Advice Conformance Verification by Reinforcement Learning agents for Human-in-the-Loop

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Abstract—Human-in-the-loop (HiL) reinforcement learning is gaining traction in domains with large action and state spaces, and sparse rewards by allowing the agent to take advice from HiL. Beyond advice accommodation, a sequential decision-making agent must be able to express the extent to which it was able to utilize the human advice. Subsequently, the agent should provide a means for the HiL to inspect parts of advice that it had to reject in favor of the overall environment objective. We introduce the problem of Advice-Conformance Verification which requires reinforcement learning (RL) agents to provide assurances to the human in the loop regarding how much of their advice is being conformed to. We then propose a Tree-based lingua-franca to support this communication, called a Preference Tree. We study two cases of good and bad advice scenarios in MuJoCo’s Humanoid environment. Through our experiments, we show that our method can provide an interpretable means of solving the Advice-Conformance Verification problem by conveying whether or not the agent is using the human’s advice. Finally, we present a human-user study with 20 participants that validates our method.

I. INTRODUCTION

Deep Reinforcement Learning has struggled with sparse reward environments resulting in several frameworks utilizing Human-in-the-Loop (HiL) that have shown promising success. These works [1], [3]–[5], [7], [8], [13] utilize advice or preferences from humans as a form of guidance, however, a missing aspect of these works is the inability of the RL agent to provide assurances to the human user regarding to what extent their advice was accommodated by the agent. We term this problem as the Advice-Conformance Verification problem which requires an RL agent to provide assurances or explanations that conveys whether the agent conforms to the human advice and how much of it the agent let go for the larger interest of completing the task.

It is well known in the field of Human-aware-AI that humans can form expectations of the agents they are interacting with via several means [14], [15], for example when they observe the agent’s behavior. Similarly, we posit that when an agent requests human advice to achieve the task as determined by environment rewards, the human in the loop may establish the belief that the agent’s success on the task is the consequence of following their advice. We leverage [5] for observing that so long the agent attempts to optimize for the underlying environment reward, even in the presence of bad advice the agent is still able to obtain a good policy (as shown in Fig. [3]). However, such a belief may be ill-placed (in the event of either a poor advice or misspecified environment rewards) and in many situations for example, where the safety of the human in the loop is of concern, such beliefs should be corrected. The Advice-Conformance Verification captures this issue by requiring agents to allow the HiL to inspect whether the advice was utilized in the intended manner and if possible what parts of the given advice were rejected by the agent.

II. BACKGROUND

In the Human in the Loop Reinforcement learning works like [1], [4], [5], [13], the learning paradigm involves the agent acting in an environment $E$ by sensing an observation $o_t \in O$ at time $t$. As in traditional reinforcement learning these methods model the environment as an MDP tuple $(O, T, A, R)$ where $O, A$ are the agent’s observation and action spaces, $T$ is the transition function governed by the environment dynamics and $R$ are the environment rewards. Additionally, several works take into account human advice in different ways for example action advice [6], policy advice [11], or reward advice [5], [13]. We are interested in leveraging works that perform reward shaping [9] as a means to accommodate human advice.

The agent’s aim in this class of problems is to come up with a policy $\pi_\theta$ such that it achieves the maximum possible returns computed over rewards $R$. Note that the agent typically would at least have the environment reward $R$ and a shaped reward $\hat{R}$ that it computes using the human advice (which itself could be represented in the form of a reward function, say $F$). The human advice, therefore, is meant to aid the agent in achieving the task specified by rewards $R$. In this work, we will take [5] as the backbone HiL RL algorithm and propose a solution to the advice conformance verification problem in this setup.

III. METHOD

Our solution to the Advice-Conformance Verification problem is to establish the lingua franca between the human user and the RL agent in the form of a Preference Tree which is a directed acyclic graph computed from the given preferences. The Preference Tree computed using the Human in the Loop is termed the Human-Preference Tree. We present a method to extract a Preference Tree from the RL agent at any time during the agent’s training regime, referred to as the Agent’s Preference Tree. We use the pair of preference trees, the one extracted by the agent from the human and the other generated by the agent, as a means to convey how the advice has been utilized by the agent in the learning process. We expect a significant deviation

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of the Agent’s Preference tree structure from the Human’s Preference Tree to imply a deviation from the human advice.

