Learning Human Contribution Preferences in Collaborative Human-Robot Tasks

Anonymous Author(s)
Affiliation
Address
email

Abstract: In human-robot collaboration, both human and robotic agents must work together to achieve a set of shared objectives. However, each team member may have individual preferences, or constraints, for how they would like to contribute to the task. Effective teams align their actions to optimize task performance while satisfying each team member's constraints to the greatest extent possible. We propose a framework for representing human and robot contribution constraints in collaborative human-robot tasks. Additionally, we present an approach for learning a human partner's contribution constraint online during a collaborative interaction. We evaluate our approach using a variety of simulated human partners in a collaborative decluttering task. Furthermore, we conducted a pilot user study to gather insights into the effectiveness of our approach on task performance and collaborative fluency. Our results demonstrate that our method improves team performance over baselines with both simulated and human partners, and human users perceived our method as more fluent and collaborative.

Keywords: human-robot collaboration, reward learning, human-robot interaction

1 Introduction

As robots transition from machines in controlled environments to collaborative partners integrated into our daily lives, it is essential for them to align their behavior with our preferences and objectives. Human preferences can reflect constraints based on individual differences in capabilities [1, 2, 3], knowledge [4], intentions [5, 6], or preferred strategies for accomplishing shared goals [7, 8]. In interactions where the human's constraints dictate the team objectives, robots must align themselves to those constraints by learning and maximizing the objectives of the human [9, 10, 11, 12]. A crucial challenge in robot learning is to develop algorithms that can learn a reward function representing human preferences in collaborative human-robot tasks [13].

Robots also have a variety of task capabilities, requirements, and activity deadlines, which impose constraints on their behaviors [14, 15, 16]. These machine constraints require efficient allocation of appropriate tasks to appropriate agents, through adaptive scheduling [2, 3], or market-based methods [3, 17, 18]. Robots that are capable of self-assessment [19, 20, 21, 22] may even be able to identify constraints for their own actions. In real-world interactions, humans collaborating with robots must also need to align themselves to the constraints of the robot [23, 24].

Consider the task of collaboratively unloading a dishwasher with a robot. In this scenario, let's say the human partner does not trust the robot to handle fragile items, like glassware and china. However, they are comfortable allowing the robot to handle non-fragile objects, such as silverware. As such, the human's preferred contribution to the task is unloading glassware and china, while they would prefer the robot to unload non-fragile items. Similarly, the robot assesses that it can most safely unload plates due to their upright position in the dishwasher. An effective team strategy that plays to each team member's strengths [25] is for the robot to unload plates and silverware, while the human unloads glassware and other china. In order to achieve this strategy, the robot must learn the human's preference through interaction, and determine how to accomplish the task while maximally adhering to the human's preferences and its own constraints.

In this work, we capture both human and robot contribution constraints via a reward function based on the actions an agent performs towards some shared goal in a given state. There have been a variety

Submitted to the 7th Conference on Robot Learning (CoRL 2023). Do not distribute.

of reward-based frameworks, including Cooperative Inverse Reinforcement Learning (CIRL) [12] which align robots to human constraints by modeling the human's constraints as a reward function the robot needs to learn and assist in maximizing [9, 10, 11]. We combine the notion of human contribution constraints with machine constraints and use a reward-based framework to represent a form of interaction: Interactive Contribution Preference Learning (ICPL), in which a robot partner must learn the human's contribution preferences under its own constraints and the objectives of the task. The robot and human operate within the same environment to complete a collaborative task under both the human's and robot's individual contribution reward functions. While the robot's individual reward is known to the team, the human's preferences must be learned by the robot. The observed human behavior, which provides insights into their preferences, is influenced by the robot's actions, its constraints, and the task objectives.

Our framework captures a novel type of collaboration in which successful teams maximize the task objectives while adhering to every partner's individual constraints. We propose a candidate approach to the collaborative task: Bayesian Information Seeking Learner (BaISL). Our approach models the human as maximizing reward under the assumption that the robot will take the optimal action, setting expectations such that the robot will eventually learn the optimal action. This human model informs online Bayesian inverse reinforcement learning [26]. The robot then plans using the expected reward under updated beliefs towards states with high information gain potential given the actions available to the human. We evaluate BaISL in experiments with simulated human models and in a preliminary user study with human partners. Our results show that BaISL improves team performance with simulated and real human partners, as well as improves the collaborative fluency self-reported by real human partners.

2 Related Work

Human-Robot Collaboration Human-robot collaboration is the process in which humans and robots work together to achieve common goals [27, 13, 28]. Human-robot collaborations that are assistive in nature, like home service [29, 30] and healthcare robots [31, 32], align closely with the assistance paradigm proposed in [33], where the goals of the task are entirely defined by the human. Conversely, collaborations without rigid principal-assistant roles can allow the human and robot to differ in their approaches for achieving shared goals [24, 7]. For example, robots designed for collaborative manipulation of physical objects [28] or collaborative games [34, 35, 36] seek to contribute to shared goals, which are not necessarily dictated by human preferences. ICPL considers learning the human's preferences in the context of a collaborative task, where the objectives of the task are partially defined by the human's preferences.

Value Alignment Value alignment in robotics refers to the design of collaborative agents that can learn and infer a human partner's objective and act towards achieving human's objective. Ensuring that robots have the correct reward function is an important problem in designing safe and reliable autonomous systems [37, 38, 9]. Existing approaches for value alignment focus on robot learning through interactions [12, 9], active learning of human preferences [39, 40], and teaching through demonstrations [41, 42]. Cooperative Inverse Reinforcement Learning (CIRL) [12] formulates value alignment as a two-player Markov game, in which human and robot must maximize a common reward function, but only the human knows the reward function. While the robot and human partner in CIRL are focused entirely on the task of ensuring the learning agent asymptotically converges to the same values as the human teacher, the robot and human in ICPL seek to balance multiple objectives. The actions taken by the human in ICPL are also in service of completing the collaborative task *and* take into account the robot's constraints.

