Lecture 9: RLHF and Guest Lecture on DPO

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CS234 Reinforcement Learning.

Spring 2024

Midterm

- In class on Wednesday
- You are allowed 1 side of 1 8.5" x 11" sheet of notes
- All material through today's lecture (Monday) is eligible for the exam
- See Ed post for additional details and past related midterm/quizzes
- Good luck!

Refresh Your Understanding L9N1

Select all that are true T

1. The Bradley Terry model expresses the probability that someone will select option b_i over b_j
2. Using preference tuples and the Bradley Terry model, one can learn a model of the reward function T
3. The resulting reward function can be shifted by any constant and will not change the resulting preferences T
4. The resulting reward function can be multiplied by any constant and will not change the resulting preferences F
5. In RLHF we update the reward model after each PPO roll out F
6. Not sure

Refresh Your Understanding L9N1 Solutions

Select all that are true

- (a) The Bradley Terry model expresses the probability that someone will select option b_i over b_j
- (b) Using preference tuples and the Bradley Terry model, one can learn a model of the reward function
- (c) The resulting reward function can be shifted by any constant and will not change the resulting preferences
- (d) The resulting reward function can be multiplied by any constant and will not change the resulting preferences
- (e) In RLHF we update the reward model after each PPO roll out
- (f) Not sure

1,2,3 are true. 4 is false: for example, we cannot multiply the rewards by -1 and preserve the ordering.

Class Structure

- Last time: Imitation Learning (Max Entropy IRL) and RLHF
- This time: RLHF and Direct Preference Optimization (best paper runner up at top ML conference) guest lecture
- Next time: Midterm

Today

- RLHF for LLM
- Direct Preference Optimization

Pairwise Comparisons

- Often easier for people to make than hand writing a reward function
- Often easier than providing scalar reward (how much do you like this ad?)

Fitting the Parameters of a Bradley-Terry Model

- Consider k-armed bandits[1]: K actions $b_1, b_2, \dots b_k$. No state/context.
- Assume a human makes noisy pairwise comparisons, where the probability she prefers $b_i \succ b_j$ is

$$P(b_i \succ b_j) = \frac{\exp(r(b_i))}{\exp(r(b_i)) + \exp(r(b_j))} = p_{ij} \tag{1}$$

- Assume have N tuples of form (b_i, b_j, μ) where $\mu(1) = 1$ if the human marked $b_i \succ b_j$, $\mu(1) = 0.5$ if the human marked $b_i = b_j$, else 0 if $b_j \succ b_i$
- Maximize likelihood with cross entropy

$$loss = -\sum_{(b_i, b_j, \mu) \in \mathcal{D}} \mu(1) \log P(b_i \succ b_j) + \mu(2) \log P(b_j \succ b_j) \tag{2}$$

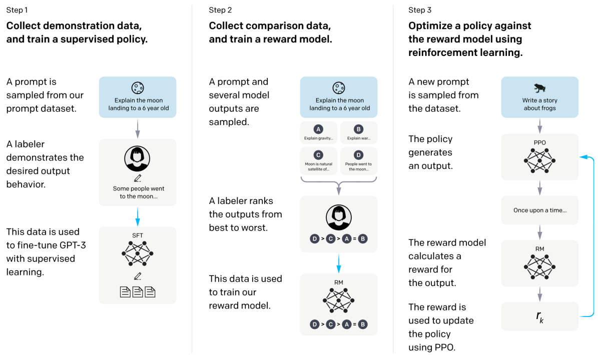
- Use learned reward model, and do PPO with this model
- See prior lecture for notes on doing this over trajectories

[1] We will see more on bandits later in the course

From Backflips to ChatGPT

- How is this used in ChatGPT?
- Next set of slides are from part of Tatsu Hashimoto's Lecture 11 in CS224N

High-level instantiation: ‘RLHF’ pipeline



- First step: instruction tuning!
- Second + third steps: maximize reward (but how??)

How do we model human preferences?

- **Problem 2:** human judgments are noisy and miscalibrated!
- **Solution:** instead of asking for direct ratings, ask for **pairwise comparisons**, which can be more reliable [Phelps et al., 2015; Clark et al., 2018]

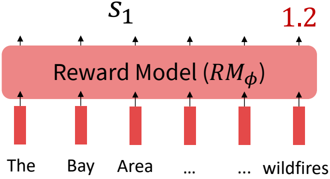
```
An earthquake hit San Francisco. There was minor property damage, but no injuries.
```
s_1

>

```
A 4.2 magnitude earthquake hit San Francisco, resulting in massive damage.
```
s_3

>

```
The Bay Area has good weather but is prone to earthquakes and wildfires.
```
s_2



Bradley-Terry [1952] paired comparison model

$$J_{RM}(\phi) = -\mathbb{E}_{(s^w, s^l) \sim D}\left[\log \sigma(RM_\phi(s^w) - RM_\phi(s^l))\right]$$

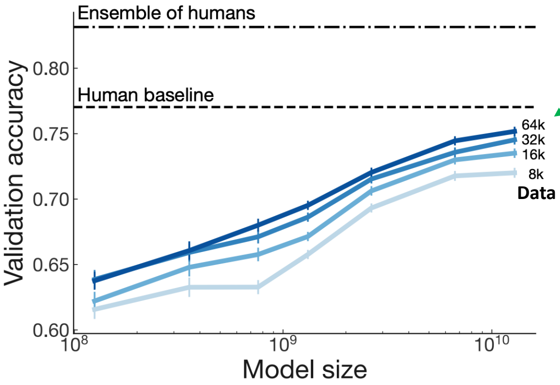
"winning" sample

"losing" sample

s^w should score higher than s^l

Make sure your reward model works first!

