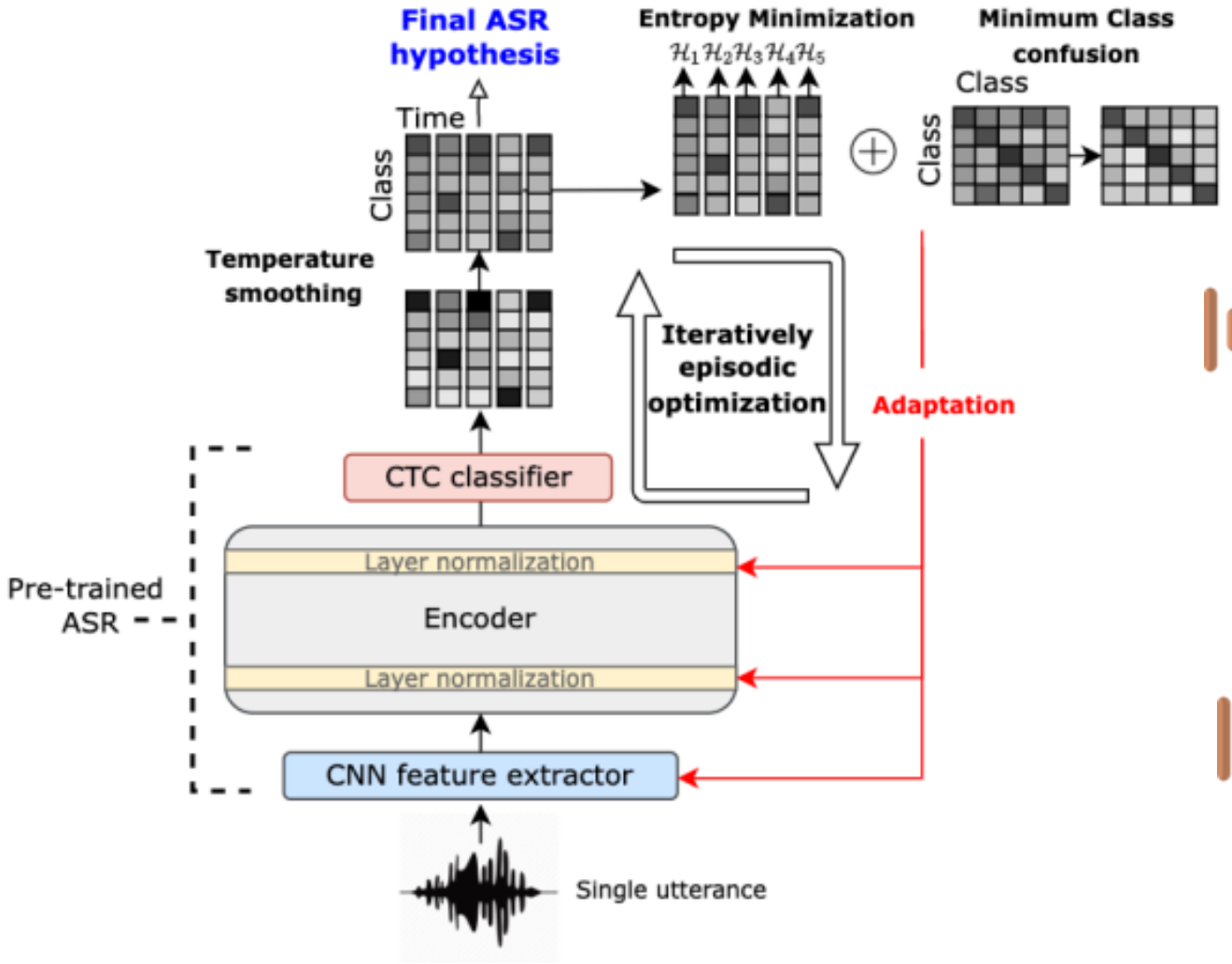


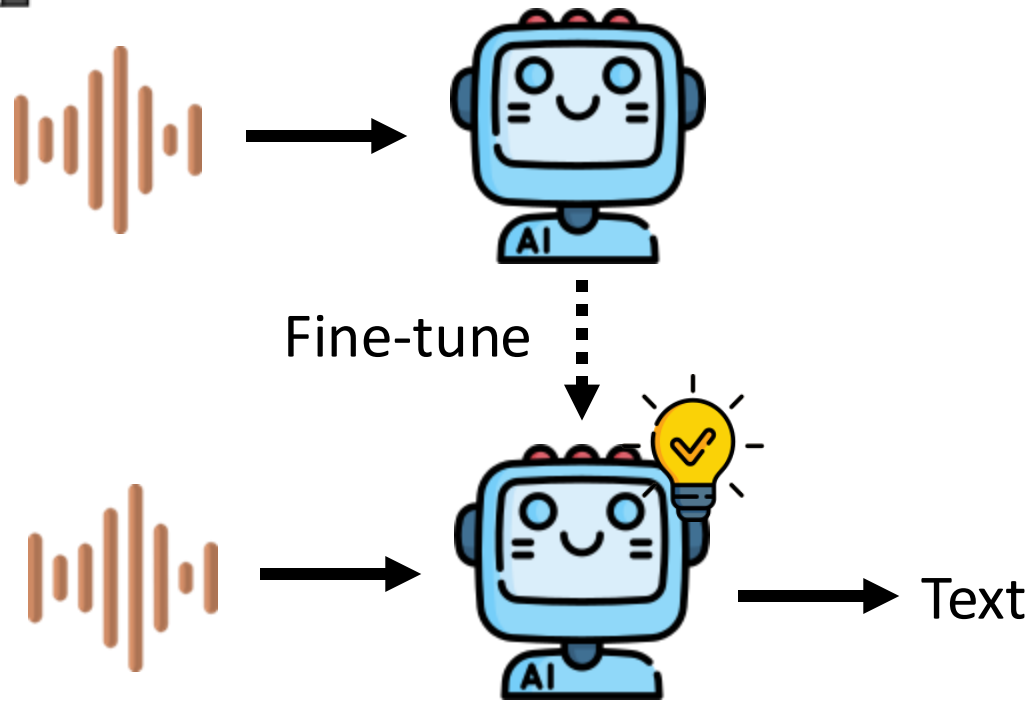
Test-Time Training for Speech Recognition

