Improved Inference of Human Intent by Combining Plan Recognition and Language Feedback

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Abstract—Conversational assistive robots can aid people, especially those with cognitive impairments, to accomplish various tasks such as cooking meals, performing exercises, or operating machines. However, to interact with people effectively, robots must recognize human plans and goals from noisy observations of human actions, even when the user acts sub-optimally. Previous works on Plan and Goal Recognition (PGR) as planning have used hierarchical task networks (HTN) to model the user/actor/human. However, these techniques are insufficient as they do not have user engagement via natural modes of interaction such as language. Moreover, they have no mechanisms to let users, especially those with cognitive impairments, know of a deviation from their original plan or about any sub-optimal actions taken towards their goal. We propose a novel framework for plan and goal recognition in partially observable domains—Dialogue for Goal Recognition (D4GR) enabling a robot to rectify its belief in human progress by asking clarification questions about noisy sensor data and sub-optimal human actions. We evaluate the performance of D4GR over two simulated domains—kitchen and blocks domain. With language feedback and the world state information in a hierarchical task model, we show that D4GR framework for the highest sensor noise performs 1% better than HTN in goal accuracy in both domains. For plan accuracy, D4GR outperforms by 4% in the kitchen domain and 2% in the blocks domain in comparison to HTN. The ALWAYS-ASK oracle outperforms our policy by 3% in goal recognition and 7% in plan recognition. D4GR does so by asking 68% fewer questions than an oracle baseline. We also demonstrate a real-world robot scenario in the kitchen domain, validating the improved plan and goal recognition of D4GR in a realistic setting.

I. INTRODUCTION

People with cognitive impairments, such as dementia, often struggle with focusing on everyday tasks and have limited attention spans. Efforts to assist people in tracking task progress have involved various approaches, including modeling tasks as a hierarchical task network (HTN), using a Bayesian Hidden Markov Model, or employing a Partially Observable Markov Decision Process (POMDP) [6, 19]. However, previous approaches focus on observing users rather than engaging them in an interaction. Our work aims to develop a model for a robot capable of assisting people complete tasks with language-based interactions; even when the users perform sub-optimal actions or switch between multiple goals. Our robot tracks the task progress using observations and question-asking using natural language. Such a robot can also benefit an operator building a machine, a child with autism doing their homework, or a child learning to do chores.

Inferring the goals and intents of the human requires plan and goal recognition (PGR) using noisy evidence from action execution that can be done efficiently using planning techniques [11]. One key challenge in human intent recognition as a PGR problem is that the robot has partial observability of human intentions. This is compounded by noisy sensors that also create partial observability of the environment. Modeling human progress during hierarchical tasks has been done using Hierarchical Task Networks (HTNs) [19, 7]. However, these recognition techniques again do not engage with the users and assume that the user acts optimally. Moreover, incorporating clarification questions and language utterances spoken by humans in PGR is challenging because of the huge space of language observations. The existing solution to this problem is heuristics [16, 5, 10], which are prone to fail as the tasks and environment sensors become complex and noisy.

The main contribution of our paper is a novel formulation that combines expressive and hierarchical task representation of HTNs to represent the human mental states with the sequential decision-making capabilities of a Partially Observable Markov Decision Process, in our Dialogue for Goal Recognition (D4GR). Our method keeps track of the environment, user state and dialogue history internally to perform PGR and guide in successful task completion.

POMDPs can model the uncertainty the robot faces as it performs intent recognitions and enables the robot to ask information-seeking questions. However, POMDP planners traditionally do not decide the relevance of the state using the task network at each sequential time step. Further, the HTNs have no notion of rewards to generate a sequence of actions to maximize the agent’s utility. To solve these challenges, we assume that the user is a planner with goals and subgoals that are represented hierarchically. Moreover, the robot is a POMDP planner performing long-horizon dialogue policy planning. This enables the robot to reason about asking meaningful questions in ambiguous settings, such as the user switching goals during multiple concurrent tasks and also performing sub-optimal actions. Using this information, the robot can better recognize human intents based on the human actions estimated from noisy sensors and their language feedback. This model also explicitly allows for sub-optimal plans by a human user, which D4GR can detect.

