Reinforcement Learning in the Era Of LLMs

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Content

- Introduction to RL
- Reinforcement Learning from Human Feedback
- RL for LLMs

Some 'Terms' You May Have Heard About...

- Markov Decision Processes
- States, Observations, Transitions (Dynamics), Actions, Rewards, Discout Factors...
- Model-Based / Model Free
- Value-Based / Policy-Based / Actor-Critic
- On-Policy / Off-Policy
- Online / Offline
- Discrete Control / Continuous Control

But those are not necessary...

- ~~Markov Decision Processes~~
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Essential Ideas

- What is RL?

  An agent learns from trials and errors, to maximize a cumulative reward.

- agent: can be human or neural networks. It has a policy (clinical guidelines, public policies)
- trials and errors: Online or Offline? Real or (data-drive) Simulator?
- cumulative reward: the *Reward Hypothesis*

Reward Can be Sparse...

- "Win the game", but how?
- Imitation Learning (IL) Can Help.
- 1. Behavior Clone

  Pros: Simple, Does not need further interactions with the environment

  Cons: Compounding error, multi-modality modeling
- 2. GAIL: Generative Adversarial Imitation Learning [1]

  Pros: Solves the above cons.

  Cons: Needs more interactions

[1] Ho, Jonathan, and Stefano Ermon. "Generative adversarial imitation learning." Advances in neural information processing systems 29 (2016).

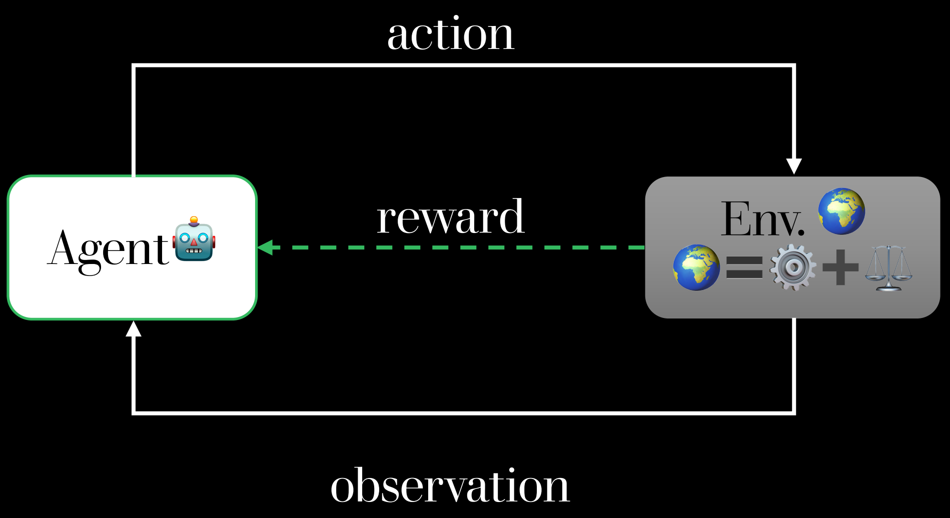
Difference between Inverse RL and IL

- Inverse-RL ≈ Imitation Learning, with an emphasis on reward learning

  Learning from logged trials and errors, to find out what cumulative reward is being optimized.

- logs can be either expert decisions or non-expert decisions. Extrapolation.
- trials and errors can be either online or offline
- (the estimated) reward can be used as an evaluator of trajectories/policies