Guan-Ting Lin

https://arxiv.org/abs/2203.14222

Single-Utterance Test-time Adaptation (SUTA)





Performance of SUTA

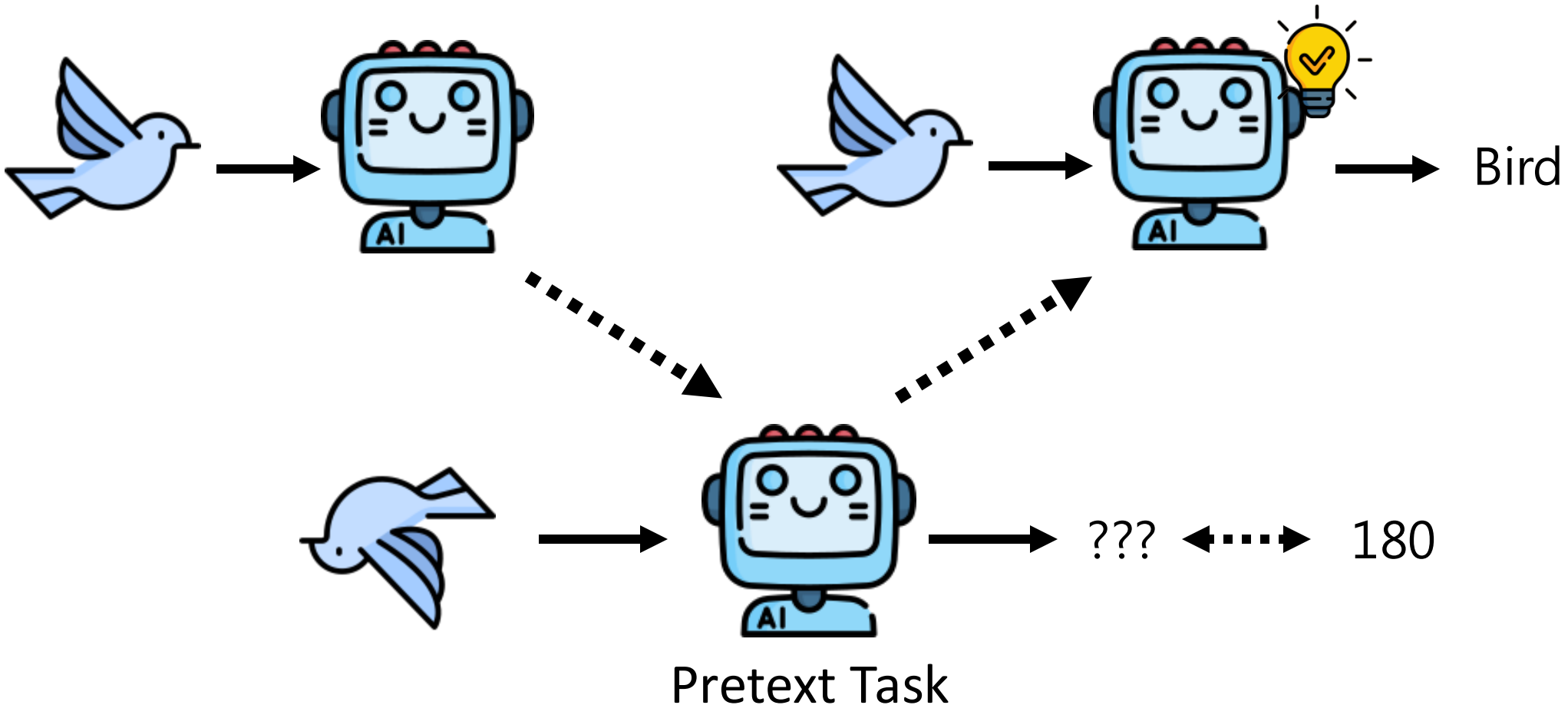
Different domains

Performance reference for source ASR model *wo/ adaptation*	LS test-o + δ 0	0.005	0.01	CH	CV	TD
SOTA (trained on target dataset)	2.5	-	-	5.8	15.4	5.6
RASR [26] (trained on LS)	6.8	-	-	-	29.9	13.0
TTA method						
(1) Our source ASR model [27] (trained on LS *wo/ adaptation*)	8.6	13.9	24.4	31.2	36.8	13.2
(1) + SDPL (Pseudo labeling)	8.3	13.1	23.1	30.4	36.3	12.8
(1) + SUTA	**7.3**	**10.9**	**16.7**	**25.0**	**31.2**	**11.9**

