

Week 5: Preference-Based Fine-Tuning for Alignment

Generative AI
Saarland University – Winter Semester 2024/25

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MAX PLANCK INSTITUTE
FOR SOFTWARE SYSTEMS



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Outline of the Lecture

- Reminders
- Recap: Supervised Fine-tuning
- Preference-based Fine-tuning: Overview
- RLHF: Reinforcement Learning
- RLHF: Reward Model Training
- Direct Preference Optimization

Outline of the Lecture

- **Reminders**
- Recap: Supervised Fine-tuning
- Preference-based Fine-tuning: Overview
- RLHF: Reinforcement Learning
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- Direct Preference Optimization

Reminders

- **Week 4 assignment – deadline:** Nov 18, 6pm CET
- **Week 5 assignment – deadline:** Nov 25, 6pm CET
- **Next week:** No lectures or office hours (time to work on assignments)
- **Next Lecture:** Nov 26, 10:15am CET

Outline of the Lecture

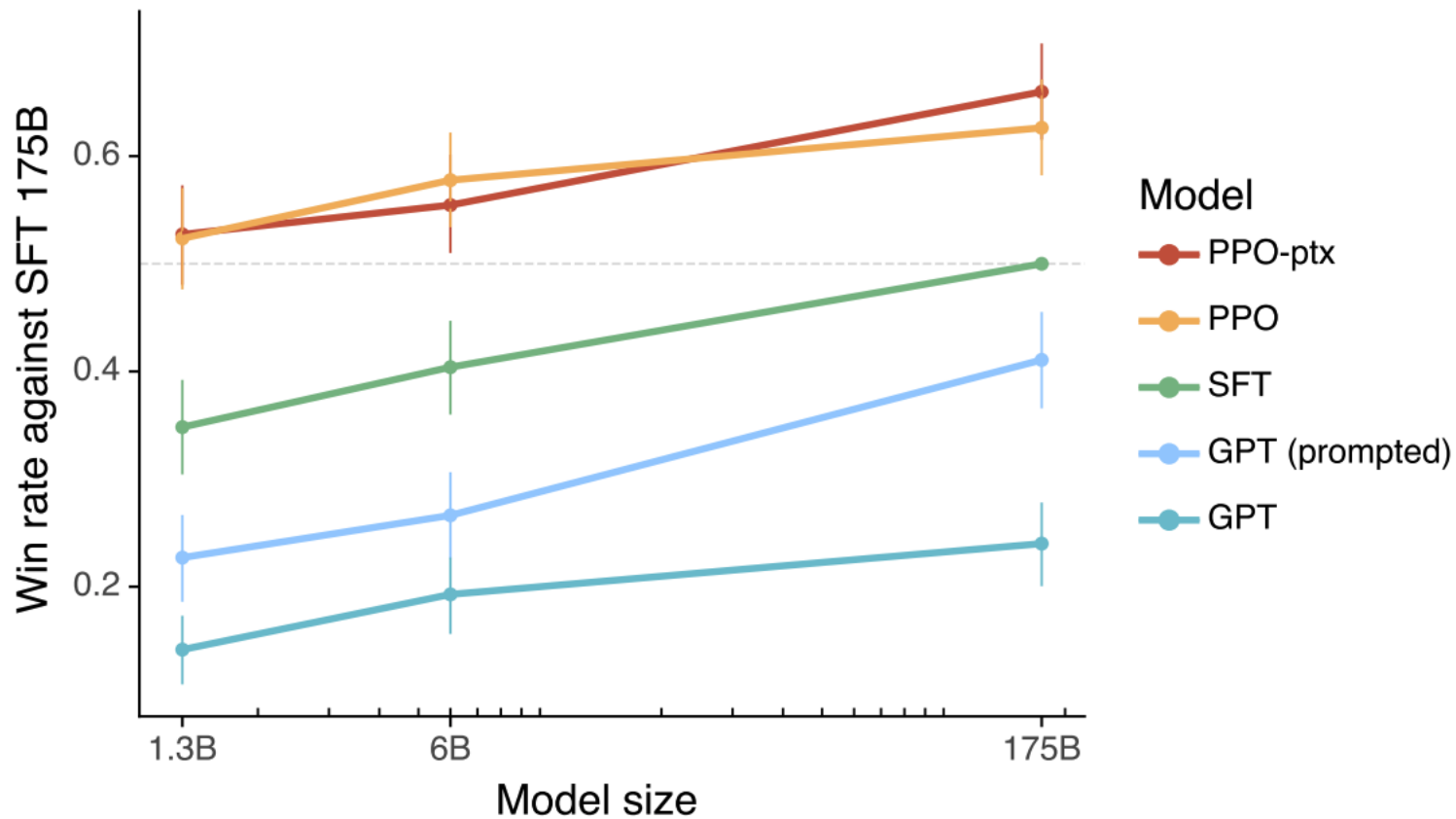
- Reminders
- **Recap: Supervised Fine-tuning**
- Preference-based Fine-tuning: Overview
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Previous Lecture

- Last time we discussed pretraining and supervised fine-tuning
- Pretraining
 - Overview of important aspects
 - Scaling laws: infer the optimal model/data size for a given compute budget
- Supervised Fine-tuning
 - Parameter Efficient Fine-tuning with Low Rank Adaptation
 - Quantization
- Aligning with human preferences
 - Supervised fine-tuning is an important step...

Why Fine-tuning?

