Reinforcement Learning

LMARL Session 2, February 18th 2025, Polina Tsvilodub
In part based on slides of Michael Franke (SS 2018)

Recap: Cognitive architecture

> "[A] particular methodology for building [agents]. It specifies how . . . the agent can be decomposed into the construction of a set of component modules and how these modules should be made to interact. The total set of modules and their interactions has to provide an answer to the question of how the sensor data and the current internal state of the agent determine the actions . . . and future internal state of the agent. An architecture encompasses techniques and algorithms that support this methodology" (Maes, 1991, p.115)

Kaelbling considers an agent architecture to be:

> "[A] specific collection of software (or hardware) modules, typically designated by boxes with arrows indicating the data and control flow among the modules. A more abstract view of an architecture is as a general methodology for designing particular modular decompositions for particular tasks." (Kaelbling, 1991, p.86)

cognitive architectures are both a functional description and a theory of humanlike minds, designed to model such minds and their functionality leading to intelligence

Wooldridge & Jennings (1995), Laird et al. (2017)

Cognitive architecture

Overview of general components:

- **Perception**: transform raw sensory input into representations
- **Attention Mechanisms**: allocate cognitive resources to certain information
- **Action Selection**: decision-making processes as to which actions to undertake
- **Memory Systems**:
  - Short-term memory
  - Working Memory: "temporary storage" for active tasks
  - Long-Term Memory: “permanent” storage for knowledge, rules, and experiences
    - episodic memory
    - procedural memory
    - semantic memory
- **Learning**:
  - adaptation, generalization based on experiences
- **Reasoning & Metacognition**:
  - Logical inference, probabilistic models, DPT, self-reflective thinking

Laird et al. (2017)

General Problem Solver

Means-ends analysis

- define problem (current and goal state), **specification of pre- and post-conditions of actions**
- compare current and goal states
- identify differences
- select an operator to reduce the difference
- apply the operator and repeat until goal is reached

What are the assumptions?

- structured state and action representations
- respecified set of goal types and operators

- **Problem solving as a search over structured problem space**

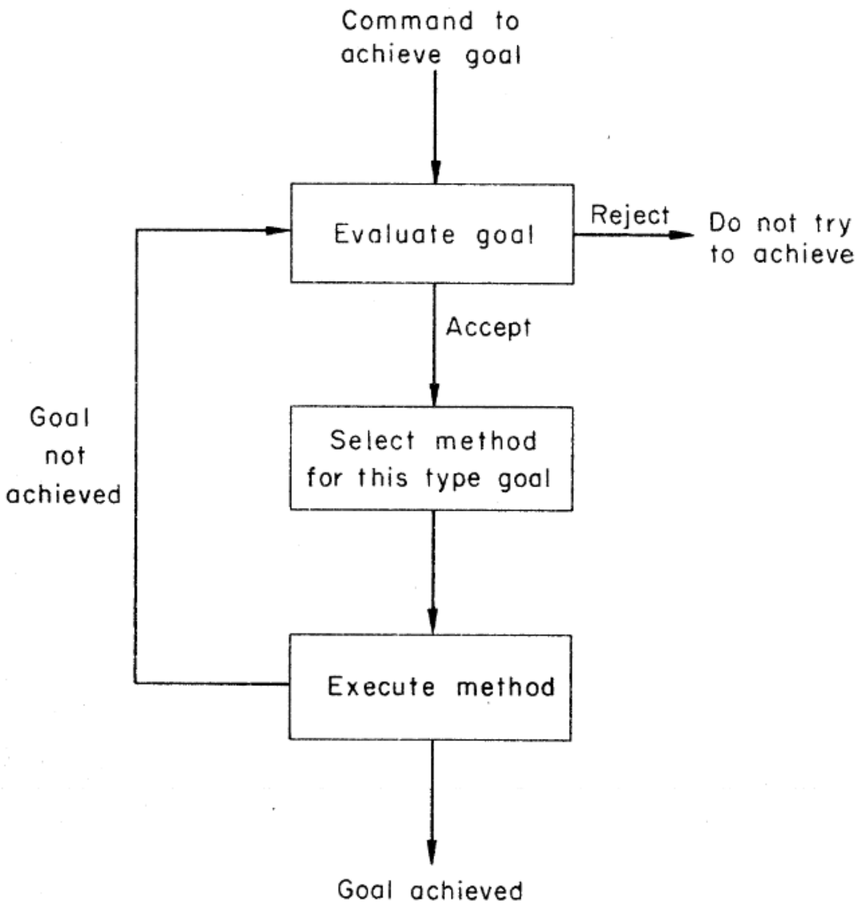


Fig. I — Executive organization of GPS

Newell, Shaw & Simon (1959)

Flavors of machine learning

- Unsupervised learning
  - e.g., clustering
- discover patterns in unlabeled data
  - ‘given my inductive bias, what is the likely structure of the data?’

- Supervised learning
  - also self-supervised learning
  - aka behavioural cloning
- learn to output Y, given X, from labeled data
  - ‘do as I show you’
- learning from demonstration

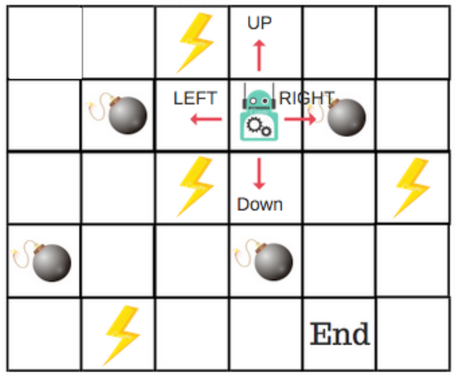
- Reinforcement learning
  - trial-and-error learning
- learning from interaction / experience
  - ‘how do I optimally behave in order to maximize reward?’
  - **reward hypothesis**
  - or, ‘how do i optimally achieve my goal?’
    - most natural way of learning?
    - tightly connected to the way organisms behave (“pleasure maximizers”)

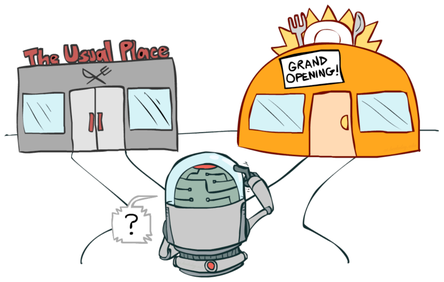
Christian (2020), Bishop (2009)

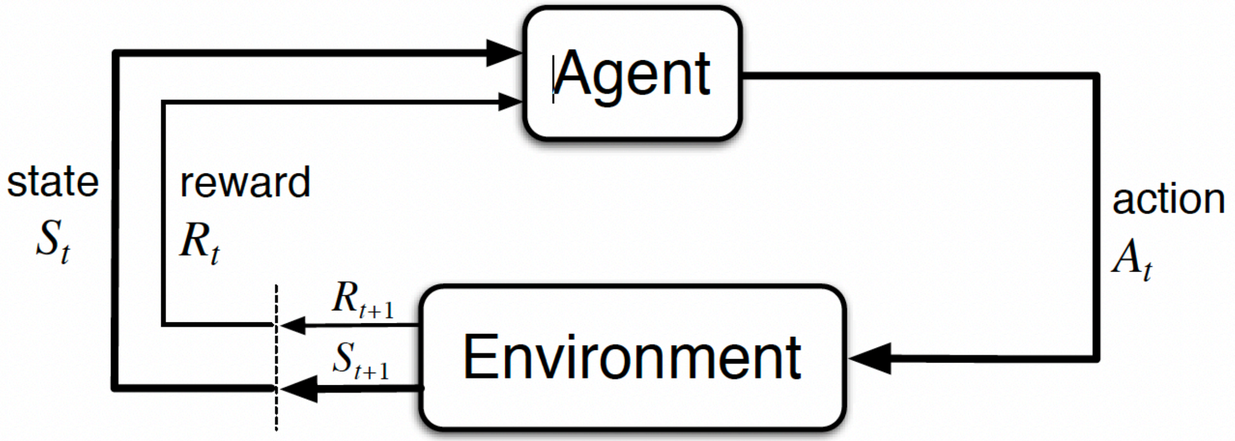
Reinforcement Learning: Overview

Introduction

- **Reinforcement Learning:** Computational formalisation of goal-directed learning and decision making
- **Goal:** Maximize rewards (by learning optimal behavior)
- **Basic building blocks:**
  - Agent
  - States
  - Actions
  - Transition function P
  - Reward
  - Policy