Graph: RL and Offline-RL

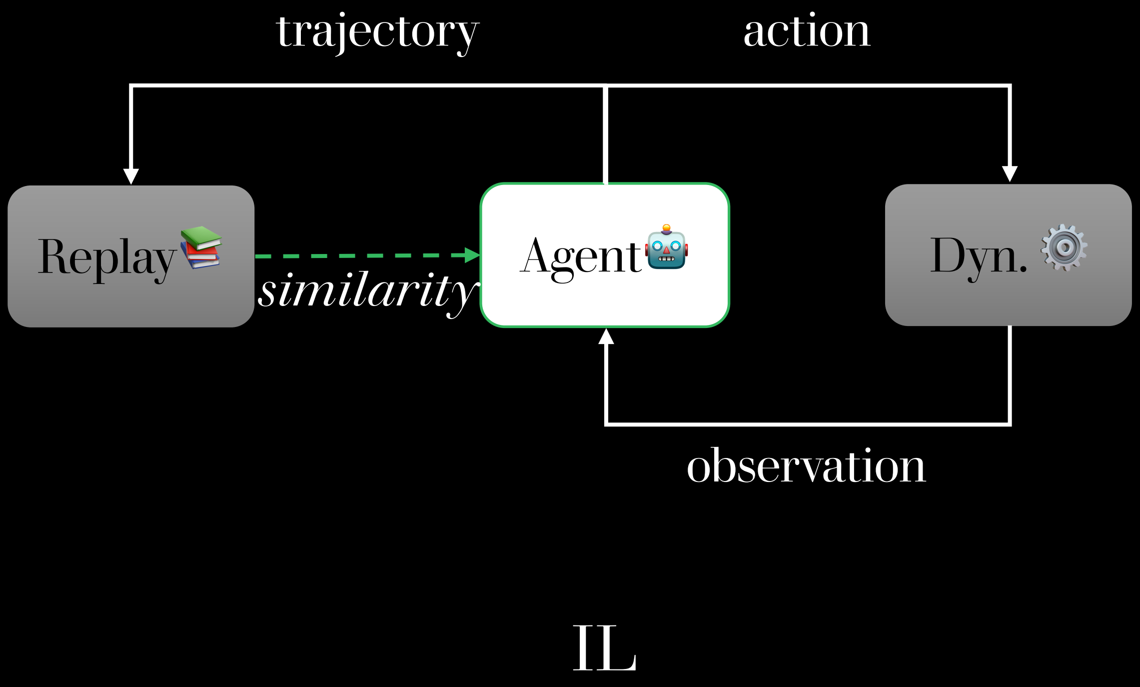


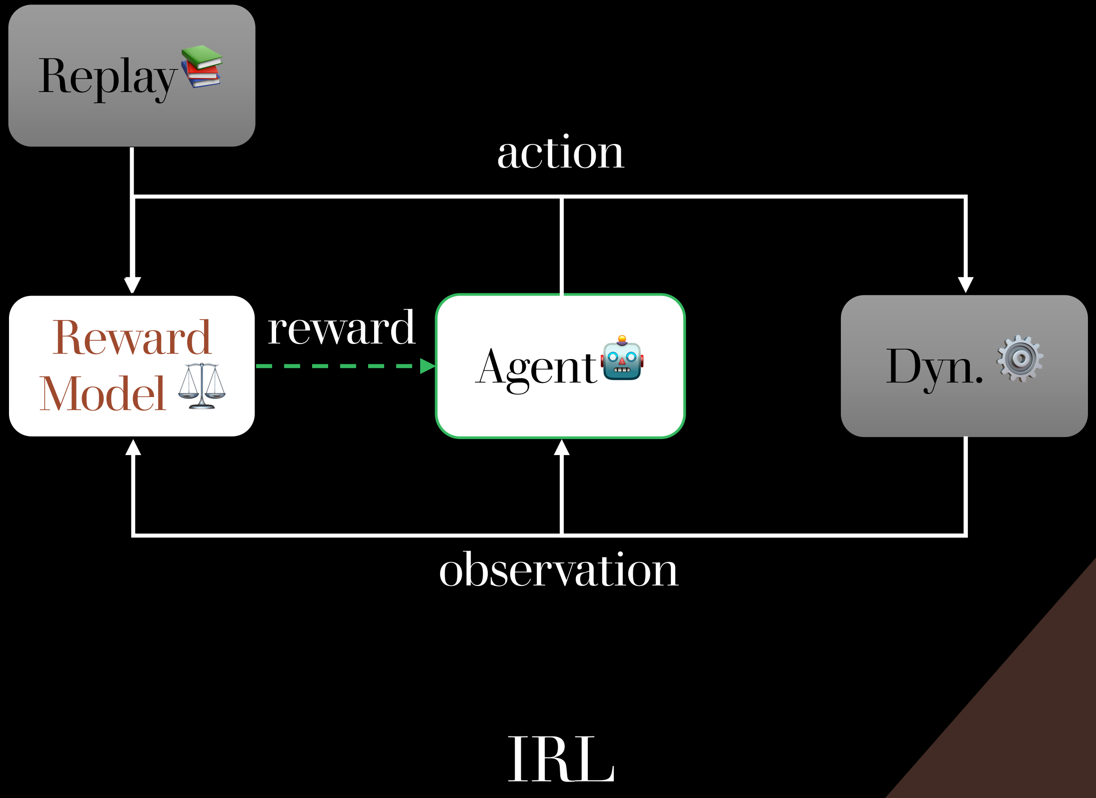
RL

Offline-RL

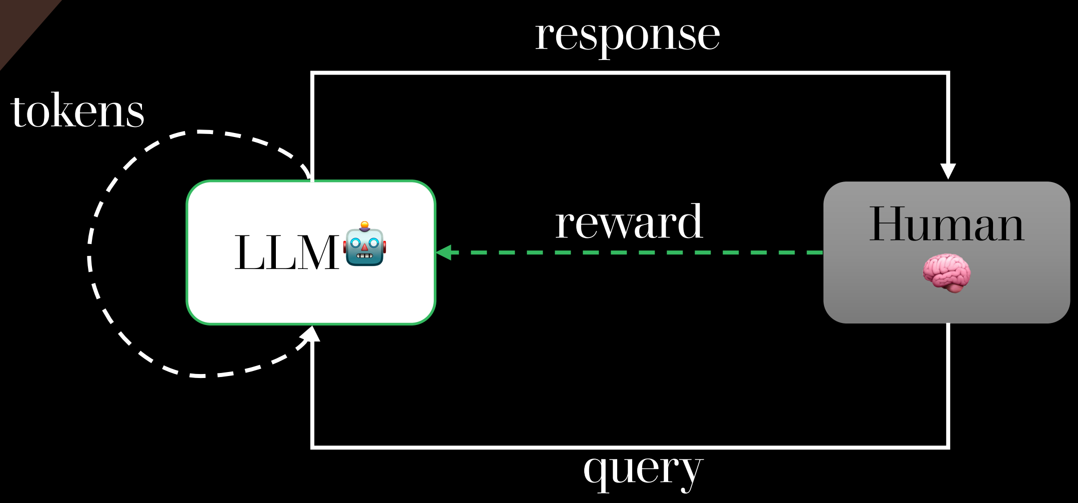
Env. 🌍 = Dyn. ⚙️ + Rew. ⚖️

Graph: IL and IRL





LLM Alignment with Human Feedback



Alignment as RL

- Why RL?

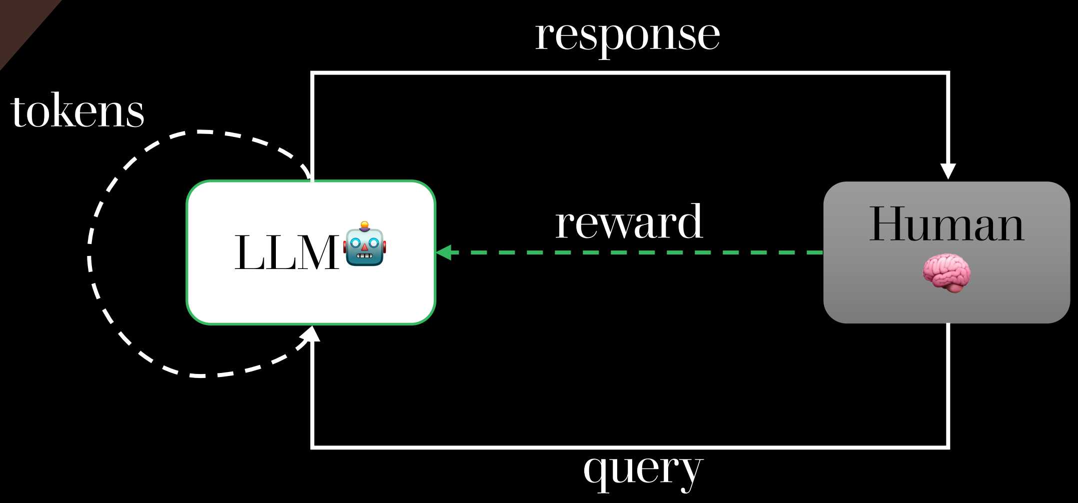
  We can not define the desired objective as a metric function.

  We can not do back-prop through a black-box 🧠

- Why not?

  Too expensive.

LLM Alignment with Human Feedback



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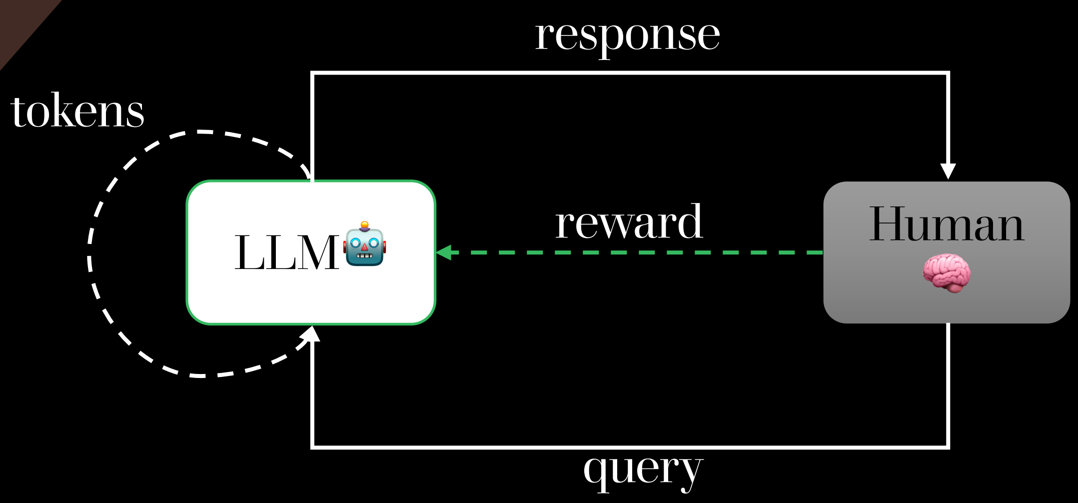
  OpenAI: unless you have enough volunteers (users)...

