THE HONG KONG UNIVERSITY OF SCIENCE AND TECHNOLOGY
DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING
RELAXED SYSTEM LAB

Reinforcement Learning Alignment

COMP4901Y

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Reinforcement Learning Preliminary

What is Reinforcement Learning?

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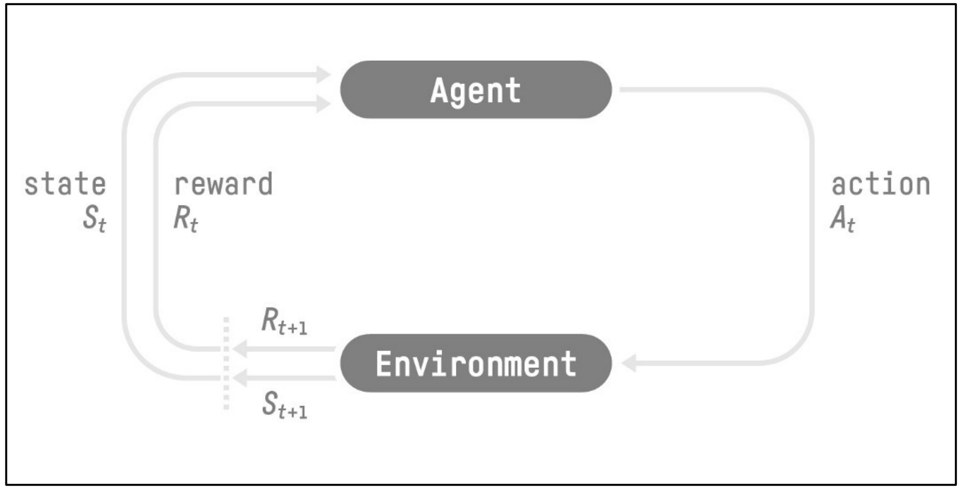
- Basic idea: Reinforcement Learning (RL) is a framework for solving decision problems by building agents that learn from the environment by interacting with it through trial and error and receiving rewards (positive or negative) as unique feedback.
- RL Framework:
  - **State**: information our agent gets from the environment;
  - **Action**: possible movement our agent can take in an environment.
  - **Reward**: the feedback our agent gets from the environment.



Markov Decision Processes

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- An MDP formalizes sequential decision-making under uncertainty. It is defined by a tuple of (S, A, P, R, γ):
  - States S: the set of possible states;
  - Actions A: the set of possible actions;
  - Transition probability $P(s'|s, a)$: transition probability of next state s' given current state s and action a;
  - Reward $R(s, a)$: reward for taking action a in state s;
  - Discount factor $\gamma \in [0,1]$: for future rewards.
- **Agent** environment loop: At each time step, the agent observes state s, takes action a, transitions to s and receives reward $R(s, a)$ from the environment.
  - The process is Markovian: the next state distribution depends only on the current state and action (Markov property).
- **Policy:** A policy π defines the agent's behavior, mapping states to actions. It can be deterministic $\pi(s) = a$ or stochastic $\pi(a|s) = P(a|s)$.

Return and Value Function

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- **<u>Return (cumulative future reward)</u>** G_t: represents the cumulative reward an agent expects to receive over time, starting from time step t. It accounts for both immediate and future rewards, incorporating the discount factor γ to prioritize immediate rewards over distant ones:

$$G_t = \sum_{k=0}^{\infty} \gamma^k R(s_{t+k}, a_{t+k}) = \sum_{k=0}^{\infty} \gamma^k R_{t+k}$$

- **<u>State-value function</u>** $V^{\pi}(s)$: The expected return (i.e., cumulative future rewards) when starting from state s and following policy π:

$$V^{\pi}(s) = \mathbb{E}_{\pi}\left[\sum_{t=0}^{\infty} \gamma^t R(s_t, a_t) \,\middle|\, s_0 = s\right]$$

Return and Value Function

- **Action-State-value function** $Q^{\pi}(s,a)$: The expected return (i.e., cumulative future rewards) after taking action a from state s and following policy π:

$$Q^{\pi}(s,a) = \mathbb{E}_{\pi}\left[\sum_{t=0}^{\infty} \gamma^{t} R(s_t,a_t)\,\middle|\, s_0 = s, a_0 = a\right]$$

- Relationship between $V^{\pi}(s)$ and $Q^{\pi}(s,a)$: The state-value function is the expected value of the action-value function over the policy's action distribution:

$$V^{\pi}(s) = \sum_{a \in A} \pi(a|s)\, Q^{\pi}(s,a)$$

Optimal Policy

- The core goal of reinforcement learning (RL) training is to enable an agent to learn an **optimal policy** that *maximizes the expected cumulative reward through interactions with an environment*.
- To obtain such an optimal policy:
  - Value based method;
  - Policy based method;
  - Combine both: actor-critic method.

Value Based Method

- *Value-based methods focus on estimating value functions*: Specifically, the expected return (cumulative future rewards) from states or state-action pairs. The agent derives its policy implicitly by selecting actions that maximize these estimated values.
- Value function estimation:
  - Learn functions $V^{\pi}(s)$ and $Q^{\pi}(s,a)$ to evaluate the desirability of states or actions.
  - $V^{\pi}(s)$ and $Q^{\pi}(s,a)$ can be parameterized by some neural networks.
  - Learning method: Monte Carlo vs Temporal Difference (https://huggingface.co/learn/deep-rl-course/en/unit2/mc-vs-td)
- Policy derivation:
  - The policy is not explicitly learned but is derived by choosing actions that maximize the estimated value, e.g., selecting the action with the highest $Q^{\pi}(s,a)$.

