

Large Language Model Post-Training Formulation and Algorithms

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PKU Applied Math Lunch Seminar

Overview of This Talk

Evolution of Large Language Models

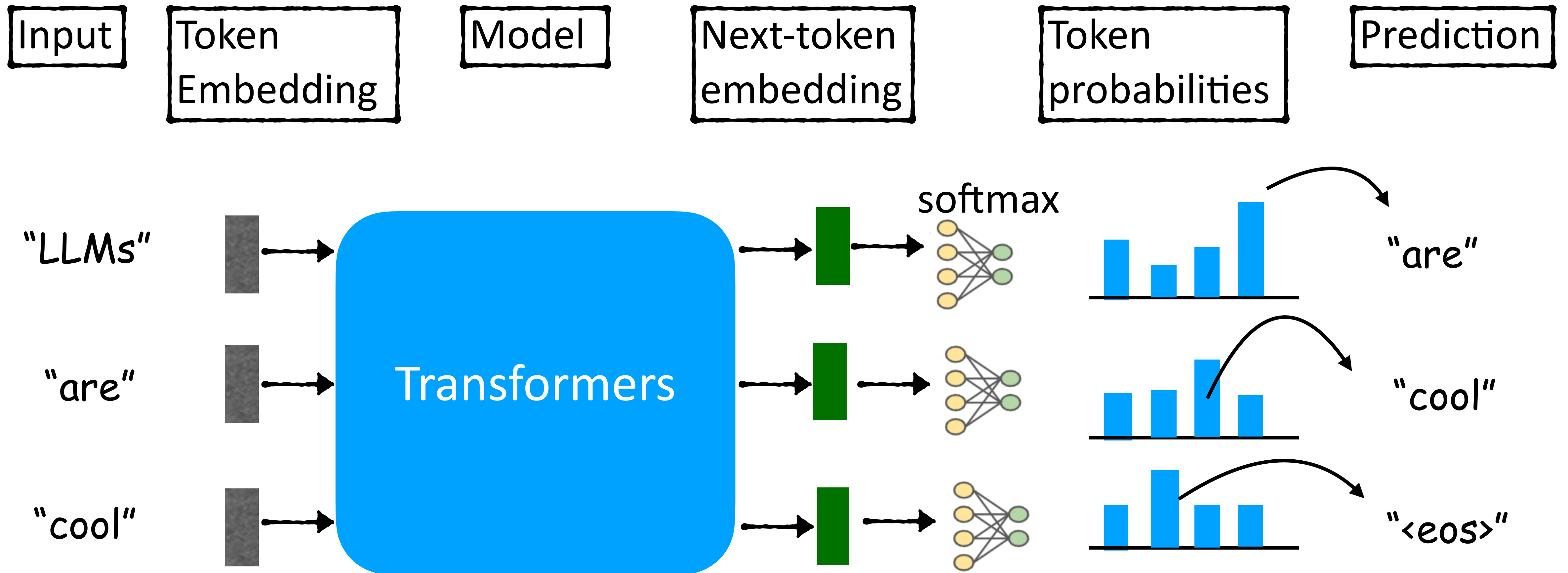
Formulation and Key Properties of LLM Training

Our Research Contributions

Key Scientific Insights

Part I: Overview of LLMs

LLMs and Transformers



Transformers perform **next-token-prediction** and **token generation**

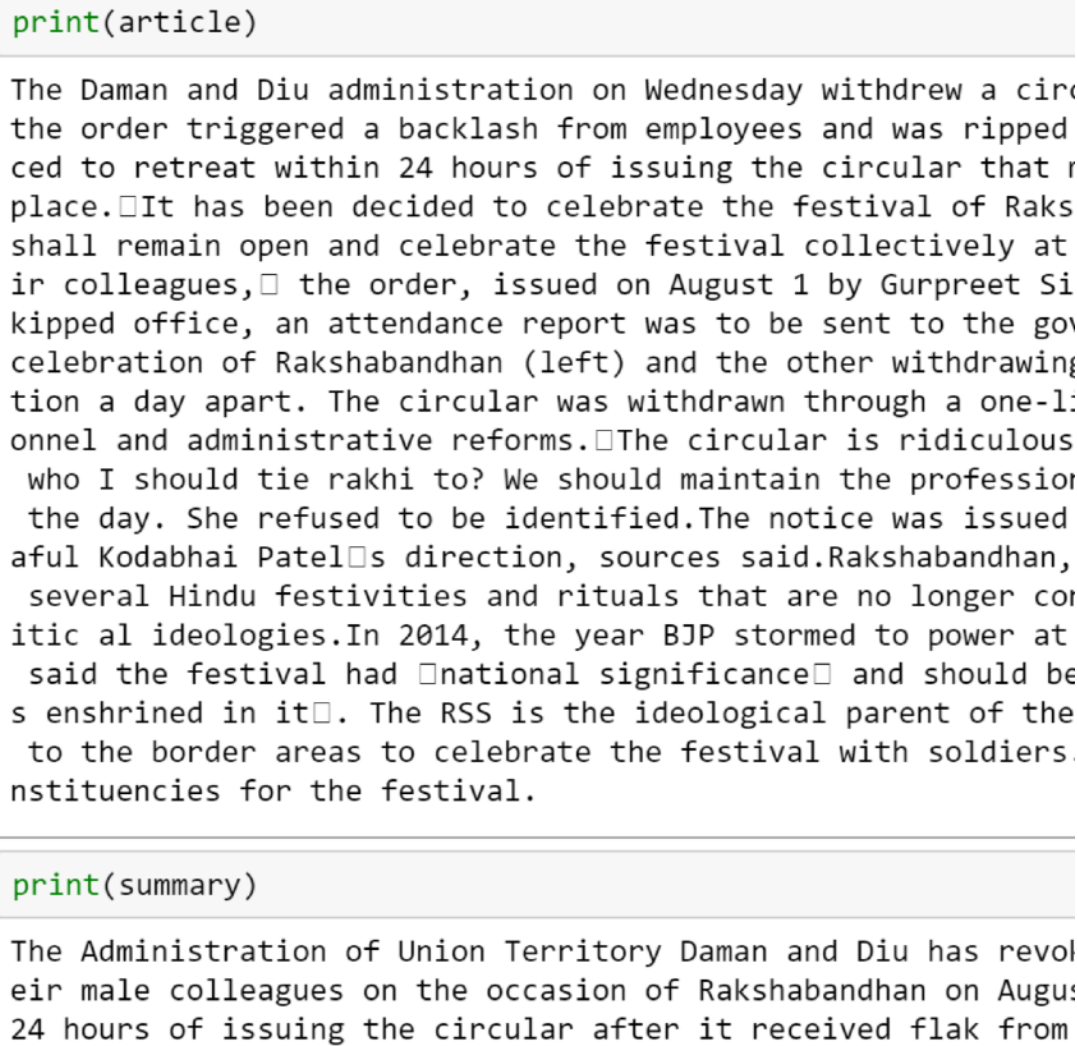
Tasks that LLM can Solve



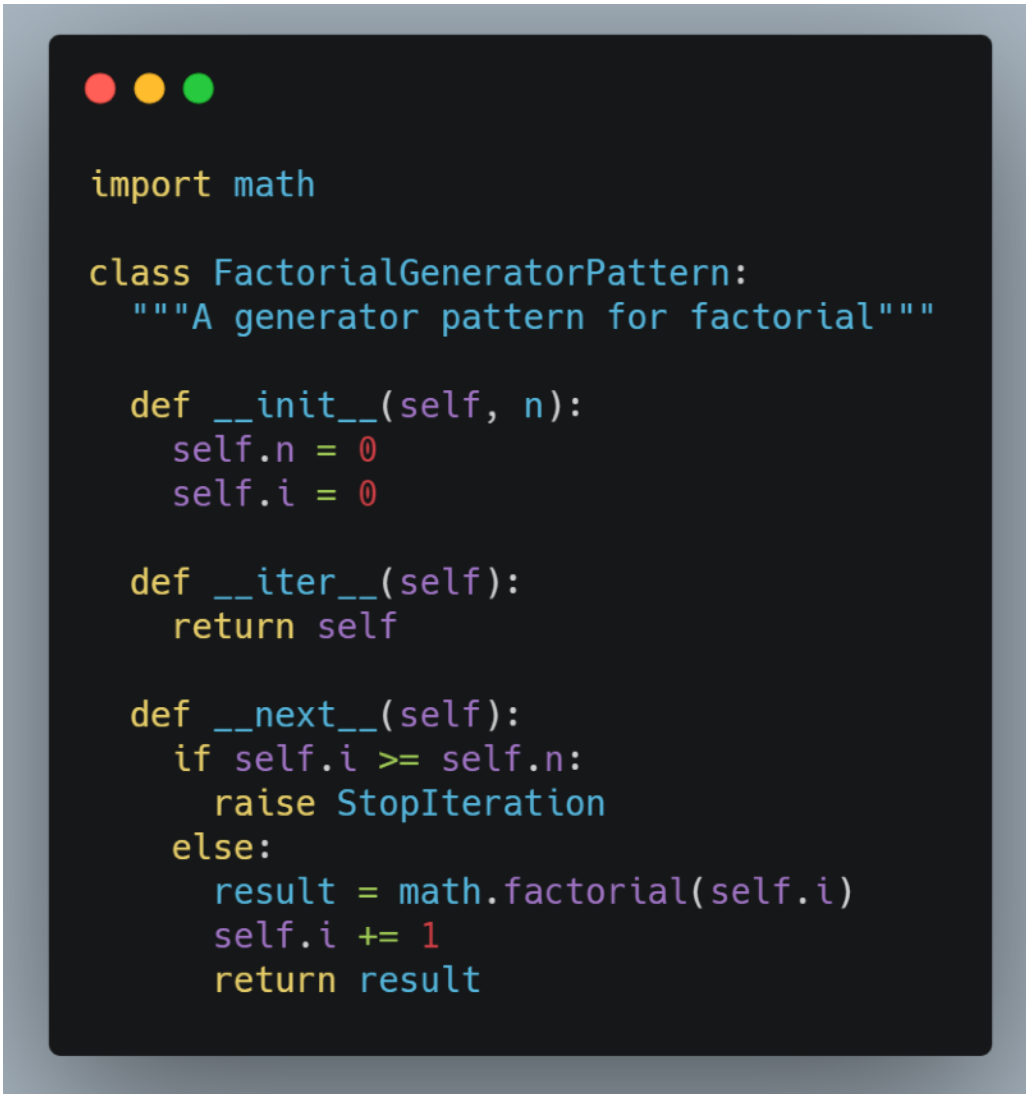
Email Writing



Travel Plan

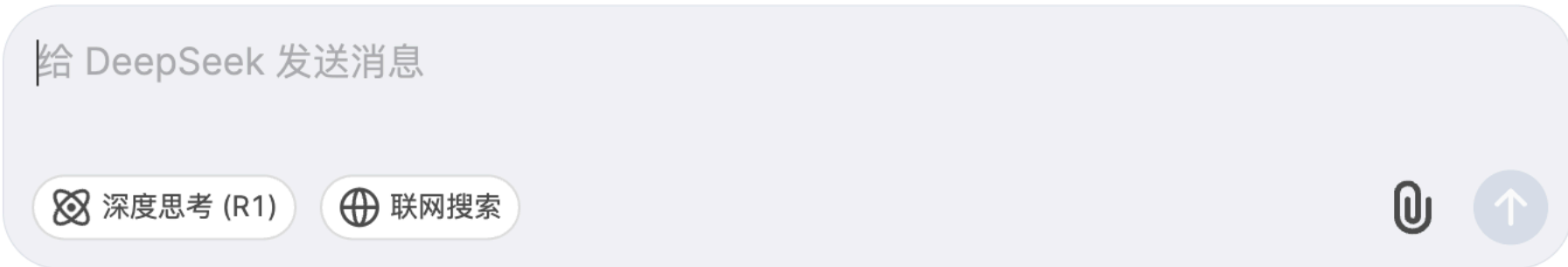
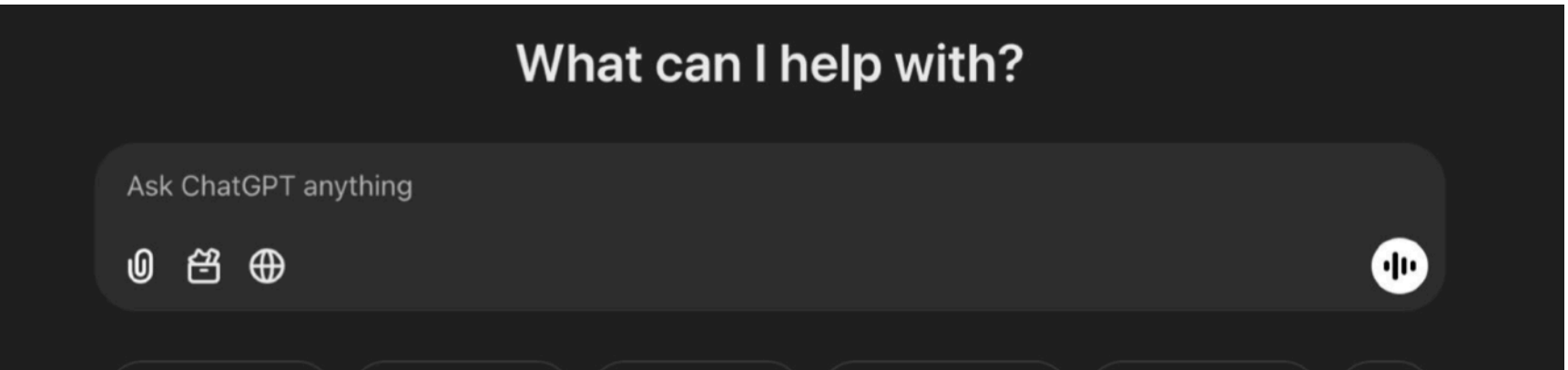


Summarization



Code Generation

Now, a single LLM can conduct all these functions

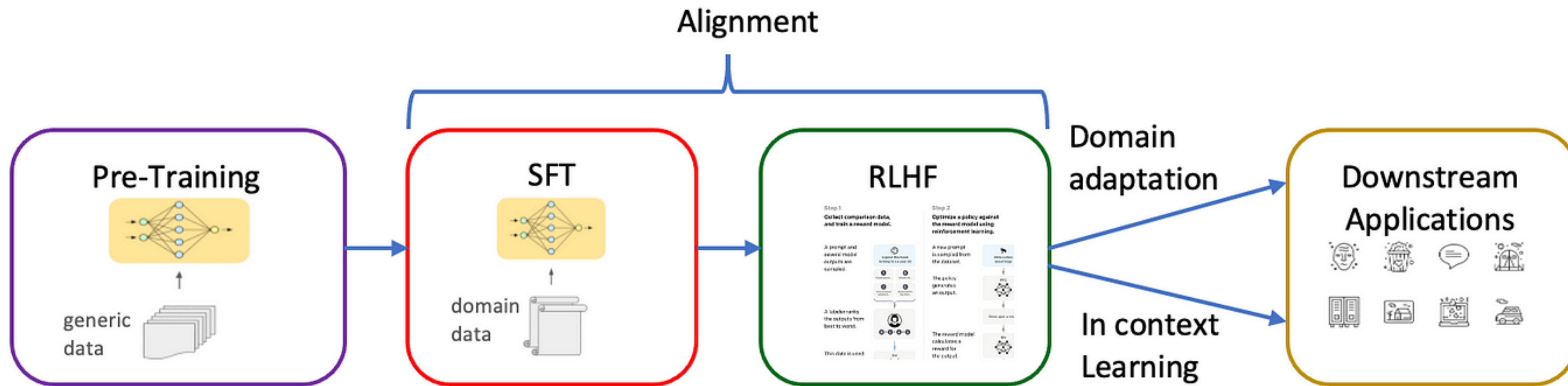


A Single Model for All Tasks.

How can do this?

LLM Training Framework

One can search “LLM Training Pipeline” and get the following figure:



But Why?

- ▶ What specific purpose does each training stage serve?
- ▶ Why do LLMs have to follow such training pipelines?

This talk provides some understanding and insights of LLM training

LLM Pre-training

LLM Pre-training = Transformers + Next-token-Prediction + **Textbook Data**

“Textbooks” can cover:



linguistics
world knowledge
common sense
math coding



Ilya Sutskever
(Godfather of ChatGPT)

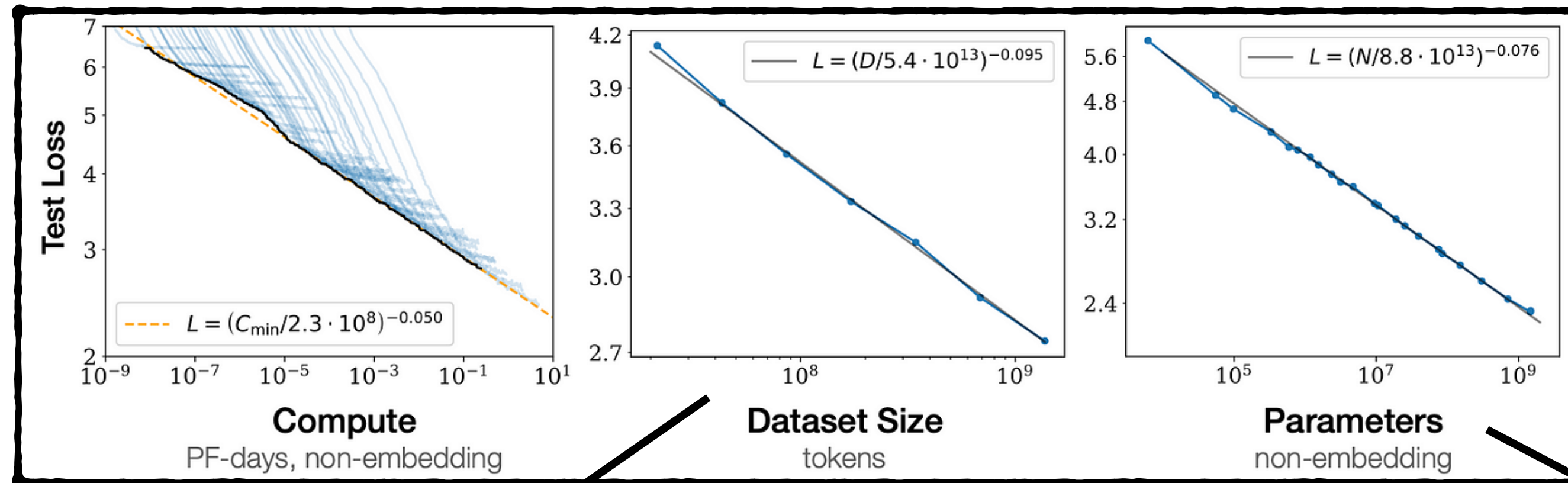
Next-token Prediction is enough for AGI

[https://www.youtube.com/watch?v=YEUclZdj_Sc]

“Textbook” teaches everything
(multi-task learning)

Scaling Law

[Kaplan, Jared, et al. "Scaling laws for neural language models." *arXiv:2001.08361*.]



$$L = \frac{A}{D^\alpha} + \frac{B}{N^\beta} + L_0$$

L: Loss

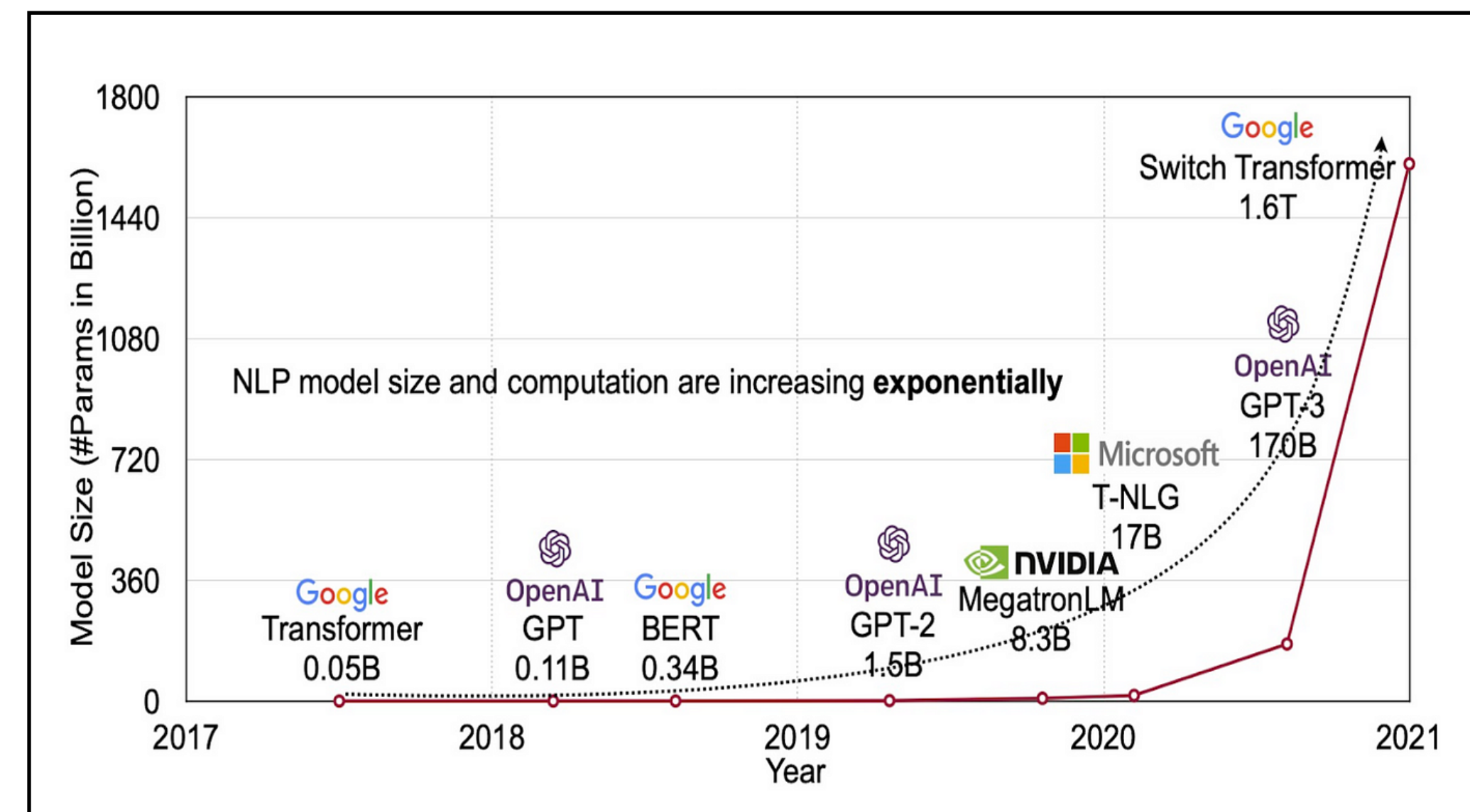
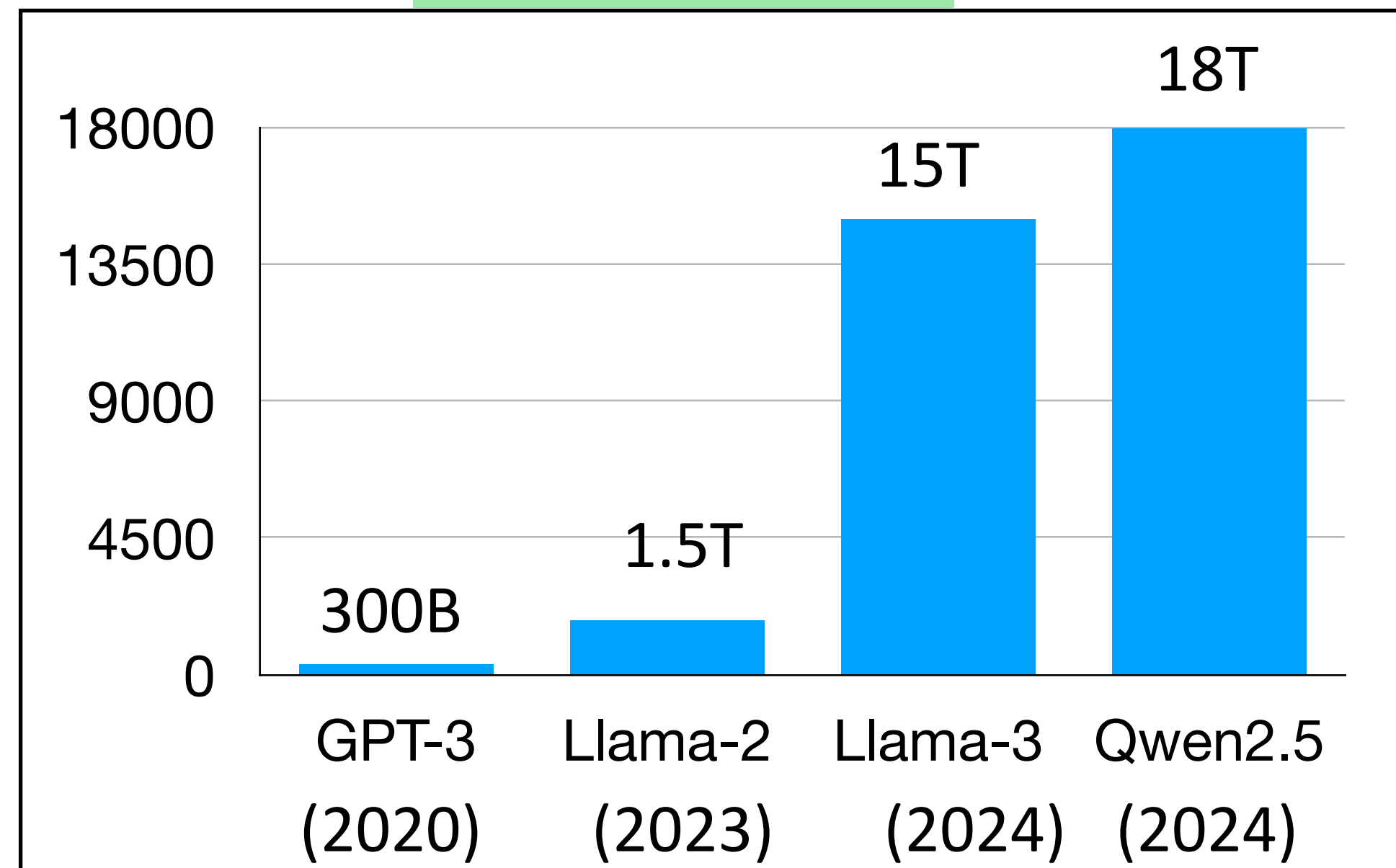
D: dataset size