LLM Alignment with GPT-4 Feedback?



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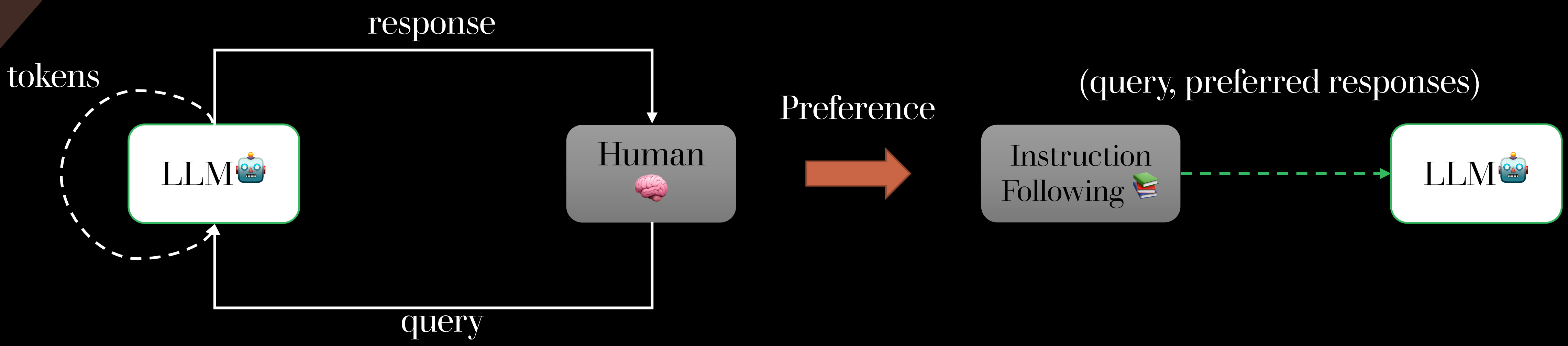
LLM Alignment with Human Feedback Logs



Preference Data Generation

Alignment as Offline-RL

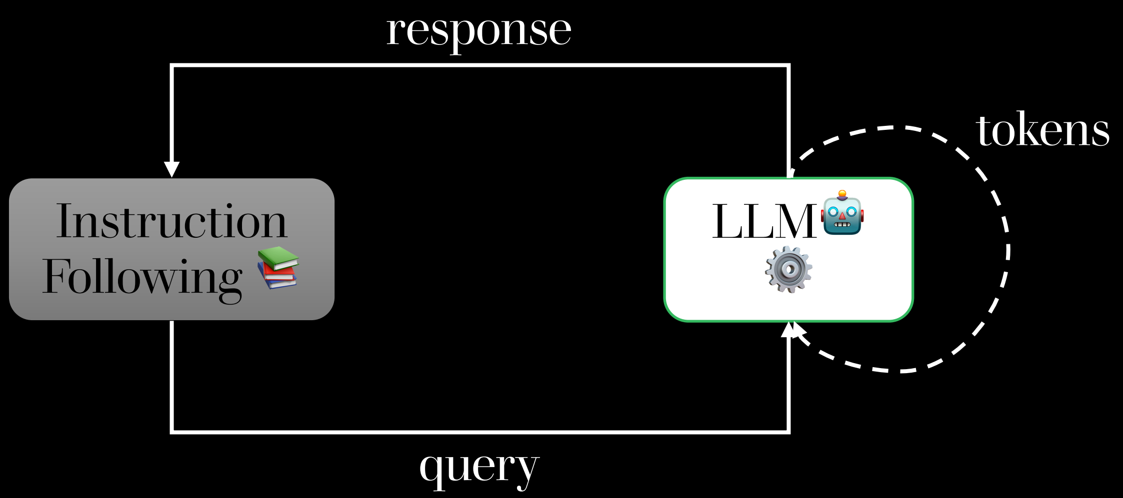
Alignment as Offline-RL: How to Learn?

Alignment as Offline-RL

- We can always use behavior clone.
  BC = SFT, supervised-fine-tuning
- It is simple, stable, efficient.
- But language modeling is not 1-step decision.
  Compounding errors

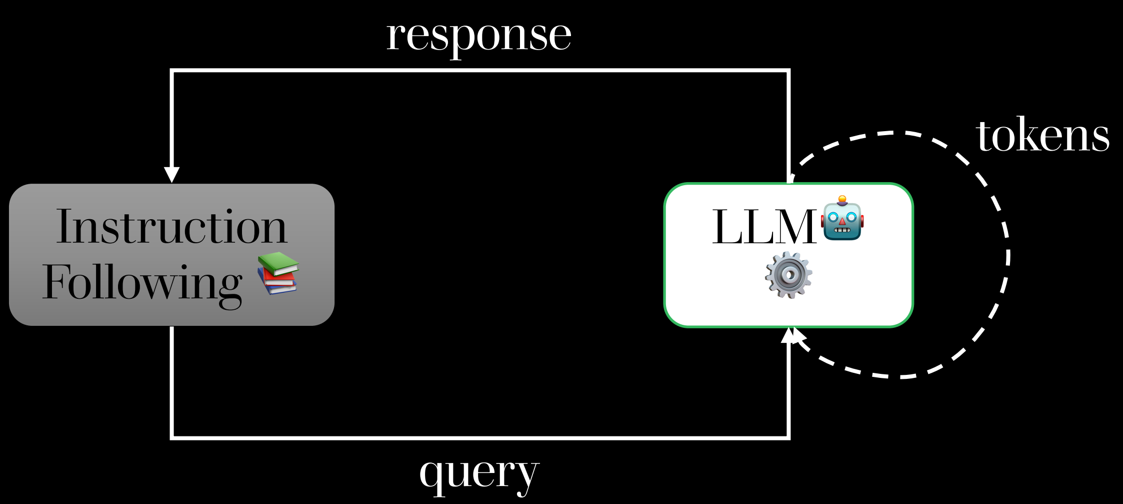
What Makes LLM Alignment Special?