Reward Learning A key part of value alignment and collaboration is understanding another agent's values, or utility functions, through observation of their actions [9, 43, 44, 45, 46, 6, 47, 48]. Markov Decision Processes (MDPs) are a common framework for reward learning [49]. Inverse reinforcement learning (IRL) [50] infers an expert's underlying reward function from its observed behavior, typically in a single-agent setting [51, 52, 53]. Furthermore, when interacting with robots seeking to learn their reward functions, humans may convey their rewards through a number of different information modalities [54], including demonstrations [55], corrections [56], observations [57], and comparisons [39, 58]. Our reward learning occurs interactively, [59], where both agents

must collaborate within the same two-agent MDP, where the robot agent lacks partial knowledge of the shared reward function.

3 Interactive Contribution Preference Learning

We formulate the problem of learning human contribution preferences subject to task objectives and individual constraints as a two-player Markov game. At a high level, an Interactive Contribution Preference Learning (ICPL) game involves both the robot and human operating simultaneously within the same environment to accomplish a known task objective. Each agent's behavior is additionally constrained by an individual reward function. The robot must learn a composite reward function that captures the **task reward**, **human individual reward**, and **robot individual reward** for the team in this collaborative task. While the human has full knowledge of the composite reward, known to the robot are only the **task reward** and **robot individual reward**. **Human individual reward** is unknown to the robot and is to be learned through interaction. An ICPL game is a two-player Markov game between a robot r, and a human, h, defined by the tuple $M = \langle \mathcal{S}, \{\mathcal{A}^r, \mathcal{A}^h\}, \mathcal{T}, \{\Theta^r, \Theta^h, \Theta^T\}, R_{\theta^T,\theta^r,\theta^h}, P_0, \gamma \rangle$.

- $\mathcal{S}$ the set of possible states: $s \in \mathcal{S}$
- A^r: action set available to the robot r: $a^r \in \mathcal{A}^r$
- A^h: action set available to the human h: $a^h \in \mathcal{A}^h$
- $\mathcal{T}(\cdot|\cdot,\cdot,\cdot)$: transition function, which is a conditional distribution on the next state, given previous state and action for both agents: $\mathcal{T}(s'|s, a^r, a^h)$
- Θ^T: the space of possible **task reward** parameters.
- Θ^h: the space of possible **human individual reward** parameters.
- Θ^r: the space of possible **robot individual reward** parameters.
- $R_{\theta^T,\theta^r,\theta^h}(\cdot,\cdot,\cdot,\cdot) = C(R_{\theta^T}(\cdot,\cdot,\cdot,\cdot), R_{\theta^r}(\cdot,\cdot,\cdot), R_{\theta^h}(\cdot,\cdot,\cdot))$: the **composite reward** function that both players must maximize. The reward function is parameterized by C, a combination function of the individual and task reward functions. In our experiments, C is the summation of the 3 reward components. $R_{\theta^T,\theta^r,\theta^h} : S \times \mathcal{A}^r \times \mathcal{A}^h \times S \times \Theta^T \to \mathbb{R}$. R_{θ^T} is known to both h and r.
- $R_{\theta^T}(\cdot,\cdot,\cdot)$: a parameterized reward function representing how both players contribute to the group's task reward. R_{θ^T} represents both players' task-related payoffs, which we refer to as **task reward**. $R_{\theta^T} : S \times \mathcal{A}^r \times \mathcal{A}^h \times S \times \Theta^T \to \mathbb{R}$
- $R_{\theta^h}(\cdot,\cdot,\cdot)$: a parameterized reward function representing **human individual reward**, which represents the actions the human would prefer to perform in contribution to the task. $R_{\theta^h} : S \times \mathcal{A}^h \times S \times \Theta^h \to \mathbb{R}$. R_{θ^h} is known to only h.
- $R_{\theta^r}(\cdot,\cdot,\cdot)$: a parameterized reward function representing how r's soft constraints enable it to contribute. R_{θ^r}, or **robot individual reward**, represents how the robot r is rewarded for the actions that it robot is able to take. The robot's capabilities may dictate these soft constraints. $R_{\theta^r} : S \times \mathcal{A}^r \times S \times \Theta^r \to \mathbb{R}$. R_{θ^r} is known to both h and r.
- $P_0(\cdot,\cdot,\cdot,\cdot)$: initial state distribution. $P_0(s_0, \theta^T, \theta^r, \theta^h)$.
- γ: a discount factor $\gamma \in [0, 1]$

The game begins in an initial state $(s, \theta^r, \theta^h, \theta^T)$ sampled from P_0. Robot r observes θ^r, θ^T, and human h observes $\theta^h, \theta^r, \theta^T$. At each timestep t, robot r and human h observe the current state s_t and select their actions a^r_t, a^h_t according to policies π^r and π^h. The environment transitions to the next state $s_{t+1} \sim \mathcal{T}(s'|s, a^r, a^h)$. The team receives, but does not observe, composite reward $R_{\theta^T,\theta^r,\theta^h}(s_t, a^r_t, a^h_t, s_{t+1}) = R_{\theta^T}(s_t, a^r_t, a^h_t, s_{t+1}) + R_{\theta^r}(s_t, a^r_t, s_{t+1}) + R_{\theta^h}(s_t, a^h_t, s_{t+1})$. The two agents observe each other's action selection. The process continues until the team reaches a terminal state, s_F, where the final reward for the team $R_F = \sum_{i=0}^{F} R_{\theta^T,\theta^r,\theta^h}(s_i, a^r_i, a^h_i, s_{i+1})$ is received. The team only observes the total reward at the end of the interaction.

4 Approach: Bayesian Information Seeking Learner (BaISL)

We propose an algorithm for the robot in ICPL, called a Bayesian Information Seeking Learner (BaISL). BaISL consists of two primary online steps: (1) Bayesian Inverse Reinforcement Learning (BIRL) [26] using a human model with optimistic expectations of the robot, (2) planning under beliefs towards informative states (Fig. 1). Implementation details in Appendix.