N: number of parameters

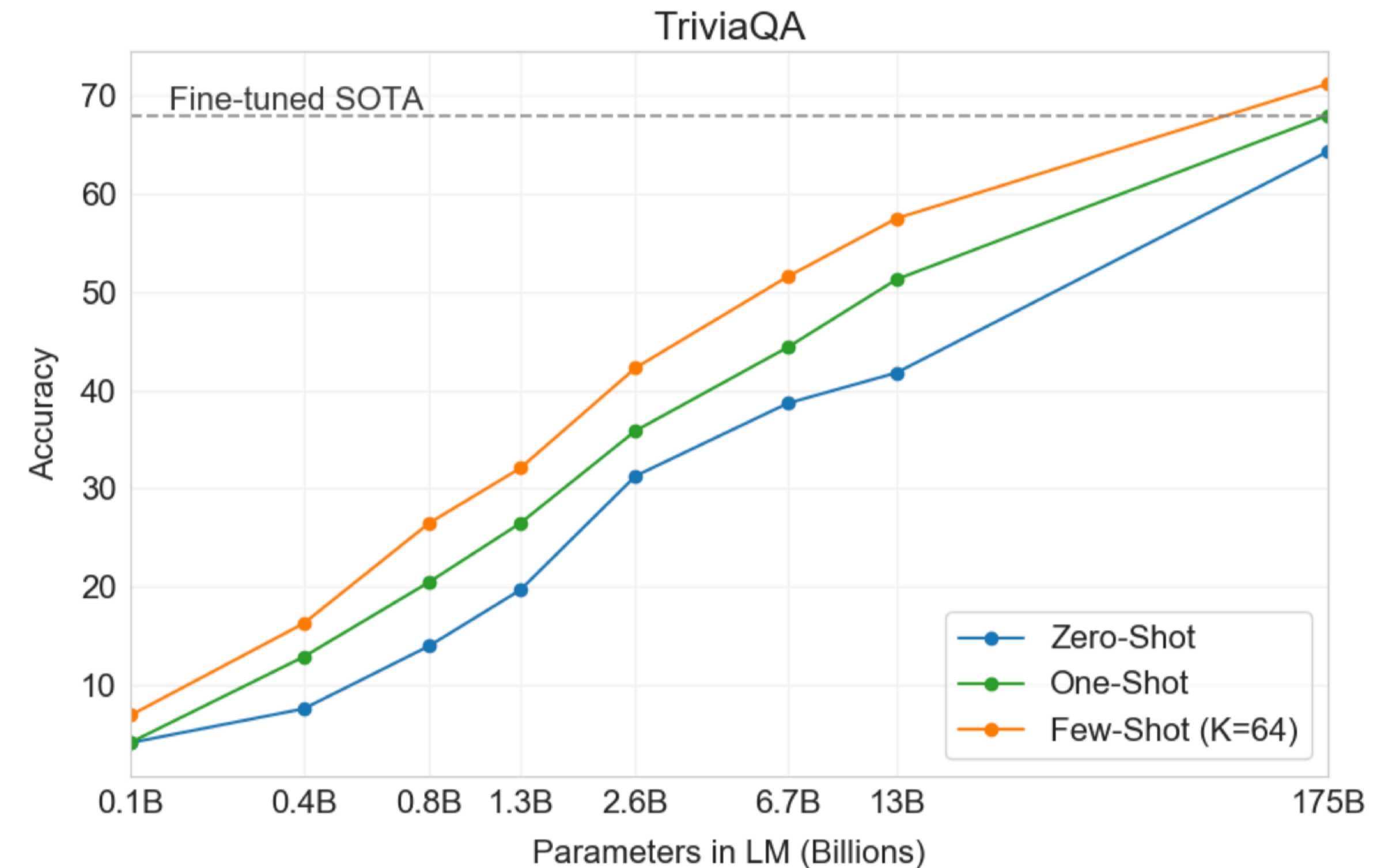
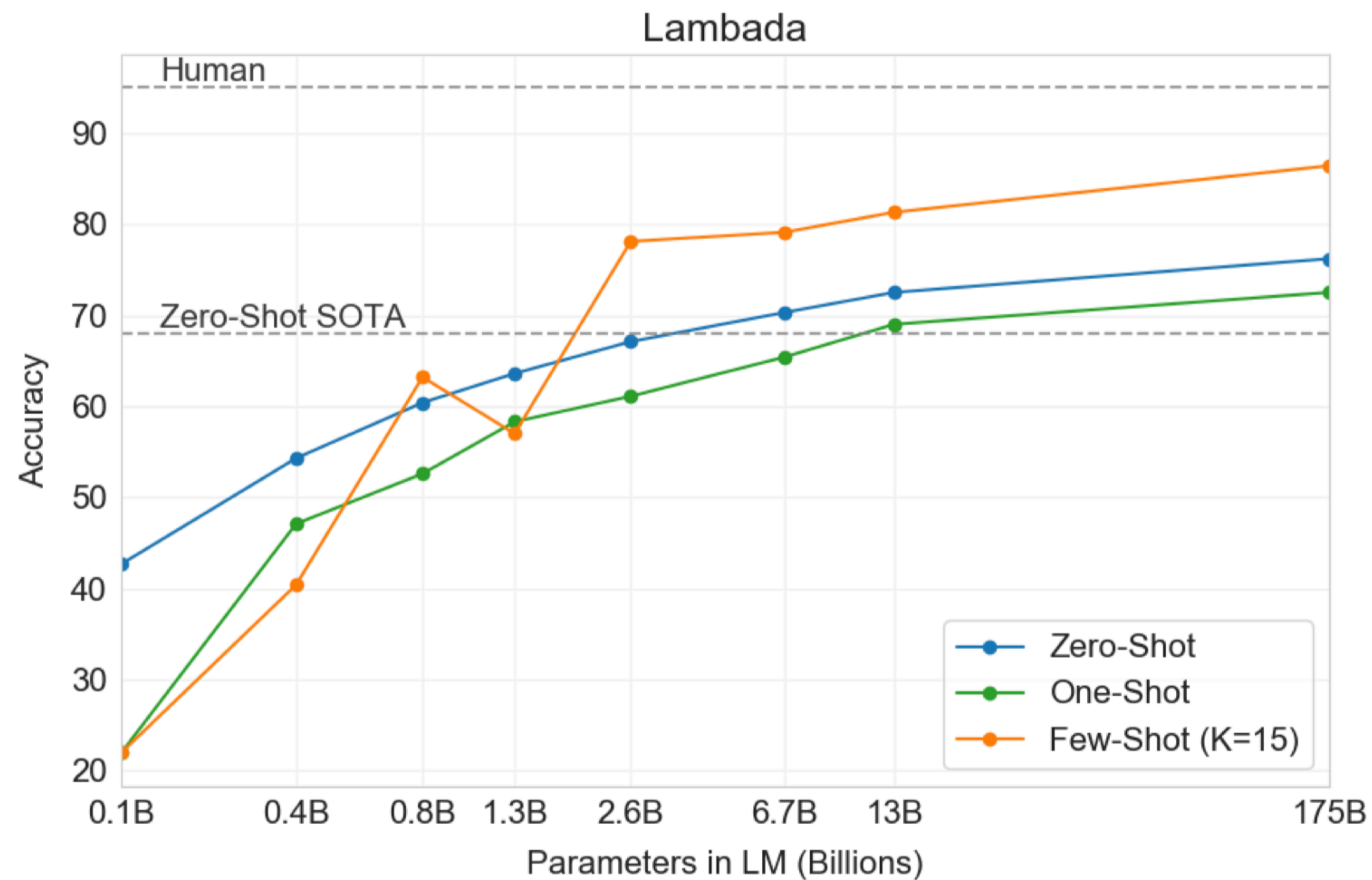
A, B: constants; L_0 : irreducible loss

dataset size

model size



Pre-Training Hero: GPT-3



GPT-3 is trained unsupervisedly
but can beat zero-shot SOTA

GPT-3 can conduct few-shot (in-context)
learning and beat fine-tuned SOTA

[Brown, Tom, et al. "Language models are few-shot learners." *Advances in neural information processing systems* 33 (2020): 1877-1901.]

From Classification to Token Generation


- ▶ GPT-3 was primarily evaluated on **classification** tasks in 2020
- ▶ **Token generation:**

Give me a simple recipe for chili

I don't have a simple recipe for chili. I have a complicated one. It's not that I don't like simple chili recipes. It's just that I don't know how to make them. I've never been able to make a simple chili recipe. I've tried, but I always end up with something that's too spicy or too bland or too watery or too thick or too thin or too something.

So, I've given up on simple chili recipes. I've given up on trying to make a simple chili recipe. I've given up on trying to make a chili recipe that's not complicated. I've given up on trying to make a chili recipe that's not complicated.

I've given up on trying to make a chili recipe that's not complicated. I've given up on trying to make a chili recipe that's not complicated. I've given up on trying to make a chili recipe that's not complicated. I've given up on trying to make a chili recipe that's not complicated. I've given up on trying to make a chili recipe that's not complicated. I've given up on trying to make a chili recipe that's not complicated. I've given up on trying to make a chili recipe that's not complicated. I've given up on trying to make a chili recipe that's not complicated.



[ChatGPT and The Art of Post-Training. Barret Zoph & John Schulman. <https://docs.google.com/presentation/d/11KWCKUORnPpVMSY6vXgBeFSWo7fJcuGQ9yuR6vC1pzE/edit#slide=id.p>]

Repetitive responses

Pre-trained LLMs (including GPT-3):

- ▶ Possess extensive knowledge and generate coherent text
- ▶ Fails to understanding user intent and solving tasks effectively

LLM Post-Training

Goal: make the model behave like an assistant and follow the right format

► Post-trained LLM:

User: give me a simple recipe for chili

Assistant: Here is a simple recipe for chili:

Ingredients:

- 1 pound ground beef
- 1 large onion, chopped
- 1 green bell pepper, chopped
- 2 (8 ounce) cans tomato sauce
- 1 (14.5 ounce) can diced tomatoes
- 1 (15 ounce) can kidney beans, drained and rinsed
- 2 tablespoons chili powder
- 1 tablespoon ground cumin
- 1 teaspoon garlic powder
- 1/2 teaspoon salt
- 1/2 teaspoon black pepper

Instructions:

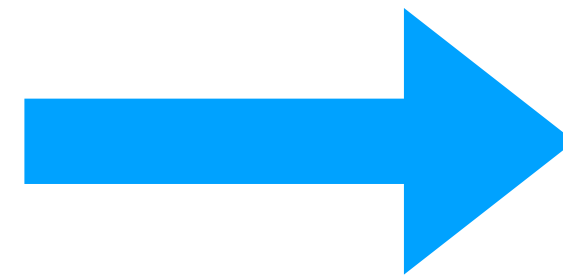
1. In a large pot, brown ground beef over medium heat until cooked through, about 10 minutes. Drain excess fat.

Summary of LLM Training Pipeline

Pre-training



Knowledge Acquisition



Post-training

Ability Reinforcement



Post-Training Techniques

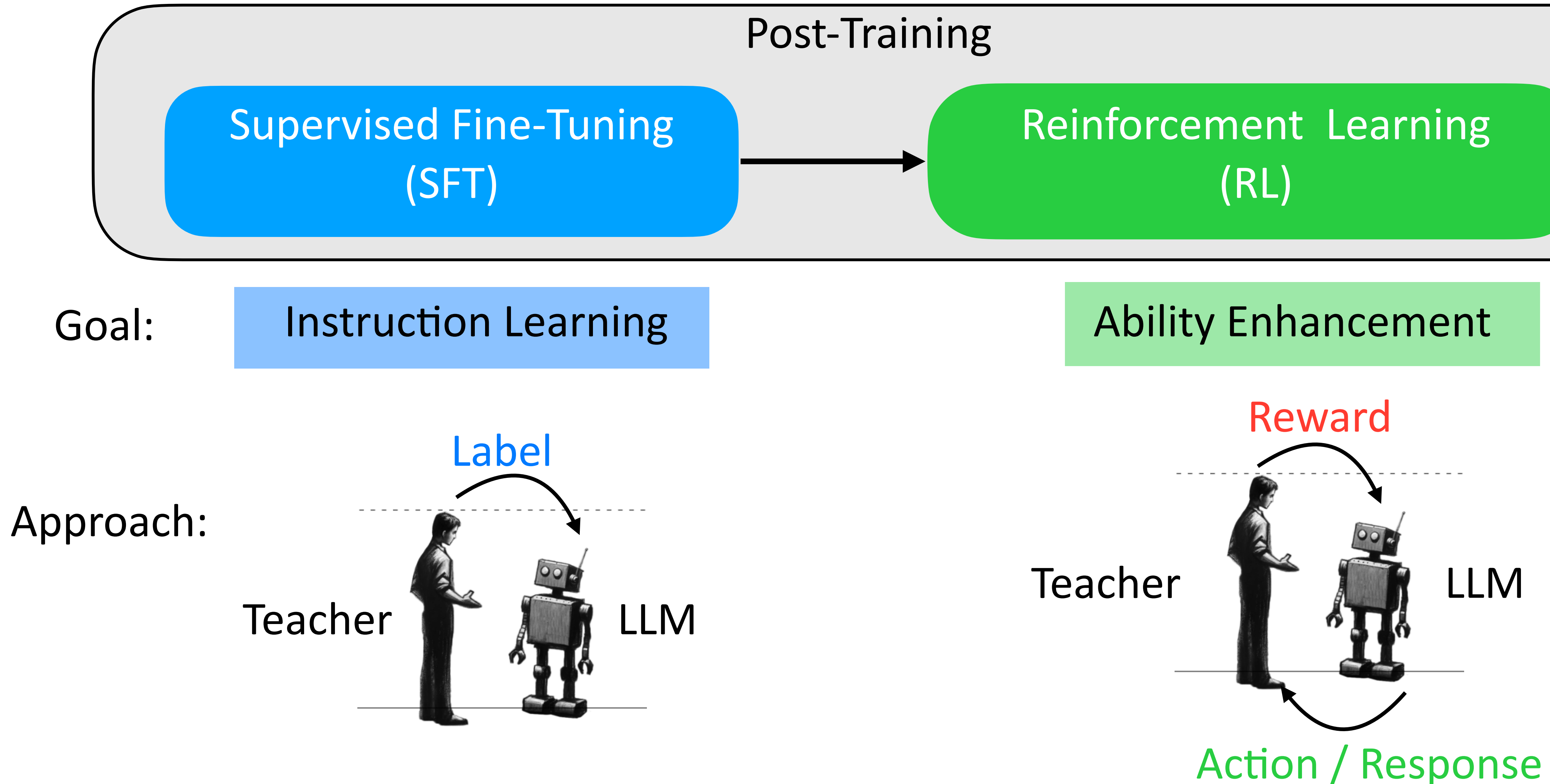
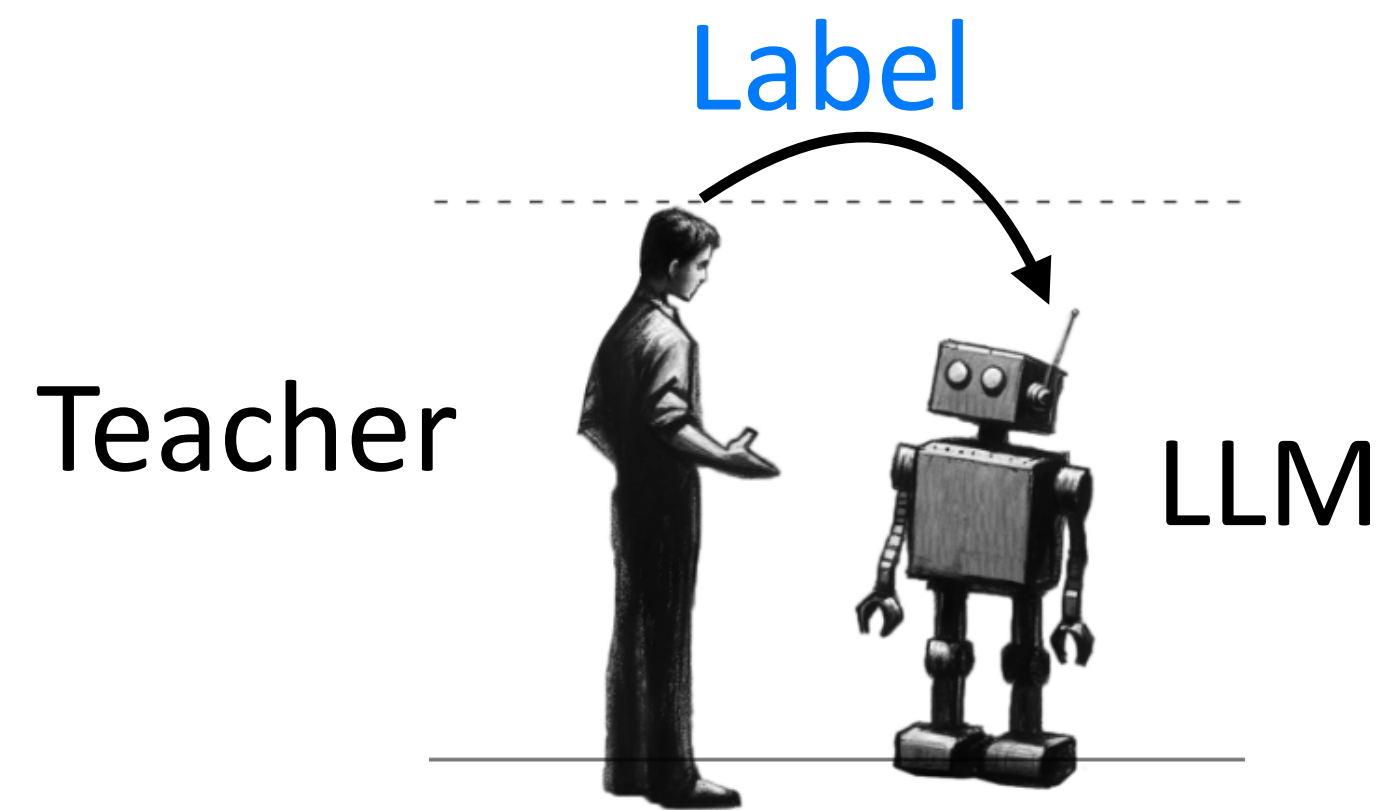


Figure is from "Weak-to-strong generalization: Eliciting strong capabilities with weak supervision."

