Reinforcement Learning & RL with Human Feedback (RLHF)

DL4DS – Spring 2024

DS598 B1 Gardos

April Dates

Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
	April 1	2	3	4 **GANs**	5	6
7	8	9 **VAEs**	10 **Discussion**	11 **Diffusion Models**	12	13
14	15	16 **Graph Neural Nets (VizWiz Leaders Share)**	17 **Discussion**	18 **Office Hours**	19	20
21	22	23 **RL/RLHF**	24 **Discussion**	25 **★ Project Presentations 1 ★**	26	27
28	29	30 **★ Project Presentations 2 ★**	May 1 **Discussion??**	2 Study Period	3 Study Period	4
5	6 Final Exams	7 Final report & Repo **	8	9	10	11

** Might be earlier. Depends on when grades are due.

Project Presentations

Format:
≤ 3 minutes screencast/video
≤ 2 minutes additional presentation
~2 minutes Q&A

Final project info updated on Gradescope and website.

April 25 – 75 minutes

1. Osama Dabbousi
2. Carmen Pelayo Fernandez
3. Anush Veeranala, Lilin Jin, Xinyu Zhang
4. Bowen Li
5. Yuta Tsukumo
6. Zhengxiong Zouxu
7. Hang Yu, Yinzhou Lu
8. Zhandong Jiao

April 30 – 75 minutes

1. Seung Hee Lee, Xinyi Hu, Yuke Zhang
2. Jessica Cannon
3. Sungjoon Park
4. Anh Pham, Farid Karimli
5. Nikhita Mantravadi
6. Ishan Ranjan, Jack Campbell, Rani Shah
7. Andy Yang, Weining Mai
8. Ruozhu Wang, Yi Liu, Zhuoyan Ma
9. Kevin Quinn

Outline

- RL basic concepts
- Deep reinforcement learning from human preferences (2017)
- Training language models to follow instructions with human feedback (2022)

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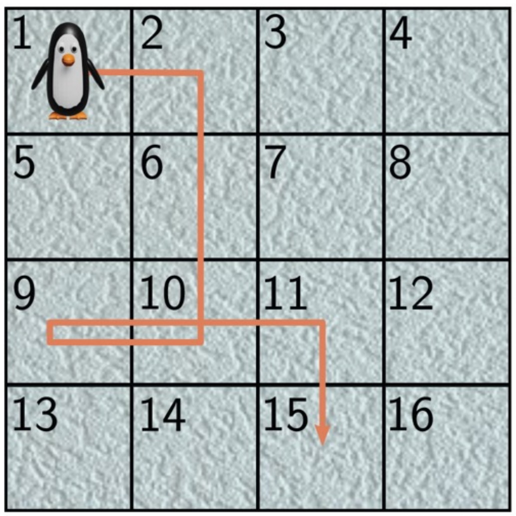
In a nutshell…

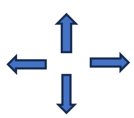
RL is the study of agents and how they learn by trial and error.

It formalizes the idea that rewarding or penalizing an agent for its behavior makes it more or less likely, respectively, to repeat that behavior in the future.

Markov Process



$$\begin{array}{c} \quad s_1, s_2, s_3, s_4, s_5, s_6, s_7, s_8 \\ \boldsymbol{\tau} = [1, 2, 6, 10, 9, 10, 11, 15] \end{array}$$

Can only go 

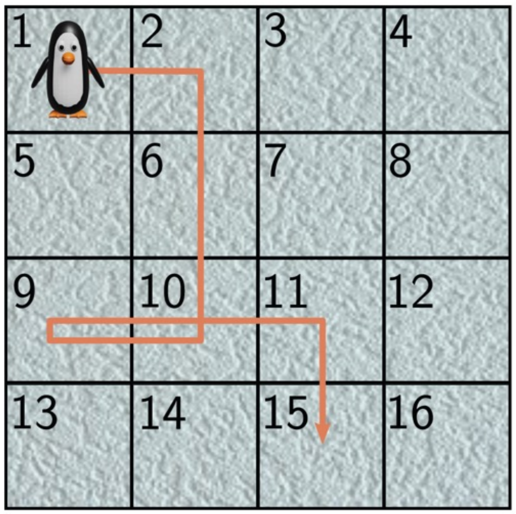
World is described by a set of states s

Changes between states are represented by *transition probabilities* $\Pr(s_{t+1}|s_t)$