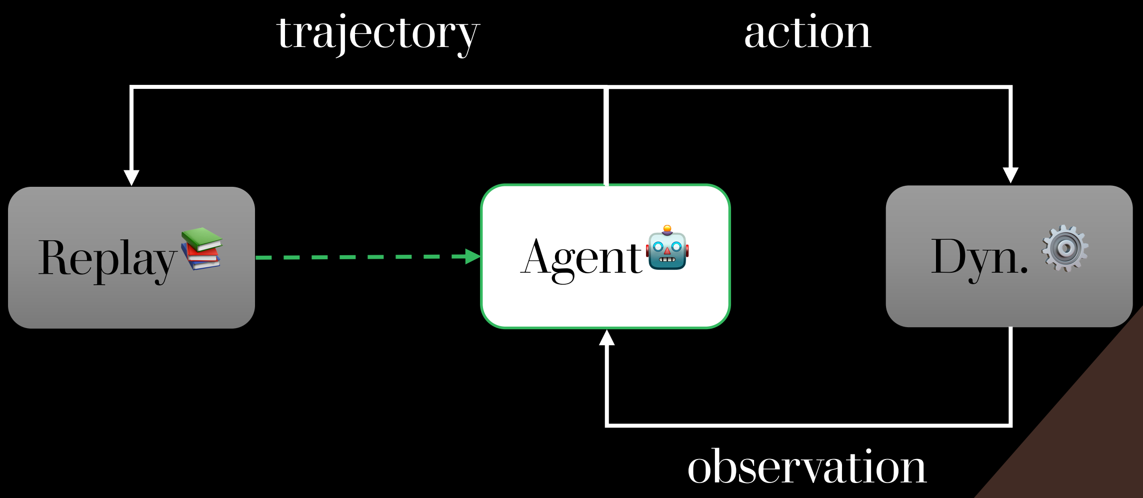
- The transition dynamics is deterministic and known!



What Makes LLM Alignment Special?

- The transition dynamics is deterministic and known!
- Recall the framework of Imitation Learning.

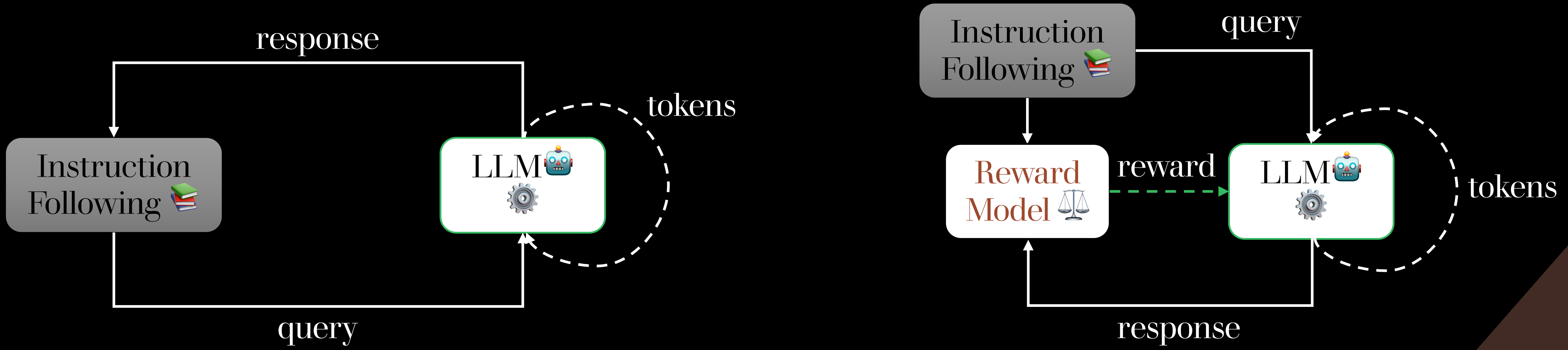




IL

RLHF: Solving Offline-RL via Online Inverse RL

- Inverse RL: learn the reward model, then optimize the policy.



SFT vs RLHF*: from the RL Perspective

- LLM alignment with logged human feedback (preference) can be interpreted as
  1. *Offline-RL --- solve it with behavior clone --- SFT*
  2. *Imitation Learning --- solve it with IRL --- RLHF*

- We can always do both:

  RLHF using SFT as a warm-start

- Potential Alternatives? Someone would try GAIL...

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* OpenAI's SFT is based on a separated high-quality response written by human.

RLHF

- Underlying assumptions:
  1. *Learning a reward model is statistically easier than directly learning aligned LLMs.*
  2. *There are some higher-level metrics that can not be captured by token-level distances.*

- Two steps
  1. *Reward Learning (Response Evaluation)*
  2. *LLM Optimization (Response Optimization)*

Step 1. Reward Model Learning

- Ranking is better than scoring, because the latter is noisier.

- LM with different sizes are used:

  OpenAI: 6B RM for 175B LM

  DeepMind: 7.5B RM for 7.5B LM

- Core Idea: The RM should be able to **understand** responses.

Step 2. Learning with RM

- RL Algorithms
  - *- PPO: ([Secrets of RLHF in Large Language Models](#))*
  - *- ILQL:*

  Challenges:
  - *- multiple LLMs required. e.g., reference model, actor, critic, reward model.*
  - *- not stable, hard to train, sensitive to hyper-params & seeds.*
- Evolution Strategies can be a scalable alternative [2]
  - *- RAFT*
  - *- RRHF*

  Sample a batch, and select the best using RM

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[2] Salimans, Tim, et al. "Evolution strategies as a scalable alternative to reinforcement learning." arXiv preprint arXiv:1703.03864 (2017).

An Empirical Study on PPO in RLHF

- Stable training of RLHF is still a puzzle
- Policy Constraints is important
- Propose PPO-Max
- Summary: smaller optimization steps