We evaluate the usefulness of D4GR by measuring the improved accuracy in PGR and comparing the planning time and number of questions asked to two state-of-the-art baselines in the simulated domain developed by Wang and Hoey [19]. Our system is able to more accurately infer human intents than these baselines using information gathered from a language.
without asking unnecessary questions. We run 880 trials for varying sensor noise levels where the simulated human tries to complete a combination of tasks in two domains - the kitchen and blocks domain. In the kitchen domain, there are three tasks - washing hands, making a cup of tea, and making a cup of coffee while in the blocks domain, tasks include an assortment of stacking letters to make 4-7 lettered words - *rote*, *tone*, *tune*, *hawk*, *capstone*. With language feedback and the world state information in a hierarchical task model, we show that our D4GR framework outperforms HTN by 4% on plan accuracy in the kitchen domain and 2% in the blocks domain. In goal accuracy, for the highest sensor noise, our D4GR performs 1% better than HTN in both kitchen and block domains. We also deployed our algorithm on a social robot Kuri as a demonstration of a socially intelligent robot helping confused users complete tasks. In this demonstration, Kuri performs improved PGR by asking clarification questions and reducing uncertainty for a challenging scenario where the user switches between multiple concurrent goals (e.g., washing hands and making coffee) and acts sub-optimally in the kitchen domain. The demo can be found here: [https://youtu.be/Om91zBiDDEY](https://youtu.be/Om91zBiDDEY). An example sequence of the user and robot interaction can be seen in Fig. 1.

**II. RELATED WORK**

**Plan and Goal Recognition as Planning:** The first work on PGR as planning was introduced by Ramírez and Geffner [15]. This research leverages classical planning systems to solve PGR problems. Wang and Hoey [19] proposed an algorithm for PGR based on hierarchical task network [4] that handles noisy sensors and sub-optimality in human actions. However, their approach detects mistakes heuristically using a manually defined threshold while performing a one-step look ahead without long-horizon planning. Additionally, it lacks dialog conversation to improve belief in the actor’s progress in the task. Another relevant work that does not engage with the user is by Zhi-Xuan et al. [22], which performs online Bayesian goal inference by modeling the agent as a boundedly rational planning agent but is not designed and evaluated for multiple concurrent hierarchical goals. Mirsky et al. [12] presents favorable results for the hypothesis that feedback from the acting agent can improve plan (goal and step) recognition, but their paper performs goal recognition as reinforcement learning and has a fixed language policy without exploring the observer’s strategy for asking clarification question. Höller et al. [7] employs HTN Planning for PGR but struggles with sub-optimal actions and noisy sensors, focusing on handling missing sensor observations instead.

**Context-aware Social Robotics:** In the past, research in social robotics has focused on developing non-verbal social behaviors for robots to assist the elderly during task completion. These works place less emphasis on incorporating language feedback/observations for user intent inference. However, the robot dialog policy (if involved) does not account for the environmental context, dialog context, and user modeling. Research in situated human-robot dialog by Bohus and Horvitz [1], Thomason et al. [18], Idrees et al. [8] grounds speech response in the environment but asks clarification questions heuristically, using rule-based/greedy approaches and without using a decision-theoretic framework. Such heuristics are prone to failure as the tasks get complex and the environment sensors become complex and noisy.

**POMDP-based Collaborative Dialog:** Partially observable Markov decision processes (POMDPs) provide a rich framework for planning under uncertainty. They excel in optimizing agents’ actions over long horizons in complex environments despite incomplete state information from noisy sensors [6].
A. POMDP Definition

We model our PGR problem as a POMDP planning problem, generating an approximately optimal action policy for the robot. Formally, a POMDP is defined as a tuple \((S, A, T, R, \Omega, \gamma, b_0)\) where \(S\) is the state space, \(A\) is the action space, \(T\) is the transition probability, \(R\) is the reward function, \(\Omega\) is a set of observations, \(\gamma\) defines an observation probability and \(\gamma\) is the discount factor. Since \(s_t\) is not known exactly, the POMDP model updates, at each timestep, the probability distribution over all possible states (belief state \(b_t\)). The POMDP agent uses a planner to generate an optimal policy for the robot’s action, which in this case is the communication with the human user.