Evaluate RM on predicting outcome of held-out human judgments



Large enough RM trained on enough data approaching single human perf

[Stiennon et al., 2020]

RLHF: Putting it all together [Christiano et al., 2017; Stiennon et al., 2020]

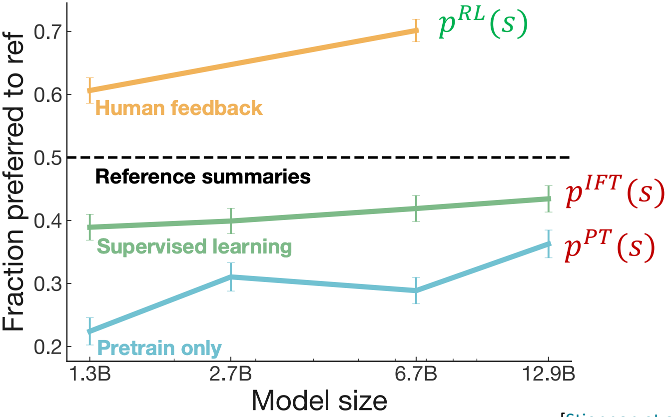
- Finally, we have everything we need:
  - A pretrained (possibly instruction-finetuned) LM $p^{PT}(s)$
  - A reward model $RM_\phi(s)$ that produces scalar rewards for LM outputs, trained on a dataset of human comparisons
  - A method for optimizing LM parameters towards an arbitrary reward function.
- Now to do RLHF:
  - Initialize a copy of the model $p_\theta^{RL}(s)$, with parameters θ we would like to optimize
  - Optimize the following reward with RL:

$$R(s) = RM_\phi(s) - \underbrace{\beta \log\left(\frac{p_\theta^{RL}(s)}{p^{PT}(s)}\right)}$$

Pay a price when $p_\theta^{RL}(s) > p^{PT}(s)$

This is a penalty which prevents us from diverging too far from the pretrained model. In expectation, it is known as the **Kullback-Leibler** (**KL**) divergence between $p_\theta^{RL}(s)$ and $p^{PT}(s)$.

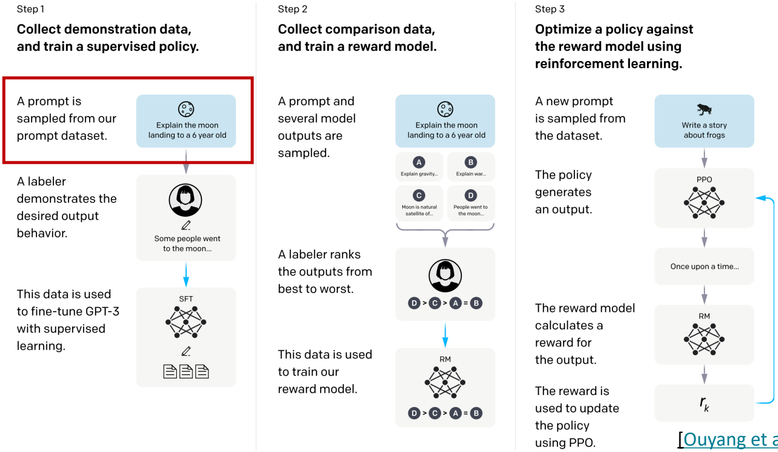
RLHF provides gains over pretraining + finetuning



[Stiennon et al., 2020]

InstructGPT: scaling up RLHF to tens of thousands of tasks

30k tasks!



[Ouyang et al., 2022]

Controlled comparisons of “RLHF” style algorithms

Method	Simulated win-rate (%)	Human win-rate (%)
GPT-4	79.0 ± 1.4	69.8 ± 1.6
ChatGPT	61.4 ± 1.7	52.9 ± 1.7
PPO	46.8 ± 1.8	55.1 ± 1.7
Best-of-n	45.0 ± 1.7	50.7 ± 1.8
Expert Iteration	41.9 ± 1.7	45.7 ± 1.7
SFT 52k (Alpaca 7B)	39.2 ± 1.7	40.7 ± 1.7
SFT 10k	36.7 ± 1.7	44.3 ± 1.7
Binary FeedME	36.6 ± 1.7	37.9 ± 1.7
Quark	35.6 ± 1.7	-
Binary Reward Conditioning	32.4 ± 1.6	-
Davinci001	24.4 ± 1.5	32.5 ± 1.6
LLaMA 7B	11.3 ± 1.1	6.5 ± 0.9

- Many works study RLHF behaviors using GPT-4 feedback (**Simulated**) as a surrogate for **Human** feedback.
- PPO (method in InstructGPT) does work
- Simple baselines (Best-of-n, Training on ‘good’ outputs) works well too

[Dubois et al 2023]

Today

- RLHF for LLM
- **Direct Preference Optimization**

Learning More

- Learning and making decisions from human preferences is a rich area intersecting social choice, computational economics and AI
- New course at Stanford on this topic: Koyejo's CS329H: Machine Learning from Human Preferences

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