Argumentative Reward Learning: Reasoning About Human Preferences

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Proceedings of the 39th International Conference on Machine Learning, Baltimore, Maryland, USA, PMLR 162, 2022. Copyright 2022 by the author(s).

Abstract

We define a novel neuro-symbolic framework, argumentative reward learning, which combines preference-based argumentation with existing approaches to reinforcement learning from human feedback. Our method improves prior work by generalising human preferences, reducing the burden on the user and increasing the robustness of the reward model. We demonstrate this with a number of experiments.

1. Introduction

Recent success has been made in (deep) reinforcement learning (RL) in settings with well-defined goals (e.g., achieving expert human level in Atari games (Mnih et al., 2013), Go (Silver et al., 2016), Starcraft (Vinyals et al., 2019)). However, RL has had limited success with real-life tasks for which the goals are not easily specified (Whittlestone et al., 2021; Hadfield-Menell et al., 2016). Past work on RLHF typically utilizes supervised deep learning (DL) to predict human preferences (Christiano et al., 2017; Leike et al., 2018; Hadfield-Menell et al., 2016).

We define a novel neuro-symbolic framework, argumentative reward learning, which combines preference-based argumentation with existing approaches to reinforcement learning from human feedback. Our method improves prior work by generalising human preferences, reducing the burden on the user and increasing the robustness of the reward model. We demonstrate this with a number of experiments.

2. Background

Reinforcement learning (RL) (Sutton & Barto, 2018) is well-known. We use the notion of Markov decision process.

Definition 2.1. A Markov decision process (MDP) is a tuple (S, A, T, P, r, γ), where: S is a set of states and A is a set of actions; T : S × A → S is a (deterministic) function mapping a state s and action a to the next world state s′; P : S → [0, 1] is a probability distribution over the initial state; r : S × A × S → R is a reward function that maps a transition (s, a, s′) to a real number; γ ∈ [0, 1] is the discount factor.

In an MDP, a trajectory is a finite sequence of state-action pairs: τ = (s0, a0), (s1, a1), . . . , (SN, aN) (where s0 may be any state); the return, R, of a trajectory is the total (time-discounted) reward earned: R(τ) = ∑γt=0 γt r(st, at, st+1); for γ = 1, we drop the subscript and write R(τ). Finally, agent behaviour is described by a policy π : S → A.

RLHF is the focus of a rich literature (Christiano et al., 2017; Wilson et al., 2012; Akrour et al., 2011; Frye & Feige, 2019; Akrour et al., 2012; Wang et al., 2016; Rahtz et al., 2019) and has become, in recent years, a standard training regime, particularly for large language models (Ziegler et al., 2019; Stiennon et al., 2020; Ouyang et al., 2022; Wu
et al., 2021; Rae et al., 2021). In section 3 we extend the method of (Christiano et al., 2017) to incorporate argumentative reasoning.

**Argumentation** is a well-known area of symbolic AI (see (Atkinson et al., 2017) for a recent overview). We use a form of argumentation accommodating preferences into the popular abstract argumentation paradigm (Dung, 1995).

**Definition 2.2.** An abstract argumentation framework (AAF) (Dung, 1995) is a pair \((A, R)\) where \(A\) is a given set (whose elements represent arguments) and \(R \subseteq A \times A\) (referred to as the attack relation). A set of arguments \(S \subseteq A\) attacks \(A \in A\) iff \((B, A) \in R\) for some \(B \in S\).

Argumentation frameworks are equipped with a semantics determining which arguments are dialectically good. We focus on the preferred semantics for AAFs (Dung, 1995).

**Definition 2.3.** For an AAF \((A, R)\), let \(A \in A\) be acceptable w.r.t. \(S \subseteq A\) if and only if \(S\) attacks every \(B \in A\) such that \((B, A) \in R\), and let \(S \subseteq A\) be conflict-free if and only if there exist no \(A, B \in S\) such that \((B, A) \in R\). Then, for any conflict free \(S \subseteq A\), \(S\) is an extension that is: admissible if every argument in \(S\) is acceptable w.r.t. \(S\); preferred if it is maximally (under set inclusion) admissible.