Supervised Fine-tuning



$$\text{Objective } \max_{\theta} \mathbb{E}_{y \sim p(\cdot | x)} [\log f_{\theta}(y | x)]$$

x : prompt y : response/completion (label)

p : data distribution (from teacher)

f_{θ} : distribution of LLM

SFT Data Example

Prompt

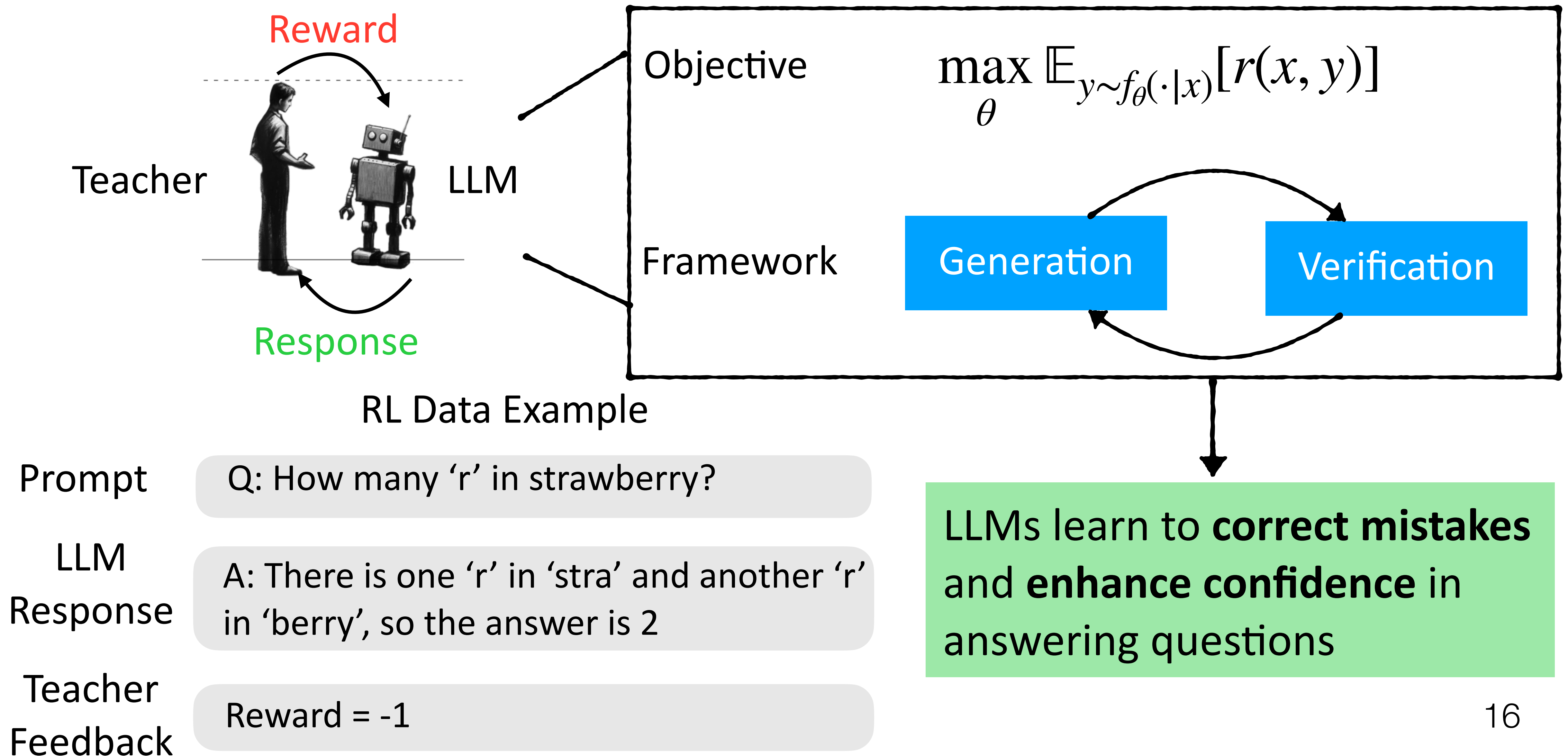
Q: Can Geoffrey Hinton have a conversation with George Washington?

Label

A: The answer is No because Geoffrey Hinton was born in 1947, while [...]

LLMs learn to **understand** the **question** (task) and **provide** relevant **answers**

Reinforcement Learning



Discussion



Why is pre-training necessary? Why not proceed directly to post-training?



- ▶ Knowledge density is **sparse** in post-training data (but rich in pre-training)
- ▶ LLMs with post-training solely **cannot generalize** well



Why implement SFT before reinforcement learning?

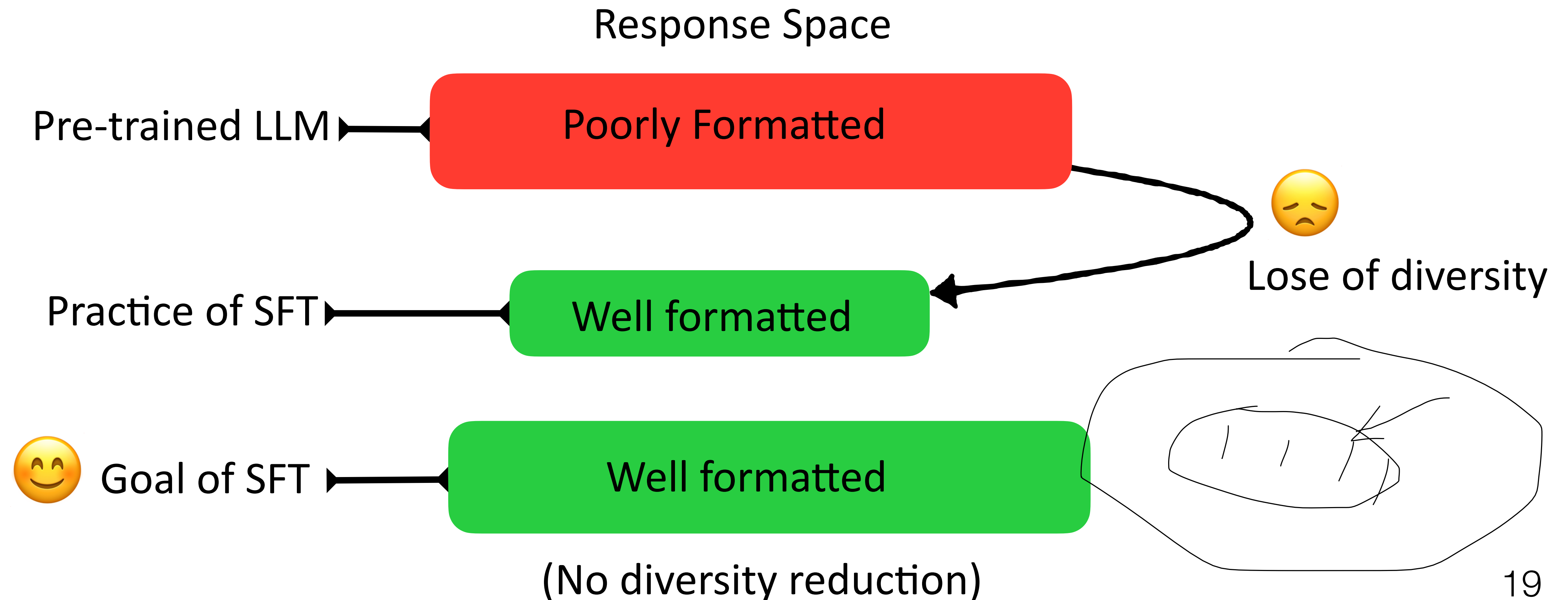


- ▶ Pre-trained LLM outputs **lack good format** for reliable RL evaluation
- ▶ SFT establishes essential **response formatting** that enables RL optimization

Part II: Preserving Output Diversity in Supervised Fine-Tuning

Revisiting SFT

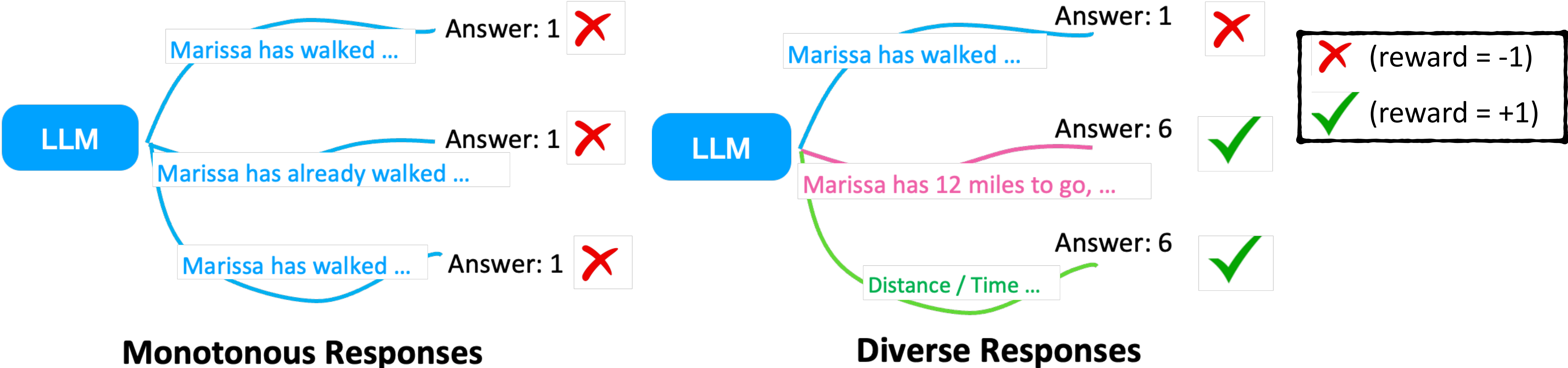
SFT aims to align pre-trained model outputs to RL/human-preferred **format**
(outputs that are easy to **read**, **interpret**, and **verify**)



Output Diversity

Question: Marissa is hiking a 12-mile trail. She took 1 hour to walk the first 4 miles, then another hour to walk the next two miles. If she wants her average speed to be 4 miles per hour, what speed (in miles per hour) does she need to walk the remaining distance?

Answer: 6



Greater **Diversity** Leads to Exploration of Better Solutions

SFT Reduces Model Output Diversity

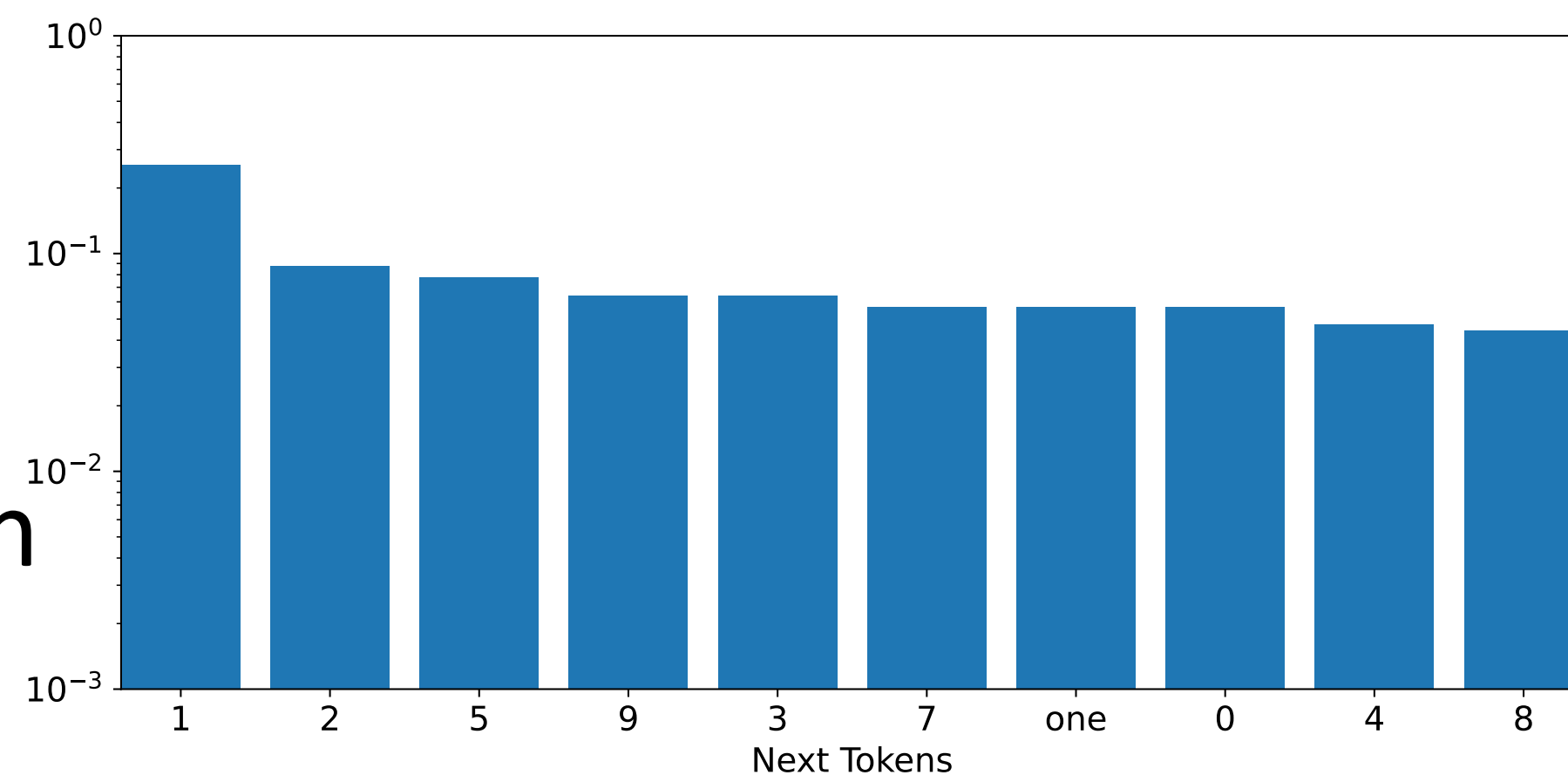
#1

Prompt

Give me a single-digit number

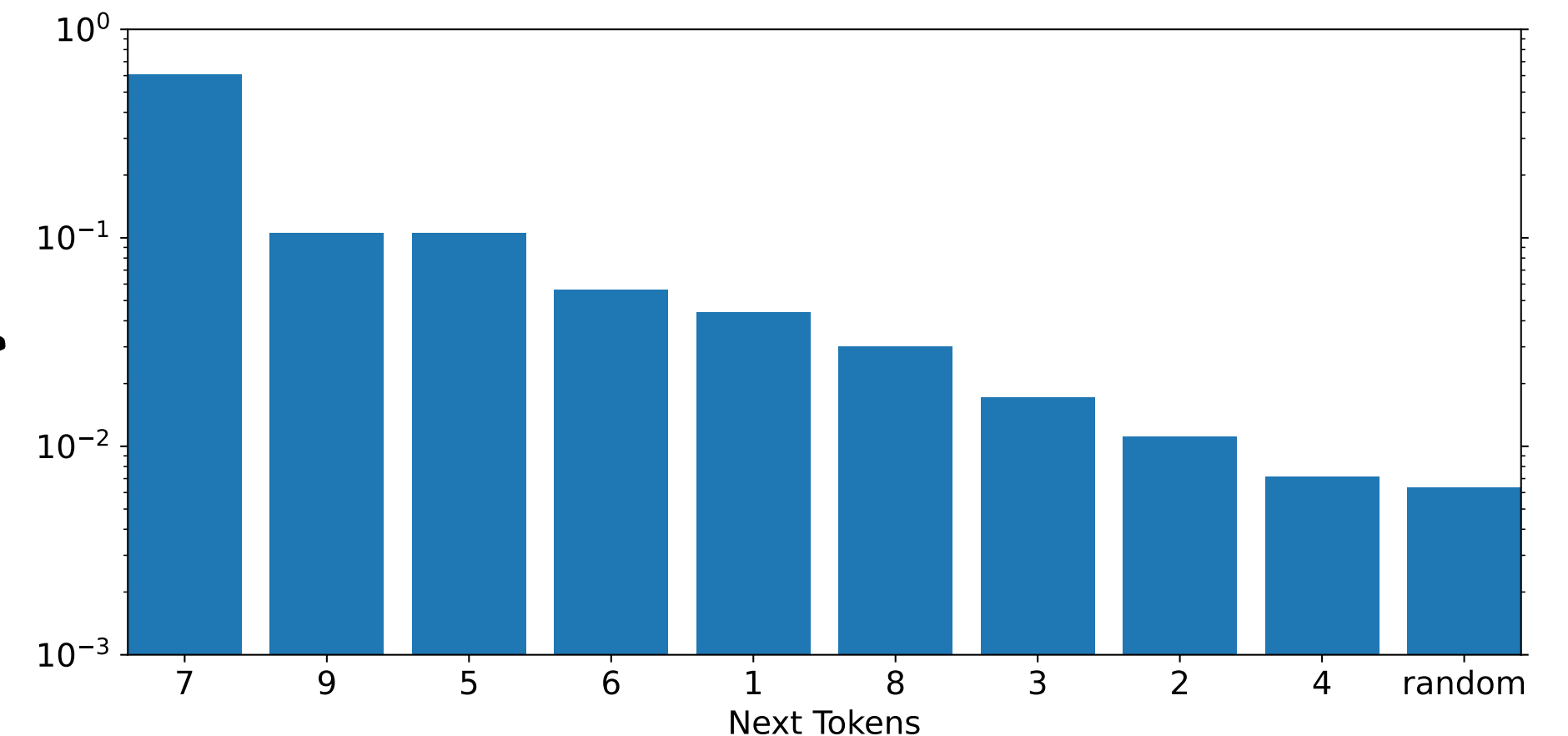
Response
Distribution

Pre-trained LLM



“near uniform”

Pre-trained LLM + SFT



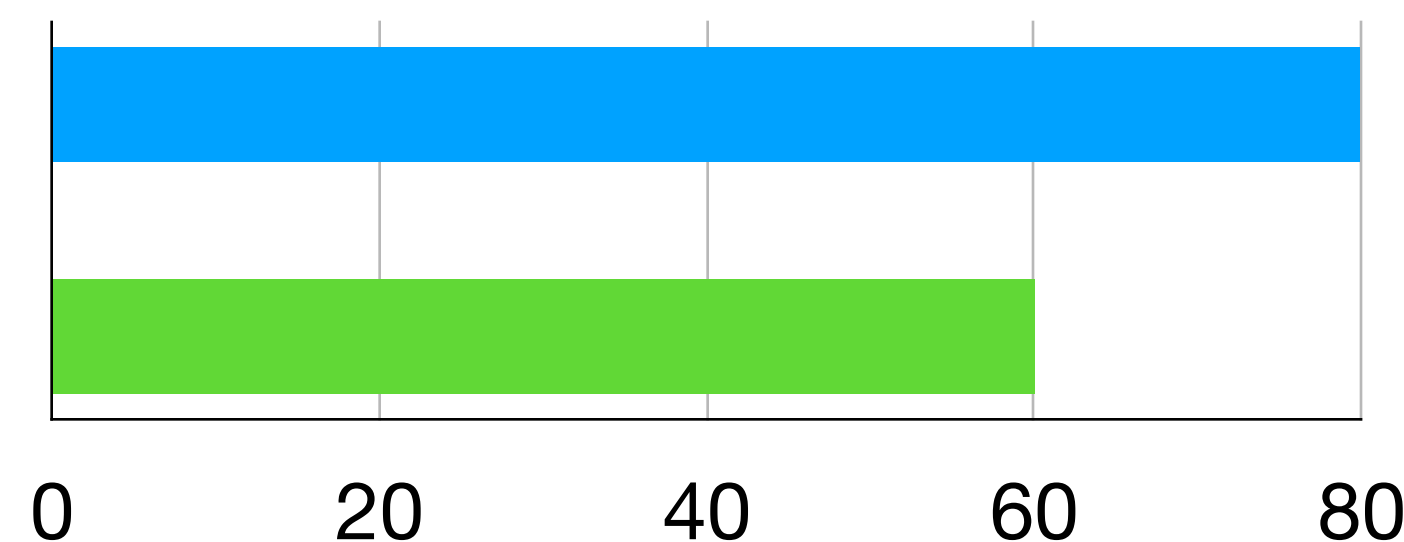
“biased toward 7”

[O’Mahony, Laura, et al. "Attributing mode collapse in the fine-tuning of large language models." *ICLR 2024 Workshop*. 2024.]

#2

Output
Diversity
Statistics

Output Diversity



Pre-training SFT

SFT reduces diversity by ~20%

21

Related Issue: Model Homogenization toward GPT-4

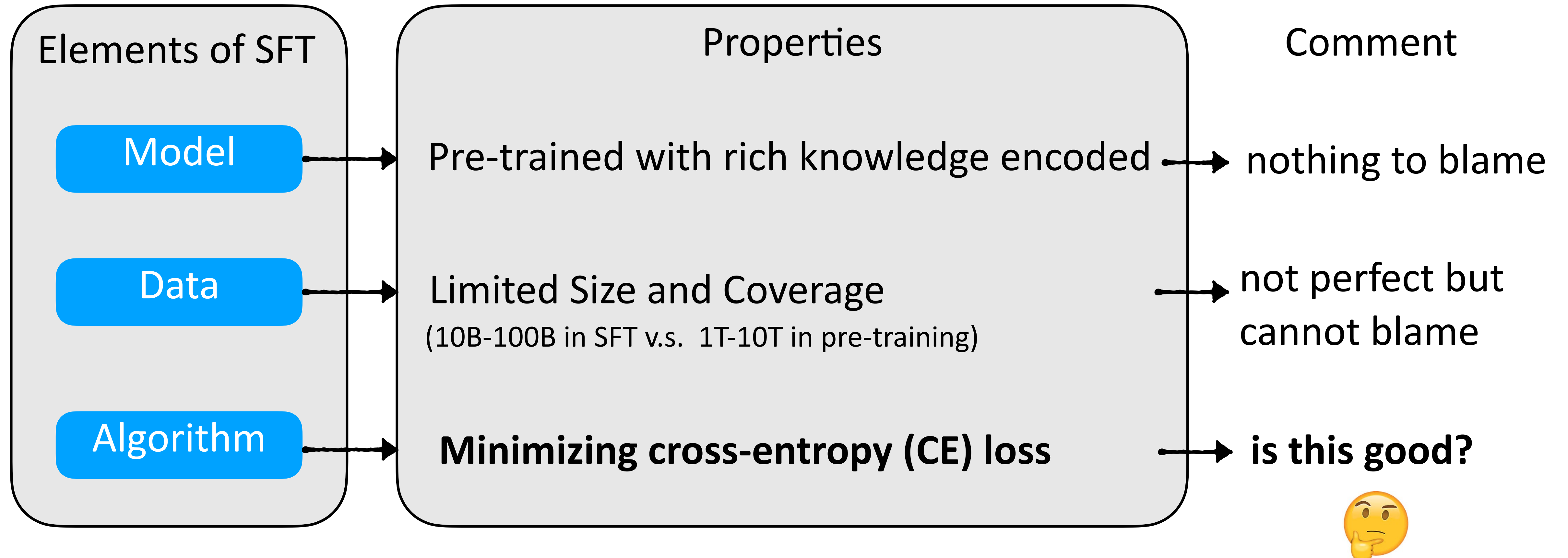
- ▶ “Small” companies use GPT-4 outputs as SFT data to fine-tune their models
- ▶ Fine-tuned models follow GPT-4’s style and behavior

Open Problems - Preserving Diversity and Interestingness

- How to restore and preserve interestingness and diversity – all the styles and worldviews present in the base models?

[ChatGPT and The Art of Post-Training. Barret Zoph & John Schulman. <https://docs.google.com/presentation/d/11KWCKUORnPpVMSY6vXgBeFSWo7fJcuGQ9yuR6vC1pzE/edit#slide=id.p>]

Let's Try to Solve the Problem



CE seems Effective for ...

Input

Model

Prediction

Label



Convolution Neural Network

"Dog"

"Cat"

Cross-Entropy Loss

Back-propagation



CE is Effective for **Classification**

"I like to drink"

Language Model

"Tea"

"Coffee"

Cross-Entropy Loss

Back-propagation



Is CE Effective for **Generation**?