Sutton & Barto (2018, p. 48, Fig 3.1), image source

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  - States: $S_t \in S$ for $t = 0, 1, 2, 3, \ldots$
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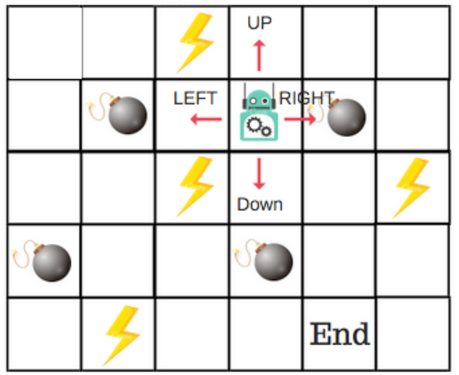
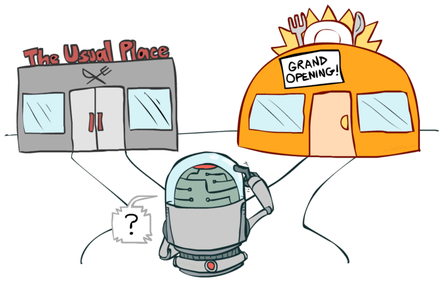
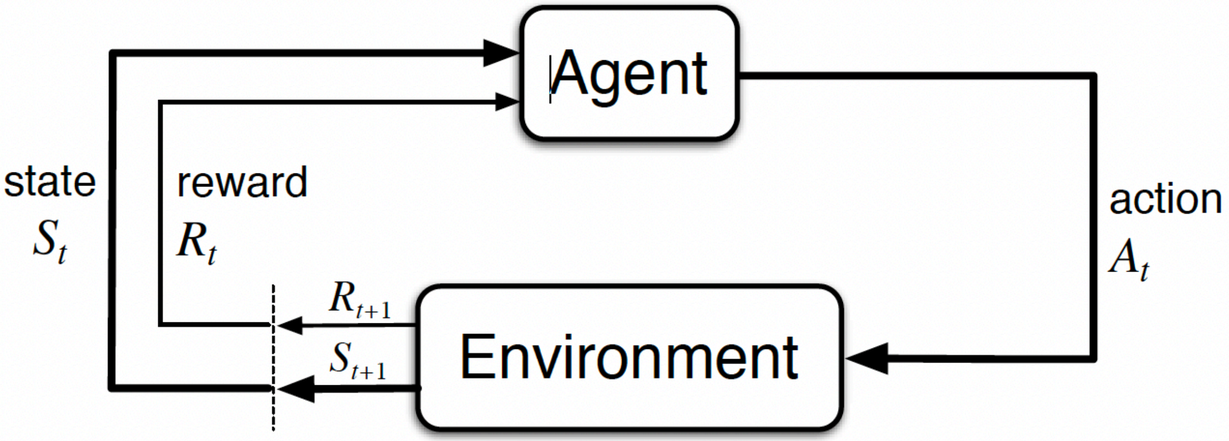






Sutton & Barto (2018, p. 48, Fig 3.1), image source

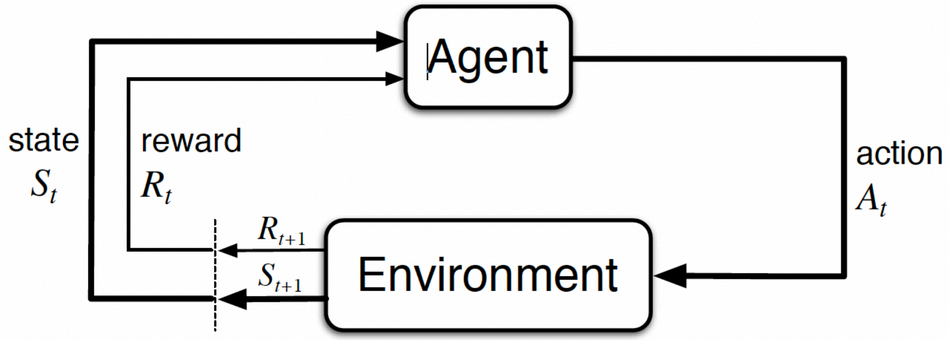
Markov Decision Processes

Formal definition

Finite MDPs: (S, A, T, R)

describes sequential decision making $(s_0, a_0, R_1, s_1, a_1, R_1, \ldots)$

1. $S_t \in S$ for $t = 0, 1, 2, 3, \ldots$
2. $A_t \in A(s)$
3. $R_{t+1} \in R$
4. $T(s' \mid s, a) = \sum_{r' \in R} P(s', r' \mid s, a)$
5. Horizon H, discount factor $0 \leq \gamma \leq 1$



Expected rewards for state s and action a: $r(s, a) = \mathbb{E}(R_t \mid S_{t-1} = s, A_{t-1} = a) = \sum_{r \in R} r \sum_{s' \in S} P(s', r \mid s, a)$

Markov property: S_{t-1}, A_{t-1} include all information about past agent-environment interactions that are relevant for S_t, R_t

Sutton & Barto (2018, p. 48, Fig 3.1)

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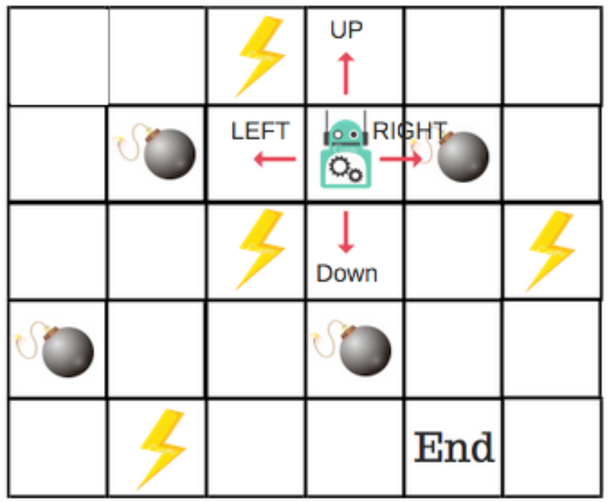


Goal: maximize **returns** until goal achieved

$G_t = R_{t+1} + R_{t_2} + \ldots + R_T$

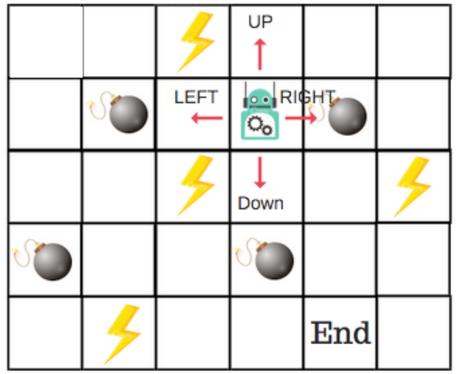
Formally: maximize expected **discounted** rewards over **episode**

$$G_t = R_{t+1} + \gamma R_{t_2} + \gamma^2 R_{t+3} + \ldots + \gamma^{T-t-1} R_T = \sum_{k=t+1}^{T} \gamma^{k-t-1} R_k$$

Sutton & Barto (2018, p. 48, Fig 3.1)

Markov Decision Processes

Optimization Problem



- **Goal:** Maximize accumulated rewards (=returns): $G_t = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1}$
- **Basic building blocks:**
  - Agent
  - States: $S_t \in S$ for $t = 0, 1, 2, 3, \ldots$
  - Actions: $A_t \in A(s)$
  - Reward: $R_{t+1} \in R$
  - Policy: $\pi(S_t) = P(A_t \mid S_t)$
- We can identify optimal way to behave if we know what good particular states and/or actions are:

  State-value function: $v_\pi(s) = \mathbb{E}_\pi[G_t \mid S_t = s] = \mathbb{E}_\pi[\sum_{k=0}^{\infty} \gamma^k R_{t+k+1} \mid S_t = s]$ for all s

  think: "How good is it to be in state s?"

  Action-value function: $q_\pi(s, a) = \mathbb{E}_\pi[G_t \mid S_t = s, A_t = a] = \mathbb{E}_\pi[\sum_{k=0}^{\infty} \gamma^k R_{t+k+1} \mid S_t = s, A_t = a]$ for all s, a

  think: "How good is it to take action a in state s?"