B. D4GR Formulation

We define a novel model, Dialogue 4 for Goal Recognition, a Partially Observable Markov Decision Process (D4GR) that combines the goal and plan recognition components as described by Wang and Hoey [19] with the POMDP formalism to allow robots to take action in the environment through dialogue for improved PGR. For efficient human intent recognition and estimation of optimal action policy, our D4GR must handle the large space of the world and language observations. Our formulation leverages the hierarchical task structure of HTN and assumes independent assumptions between state variables set of goals \(G\), human user action \(\alpha\), and world state \(W\) for efficient belief update. Our D4GR has the following components: \((S, A, T, R, \Omega, \gamma; b_0)\).

**State (S):** The state, \(s_t \in S\), consists of a tuple of the user’s mental state, \(M_t\), and the world state, \(W_t\), along with information needed to track the dialog state. We represent the user mental state using HTNs. We assume access to the HTN’s fixed knowledge graph TaskNet for the tasks, where the root node(s) represent the high-level tasks/goals \(G\) that the human can do. The internal nodes are sub-tasks that can be decomposed into leaf nodes depicting primitive human actions. \(\alpha\) denotes the current primitive human action. We model the user’s mental state \(M\) represented by \(G\) and \(\alpha\). The partial TaskNet for our kitchen domain is shown in Fig 2.

The world state \(W\) combines the states of world smart sensors \(ss\) and the attributes of objects involved in the task \(att\_t\), such as dryness of the hand, state of the faucet, etc. The
The dialog state variable $q_t$ stores the latest primitive human action referenced by the robot in its clarification question. Thus, the state $s_t$ can be factorized into the following components: $s_t = (M_t, q_t, W_t)$ where $W_t = (s_{t-1}, a_{t-1})$, $M_t = (G_t, o_t)$. Here $G_t, a_t, W_t, s_{t-1}$ are the hidden variables, while $q_t$ is the known variables, hence making this a Mixed Observable Markov Decision Process (MOMDP) [13]. The influence diagram can be seen in Fig 4.

**Action** includes the actions of the agent. The robot for this research can perform the following predefined language-based actions: 1) **Wait**: does nothing but advances the time step. 2) **Ask**\{argmax($a$)\}: The robot asks a clarification question about the primitive action $a$ with the highest belief. The question template used is: “I believe that you just did **(α)**, is this correct?” 3) **Inform_next_instruction**: informs the next action that the user should perform at the current timestep based on the current belief. This action is chosen based on a fixed policy and is executed when the user provides a negative language response to the robot’s clarification question.

**Observations** ($O$) encompass both the user’s language ($o_t$) and observations about the world state ($o_w$). $o_w$ includes discrete observations of the world smart sensor’s state $s_{t-1}$ and the attributes of the task-related objects $a_{t-1}$ such as hand_dry == true, faucet_on == false, etc. These observations are binary for the states in $W_t$, so the faucet can only be on or off. The language observations are natural language responses.

**Observational Model** ($O$): The robot needs a model of $p(o|s) = p(a_t, o_w|s_t)$ to update its belief. Most of the complexity of our model is captured in this observation model and belief update defined in the sec 3.1.3

**Transition Model** ($T$) : $T(s, a, s') = p(s_{t+1}|s_t, a_t)$. Our stochastic transition function is factorized as shown in Eq [1] following a similar approach to Wang and Hoey [19]. We factor our mental model $M_t$ into $G_t$ and $o_t$. Additionally, we assume that the last question asked, $q_t$, is independent of $G$, $o_t$, and $W_t$.

