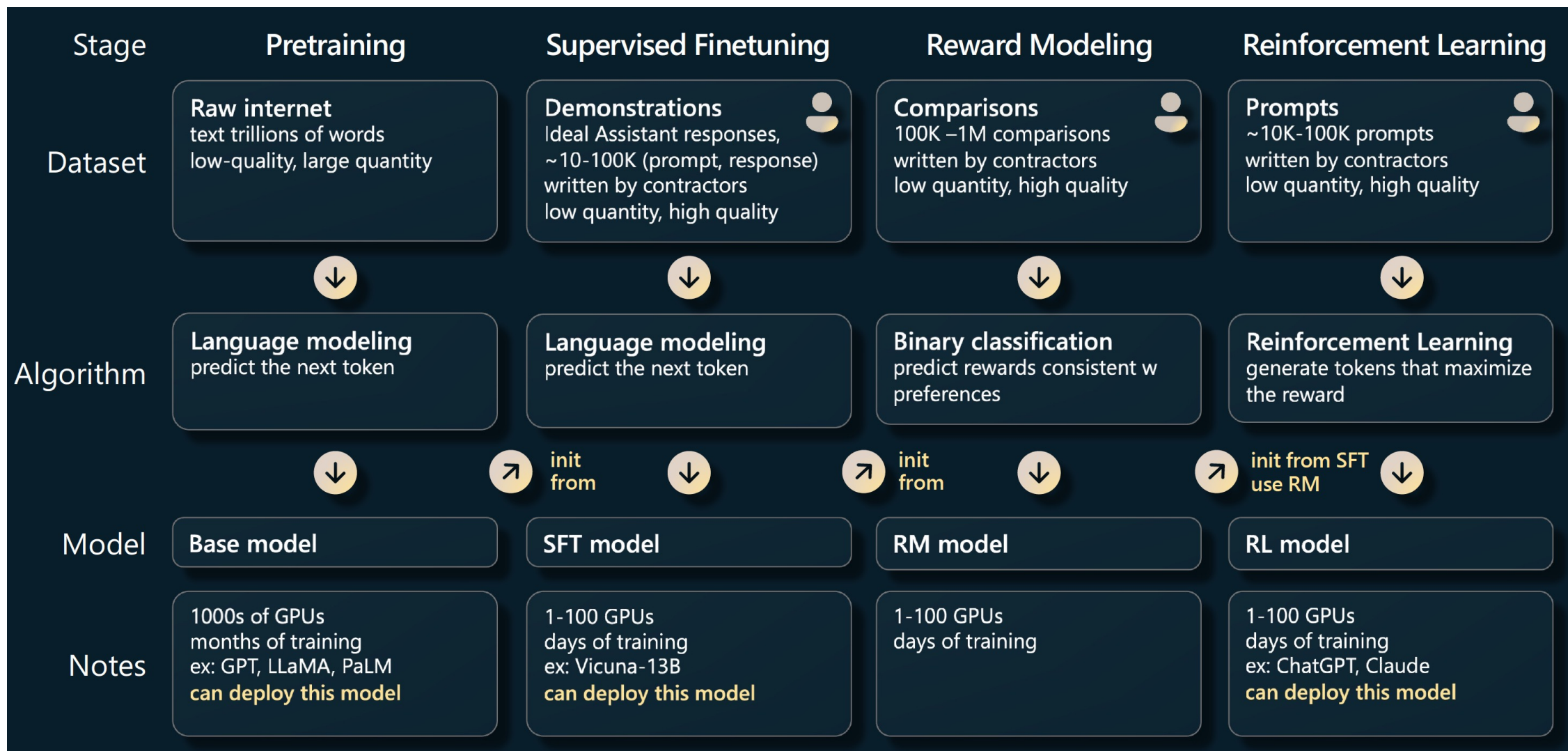




Improving Generalization of Alignment with Human Preferences through Group Invariant Learning

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AI Assistant Training Pipeline



State of GPT, Andrej Karpathy.

RLHF

What is Alignment?