Policy Based Method

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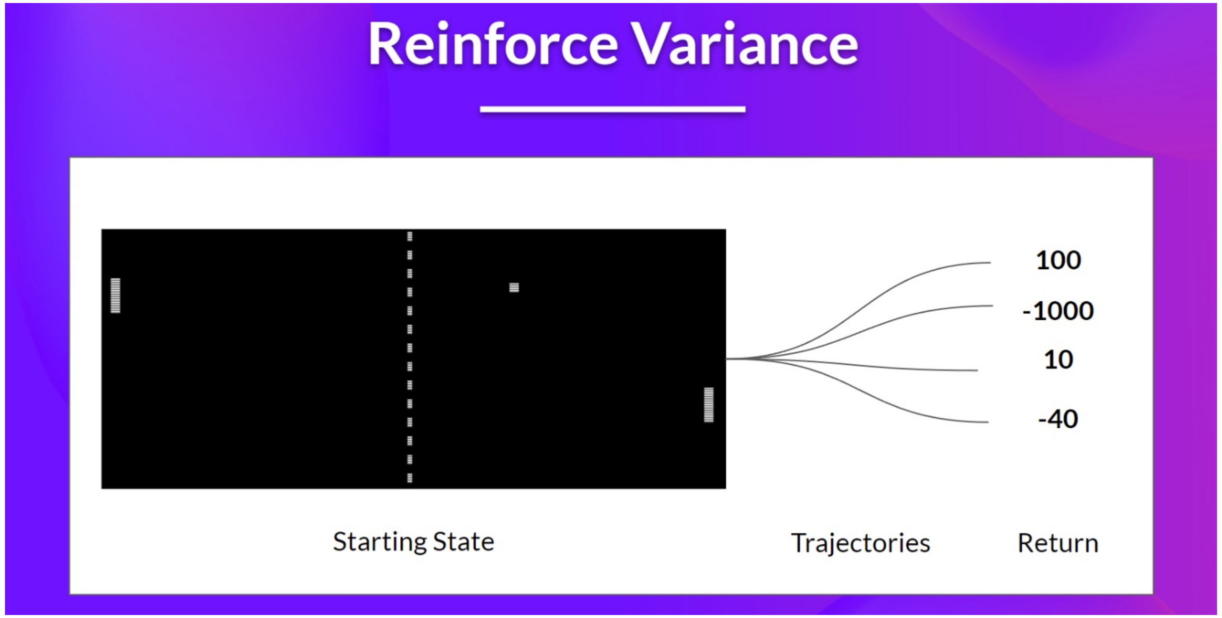
- Policy-based methods *directly parameterize and optimize the policy* $\pi(a|s)$, which defines the agent's behavior by *mapping states to action probabilities*.
- Well-suited for environments with continuous or high-dimensional action spaces.
- Policy optimization:
  - The policy is explicitly represented (e.g., by some neural network) and optimized, often using gradient based optimization methods.
  - Training based on policy gradient:
    - Objective function: $J(\theta) = \mathbb{E}_{\tau \sim \pi}[R(\tau)]$;
    - where τ is a sampled trajectory of the policy π;
    - Policy gradient estimation: $\nabla_\theta J(\theta) \approx \sum_{t=0}^{|\tau|} \nabla_\theta \log \pi_\theta (a_t|s_t) R(\tau)$.

Discussion about Policy Gradients

- We collect a trajectory and calculate the discounted return;
- We use this score to increase or decrease the probability of every action taken in that trajectory.
  - If the return is good, all actions will be "reinforced" by increasing their likelihood of being taken.
  - The estimation is unbiased — we use only the true return we obtain.
- Given the stochasticity of the environment (random events during an episode) and stochasticity of the policy:
  - Trajectories can lead to different returns, which can lead to high variance.
  - The same starting state can lead to very different returns.
  - The return starting at the same state can vary significantly across episodes.



Actor-Critic Methods

- Actor-critic methods integrate value-based and policy-based approaches to leverage their respective strengths:
  - **Actor**: Represents the policy $\pi(a|s)$ and is responsible for selecting actions.
  - **Critic**: Estimates the value function $V^{\pi}(s)$ or $Q^{\pi}(s, a)$ to evaluate the actions made by the actor.
- Modify the policy gradients by the **advantage function** $A(s, a)$:
- $A(s, a)$quantifies the relative value of taking action a in state s compared to the average expected value of state s: $A(s, a) = Q^{\pi}(s, a) - V^{\pi}(s)$
- Policy gradient estimation changes to $\nabla_\theta J(\theta) \approx \sum_{t=0}^{|\tau|} \nabla_\theta \log \pi_\theta (a_t|s_t) A(s_t, a_t)$.