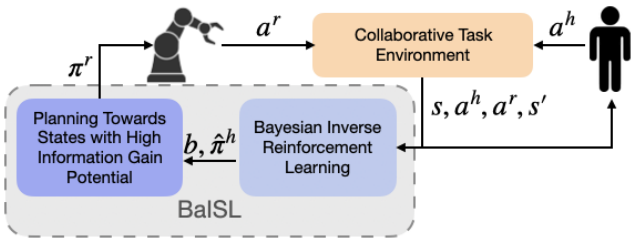

Figure 1: Upon observing the action of the human, current state, and next state, the robot updates its beliefs (b) over the hypothesis space (Θ^h) and produces a predicted policy for the human ($\hat{\pi}^h$). The robot then replans its actions seeking information gain.

Human Model for Bayesian Inverse Reinforcement Learning. The robot estimates a belief, b, over the hypothesis space Θ^h of possible human individual rewards. In order to update its beliefs, the robot relies on a model of human decision-making in order to evaluate the likelihood of human actions. We model an *optimistic reward human* as a noisily rational actor who selects actions based on the expectation that the robot will take the optimal complementary action to maximize the team's reward. By understanding these expectations, the robot is able to deduce which human individual reward function would lead to such expectations. We also adopt the Boltzmann rational model of human behavior [60, 61], which models that the probability of choosing a particular option increases exponentially as its utility, or reward, increases compared to other available options. Over t timesteps, the robot observes a trajectory of human actions, $\tau_t = \{(s_1, a_1^h, s_2), (s_2, a_2^h, s_3), ..., (s_t, a_t^h, s_{t+1})\}$. Since the human has full knowledge of the composite reward, we assume the human's policy is a stationary expert policy and can make the following independence assumption for all candidate human reward functions $\hat{\theta}^h \in \Theta^h$ (Eq. 1).

$$b(\hat{\theta}^h) = P(\hat{\theta}^h|\tau_t) \propto P((s_1, a_1^h)|\hat{\theta}^h)P((s_2, a_2^h)|\hat{\theta}^h)...P((s_t, a_t^h)|\hat{\theta}^h)P(\hat{\theta}^h) \tag{1}$$

Best-case reward, r_{bc}, is the reward $R_{\theta^T,\theta^r,\hat{\theta}^h}$ the team would receive, computed with candidate $\hat{\theta}^h$, if the robot had taken the action that would maximize the composite reward (Eq. 2).

$$r_{bc}(s_t, a_t^h|\hat{\theta}^h) = \max_{a^r \in \mathcal{A}^r} \sum_{s_{t+1}} R_{\theta^T,\theta^r,\hat{\theta}^h}(s_t, a_t^h, s_{t+1})\mathcal{T}(s_{t+1}|s, a_t^h, a_t^r) \tag{2}$$

Under the Boltzmann model, $r_{bc}(s_t, a_t^h|\hat{\theta}^h)$ serves as a potential function (Eq. 3), where β is a rationality coefficient. The BIRL update yields a predicted human policy over all beliefs is $\hat{\pi}^h(a^h|s) = \sum_{\hat{\theta}^h} b(\hat{\theta}^h)P((s, a^h)|\hat{\theta}^h)$.

$$P((s_t, a_t^h)|\hat{\theta}^h) \propto \exp(\beta \cdot r_{bc}(s_t, a_t^h|\hat{\theta}^h)) \tag{3}$$

Planning Towards States with High Information Gain Potential. We leverage the key insight that the robot's actions in a current state will affect the available actions of the human in the next state, which will in turn affect the human's ability to provide informative actions. Hence, the robot should seek to maximize team reward under its beliefs while seeking to allow the human to provide informative demonstrations or actions. First, we perform a Bellman backup to compute a task-based Q given the current beliefs b (Eq. 4). $Q(s, a^r, a^h, b)$ represents expected discounted future composite team rewards given b.

$$Q(s, a^r, a^h, b) = \sum_{\hat{\theta}^h} b(\hat{\theta}^h) \sum_{s' \in S} T(s'|s, a^r, a^h)\Big(R_{\hat{\theta}^h,\theta^r,\theta^T}(s, a^r, a^h, s') + \gamma V(s')\Big) \tag{4}$$

We want some measure of information gain $I(b, s, a^r)$ the robot would receive if it takes action a^r in state s with the current set of beliefs b. $H(b)$ represents the entropy of the current beliefs b over Θ^h. We can easily measure the entropy of the new beliefs, $H(b|(s, a^h))$, given the human takes action a^h in state s. We compute this value by updating the beliefs using the likelihood in Eq. 3, which yields updated belief b' and estimated human policy $\hat{\pi}^h$. Then, the conditional entropy $H(b|(s, a^h))$ is measured by computing the entropy over b', $H(b|(s, a^h)) = H(b')$. Since we want to evaluate the information gain for a^r instead of a^h, we need some measure of $H(b|s, a^r)$, where $I(b, s, a^r) = H(b) - H(b|s, a^r)$. However, the robot and human act simultaneously, so the human will not be impacted by the action of the robot until the next timestep, once both actions of the human and robot are revealed and the environment transitions to the next state. Thus, the robot evaluates information gain potential, as the info gain achieved by the human giving the best entropy-minimizing action in the next state.

$$\mathbb{E}_{f,T}[H(b|s, a^r)] = \sum_{a^h \in \mathcal{A}^h} \sum_{s' \in \mathcal{S}} \mathcal{T}(s'|s, a^r, a^h)\hat{\pi}^h(a^h|s)H_{bc}(s', s, a^r, a^h) \tag{5}$$