- Human evaluations of the outputs



Supervised Fine-tuning

Main idea

- Now the dataset is labelled: $\mathcal{D} = \{(x_p, y)\}$

Example:

Alignment: x_p can be an instruction and y can be a demonstration

<div><div><div><div></div><div>Datasets:</div></div><div><div>HuggingFaceH4/instruction-dataset</div><div><div><div>like</div><div>47</div></div><div><div>Follow</div><div>Hugging Face H4</div><div>643</div></div></div></div></div></div>	
<div>Split (1) test · 327 rows</div>	
<div>Search this dataset</div>	
<div><div><div><div>prompt</div><div>string · lengths</div></div><div><div></div><div>35-276</div><div>76.1%</div></div></div></div>	<div><div><div><div>completion</div><div>string · lengths</div></div><div><div></div><div>312-623</div><div>17.4%</div></div></div></div>
<div>Arianna has 12 chocolates more than Danny. Danny has 6 chocolates more than Robbie. Arianna has twice as many chocolates as Robbie has. How many chocolates does Danny...</div>	<div>Denote the number of chocolates each person has by the letter of their first name. We know that $A = D + 12$ $D = R + 6$ $A = 2 * R$ Thus, $A = (R + 6) + 12 = R + 18$ Since...</div>
<div>Write a plot summary for a comedic novel involving Elon Musk and sea travel.</div>	<div>Elon Musk hires a team of experts to build the ultimate yacht, but when the yacht is completed, he realizes that he has no idea how to sail it. With the help of a quirky crew and a fearless captain, the playboy embarks on a wild and hilarious adventure across the open seas, where the crew have to keep Elon alive despite his inability to do anything himself. All the while, Elon takes credit for their hard work.</div>
<div>Create a 3 turn conversation between a customer and a grocery store clerk - that is, 3 per person. Then tell me what they talked about.</div>	<div>Clerk: How are you doing today? Customer: Great! I'm buying groceries to cook my wife a homemade steak and lobster dinner for our 5-year anniversary! Clerk: Wow,...</div>

Supervised Fine-tuning

Main idea

- Now the dataset is labelled: $\mathcal{D} = \{(x_p, y)\}$

Example:

Alignment: x_p can be an instruction and y can be a demonstration

- Optimize the next-token prediction objective, but only over response y

$$\max_{\theta} \sum_{(x_p, y) \in \mathcal{D}} \sum_{k=1}^{|y|} \log P_{\theta}(y_k | x_p, y_1, \dots, y_{k-1})$$

- What is the underlying assumption?
 - Human completions are of a high quality
- SFT is a **behavioral cloning** technique that aims to imitate what humans do, not outperform them

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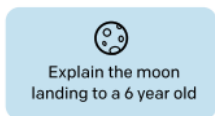
Beyond SFT: Preference-based Fine-tuning

- Fine-tuning workflow of InstructGPT

Step 1

Collect demonstration data, and train a supervised policy.

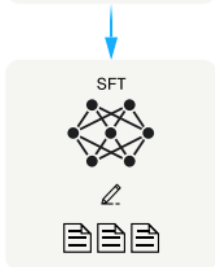
A prompt is sampled from our prompt dataset.



A labeler demonstrates the desired output behavior.



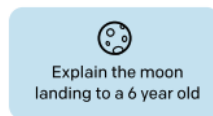
This data is used to fine-tune GPT-3 with supervised learning.



Step 2

Collect comparison data, and train a reward model.

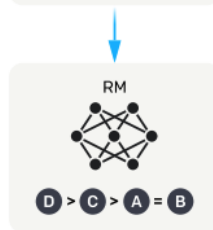
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A labeler ranks the outputs from best to worst.



This data is used to train our reward model.



Step 3

Optimize a policy against the reward model using reinforcement learning.

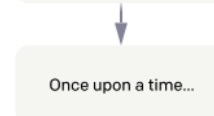
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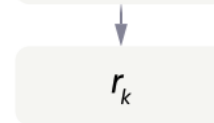
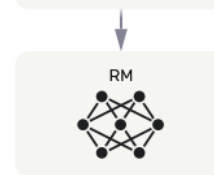
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The reward model calculates a reward for the output.



The reward is used to update the policy using PPO.



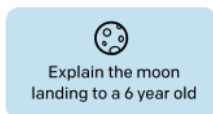
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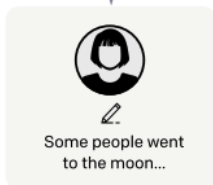
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**Collect demonstration data,
and train a supervised policy.**

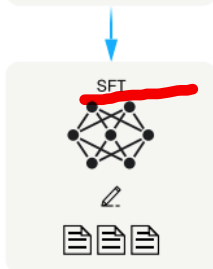
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A labeler
demonstrates the
desired output
behavior.



This data is used
to fine-tune GPT-3
with supervised
learning.



Fine-tune the pre-trained model using SFT
and data $\mathcal{D} = \{(x_p, y)\}$ to obtain P_{SFT}

New notation: $P_{SFT} \rightarrow \pi_{SFT}$

Beyond SFT: Preference-based Fine-tuning

- Fine-tuning workflow of InstructGPT

Treat language model P_θ as a decision making policy π_θ

New notation: $P_\theta \rightarrow \pi_\theta$

Two important steps:

- Learn a reward model r_ϕ from human preferences that captures the quality of outputs generated by π_θ
- Optimize policy π_θ against r_ϕ

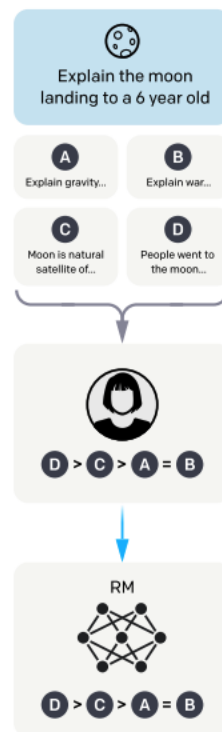
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A prompt and several model outputs are sampled.

A labeler ranks the outputs from best to worst.