PBA offers a natural way to reason about human preferences (Modgil, 2009; Zeng et al., 2020).

**Definition 2.4.** A preference-based AAF (PAF) (Amgoud & Cayrol, 2013) is a triple \((A, R, \succ)\) where \((A, R)\) is an AAF and \(\succ A \times A\) is a transitive and asymmetric binary relation on \(A\); \(A \succ B\) means that \(A\) is preferred to \(B\).

PAFs \((A, R, \succ)\) can be reduced to AAFs \((A, R, \succ)\) where \(R, \succ = R \setminus \{(B, A) | A \succ B\}\) (that is, by removing attacks from \(B\) to \(A\) for all \(A \succ B\)).

### 3. Method: Argumentative Reward Learning

Here we present ARL, which interprets trajectories in an MDP as arguments in an AAF and uses preferred semantics to generalise HF. We start with an agent interacting with an MDP environment to generate trajectories. We then define an AAF from these trajectories and generate a PAF by using and generalising the HF. We train a reward model on this PAF and then use this reward model to train the RL agent. Hence, we split the method into six steps as seen in Fig. 1.

**Step 1: Collecting Agent Trajectories.** We start with a randomly initialised policy (Christiano et al., 2017).

**Step 2: Defining the AAF.** We now take trajectories to be arguments in an AAF. We define the attack relation based on a notion of similarity between trajectories: dissimilar trajectories are deemed to “disagree” about the correct behaviour and are thus taken to be mutually attacking arguments.

**Step 3: Querying the Human.** We elicit preferences over trajectories from the human in the loop, by querying pairs of attacking trajectories, ensuring that queried trajectories actually exhibit different behaviour (differently from past work on preference elicitation, which samples trajectories uniformly at random (Ibarz et al., 2018) or based on the uncertainty in the reward model (Christiano et al., 2017)).

**Step 4: Defining the PAF.** The human preferences collected at Step 3 can be used as preferences over arguments. However, with limited HF these preferences are only partial. In order to generalise them, we use the preferred semantics of the AAF to determine preferred sets of trajectories. Because of our notion of attack, these preferred extensions only include similar trajectories. Then, we determine a preference order \(\succ\) over preferred extensions (see Section 5 for details). Finally, for trajectories \(\tau_1, \tau_2\) in the set of arguments in the AAF, we take \(\tau_1 \succ \tau_2\) if \(\exists p_1\) (a preferred extension of the AAF) with \(\tau_1 \in p_1\) such that \(\forall p_2\) (also preferred extensions of the AAF) with \(\tau_2 \in p_2\) it holds that \(p_1 \succ p_2\). This results in a PAF, which can be reduced to \((A, R, \succ)\) (as defined in Section 2). This process is a simple way to generalise the stated human preferences (i.e. a small amount of HF) to a larger set of (similar) trajectories: more sophisticated ways to generalise the preferences are left for future work. Next, we train the reward model to predict these preferences.

**Step 5: Training the Reward Model.** As in (Christiano et al., 2017), we train a neural network to predict the immediate reward, \(\hat{r} : S \times A \rightarrow \mathbb{R}\), based on the preferences derived in the previous step (we use \(\hat{r}\) to distinguish a learned reward
model from the true reward function $r$. We assume the preferences between trajectories drawn from Step 3 are functions of the reward that we aim to obtain at this step, such that the probability of $\tau_1 \succ \tau_2$ is given by

$$ \Pr(\tau_1 \succ \tau_2) = \frac{\exp(\hat{R}(\tau_1))}{\exp(\hat{R}(\tau_1))+\exp(\hat{R}(\tau_2))}, $$

where $\hat{R}(\tau)$ is the non-discounted return, using $\hat{r}$, for trajectory $\tau$ (i.e. $\hat{R}_\gamma$ for $\gamma = 1$).