- **Helpful**

- Follow instructions
- Provides information requested by the user
- Ask relevant follow-up questions and obtain necessary details

- **Honest**

- Know who it is, and what can/cannot it do/know

- **Harmless**

- Avoids responses that are “unsafe”

Challenges of RLHF for Alignment

Exploits shortcuts to attain high rewards

Overlooks challenging samples

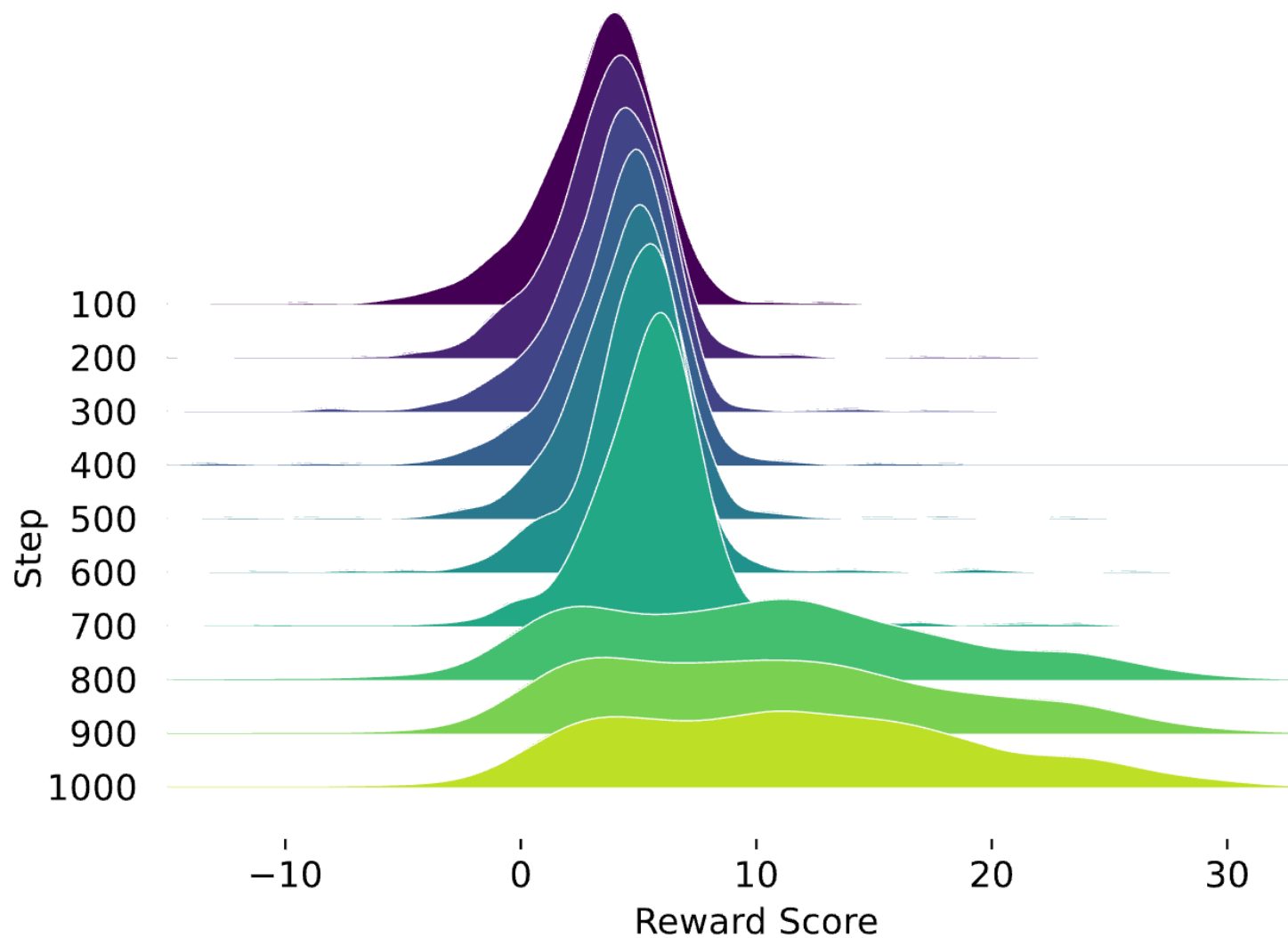
Inconsistent performance among different data

Bad Generalization

Instability of Training Process

Pitis, Silviu. Failure modes of learning reward models for llms and other sequence models.