Markov process produces a sequence of states $s_1, s_2, s_3, \ldots$

A *trajectory* is the sequence of states $\tau = [s_1, s_2, s_3, \ldots]$

Markov Process – Transition Probabilities



$$s_1, s_2, s_3, s_4, s_5, s_6, s_7, s_8$$

$$\boldsymbol{\tau} = [1, 2, 6, 10, 9, 10, 11, 15]$$

$$\begin{array}{cc} & s_t \\ s_{t+1} & \begin{bmatrix} 0 & 0.33 & 0 & 0 & 0.33 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.5 & 0 & 0.33 & 0 & 0 & 0.25 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.33 & 0 & 0.5 & 0 & 0 & 0.25 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.33 & 0 & 0 & 0 & 0 & 0.33 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.5 & 0 & 0 & 0 & 0 & 0.25 & 0 & 0 & 0.33 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.33 & 0 & 0 & 0.33 & 0 & 0.25 & 0 & 0 & 0.25 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.33 & 0 & 0 & 0.25 & 0 & 0.33 & 0 & 0 & 0.25 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.5 & 0 & 0 & 0.25 & 0 & 0 & 0 & 0 & 0.33 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.33 & 0 & 0 & 0 & 0 & 0.25 & 0 & 0 & 0.5 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.25 & 0 & 0 & 0.33 & 0 & 0.25 & 0 & 0 & 0.33 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.25 & 0 & 0 & 0.25 & 0 & 0.33 & 0 & 0 & 0.33 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.33 & 0 & 0 & 0.25 & 0 & 0 & 0 & 0 & 0.5 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.33 & 0 & 0 & 0 & 0 & 0.33 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.25 & 0 & 0 & 0.5 & 0 & 0.33 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.25 & 0 & 0 & 0.33 & 0 & 0.5 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.33 & 0 & 0 & 0.33 & 0 \end{bmatrix} \end{array}$$

$$Pr(s_{t+1} | s_t)$$

Transition probability from square 1 to square n

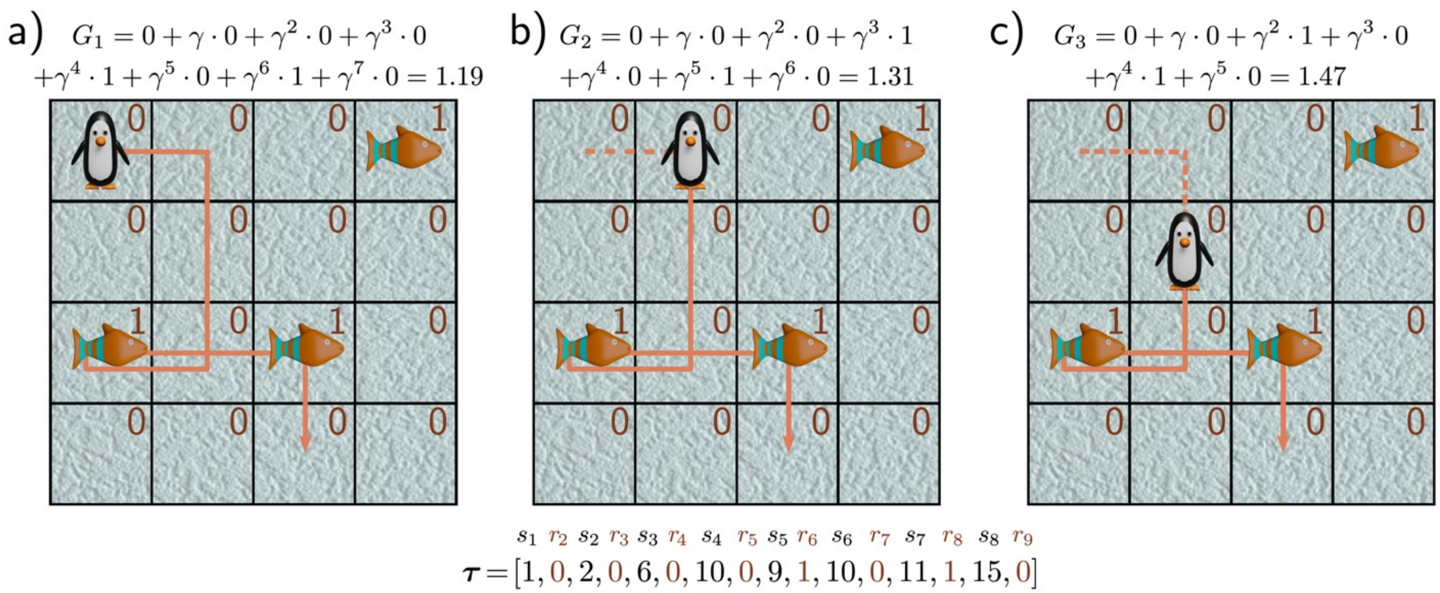
Equally likely to go in any allowable direction.

Markov reward process

Distribution of rewards at next time step given current state: $\Pr(r_{t+1}|s_t)$

The *return* G_t is the sum of discounted future rewards

$$G_t = \sum_{k=0}^{\infty} \gamma^k r_{t+k+1} \quad \text{where} \quad \gamma \in (0,1]$$