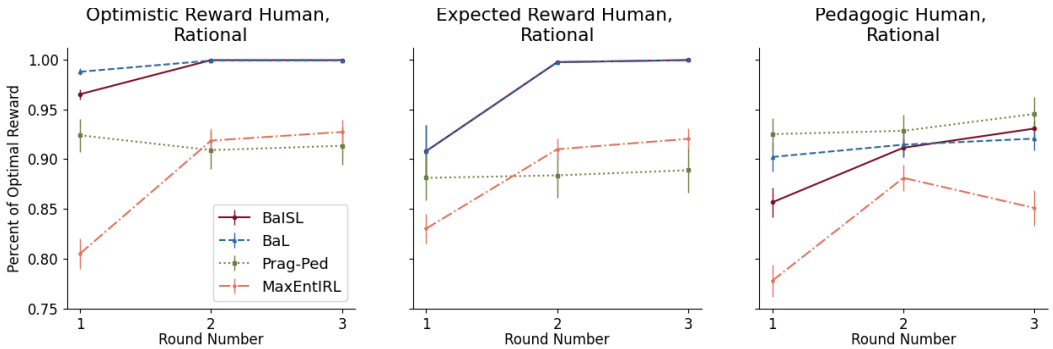

Figure 2: The human models are fully rational with $\beta = \infty$. Information gain incurs cost during the first round with the human partner, BaISL and BaL perform optimally in rounds 2 and 3 with *optimistic reward human* and the *expected reward human*. BaISL outperforms BaL on the *pedagogic human* in the third round. When paired with the rational *pedagogic human*, Prag-Ped outperforms the other three methods, due to the human model being the one Prag-Ped expects.

$$H_{bc}(s', s, a^r, a^h) = \min_{a^{h'} \in \mathcal{A}^h} H(b|(s', a^{h'})) \tag{6}$$

We compute expected entropy using Equation 5. H_{bc} represents the best-case entropy achieved from updating the beliefs given the human takes the most entropy-minimizing action in the next state (Eq. 6). It's important to note that the robot does not necessarily expect the human to always take the most entropy-minimizing action in every state; the robot simply seeks states that would provide the human the opportunity to give more informative decisions. Subsequently, the information gain of a^r in state s is added to the Q-value as a boost to actions that would guide the team towards states with the highest potential info gain (Eq. 7), where $I(b, s, a^r) = H(b) - \mathbb{E}_{\hat{\pi}^h, T}[H(b|s, a^r)]$. The α term (Eq. 8) is a switch that turns off the information gain boost when the hypotheses with maximum weight converge to predicting the same human action. The BaISL robot acts according to the resulting policy π^r.

$$\pi^r(s) \leftarrow \max_{a^r \in \mathcal{A}^r} \sum_{a^h \in \mathcal{A}^h} \sum_{\hat{\theta}^h} b(\hat{\theta}^h) \hat{\pi}^h(a^h|s; \hat{\theta}^h) \Big(Q(s, a^r, a^h, b) + \alpha I(b, s, a^r) \Big) \tag{7}$$

$$\alpha = |\bigcap_{\hat{\theta}^h \in \Theta^h} \{a \mid \pi^h(a|s; \hat{\theta}^h) = \max_b \hat{\pi}^h(b|s; \hat{\theta}^h) \wedge b(\hat{\theta}^h) = \max_{\bar{\theta}^h} b(\bar{\theta}^h)\}| \tag{8}$$

5 Simulated Evaluation

Task Scenario. We evaluate our approach on a simulated collaborative task, with a series of simulated human partners. The human-robot team must clean up objects from a shared workspace. There exist $K = 3$ object types, where objects differ by fragility and weight. The three types of objects are (1) heavy and fragile, (2) heavy and non-fragile, and (3) light and fragile. The action space available to each player is {cleanup (heavy, fragile) object, cleanup (heavy, non-fragile) object, cleanup (light, fragile) object, No-Op}. The heavy objects require both agents to jointly select the same action. Since the task objective is to declutter all objects, task reward is $+2$ for each object, with a -1 step cost. The human's individual reward, θ^h, for each object type is randomly sampled from $\mathcal{U}(1, 10)$. The human's individual reward θ^h is observed only by the human. However, the robot has does access to Θ^h: the hypothesis space for the human individual reward, which is the set of all permutations of θ^h values. The robot's individual reward θ^r is a random permutation of the same set of four reward values in θ^h, and is known to both agents. In each instance of this game, the human and robot collaborate over $N = 3$ interactions. At the start of each interaction, there exists one object of each type to be decluttered. When all objects have been cleaned up, the interaction ends and the team receives the total composite reward achieved.

Performance Metric. We ran 100 random configurations of individual rewards in this collaborative task. We solve the full-information MDP with joint actions to obtain the optimal composite reward. Performance is measured by the percentage of optimal reward achieved in the final Nth round.

Baselines. We compare our method BaISL against an ablation in which we eliminate the information gain boost, which we call just Bayesian Learner (BaL). We also compare our method to an alternative learning approach: Maximum Entropy Inverse Reinforcement Learning (MaxEnt IRL)[51].

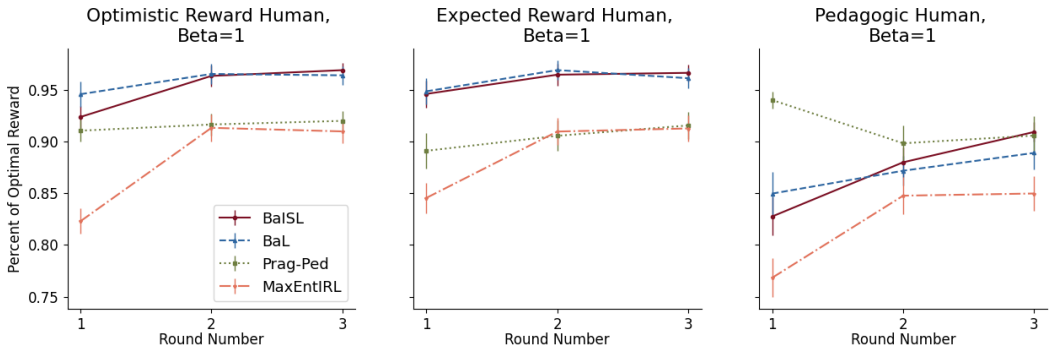

Figure 3: Boltzmann $\beta = 1$. With the *optimistic reward human* and the *expected reward human*, BaISL incurs cost due to the information gain objective during the first round with the human partner but is able to outperform BaL in the third round. When paired with the rational *pedagogic human*, Prag-Ped outperforms the other three methods in the first round. In the third round, however, BaISL outperforms BaL and even Prag-Ped with the *pedagogic human*.

which approximates the composite reward, bypassing the need for individual components, while maintaining the same value-based planning method. This baseline examines the efficacy of separating out the three reward components versus learning a single joint reward function to approximate the composite. Lastly, we consider a third baseline: Pragmatic-Pedagogic Value Alignment (Prag-Ped)[10], a solution to CIRL in which the robot policy assumes that the human will act pedagogically accounting for the robot's beliefs. Technical details can be found in the Appendix.