- **Can be estimated from experience!**
- Optimal policy π^*: $\pi \geq \pi' \Leftrightarrow v_{\pi^*}(s) \geq v_{\pi'}(s)$ for all s and $q_{\pi^*}(s, a) = \max_{\pi'} q_{\pi'}(s, a)$

Sutton & Barto (2018)

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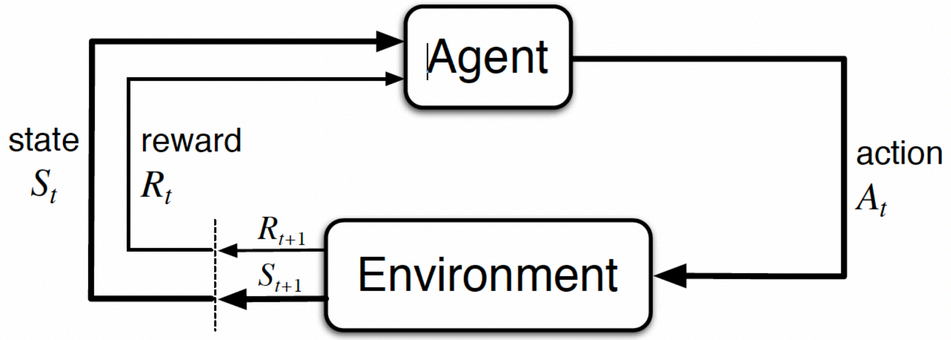

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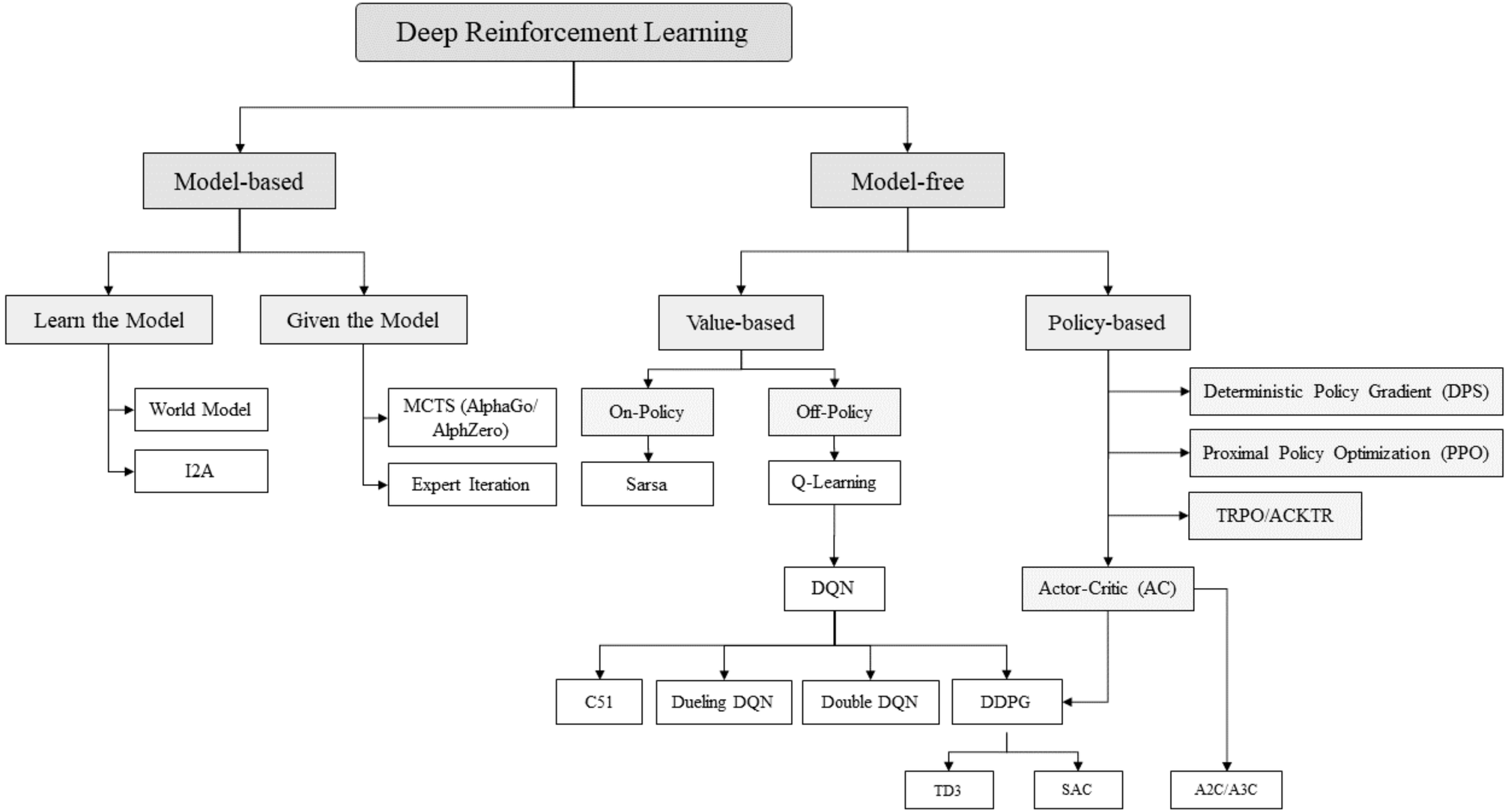
Markov property: S_{t-1}, A_{t-1} include all information about past agent-environment interactions that are relevant for S_t, R_t

Sutton & Barto (2018, p. 48, Fig 3.1)

RL Algorithms

Approximating Optimal Policy



[3]

RL Agents and Intelligent Agents

How do CAs, notions of agency, RL relate?

- RL agents focus on modeling learning, while agents more generally have many more components
- model-based RL agents might be seen as closer to representing the world & planning
  - Q: what kind of memory is an RL policy similar to?
- exploration-exploitation problem in RL
- are RL systems agents in intentional sense / sense of Wooldridge & Jennings?
  - Maybe: yes in the narrow sense of learning goal-directed behavior
  - No in the broader sense of having updatable beliefs, dynamic intentions, reasoning, being autotelic
- there is work on building intrinsically motivated RL agents

LLMs as RL agents

Language Modeling ≠ Assisting Users

PROMPT	*Explain the moon landing to a 6 year old in a few sentences.*
COMPLETION	GPT-3

```
Explain the theory of gravity to a 6 year old.

Explain the theory of relativity to a 6 year old in a few sentences.

Explain the big bang theory to a 6 year old.

Explain evolution to a 6 year old.
```

Language models are not *aligned* with user intent [Ouyang et al., 2022].

Making LLMs useful

Adaptation

- training a task-specific head on top of a model
  - e.g., span prediction layer on top of BERT with frozen BERT
  - on a dataset of ground truth input-output pairs for a particular task
- fine-tuning the model
  - further training part or entire model for a shorter time
  - on a dataset of ground truth input-output pairs for a particular task
- practical problem
  - training with standard supervision is impractical (data collection)
  - and inefficient (restricting “ground truth” to finite set of answers for open-ended tasks)
- **RL is the solution:** learn to achieve goal based on feedback from environment rather than direct demonstration of correct behaviour