Source of table: https://arxiv.org/abs/2203.14222

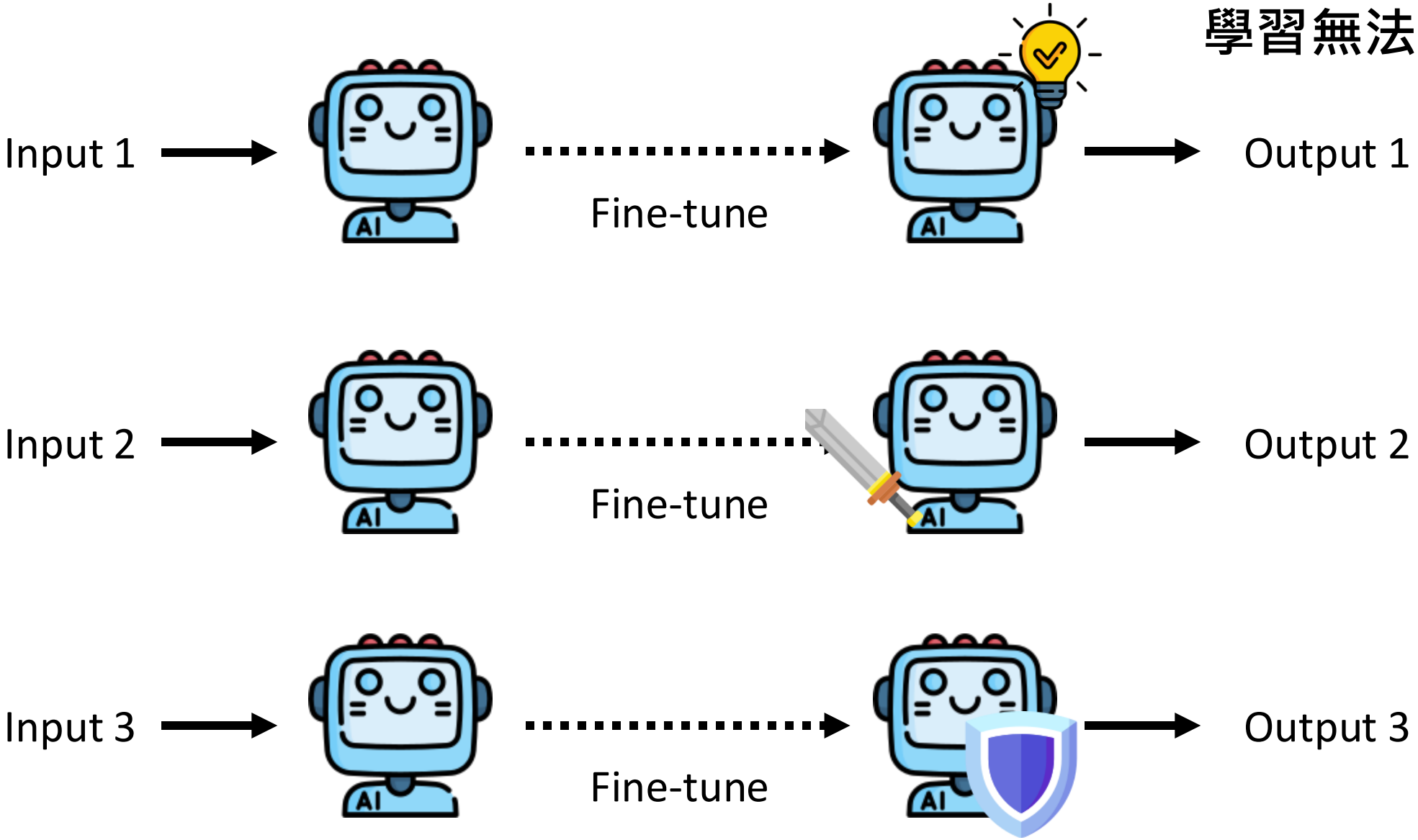
https://arxiv.org/abs/1909.13231

Test-Time Training (TTT) using Pre-text Task



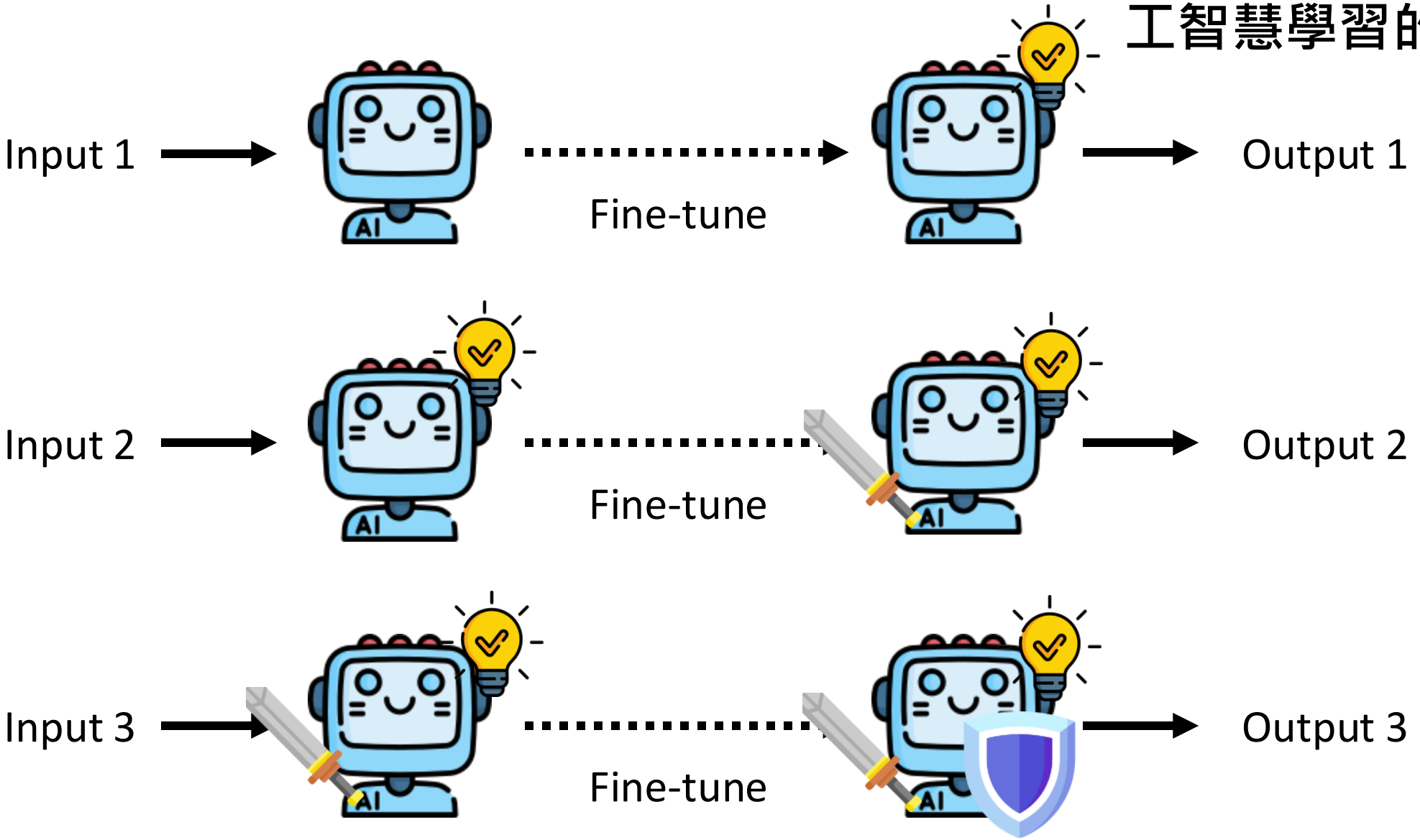
Standard Test-Time Training (TTT)

缺點：
學習無法累積



Continuous Test-Time Training (TTT)

接近一般人對於人工智慧學習的想像!