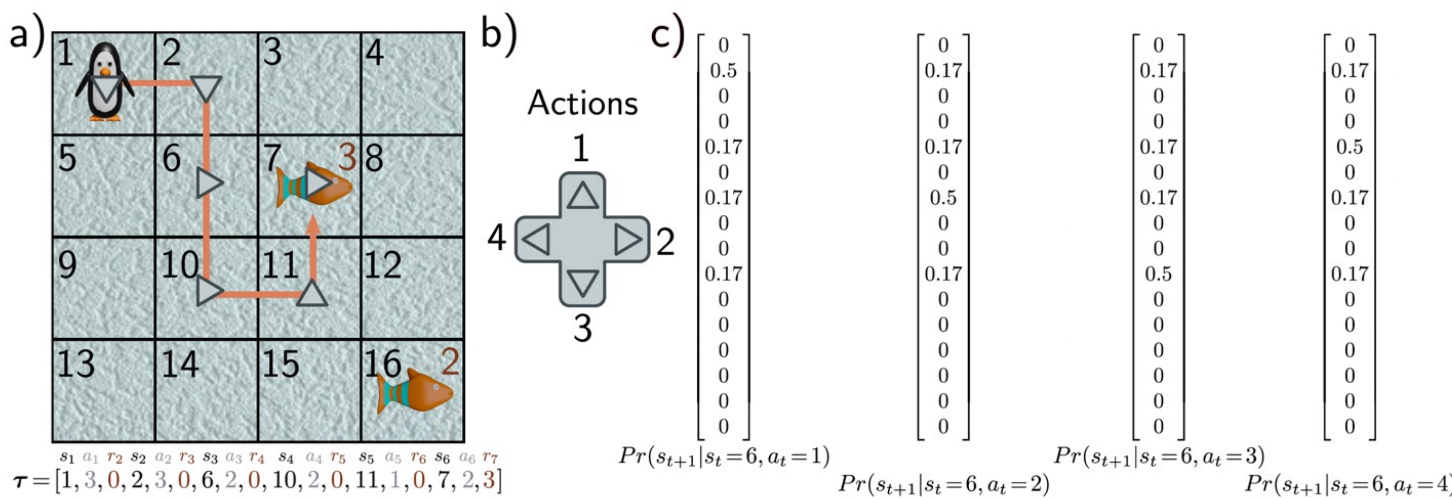


Trajectory now comprised of state and the next reward

Markov decision process (MDP)

Adds a set of of possible actions at each time step that changes transition and reward probabilities

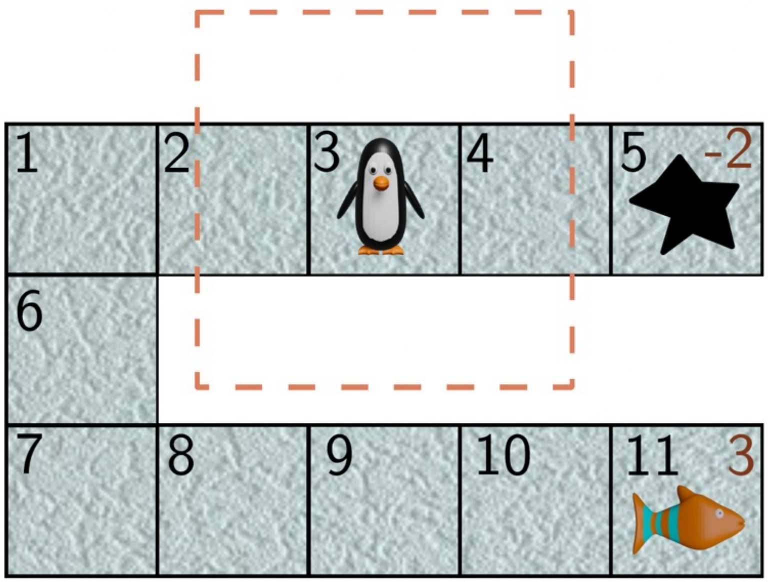
$$\Pr(s_{t+1}|s_t, a_t) \quad \text{and} \quad \Pr(r_{t+1}|s_t, a_t)$$



Trajectory now consists of states, actions and rewards

Action is not deterministic

Partially observable Markov decision process (POMDP)



The state is not directly visible, but instead receives an observation o_t drawn from $\Pr(o_t|s_t)$

Penguin can only see what is in the dashed box.

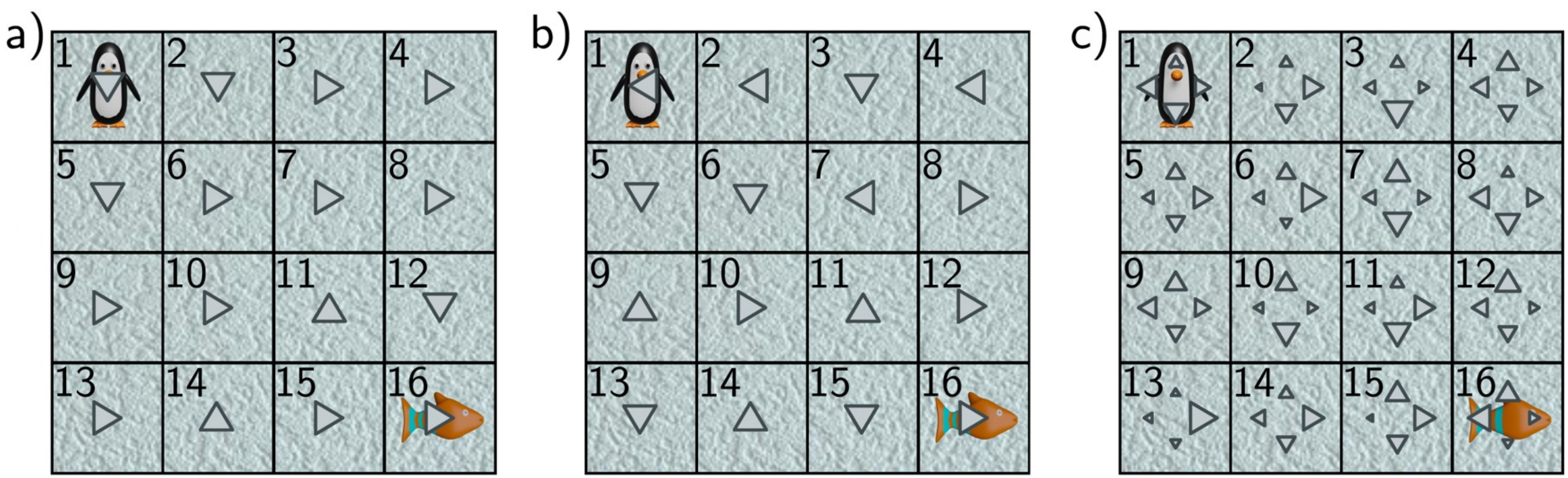
Indistinguishable from what it would see from box 9.

