Are We On The Same Page?
Hierarchical Explanation Generation for Planning Tasks in Human-Robot Teaming using Reinforcement Learning

Mehrdad Zakershahrak, 1 Samira Ghodratnama, 2
1 School of Computing, Informatics and Decision Systems Engineering
Arizona State University, Tempe, AZ
2 Department of Computing, Macquarie University
mzakersh@asu.edu, samira.ghodratnama@mq.edu.au

Abstract
Providing explanations is considered an imperative ability for an AI agent in a human-robot teaming framework. The right explanation provides the rationale behind an AI agent’s decision making. However, to maintain the human teammate’s cognitive demand to comprehend the provided explanations, prior works have focused on providing explanations in a specific order or intertwining the explanation generation with plan execution. These approaches, however, do not consider the degree of details they share throughout the provided explanations. In this work, we argue that the explanations, especially the complex ones, should be abstracted to be aligned with the level of details the teammate desires to maintain the cognitive load of the recipient. The challenge here is to learn a hierarchical model of explanations and details the agent requires to yield the explanations as an objective. Moreover, the agent needs to follow a high-level plan in a task domain such that the agent can transfer learned teammate preferences to a scenario where lower-level control policies are different, while the high-level plan remains the same. Results confirmed our hypothesis that the process of understanding an explanation was a dynamic hierarchical process. The human preference that reflected this aspect corresponded exactly to creating and employing abstraction for knowledge assimilation hidden deeper in our cognitive process. We showed that hierarchical explanations achieved better task performance and behavior interpretability while reduced cognitive load. These results shed light on designing explainable agents utilizing reinforcement learning and planning across various domains.

Introduction
Intelligent agents, mostly in the form of robots, continuously increase their impact in our daily life. An important social aspect of this phenomenon is the evolution of the robot’s role as a team player in various domains. In this regard, a robotic teammate is expected to be compatible with a human peer in a teaming interaction scheme (Cooke 2015). Therefore, the robotic teammate is desired to act comprehensible and explain the rationale behind its decision making if necessary.

In a teaming context, explanations provide the rationale behind an individual agent’s decision making (Lombrozo 2006) and help build a shared situation awareness and maintain trust between teammates (Cooke 2015; Endsley 1988; Zakershahrak et al. 2020). Explanations could be interactive, i.e., both explainer and the recipient have goals in the exchange, which could be conflicting. Their goals affect what is to be considered as an acceptable explanation (Sormo, Cassens, and Aamodt 2005). In this regard, a social agent would construct explanations as excuses when a task cannot be achieved (Chakraborti et al. 2017a; Göbelbecker et al. 2010).

There exists prior work on generating explanations, and the focus has been on generating the right explanations from the explainer’s perspective rather than good explanations for the recipient of the explanations (Göbelbecker et al. 2010; Hanheide et al. 2017; Sohrabi, Baier, and McIlraith 2011). Moreover, there is a gap in human-robot teaming research when the teammate’s goal and plan are ambiguous at the same time concerning plan explainability, predictability, and legibility all together (Chakraborti et al. 2019; Zakershahrak et al. 2018). In a teaming scheme, the human peer potentially asks the robotic agent questions along the lines of (1) Why did you do that?, and (2) Why can’t you do that? The answer to these questions can be complicated, depending on the social agent’s high-level intention, and requires alternate model-checking. On the other hand, humans are known to have a limited attention span that makes it cognitively demanding for them to understand the robotic teammate’s explanations. Accordingly, providing the right explanation might not be an adequate remedy, especially when the task is complex.

Prior work in maintaining cognitive demand in explainable planning tasks focused on (i) the influence of information order (Zakershahrak et al. 2020); (ii) information breakdown in an explanation generation progression framework (Zakershahrak et al. 2019). Progression builds later concepts on previous ones and is known to contribute to better learning and to model the humans’ preferences for information order in receiving such explanations to assist understanding in an inverse reinforcement learning setting (Zakershahrak et al. 2020). On the other hand, information breakdown should be intertwined with plan execution, which helps spread out the information to be explained and thus reduce humans’ mental workload in highly cognitive demanding tasks (Zakershahrak et al. 2019).
A significant similarity between planning and reinforcement learning (RL) is that both approaches are trying to provide a policy. While RL creates a policy based on interactions with the world, planning uses a model of the environment to create a policy. However, a distinctive difference between these two approaches is the access to the transition and reward functions. RL assumes visiting the states once per episode, known as irreversible sample environment. At the same time, planning assumes having access to the transition function without knowing the underlying probability, known as reversible sample environment (Moerland, Broekens, and Jonker 2020). Therefore, RL focuses on developing an “unknown model” while planning starts with a “known model”.