We then order $\hat{r}$ by minimizing the binary cross-entropy loss between these predictions and the preferences between trajectories in the PAF: $\text{loss}(\hat{r}) = -\sum_{(\tau_1, \tau_2) \in \mathcal{R}_\succ} \log \Pr(\tau_1 \succ \tau_2)$.

**Step 6: Training the Policy.** Once we have trained $\hat{r}$ we are left with a standard RL problem. To train the policy $\pi$ we use deep Q-learning (Mnih et al., 2015).

4. Experiments: Maze Solving

**Environment definition.** We conduct a number of experiments in a maze-solving MDP environment (Fig. 2), defined by: $S = \{(x, y) | x, y \in [0, 1]\}$, including randomly generated walls; $A = \{(0, 0.02), (0.02, 0), (0, -0.02), (-0.02, 0)\}$ (i.e. up, right, down, left); and $T(s, a)$ and $r(s, a, s')$ given by

$$ T(s, a) = \begin{cases} 
  s, & \text{if } s' \text{ is a wall} \\
  s', & \text{otherwise}
\end{cases} $$

where $s' := s + a$;

$$ r(s, a, s') = \begin{cases} 
  1, & \text{if } d \leq 0.3, \\
  (1 - d)^2 - 0.1, & \text{if } s = s', \\
  (1 - d)^2, & \text{otherwise}
\end{cases} $$

where $d$ is the Euclidean distance from $s'$ to the goal, normalised to $[0, 1]$. Note that this reward function is the result of approximately 10 hours of reward design in combination with other hyper-parameter tuning.

**Experiment outline.** We train eight reward models for the continuous maze environment in Fig. 2. We apply the method of Christiano et al. (2017) to train four benchmark models: one from synthetic preferences, two from 100 and 200 human preferences, respectively, and one trained iteratively by cycling through the steps 1-6. We train four analogous models using our ARL method.

**Step 1.** We first generate 100 random trajectories in the maze; these trajectories start from random initial states and have length 20.

**Step 2.** From these initial trajectories we generate an AA framework with the (symmetric) attack relation: $(\tau_1, \tau_2) \in \mathcal{R}$ iff $\exists i \in \{0, \ldots, N\}$ s.t. $||s_1(i) - s_2(i)|| > \delta$, where $s_1$ and $s_2$ are the sequences of states in $\tau_1$ and $\tau_2$ respectively, $s_j(i)$ is the $i$-th element of sequence $s_j$ for $j = 1, 2$, $||.||$ is the Euclidean distance, $N = 19$, and the threshold value of $\delta$ is heuristically chosen (for this experiment we use $\delta = 0.2$). This attack relation captures a form of similarity between trajectories, whereby if two trajectories are close to each other at every time step then they do not attack one another. From our 100 trajectories, with our choice of parameters, we get an AAF with 8230 attacks.

**Step 3.** We consider two settings, respectively with synthetic preferences and preferences drawn from HF.

**Synthetic Preferences.** As in (Christiano et al., 2017) we use the true reward $r$ to simulate human preferences.

**Human Preferences.** To collect HF we present a short video of the maze with two agents rolling out their trajectories. We then ask the human, $\mathcal{H}$, to select a preference over the trajectories. We take a random sample of attacks between the 100 trajectories and collect 200 preferences.

**Step 4.** We generalise both the synthetic and human preferences over trajectories to preferences over preferred extensions, as described in Section 3. To order the preferred extensions of the AAF in order to generalise the (synthetic or human) preferences, we perform a binary insertion sort, which makes the minimum number of comparisons. **Generalising Synthetic Preferences:** We order the preferred extensions by the total return of the trajectories in them, that is, for preferred extensions $p_i$ and $p_j$:

$p_i \gg p_j$ iff $\sum_{\tau \in p_i} R(\tau) > \sum_{\tau \in p_j} R(\tau)$.