**Sampling Candidate states for the Preference Tree:** For this work, we will use state-based binary preference between two observations to get the tuple $H = \{(o_i, o_j, b_{ij})\}_k$ where $o_i, o_j$ are image observation shown to the user for underlying MDP states $s_i, s_j$ and the binary label $b_{ij} \in \{0, 1\}$ where 0 implies human preference of $o_i$ over $o_j$ and vice versa for 1. $k$ such preference labels are collected. The choice of $o_i, o_j, k$ could be domain-dependent, but typically works like [3], [8] have obtained $o_i, o_j$ via uniform sampling techniques (figure 1 Step 1). As will be discussed in Section V better state clustering and exploration techniques are potential methods of extending our work for better interpretable Preference Trees.

**Creating a Single-Elimination Tournament Tree with HiL:** Since the human is queried pairs of states, we must create the initial pairs from the candidate states. We use the Braverman–Mossel Noisy sampling model [2], [10] to create a single-elimination tournament tree, where each candidate state is treated as a “player” and its corresponding environment reward as the player’s intrinsic ability. The state which ends up being preferred by the human can be treating as that state “beating” the alternative. To allow for the possibility that weaker states can beat stronger players the BM model allows, as input, a probability $p$ where a high value of $p$ entails a random tournament. The “winner” states are further pitched against each other as a query to the HiL and this process continues until we get a single winner state. Theory on single-elimination tournaments also points to “rigged” tournaments [10] where there does exist an initial pairing such that a given state would win the tournament, however, we curtail this issue with a high $p$ value to obtain a random tournament tree.

**Conversion of Single-Elimination Tournament Tree to a Preference Tree:** From the obtained single-elimination tournament dendrogram we use the algorithm 1 to convert it into a Preference Tree. A preference tree can be thought of as a condensed tournament tree where no nodes are repeated. Algorithm 1 achieves this in a standard depth-first search recursive manner. In a preference tree, the edge from a node $i$ to $j$ has a weight of $w_{ij} = \text{height}(i) - \text{height}(j)$ where $\text{height}(x)$ is computed in the dendrogram.
(leaves have a height of 0).

Algorithm 1 Dendrogram to Preference Tree

```python
procedure RECURSE(head, Preference Tree T = {head})
    while child in head.child do
        if child.value is head.value then
            RECURSE(child) # Skip
        else
            T.head.children ← NewNode(child)
        end if
        RECURSE(child) # Add new node to T
    end while
    return T # Constructed Preference Tree
end procedure
```

Utilizing the Preference tree for Advice Accommodation: We extend [5] to utilize this preference tree as the given preference reward function $F$ by grounding the preference tree nodes to reward values using the equation [1] where $T$ is the constructed Preference-Tree, $r_e$ is a positive constant (edge reward), $r_b$ is a positive constant (reward to leaves), $w_{se}$ is the edge weight from node $s$ to child $c$ in $T$. $T_r$ is the reward computed for a node $c$ in a previous step of this bottom up method and $C(s)$ is the set of children of node $s$.

$$T_r(s) = \begin{cases} 
-r_b, & \text{if } s \in T.leaves \\
\frac{1}{|C(s)|} \sum_{c \in C(s)} T_r(c) + r_e \ast w_{se}, & \text{otherwise}
\end{cases}$$

To assign preference rewards to states absent in the Preference tree, we use a similarity measure like cosine similarity ($d_{sim}$) between state observations. Hence, preference reward for a state, for some $s' \in T.nodes$, is computed as :

$$F(s) = \min_{s'} d_{sim}(s, s') \ast T_r(s') \ast T_d(s')$$

(2)

Where $T_d(s')$ is the depth of state $s'$ in the Human Preference-Tree.