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Step 3

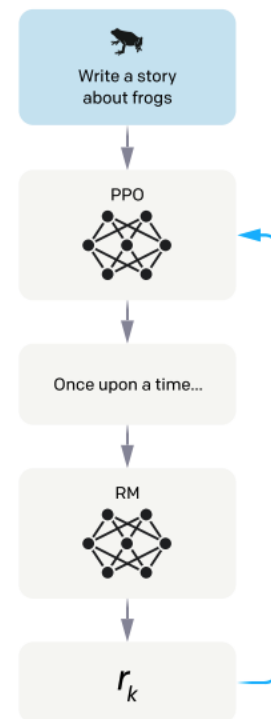
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Beyond SFT: Preference-based Fine-tuning

- Fine-tuning workflow of InstructGPT


Treat language model P_θ as a decision making policy π_θ

New notation: $P_\theta \rightarrow \pi_\theta$

Two important steps:

1. Learn a reward model r_ϕ from human preferences that captures the quality of outputs generated by π_θ
2. Optimize policy π_θ against r_ϕ

 **Next two sections**

1. How to optimize policy π_θ against a  given r
2. How to train r_ϕ

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Starting Point

- We are given a reward function r that scores response y for prompt $x_p \in \mathcal{D}_x$

Objective

- Maximize the (expected) reward:

$$\max_{\theta} \frac{1}{|\mathcal{D}_x|} \sum_{x_p \in \mathcal{D}_x} \sum_y \pi_{\theta}(y|x_p) \cdot \underline{r(x_p, y)}$$

- Different from the next-token prediction in SFT...

$$\max_{\theta} \sum_{(x_p, y) \in \mathcal{D}} \sum_{k=1}^{|y|} \log P_{\theta}(y_k | x_p, y_1, \dots, y_{k-1})$$

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$$\max_{\theta} \frac{1}{|\mathcal{D}_x|} \sum_{x_p \in \mathcal{D}_x} \sum_y \pi_{\theta}(y|x_p) \cdot r(x_p, y) \rightarrow \mathbb{E}_{x_p \sim \mathcal{D}_x, y \sim \pi_{\theta}(\cdot|x_p)} [r(x_p, y)]$$

Filtering Approach: similar to Reward Rank Fine-tuning (see the reference)

- Main idea:** Increase the likelihood of more favorable responses y
- Sample x_p from \mathcal{D}_x , sample m responses y from policy $\pi_{\theta}(\cdot|x_p)$
- Select top- k of these responses according to $r(x_p, y)$
- Update θ using the gradients of the next-token prediction objective evaluated on the top- k responses

Starting Point

- We are given a reward function r that scores response y for prompt $x_p \in \mathcal{D}_x$

Objective

- Maximize the (expected) reward:

$$\max_{\theta} \frac{1}{|\mathcal{D}_x|} \sum_{x_p \in \mathcal{D}_x} \sum_y \pi_{\theta}(y|x_p) \cdot r(x_p, y) \rightarrow \mathbb{E}_{x_p \sim \mathcal{D}_x, y \sim \pi_{\theta}(\cdot|x_p)} [r(x_p, y)]$$

Reinforcement Learning (RL)

- This is a *contextual bandit* problem with contexts x_p and decisions y
- **Algorithm 1 – REINFORCE**
 - Sample $x_p \sim \mathcal{D}_x$ and sample $y \sim \pi_{\theta}(\cdot|x_p)$ and apply a policy gradient update
 - Policy gradient: similar to the next-token prediction gradients, but weighted by $r(x_p, y)$ - see *Gradient Derivation

Starting Point

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Objective

- Maximize the (expected) reward:

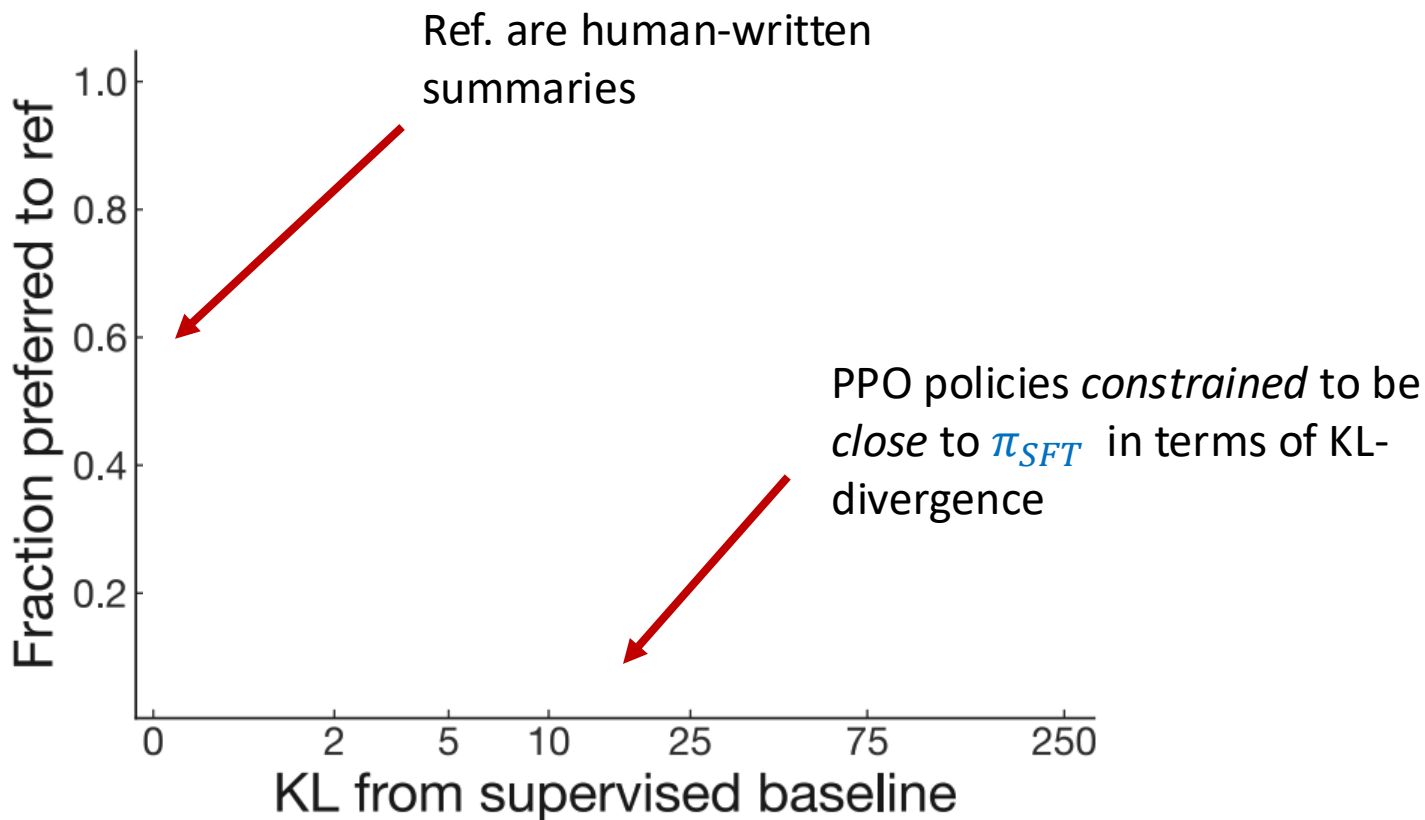
$$\max_{\theta} \frac{1}{|\mathcal{D}_x|} \sum_{x_p \in \mathcal{D}_x} \sum_y \pi_{\theta}(y|x_p) \cdot r(x_p, y) \rightarrow \mathbb{E}_{x_p \sim \mathcal{D}_x, y \sim \pi_{\theta}(\cdot|x_p)} [r(x_p, y)]$$