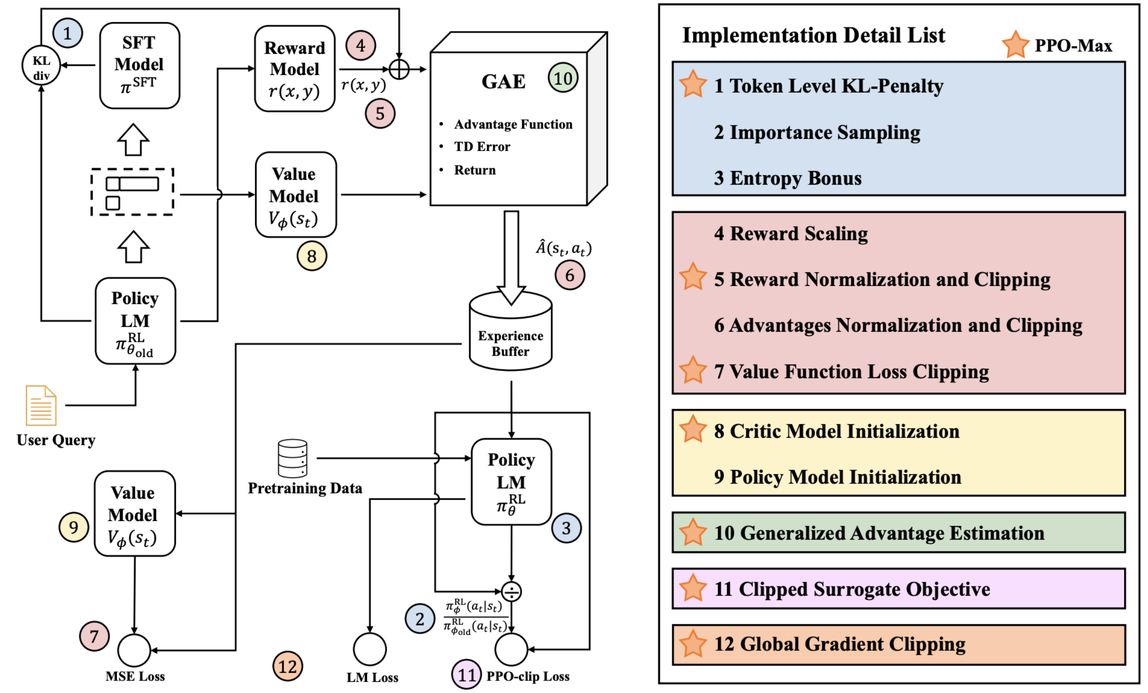


Figure 5: **Left** shows an equivalent structure to the RLHF framework in Figure 1. **Right** shows an implementation detail list for PPO. The number with circle indicates where this strategy is used in the PPO training. The pentagram indicates the method used by PPO-max.

RAFT: Reward rAnked Fine Tuning

- Best-of-N: 1. sample N for each query; 2. select the best-of-N; 3. supervised update
- Much less hyper-params.

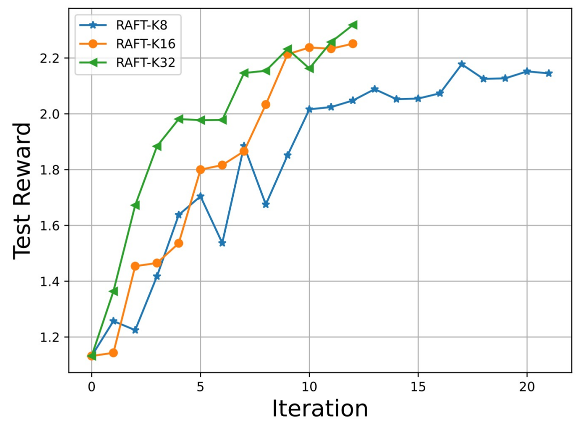
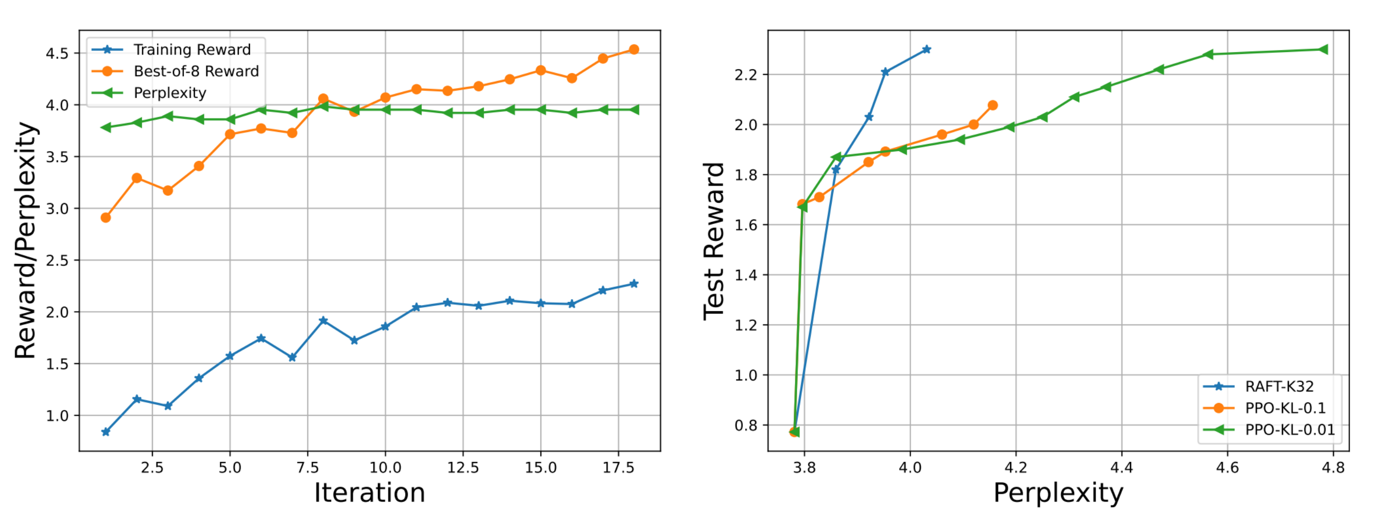


Figure 2: The test reward w.r.t. the iteration under different $K \in \{8, 16, 32\}$.



Resources

- GitHub Repo on RLHF: https://github.com/opendilab/awesome-RLHF
- Secrets of RLHF in Large Language Models https://github.com/OpenLMLab/MOSS-RLHF
- RAFT Official Implementation: https://github.com/OptimalScale/LMFlow
- TRL/ TRLx by huggingface: https://github.com/huggingface/trl
- RL4LMs: https://github.com/allenai/RL4LMs

Instruction Following by Prompting

- Prompt engineering is an effective approach in eliciting the abilities of LLMs
- In-context Learning/Fine-tuning

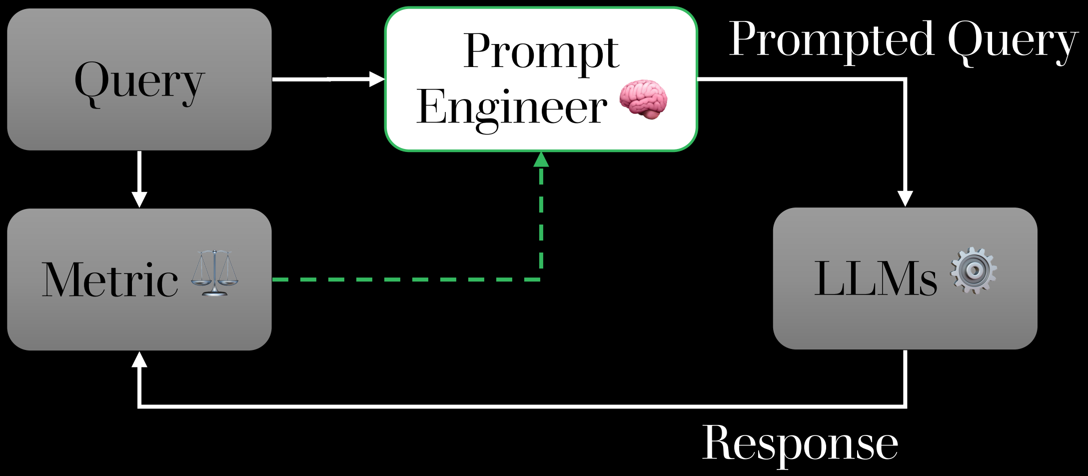
  Few-Shot Prompting + In-Context Learning

  Zero-Shot Prompting
- Examples:

  CoT: let's think step by step...