Recently, there is a growing focus on hierarchical approaches in reinforcement learning (RL) employing the options framework (Barto and Mahadevan 2003; Konidaris and Barto 2007; Sutton, Precup, and Singh 1999). Combining planning with RL has been studied before for robotic and control mostly focused on gradient-based planning methods (Levy et al. 2017; Grounds and Kudenko 2005; Illanes et al. 2020; Yang et al. 2018). These approaches provides the ability to learn elaborated policy containing low-level actions while focusing on learning skills on a higher level. However, focusing on providing explanations as answers to the model checking questions mentioned above, one can formulate planning as a black-box optimization problem (Bock and Plitt 1984). The domain dynamics would be treated as constraints to the (non-linear) optimization problem by knowing the objective. Therefore, performing policy search using RL in this parameter space yields an optimal plan (Moerland, Broekens, and Jonker 2020).

This work takes a step further by proposing a generalized hierarchical framework investigating sub-explanations as well as more than one unit feature change, which is called options. It implies that the robot may be allowed to explain multiple aspects at the same time. It is useful for explaining highly correlated aspects. Further, we investigate how abstract or in-depth an AI agent should be considered sufficient for its human peer. As a result, we consider the attention span and the detail level a human peer requires to clarify goal and plan ambiguity by creating a framework to communicate differences in hierarchies in the form of explanations. Finally, we explore composing different options to present more complex information. Our framework is

1. Taskable since the user can define tasks as goal conditions in the symbolic domain
2. It improves sample efficiency as the high-level policies can be used for transferring learning from previously learned policies, and
3. It can learn elaborate low-level plans as it relies on RL to accommodate all the information abstracted in the high-level model.

To this end, a general formulation based on goal-based Markov Decision Processes for generating progressive explanation is presented given the hierarchical information communication in an explanation. We propose to learn a quantification of the cognitive effort for each step as a policy in a reinforcement learning framework (Sutton 1990; Sutton, Precup, and Singh 1999; Konidaris, Kaelbling, and Lozano-Perez 2018). We set out to validate the following hypothesis:

- **H1.** Our learning method can learn about humans’ preferences in receiving abstract or in-depth explanations.
- **H2:** Assuming that cognitive load is correlated with re-planning cost, hierarchical explanations reduce cognitive load and improve task performance.

Comparison with two baseline methods validated H2. We showed that the hierarchy of explanations corresponded well to the “abstraction” of the curve on domain features. These hypotheses are about the effectiveness of hierarchical explanations. We evaluated these hypotheses on a scavenger-hunt domain.

**Related Work**

**Planning**

A planning task is defined using a tuple \( \mathcal{P} = (\mathcal{F}, A, I, G) \). Where \( \mathcal{F} \) is the set of predicates used to specify the state and \( A \) the set of actions used to update the state. Each action \( a \in A \) changes the state of the world by adding or deleting predicates. \( a \in \{ \text{pre}(a), \text{eff}^+(a), \text{eff}^-(a), \text{ca} \} \); where \( \text{pre}(a) \) denotes the preconditions of the action and, \( \text{eff}^+(a), \text{eff}^-(a) \) indicate add and delete effects, respectively, and \( \text{ca} \) is the cost of the action.

A goal-based Markov Decision Process (MDP) is defined as a tuple \( \mathcal{M} = (S, A, T, \gamma, G) \). Where \( S \) represents a unique state in which a set of predicates, \( f \subseteq \mathcal{F} \), is available and \( \{ f \} \ \mathcal{F} \) is unavailable. An action \( a \subseteq A \), is legible in state \( S \) when the set of preconditions of action \( a \) is available in \( f \), that is \( \text{pre}(a) \subseteq f \). Similarly, the transition function \( T(S, a, S') \), is transferring the current state to the state \( S' \), where \( S' = \{ f \cup \text{eff}^+(a) \} \ \text{eff}^-(a) \). The domain dynamics is represented as the transition function \( T \) that determines the probability of transitioning into state \( S' \) when taking an action \( a \) in state \( s \) (i.e., \( P(s'|s, a) \)). \( R \) is the reward function and the goal of the agent is to maximize the expected cumulative reward. \( \gamma \) is the discount factor that

![Figure 1: Explanation generation as model reconciliation](Chakrabarti et al. 2017b). \( M^R \) denotes the robot model, and \( M^H \) denotes the human model used to generate her expectation of the robot’s behavior (\( \pi_{MH} \)). When the expectation does not match the robot’s behavior, \( \pi_{MH} \), explanations must be generated.
Thus, the maximum discounted reward of an optimal policy is

\[ V^*(s) = \max_{a \in A} \sum_{s' \in S} P(s'|s,a)[R(s,a,s') + \gamma V^*(s')] \]

**Theorem 2.** An optimal policy \( \pi^* \) of a Goal-based MDP, \( M \), is plausible and maximizes the discounted reward of reaching a goal state.

**Proof.** Let’s assume that the optimal policy \( \pi^* \) is not plausible. Therefore, \( \exists s \in s_p^* \) s.t. \( \forall a \in A, P(g|s,a) = 0 \). This contradicts with the Equation [1] Therefore, an optimal policy is plausible. On the other hand, let us assume that the optimal policy \( \pi^* \) does not maximize the reward of reaching the goal state. As a result, \( \exists s \in s_p^* \) s.t. \( \forall a \in A, P(g|s,a) < P(g|s',a) \) where \( s' \not\in s_p^* \). This also contradicts with Equation [2] Consequently, an optimal policy maximizes the discounted reward of reaching a goal state.