Policy

The rules that determine the agent's (e.g. penguin's) action for each state: $\pi[a|s]$

Can be *deterministic* or *stochastic*

Can be *stationary* or *non-stationary (time dependent)*

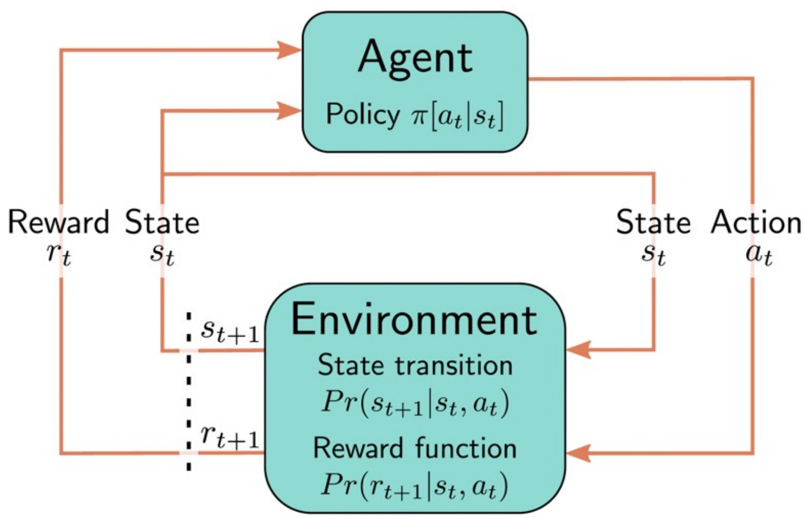


Better deterministic policy

Poorer deterministic policy

Stochastic policy

Full reinforcement learning loop



Agent receives the state (or observation) and reward.

Then (optionally modifies the policy and) choose next action.

Environment then assigns next state and reward according to transition probabilities.

RLHF as RL

"We can think of the main model as an agent that takes sequential actions (choose tokens) and receives a delayed reward from the reward model when the last token is chosen"

Prince, "Training and fine-tuning large language models," 2023, blog

Outline

- RL basic concepts
- Deep reinforcement learning from human preferences (2017)
- Training language models to follow instructions with human feedback (2022)

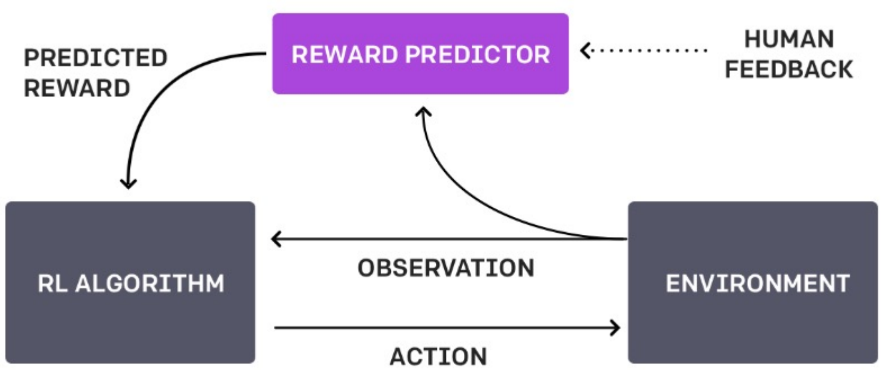
Aligning to Human Preferences

"One step towards building safe AI systems is to remove the need for humans to write goal functions, since using a simple proxy for a complex goal, or getting the complex goal a bit wrong, can lead to undesirable and even dangerous behavior.

…, we've developed an algorithm which can infer what humans want by being told which of two proposed behaviors is better."