  OPRO: *take a deep breath ...*
- How to design? Previous approaches: learning from trial and error.

Instruction Following by Prompting



Prompt Engineers are doing RL

- Make it automatic?

  RL Agent 🤖 as Prompt Engineer

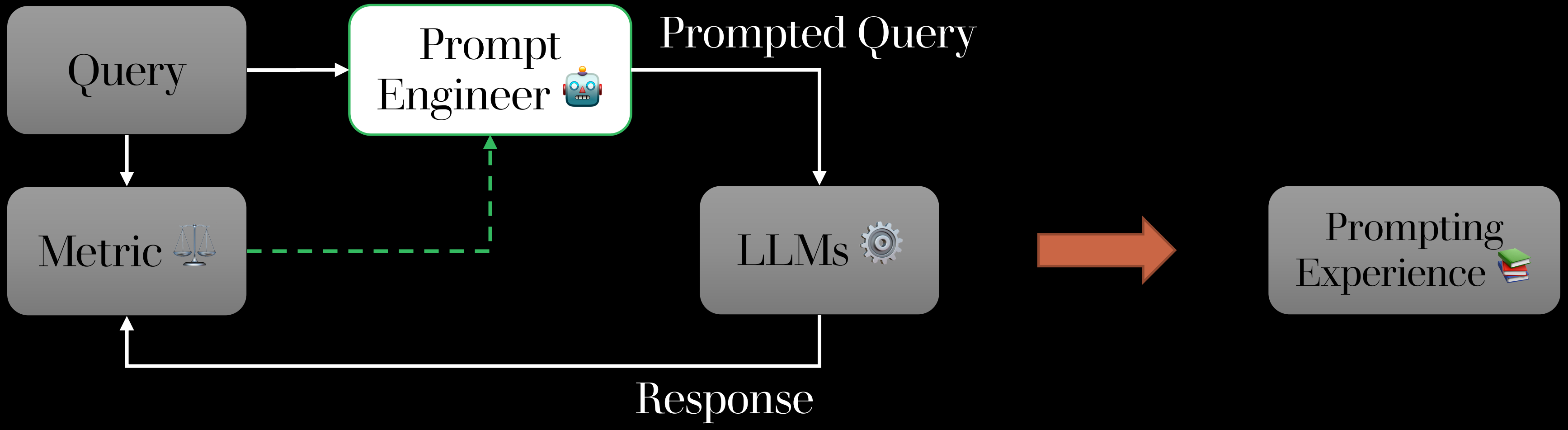
- Challenges:

  Too expensive to explore

  The action space is too large

Prompter Alignment with LLM Feedback

- We are aligning prompter using feedback from LLMs.
- Inspired by the great success of RLHF, can we do Imitation Learning?



Evaluate Existing Prompts as Offline Dataset

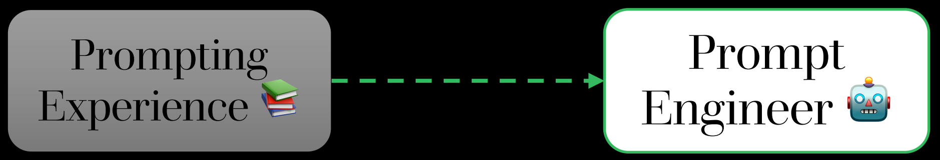
- For the same query, prompt engineers have tried different prompts

  e.g., on the GSM8K dataset, CoT, APE, ToT prompts are evaluated

  consider there are N queries with golden answers, and M prompting strategies.

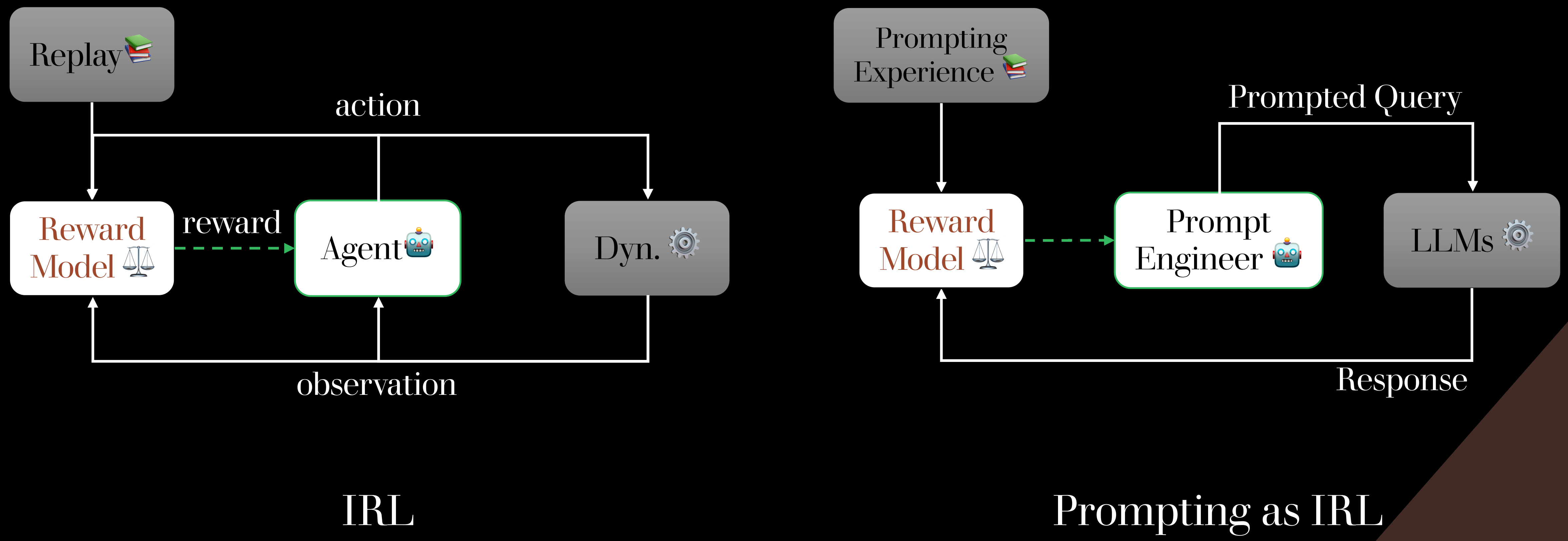
  (querie, prompt, response, correctness of answer)