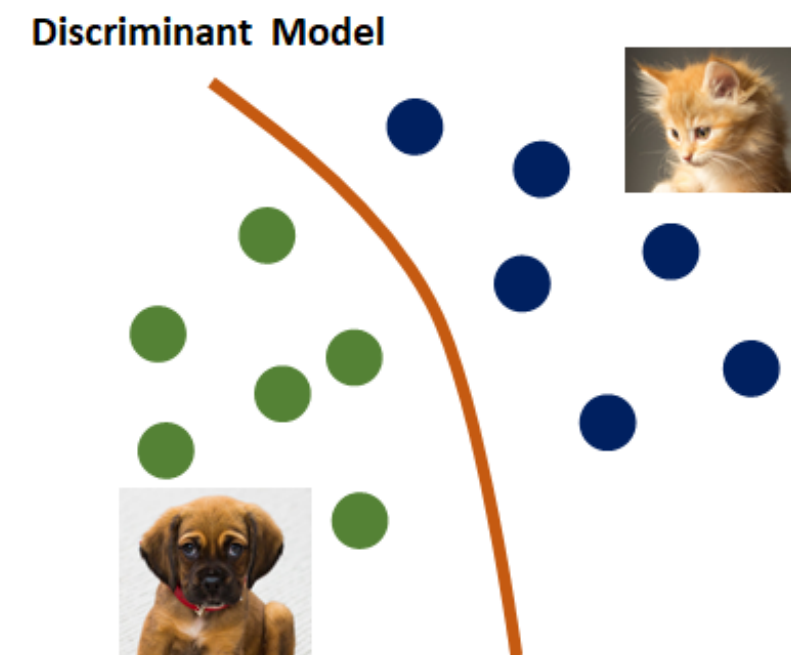
Understanding Generation Tasks

Classification

Target

$$\mathcal{X} \mapsto \mathcal{Y}$$

(**function**: many-to-one)

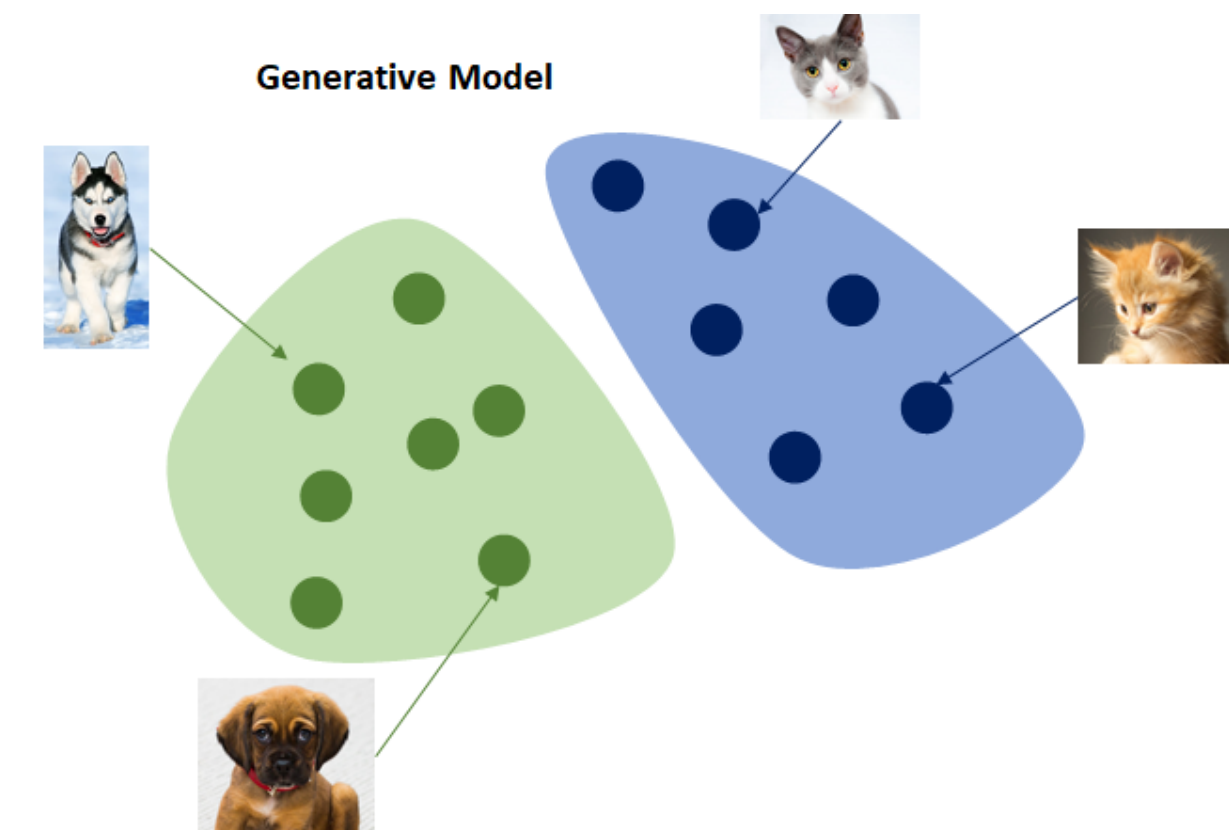


Illustration

Generation

$$\mathcal{X} \mapsto \Delta(\mathcal{Y})$$

(**distribution**: one-to-many)



Remark for LLMs:

- ▶ responses are **not unique**
(variation in formats, styles, or reasoning paths)
- ▶ (SFT) data is hard to cover all cases

Theory of CE

CE Loss (Empirical)

$$\min_{\theta} - \sum_{(x_i, y_i) \sim D} y_i^{\top} \log f_{\theta}(y_i | x_i)$$

(x_i, y_i) : input-label pair

$f_{\theta}(y | x)$: the conditional prediction distribution

θ : parameters of neural network

CE Loss (Population)

$$\max_{\theta} \mathbb{E}_{x \sim \rho} \mathbb{E}_{y \sim p(\cdot | x)} \log f_{\theta}(y | x)$$

ρ : prompt distribution

$p(\cdot | x)$: the conditional data distribution to learn

Equivalence

Forward KL Divergence

$$\min_{\theta} \mathbb{E}_{x \sim \rho} \text{KL}(p(\cdot | x), f_{\theta}(\cdot | x)) + \text{constant}$$

Distribution Matching

CE can be used to learn a distribution

If the data samples are “abundant”



Classification
(one label sample is enough)



Pre-training
(huge data)



SFT
(data is limited)

Summary

Challenge:

We need to protect LLM's output diversity during SFT

Understanding:

CE easily fits to the empirical data and loses the diversity

Goal:

Designing new formulation and algorithm for SFT

Analyzing Cross-Entropy Loss

Setting: $y \sim f_\theta(\cdot | x)$ and $f_\theta(i | x) = \frac{\exp(\theta_i)}{\sum_{j=1}^K \exp(\theta_j)}$

Gradient of CE: assuming i -th token is the label

$$-\nabla_\theta \mathcal{L}_{\text{CE}}(\theta) = [-f_\theta(1|x), -f_\theta(2|x), \dots, 1 - f_\theta(i|x), \dots, -f_\theta(K|x)].$$

Implication:

Target token (label)'s logit \uparrow while other tokens' logits \downarrow

Distribution Matching as Flow Transfer

Proposition 1. *The gradient of CE specifies a logit flow map: each source token j transfers $f_\theta(j|x)$ logits to the target token i . Formally,*

$$\begin{aligned} -\nabla_\theta \mathcal{L}_{\text{CE}}(\theta) &= \sum_{j=1, j \neq i}^K w_{i \leftarrow j} \cdot e_{i \leftarrow j} \\ w_{i \leftarrow j} &= f_\theta(j|x) \\ e_{i \leftarrow j} &= [0 \ \cdots \underbrace{1}_{i\text{-th position}} \ \cdots \underbrace{-1}_{j\text{-th position}} \ \cdots \ 0] \end{aligned} \quad (2)$$

Example: $f_\theta = [0.1, 0.3, 0.6]$ Label: #2

Gradient: $g = [-0.1, 0.7, -0.6]$

Flow perspective: $g = 0.1 * [-1 \ 1 \ 0] + 0.6 * [0 \ 1 \ -1]$

Logits flow from **source** tokens = Logits flow to **target** token

Limitations of CE

#1 While there exists source token $j \neq i$ with $f_{\theta_k}(j|x) > 0$, continue the following steps.

- Find any j with $f_{\theta_k}(j|x) > 0$
- Decrease the logit for source token j by learning rate η and weight $w_{i \leftarrow j}$:

$$\theta_{k+1}[j] = \theta_k[j] - \eta * w_{i \leftarrow j}$$

- Increase the logit for the target token i in a similar manner:

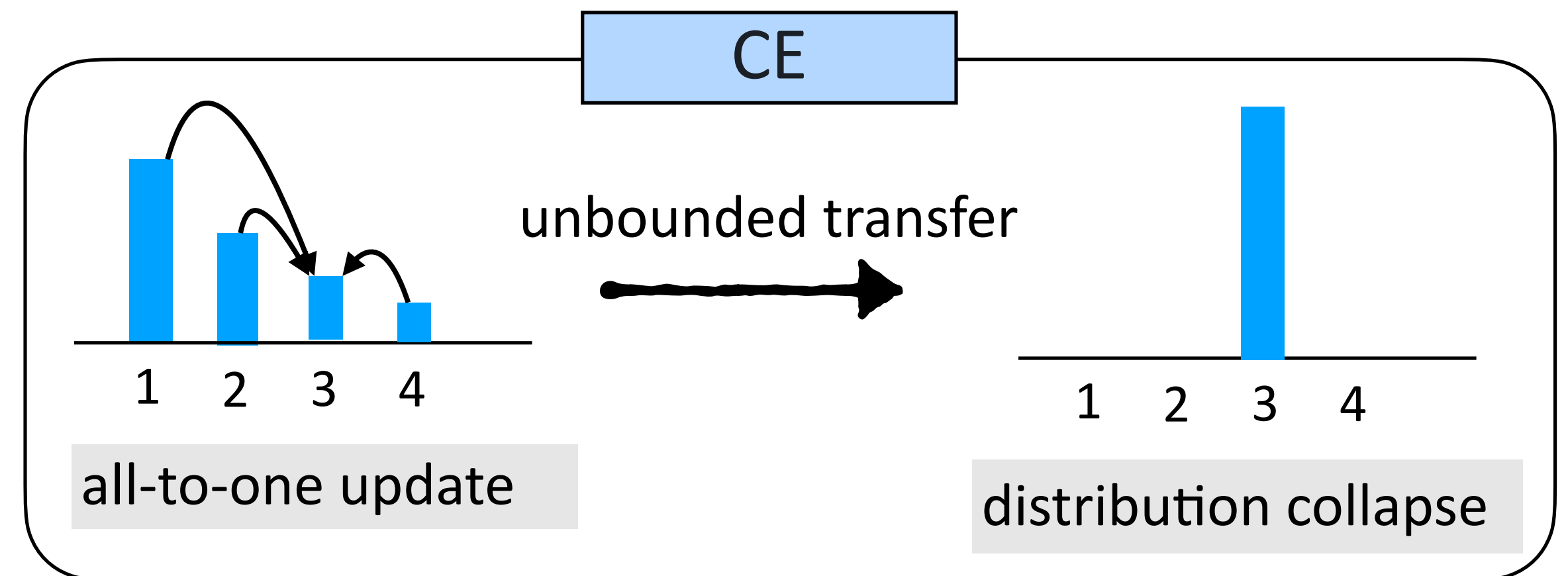
$$\theta_{k+1}[i] = \theta_k[i] + \eta * w_{i \leftarrow j}$$

Procedure of CE

#2

Limitation 1: Unbounded Transfer

Limitation 2: All-to-one Update



Proposed Solutions

Procedure of Our Method

#1

While the target token $i \notin \operatorname{argmax} f_{\theta_k}(\cdot|x)$, continue the following steps.

#2

- Calculate the model's best prediction $j = \operatorname{argmax} f(\cdot|x)$
- Decrease the logit for source token j by learning rate η and weight $w_{i \leftarrow j}$:

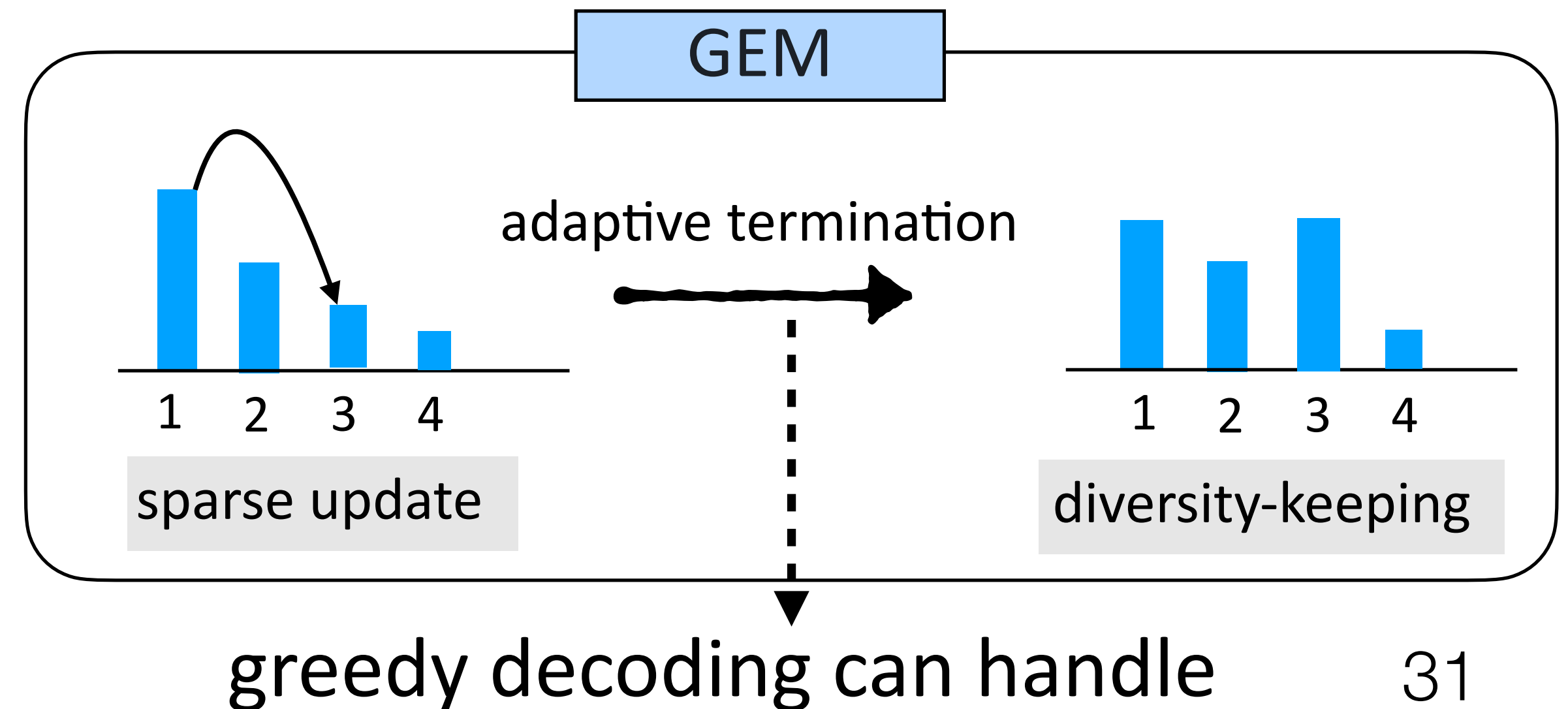
$$\theta_{k+1}[j] = \theta_k[j] - \eta * w_{i \leftarrow j}$$

- Increase the logit for the target token i in a similar manner:

$$\theta_{k+1}[i] = \theta_k[i] + \eta * w_{i \leftarrow j}$$

Technique 1: Adaptive Termination

Technique 2: Sparse Update



Our Insight: Dimension Increase

Procedure of Our Method

While the target token $i \notin \operatorname{argmax} f_{\theta_k}(\cdot|x)$, continue the following steps.

- Calculate the model's best prediction $j = \operatorname{argmax} f(\cdot|x)$
- Decrease the logit for source token j by learning rate η and weight $w_{i \leftarrow j}$:

$$\theta_{k+1}[j] = \theta_k[j] - \eta * w_{i \leftarrow j}$$

- Increase the logit for the target token i in a similar manner:

$$\theta_{k+1}[i] = \theta_k[i] + \eta * w_{i \leftarrow j}$$



What is the magic? Can we generalize this to neural network training?



Introduce an **auxiliary variable** (dimension increase) that implements the scheme of sparse update and adaptive termination

Towards a Game Formulation

High-level design: introduce an another player q to the distribution matching

$$\min_f \quad \mathcal{L}(f, q) \triangleq \mathbb{E}_x \mathbb{E}_{y^{\text{real}} \sim p(\cdot|x)} \mathbb{E}_{y^{\text{gene}} \sim q(\cdot|x)} [\log f(y^{\text{gene}}|x) - \log f(y^{\text{real}}|x)]$$

$$\max_q \quad \mathcal{Q}(f, q) \triangleq \mathbb{E}_x \mathbb{E}_{y^{\text{gene}} \sim q(\cdot|x)} [\log f(y^{\text{gene}}|x)] + \beta \cdot \mathcal{H}(q(\cdot|x)).$$

Intuitive Understanding:

- ▶ f : increase the likelihood on real data and decrease likelihood on the generated data
- ▶ q : increase the energy induced by $\log f$ with entropy regularization

Understanding the Game

main player

$$-\nabla_{\theta} \mathcal{L}(f_{\theta}, q) = \sum_{j=1, j \neq i}^K w_{i \leftarrow j} \cdot e_{i \leftarrow j},$$

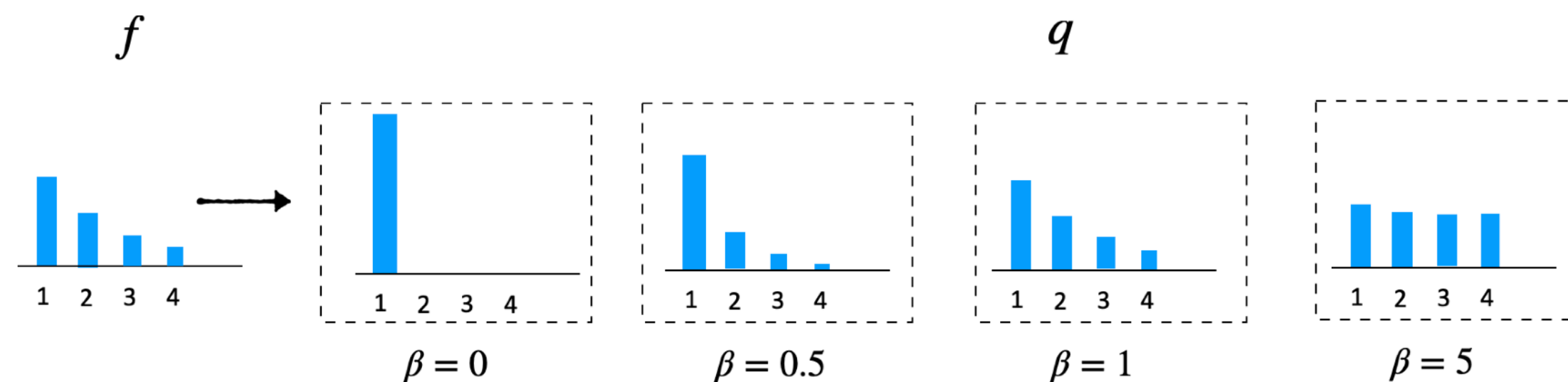
$$w_{i \leftarrow j} = q(j|x).$$

→ flow transfer

→ controller

meta-controller

$$\operatorname{argmax}_q \mathcal{Q}(q, f) = \begin{cases} \delta_j(x) \text{ with } j = \operatorname{argmax} f_i(\cdot|x) & \text{if } \beta = 0 \\ \operatorname{softmax}(1/\beta * \log f(y|x)) & \text{if } \beta > 0 \end{cases}$$



$\beta \rightarrow 0$: sparse update

$\beta \rightarrow 1$: same as CE

$\beta \rightarrow \infty$: uniform update

Connection with Probability Transfer

Proposition 2. For a data distribution satisfying $p(y|x) > 0$, with $\beta > 0$, the game in Equations (3) and (4) possesses a unique Nash equilibrium point:

$$\begin{cases} f^* = \text{softmax}(\beta * \log p) \\ q^* = p \end{cases} \quad (7)$$

Furthermore, f^* corresponds to the optimal solution to the distribution matching problem (with $1/\beta = (\gamma + 1)$), which minimizes the reverse KL divergence with entropy regularization:

$$f^* = \underset{f}{\operatorname{argmin}} \mathbb{E}_x [D_{\text{KL}}(f(\cdot|x), p(\cdot|x)) - \gamma \mathcal{H}(f(\cdot|x))] . \quad (8)$$

Terminology

Reverse KL Minimization

Entropy Maximization

Role

Fit the data distribution

Protect the output diversity

For $\beta = 0$, there are **multiple** Nash equilibrium points with non-closed-form solutions \rightarrow future work

Training Algorithm

Idea: block-wise gradient-descent and coordinate descent

$$\begin{cases} f_{\theta_{k+1}} = f_{\theta_k} - \nabla_{\theta} \mathcal{L}(f_{\theta}, q_k) |_{\theta=\theta_k} \\ q_{k+1} = \operatorname{argmax}_q \mathcal{Q}(f_{\theta_{k+1}}, q) = \operatorname{softmax}(1/\beta * \log f_{\theta_{k+1}}) \end{cases}$$

Feature 1: **Single**-model optimization

↳ There is no need of storing and explicit training of q

Optimization with the token space (**discrete**)

Feature 2: **Variance-reduced** gradient estimation

$$\mathcal{L}_{\text{GEM}}(\theta) = \sum_i \sum_{y^{\text{gene}}} q_k(y^{\text{gene}} | x_i) \cdot [\log f_{\theta}(y^{\text{gene}} | x_i) - \log f_{\theta}(y_i^{\text{real}} | x_i)]$$

↳ We use the exact distribution (in GANs, stochastic approximation is used)

Discussion: Difference with GANs

GAN

(generative adversarial network)

GEM

(game-theoretic entropy maximization)