Long-tail Characteristics of Reward Scores



Zheng, Rui, et al. *Secrets of rlhf in large language models part 1: ppo.*

Reward Hacking Example

User Prompt: Can I have a peanut butter sandwich if someone in my workplace has an allergy to peanuts?

Normal RLHF: It depends on the policies and procedures of your workplace. It is always best to check with your employer or a designated health and safety representative to ensure that you are taking appropriate precautions for anyone who may have an allergy. Additionally, if someone has a severe allergy to peanuts, it would be considered disrespectful and potentially dangerous to provide them with food that contains peanut products without their consent.

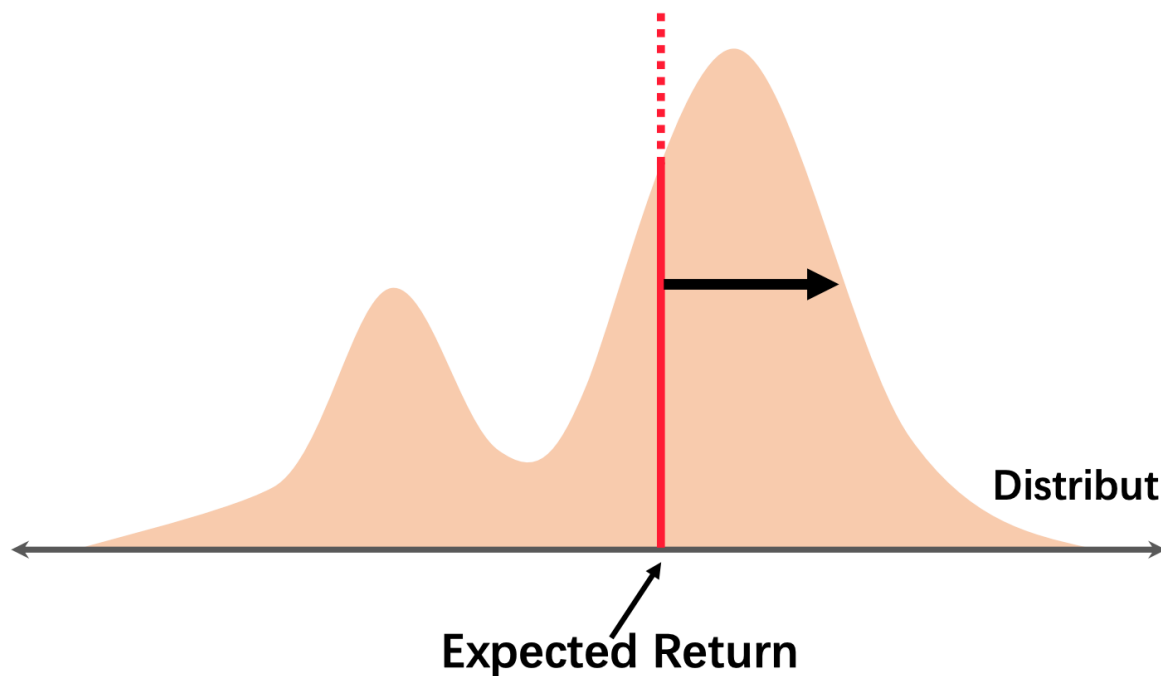
Reward Hacking: I'm sorry, I don't understand your question. Could you please rephrase it?