$$p(s_{t+1}|s_t, a_t) = p(G_{t+1}|W_{t+1}, G_t) \times p(W_{t+1}|W_t, o_{t+1}) \times p(o_{t+1}|W_t, G_t) \times p(q_{t+1}|q_t, a_t). \tag{1}$$

In Eq 1, we assume that $q_t$ changes deterministically from null to max($\alpha$) after the robot asks a clarifying question. Further, $G$ is deterministically carried forward to the next time step.

$$p(q_{t+1}|q_t, a_t) = \begin{cases} 1 & \text{for max(\alpha)} \text{ else 0, if } a \neq \text{NULL} \\ 1 & \text{for } q_t, \text{ else 0 } a_t = = \text{NULL.} \end{cases}$$

**Reward** ($R(s, a)$): We provide a positive reward (5) for asking a clarifying question when the user is doing the wrong or suboptimal lowest primitive step. A negative reward (−5) for asking a clarifying question when the human user is doing the correct primitive step or when the agent asks a question about a wrong primitive action. Thus, doing nothing accumulates zero rewards until the right question is asked, while not asking a question or asking a wrong one results in a penalty.

**C. Belief Update for Goal Recognition and Planning**

Our belief update performs human intent recognition by maintaining a belief over the hidden user’s mental state $M_t = (G_t, o_t)$ and the world state $W_t$. The actions executed by the user produce an observation of the world state $o_w$ indicating the change in the world state $W_t$. The user can also provide speech/language feedback $o_t$ in response to the clarification question asked. We classify the intent of each sentence into positive or negative feedback using the bag of words approach. Negative responses $r_n$ include { ‘no’, ‘nopes’, ‘other’, ‘not’ } while positive responses $r_p$ include the words { ‘yes’, ‘yeah’, ‘sure’, ‘yup’ }. Further, our world sensor noise model generates the correct sensor state with probability $sr$ and the incorrect sensor state with $1 - sr$. We adopt the noise model for the sensor described by Wang and Hoey [19].

The observation model can be further expanded and approximated as follows:

$$p(o_t|s_t; a_{t-1}) \propto p(s_t|o_t, a_{t-1}) \ast p(a_t|a_{t-1}). \tag{2}$$

Overall, the probability of $s_t$ given $o_t$ and $a_{t-1}$ can be factored into the world observation model and language observation model in Eq 2. We assume that the world observation $o_{w,t}$ solely provides information about the $W$ and $o_t$. Meanwhile, the language observation is relevant to the human action $a_t$, the last question asked $q_t$, subsequently affecting the goal.

$$p(s_t|o_t, a_{t-1}) \propto p(G_t|W_t) \ast p(W_t|o_{w,t}) \ast p(a_t|o_{w,t}) \ast p(o_{w,t}). \tag{3}$$

**Language observational model**

For both the world and primitive action belief update in Eq 3, the components $p(W_t|o_{w,t})$ and $p(o_t|o_{w,t})$ are derived from Wang and Hoey [19]. The Bayesian update is as follows:

$$p(a_t|o_{w,t}) \propto \sum_{w_{t-1} \in W_{t-1}} \sum_{w_t \in W_t} p(a_t, o_{w,t}, w_{t-1}, w_t), \tag{4}$$

$$p(W_t|o_{w,t}) = \sum_{w_{t-1} \in W_{t-1}} \sum_{o_{t}, o_{w,t}, w_{t-1}, w_t} p(a_t, o_{w,t}, w_{t-1}, w_t). \tag{5}$$

We adopt the proposed algorithm for goal recognition, $p(G_t|W_t)$ in Wang and Hoey [19]. The algorithm maintains a goal belief distribution by generating a probabilistic explanation set - ExplaSet. Each expla ∈ ExplaSet uses HTN planning to explain the observations so far. The probability of each goal $g_i$ in $G$ given the world state is the sum of probabilities of expla ∈ ExplaSet whose PredictedGoal == $g_i$. Our algorithm reweights primitive actions probabilities based on the language observational model described below, influencing the world belief update according to Eq 5 and, consequently, the goal recognition update.
The derivation of the language observational model is:

\[
    p(\alpha_t, q_t | o_{t,t}) \propto p(o_{t,t} | \alpha_t, q_t).
\]

We adopt a bag-of-words approach as our POMDP’s observational model instead of utilizing a large language model (LLM) like GPT3. LLMs are not inherently grounded. Our model explicitly establishes a connection between sensor information and semantics through a transition model in the POMDP. Although LLMs could be incorporated for intent classification using the right prompt, we did not pursue this direction as it falls outside the focus of our paper.