Task

Image Generation

Text Generation

Challenge

Estimation the distance
among two images is hard

Overfitting the data and
losing output diversity

Idea

Introduction of discriminator

Introduction of flow-controller

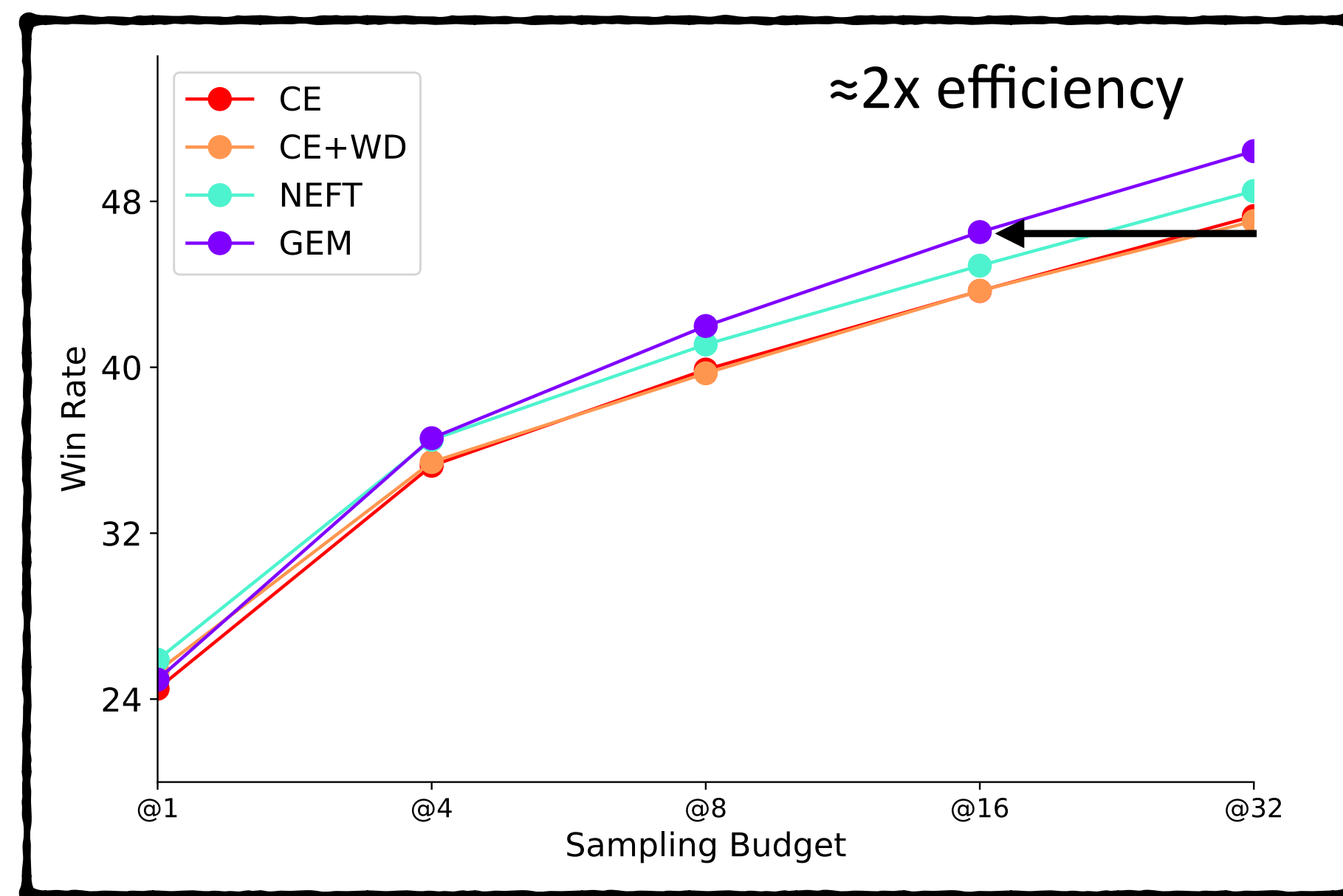
**Computation
Complexity**

High

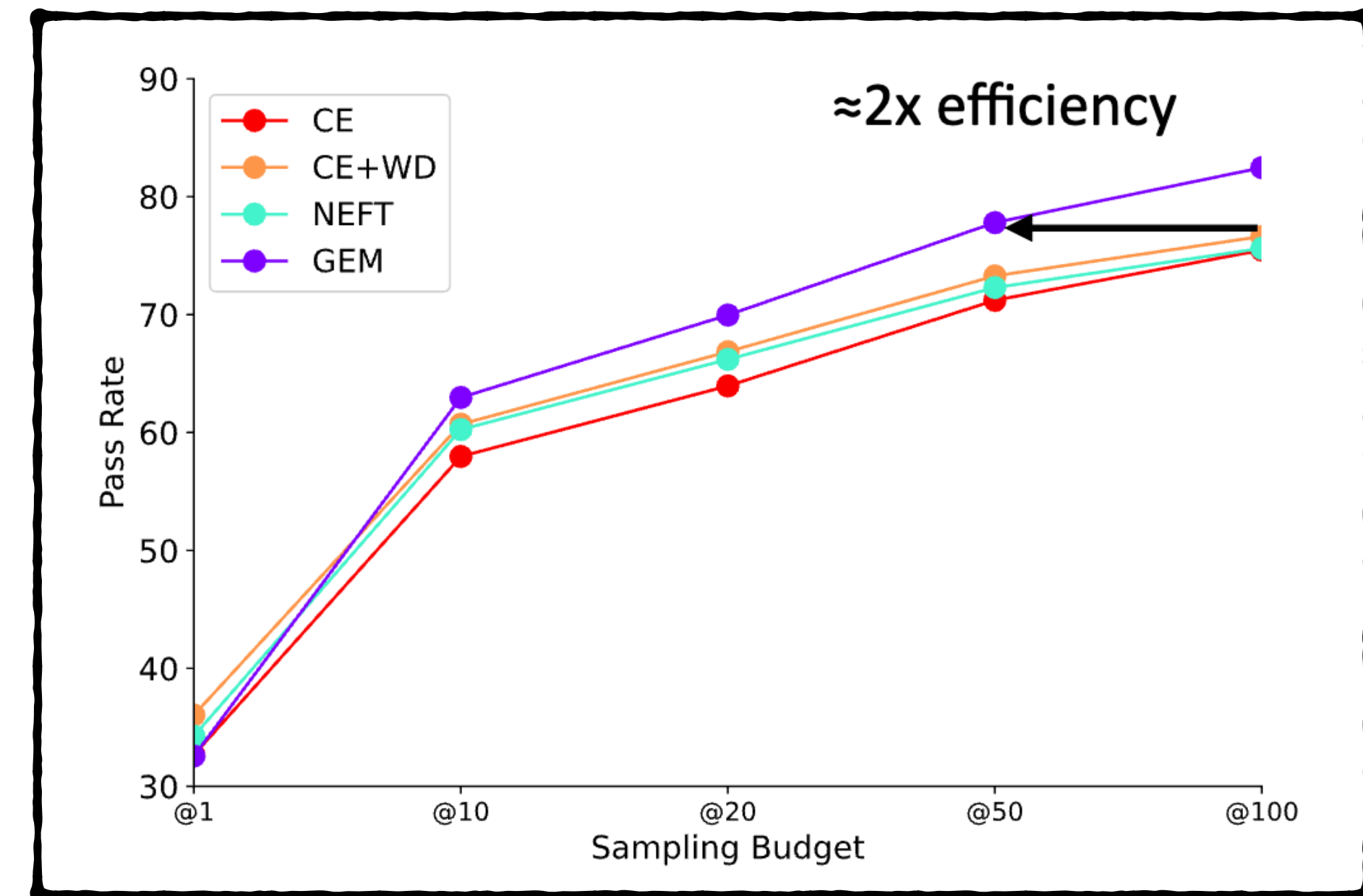
Low

Test-Time Scaling

- ▶ Evaluation Method: Best-of-N Sampling
- ▶ Model: Llama-3.1-8B; Dataset: Ultrafeedback



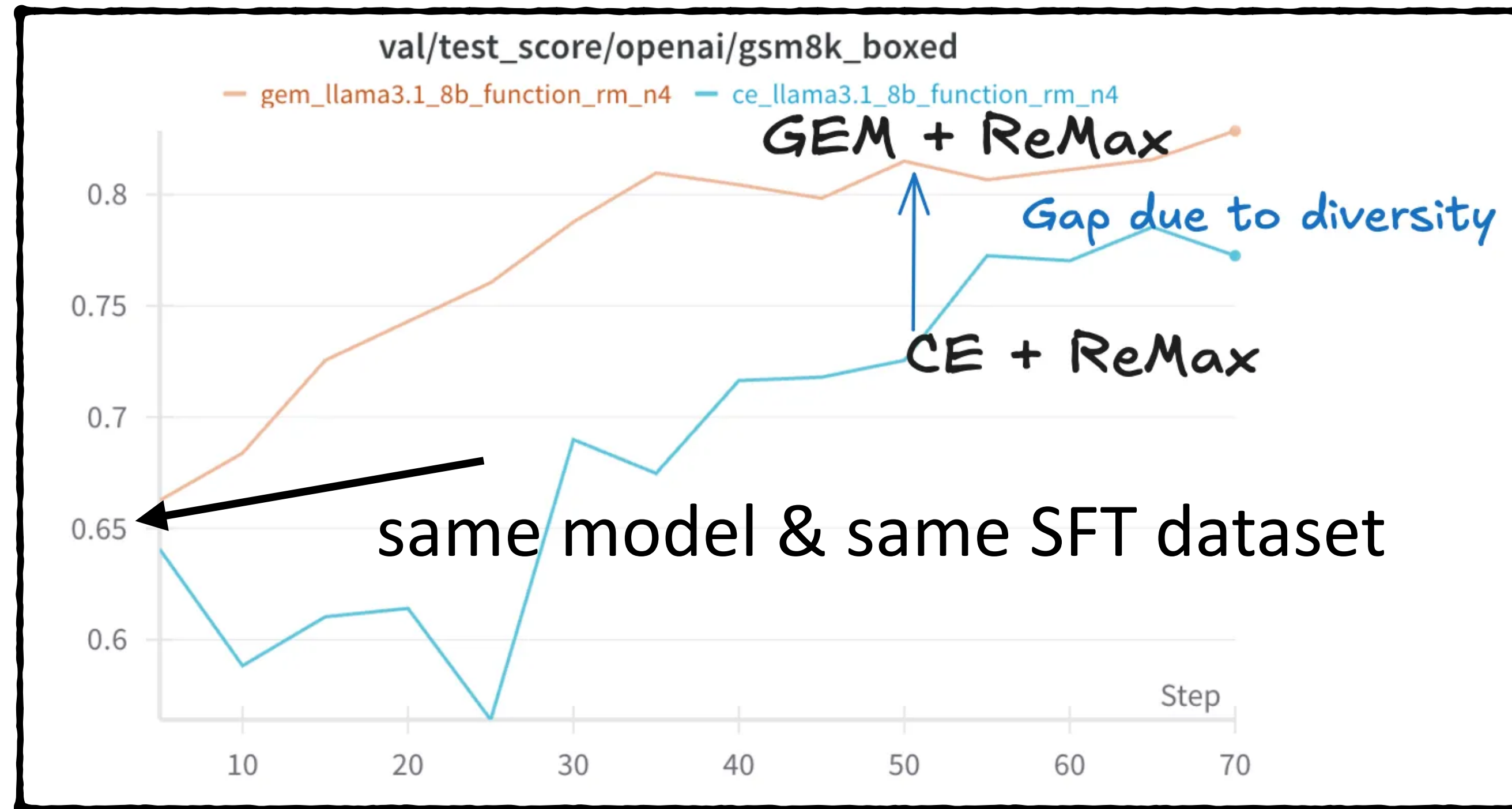
RLHF Alignment (Chat)



Code Generation

GEM requires about **2x** less sampling budget for comparable performance

Math Reasoning



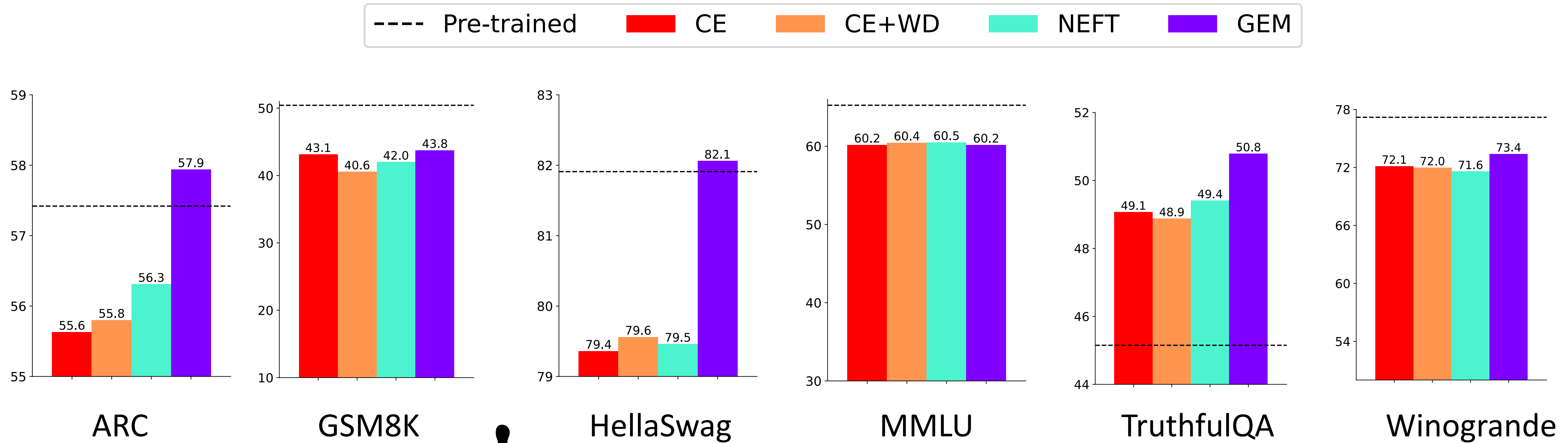
[<https://tangible-polo-203.notion.site/>]

- ▶ Task: optimize CoT (reasoning steps) to answer math questions
- ▶ Reward: accuracy of final reward
- ▶ Model: Qwen-2.5-3B
- ▶ RL Algo: ReMax

[Li, Ziniu, et al. "Remax: A simple, effective, and efficient reinforcement learning method for aligning large language models." ICML 2024.]

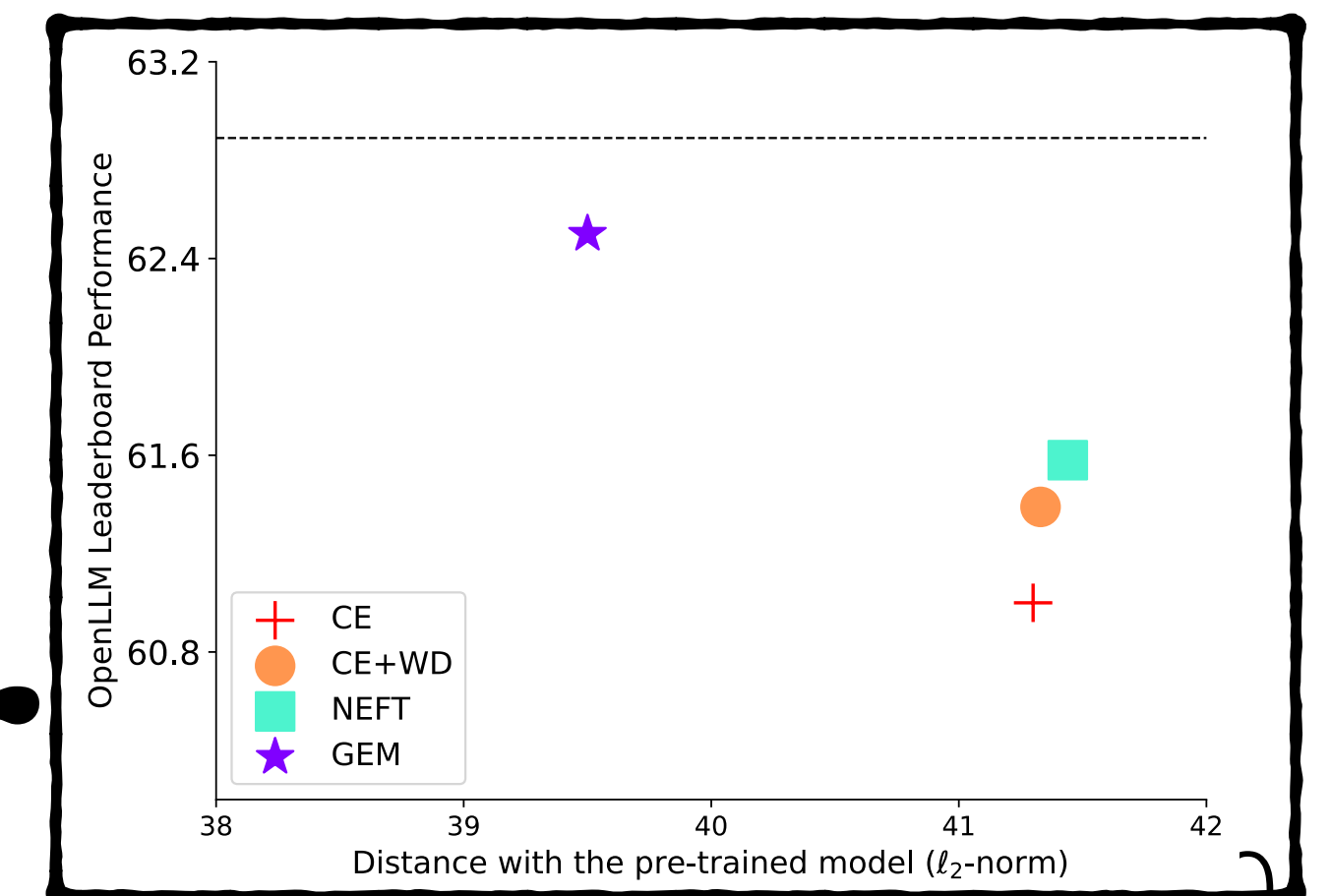
GEM improves the performance limit of RL training

Alignment Tax



GEM fine-tunes the model with 83% less alignment tax

GEM-tuned model shows less overfitting to the data



PRESERVING DIVERSITY IN SUPERVISED FINE-TUNING OF LARGE LANGUAGE MODELS

**Ziniu Li^{1,2}, Congliang Chen^{1,2}, Tian Xu³, Zeyu Qin⁴, Jiancong Xiao⁵,
Zhi-Quan Luo^{1,2}, and Ruoyu Sun^{1,2,†}**

ICLR 2025

NeurIPS 2024 FITML Workshop Best Paper Runner-up



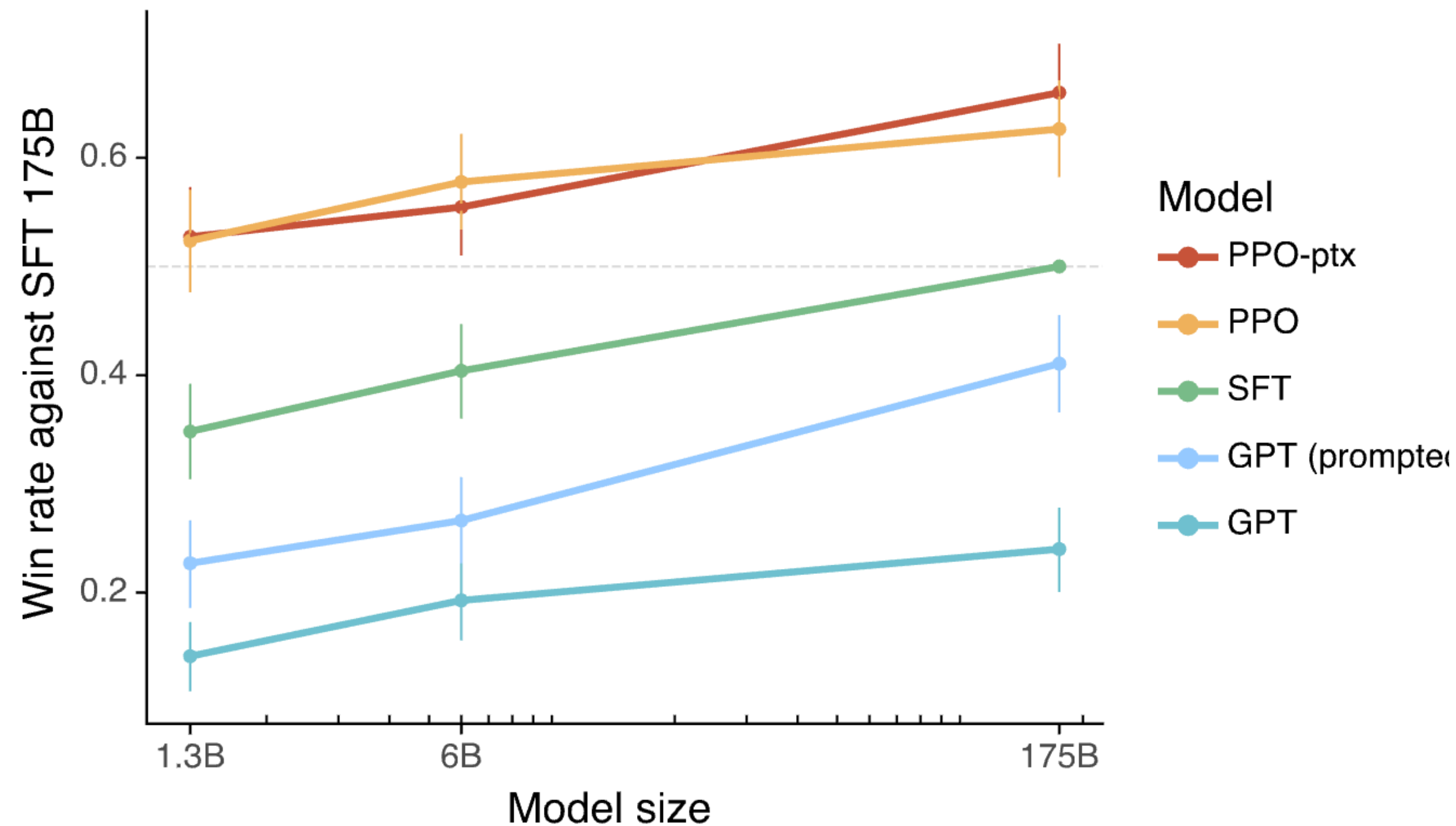
Paper



Code

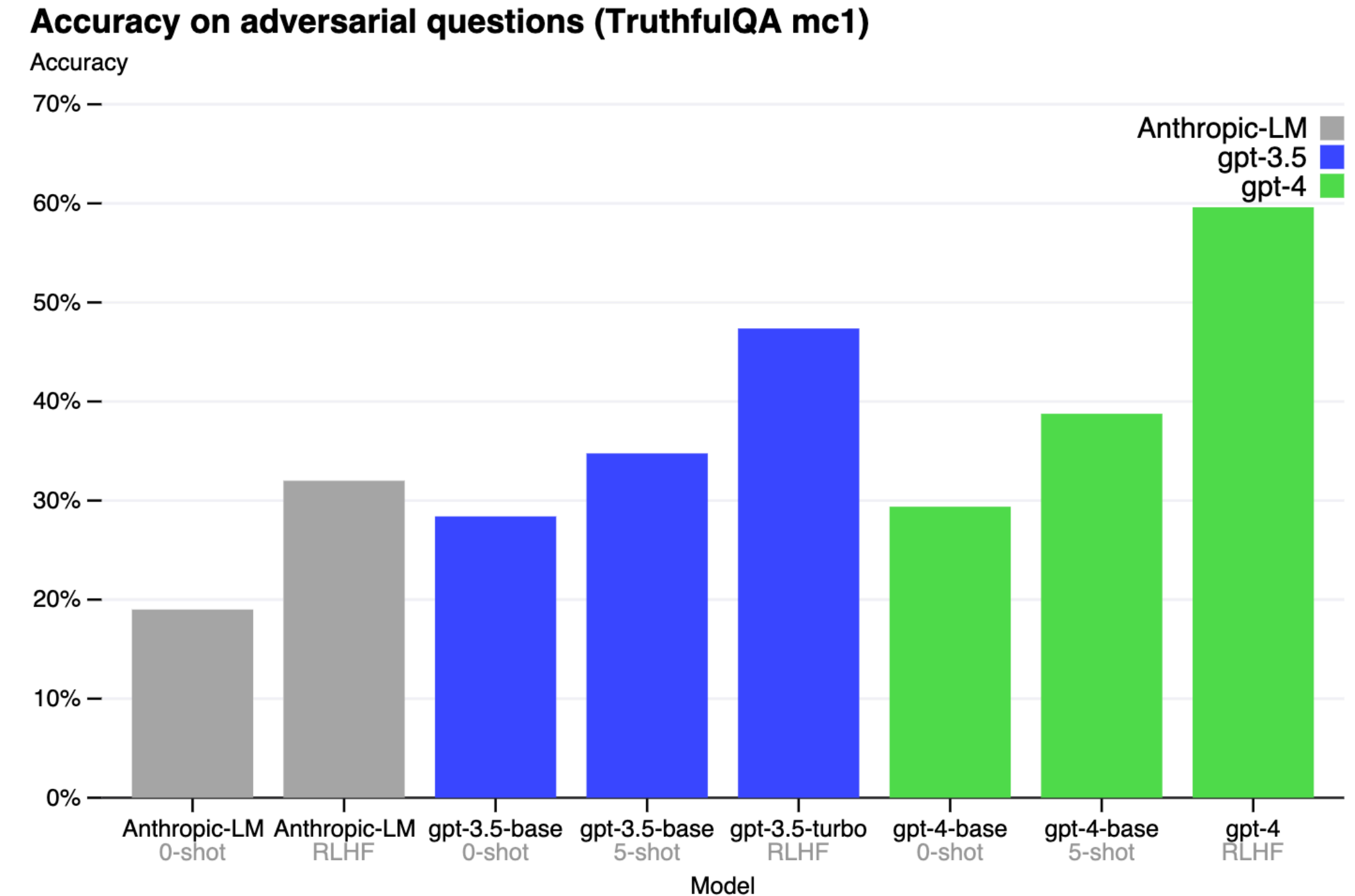
Part IV: Efficient and Scalable Reinforcement Learning in LLMs

RL Task: Alignment



Only PPO Achieves a Win Rate Above 50%

[Ouyang, Long, et al. "Training language models to follow instructions with human feedback." *NeurIPS 2022*.]