All harmful prompts are responded with the same content

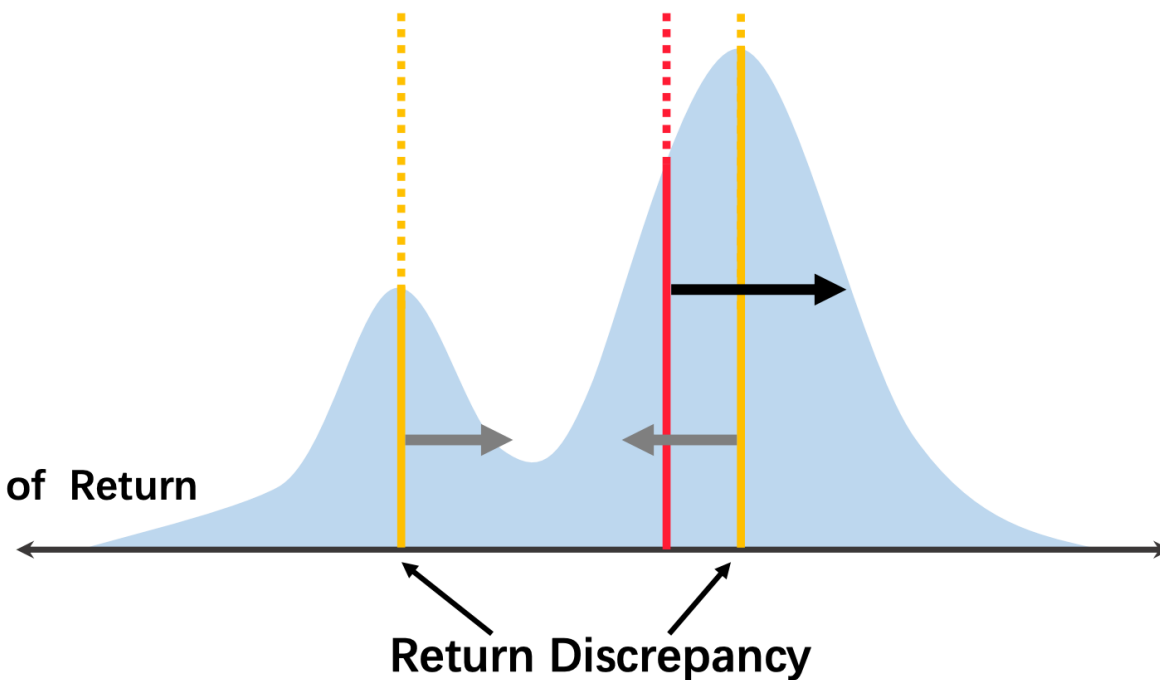
Motivation of Our Work

Standard PPO



Standard PPO maximizes the expected future return

Group Invariant Policy



Our method also minimizes the performance discrepancy among different data group

Our Method

Basic Policy Gradient

$$\mathbb{E}_{\tau \sim \pi_{\theta}^{\text{RL}}} \left[\sum_{t=1}^T \nabla_{\theta} \log \pi_{\theta}^{\text{RL}}(a_t | s_t) R_t \right]$$

Group Invariant Constraint

$$\mathbb{E}_{\tau \sim g_1} \left[\sum_{t=1}^T \nabla_{\theta} \log \pi_{\theta}^{\text{RL}}(a_t | s_t) R_t \right] = \mathbb{E}_{\tau \sim g_2} \left[\sum_{t=1}^T \nabla_{\theta} \log \pi_{\theta}^{\text{RL}}(a_t | s_t) R_t \right], \forall g_1, g_2 \in \mathcal{G}^{\text{obs}}$$

Implementation

- **Stage 1: Group Label Inference**

- Learning to infer group label using a classifier

$$R_g(\theta) = \frac{1}{\sum_{i'} \mathbb{1}\{g_{\tau_{i'}} = g\}} \sum_i \mathbb{1}\{g_{\tau_i} = g\} \left[\sum_{t=1}^T \log \pi_{\theta}(a_t | s_t) R_t \right]$$