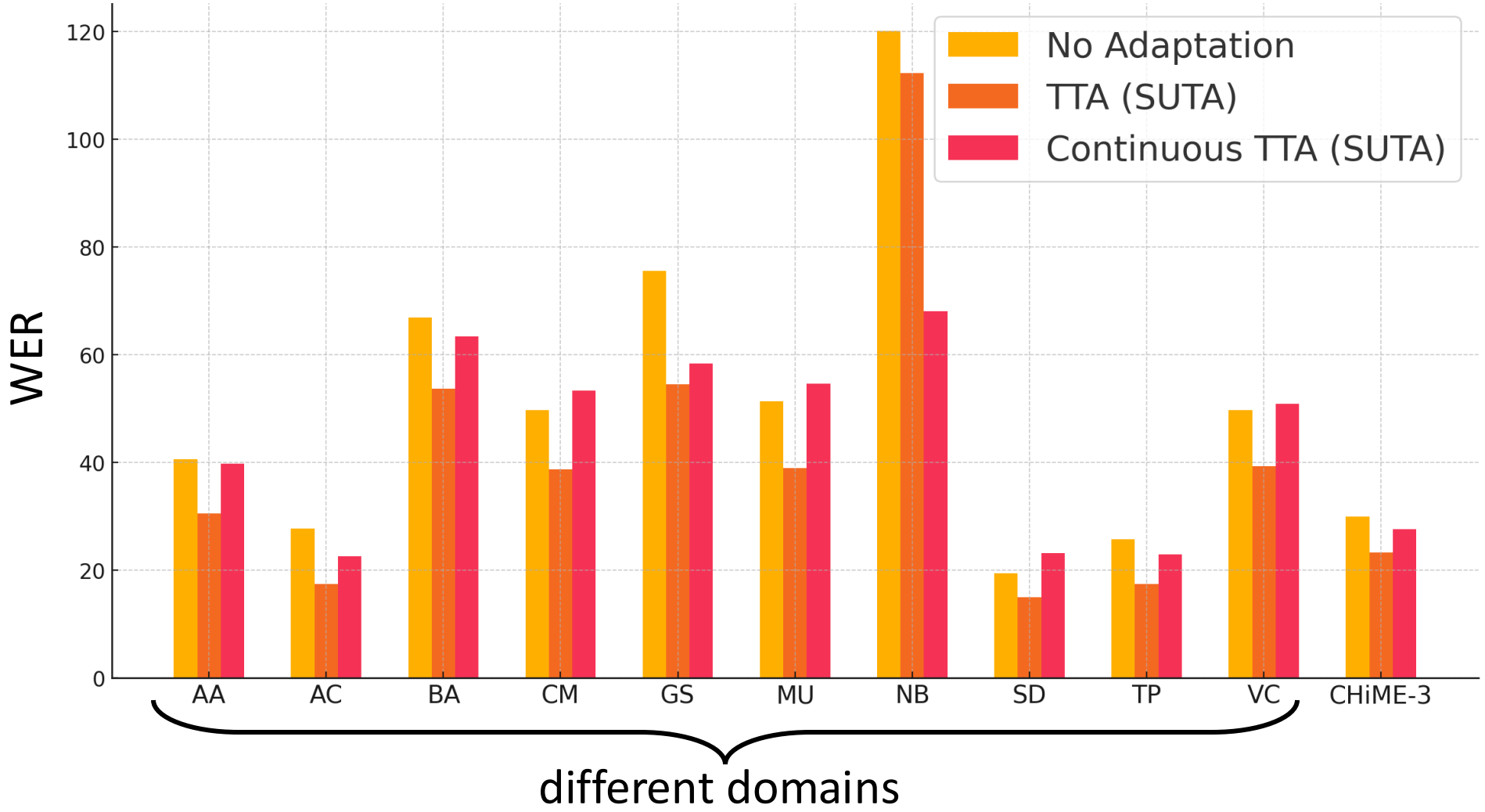


Continuous TTA

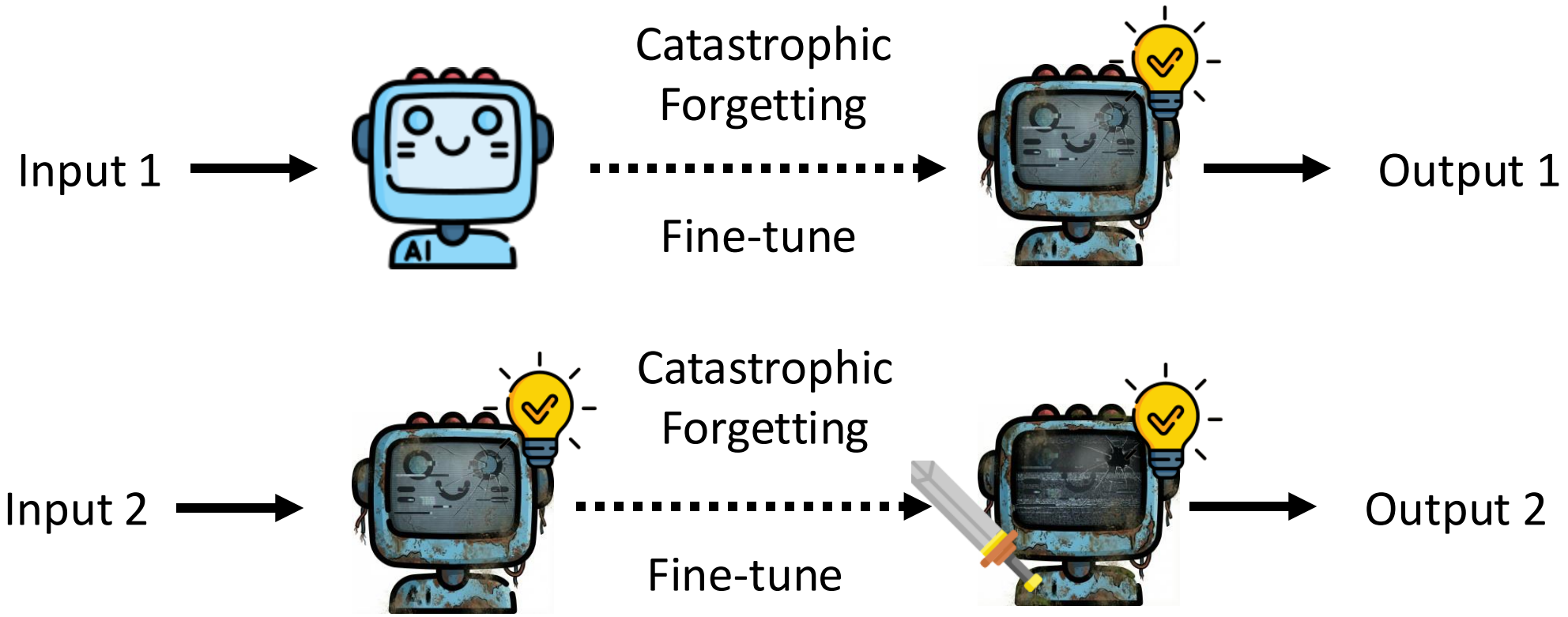
https://arxiv.org/abs/2406.11064

This situation is typical.

https://arxiv.org/abs/2306.05401



Continuous Test-Time Training (TTT)