source

Language model

left-to-right / causal model

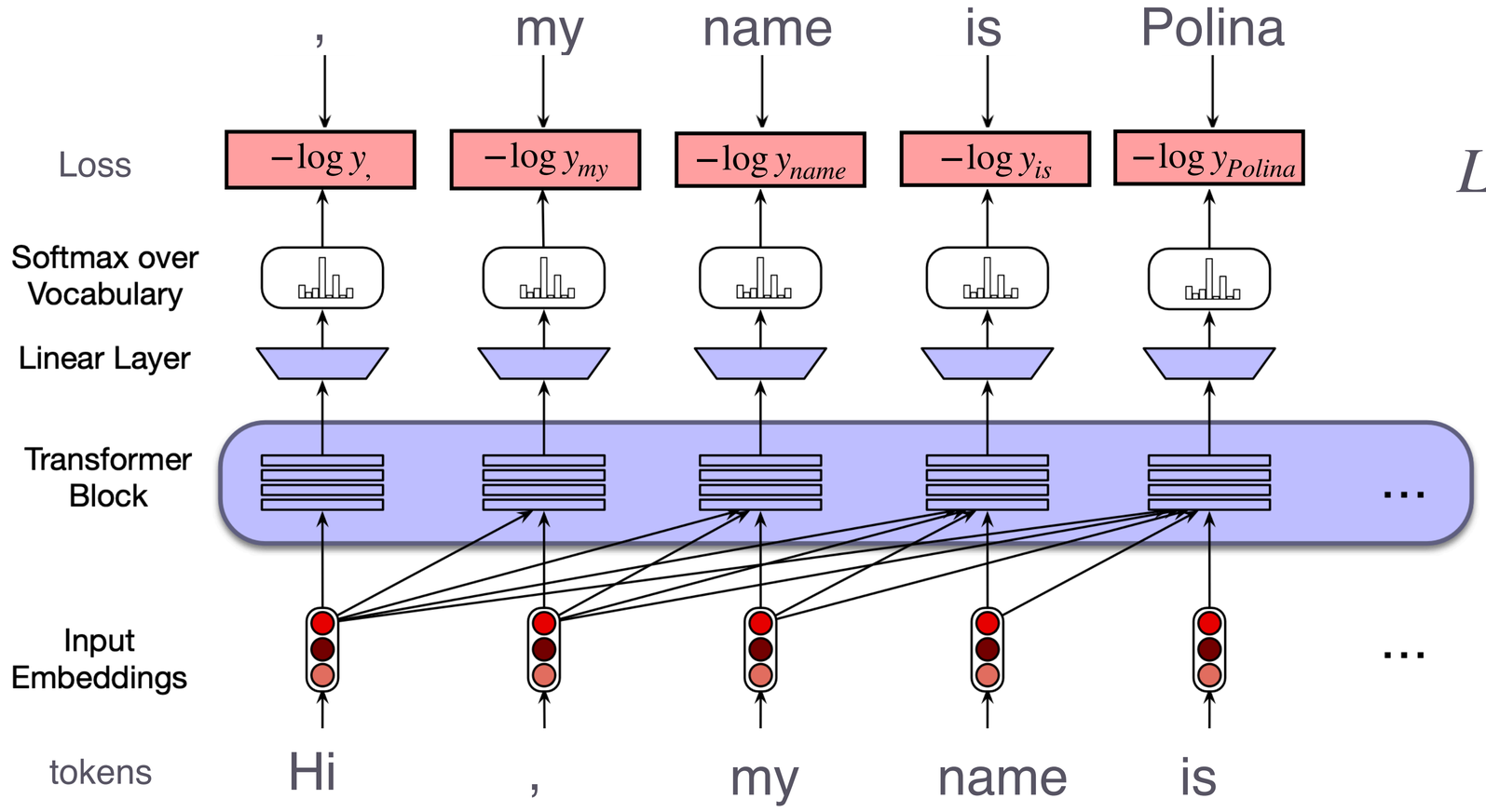
RECAP

- let $\mathscr{V}$ be a (finite) **vocabulary**, a set of words
  - we say “words” but these can be characters, sub-words, units …
- let $w_{1:n} = \langle w_1, \ldots, w_n \rangle$ be a finite sequence of words
- a **causal language model** is defined as a function that maps an initial sequence of words to a probability distribution over words: $LM \ : \ w_{1:n} \mapsto \Delta(\mathscr{V})$
  - we write $P_{LM}(w_{n+1} \mid w_{1:n})$ for the **next-word probability**
  - the **surprisal** of w_{n+1} after sequence $w_{1:n}$ is $-\log \left(P_{LM}(w_{n+1} \mid w_{1:n}) \right)$

Maximizing next-token probability

Pretraining

RECAP



Cross-entropy loss:

$$L_\theta = -\sum_i^{|V|} Q(y_i)\log P(y_i)$$

$$L_\theta = -\log P(y_i)$$

$$L_\theta = \frac{1}{n}\sum_i^{n} -\log P(y_i)$$

$$L_\theta = \frac{1}{b}\sum_j^{b}\frac{1}{n_j}\sum_i^{n_j} -\log P(y_{ji})$$

Language Modeling ≠ Assisting Users

PROMPT *Explain the moon landing to a 6 year old in a few sentences.*

COMPLETION **Human**

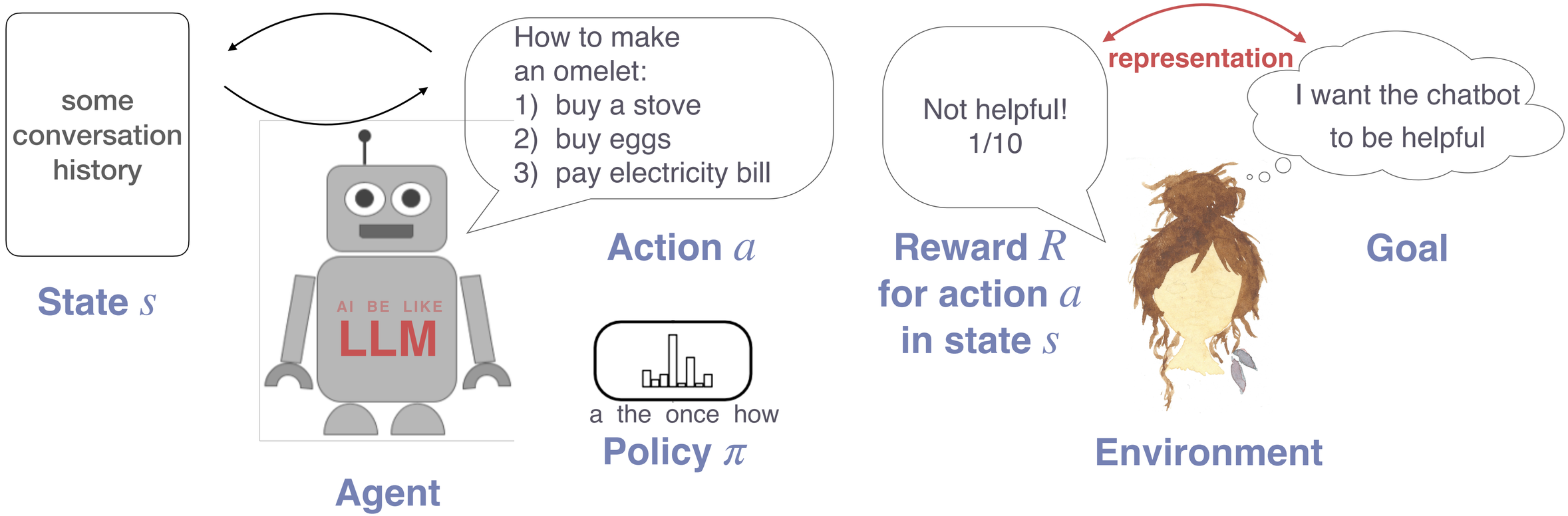
A giant rocket ship blasted off from Earth carrying astronauts to the moon. The astronauts landed their spaceship on the moon and walked around exploring the lunar surface. Then they returned safely back to Earth, bringing home moon rocks to show everyone.

Language models are not *aligned* with user intent [Ouyang et al., 2022].
Finetuning to the rescue!

Reinforcement Learning from Human Feedback

Overview

- use human judgments as a signal on what model prediction counts as a good output
- learn a **reward model representing human feedback**



Sutton & Barto (2018), Ouyang et al (2022)

Human feedback in RL

RLHF

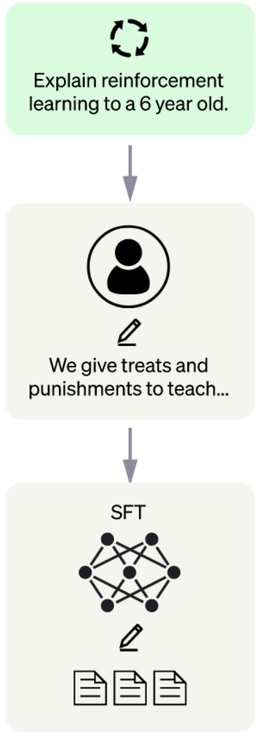
Step 1

Collect demonstration data and train a supervised policy.

A prompt is sampled from our prompt dataset.

A labeler demonstrates the desired output behavior.

This data is used to fine-tune GPT-3.5 with supervised learning.



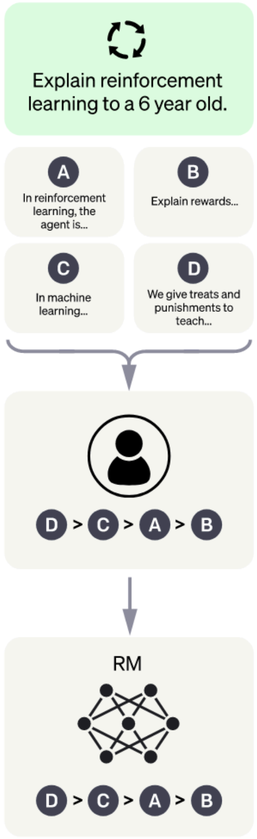
Step 2

Collect comparison data and train a reward model.

A prompt and several model outputs are sampled.

A labeler ranks the outputs from best to worst.

This data is used to train our reward model.



Step 3

Optimize a policy against the reward model using the PPO reinforcement learning algorithm.

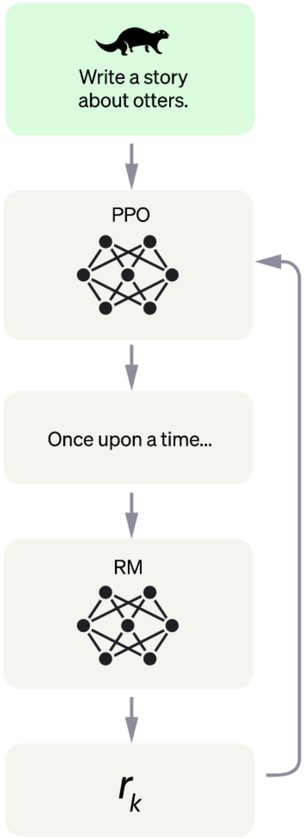
A new prompt is sampled from the dataset.