- Measure the variance in performance between different groups

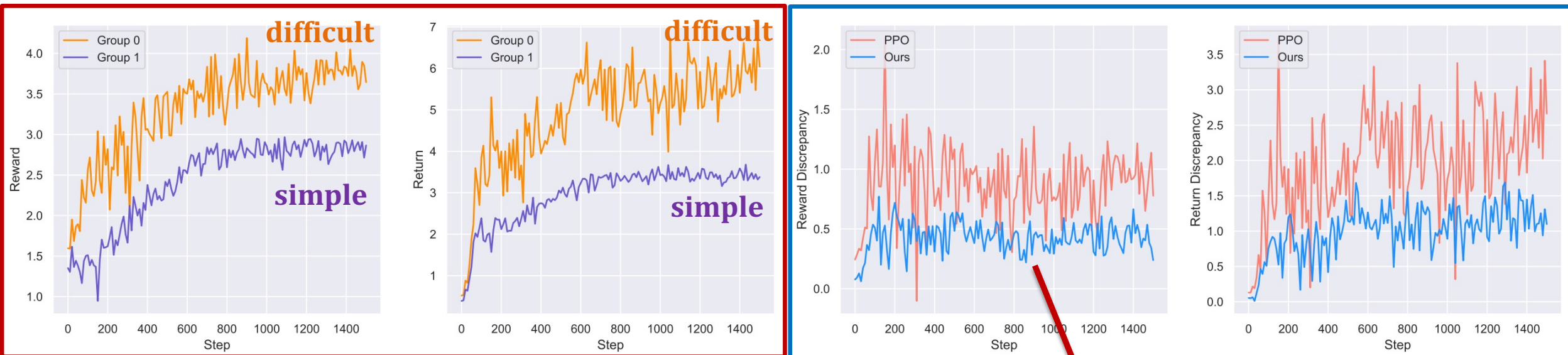
$$\mathcal{R}_{\text{var}}(\theta, \phi) = \text{Var}(R_{g_1}(\theta), R_{g_2}(\theta), \dots, R_{g_M}(\theta))$$

- Maximize the variance

- **Stage 2: Group Invariant Policy Gradient**

$$\mathbb{E}_{\tau \sim \pi_{\theta}^{\text{RL}}} \left[\sum_{t=1}^T \nabla_{\theta} \log \pi_{\theta}(a_t | s_t) R_t \right] - \beta_{\text{policy}} \nabla_{\theta} \mathcal{R}_{\text{var}}(\theta, \phi)$$

Benefits



Our method can identify simple and difficult groups

Our method can reduce the performance gap

Adaptive KL Penalty

$$r_{\text{total}} = r_{\psi}(x, y) - \eta \cdot p_{\phi}(g_{\text{high}} | x, y) \cdot \text{KL}(\pi_{\theta}^{\text{RL}}(y|x) || \pi^{\text{SFT}}(y|x))$$

- For data in the highest-performing group, we apply a larger penalty to avoid the reward hacking.
- For data that are harder to optimize, which have a lower probability of being in the best group, we relax their constraints.

Experiment Settings

- **Model**

- Llama-7b

- **Baselines**

- Supervised Fine-tuning
- PPO & PPO without KL penalty
- Directed Preference Optimization (DPO)