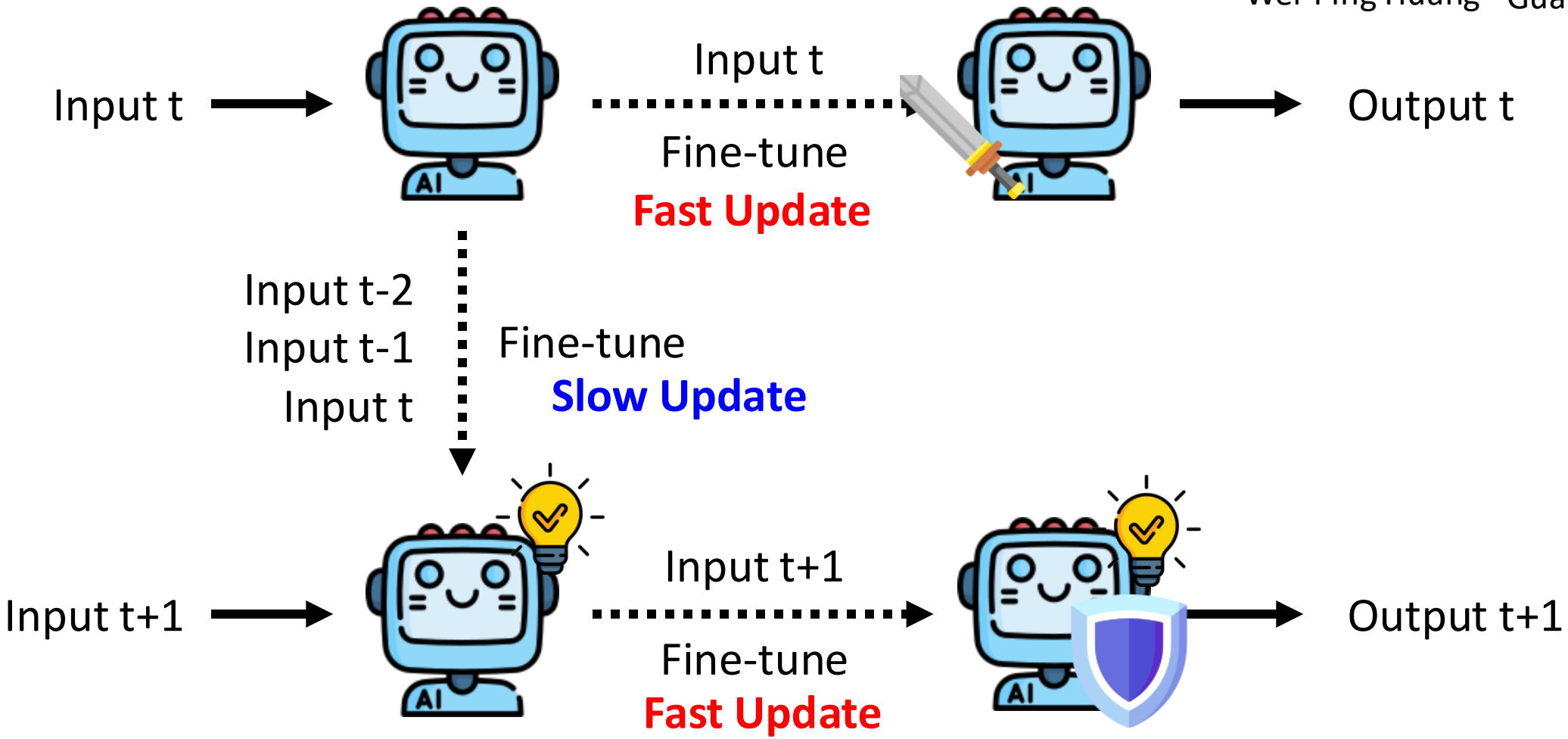


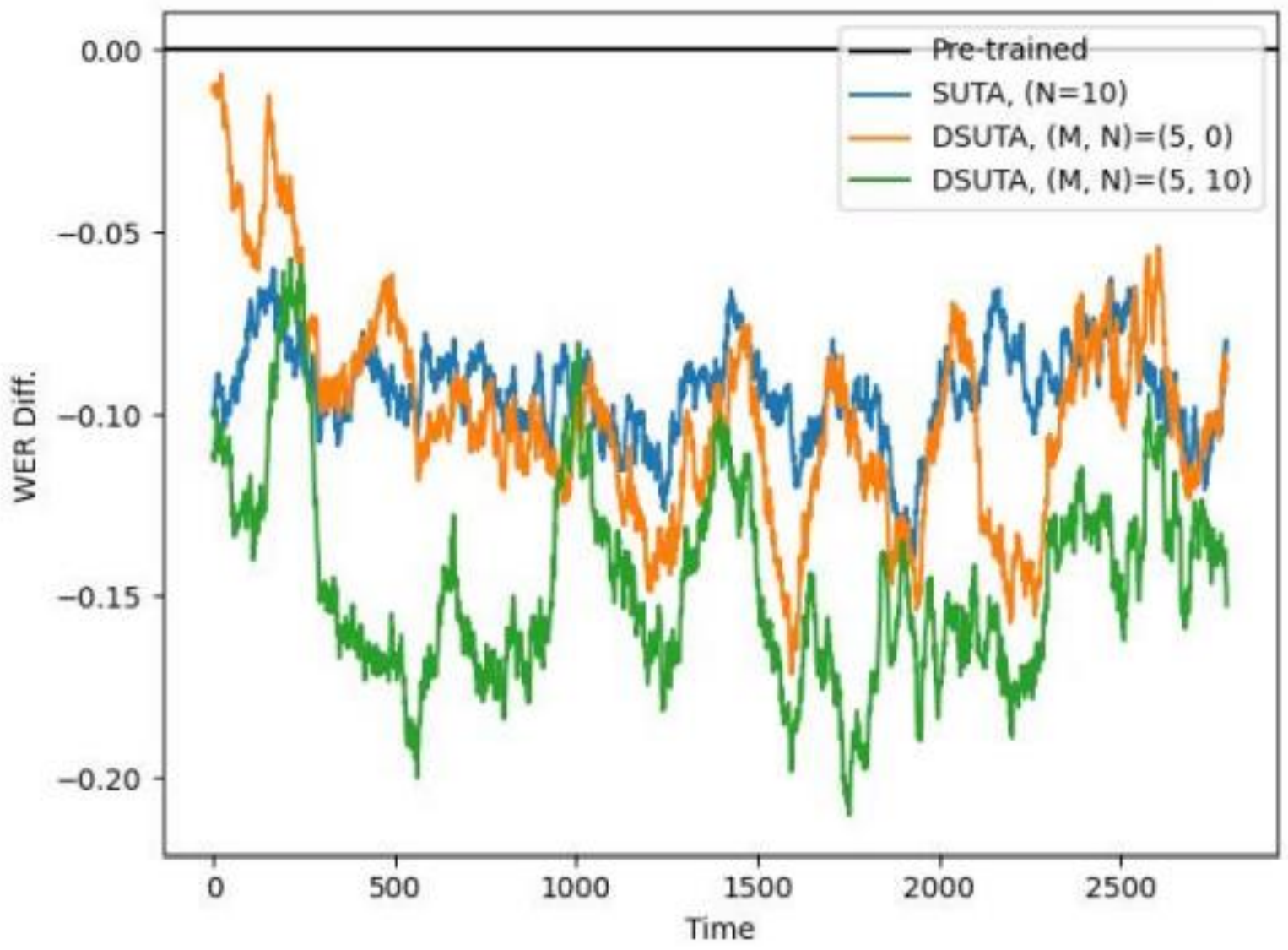
RDumb: https://arxiv.org/abs/2306.05401
EATA: https://arxiv.org/abs/2204.02610
CoTTA: https://arxiv.org/abs/2203.13591
SAR: https://arxiv.org/abs/2302.12400
REALM: https://arxiv.org/abs/2309.03964

