Lecture 9: RLHF and Guest Lecture on DPO

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CS234 Reinforcement Learning.

Spring 2024
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!
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
Select all that are true

(a) The Bradley Terry model expresses the probability that someone will select option $b_i$ over $b_j$

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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 $b_1, b_2, \ldots b_k$. No state/context.
- Assume a human makes noisy pairwise comparisons, where the probability she prefers $b_i \succ b_j$ is

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

- Assume have $N$ tuples of form $(b_i, b_j, \mu)$ 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

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

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

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

Bradley-Terry [1952] paired comparison model

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

“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 $p^{RL}_{\theta}(s)$, with parameters $\theta$ we would like to optimize
  • Optimize the following reward with RL:
    \[
    R(s) = RM_{\phi}(s) - \beta \log \left( \frac{p^{RL}_{\theta}(s)}{p^{PT}(s)} \right)
    \]
    Pay a price when $p^{RL}_{\theta}(s) > p^{PT}(s)$

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 $p^{RL}_{\theta}(s)$ and $p^{PT}(s)$.
RLHF provides gains over pretraining + finetuning

\[ \text{Human feedback} \]
\[ p^{RL}(s) \]

\[ \text{Reference summaries} \]
\[ p^{IFT}(s) \]
\[ p^{PT}(s) \]

\[ \text{Supervised learning} \]

\[ \text{Pretrain only} \]

Model size

\[ \text{Fraction preferred to ref} \]

[Stiennon et al., 2020]
InstructGPT: scaling up RLHF to tens of thousands of tasks

**Step 1**
Collect demonstration data, and train a supervised policy.

- A prompt is sampled from our prompt dataset.
  - Explain the moon landing to a 6 year old
- A labeler demonstrates the desired output behavior.
  - Some people went to the moon...
- This data is used to fine-tune GPT-3 with supervised learning.

**Step 2**
Collect comparison data, and train a reward model.

- A prompt and several model outputs are sampled.
  - Explain the moon landing to a 6 year old
- A labeler ranks the outputs from best to worst.
  - D > C > A = B
- This data is used to train our reward model.

**Step 3**
Optimize a policy against the reward model using reinforcement learning.

- A new prompt is sampled from the dataset.
  - Write a story about frogs
- The policy generates an output.
  - Once upon a time...
- The reward model calculates a reward for the output.
  - The reward is used to update the policy using PPO.

[Ouyang et al., 2022]
Controlled comparisons of “RLHF” style algorithms

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

- 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 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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