Obtaining Agent Preference Tree: Since our approach is “anytime” we use the agent’s shaped reward function $\hat{R}$ to provide a preference on a pair of states $s_i, s_j$ as,

$$b_{ij} = \begin{cases} 
1, & T_r(s_i) > T_r(s_j) \\
0, & \text{otherwise}
\end{cases}$$

(3)

Therefore, we start with the same initial pairings in our single-elimination tournament constructed using the BM model, however, use our agent’s shaped reward function $\hat{R}(s, a) = R(s, a) + z_\phi F(s)$ to specify the winner states and construct the Agent’s Preference Tree.

IV. EXPERIMENTS

For our experiments, we focus on the MuJoCo environment Humanoid-V2 [12] where the optimal policy on environment rewards allow the humanoid to walk. We take two cases of human advice,

1) Case 1 / Good advice: Preference is exactly aligned with environment rewards $R$, i.e. $F(s) = R(s) \forall s \in S$.

2) Case 2 / Bad advice: Human prefers the robot in “standing position”. Note that this piece of advice maybe valid in human’s mental model, however does not align with the environment rewards which is why it is termed as Bad advice. We collect data from human in the loop for their preferences using a web interface as in figure [I].

In Case 1, since the given advice is aligned with the environment rewards, in the shaped reward $\hat{R}(s) = R(s) + z_\phi F(s)$ and $F(s) = R(s)$, we find that the learnt $z_\phi$ using [5] tends to be a constant value across all states thereby retaining all the preference orderings $b_{ij}$, which is what one expects with good-advice. As a consequence, the preference tree generated by the agent in Case 1 correctly matches the Human Preference tree. This shows the effectiveness of Preference Trees in correctly identifying whether the agent is using the advice in the intended manner for aligned advice.

In Case 2, since the performance of the agent reaches close to optimal as shown in figure [I], given just this performance measure, the human might believe that their advice was incorporated and the agent prefers “standing posture”. As discussed before, this can cause the human to develop false expectations on the agent’s behavior as well assign false credit to the effectiveness of their advice. When we apply our method to generate the two Preference trees - the Human Preference Tree and the Agent’s Preference tree, we find that the agent in fact prefers the “bent postures” over the ‘straight posture of “standing position” as shown in figure [I]. Hence, we can clearly recognize that the agent had to reject the human advice, a fact that was not reflected without the use of Preference Trees.

We are also interested in recognizing the effectiveness of our explanation strategy via Preference Trees. We conducted a human study with 20 participants to check two hypotheses. First, Can the human correctly recognize that the two trees shown to them imply different preferences? This study attempts to verify our claim that the use of Preference trees is a good means to realize that there is a deviation from the given Human preferences. All of the users...
(100%) were able to identify and conclude that the trees convey different preferences. Second, we wanted to verify our claim that Preference Trees can help the human user characterize the deviation. We queried the participants with the two Preference trees and an accompanying text that the first Tree prefers “agent should prefer a straight posture”. We asked them whether they believed that the second tree prefers a “bent posture”. 85% of the users found that the second tree prefers “bent postures” hence bolstering our claim that Preference Trees aids in characterizing the agent’s deviation from human advice.

V. DISCUSSION

We presented the problem of Advice Conformance Verification a solution to which requires a Reinforcement Learning agent to provide a means for the Human in the Loop to inspect whether the agent is utilizing the given advice in the intended manner. We did so using the proposed Preference Trees and showed how they can be used with the HiL work proposed in [5]. We ran an experiment on MuJoCo’s Humanoid-v2 environment with good and bad advice. We conducted a user study to verify that Preference Trees are a good means to identify whether the agent’s shaped reward function deviates from the Human specified preferences and further characterize the possible deviation.

Our initial results on obtaining Preference trees on better, more diverse states have been very promising. Our future work includes the use of clustering techniques to query diverse states to the human in the loop such that the obtained Preference trees are even more interpretable. We also plan on conducting extensive evaluations on other domains, differing advice, and HiL algorithms that operationalize human advice accommodation via reward shaping techniques.

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