Continuous Test-Time Training (TTT) – Dynamic SUTA

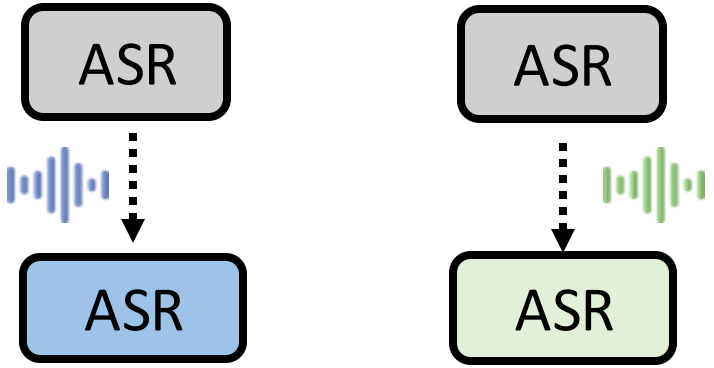
Wei-Ping Huang

Guan-Ting Lin

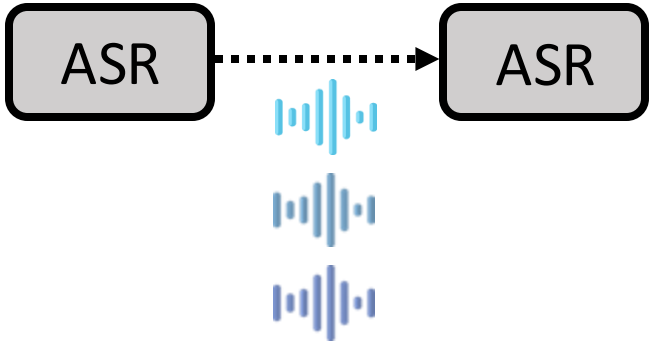




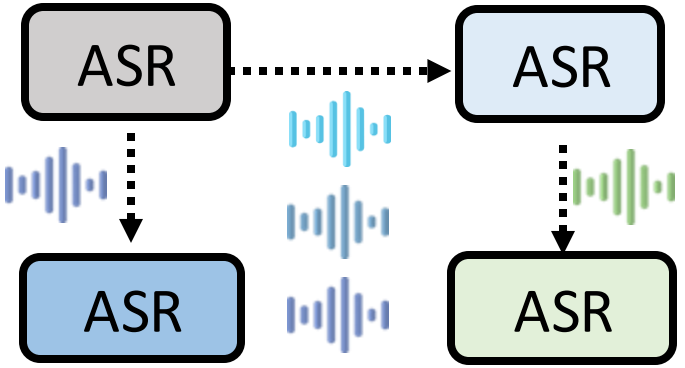
Blue Curve



Orange Curve

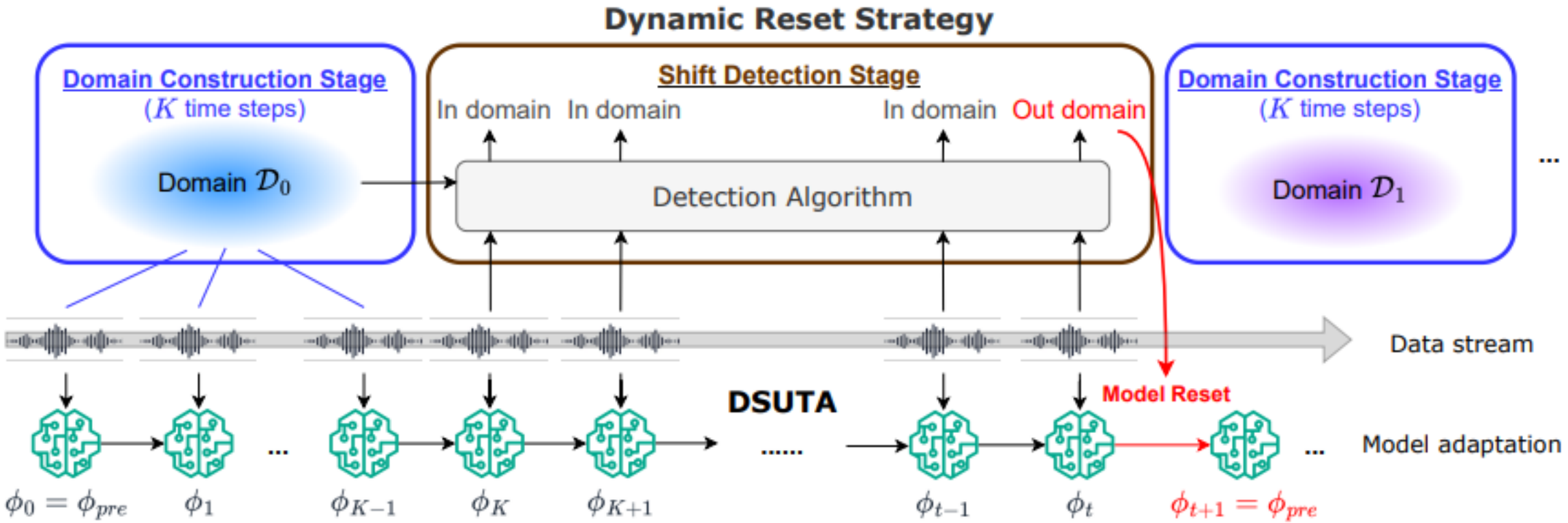


Green Curve