https://openai.com/research/learning-from-human-preferences, 2017

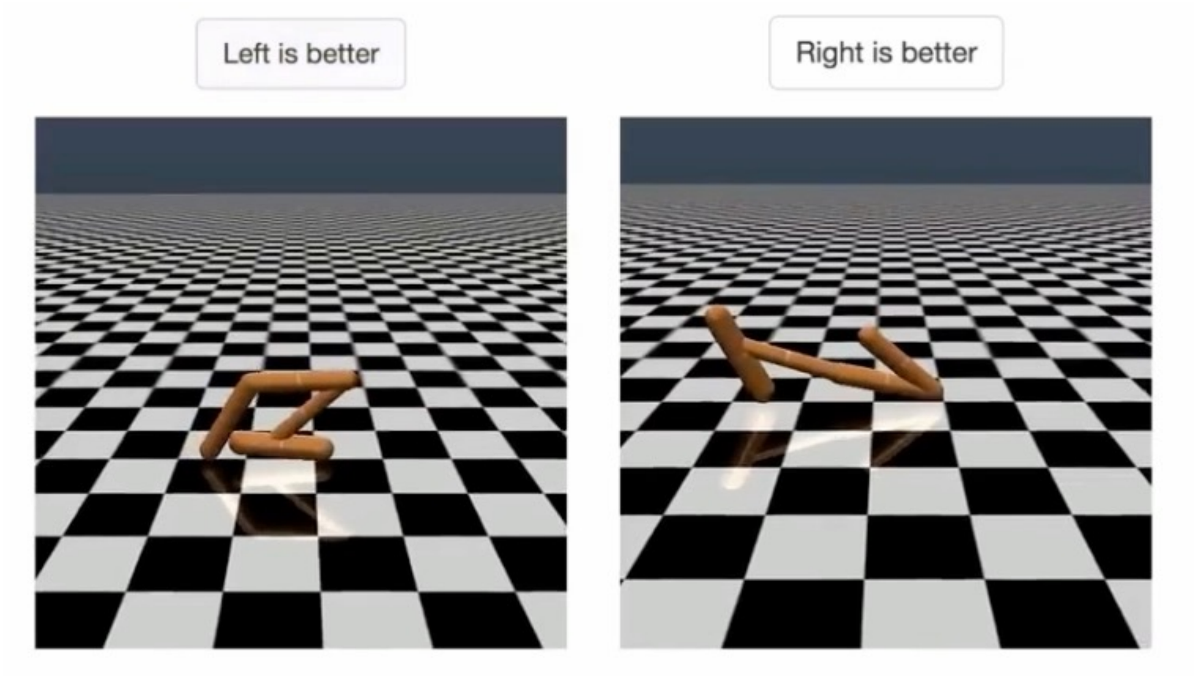
Originally developed to improve RL systems



- Starts by acting randomly
- Gives 2 examples to a human who votes on which is closer to achieving goal
- AI builds reward model to match human votes
- Continues to seek feedback on trajectory pairs that are most uncertain

Christiano et al (OpenAI), "Deep Reinforcement Learning from Human Preferences," 2017

Originally developed to improve RL systems

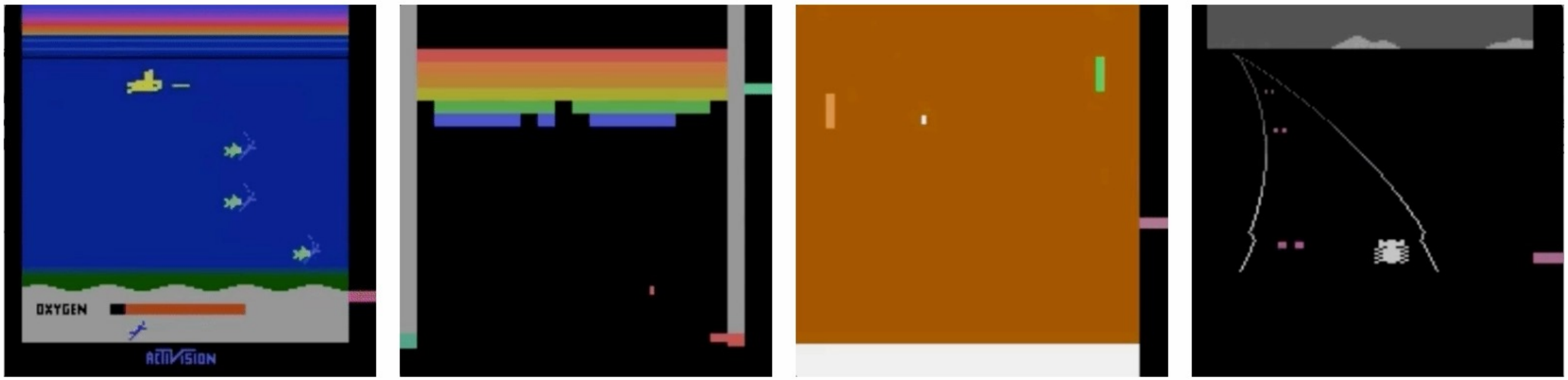


- Trained with ~1 hour of evaluator time
- Background policy accumulated ~70 hours of experience

https://openai.com/research/learning-from-human-preferences, 2017

Christiano et al (OpenAI), “Deep Reinforcement Learning from Human Preferences,” 2017

Originally developed to improve RL systems



- Learned Atari with only human reward model (right vertical bar)
- Without access to game score as reward
- Human feedback sometimes does better than normal reward function

https://openai.com/research/learning-from-human-preferences, 2017

Christiano et al (OpenAI), "Deep Reinforcement Learning from Human Preferences," 2017

Deep RL from Human Preferences

Assume human overseer who can express preferences between trajectory segments

$$\sigma = \big((o_0, a_0), (o_1, a_1), \ldots, (o_{k-1}, a_{k-1})\big) \in (\mathcal{O} \times \mathcal{A})^k$$

We write

$$\sigma^1 \succ \sigma^2$$

to indicate that the human preferred trajectory σ^1 to σ^2.