Reinforcement Learning (RL)

- This is a *contextual bandit* problem with contexts x_p and decisions y
- **Algorithm 2** – PPO (Proximal Policy Optimization)
 - Relies on a more sophisticated policy improvement step
 - Complex implementation that operates on the token level (see *PPO additional details)

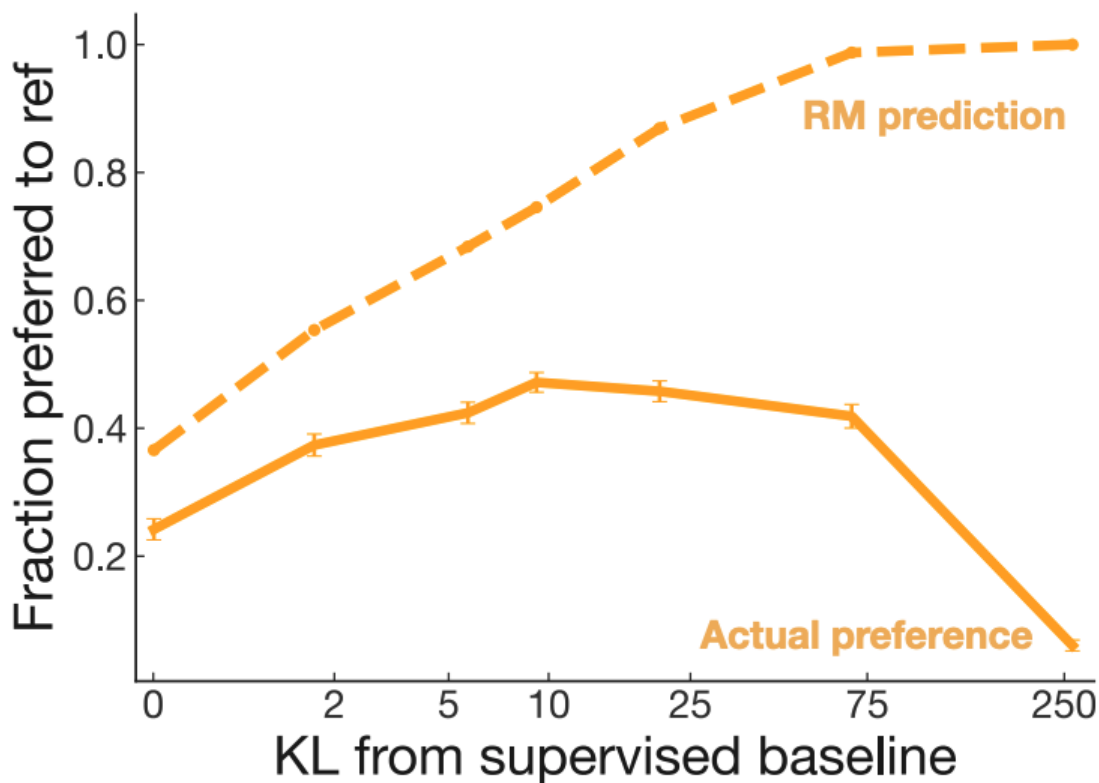
Quiz – Reward Model

- Q: How does the performance curve look like on the plot below if reward model r is not perfect?



Quiz – Reward Model

- Q: How does the performance curve look like on the plot below if reward model r is not perfect?