Simulated Human Partner. We experiment with three types of simulated humans. For each agent type, we experiment with temperatures $\beta \to \infty$ (rational), and the other with $\beta = 1$ (noisy). (1) The *optimistic reward human* selects actions that maximize composite reward assuming the human takes the optimal complementary action. (2) The *expected reward human* selects actions that maximize *expected* composite reward under a uniform probability over all robot actions. (3) The *pedagogic human* uses the Prag-Ped solution in Fisac et al. [10] to act pedagogically by rolling out the robot's belief update.

Results. Our experiments with the noiseless, rational simulated human models ($\beta = \infty$) demonstrate that the robot policies which pair with human models that match their prediction of human behavior outperform the misaligned human-robot teams. For example, our ICPL solution, BaISL as well as baseline BaL, assumes the human will act using the optimistic reward model, meaning the human will choose the action that maximizes reward assuming the robot takes the ideal complementary action. This optimistic reward model is exactly the *optimistic reward human*. The BaISL and BaL approaches achieve optimal performance with the *optimistic reward human*. Surprisingly, they also achieve maximal performance with the *expected reward human*. The *expected reward human* does not match any of the human models used by BaISL, BaL, and Prag-Ped. BaISL and BaL outperform Prag-Ped with the rational, *expected reward human*, achieving optimal performance. As the matching would lead us to expect, the Prag-Ped robot outperforms BaISL and BaL with the rational, *pedagogic human* (see Figure 2).

As the Boltzmann rationality parameter, β, of the simulated human model approaches 0, the human makes increasingly noisy decisions, which are dictated less by the potential function. In our second set of experiments, $\beta = 1$ simulated humans make more noisy decisions, causing the robot's beliefs to become prone to erroneous updates, which may lead to worse performance. BaISL marginally outperforms BaL by 1% when teaming with the *optimistic reward human* and *expected reward human*. When paired with the *pedagogic human*, which is out of distribution for both BaISL and BaL, the BaISL agent is able to outperform BaL by 3%, by learning a more accurate reward function in more interaction instances. With the *pedagogic human*, BaISL is even able to marginally outperform Prag-Ped, which has the advantage of a matching human model, by 1%. Generally, the BaISL robot performs more information-seeking actions, which are sometimes No-Op actions, early on during the first round. This tends to lead to lower performance in the first round than BaL, which immediately seeks to maximize expected reward. However, by taking the time to learn the human's reward, BaISL is able to perform better than BaL over time, such that by the third round, BaISL performance is equivalent to or better than BaL across all three simulated human models (see Figure 3).

Figure 4: The user study interface requires the human to control one of two manipulators. The robot partner is the manipulator on the right. Users select actions at the object level using an interface.

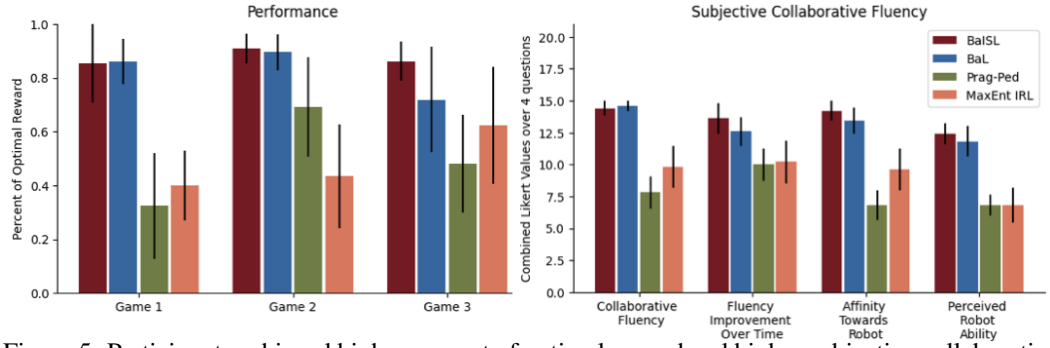

Figure 5: Participants achieved higher percent of optimal reward and higher subjective collaborative fluency with BaISL and BaL over Prag-Ped and MaxEnt IRL. In the second and third rounds, teams with BaISL outperformed BaL in performance.

6 User Study

We ran a pilot user study, with five participants, to compare the collaboration of human partners with our BaISL agent against several baselines. We investigated the impact of the independent variable: agent type, on dependent variables: task performance, and collaborative fluency. Task performance is defined by the percentage of optimal reward achieved. We measured four collaborative fluency variables [62]: overall fluency, the improvement of fluency over time, affinity towards the robot as a collaborative partner, and the perceived ability of the robot to learn the correct human individual reward, using four 5-point Likert scale questions whose values we aggregated in order to treat as a continuous variable [63]. As with the simulated evaluation, our baselines were BaL, Prag-Ped, and MaxEnt IRL. Each participant performed an ICPL task four times, once with each agent. The ICPL task was a decluttering task similar to the simulated task scenario, with $K = 3$ object types, where objects differ by color (representing fragility) and weight (Fig 4). Each round began with 1-2 objects of each type, where the starting configuration of objects was identical per round. After each task, participants were asked a series of survey questions. Participants were given two scaffolded training tasks to familiarize themselves with the online game's controls prior to beginning the trials.