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RL Alignment for Language Model

Overview

- Under the context of LLM alignment by RL:
  - **State**: The state corresponds to the input prompt provided to the language model. In RL terms, this is the observation that informs the agent's next action.
  - **Action**: The action is the response generated by the LLM in reaction to the input prompt. Each token produced can be considered an individual action, making the entire response a sequence of actions. This sequential generation aligns with the token-by-token decision-making process in reinforcement learning.
  - **Policy**: The policy in this context is the LLM itself, which maps input prompts (states) to probability distributions over possible next tokens (actions).
  - **Reward**: The reward is a scalar value representing the quality of the generated response, which guides the policy updates, encouraging the model to produce outputs that align with human expectations.

More on Rewards

- Two main categories of rewards: model-based reward v.s. rule-based reward.
- Model-based reward:
    - Model-based rewards utilize learned models—often neural networks—to predict the quality of a model's output. These models are trained on datasets reflecting some desired behaviors.
    - E.g., the reward model that learns human preferences in RLHF.
- Rule-based reward:
    - Rule-based rewards are determined using explicit, predefined rules or heuristics that assess the correctness or quality of outputs.
    - E.g., mathematical correctness verifier, program execution results (a set of unit tests associated with the problem).

OpenAI InstructGPT First Introduces RLHF

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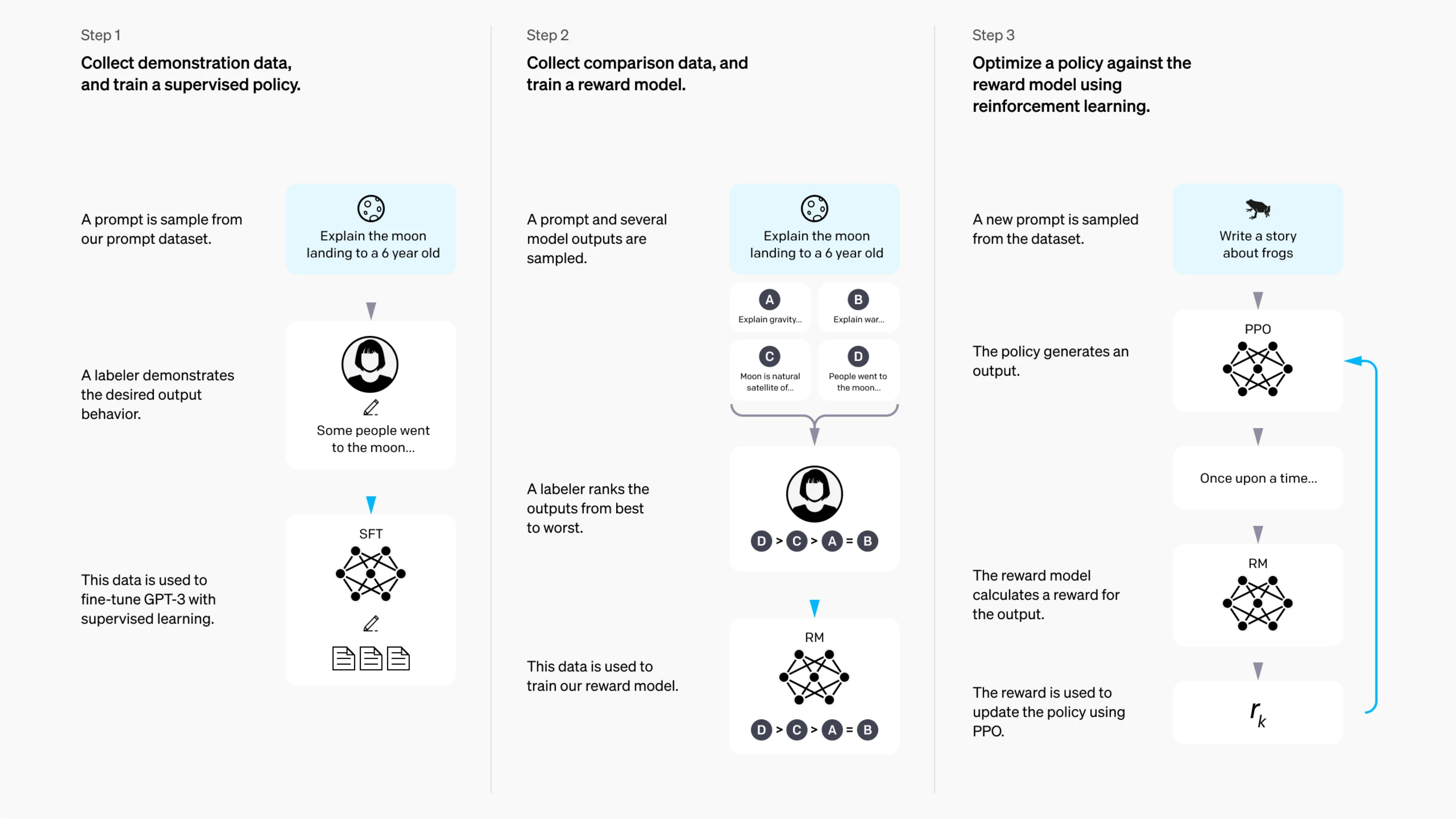
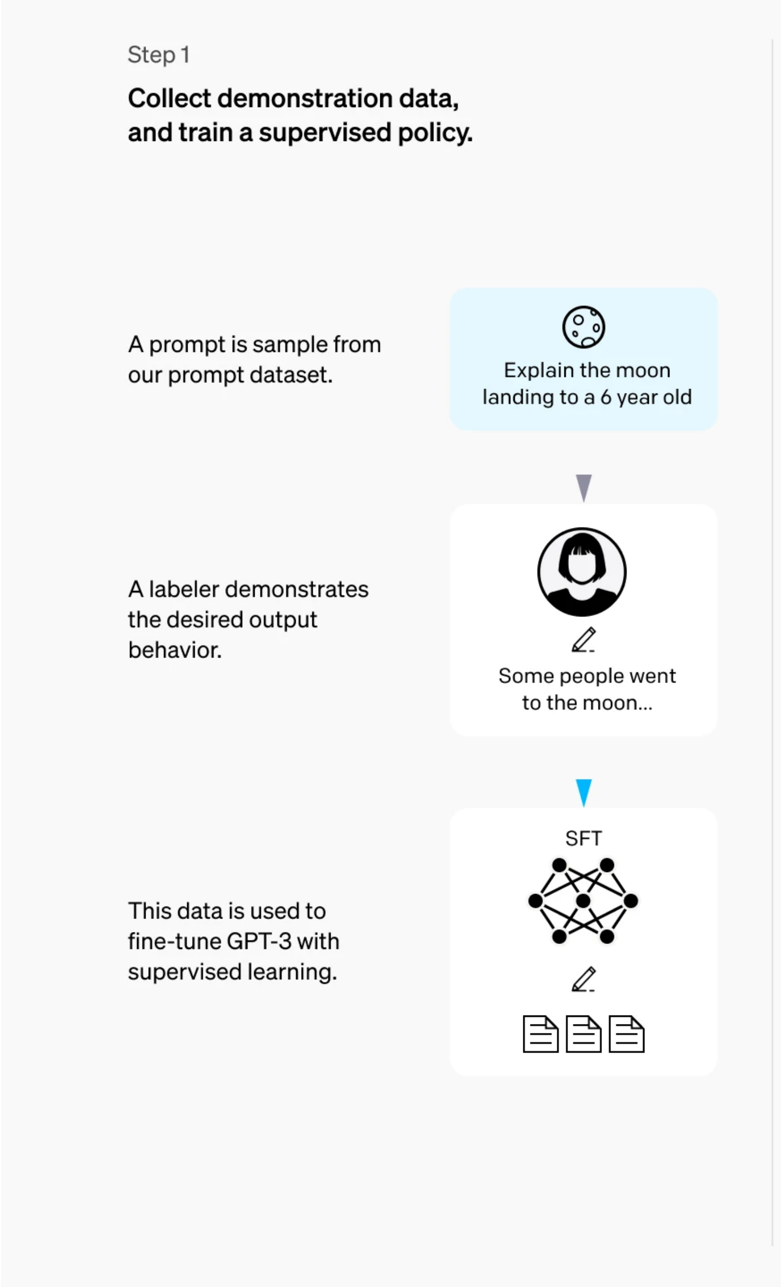