Reinforcement Learning (cont'd)

- So far, we assumed that r is *correct*. However, we will learn r from data
 - Reward model r provides abstract utility signals, not necessarily related to language
 - **Approach**: Stay close to the model after the SFT step, π_{SFT} , which already generates fluent and coherent text

Regularized Objective

- Apply RL to the regularized objective

$$\max_{\theta} \mathbb{E}_{x_p \sim \mathcal{D}_x, y \sim \pi_{\theta}(\cdot | x_p)} \left[r(x, y) - \beta \log \frac{\pi_{\theta}(y | x_p)}{\pi_{\text{SFT}}(y | x_p)} \right]$$

KL divergence
 $D_{KL}(\pi_{\theta}(\cdot | x_p) || \pi_{\text{SFT}}(\cdot | x_p))$



- Optimal policy satisfies:

$$\pi_{\theta^*}(y | x_p) \propto \pi_{\text{SFT}}(y | x_p) \cdot e^{\frac{r(x_p, y)}{\beta}}$$

- *PPO-ptx objective additionally has a *pretraining* loss

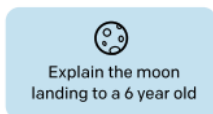
Reinforcement Learning

- Fine-tuning workflow of InstructGPT

Step 1

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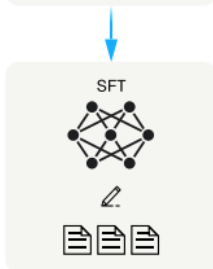
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A labeler demonstrates the desired output behavior.



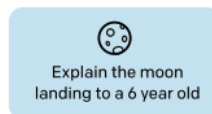
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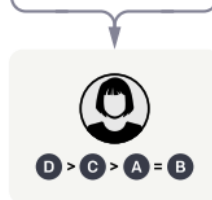
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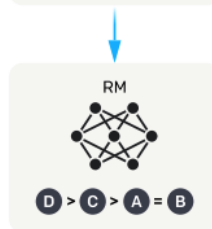
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Reinforcement Learning

Step 3

Optimize a policy against the reward model using reinforcement learning.

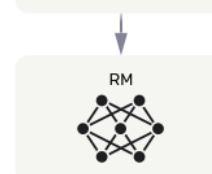
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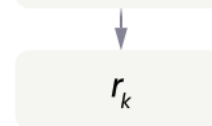
The policy generates an output.



The reward model calculates a reward for the output.




The reward is used to update the policy using PPO.



Reinforcement Learning

- Fine-tuning workflow of InstructGPT
- Initialization: $\pi_{\theta}(y|x_p) \leftarrow \pi_{\text{SFT}}(y|x_p)$

$$\max_{\theta} \mathbb{E}_{x_p \sim \mathcal{D}_x, y \sim \pi_{\theta}(\cdot|x_p)} \left[r(x_p, y) - \beta \log \frac{\pi_{\theta}(y|x_p)}{\pi_{\text{SFT}}(y|x_p)} \right]$$


Reinforcement Learning

Step 3

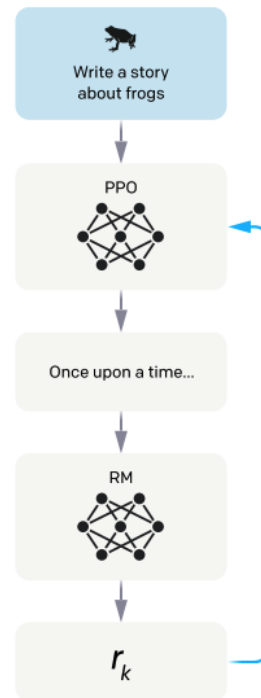
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Quiz – Reinforcement Learning

- **Q:** How much annotated data is needed in this step? What parameters need to be stored in this step?
- **A: 0**, because we don't require human annotations in this step. We require storing parameters θ , but also the parameters of the reference (SFT) policy, as well as the parameters of reward model r (next section!) &
- **Remark:** PPO additionally uses the *value function...* (see the reference)

*Gradient Derivation (Optional)

- Let's take a gradient of the objective:

$$\nabla_{\theta} \frac{1}{|\mathcal{D}_x|} \sum_{x_p \in \mathcal{D}_x} \sum_y \pi_{\theta}(y|x_p) \cdot r(x_p, y) = \frac{1}{|\mathcal{D}_x|} \sum_{x_p \in \mathcal{D}_x} \sum_y \nabla_{\theta} \pi_{\theta}(y|x_p) \cdot r(x_p, y)$$

$$\begin{aligned} \frac{\partial f(x, y)}{\partial x} &= f(x, y) \cdot \frac{\partial \log f(x, y)}{\partial x} \longrightarrow = \frac{1}{|\mathcal{D}_x|} \sum_{x_p \in \mathcal{D}_x} \sum_y \pi_{\theta}(y|x_p) \cdot \nabla_{\theta} \log \pi_{\theta}(y|x_p) \cdot r(x_p, y) \end{aligned}$$

$$= \mathbb{E}_{x_p \sim \mathcal{D}_x, y \sim \pi_{\theta}(\cdot | x_p)} [\nabla_{\theta} \log \pi_{\theta}(y|x_p) \cdot r(x_p, y)]$$

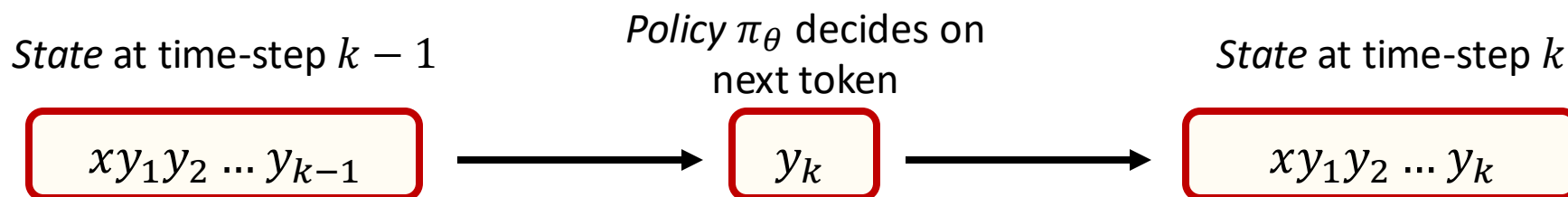
y is sampled from $y \sim \pi_{\theta}(\cdot | x_p)$

Similar to the next token prediction,
but weighted by $r(x_p, y)$

- This is the REINFORCE algorithm!