While we did not perform statistical analyses due to the small sample size, we found general trends indicating that users performed closest to optimally when working with the BaISL and BaL robots. Teams with BaISL robot were able to more consistently maintain close to optimal rewards over the three rounds. On average, in the third and final round, the BaISL teams achieved 86% of the total reward, while BaL teams achieved 72%, Prag-Ped teams achieved 48%, and MaxEnt IRL teams achieved 62%. This indicates that the *optimistic reward human* model might more closely resemble human reasoning in this collaborative task than the *pedagogic human* model. The MaxEnt baseline suffers in the first round because it relies on successful demonstrations in order to begin learning the reward. Its performance improves throughout the three rounds but never reaches the performance of BaISL and BaL. Participants also self-reported higher collaborative fluency with the BaISL and BaL models than the other two baselines. They also perceived the largest improvement in fluency over time with BaISL and BaL, with BaISL slightly higher than BaL. This may be related to our expectation that the BaISL model begins by taking information-seeking actions, rather than optimizing for reward, which may result in lower fluency in earlier rounds. Participants rated their affinity towards the robot as a collaborative partner the highest with the BaISL agent on average, and most strongly perceived that BaISL had learned their correct individual reward functions (Figure 5).

7 Discussion and Limitations

In this work, we formulate a type of collaborative interaction where the robot must align itself to the human's contribution preferences while adhering to task objectives and its own constraints as an ICPL game. ICPL games are limited to interactions that are based on reward learning, which does not span all types of human-robot collaborations. In ICPL, the robot's constraints are assumed to take the form of a reward function. However, this is not the only form of robot constraint possible; there include activity deadlines, probable errors, and task specifications. Furthermore, this formulation limits the human individual reward as it only captures the notion of the human's preferences for their own contribution, since only the human action is taken as a parameter. However, humans may have preferences or expectations for how they want the robot to contribute. Capturing this contribution preference requires modifying the human reward function to include other agents' actions as input. Despite its limitations, ICPL poses a flexible, interaction paradigm in which robots can represent and learn human contribution preferences in collaborative human-robot tasks.

Our BaISL approach, as well as Prag-Ped, requires that the robot assume some model of human behavior in order to define the likelihood function for human actions. In our simulated evaluations, we find that, naturally, teams consisting of a rational human partner matching the robot's hypothesized human model yields the highest team rewards. This presents a drawback in testing with simulated human models, which all rely on predefined decision models. This motivates future work in running larger user studies with human participants, whose decision-making may be more variable and not captured by our predefined models. Another limitation is that our information gain objective does not construct long-horizon multi-state plans towards states with high information potential. Rather, BaISL evaluates whether the next state can be informative and seeks out next states with high information gain potential. BaISL is myopic in its information gain computation, in which the algorithm can only reason about the next state, without a more long-term vision. While this is one limitation of our approach, we believe this also affords the algorithm simplicity and interpretability of its learning process to human partners, demonstrated by the perceived robot's ability to learn in our preliminary user study (Fig. 5). Future work includes active learning methods [54] which consider longer-horizon plans for learning about human partners in collaborative tasks.

We compare the efficacy of our model on a single task domain for both simulated and real user experiments: a collaborative decluttering task with different object types. In cases where the human is noisily rational, our method BaISL achieves the highest reward in the final round compared to baselines. While the task includes a coordination complexity in which particular actions must be performed jointly in order for the team to receive reward, it still remains rather simple in the state and action space. We view BaISL as a candidate approach to robot decision-making in more complex collaborative interactions, and for these evaluations to serve as a starting point from which to investigate more complex tasks and algorithms. In future work, we plan to scale up task complexity to include more agent interdependencies and preconditons for different actions.

8 Conclusion

We introduce a collaborative paradigm, ICPL, where successful teams optimize task objectives while adhering to individual agent constraints. We also contribute an candidate approach, BaISL, which models humans as maximizing rewards with the assumption that the robot will choose the optimal action, facilitating the robot's eventual learning of optimal actions. This human model guides online reward learning. The robot plans its actions based on expected rewards, taking into account updated beliefs about states with high potential for information gain given the human's available actions. We evaluated BaISL through experiments with simulated human models and a preliminary user study involving human partners. Our results demonstrate that BaISL enhances team performance with both simulated and real human partners. Our framework aims to equip robots with the ability to represent, learn, and accommodate human contribution preferences in collaborative human-robot tasks.

References

[1] M. Dunnette. Critical concepts in the assessment of human capabilities. *Human Performance and Productivity: Volumes 1, 2, and 3*, 2014.

[2] S. Zhang, Y. Chen, J. Zhang, and Y. Jia. Real-time adaptive assembly scheduling in human-multi-robot collaboration according to human capability. In *2020 IEEE International Conference on Robotics and Automation (ICRA)*, pages 3860–3866. IEEE, 2020.

[3] N. Iijima, A. Sugiyama, M. Hayano, and T. Sugawara. Adaptive task allocation based on social utility and individual preference in distributed environments. *Procedia computer science*, 112: 91–98, 2017.

[4] S. J. Motowildo, W. C. Borman, and M. J. Schmit. A theory of individual differences in task and contextual performance. *Human performance*, 10(2):71–83, 1997.

[5] J. G. Nicholls, P. C. Cheung, J. Lauer, and M. Patashnick. Individual differences in academic motivation: Perceived ability, goals, beliefs, and values. *Learning and individual differences*, 1(1):63–84, 1989.

[6] T. Bandyopadhyay, S. Kok, E. Won, D. Frazzoli, W. Hsu, D. Lee, and D. Rus. Intention-aware motion planning. *Springer Tracts in Advanced Robotics, Algorithmic Foundations of Robotics X*, 86, 02 2013. doi:10.1007/978-3-642-36279-8_29.

[7] F. Gobet, H. Richman, J. Staszewski, and H. A. Simon. Goals, representations, and strategies in a concept attainment task: The epam model. 1997.

[8] S. Nikolaidis, Y. X. Zhu, D. Hsu, and S. S. Srinivasa. Human-robot mutual adaptation in shared autonomy. *2017 12th ACM/IEEE International Conference on Human-Robot Interaction (HRI*, pages 294–302, 2017.