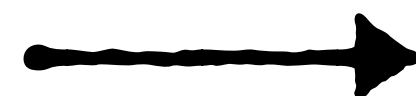


RLHF Enhances Acc. by More Than 10%

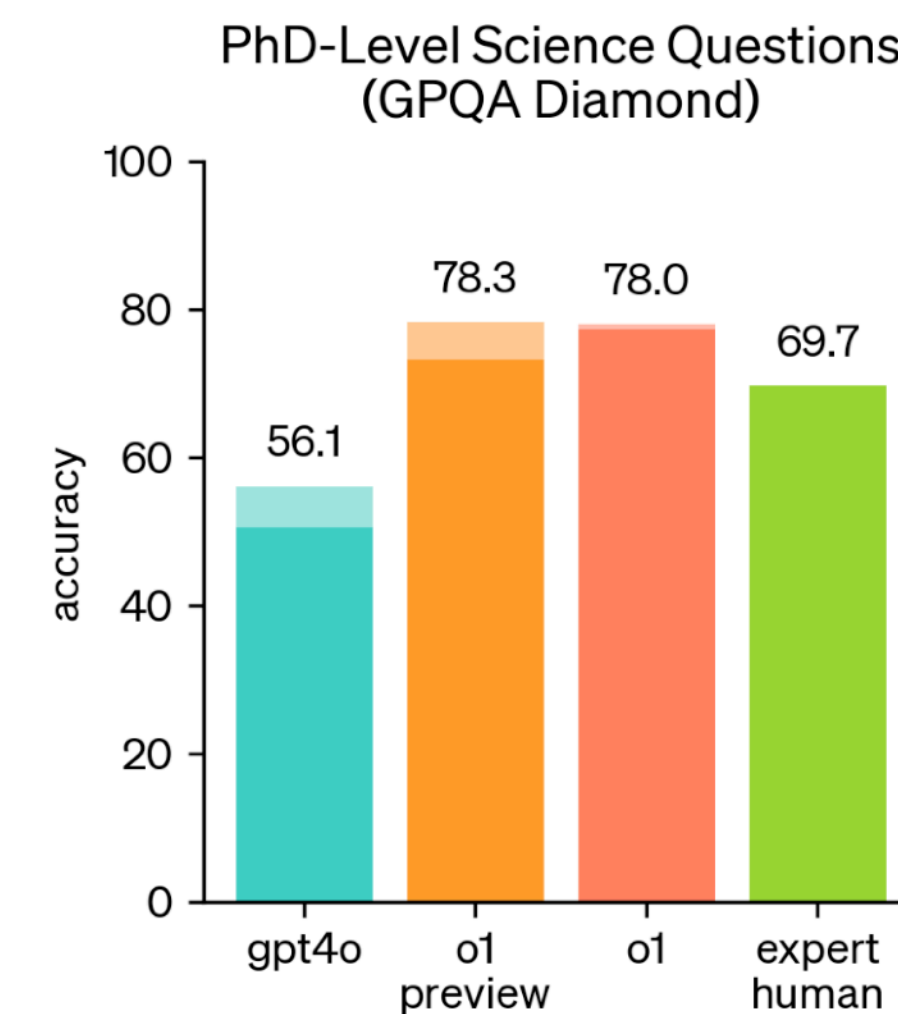
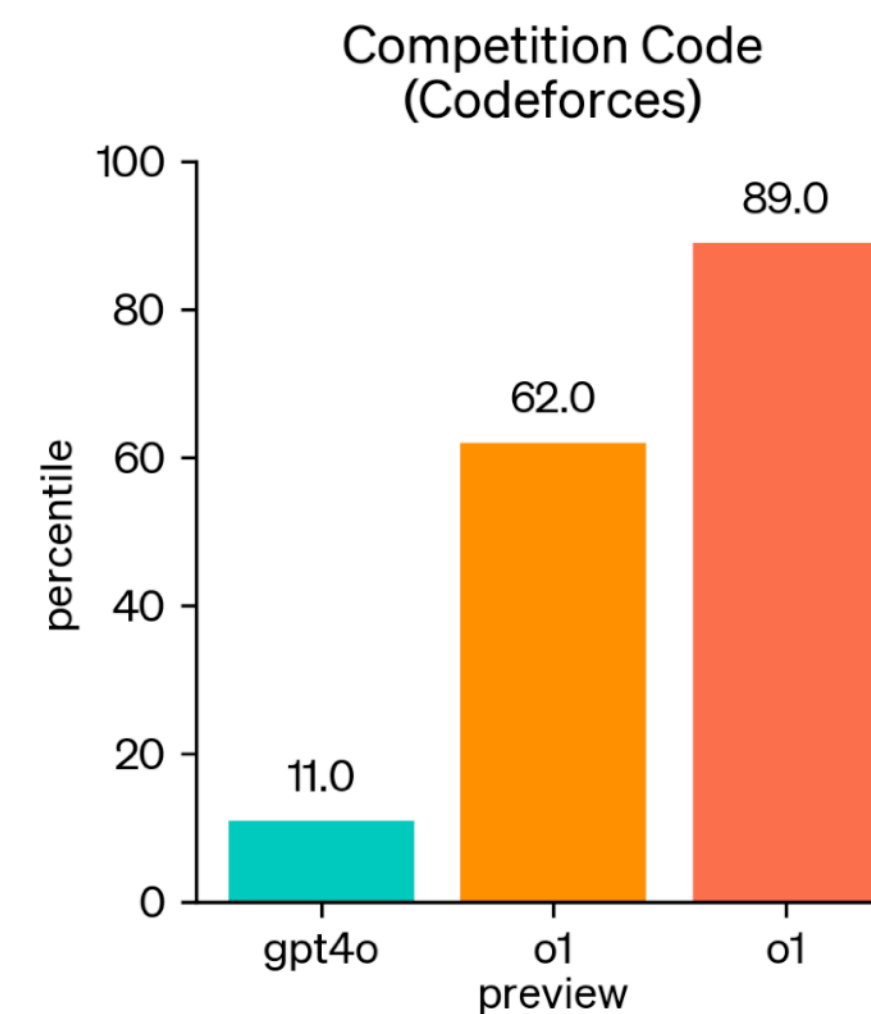
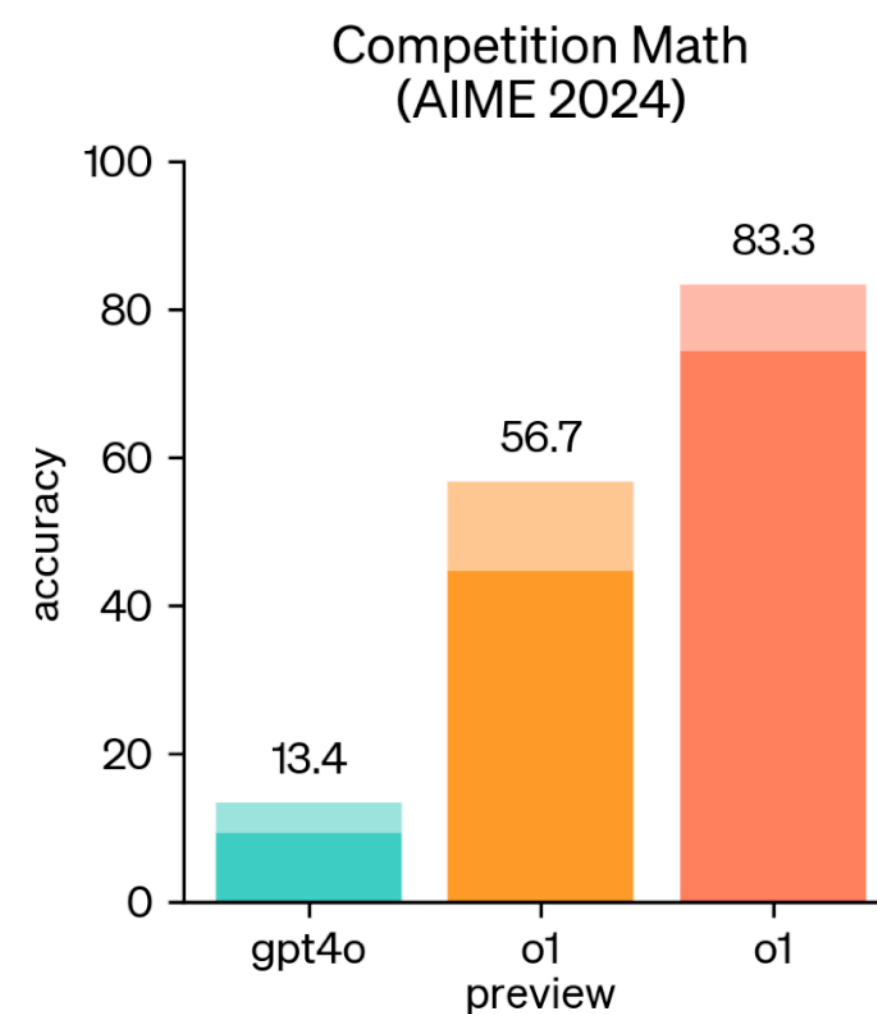
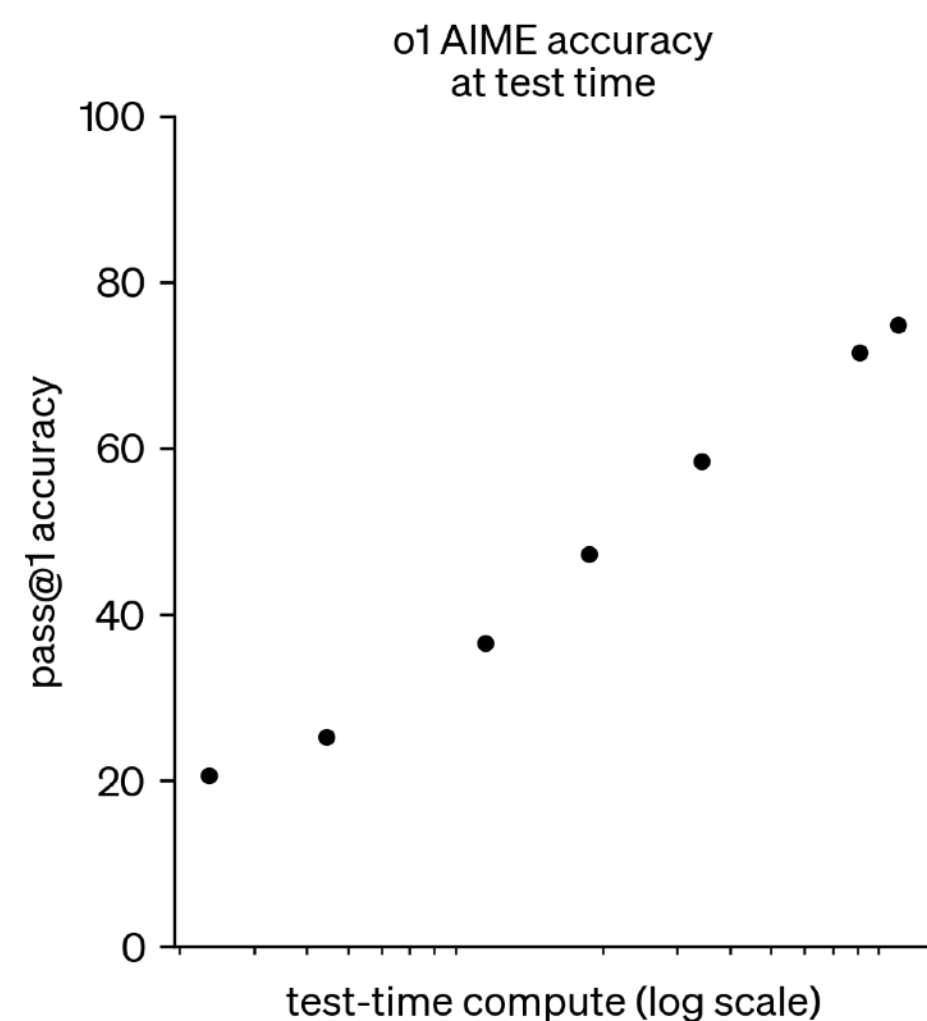
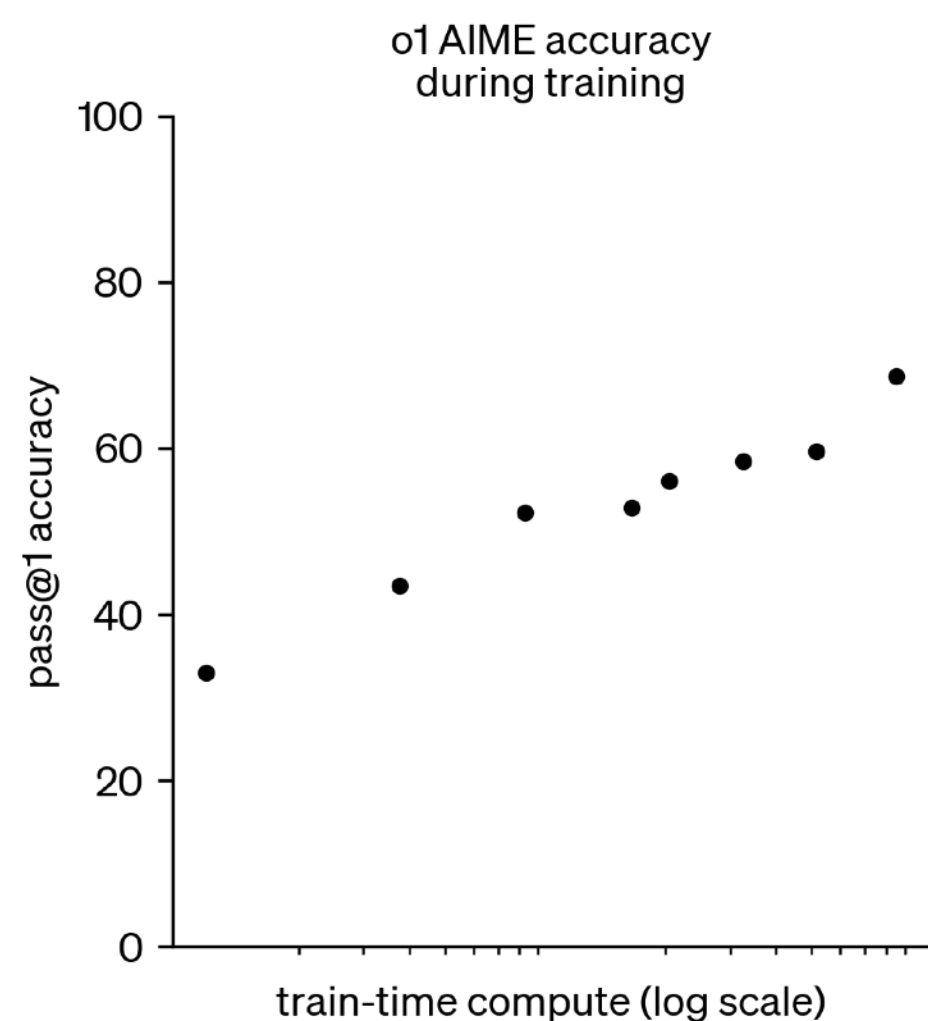
[Achiam, Josh, et al. "Gpt-4 technical report." *arXiv preprint arXiv:2303.08774* (2023).]

RL Task: Eliciting Reasoning

Test-time Scaling



Huge Improvement in Challenging Tasks

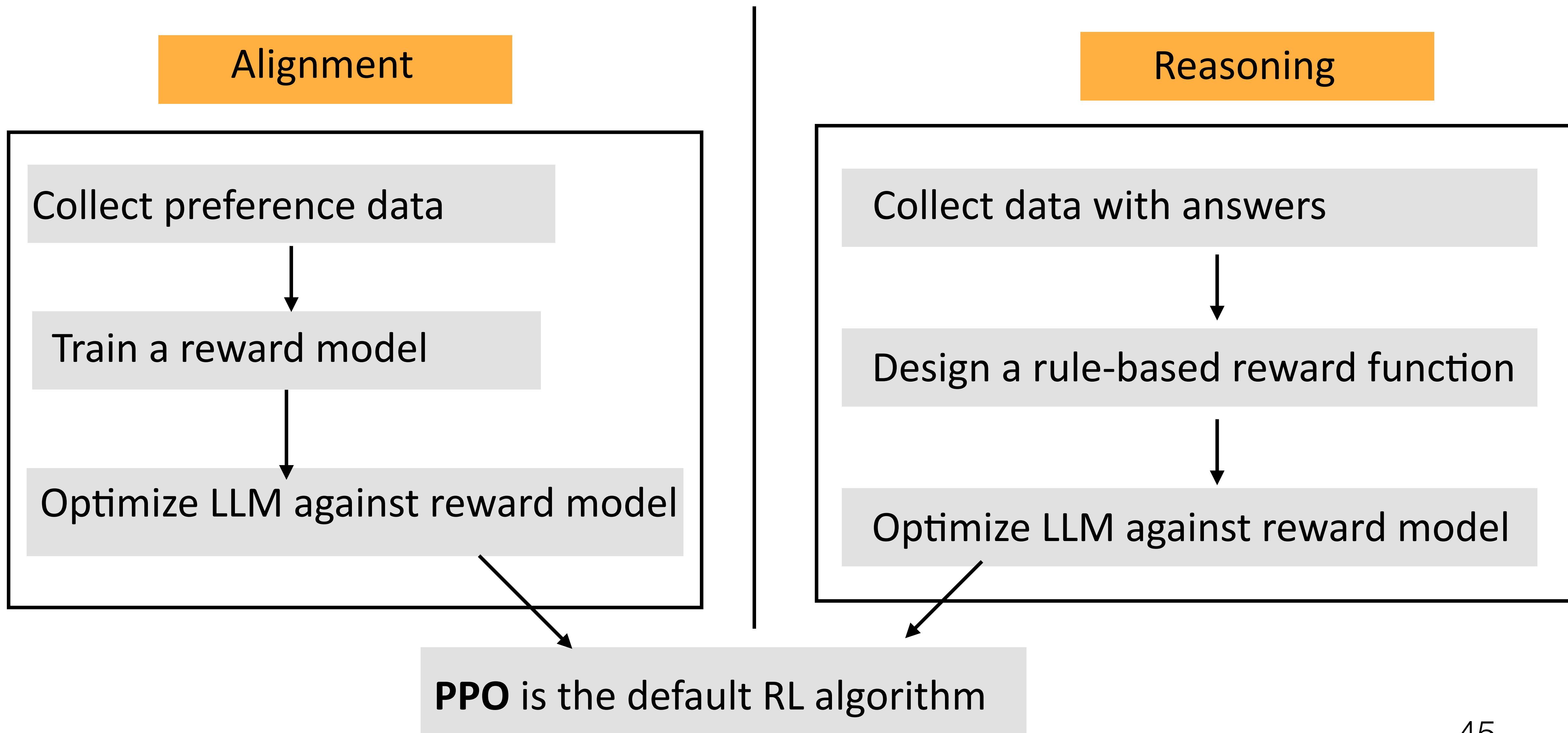


[<https://openai.com/index/learning-to-reason-with-llms/>]

RL training enables models to think deep

o1 can exceeds GPT-4o by 40+ points on MATH, code, and PhD-Level QA

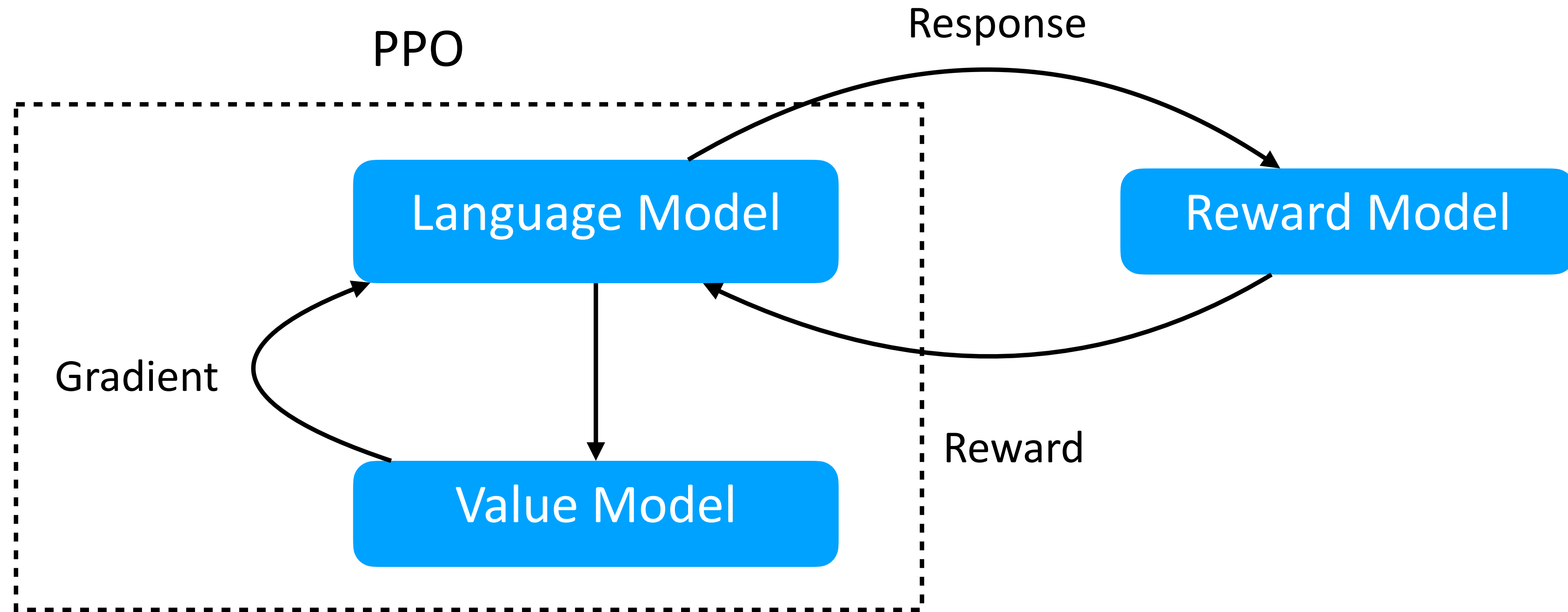
How does RL work in LLMs?