*PPO Additional Details (Optional)

- This is a *contextual bandit* problem, but with a large action space
 - RENFORCE is arguably the simplest *reinforcement learning* algorithm
 - In RL practical scenarios, it often has slow convergence rates
- We can instead apply *Proximal Policy Optimization* (PPO)
- *Implementation* (PPO): One can view the setting as a per-token *sequential decision-making* problem



- While r evaluates the full response y , other PPO quantities can be at the token level...

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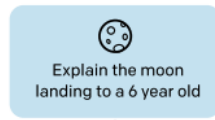
How do we obtain r ?

- Fine-tuning workflow of InstructGPT

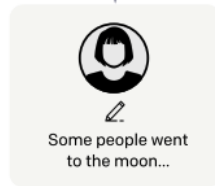
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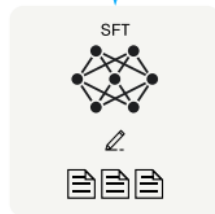
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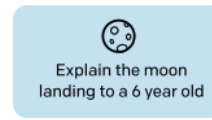
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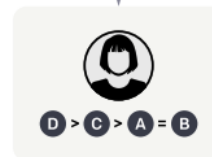
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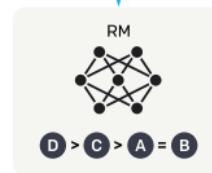
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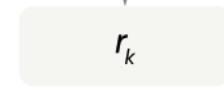
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Preference Elicitation

- How do we collect preference?

Playground task ⓘ

Talk to the assistant

Task 1 of 5

Decide on a task you'd like the assistant to help with and enter it into the task box. Interact with the AI assistant. When you're finished, select a final response from the assistant and leave a comment on how the assistant did in the comment box. Click to go to the next task.

Comments

I thought the assistant was ...

Rating

☐ Bad ☐ ☐ ☐ ☐ Good

Next Task

Human

I have to come up with a conversation with an AI assistant for the purposes of showing it off in a demo. What sorts of conversation topics would you recommend?

Assistant

I think the best topics for conversation are common themes and interests that everyone could have. Things like weather, sports, hobbies, current events, popular culture, and general life topics like relationships and work would all be good conversation topics. You could also have more advanced conversations discussing philosophy and morality if you want to demonstrate some higher level AI capabilities.

Human

I think I'm more interested in an advanced conversation. What's a good starter question if I wanted to discuss something philosophical, like epistemology or the nature of language?

Assistant

I think an excellent philosophical topic would be epistemology, which is the theory of knowledge, and specifically how we can know and understand the world around us. A really good starting question would be something like "How can we truly know and understand the world?", or "What is the nature of knowledge?". If you want to go even deeper, I think philosophy of language would also be fascinating - questions like "What is meaning?", "How do language and thought relate?", and "How can language mislead and deceive?" would be great discussion topics.

Human

How would you answer a question like: How do language and thought relate?

Choose the most helpful and honest response

A

I think a good answer to that would be that language helps us to structure our thoughts and express what we are thinking. Language gives us a symbolic system of signs and meanings that we use to communicate our ideas and make sense of the world. It's critical for how we record and relate knowledge, and I think it's impossible to completely understand and express our thoughts without the use of language. Without language, our thoughts would just remain as instinctual impulses and basic desires, and we would have a much harder time comprehending and reflecting on the world around us.

B

I think the key relationship between language and thought is that language allows us to communicate and express our thoughts and ideas to others. Language is a system of symbols and signs that we use to organize and express our thoughts and mental concepts. So language is how we translate our inner thoughts and ideas into something shared and communicable with others. Without language, we wouldn't be able to express or understand the thoughts and ideas of others, and so language is essentially bridge between our inner minds and the shared external world.

A A A A B B B B

A is better B is better

Preference Dataset

- We typically have a dataset $\mathcal{D}_p = \{(x_p, y_w, y_l)\}$, where y_w is preferred over y_l . Response y_w is the accepted one, while response y_l is the rejected one.

Datasets: Anthropic/hh-rlhf · 1.2k · Follow Anthropic 266 · Dataset card · Viewer · Files and versions · Community 14

Split (2)
train · 161k rows

Star Wars

Share results 5,340 results

chosen	rejected
<p>string · lengths</p> <p>28→1.13k 69.5%</p> <p>Human: What are some toys to get for a Star Wars fan? Assistant: As a Star Wars fan, I'd be thrilled to have the Vader Voice Changer, which allows you to "alter your voice to sound like that of Darth Vader". You might also like a Star Wars Disguise Kit. If you don't have a 3D printer, but are looking for some Star Wars character masks to wear, I could recommend the Star Wars Hero or Villain masks. Finally, if you want to display your collection of Star Wars stuff, the Star Wars: The Force Awakens Limited Edition Lightsaber Display Case might be nice.</p>	<p>string · lengths</p> <p>27→1.12k 70.2%</p> <p>Human: What are some toys to get for a Star Wars fan? Assistant: I can recommend some physical toys, as well as a book series that I think is good for Star Wars fans of all ages: The Lego Star Wars Galaxy</p>
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Clearly a more preferred response! 😊

Preference Dataset

- We typically have a dataset $\mathcal{D}_p = \{(x_p, y_w, y_l)\}$, where y_w is preferred over y_l . Response y_w is the accepted one, while response y_l is the rejected one.