https://openai.com/index/instruction-following/

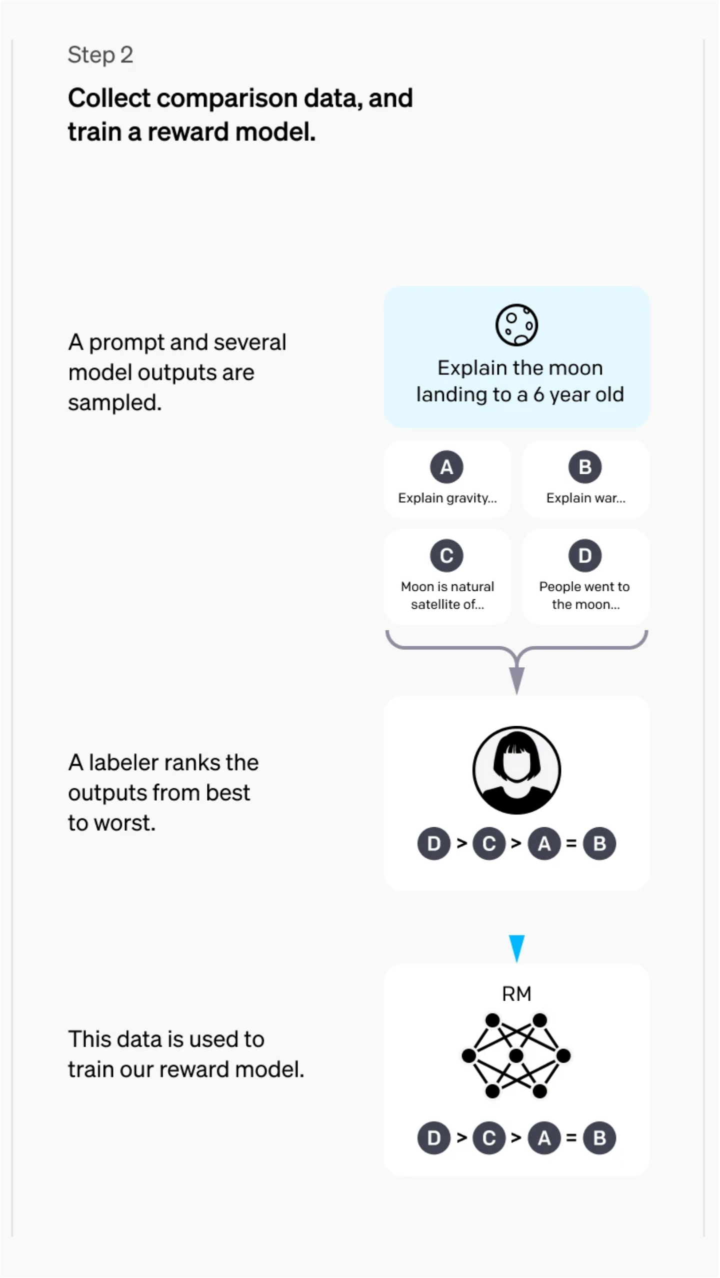
RLHF Step 1

- **<u>Supervised Fine-Tuning (SFT):</u>**
  - In this initial phase, human labelers provide demonstrations of desired model behavior by writing ideal responses to a variety of prompts.
  - These demonstrations are used to fine-tune a pre-trained language model, teaching it to generate outputs that align more closely with human expectations.



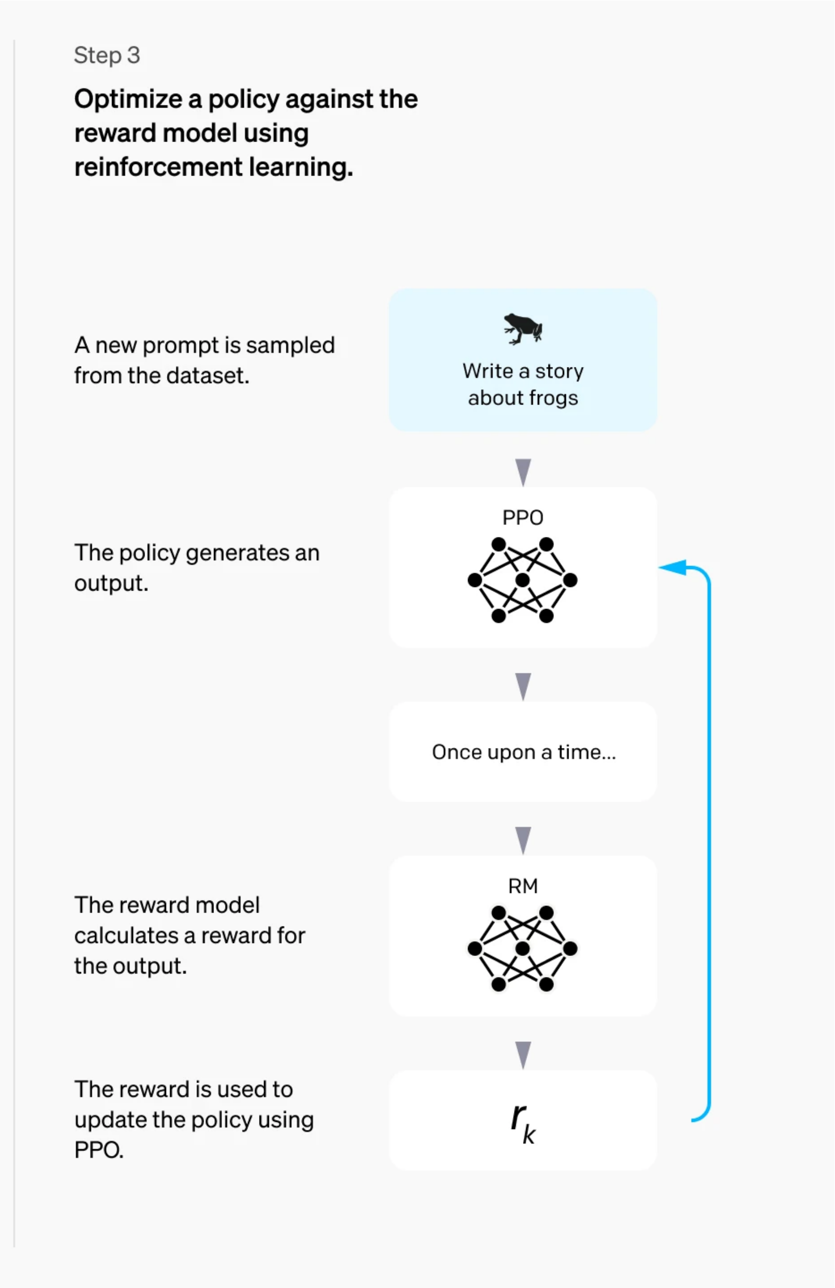
RLHF Step 2

- <u>**Reward Model Training**</u>:
  - The fine-tuned model generates multiple responses to a set of prompts.
  - Human labelers then rank these responses based on their quality.
  - These rankings are used to train a reward model that can predict the quality of responses, effectively learning to assess how well a response aligns with human preferences.



RLHF Step 3

- **<u>Reinforcement Learning</u>:**
  - In the final stage, the model is further fine-tuned using RL (PPO algorithm), guided by the reward model developed in the previous step.
  - This process encourages the model to produce outputs that maximize the predicted reward, leading to responses that better adhere to human instructions and values.