$$\left(q_i, p_j, a_{ij}, r_{ij}\right)_{i\in[N], j\in[M]}$$

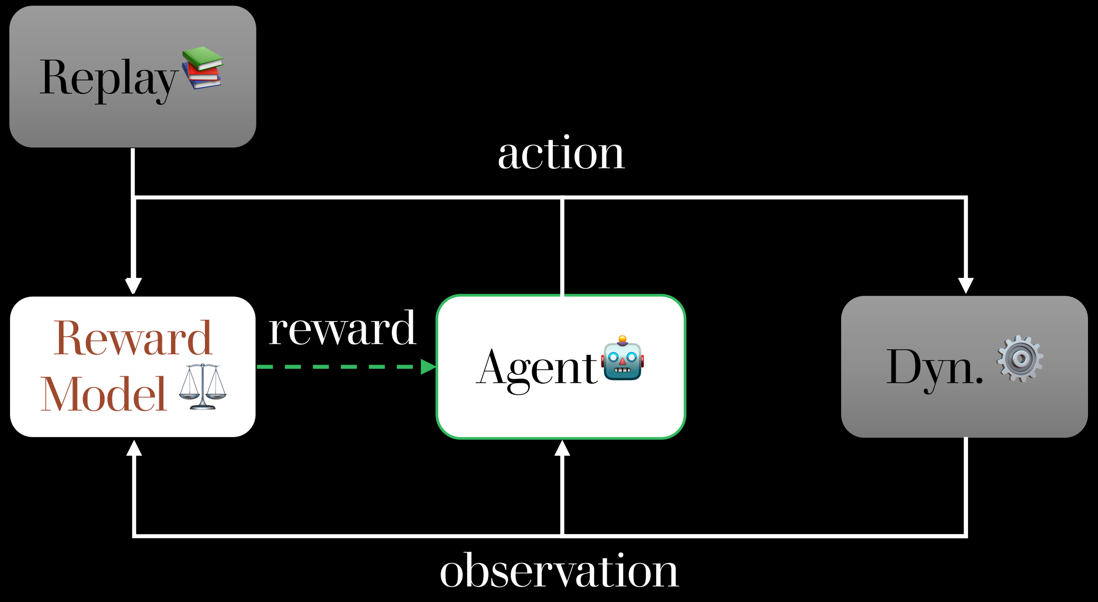


How to learn?

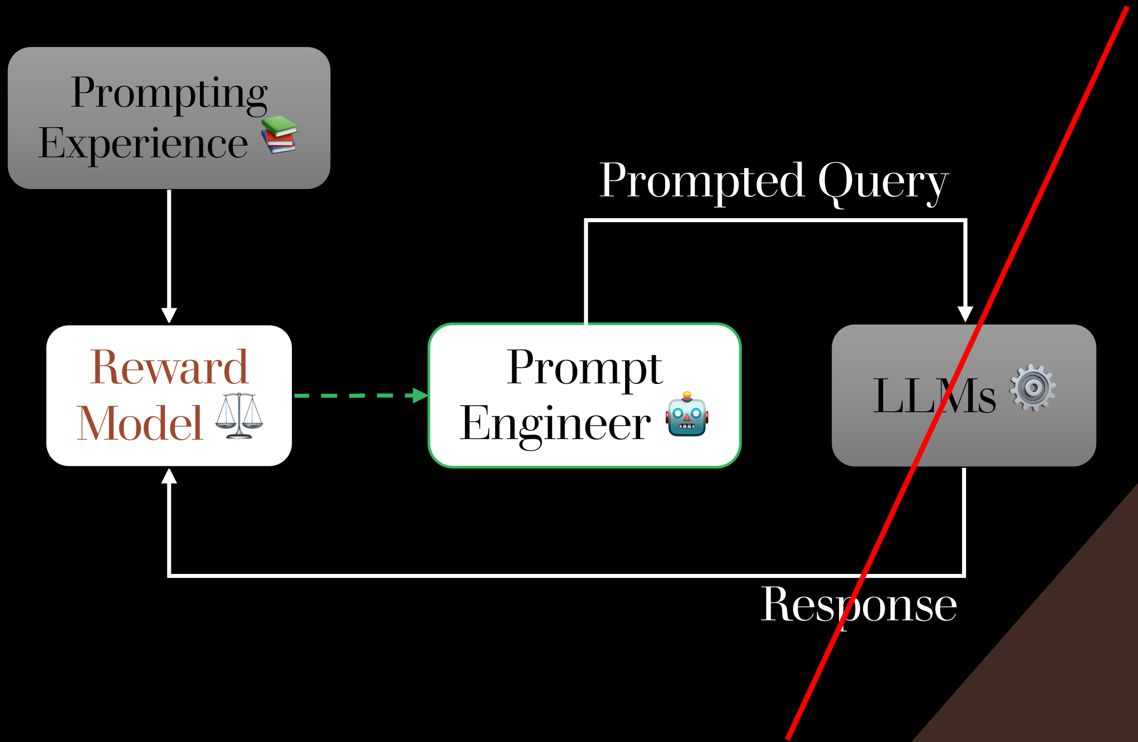
Inverse RL


Replay
action
Reward Model
reward
Agent
Dyn.
observation
IRL
Prompting Experience
Prompted Query
Reward Model
Prompt Engineer
LLMs
Response
Prompting as IRL