[9] D. S. Brown, J. Schneider, A. Dragan, and S. Niekum. Value alignment verification. In *International Conference on Machine Learning*, pages 1105–1115. PMLR, 2021.

[10] J. F. Fisac, M. A. Gates, J. B. Hamrick, C. Liu, D. Hadfield-Menell, M. Palaniappan, D. Malik, S. S. Sastry, T. L. Griffiths, and A. D. Dragan. Pragmatic-pedagogic value alignment. In *Robotics Research*, pages 49–57. Springer, 2020.

[11] T. Munzer, M. Toussaint, and M. Lopes. Preference learning on the execution of collaborative human-robot tasks. In *2017 IEEE International Conference on Robotics and Automation (ICRA)*, pages 879–885. IEEE, 2017.

[12] D. Hadfield-Menell, S. J. Russell, P. Abbeel, and A. Dragan. Cooperative inverse reinforcement learning. *Advances in neural information processing systems*, 29, 2016.

[13] A. Ajoudani, A. M. Zanchettin, S. Ivaldi, A. Albu-Schäffer, K. Kosuge, and O. Khatib. Progress and prospects of the human–robot collaboration. *Autonomous Robots*, 42(5):957–975, 2018.

[14] T. T. Nguyen, M. Roos, and J. Rothe. A survey of approximability and inapproximability results for social welfare optimization in multiagent resource allocation. *Annals of Mathematics and Artificial Intelligence*, 68(1-3):65–90, 2013.

[15] P. Krysta, O. Telelis, and C. Ventre. Mechanisms for multi-unit combinatorial auctions with a few distinct goods. *Journal of Artificial Intelligence Research*, 53:721–744, 2015.

[16] V. Singhal and D. Dahiya. Distributed task allocation in dynamic multi-agent system. In *International Conference on Computing, Communication & Automation*, pages 643–648. IEEE, 2015.

[17] A. Asadpour and A. Saberi. An approximation algorithm for max-min fair allocation of indivisible goods. In *Proceedings of the thirty-ninth annual ACM symposium on Theory of computing*, pages 114–121, 2007.

[18] H. Aziz, P. Biró, J. Lang, J. Lesca, and J. Monnot. Optimal reallocation under additive and ordinal preferences. 2016.

[19] A. Norton, H. Admoni, J. Crandall, T. Fitzgerald, A. Gautam, M. Goodrich, A. Saretsky, M. Scheutz, R. Simmons, A. Steinfeld, et al. Metrics for robot proficiency self-assessment and communication of proficiency in human-robot teams. *ACM Transactions on Human-Robot Interaction (THRI)*, 11(3):1–38, 2022.

[20] A. Jauffret, C. Grand, N. Cuperlier, P. Gaussier, and P. Tarroux. How can a robot evaluate its own behavior? a neural model for self-assessment. In *The 2013 International Joint Conference on Neural Networks (IJCNN)*, pages 1–8. IEEE, 2013.

[21] K. Odette, J. Rivera, E. K. Phillips, and F. Jentsch. Robot self-assessment and expression: A learning framework. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, volume 61, pages 1188–1192. SAGE Publications Sage CA: Los Angeles, CA, 2017.

[22] T. Dai, K. Sycara, and M. Lewis. A game theoretic queueing approach to self-assessment in human-robot interaction systems. In *2011 IEEE International Conference on Robotics and Automation*, pages 58–63. IEEE, 2011.

[23] L. Yuan, X. Gao, Z. Zheng, M. Edmonds, Y. N. Wu, F. Rossano, H. Lu, Y. Zhu, and S.-C. Zhu. In situ bidirectional human-robot value alignment. *Science robotics*, 7(68):eabm4183, 2022.

[24] T. Fong and I. R. Nourbakhsh. Peer-to-peer human-robot interaction for space exploration. In *AAAI Technical Report (5)*, pages 87–90, 2004.

[25] K. v. d. Bosch, T. Schoonderwoerd, R. Blankendaal, and M. Neerincx. Six challenges for human-ai co-learning. In *International Conference on Human-Computer Interaction*, pages 572–589. Springer, 2019.

[26] D. Ramachandran and E. Amir. Bayesian inverse reinforcement learning. In *IJCAI*, volume 7, pages 2586–2591, 2007.

[27] A. Bauer, D. Wollherr, and M. Buss. Human–robot collaboration: a survey. *International Journal of Humanoid Robotics*, 5(01):47–66, 2008.

[28] A. Levratti, A. De Vuono, C. Fantuzzi, and C. Secchi. Tirebot: A novel tire workshop assistant robot. In *2016 IEEE international conference on advanced intelligent mechatronics (AIM)*, pages 733–738. IEEE, 2016.

[29] K. Kosuge, M. Sato, and N. Kazamura. Mobile robot helper. In *Proceedings 2000 ICRA. Millennium Conference. IEEE International Conference on Robotics and Automation. Symposia Proceedings (Cat. No. 00CH37065)*, volume 1, pages 583–588. IEEE, 2000.

[30] H. S. Koppula, A. Jain, and A. Saxena. Anticipatory planning for human-robot teams. In *Experimental robotics*, pages 453–470. Springer, 2016.

[31] M. Montemerlo, J. Pineau, N. Roy, S. Thrun, and V. Verma. Experiences with a mobile robotic guide for the elderly. *AAAI/IAAI*, 2002:587–592, 2002.

[32] A. Mertens, U. Reiser, B. Brenken, M. Lüdtke, M. Hägele, A. Verl, C. Brandl, and C. Schlick. Assistive robots in eldercare and daily living: Automation of individual services for senior citizens. In *International Conference on Intelligent Robotics and Applications*, pages 542–552. Springer, 2011.

[33] B. A. Newman, R. M. Aronson, K. Kitani, and H. Admoni. Helping people through space and time: Assistance as a perspective on human-robot interaction. *Frontiers in Robotics and AI*, 8, 2022. ISSN 2296-9144. doi:10.3389/frobt.2021.720319. URL https://www.frontiersin.org/articles/10.3389/frobt.2021.720319.