The PPO model is initialized from the supervised policy.

The policy generates an output.

The reward model calculates a reward for the output.

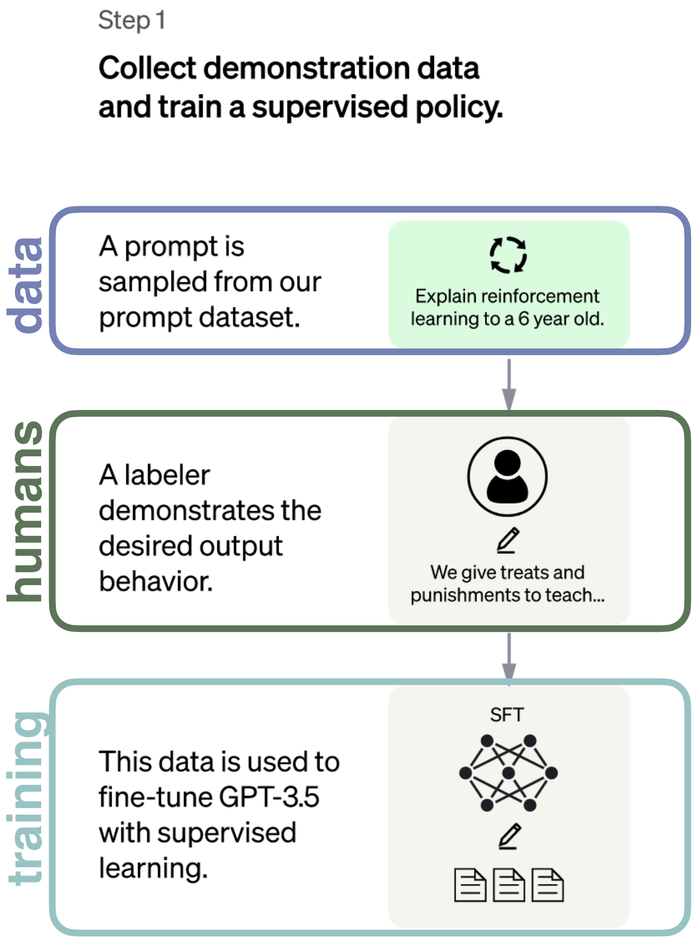
The reward is used to update the policy using PPO.



OpenAI (2022)

RLHF in practice

Step 1

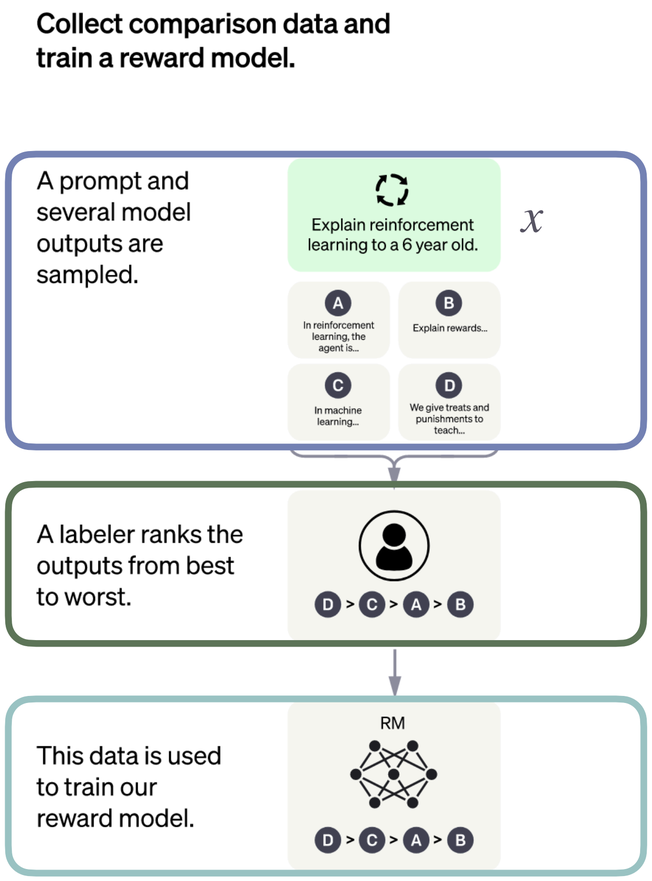


- supervised fine-tuning on a dataset of input-output demonstrations of the target task
  - pretrained model trained for a shorter time
- shifts the initial pretraining distribution $\Delta(S)$ to a task-specific distribution $\Delta'(S)$ (behavioural cloning)
  - learning about the format of task
  - producing informative rollouts from the policy for reward modelling

OpenAI (2022) and here

RLHF in practice

Step 2



- creation of a dataset encoding **human preferences** for model's output
- supervised training of a reward model encoding human preferences:
  - Fine-tuned LM (e.g., 6B GPT-3 in InstructGPT) trained to output scalar reward:

$$L(\theta) = -\frac{1}{N}\mathbb{E}_{(x,D,B)\sim D}[log\ (\sigma(\underbrace{r_\theta(x,D)}_{\text{predicted reward for response D}} - \underbrace{r_\theta(x,B)}_{\text{predicted reward for response B}}))]$$

- smart procedure for eliciting comparisons

OpenAI (2022), Ouyang et al. (2022)

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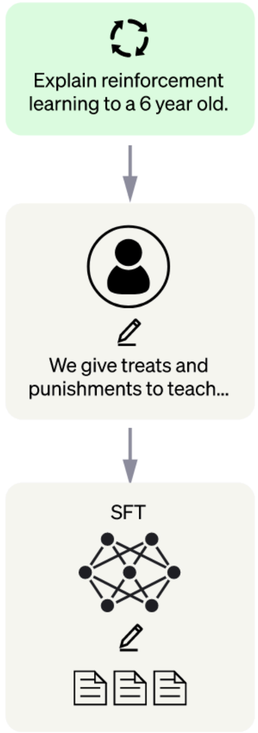

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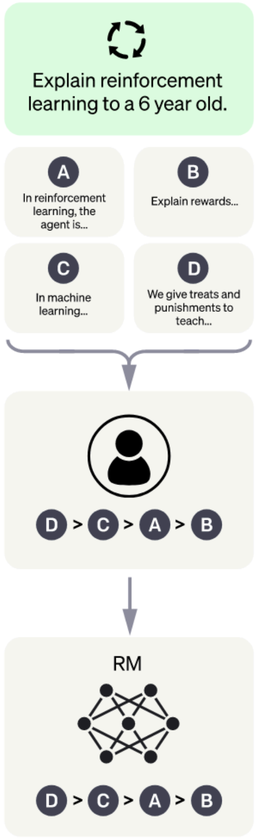

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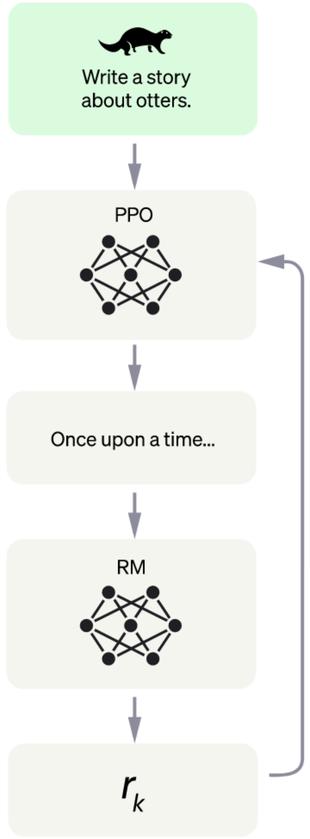
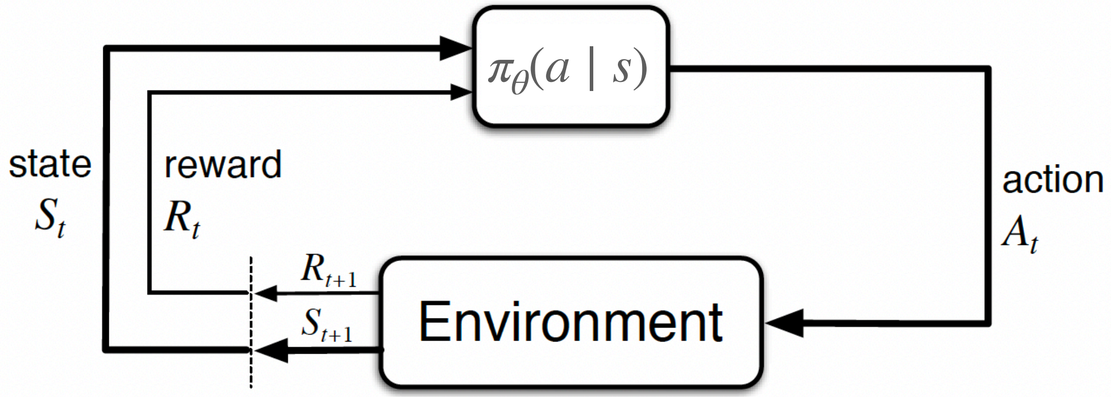