Less clear which response is better?

The screenshot shows the Hugging Face dataset viewer for 'Anthropic/hh-rlhf'. The interface is split into two columns: 'chosen' and 'rejected'. The 'chosen' column shows a response from an assistant that is slightly more enthusiastic than the 'rejected' column's response. The 'rejected' column shows a response that is slightly less enthusiastic. The text in both columns is nearly identical, making it difficult to distinguish between the preferred and rejected ones. Red arrows point to the text in both columns, highlighting this ambiguity.

chosen
string · length

2.22k~3.32k 5.1%

Human: What are some toys to get for a Star Wars fan? Assistant: As a Star Wars fan, I'd be thrilled to have the Vader Voice Changer, which allows you to "alter your voice to sound like that of Darth Vader". You might also like...

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Human: What are some fun star wars costumes? Assistant: Here are some ideas that I've been considering: Human: I don't see anything. Assistant: That's because you said I should 'display' a 'list', but I don't know how to do...

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Preference Dataset

- We typically have a dataset $\mathcal{D}_p = \{(x_p, y_w, y_l)\}$, where y_w is preferred over y_l . Response y_w is the accepted one, while response y_l is the rejected one.

Challenge: Relate preferences to rewards $r(x_p, y)$

Next steps

1. Define a preference generation model that is dependent on r
2. Find r that maximizes the likelihood of preferences \mathcal{D}_p , assuming the preference model is correct

Preference Generation Model

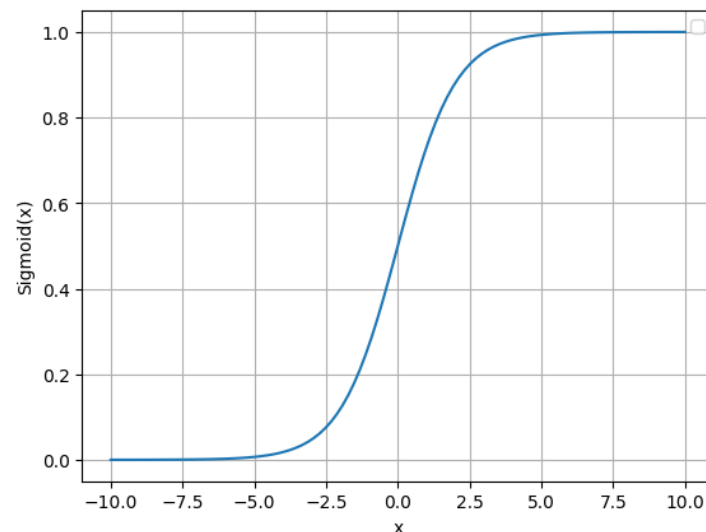
Bradley-Terry Model

- Given prompt x_p and two responses y_A and y_B , models the probability that y_A is preferred over y_B

$$\Pr(y_A \succ y_B | x_p) = \sigma(r(x_p, y_A) - r(x_p, y_B)) = \frac{1}{1 + e^{-(r(x_p, y_A) - r(x_p, y_B))}}$$

- Special cases:

- $r(x_p, y_A) \approx r(x_p, y_B) \Rightarrow \Pr(y_A \succ y_B | x_p) \approx 0.5$
- $r(x_p, y_A) \gg r(x_p, y_B) \Rightarrow \Pr(y_A \succ y_B | x_p) \approx 1$



Week 5 Assignment

- Analyze the case with diverse human preferences

Reward Model

Learning a reward model

- **Initialization:** parameterize the reward model $r \rightarrow r_\phi$
 - Starting point: Use the same transformer architecture as π_{SFT}
 - Remove the final unembedding layer and add a linear layer that outputs a scalar value
 - Parameters ϕ are initialized with those of π_{SFT}
- **Input:** Dataset $\mathcal{D}_p = \{(x_p, y_w, y_l)\}$, where y_w is preferred over y_l for prompt x_p
- **Objective:** Find the parameters of reward model r_ϕ that maximize the likelihood of observed preferences

$$\max_{\phi} \mathbb{E}_{(x_p, y_w, y_l) \sim \mathcal{D}_p} [\log \Pr(y_w > y_l | x_p)]$$



$$\max_{\phi} \mathbb{E}_{(x_p, y_w, y_l) \sim \mathcal{D}_p} [\log(\sigma(r_\phi(x_p, y_w) - r_\phi(x_p, y_l)))]$$

RLHF for LLMs: Summary

Important steps

1. SFT to obtain π_{SFT}
 - **Remark:** We can use some other ref. policy (see the reference)
2. Generate data to annotate using π_{SFT}
3. Elicit human annotations (pairwise comparison)
4. Learn the reward model r_ϕ that maximizes the likelihood of the elicited preferences, assumed to be generated by the Bradley-Terry model
5. Utilize the reward model and RL to optimize π_θ
 - Steps 2-5 can be repeated with the new model

Outline of the Lecture

- Reminders
- Recap: Supervised Fine-tuning
- Preference-based Fine-tuning: Overview
- RLHF: Reinforcement Learning
- RLHF: Reward Model Training
- **Direct Preference Optimization**

Toward Direct Preference Optimization

- Applying RL in this setting is challenging: we operate with three different models - π_{SFT} , π_θ , r_ϕ (see the remark on slide 25 for PPO)
- Now we ask: *Can we more directly optimize the model using preference data?*

“Unlikelihood” Approach:

- **Basic idea:** Increase the likelihood of y_w and decrease the likelihood of y_l
- Sample a datapoint (x_p, y_w, y_l) from \mathcal{D}_p
- Optimize a “contrastive” prediction likelihood: maximize the next-token prediction *likelihood* for y_w and the next-token prediction *unlikelihood* for y_l
- **Challenge:** We are not constraining the unlikelihood updates \Rightarrow the model can degenerate