[34] M. Zhao, R. Simmons, and H. Admoni. Coordination with humans via strategy matching. In *2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 9116–9123. IEEE, 2022.

[35] D. Strouse, K. McKee, M. Botvinick, E. Hughes, and R. Everett. Collaborating with humans without human data. *Advances in Neural Information Processing Systems*, 34:14502–14515, 2021.

[36] M. Carroll, R. Shah, M. K. Ho, T. Griffiths, S. Seshia, P. Abbeel, and A. Dragan. On the utility of learning about humans for human-ai coordination. *Advances in neural information processing systems*, 32, 2019.

[37] D. Amodei, C. Olah, J. Steinhardt, P. Christiano, J. Schulman, and D. Mané. Concrete problems in ai safety. *arXiv preprint arXiv:1606.06565*, 2016.

[38] S. Russell, D. Dewey, and M. Tegmark. Research priorities for robust and beneficial artificial intelligence. *Ai Magazine*, 36(4):105–114, 2015.

[39] D. Sadigh, A. D. Dragan, S. Sastry, and S. A. Seshia. *Active preference-based learning of reward functions*. 2017. doi:10.15607/RSS.2017.XIII.053.

[40] P. F. Christiano, J. Leike, T. Brown, M. Martic, S. Legg, and D. Amodei. Deep reinforcement learning from human preferences. *Advances in neural information processing systems*, 30, 2017.

[41] M. S. Lee, H. Admoni, and R. Simmons. Machine teaching for human inverse reinforcement learning. *Frontiers in Robotics and AI*, 8:188, 2021.

[42] J. Zhu. Machine teaching for bayesian learners in the exponential family. *Advances in Neural Information Processing Systems*, 26, 2013.

[43] J. Perner. *Understanding the representational mind.* The MIT Press, 1991.

[44] A. Tabrez, M. B. Luebbers, and B. Hayes. A survey of mental modeling techniques in human–robot teaming. *Current Robotics Reports*, 1(4):259–267, 2020.

[45] H. Wimmer and J. Perner. Beliefs about beliefs: Representation and constraining function of wrong beliefs in young children's understanding of deception. *Cognition*, 13(1):103–128, 1983.

[46] S. Baron-Cohen, A. M. Leslie, and U. Frith. Does the autistic child have a "theory of mind"? *Cognition*, 21(1):37–46, 1985.

[47] S. M. Carlson, M. A. Koenig, and M. B. Harms. Theory of mind. *Wiley Interdisciplinary Reviews: Cognitive Science*, 4(4):391–402, 2013.

[48] C. Baker, R. Saxe, and J. Tenenbaum. Bayesian theory of mind: Modeling joint belief-desire attribution. In *Proceedings of the annual meeting of the cognitive science society*, volume 33, 2011.

[49] R. S. Sutton and A. G. Barto. *Reinforcement learning: An introduction*. MIT press, 2018.

[50] A. Y. Ng and S. Russell. Algorithms for inverse reinforcement learning. In *in Proc. 17th International Conf. on Machine Learning*, pages 663–670. Morgan Kaufmann, 2000.

[51] B. D. Ziebart, A. L. Maas, J. A. Bagnell, A. K. Dey, et al. Maximum entropy inverse reinforcement learning. In *Aaai*, volume 8, pages 1433–1438. Chicago, IL, USA, 2008.

[52] C. L. Baker, J. B. Tenenbaum, and R. Saxe. Bayesian models of human action understanding. *Advances in neural information processing systems*, 18:99, 2006.

[53] B. Ziebart, N. Ratliff, G. Gallagher, C. Mertz, K. Peterson, J. Bagnell, M. Hebert, A. Dey, and S. Srinivasa. Planning-based prediction for pedestrians. pages 3931–3936, 12 2009. doi: 10.1109/IROS.2009.5354147.

[54] E. Bıyık, A. Talati, and D. Sadigh. Aprel: A library for active preference-based reward learning algorithms. In *Proceedings of the 2022 ACM/IEEE International Conference on Human-Robot Interaction*, pages 613–617, 2022.

[55] L. Shao, T. Migimatsu, Q. Zhang, K. Yang, and J. Bohg. Concept2robot: Learning manipulation concepts from instructions and human demonstrations. *The International Journal of Robotics Research*, 40(12-14):1419–1434, 2021.

[56] M. Li, A. Canberk, D. P. Losey, and D. Sadigh. Learning human objectives from sequences of physical corrections. In *2021 IEEE International Conference on Robotics and Automation (ICRA)*, pages 2877–2883. IEEE, 2021.

[57] B. C. Stadie, P. Abbeel, and I. Sutskever. Third-person imitation learning. *International COnference on Learning Representations (ICLR)*, 2017.

[58] D. J. Hejna III and D. Sadigh. Few-shot preference learning for human-in-the-loop rl. In *6th Annual Conference on Robot Learning*, 2022.

[59] T. K. Büning, A.-M. George, and C. Dimitrakakis. Interactive inverse reinforcement learning for cooperative games. In *International Conference on Machine Learning*, pages 2393–2413. PMLR, 2022.

[60] H. J. Jeon, S. Milli, and A. Dragan. Reward-rational (implicit) choice: A unifying formalism for reward learning. *Advances in Neural Information Processing Systems*, 33:4415–4426, 2020.

[61] C. Laidlaw and A. Dragan. The boltzmann policy distribution: Accounting for systematic suboptimality in human models. *arXiv preprint arXiv:2204.10759*, 2022.

[62] G. Hoffman. Evaluating fluency in human–robot collaboration. *IEEE Transactions on Human-Machine Systems*, 49(3):209–218, 2019.

[63] J. Carifio and R. J. Perla. Ten common misunderstandings, misconceptions, persistent myths and urban legends about likert scales and likert response formats and their antidotes. *Journal of social sciences*, 3(3):106–116, 2007.