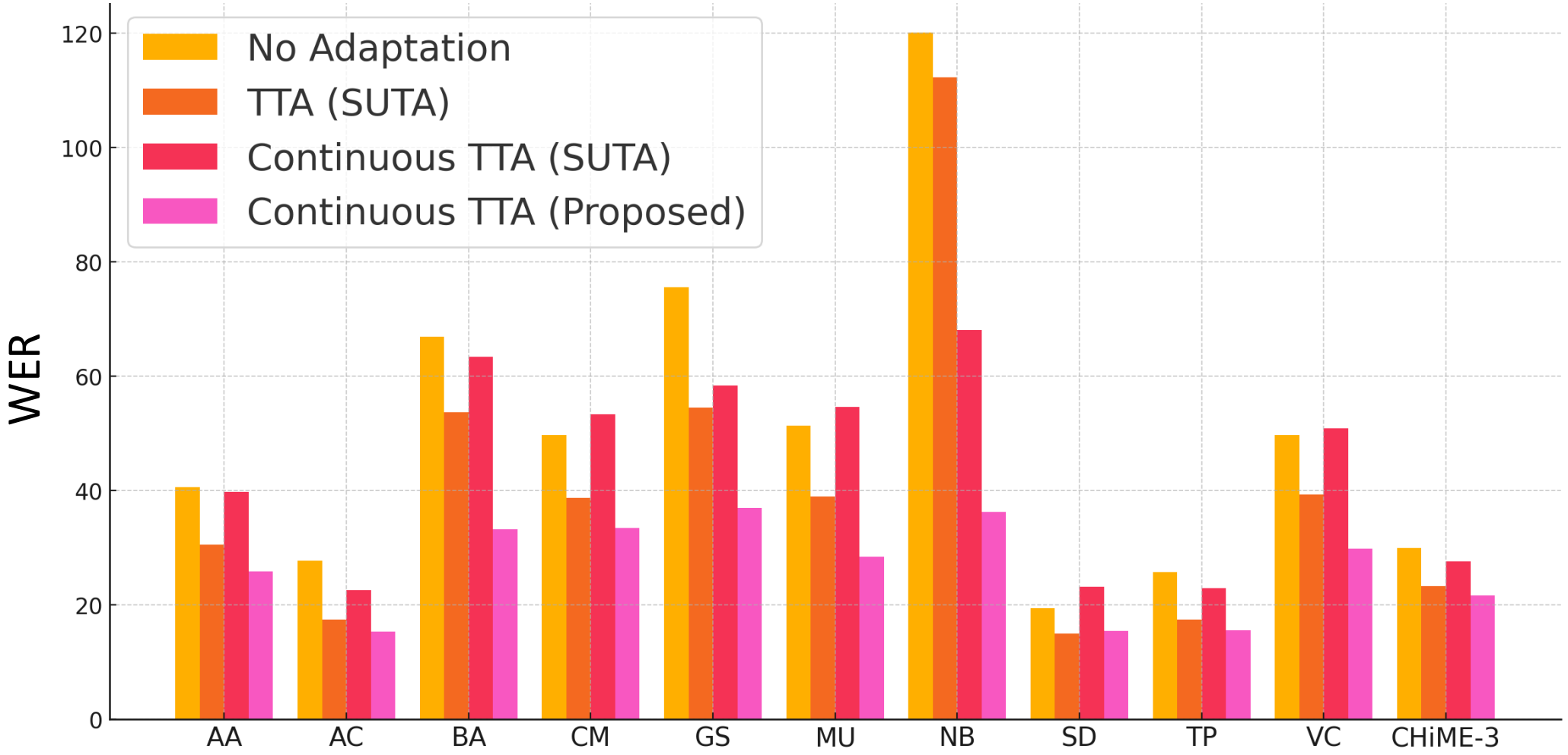
Continuous TTA – Dynamic SUTA

https://arxiv.org/abs/2406.11064



Continuous TTA – Dynamic SUTA

https://arxiv.org/abs/2406.11064



Concluding Remarks

Fine-tune with Gradient Descent

Model Editing

Model Merging

Test-Time Training (TTT)