Goal of Agent: Produce trajectories preferred by human, while making as few queries as possible to the human.

Christiano et al (OpenAI), "Deep Reinforcement Learning from Human Preferences," 2017

Deep RL from Human Preferences

Preferences are *generated* by a reward function $r : \mathcal{O} \times \mathcal{A} \to \mathbb{R}$ if

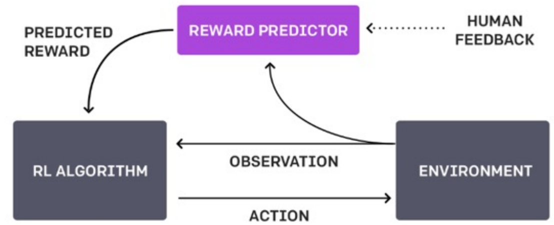
$$\left((o_0^1, a_0^1), \ldots, (o_{k-1}^1, a_{k-1}^1)\right) \succ ((o_0^2, \quad a_0^2), \ldots, (o_{k-1}^2, \quad a_{k-1}^2))$$

whenever

$$r(o_0^1, a_0^1) + \cdots + r\left(o_k^1, a_k^1\right) > r(o_0^2, a_0^2) + \cdots + r(o_{k-1}^2, o_{k-1}^2)$$

Christiano et al (OpenAI), "Deep Reinforcement Learning from Human Preferences," 2017

Deep RL from Human Preferences -- Method



At each point in time,

- maintain a policy $\pi : \mathcal{O} \to \mathcal{A}$
- and a reward function estimate $\hat{r} : \mathcal{O} \times \mathcal{A} \to \mathbb{R}$

each parameterized by deep neural networks.

Christiano et al (OpenAI), “Deep Reinforcement Learning from Human Preferences,” 2017

Deep RL from Human Preferences -- Method

The policy and reward estimate networks are updated by three processes

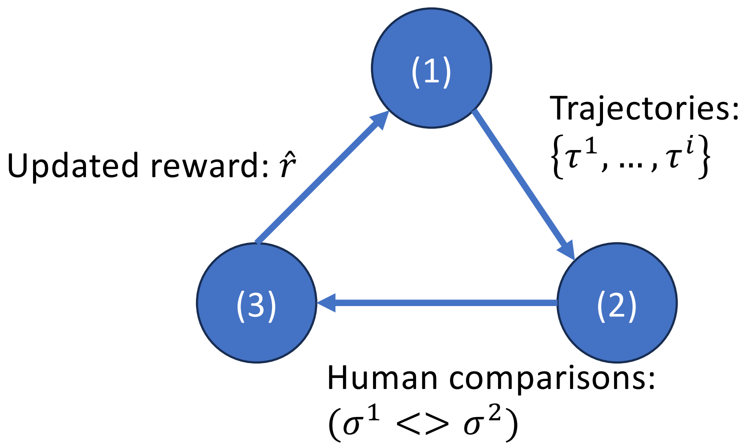
1. Policy π interacts with the environment to produce a set of trajectories $\{\tau^1, \dots, \tau^i\}$, where π is updated with traditional RL to maximize sum of predicted rewards
2. Select pairs of segments $(\sigma^1, \sigma^2)$from trajectories $\{\tau^1, \dots, \tau^i\}$ and query human for comparison.
3. Parameters of reward estimate $\hat{r}$ are optimized via supervised learning to fit human comparisons

Christiano et al (OpenAI), "Deep Reinforcement Learning from Human Preferences," 2017

Deep RL from Human Preferences -- Method

The policy and reward estimate networks are updated by three processes

1. Learn policy π and produce trajectories $\{\tau^1, \ldots, \tau^i\}$
2. Select pairs of segments (σ^1, σ^2) and query human
3. Update reward estimate $\hat{r}$ to match human comparisons



Processes run asynchronously

Christiano et al (OpenAI), "Deep Reinforcement Learning from Human Preferences," 2017