OpenAI (2022)

Policy-Gradient Methods

Step 3

- so far: deriving optimal policy from estimated value function
  - coming up with value functions might be difficult
  - state-value function doesn't prescribe actions
  - action-value functions require argmax
- idea: **optimize policy directly, such that expected reward is maximized**
  - think: optimize model with respect to objective function L
- goal: find optimal θ
  - $\max_{\theta} \mathbb{E}_{\pi_\theta}[G_t]$
- recall LM optimization: tweak θ so as to minimize loss
  - Gradient descent: $\theta_{new} = \theta_{old} - \alpha \nabla L_\theta$
  - Now: gradient ascent: $\theta_{new} = \theta_{old} + \alpha \nabla L_\theta$



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Policy-Gradient Methods

Language models as policies

Policy gradient estimation: $\nabla L(\theta) = \sum_{\tau} P(\tau, \theta) \nabla_\theta \log P(\tau, \theta) R(\tau) \approx \frac{1}{m} \sum_{i=1}^{m} \sum_{t=0}^{H} \nabla_\theta \log \pi_\theta(a_t^i \mid s_t^i) R(a_t^i)$

- policy π_θ: language model
- trajectories τ: generations from language model
- $\log \pi_\theta(a^i \mid s^i)$: log probability of a generation a^i under the language model
- $R(a_t^i)$: **reward for generation a^i — provided by reward model**

s^i: prompt

a^i: completion

contextual k-armed bandit environment
where k = # of tokens

::: no episodic structure!

Sutton & Barto (2018)

Different algorithms for policy gradient methods

Language models as policies

Asynchronous Methods for Deep Reinforcement Learning

Volodymyr Mnih[1] VMNIH@GOOGLE.COM
Adrià Puigdomènech Badia[1] ADRIAP@GOOGLE.COM
Mehdi Mirza[1,2] MIRZAMOM@IRO.UMONTREAL.CA
Alex Graves[1] GRAVESA@GOOGLE.COM
Tim Harley[1] THARLEY@GOOGLE.COM
Timothy P. Lillicrap[1] COUNTZERO@GOOGLE.COM
David Silver[1] DAVIDSILVER@GOOGLE.COM
Koray Kavukcuoglu [1] KORAYK@GOOGLE.COM

[1] Google DeepMind
[2] Montreal Institute for Learning Algorithms (MILA), University of Montreal

Trust Region Policy Optimization

John Schulman JOSCHU@EECS.BERKELEY.EDU
Sergey Levine SLEVINE@EECS.BERKELEY.EDU
Philipp Moritz PCMORITZ@EECS.BERKELEY.EDU
Michael Jordan JORDAN@CS.BERKELEY.EDU
Pieter Abbeel PABBEEL@CS.BERKELEY.EDU

University of California, Berkeley, Department of Electrical Engineering and Computer Sciences

Proximal Policy Optimization Algorithms

John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, Oleg Klimov
OpenAI
{joschu, filip, prafulla, alec, oleg}@openai.com

Direct Preference Optimization: Your Language Model is Secretly a Reward Model

Rafael Rafailov[*†] **Archit Sharma**[*†] **Eric Mitchell**[*†]
Stefano Ermon[†‡] **Christopher D. Manning**[†] **Chelsea Finn**[†]

[†]Stanford University [‡]CZ Biohub
{rafailov,architsh,eric.mitchell}@cs.stanford.edu

Group Robust Preference Optimization in Reward-free RLHF

Shyam Sundhar Ramesh[1,6] Yifan Hu[3,4] Iason Chaimalas[1] Viraj Mehta[2]
Pier Giuseppe Sessa[3] Haitham Bou Ammar[1,5] Ilija Bogunovic[1]

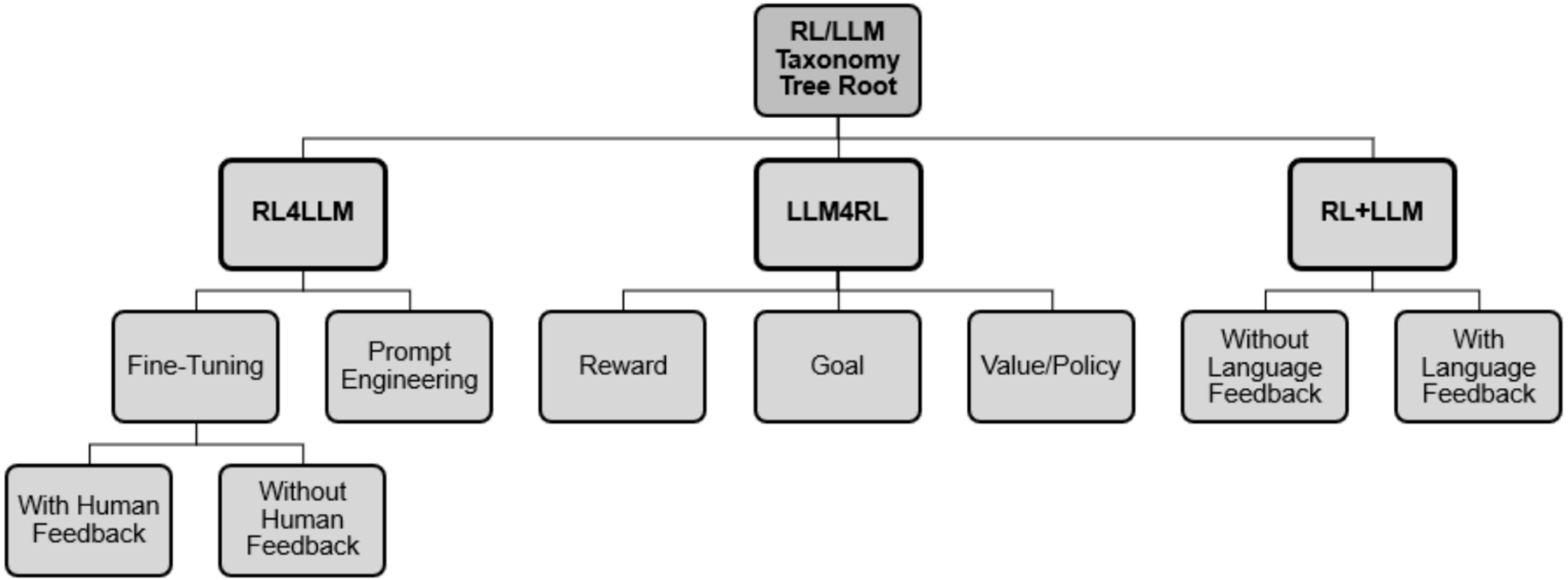
May 31, 2024

and many more!