To estimate the effect of the language observation \( o_{t,t} \) on \( \alpha_t \) and \( q_t \), we calculate \( p(o_{t,t} | \alpha_t, q_t) \). For this, we consider three possibilities for the state: If the highest belief primitive action \( \alpha_{max,t} = q_t \), then the user is likely to respond with positive/confirmation feedback. The opposite is true if \( \alpha_{max,t} \neq q_t \). If \( q_t = \text{Null} \), then no question has been asked, so both types of responses are equally likely. The mathematical representation of \( p(o_{t,t} | \alpha_t, q_t) \) is governed by the following conditional probability table:

<table>
<thead>
<tr>
<th>Condition</th>
<th>Probability (Y)</th>
<th>Probability (N)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha_{max,t} = q_t )</td>
<td>0.99</td>
<td>0.01</td>
</tr>
<tr>
<td>( \alpha_{max,t} \neq q_t )</td>
<td>0.01</td>
<td>0.99</td>
</tr>
<tr>
<td>( q_t = \text{Null} )</td>
<td>0.5</td>
<td>0.5</td>
</tr>
</tbody>
</table>

**TABLE I**

**CONDITIONAL PROBABILITY FOR** \( p(o_{t,t} | \alpha_t, q_t) \)

At each time step as the human performs an action, we solve the MOMDP using the POUCT solver [17] to approximate the optimal policy for the robot’s communication with the human. The observational model is then employed to update the robot’s belief of user’s mental state \( M = \{G, \alpha\} \).

**IV. EVALUATION**

Our evaluation aims to test the hypothesis that our hierarchical decision-theoretic framework D4GR improves 1) the accuracy of goal recognition and plan recognition of human activity and 2) the robot’s ability to guide the person towards task success. We evaluate the enhanced performance of our algorithm by measuring the accuracy of goal recognition and prediction of the next human action, also referred to as plan recognition, at every time step. We also measure the planning time, the cumulative expected return, and the number of clarification questions asked for completing the tasks by D4GR and compare it against the three presented methods in simulation. We also perform a robot demonstration of D4GR for the scenario where the human switches between washing hand and making tea tasks.

We use the simulation environment introduced by Wang and Hoey [19] for our experiments. The simulator models real environment state changes that result from the primitive actions specified in the HTN for the virtual human. In the simulator, 44 binary virtual sensors are observing the world state. Some of the examples include sensors for hand dry, faucet on, block picked up. For our experiments, we vary sensor reliability from 99% to 80%.

**A. Domain and Experiment Test Cases**

We test our algorithm in two domains: a block domain and a kitchen domain. The Knowledge Base, TaskNet of the HTN for the kitchen has three goals: wash hands, make tea, and make coffee. and the block domain has five goals of stacking blocks to make words with varying lengths of 4 to 7. The five goals of our block domain are rote, tone, tune, hawk, and capstone. The two domains differ in their HTN planning structure, as the block’s domain has higher goals (root nodes) but a shorter tree depth than the kitchen domain. Such a setup allows us to explore the effect of HTN structure on goal and plan recognition performance. We evaluate the performance of our algorithm over four categories of test case scenarios:

**Single Goal & Correct Steps**: Captures scenarios where the human always executes a correct action sequence for achieving a single goal.
**Multiple Goals & Correct Steps:** The person works on multiple goals simultaneously by switching back and forth.