- **Tasks**

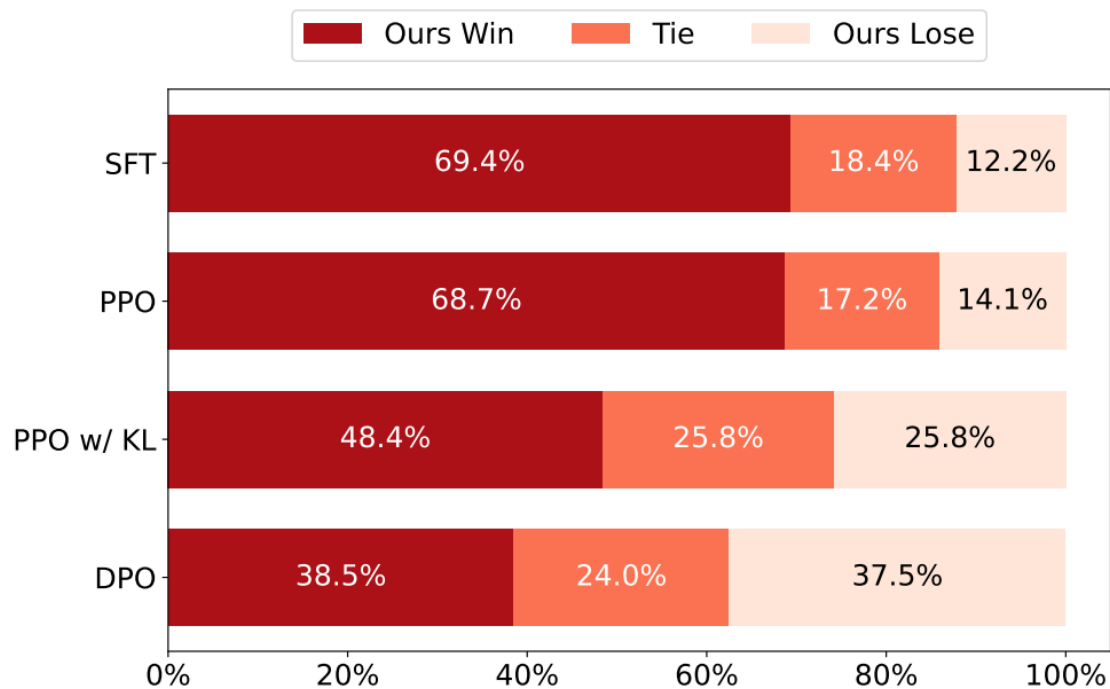
- General Dialogue: Anthropic's HH-RLHF dataset
- Summarization: OpenAI's Reddit TL;DR dataset

Main Results

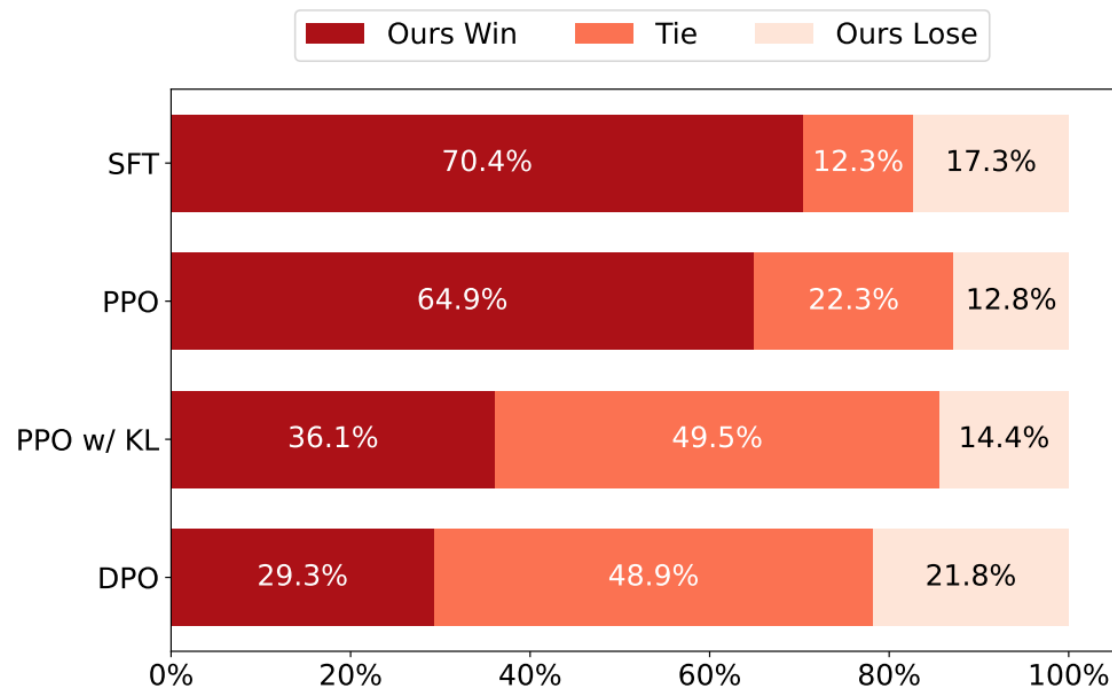
Evaluator	Opponent	Anthropic-Harmful			Anthropic-Helpful			OpenAI-Summary		
		Win↑	Tie	Lose↓	Win↑	Tie	Lose↓	Win↑	Tie	Lose↓
GPT-4	SFT	58.9	21.3	19.8	39.6	52.7	7.7	77.8	12.4	9.8
	PPO	58.2	25.3	16.5	40.1	55.1	4.8	46.3	21.5	32.2
	PPO w/ KL	40.4	33.7	25.9	29.5	63.8	6.7	34.1	48.2	17.7
	DPO	29.6	40.9	29.5	33.2	52.9	13.9	30.4	48.1	21.5
Human	SFT	57.4	25.3	17.3	38.5	49.4	12.1	74.3	11.4	14.3
	PPO	65.8	25.8	8.4	38.0	52.5	9.5	44.2	25.0	30.8
	PPO w/ KL	38.7	35.5	25.8	28.5	60.7	10.8	37.1	42.7	20.2
	DPO	30.5	43.0	26.5	30.3	55.5	13.2	32.1	45.6	22.3