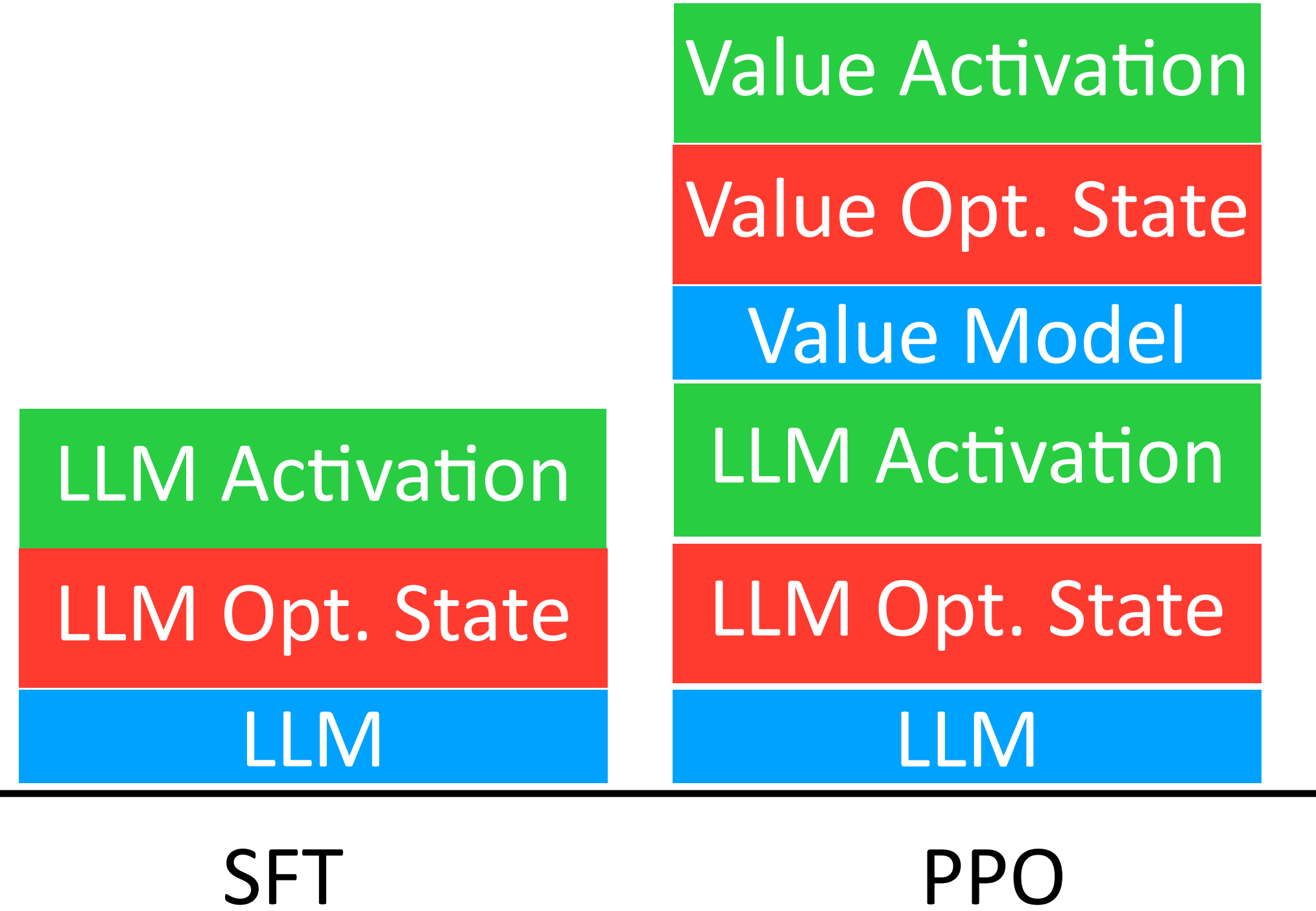
Introduction to PPO

Objective:

$$\max_{\theta} \mathbb{E}_{y_{1:T} \sim \pi_{\theta}(\cdot|x)} [r(x, y_{1:T})]$$



PPO is Computationally Inefficient



PPO's training takes more memory

SFT RM PPO

Table 4: E2E time breakdown for training a 13 billion parameter ChatGPT model via DeepSpeed-Chat on a single DGX node with 8 NVIDIA A100-40G GPU.

Model Sizes	Step 1	Step 2	Step 3	Total
Actor: OPT-13B, Reward: OPT-350M	2.5hr	0.25hr	10.8hr	13.6hr

[Yao, Zhewei, et al. "DeepSpeed-Chat: Easy, Fast and Affordable RLHF Training of ChatGPT-like Models at All Scales." *arXiv:2308.01320* (2023)]

PPO's training is slow

Value model is the bottleneck of PPO

Can We Improve PPO?



Can we achieve RL training without the value model?



If Yes, we can save memory and accelerate training



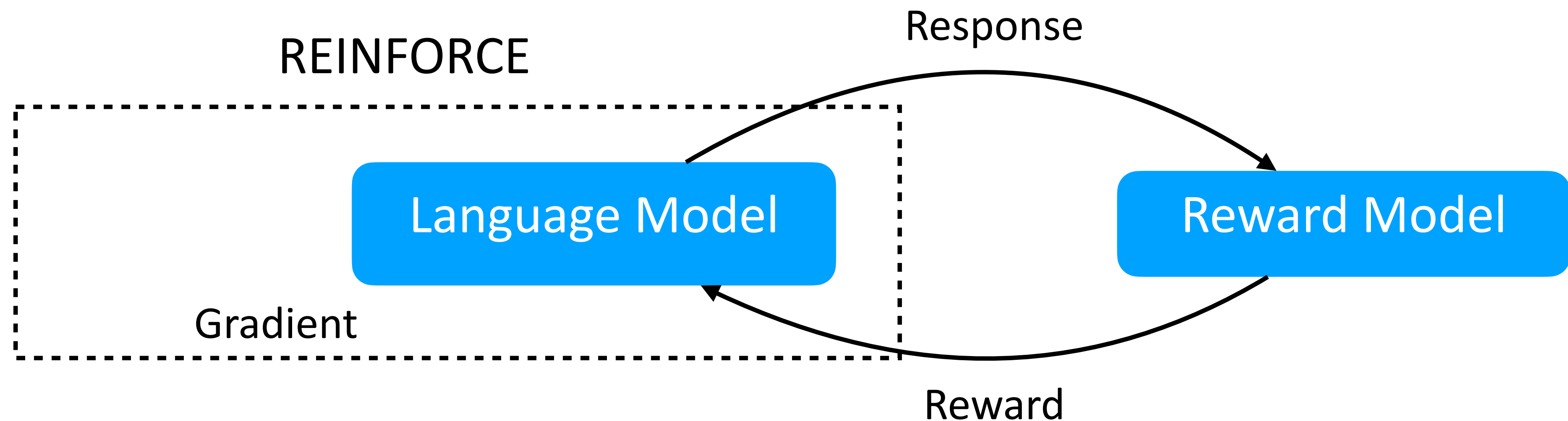
REINFORCE is an RL algorithm without value model

[Williams, Ronald J. "Simple statistical gradient-following algorithms for connectionist reinforcement learning." *Machine learning* 8 (1992): 229-256.]

Introduction to REINFORCE

Objective:

$$\max_{\theta} \mathbb{E}_{y_{1:T} \sim \pi_{\theta}(\cdot|x)}[r(x, y_{1:T})]$$



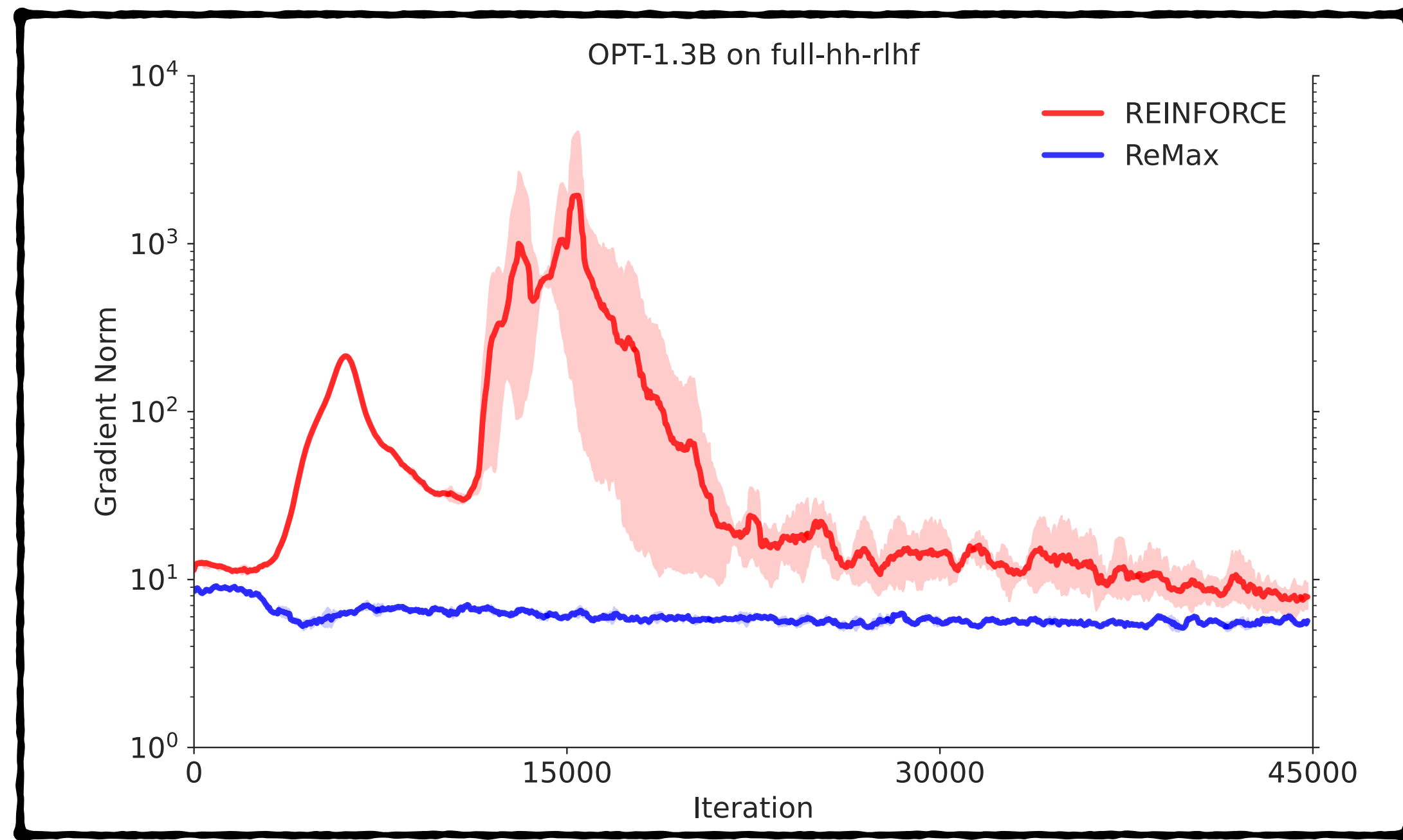
[Williams, R. J. Reinforcement-learning connectionist systems. College of Computer Science, Northeastern University, 1987.]

REINFORCE: $\text{gradient} = \mathbb{E}_{y_{1:T} \sim \pi_{\theta}(\cdot|x)}[r(x, y_{1:T}) \cdot \nabla_{\theta} \log \pi_{\theta}(y_{1:T}|x)]$

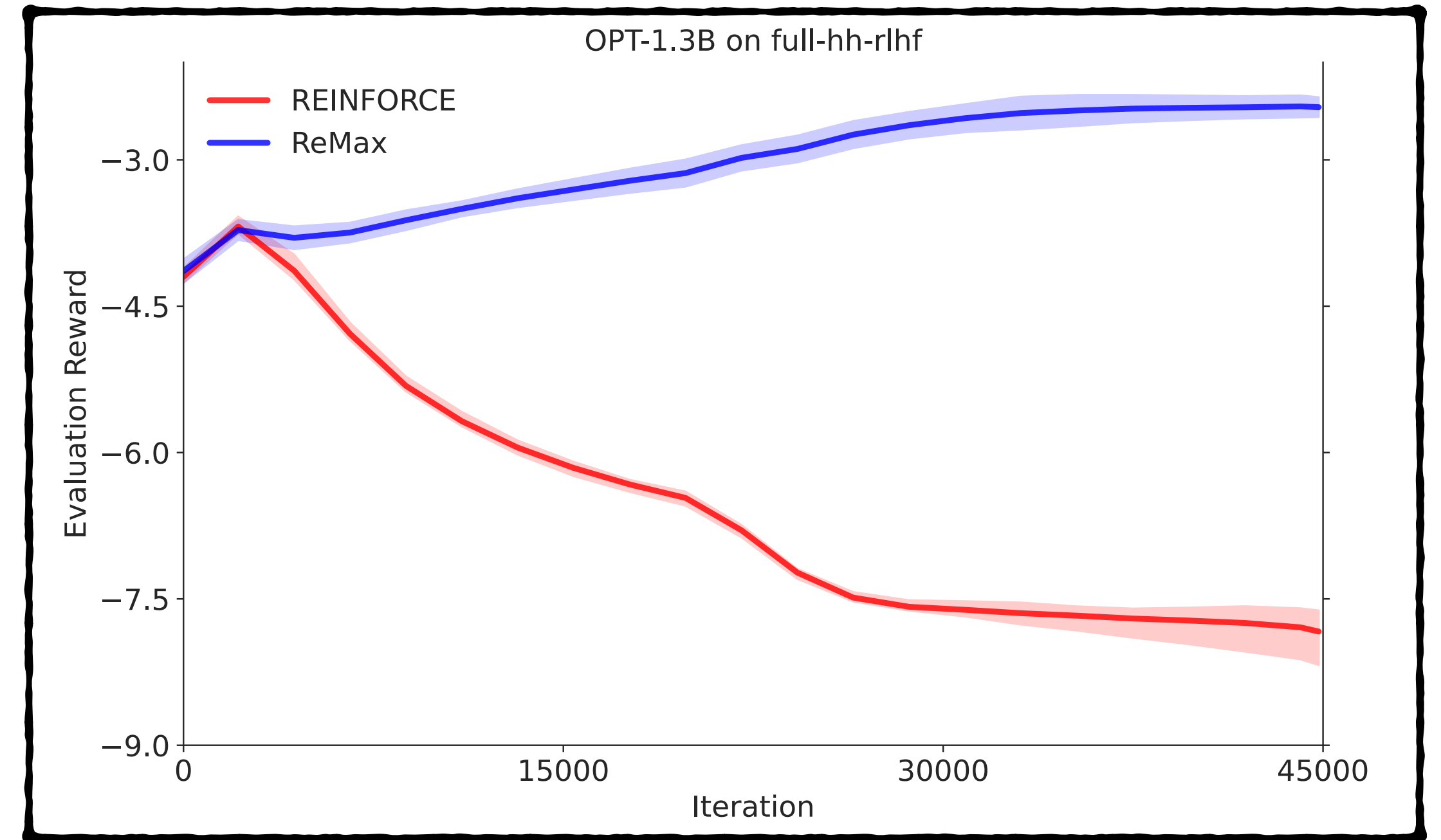
No Value Model

Stochastic Gradient Estimation in Practice

However, REINFORCE does not Work



REINFORCE's gradient has a high variance



REINFORCE's reward does not increase

Why is Variance so High?



REINFORCE is often criticized for a high gradient variance. But why?

[Sutton, Richard S., and Andrew G. Barto. *Reinforcement learning: An introduction*. MIT press, 1998.]

$$\text{gradient} = \mathbb{E}_{a_{1:T} \sim \pi_{\theta}(\cdot|x)} [r(x, a_{1:T}) \cdot \nabla_{\theta} \log \pi_{\theta}(a_{1:T}|x)]$$



Sample space is large

Size: (vocabulary size)^{sequence length}

Llama-3: (128k)^{8k}

Rewards vary across samples

Reward range of open-ended
question-answers: [-14, 7]

Introduction to ReMax

Key Idea: Introduce a **baseline value** for accurate gradient estimation

$$\nabla_{\theta} \mathbb{E}_{x,y}[r(x, y_{1:T})] = \mathbb{E} \left[\nabla_{\theta} \log \pi_{\theta}(y_{1:T} | x) \cdot \boxed{r(x, y_{1:T}) - b(x)} \right]$$

Advantage

$$b(x) = r(x, y'_{1:T}), \quad y'_t = \arg \max_{y_t} \pi_{\theta}(y_t | x_t, y_{1:t})$$

Greedy Decoding

Remark: 1) Subtracting a RV by a constant does not change the variance
2) ReMax introduces a RV $b \cdot \nabla_{\theta} \log \pi_{\theta}(y_{1:T} | x) \rightarrow$ **control variate**

Why Greedy Decoding?

$$\nabla_{\theta} \mathbb{E}_{x,y}[r(x, y_{1:T})] = \mathbb{E} \left[\nabla_{\theta} \log \pi_{\theta}(y_{1:T} | x) \cdot [r(x, y_{1:T}) - b(x)] \right]$$

$$b(x) = r(x, y'_{1:T}), \quad y'_t = \arg \max_{y_t} \pi_{\theta}(y_t | x_t, y_{1:t})$$

Reason 1: greedy decoding corresponds to **mode** of the distribution → **effective estimation**

Reason 2: value of greedy decoding ensures **independence** between the baseline and original RVs → **stable estimation**

Reason 3: if there is a response better than the greedy one, improve it's likelihood

ReMax Algorithm

Algorithm 2 ReMax for Aligning Large Language Models

Input: reward_model and language_model

```
1: for prompts in datasets do
2:   seqs = language_model.generate(prompts, do_sample=True)
3:   seqs_max = language_model.generate(prompts, do_sample=False)
4:   rews = reward_model(prompts, seqs) - reward_model(prompts, seqs_max)
5:   log_probs = language_model(prompts, seqs)
6:   loss = -(log_probs.sum(dim=-1) * rews).mean()
7:   lanugage_model.minimize(loss)
8: end for
```

Newly added

Output: language_model

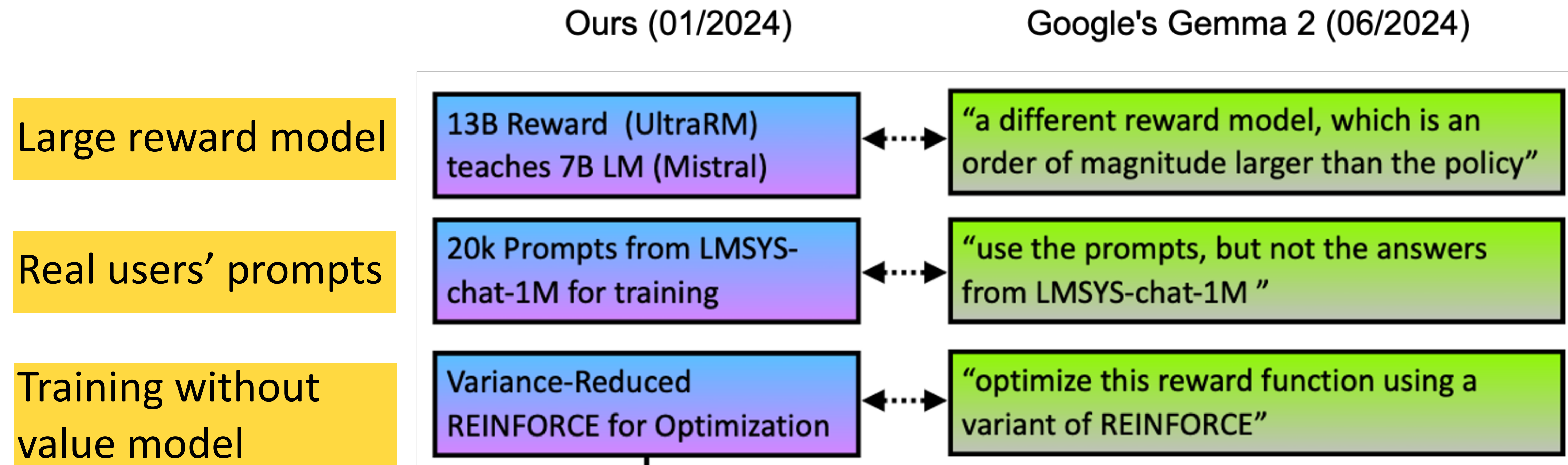
ReMax is Simple

8 Lines of code to implement (PPO: 50+)

1 Hyper-parameter (lr) to tune (PPO: 5+)

Comparing with Google's Method

ReMax's training strategies are also used in Google's Gemma 2



[Team, Gemma, et al. "Gemma 2: Improving open language models at a practical size." arXiv preprint arXiv:2408.00118 (2024).]

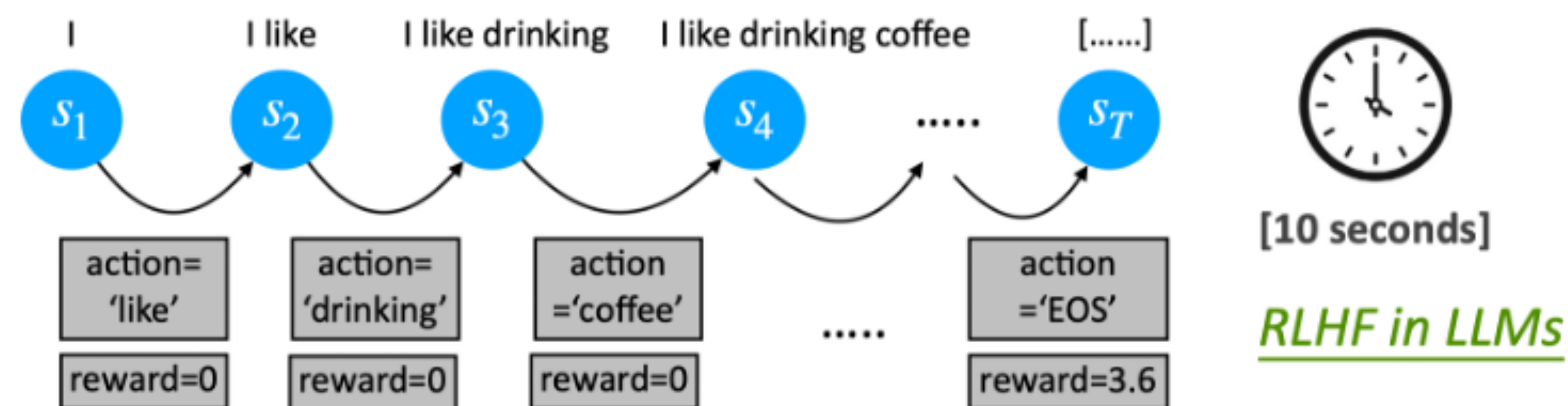
Can We Safely Remove Value Model?