**Single Goal & Wrong Steps:** A human has a single goal but can execute wrong steps affecting progress toward the goal.

**Multiple Goals & Wrong Steps:** The human moves back and forth between goals and executes wrong actions.

The easiest case is Single Goal & Correct Steps, and the hardest is Multiple Goals & Wrong Steps.

**B. Baselines:**

We compare D4GR’s performance in simulation with three other methods. Our first baseline is HTN, a previous method of HTN-based goal recognition introduced by Wang and Hoey [19]. This method passively incorporates partially observable world observations for PGR without engaging with the user. Our second method is ALWAYS-ASK which acts as an oracle that always asks the correct clarification question and uses the language feedback for the belief update of D4GR. This baseline always has the highest goal and step recognition accuracy but receives a lower reward because it asks unnecessary questions. Our third baseline is SIPS1 introduced by Zhi-Xuan et al. [22]. This algorithm is not equipped to handle hierarchical nature of goals.

**C. Metric Definitions:**

We measure 1) Top 1 Accuracy for Goal recognition, 2) Accuracy for Plan Recognition similar to Wang and Hoey [19] averaged over all timesteps. These metrics measure the accuracy of our belief update. To evaluate our POMDP formulation, we also measure the planning time taken: runtime averaged over the steps, the cumulative reward for the whole human action sequence, and the number of questions asked averaged over trials.

1The SIPS baseline is adopted from the code repository cited in Zhi-Xuan et al. [22] and uses their default setting: static goal transition.

**V. RESULTS**

Our proposed algorithm aims to improve the capability of the robot for goal and plan recognition. The performance of D4GR depends on how accurately our cognitive assistive robot estimates the belief states for the human mental model $M_t$: the likelihood of goals $G$ and the human actions $\alpha$ at each simulated step. The ground truth of each human action’s $\alpha$ given the goal $G$ can be obtained from the knowledge base.

**A. Exp 1 - Goal Accuracy Performance**

In Fig 4, we present results for the average goal accuracies of D4GR and compare them with the baselines over varying sensor reliability and test case categories. The reason for choosing the sensor reliability range from [0.8 to 0.99] is because most of the deep-learned vision and human action detectors have similar average accuracy [14]. Overall, as the sensor reliability decreases, the accuracy performance of HTN-based methods (ALWAYS-ASK, D4GR, HTN) suffers. The oracle baseline, ALWAYS-ASK, always has the highest goal accuracy. Even at lower sensor reliabilities (higher sensor noise), D4GR’s accuracy remains higher than HTN in all experiment categories by 1% on average in both domains. This trend indicates that even when the sensor’s observational model fails, D4GR can better predict the belief states than HTN. The SIPS method did not generate functional plans for our kitchen domain even when the input specification was correct. Their particle filter algorithm could not find feasible plans for the goals. Hence, presenting the results in the blocks domain. Compared to the SIPS baseline, our method is 30% better in the blocks domain. We significantly outperform the SIPS baseline in the multiple goals scenario by almost 43% because SIPS does not handle the hierarchical nature of goals. The problem categories with single goals (correct steps & wrong steps) have the best performance for the lowest sensor reliability. We see D4GR performance boost by 2.8% in the kitchen domain and 1.4% in the blocks domain as compared to
HTN. The Oracle, on average, is 6.3% more accurate than the HTN baseline in this category. Our D4GR improves accuracy by inferring when and what to ask a question rather than always asking.

### B. Exp 2 - Plan Accuracy Performance

Similar to goal accuracy, we plot the planning accuracy for D4GR and compare it with the baselines for varying sensor noise in Fig.5. Our algorithm overall is 3% more accurate than HTN in both domains. For the lowest sensor reliabilities, D4GR is 4% better than HTN in the kitchen domain and 2% better than HTN in the block domain. For the multiple goal scenarios (correct and wrong steps), D4GR performs the best with an accuracy improvement of 2.7% in the kitchen domain and 2.3% in the block domain.