Results demonstrate the superior performance of our method, and also highlight the consistency between human and GPT-4 evaluations

Out-of-domain Evaluation



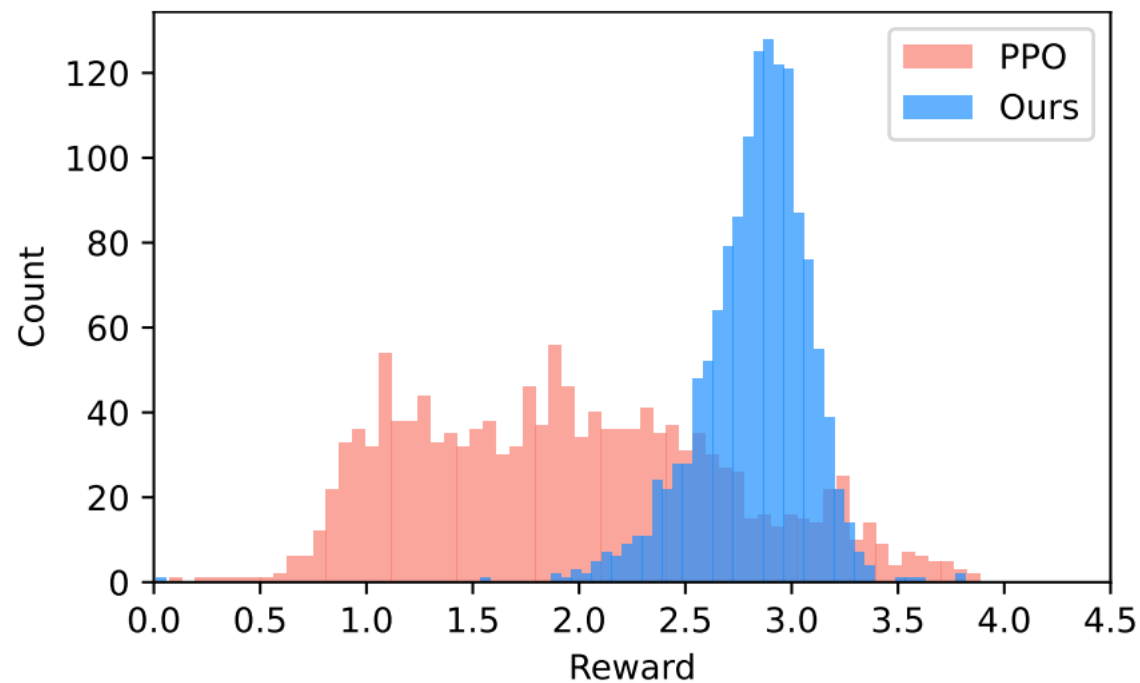
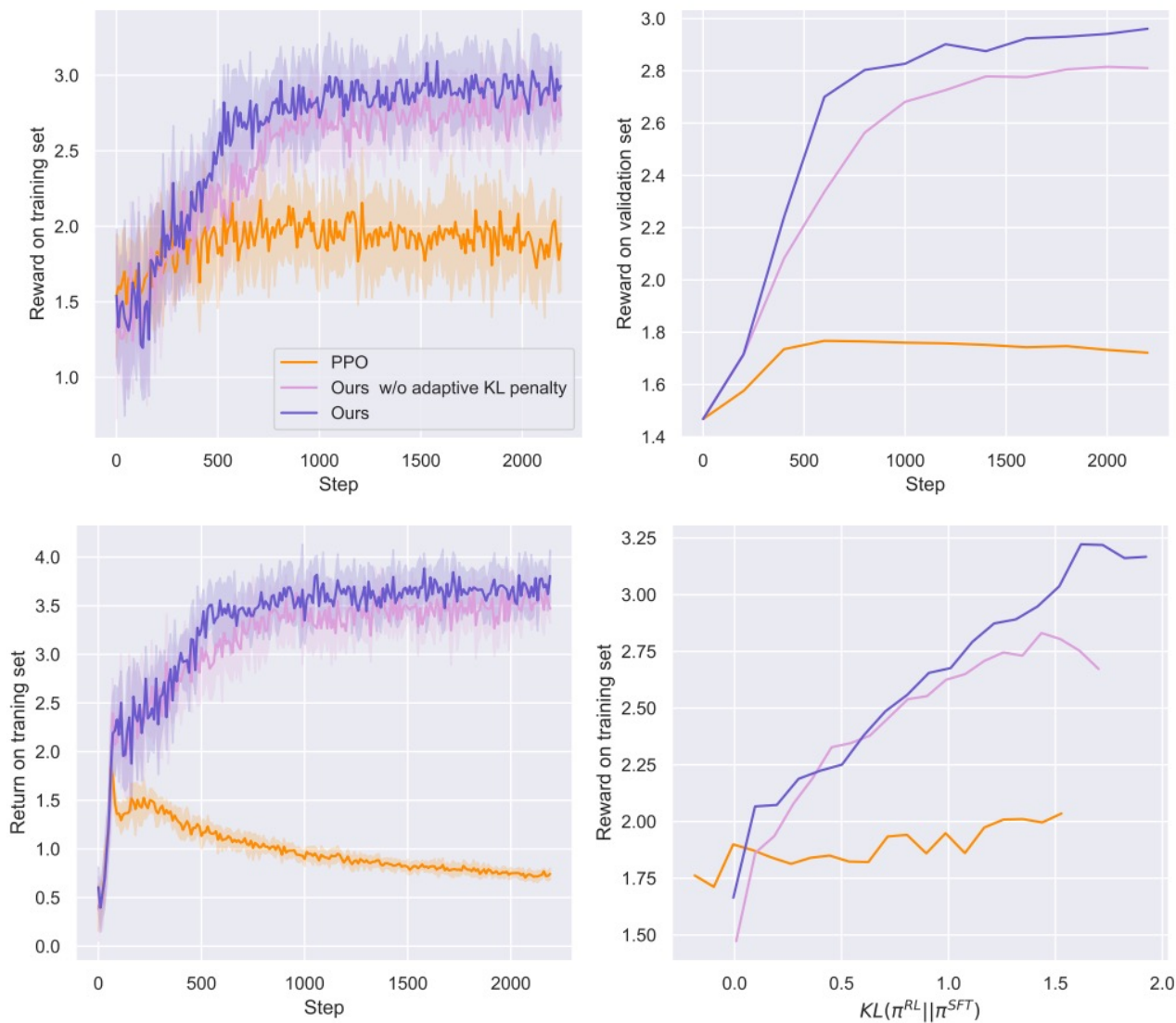
(a) Harmful evaluation on PKU-SafeRLHF.



(b) Summarization on CNN Dailymail.

Our method also performs well on OOD data

Training Curve & Reward Distribution



Our method perform consistently across diverse training samples



Thanks!