Then we take $\tau_1 \succ \tau_2$ as described in Section 3. This gives us our PAF from an order $\gg$ over preferred extensions. **Generalising Human Preferences:** To determine the preference between preferred extensions $p_i$ and $p_j$, we count the number of preferences between the trajectories in $p_i$ and $p_j$, as follows: let $\text{count}_{p_i,p_j} = \sum_{\tau_1 \in p_i, \tau_2 \in p_j} 1(\tau_1 \succ \tau_2)$; where $1$ is the indicator function. Then $p_i \gg p_j$ iff $\text{count}_{p_i,p_j} > \text{count}_{p_j,p_i}$.

We generate the PAF following the approach in Section 3.

**Step 5.** We follow the process described in Section 3.

**Step 6.** For each reward model resulting from Step 5 we use the RL algorithm as indicated in Section 3 to train a policy.
Figure 3. Reward heatmaps normalised over whole state space (yellow is high and blue is low reward).

Figure 4. Reward heatmaps showing best action at each point.

5. Results

We compare the performance of the reward models described in the previous section in Table 1. In each case we train the policy three times to collect mean (and standard deviation) distance to goal which the resultant greedy Q-network achieves. We also examine reward heatmaps over the state space (see Fig. 3 and Fig. 4) in order to visualise what the reward models have actually learned.

We note that the reward model trained on 100 human preferences without generalisation, \( r_{h,100} \), over-fits the training data and gives high reward for moving down near the initial state (and we can observe from Fig. 3a that the reward is not well distributed throughout the state-space). Hence, the policy trained on \( r_{h,100} \) learns to just move downwards. When we generalise these same 100 preferences we observe much better performance (MPPA 0.847 compared to 0.798). We see in Fig. 3b that the reward is more sensibly distributed around the state space and we see by comparing Fig. 4a to Fig. 4b that generalising preferences improves the reward model’s predicted best action in each state. As expected, using 200 preferences instead of 100 improves performance, and generalisation again improves the policy (the MPPA is around 0.89 for both \( r_{h,200} \) and \( r_{g,200} \)). Similarly, generalising synthetic preferences improves both MPPA and the policy. Surprisingly, in the iterative learning experiments, generalisation decreases performance. However, these experiments do not use fixed trajectories or HF (since the point of the iterative process is to generate increasingly better trajectories based on the current reward).

Table 1. Performance of Reward models. Our reward models highlighted in blue. \( r \) is the true reward and \( \hat{r} \) is the learnt reward, with \( s \) = synthetic preferences, \( h \) = human preference, \( g \) = generalised, \( i \) = iterated. We present the number of preferences used to train the model (and, if the preferences were generalised, the number of human labels used), the mean preference prediction accuracy (MPPA) on a test set, and the distance to the goal achieved by each policy. A lower distance to goal does not necessarily correspond to a better policy, since the agent may need to travel further away from the goal to navigate deeper into the maze, therefore we highlight “good” runs (meaning that the agent moves meaningfully through the maze) in green and “bad” runs (in which the agent does not move meaningfully through the maze) in red.

| Reward | # Preferences | MPPA (Test) | Distance to goal (normalised to state space) |
|--------|--------------|-------------|---------------------------------------------|
| \( r_{h,100} \) | 100 | 0.738 ± 0.023 | 0.847 ± 0.068 |
| \( r_{h,200} \) | 200 | 0.766 ± 0.060 | 0.899 ± 0.020 |
| \( r_{g,100} \) | 100 | 0.725 ± 0.021 | 0.762 ± 0.083 |
| \( r_{g,200} \) | 200 | 0.762 ± 0.071 | 0.899 ± 0.020 |

6. Conclusion

Summary. We presented a novel neuro-symbolic framework, argumentative reward learning (ARL). ARL incorporates argumentative reasoning into the reinforcement learning from human feedback loop, in order to generalise human preferences. ARL improves past work, increasing the accuracy with which the reward model predicts preferences (especially when there is only limited human feedback available) in addition to improving the learned policy.

Future work. Other methods for reasoning about human preferences could be explored, and more principled methods for active learning might be developed (e.g. in which a dialogue between the system and human in the loop can be used to extract the most useful information about the human’s preferences).
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