### C. Exp 3 - Trend in Questions Asked, Rewards Accumulated and Runtime (Sensor reliability varies from 80% to 99%)

<table>
<thead>
<tr>
<th>Domain</th>
<th>Method</th>
<th>Runtime (s) ↓</th>
<th>Cumulative Expected Return †</th>
<th>Question Frequency ↓</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>0.8</td>
<td>0.9</td>
<td>0.95</td>
</tr>
<tr>
<td>Block</td>
<td>ALWAYS-ASK</td>
<td>2.085</td>
<td>1.609</td>
<td>1.563</td>
</tr>
<tr>
<td></td>
<td>D4GR</td>
<td>28.750</td>
<td>20.445</td>
<td>18.814</td>
</tr>
<tr>
<td></td>
<td>HTN</td>
<td>9.056</td>
<td>1.524</td>
<td>1.371</td>
</tr>
<tr>
<td></td>
<td>SIPS</td>
<td>43.173</td>
<td>41.615</td>
<td>40.654</td>
</tr>
<tr>
<td>Kitchen</td>
<td>ALWAYS-ASK</td>
<td>0.484</td>
<td>0.425</td>
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</tr>
<tr>
<td></td>
<td>D4GR</td>
<td>13.912</td>
<td>13.439</td>
<td>13.572</td>
</tr>
<tr>
<td></td>
<td>HTN</td>
<td>0.415</td>
<td>0.380</td>
<td>0.391</td>
</tr>
</tbody>
</table>

**TABLE II**

Our algorithm shows promising improvements in PGR accuracy, although it comes with increased runtime compared to HTN. Our algorithm is designed to assist users with cognitive impairment in their daily tasks, focusing on non-time-critical activities. By providing delayed feedback, our social assistive robot increases the likelihood of users learning from mistakes.
and avoiding continuous repetition of errors compared to using HTN. We can reduce runtime further by retaining only the highest probable explanation sets, denoted as ExplaSet in HTN planning. However, this impacts the PGR accuracy since ExplaSet with multiple goals during initial steps can get pruned due to their lower probabilities. In the multi-goal and low sensor reliability setting, D4GR shows slightly lower PGR accuracy than HTN. This is due to D4GR’s reliance on noisy beliefs and user switching goals, leading to a higher probability of asking questions about irrelevant actions. The rational language feedback also adversely affects the update of the explaset, potentially diminishing its utility in later timesteps of the episode.

Our work is also limited by the type of clarification questions the robot can ask. We have a fixed template for the question. It will be interesting to see how humans respond to various clarification strategies and how the robot can plan over a space of such categories. This will increase the action space requiring more exploration by the POMDP solver. Further, our language observational model is a bag of words model. It can be more expressive by incorporating inference from LLMs.

Further, our work assumes access to a pre-defined knowledge base for the tasks. One thing that we will be exploring in the future is how to make the knowledge base adaptive to a layman user’s needs and preferences as the task progresses through interactive dialogue. Our research opens venues for language grounding and human intent recognition in other collaborative tasks like building machines/complex furniture together by humans and robots. This is an encouraging step toward enhancing the sensory capabilities of home-service robots that can assist people in completing tasks with language-based interactions.

VII. CONCLUSION

We propose a novel algorithm for robots to interactively keep track of people’s ongoing progress in a task using questions. Moreover, our D4GR framework can suggest plan improvements to users in solving a task if required. Our work shows that: 1) modeling the user as an HTN and incorporating language feedback improves robots’ belief of human’s progress in simulation; 2) POMDPs are effective methods for tracking a task’s progress and asking clarification questions. Our D4GR formulation has a similar goal and step recognition accuracy as the best baseline ALWAYS-ASK method while asking 68% fewer questions. In future work, we aim to conduct a user study with the targeted population to measure our approach’s usefulness during the interaction. D4GR’s ability to intelligently balance between clarifying uncertainty with a lesser number of questions allows for realistic interactions between a social robot and a human. This ability in the future can allow for realistic interactions with human users during collaborations over tasks between humans and robots.

VIII. ACKNOWLEDGEMENT

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