Toward Direct Preference Optimization

- The unlikely approach can yield meaningless responses
- **Example:** A sample from TL;DR prompts

[illegible]

Direct Preference Optimization (DPO)

Insights from RLHF

- i. The preference model is $\Pr(y_A \succ y_B \mid x_p) = \sigma(r(x_p, y_A) - r(x_p, y_B))$
- ii. The optimal model is $\pi_{\theta^*}(y \mid x_p) \propto \pi_{SFT}(y \mid x_p) \cdot e^{\frac{r(x_p, y)}{\beta}}$

↑ Substitute r

DPO Approach

- **Main idea:** Maximize $\mathbb{E}_{(x_p, y_w, y_l) \sim \mathcal{D}_p} [\log \Pr(y_w \succ y_l \mid x_p)]$ as in the reward modeling phase, but now over the policy parameters
- From i and ii, we can express $\Pr(y_w \succ y_l \mid x_p)$ in terms of the optimal policy π_{θ^*}

Direct Preference Optimization (DPO)

Insights from RLHF

i. The preference model is $\Pr(y_A \succ y_B | x_p) = \sigma(r(x_p, y_A) - r(x_p, y_B))$

↑ Substitute r

ii. The optimal model is $\pi_{\theta^*}(y|x_p) \propto \pi_{SFT}(y|x_p) \cdot e^{\frac{r(x_p, y)}{\beta}}$

DPO Objective

- Find π_{θ} that maximizes the likelihood of the observed preferences

$$\max_{\theta} \mathbb{E}_{(x_p, y_w, y_l) \sim \mathcal{D}_p} \left[\log \left(\sigma \left(\beta \frac{\pi_{\theta}(y_w|x_p)}{\pi_{SFT}(y_w|x_p)} - \beta \frac{\pi_{\theta}(y_l|x_p)}{\pi_{SFT}(y_l|x_p)} \right) \right) \right]$$

Direct Preference Optimization (DPO)

Intuition

- The gradients are similar to the ones in the unlikelihood approach: increase the likelihood of generating y_w and decrease the likelihood of generating y_l
- However, the gradients are scaled; e.g., two interesting cases:
 - When $\pi_\theta(y_w|x_p) \ll \pi_{SFT}(y_w|x_p)$ and $\pi_\theta(y_l|x_p) \gg \pi_{SFT}(y_l|x_p)$, scale up
 - When $\pi_\theta(y_w|x_p) \gg \pi_{SFT}(y_w|x_p)$ and $\pi_\theta(y_l|x_p) \ll \pi_{SFT}(y_l|x_p)$, scale down

Main Steps of DPO

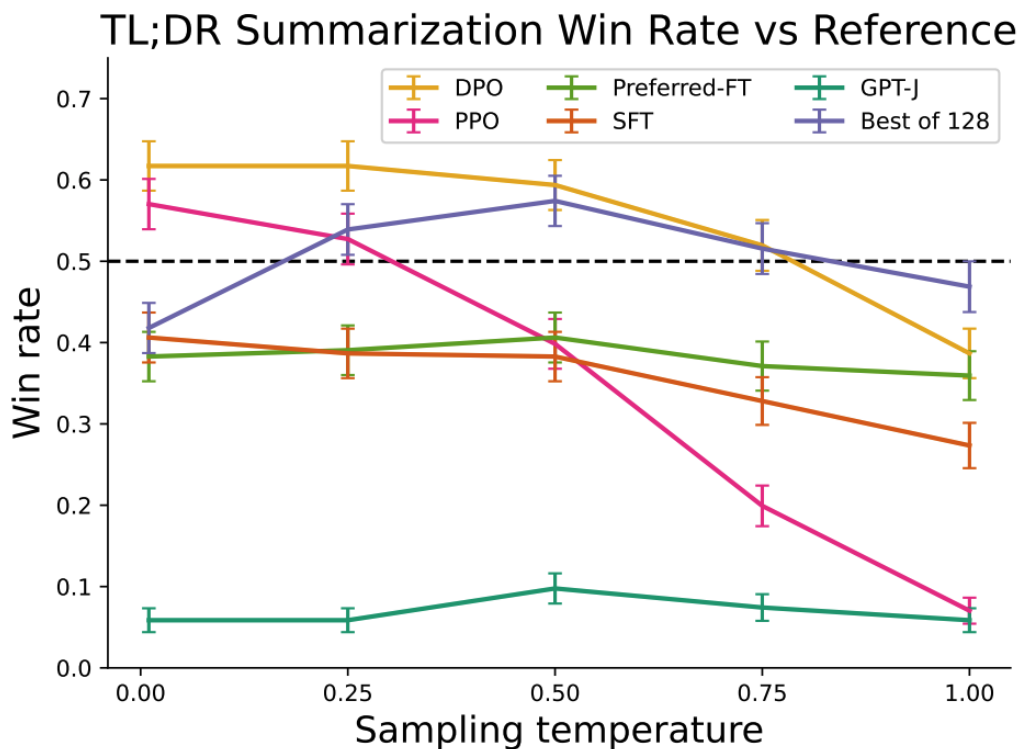
1. SFT to obtain π_{SFT}
2. Collect preference dataset \mathcal{D}_p
3. Use \mathcal{D}_p to optimize the DPO objective and obtain π_θ

Week 5 Assignment

- An exercise comparing DPO (*offline* method) and RLHF (*online* RL approach)

DPO vs. RLHF (PPO)

- DPO can have performance comparable to PPO and is simpler to implement



Week 5 Assignment

- An implementation exercise comparing preference-based tuning vs. SFT

References

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