PPO Algorithm

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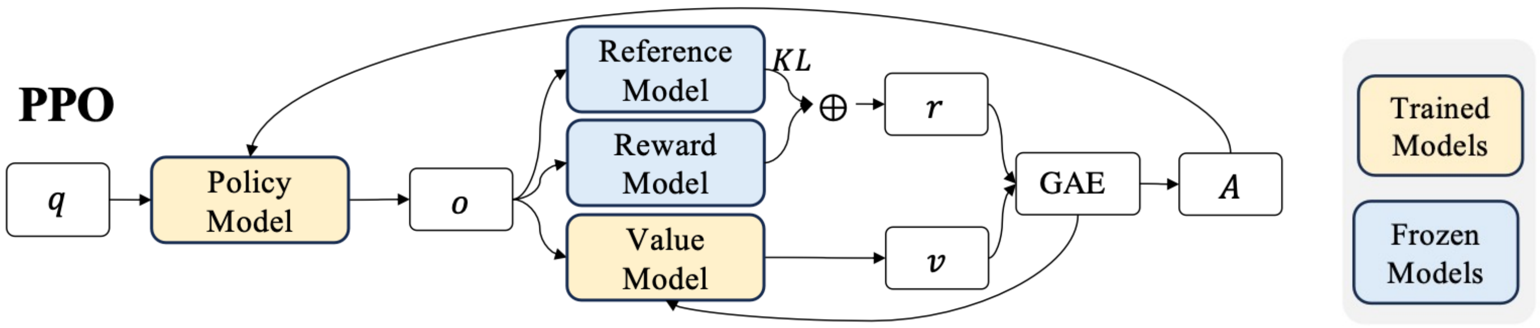
- Four different model works jointly in PPO:
- **Actor Model (Policy Model)** π_θ:
  - Generates responses to prompts;
  - The model to be aligned as the output of RLHF;
  - Parameter θ is updated during PPO;
- **Reward Model** r:
  - Provides scalar rewards indicating the quality of responses.
  - Trained separately using human-labeled data.
  - Remains fixed during PPO training. (so we ignore the parameter notation here).
- **Reference Model** π_{ref}:
  - Acts as a baseline to prevent the actor model from deviating excessively from its original behavior;
  - Used to compute the Kullback-Leibler (KL) divergence penalty, discouraging the actor from straying too far from its initial policy.

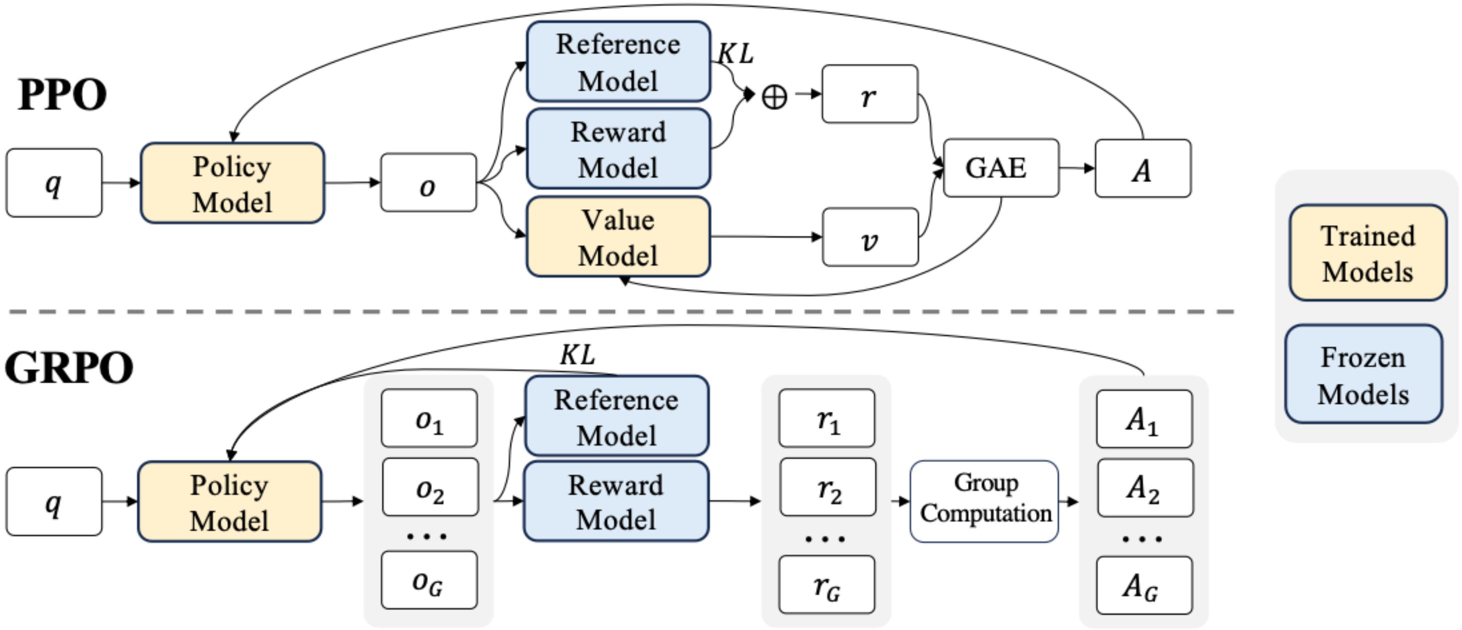
PPO Algorithm

- <u>**Critic Model (Value Function)**</u> V_{ϑ}:
  - Estimates the expected future reward (value) of a given state or prompt.
  - Reduce variance in policy updates.
  - Parameter ϑ is updated during PPO training.