General RL Tasks

RL in LLMs



- Slow simulation
- Stochastic transition
- Dense reward



- Fast simulation
- Deterministic transition
- Trajectory-level reward

We conjecture that value-free methods are “optimal” for RL in LLMs

PPO = REINFORCE with Baseline

General PPO

$$\mathcal{L}_{\text{ppo}} = \mathbb{E}_{x \sim \rho} \mathbb{E}_{a_{1:T} \sim \pi_{\theta_{\text{old}}}} \left[\sum_{t=1}^T \tilde{A}(s_t, a_t) \min \{ \psi(s_t, a_t), \text{clip}(\psi(s_t, a_t), 1 - \delta, 1 + \delta) \} \right].$$

$$A(s_t, a_t) = \sum_{j=0}^{T-t} \lambda^j \text{advantage}_{t+j} = \sum_{j=0}^T \lambda^j [r(s_{t+j}, a_{t+j}) + \gamma V(s_{t+1+j}) - V(s_{t+j})],$$

Best Practice $\gamma = 1, \lambda = 1$

[Ahmadian, Arash, et al. "Back to basics: Revisiting reinforce style optimization for learning from human feedback in llms." *arXiv preprint arXiv:2402.14740* (2024).]

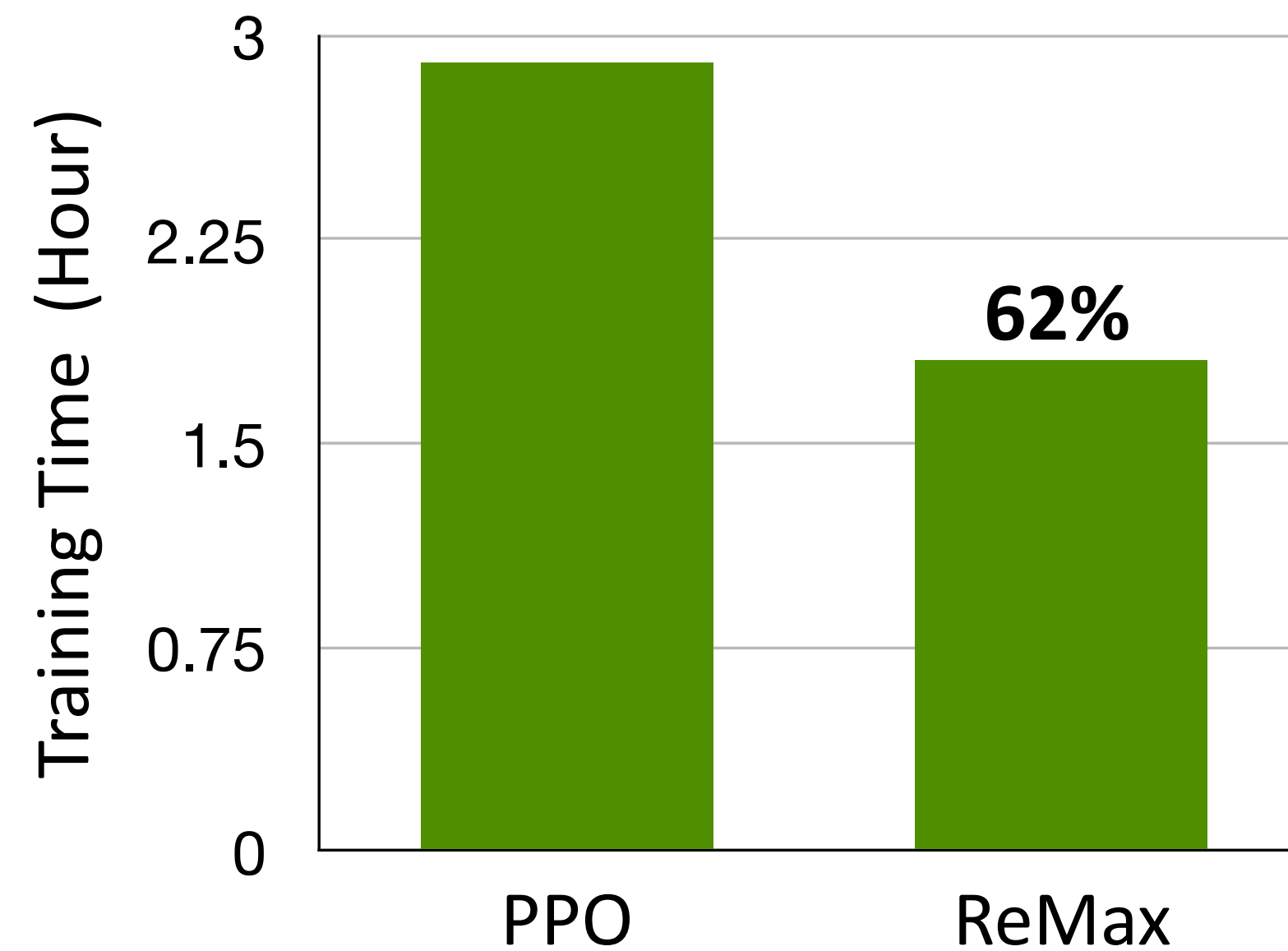
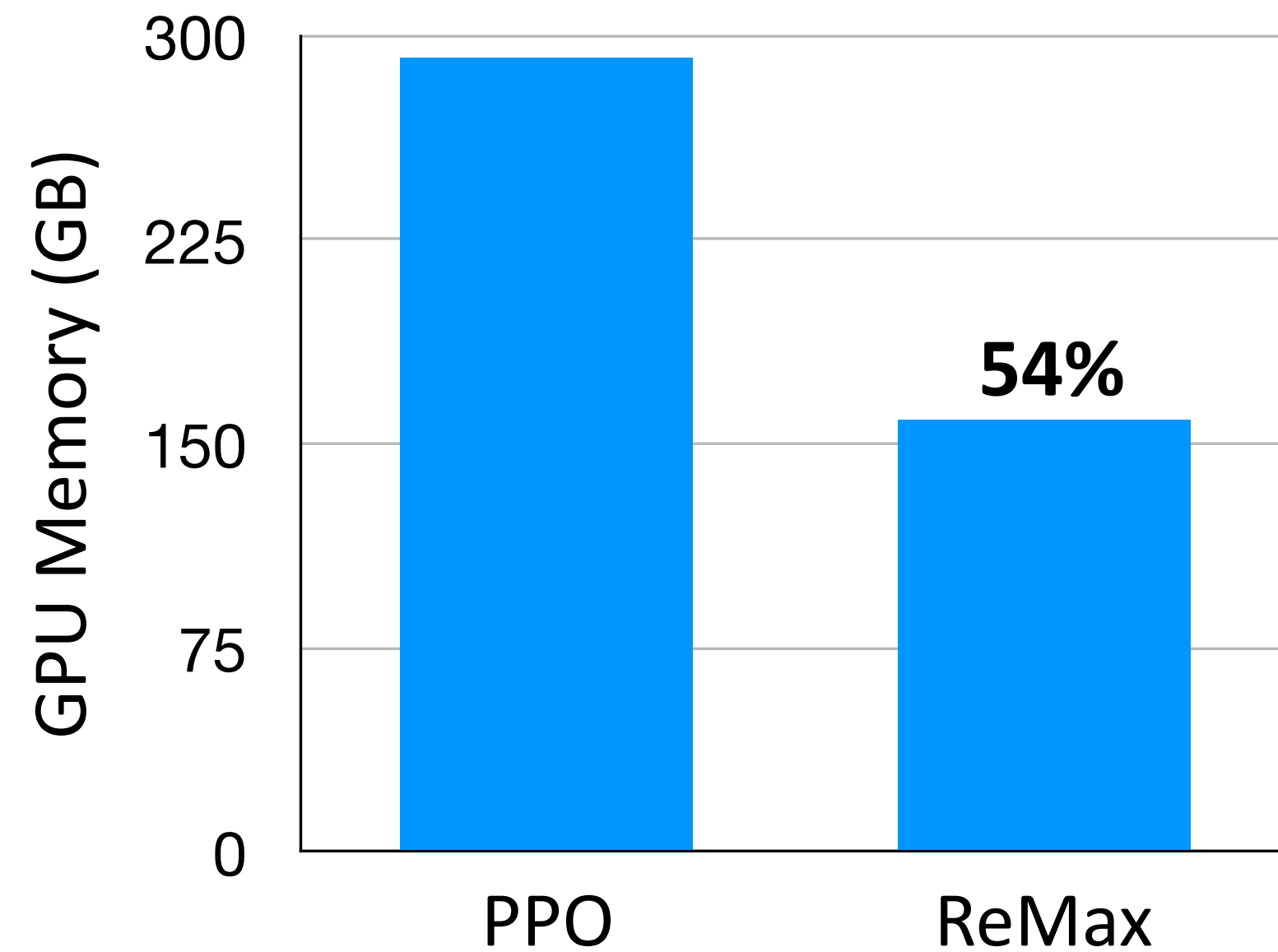
PPO in LLM

$$\mathcal{L}_{\text{ppo}}(\theta) = \mathbb{E}_{x \sim \rho} \mathbb{E}_{a_{1:T} \sim \pi_{\theta}} \left[\sum_{t=1}^T r(x, a_{1:T}) - V(x, a_{1:t}) \right]$$

Outcome reward in
REINFORCE's estimator

Model-learned
Baseline

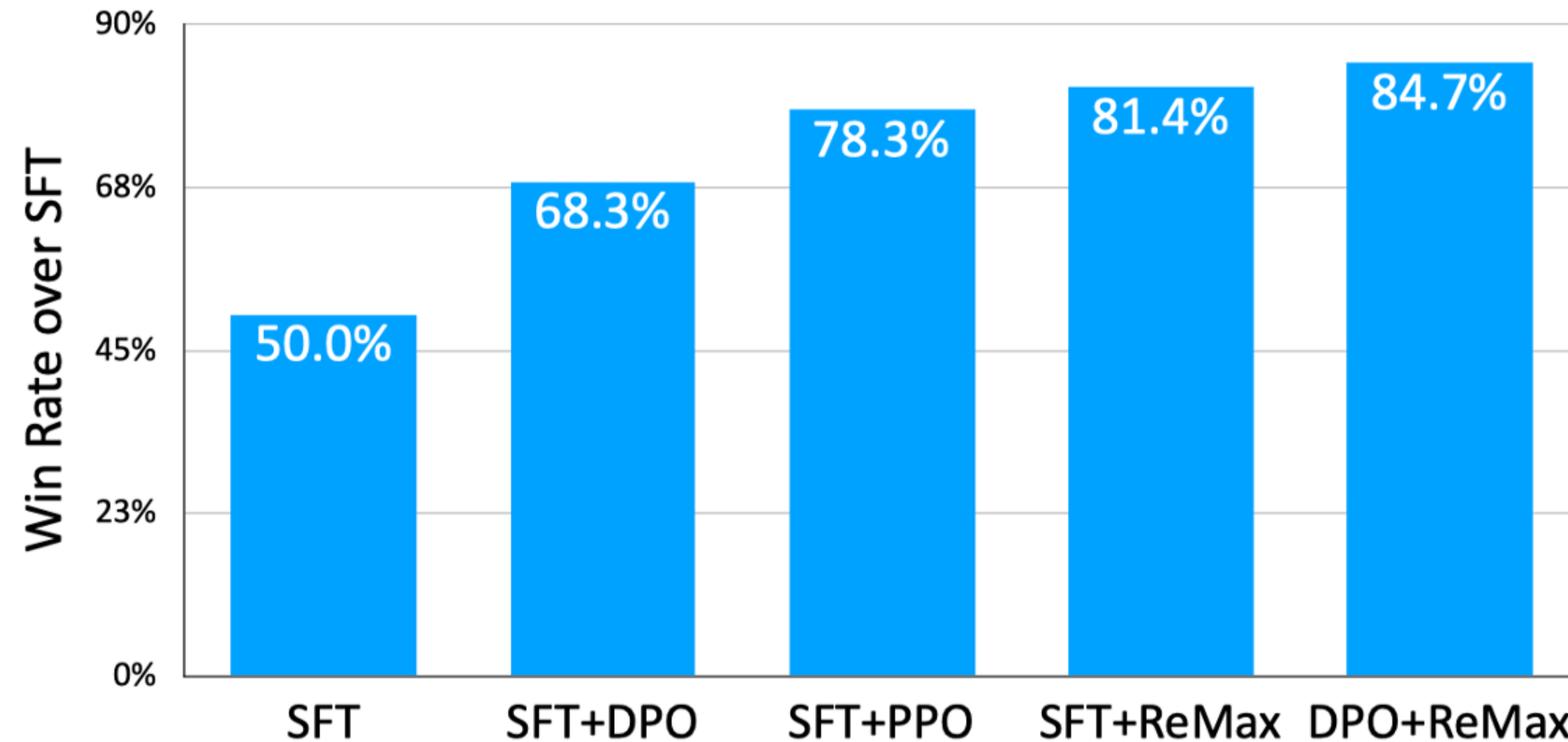
ReMax is Computationally Efficient



[Li, Ziniu, et al. "Remax: A simple, effective, and efficient reinforcement learning method for aligning large language models." *arXiv preprint arXiv:2310.10505* (2023).]

ReMax saves about 2x GPU memory and training time on Llama-2-7B

Performance in RLHF Task



[Li, Ziniu, et al. "Remax: A simple, effective, and efficient reinforcement learning method for aligning large language models." *arXiv preprint arXiv:2310.10505* (2023).]

ReMax is superior to DPO and PPO

Performance in RLHF Task

Table 4. Performance against strong open-source and private models: Llama-2-Chat models (7B and 70B) apply RLHF (via PPO) using secret datasets; Zephyra-7B-beta (Tunstall et al., 2023) is based on the pretrained Mistral-7B-v0.2 with DPO. GPT-3.5 and GPT-4 utilize RLHF (via PPO) with secret datasets.

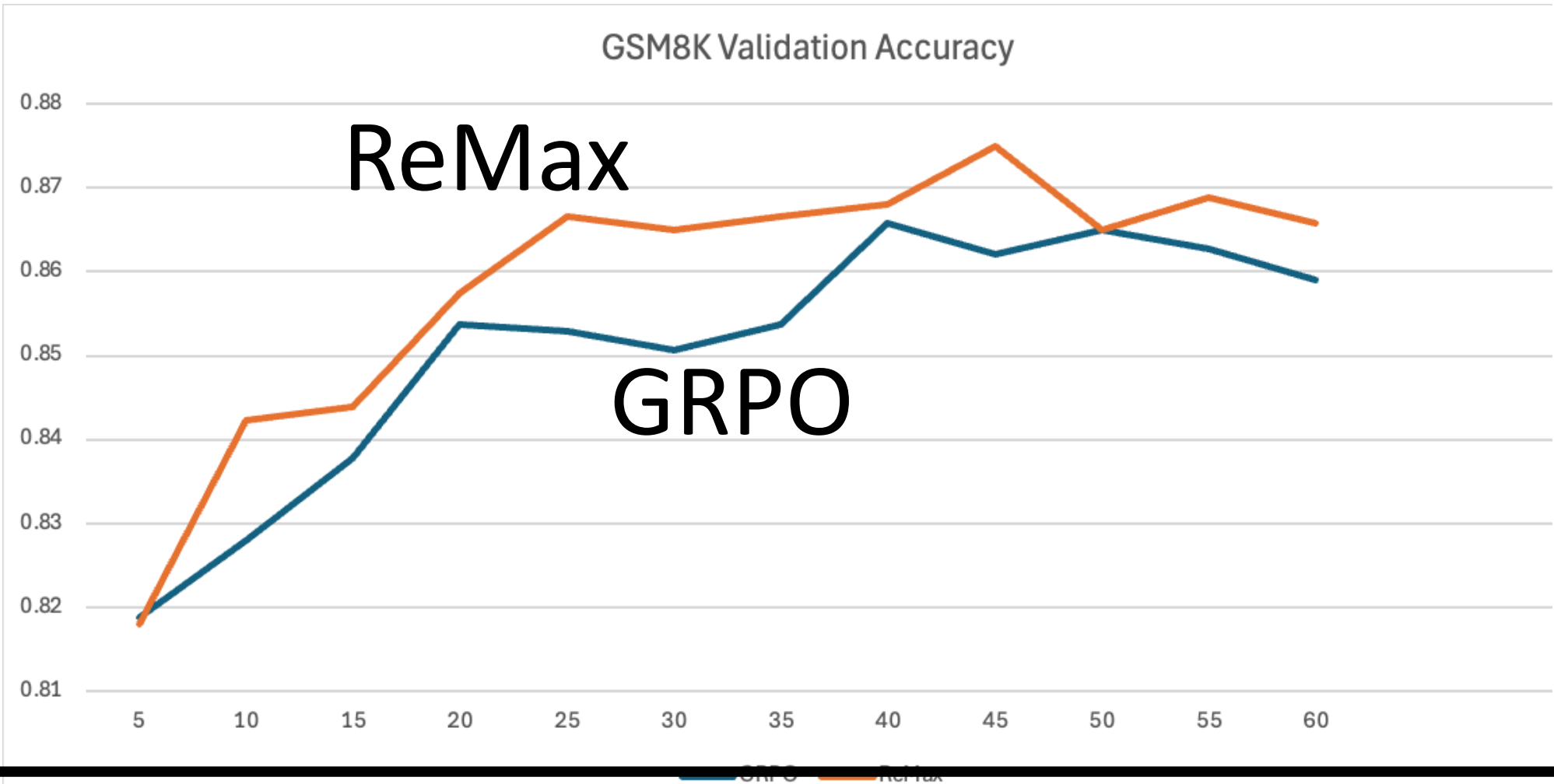
	AlpacaEval	MT-Bench
Llama-2-7B-Chat	71.37%	6.269
Zephyr-7B-beta	90.60%	7.356
Mistral-7B-Instruct-v0.2	92.78%	7.516
Mistral (via ReMax)	94.78%	7.739
Llama-2-70B-Chat	92.66%	6.856
GPT-3.5-turbo	93.42%	7.944
GPT-4-turbo	95.28%	8.991

[Li, Ziniu, et al. "Remax: A simple, effective, and efficient reinforcement learning method for aligning large language models." *arXiv preprint arXiv:2310.10505* (2023).]

ReMax achieves SOTA among 7B models (measured at Jan., 2024)

Performance in Reasoning Task

Our
Evaluation



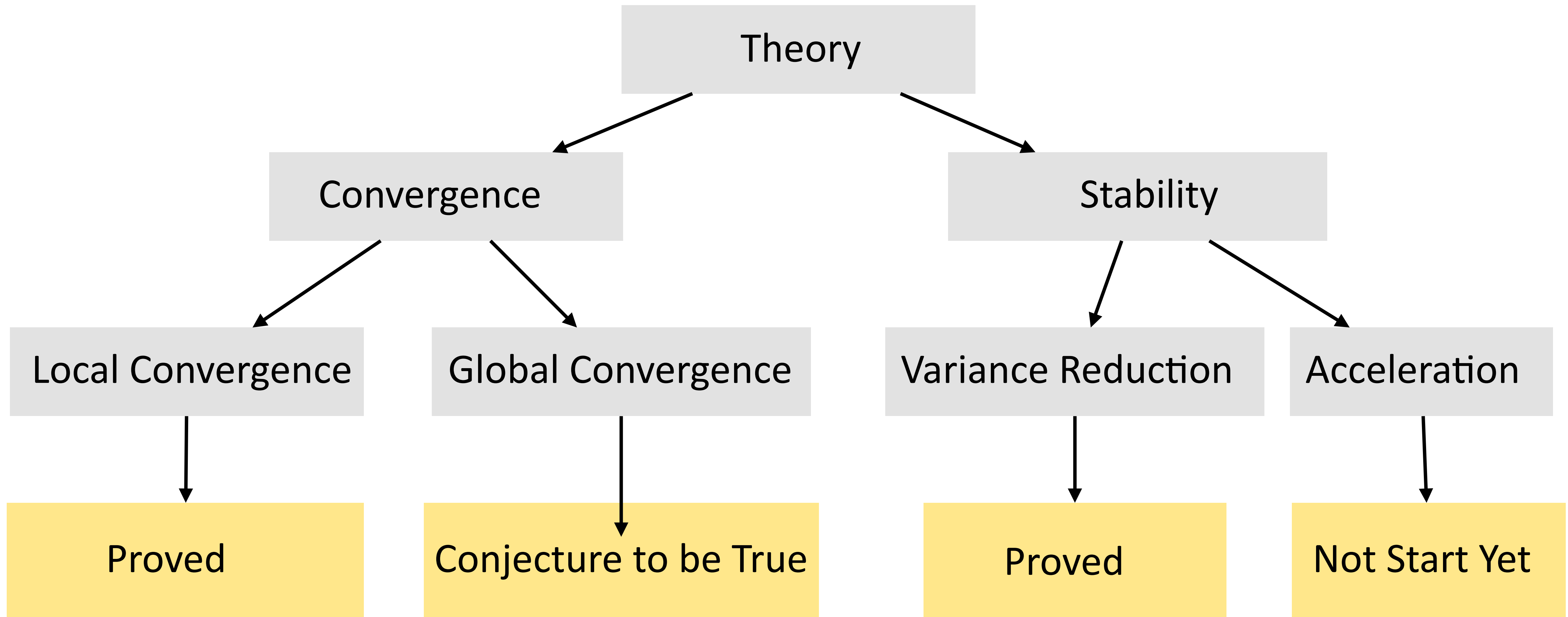
Others’
Evaluation

	Mineva Math	Olimpiad Bench	HumanEval	LeetCode	LiveCode Bench	Avg.
ReMax	24.6	17.3	61.0	21.1	18.6	28.5
GRPO	22.4	20.3	57.3	13.3	18.7	26.4

[<https://curvy-check-498.notion.site/Process-Reinforcement-through-Implicit-Rewards-15f4fcb9c42180f1b498cc9b2eaf896f>]

ReMax is superior to DeepSeek’s GRPO

Overview of ReMax's Theory



Variance Reduction

Setting: 2-action armed bandit (assuming $r(a_1) > r(a_2)$)

Our result: $\text{Variance}(\text{ReMax}) < \text{Variance}(\text{REINFORCE})$ if

$$\pi(a_1) \leq 0.5 + 0.5 \frac{r(a_1)}{r(a_1) - r(a_2)}$$

Implication:

- 1) variance reduction when the optimal action is **not dominated**
- 2) slow convergence when the policy is near-optimal
→ good if reward is imperfect (**mitigating overfitting**)

ReMax: A Simple, Effective, and Efficient Reinforcement Learning Method for Aligning Large Language Models

Ziniu Li^{1 2} Tian Xu^{3 4} Yushun Zhang^{1 2} Zhihang Lin¹ Yang Yu^{3 4 5 †} Ruoyu Sun^{1 6 2 †} Zhi-Quan Luo^{1 2}

ICML 2024



Paper



Code

Conclusive Remark

Part I: LLM Training Pipeline

- ▶ Pre-training: knowledge acquisition
- ▶ Post-training: instruction following and ability enhancement

Part II: Preserving Diversity in SFT

- ▶ CE's formulation lack of consideration of diversity
- ▶ GEM: a game-theoretic approach with entropy regularization

Part III: Efficient RL Training

- ▶ PPO's formulation are overshoot for LLM
- ▶ ReMax: variance-reduced REINFORCE

Thank You!