Inverse RL

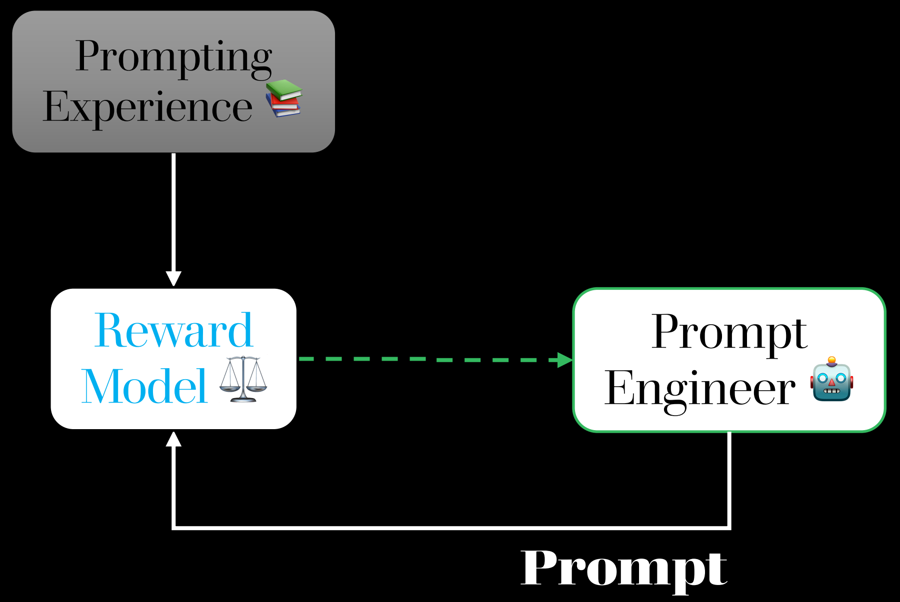


IRL

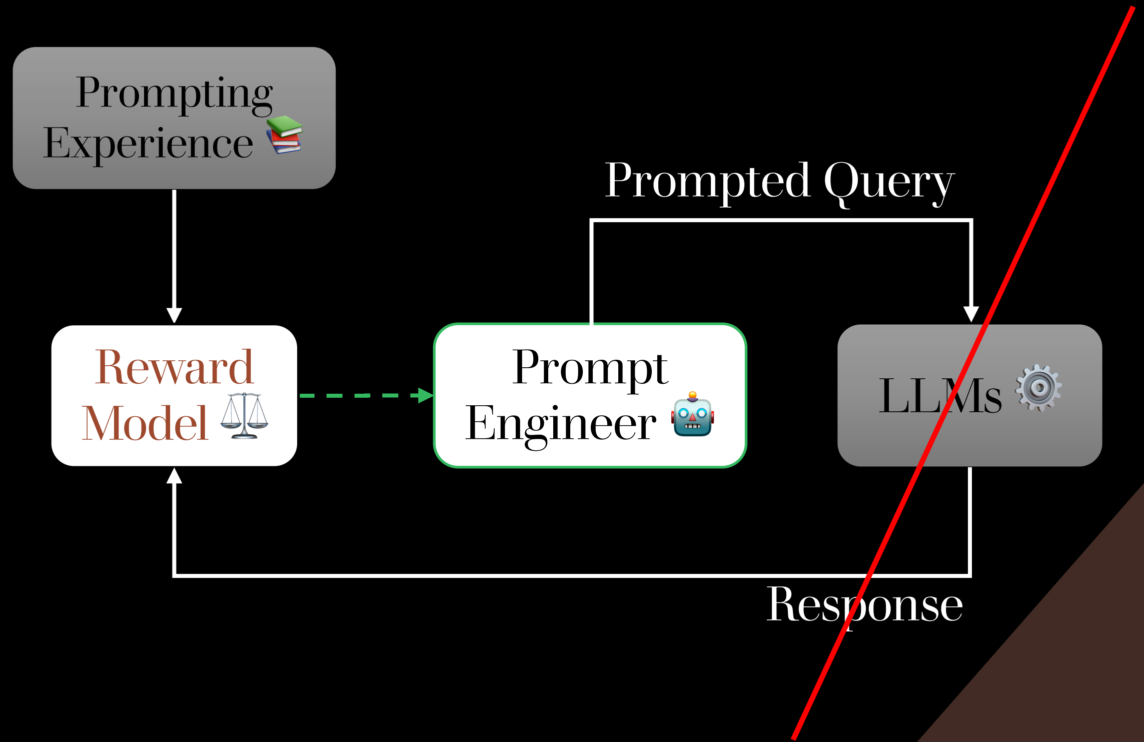


Prompting as IRL

Offline Inverse RL



Prompting as Offline IRL



Prompting as IRL

Reward Model: $q_i, p_j \mapsto r_{ij}$; Reward Model: $q_i, a_{ij} \mapsto r_{ij}$

Prompt-OIRL

- Offline Prompt Evaluation and Optimization with Inverse Reinforcement Learning [3]
- Two Steps:
  1. *Reward Model Learning --- for Prompt Evaluation*

  2. *Prompt Optimization --- with the learned reward model*

[3] Sun, Hao et al. "Offline Prompt Evaluation and Optimization with Inverse Reinforcement Learning." arXiv preprint arXiv:2309.06553 (2023).

Reward Model Learning

- $\hat{r}$ is learned by supervised learning:

$$\mathcal{L}_{CE}(\hat{r}) = -\mathbb{E}_{ij}\left[r_{ij}\log\sigma\left(\hat{r}(q_i, p_j)\right) + (1 - r_{ij})\log\left(1 - \sigma\left(\hat{r}(q_i, p_j)\right)\right)\right]$$

- $\hat{r}$ is different from the original evaluation metric function in that

  $\hat{r} = \hat{r}(q_i, p_j)$ *does not require access to the LLMs, yet* $r = r(q, llm(p + q))$

  $\hat{r}$ *can do evaluation, but* r *can not (estimate whether the answer is correct in test time)*

- *q and p in experiments are represented by their embeddings.*

Prompt Optimization

- With $\hat{r}$, prompt optimization can be executed without LLMs:

$$p_i^*(q_i) = \underset{p}{\operatorname{argmax}}\, \hat{r}(q_i, p)$$

- The optimized prompt is query-dependant
- How to instantiate this max?

1. *Reinforcement learning: train a prompting LM*
2. *Sample N and select the best*

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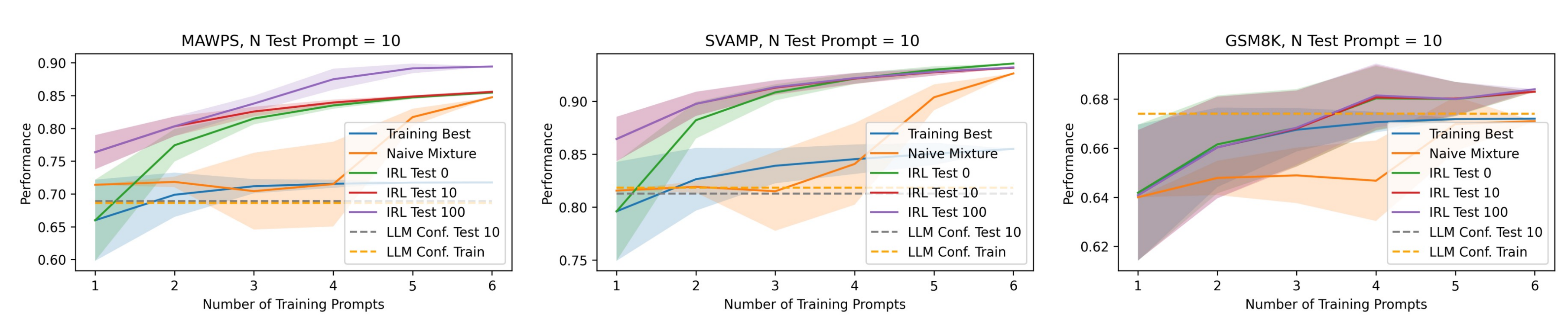
Results

- Experiments on Arithmetic Reasoning Datasets (GSM8K, SVAMP, MAWPS)
- TakeAways:
  1. *Prompt-OIRL further improve the ability of LLMs in inference.*
  2. *It is extremely cheap to train and deploy Prompt-OIRL.*



Summary

- RL is learning from trial and errors to maximize a cumulative reward.
- Define reward function can be easy, but exploration of RL is hard.
- With expert demonstrations, IL can improve learning efficiency.
- Behavior Clone is the simplest IL, but it suffers from compounding errors.
- IRL first learns a RM, and then use the learned RM to optimize policy.
- SFT is behavior clone, RLHF is online IRL.
- Given an RM, there are multiple approaches to optimize LLMs to align with human.
- Prompt optimization can be formulated as an (extremely hard) RL problem.
- Using Offline-IRL, prompt optimization can be much easier.
- Prompt-OIRL is able to effectivly and efficiently perform offline promt evaluation and optimization.