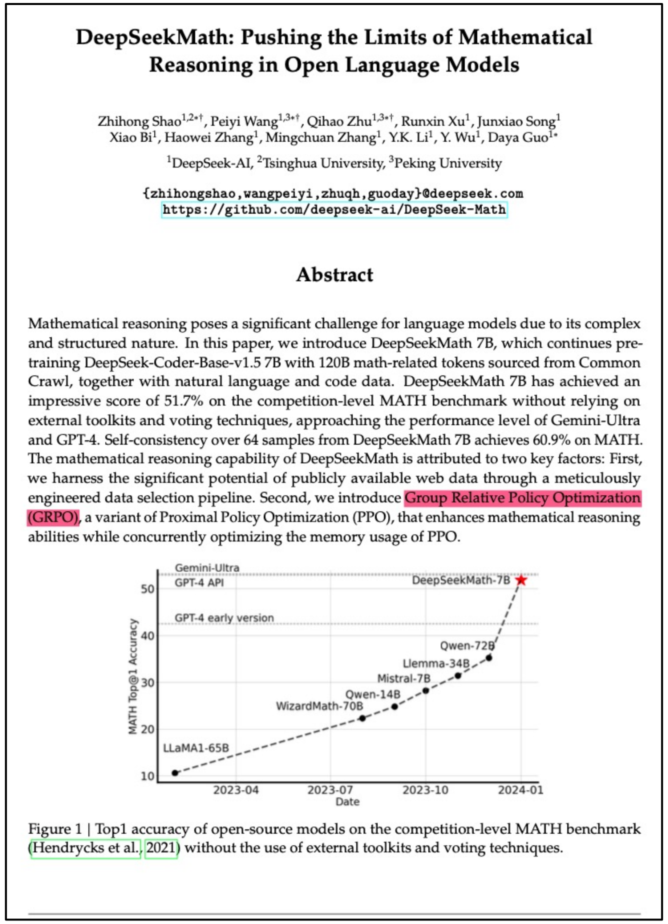


- q is the input question prompt; o is the output generated by the policy model;
- r is the adjusted reward with KL divergence;
- v is the value estimated by the value model;
- A is the advantage, which is computed by applying Generalized Advantage Estimation (GAE): https://arxiv.org/abs/1506.02438

GRPO



- Value function employed in PPO is typically another model of comparable size as the policy model, which brings a substantial memory and computational burden.
- Group Relative Policy Optimization (GRPO) uses the average reward of multiple sampled outputs, produced in response to the same question, as the estimation to replace the value model.



DeepSeekMath: Pushing the Limits of Mathematical Reasoning in Open Language Models

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Abstract

Mathematical reasoning poses a significant challenge for language models due to its complex and structured nature. In this paper, we introduce DeepSeekMath 7B, which continues pre-training DeepSeek-Coder-Base-v1.5 7B with 120B math-related tokens sourced from Common Crawl, together with natural language and code data. DeepSeekMath 7B has achieved an impressive score of 51.7% on the competition-level MATH benchmark without relying on external toolkits and voting techniques, approaching the performance level of Gemini-Ultra and GPT-4. Self-consistency over 64 samples from DeepSeekMath 7B achieves 60.9% on MATH. The mathematical reasoning capability of DeepSeekMath is attributed to two key factors: First, we harness the significant potential of publicly available web data through a meticulously engineered data selection pipeline. Second, we introduce Group Relative Policy Optimization (GRPO), a variant of Proximal Policy Optimization (PPO), that enhances mathematical reasoning abilities while concurrently optimizing the memory usage of PPO.

Figure 1 | Top1 accuracy of open-source models on the competition-level MATH benchmark (Hendrycks et al., 2021) without the use of external toolkits and voting techniques.

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System Challenges for RL Alignment

The RL Alignment Workflow is Unique

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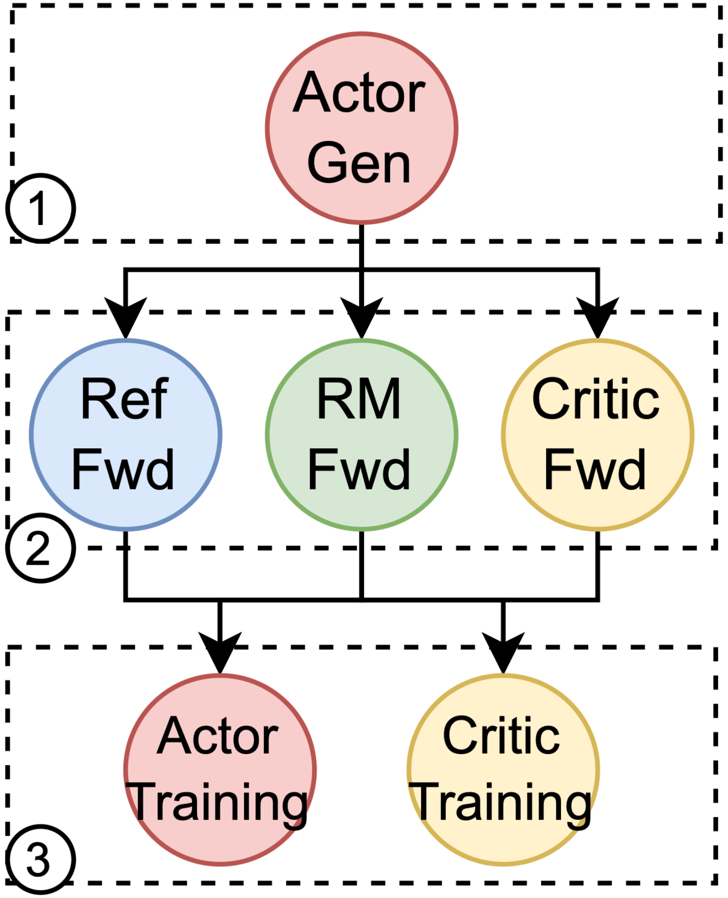
- **<u>Stage 1 Generation</u>**: The actor produces responses from a batch of prompts using generative inference.
- **<u>Stage 2 Preparation</u>**: Using prompts and generated responses, the critic computes their values, the reference policy computes their reference log probabilities, and the reward model computes their rewards, all via a single pass of forward computation of the respective model.
- **<u>Stage 3 Training</u>**: The actor and the critic are updated via gradient based optimization, using the batch of data produced by previous stages and the loss function.