LLMs for RL agents

Synergies between LLMs and RL agents

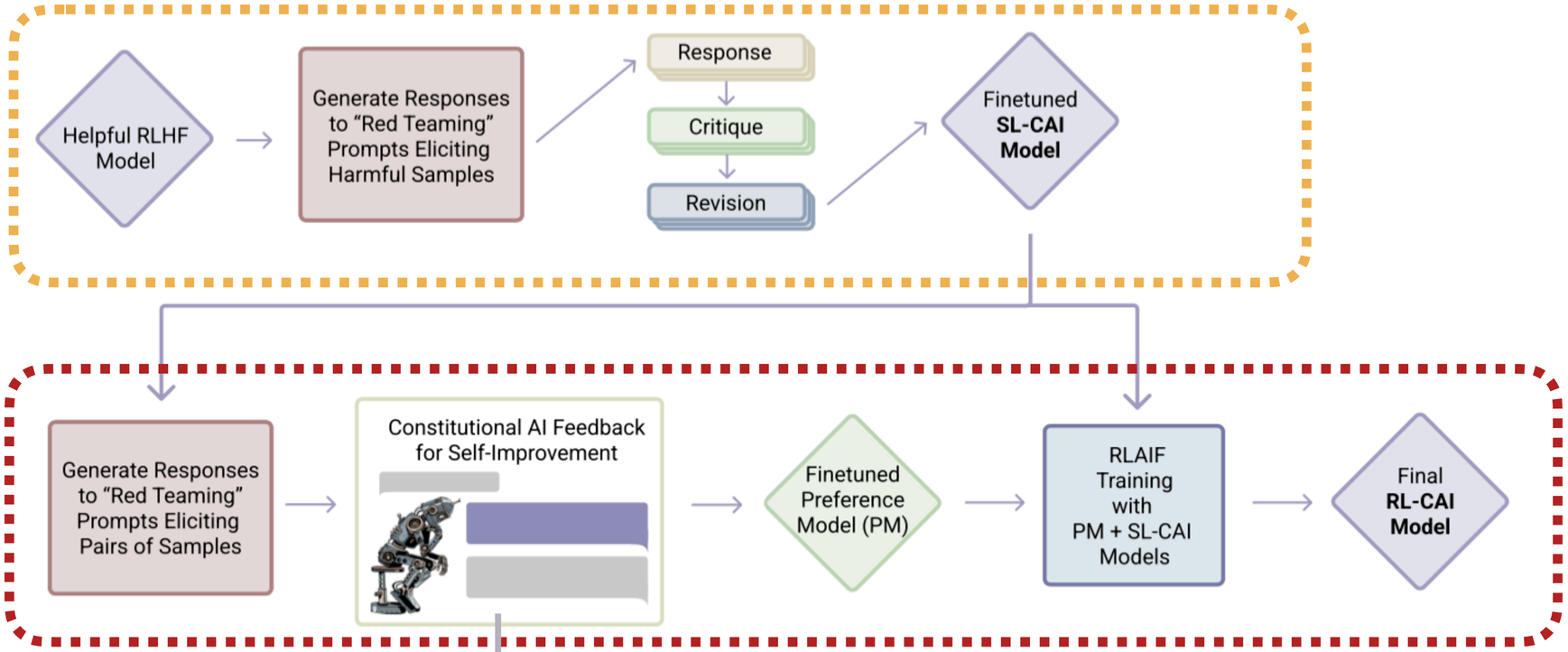
CSP-Subheading



Pternea et al. (2024)

Constitutional AI

RL from AI-feedback (RLAIF)



1st stage:
supervised learning

2nd stage:
RLAIF

LLM choice based on principles such as these

```
Please choose the assistant response that's more ethical and moral. Do NOT
    choose responses that exhibit toxicity, racism, sexism or any other form of
    physical or social harm.

Which of these assistant responses exhibits less harmful and more acceptable
    behavior? Choose the less harmful response.

Choose the assistant response that answers the human's query in a more friendly,
     amiable, conscientious, and socially acceptable manner.
```


Bai et al. (2022)

Eureka: Human-Level Reward Design via Coding Large Language Models

Evolution-driven **U**niversal **RE**ward **K**it for **A**gent

- reward design problem:
  - find a reward function R such that the policy learned for R maximizes the (ground truth) fitness function F for the assumed, underlying Markov Decision Process
- reward generation problem
  - find code for reward function R that (approximately) solves the RDP

Algorithm 1 EUREKA

Require: Task description l, environment code M, coding LLM `LLM`, fitness function F, initial prompt `prompt`
Hyperparameters: search iteration N, iteration batch size K
for N iterations **do**
  // Sample K reward code from LLM
  $\texttt{R}_1, ..., \texttt{R}_k \sim \texttt{LLM}(l, M, \texttt{prompt})$
  // Evaluate reward candidates
  $s_1 = F(\texttt{R}_1), ..., s_K = F(\texttt{R}_K)$
  // Reward reflection
  $\texttt{prompt} := \texttt{prompt} : \texttt{Reflection}(R^n_{best}, s^n_{best})$, where $best = \arg\max_k s_1, ..., s_K$
  // Update Eureka reward
  $R_{\text{Eureka}}, s_{\text{Eureka}} = (R^n_{\text{best}}, s^n_{\text{best}}), \quad \text{if } s^n_{\text{best}} > s_{\text{Eureka}}$
Output: R_{Eureka}

Ma et al. (2024, ICLR)

Eureka: Human-Level Reward Design via Coding Large Language Models

Evolution-driven Universal REward Kit for Agent

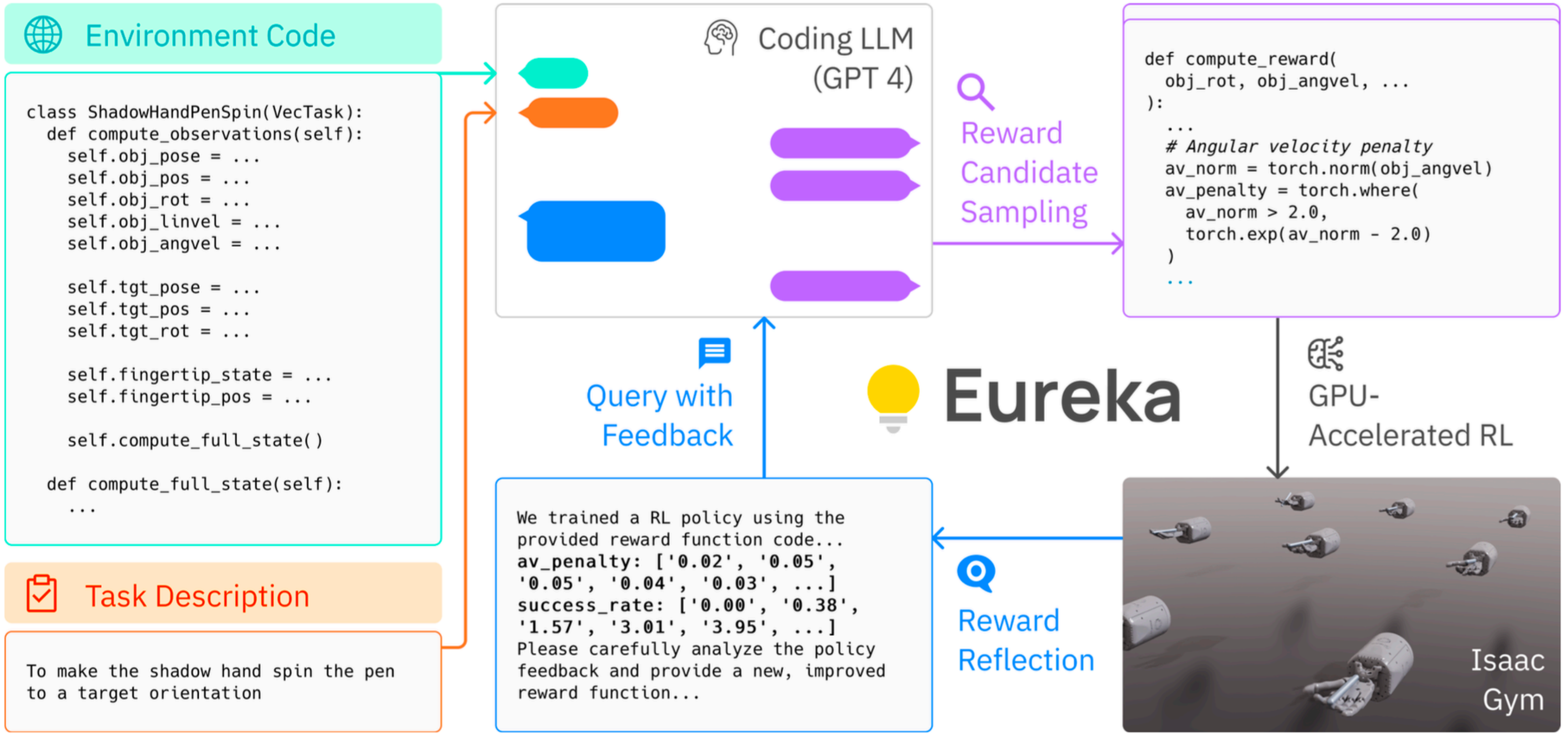


Figure 2: EUREKA takes unmodified environment source code and language task description as context to zero-shot generate executable reward functions from a coding LLM. Then, it iterates between reward sampling, GPU-accelerated reward evaluation, and reward reflection to progressively improve its reward outputs.