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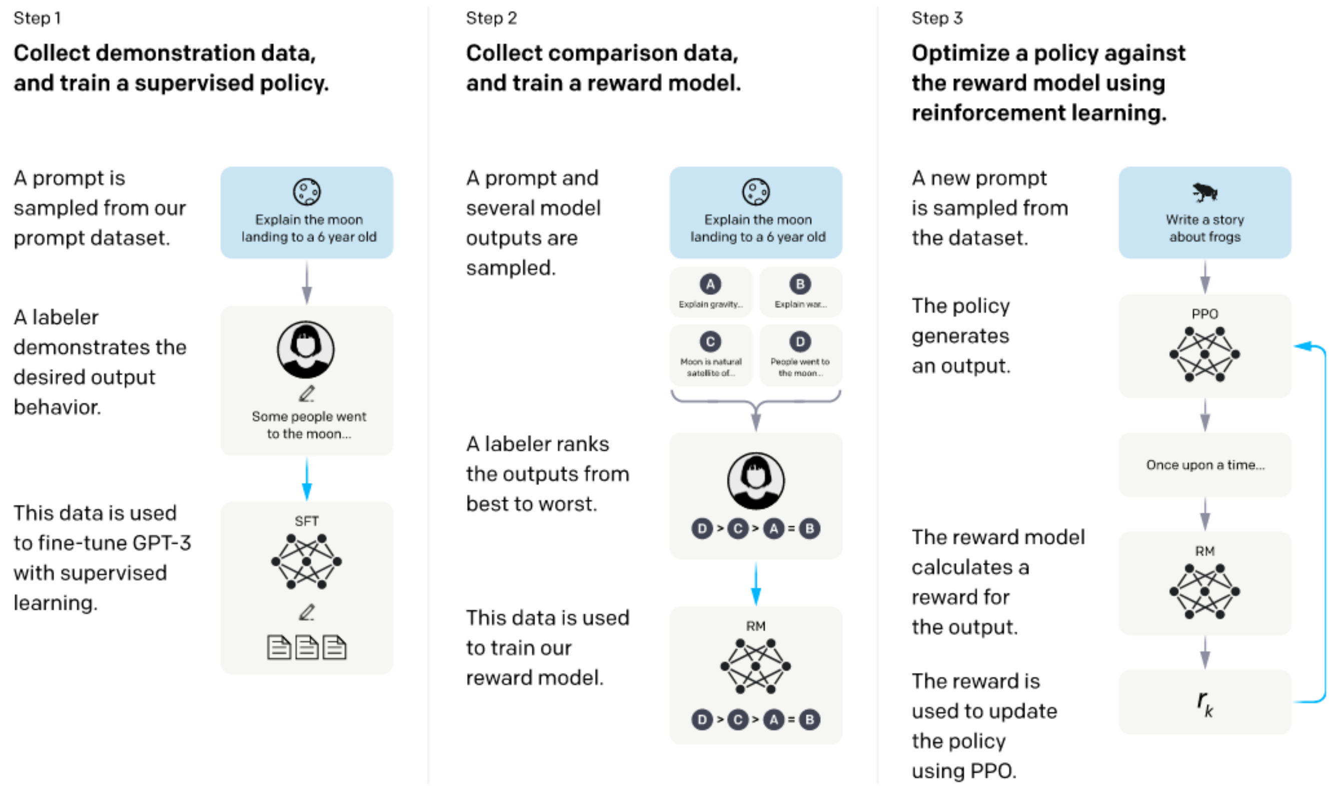
3 Steps



Supervised Fine-Tuning

Reward Model (RM) Training

Reinforcement Learning via Proximal Policy Optimization on this Reward Model

L. Ouyang *et al.*, “Training language models to follow instructions with human feedback,” 2022

Supervised (Instruction) Fine Tuning

Create a dataset of ~10,000 prompts and fine-tuned responses.

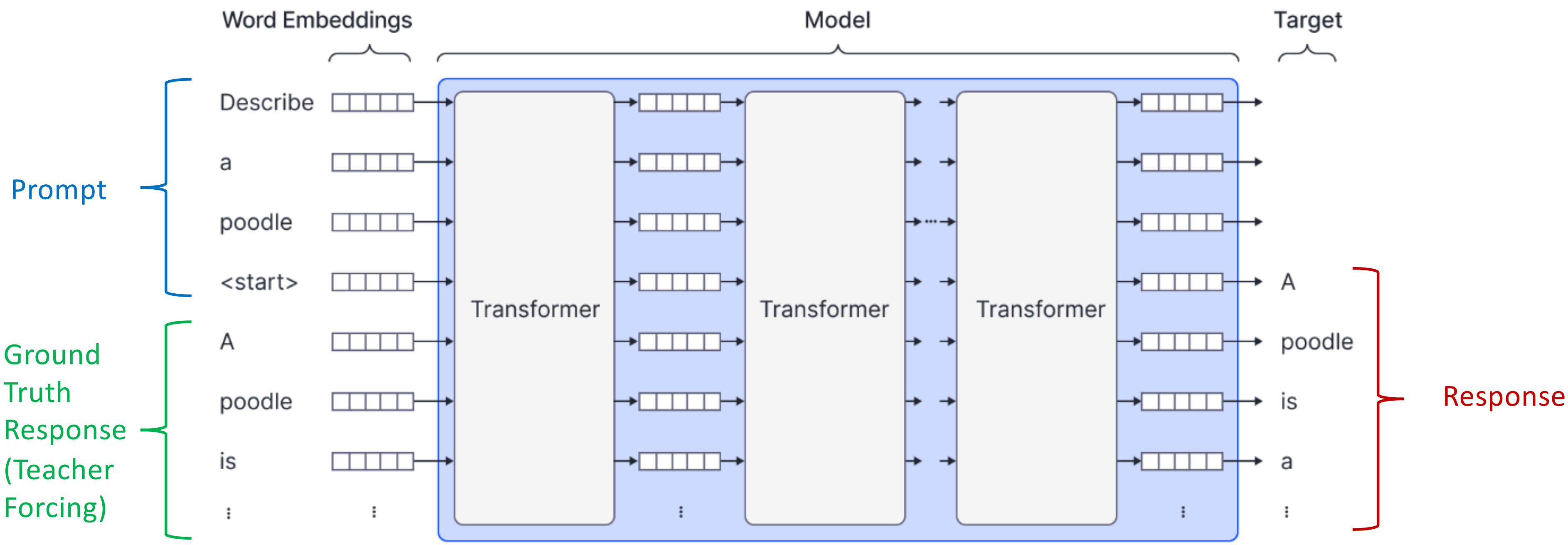
Denoting the tokens for the i^{th} prompt by $\mathbf{x}_i = [x_{i,1}, x_{i,2}, \ldots]$ and the tokens in the corresponding response by $\mathbf{y}_i = [y_{i,1}, y_{i,2}, \ldots y_{i,T_i}]$, the loss function can now be written as:

$$L[\boldsymbol{\phi}] = -\sum_{i=1}^{I}\sum_{t=1}^{T_i} \log\Big[Pr(y_{i,t+1}|\mathbf{x}_i, y_{i,1\ldots t}, \boldsymbol{\phi})\Big].$$

where once more $\boldsymbol{\phi}$ represents the model parameters.

Prince, "Training fine-tuning LLMs", 2023, blog

Supervised (Instruction) Fine Tuning



Prince, “Training fine-tuning LLMs”, 2023, blog

Reward Modeling

Train a neural network, e.g. start with the SFT model with the last layers replaced.

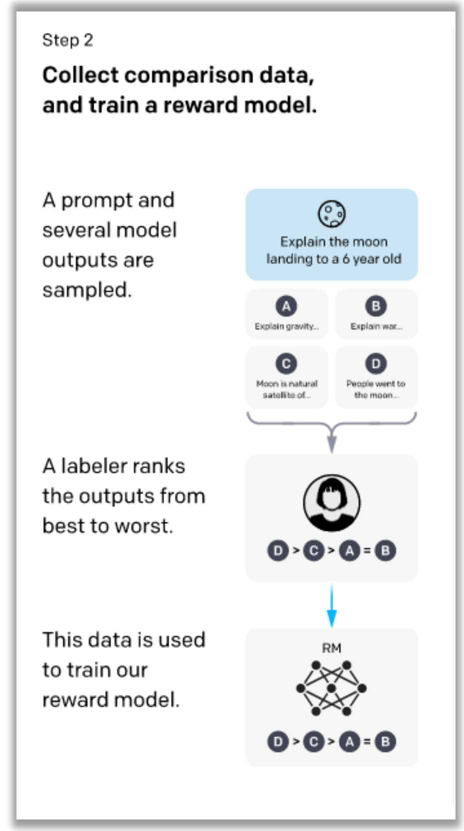
Present labelers between $K = 4$ and $K = 9$ responses to rank.

This produces $\binom{K}{2}$ comparisons for each prompt.

The loss function for the reward model is:

$$\operatorname{loss}(\theta) = -\frac{1}{\binom{K}{2}} E_{(x, y_w, y_l) \sim D}\left[\log\left(\sigma\left(r_\theta\left(x, y_w\right) - r_\theta\left(x, y_l\right)\right)\right)\right]$$

where $r_\theta(x, y)$ is the scalar output of the reward model for prompt x and completion y with parameters θ, y_w is the preferred completion (winner) versus y_l, and D is the data set of human comparisons.

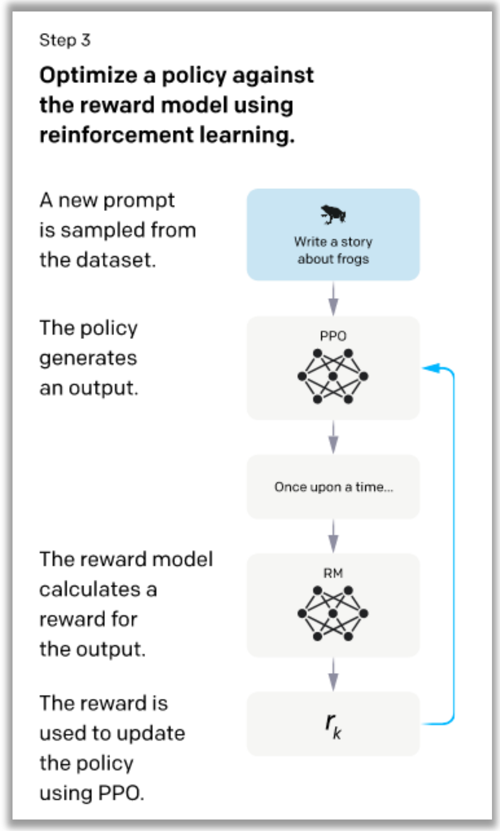


L. Ouyang *et al.*, "Training language models to follow instructions with human feedback," 2022

Reinforcement Learning (RL)

Continue training the SFT model to maximize the following objective:

$$\max_{\pi_\theta} \mathbb{E}_{x\sim\mathcal{D}, y\sim\pi_\theta(y|x)}\left[r_\phi(x,y)\right] - \beta\mathbb{D}_{\mathrm{KL}}\left[\pi_\theta(y \mid x) \;||\; \pi_{\mathrm{ref}}(y \mid x)\right]$$



L. Ouyang *et al.*, "Training language models to follow instructions with human feedback," 2022
N. Lambert, "Reinforcement Learning from Human Feedback," 2023

Next

- Project Presentations
- Fill out course evaluations