Unique Challenges

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- ***Heterogeneous model workloads***:
  - The actor, critic, reference and reward models in RLHF may execute training, inference or generation at different stages, with different memory footprint and computation demand.
- ***Unbalanced computation between actor training and generation***:
  - Actor training is computation bounded, which requires a carefully tuned configuration of large-degree parallelism;
  - The same configuration might make the inference efficiency decreases;
- ***Diverse model placement requirements***:
  - Strategic device placement of models in the RLHF dataflow is necessary, according to computation workloads and data dependencies of the models.

Still Open Questions

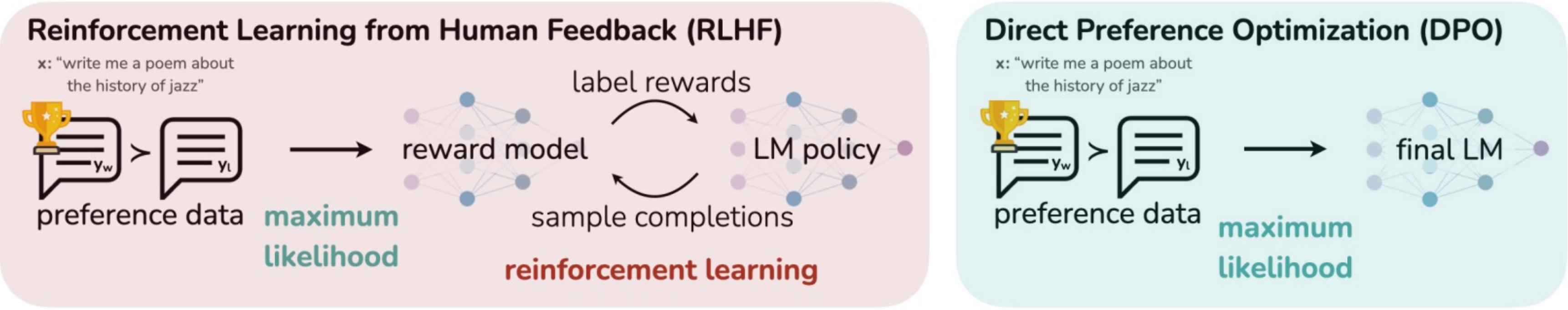
- Some existing systems:
  - https://github.com/volcengine/verl
  - https://github.com/inclusionAI/AReaL
  - https://github.com/OpenRLHF/OpenRLHF
  - https://github.com/huggingface/trl
  - …

Other Relevant Alignment Methods

Rejection Sampling Fine-tuning

- **Standard Supervised Fine-tuning (SFT)**: Standard maximization of the autoregressive LM probability for the (question, output) pairs;
- **Rejection Sampling Fine-tuning (RFT)**: First, samples multiple outputs from the supervised fine-tuned LLMs for each question, and then fine-tunes LLMs on the sampled outputs with the correct answer.
- **Online Rejection Sampling Fine-tuning**: The outputs of Online RFT are sampled from the real-time policy model, rather than from the previous SFT model.

DPO



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- **<u>Direct Preference Optimization (DPO)</u>**: align language models with human preferences without employing traditional reinforcement learning techniques.
  - Instead of learning from scalar reward signals, DPO learns directly from pairwise preference data, optimizing the model to prefer outputs that align with human judgments.
  - No explicit reward Model: No separate reward model in RL-based methods.
- Given a dataset of human preference comparisons $\mathrm{D} = \{(x, y_w, y_l)\}$: x is the input question prompt; y_w is the preferred answer by user; y_l is the less preferred answer by user.
- DPO constructs a loss that is analogous to a logistic regression: it treats the pair (x, y_w, y_l) as a positive vs negative example:

$$L_{DPO}(\theta) = -\mathbb{E}_{(x,y_l,y_w)\sim D}\left[\log\sigma\left(\beta\log\left(\frac{\pi_\theta(y_w|x)}{\pi_{\mathrm{ref}}(y_w|x)}\right) - \beta\log\left(\frac{\pi_\theta(y_l|x)}{\pi_{\mathrm{ref}}(y_l|x)}\right)\right)\right]$$

  - σ is the logistic function; β is some coefficient.

Reference

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