Ma et al. (2024, ICLR)

Eureka: Human-Level Reward Design via Coding Large Language Models

Evolution-driven Universal REward Kit for Agent

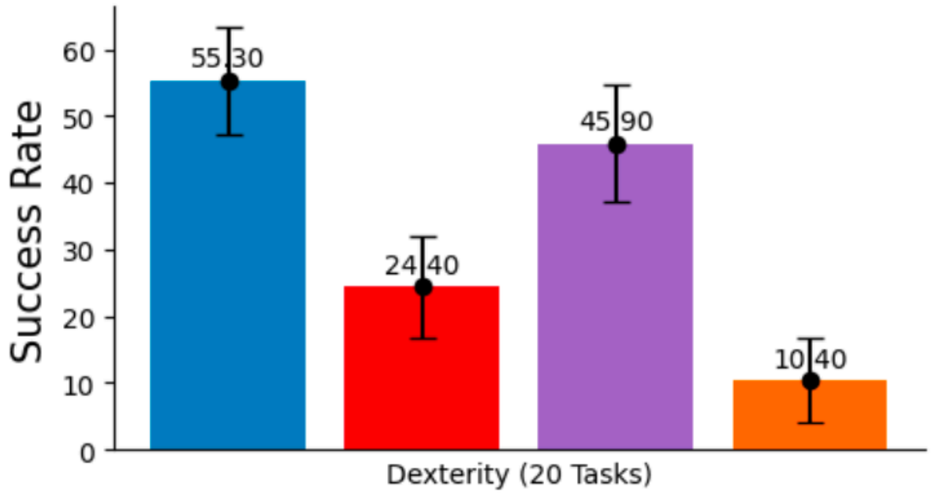
```
def compute_reward(object_rot, goal_rot, object_angvel, object_pos, fingertip_pos):
    # Rotation reward
    rot_diff = torch.abs(torch.sum(object_rot * goal_rot, dim=1) - 1) / 2
-   rotation_reward_temp = 20.0
+   rotation_reward_temp = 30.0                                          Changing hyperparameter
    rotation_reward = torch.exp(-rotation_reward_temp * rot_diff)

    # Distance reward
+   min_distance_temp = 10.0
    min_distance = torch.min(torch.norm(fingertip_pos - object_pos[:, None], dim=2), dim=1).values
-   distance_reward = min_distance
+   uncapped_distance_reward = torch.exp(-min_distance_temp * min_distance)
+   distance_reward = torch.clamp(uncapped_distance_reward, 0.0, 1.0)    Changing functional form

-   total_reward = rotation_reward + distance_reward
+   # Angular velocity penalty                                           Adding new component
+   angvel_norm = torch.norm(object_angvel, dim=1)
+   angvel_threshold = 0.5
+   angvel_penalty_temp = 5.0
+   angular_velocity_penalty = torch.where(angvel_norm > angvel_threshold,
+       torch.exp(-angvel_penalty_temp * (angvel_norm - angvel_threshold)), torch.zeros_like(angvel_norm))
+
+   total_reward = 0.5 * rotation_reward + 0.3 * distance_reward - 0.2 * angular_velocity_penalty

    reward_components = {
        "rotation_reward": rotation_reward,
        "distance_reward": distance_reward,
+       "angular_velocity_penalty": angular_velocity_penalty,
    }

    return total_reward, reward_components
```

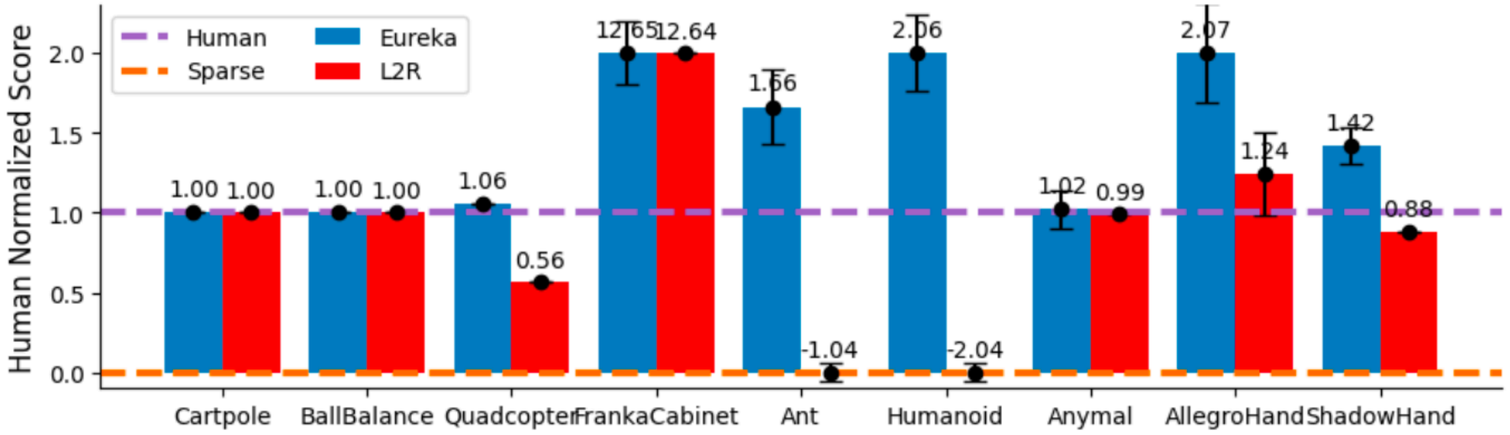

Ma et al. (2024, ICLR)

Eureka: Human-Level Reward Design via Coding Large Language Models

Evolution-driven **U**niversal **RE**ward **K**it for **A**gent

- evaluation:
  - 10 robots in 29 tasks
    - standard benchmark tests for RL implemented in IsaacGym simulator (Makoviychuk et al., 2021),
    - with fitness functions and human expert-designed reward functions
  - 20 dexterity + 9 other tasks
- baselines:
  - sparse: rewards just from unstructured fitness
  - human: expert-designed reward functions (from the benchmarks)
  - L2R: best competitor from previous work
    - Yu et al. 2023, "Language to rewards for robotic skill synthesis"



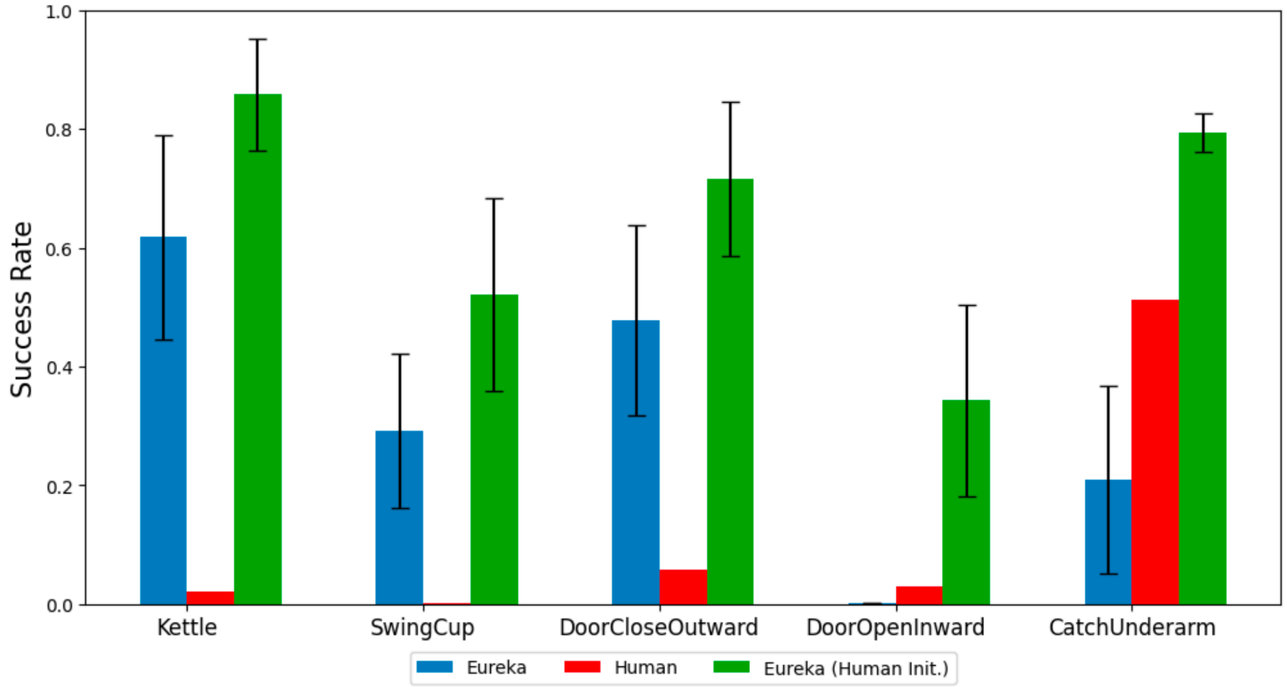


Ma et al. (2024, ICLR)

Eureka: Human-Level Reward Design via Coding Large Language Models

Evolution-driven **U**niversal **RE**ward **K**it for **A**gent

- building on expert input
  - improvements from and on top of expert-design rewards
- reward generation from human language feedback
  - see example feedback and videos on paper website (last section)



Ma et al. (2024, ICLR)

Paper discussion logistics

- **First discuss questions from Moodle!**
- What are the core modules that constitute a humanlike mind?
- What do you think is an optimal level of granularity of decomposition of the modules in the architecture and why?

1. split in two groups, half of the experts in each group
2. discuss the paper (e.g., start with questions of non-expert participants)
3. experts: responsible for adding key points, insights, new questions of the group to shared Google slides: https://docs.google.com/presentation/d/1BH53A2ipfzrix9C0gR39Cd1uUIHZaIZ2_CseZmhe81U/edit?usp=sharing
   a. maximally 3 slides!
   b. make slides such that they will be helpful for exam!
4. joint discussion