**Theorem 3.** An optimal plan \( \pi^* \) has the optimal number of steps between the initial state \( i \) and a goal state \( g \), assuming \( \gamma < 1 \).

**Proof.** Following Theorem [3] we know \( \pi^* \) maximizes the discounted reward of reaching the goal state. Also, from the definition of goal-based MDP, we know that reaching the goal is the only non-zero reward compared to the reward of other non-goal states. By applying Equation [4] for an optimal policy, the reward is maximizing when we reach the goal state. Therefore, assuming \( \gamma < 1 \), the number of steps between \( i \) and \( g \) is minimized.

**Reinforcement Learning (RL)**

We define the problem of RL on a goal-based MDP, \( M = (S,A,T,r,\gamma,G) \), as finding an optimal policy \( \pi^* \) that maximizes the expected discounted cumulative reward for all of the states in the optimal policy, given an initial state \( i \).

\[ V_\pi(s) = E \left[ \sum_{t=0}^{\infty} \gamma^t r_t | s_0 = i \right] \]

Initially, the agent starts with a random policy, observes the current state, and chooses an action based on the policy. Then, based on the sampled probability, \( P(s'|s,a) \), and using the reward, the agent updates its current policy.

In our work, we use q-learning to select the next action and improve the current policy. This approach estimates the optimal q-function, \( q^*(s,a) \) as follows:

\[ q(s,a) = r' + \gamma \max_{a' \in A} q(s',a') \]

Q-learning explores the environment using \( \epsilon \)-greedy policy. Consequently, only with a small probability \( \epsilon \) a random action would be chosen and more probably \( (1 - \epsilon) \), the largest from the q-function.

**Hierarchical RL using Goal-based MDP**

Traditional RL approaches require lots of training to converge. Therefore, they have a scaling issue when applied to large-scale problems. The popular solution to deal with this issue is to introduce options throughout which high-level actions are possible. Furthermore, the learned options can be put in use in different scenarios as long as the options’ semantics, i.e., their intent, remains consistent with the learned domain. Therefore, the action level states can change while
the higher-level options remain the same across different tasks.

An option is defined as a tuple \( o = (I_o, \pi_o, r_o, T_o) \), where \( \pi_o, r_o \) and \( T_o \subseteq S \) are the option’s policy, reward and the set of termination states for the set of initial states \( I_o \) respectively. Each option, \( o \in O \) is a hierarchical action in planning that consists of a set of action-level states. Since each abstract action (option) is a set of states on the planning level, following each option removes/adds multiple predicates. The goal states determine termination of the options and their legibility [Konidaris and Barto 2007]. Learning policies employing options provides the opportunity to achieve high-level behaviors while defining low-level states’ distribution for their termination [Sutton, Precup, and Singh 1999]. The q-function is defined for one option as:

\[
q(s, a) = r(s, a, s') + \gamma \cdot q(s', a'), \forall s \in \pi_o
\]

(9)

similarly,

\[
q^*(s, a) = \max q(s, a), \forall s \in \pi_o
\]

(10)

The terminations states \( T_o \) of the option are considered sub-goals, or option goals. Therefore, \( q(s, a) = 1 \) where \( s \in T_o \), and \( q(s', a') \) otherwise, and \( s, s' \in \pi_o \). This means the reward of the sub-goals are the only non-zero rewards compared to the reward of the non-sub-goal states.

This representation of reward is well-positioned in the literature [Koenig and Simmons 1993; Sutton 1990; Peng and Williams 1993; White and Sojge 1992].

If Q-learning initializes the states with zero, the agent will perform a random walk. In the worst-case scenario, the agent explores \( 2^n \) states. Cooperative Reinforcement learning uses directed exploration since the agent is aware of the goal and decreases the worst-case complexity to polynomial w.r.t the number of the states required to be explored.

Therefore an admissible q-function would be:

\[
q^*(s, a) = \arg\max_{q_o \in o^*}(s, a')
\]

(11)

Consequently, given a set of options, the on-policy method SARSA (Rummery and Niranjan 1994) updates the intent-level value function, the Q-function, as follows:

\[
Q(s, o) = Q(s, o) + \alpha (r_o + \gamma Q(s', o') - Q(s, o)), \forall o \in O
\]

(12)

Where \( \alpha \) is the learning rate and \( \gamma \) is the discount factor. The on-policy SARSA for estimating Q is presented at Algorithm 2.

Theorem 4. An optimal option’s policy \( \pi^*_o \) has the optimal number of steps between the initial state \( i \) and a goal state \( g \in T_o \), assuming \( \gamma < 1 \).

Proof. Following proof of Theorem 3 since the reward of reaching the goal is comparatively much bigger than the reward of other states, by applying Equation 6 for an optimal policy, the reward is maximized when we reach the goal state. Therefore, assuming \( \gamma < 1 \), the number of steps between \( i \) and \( g \) are minimized.

Mindset Adaptation in Hierarchical RL

A mindset is defined using a tuple \( M = (M, O) \) Where \( I \) is a set of all initial states, \( O \) are options on the abstract level given to the robot, and \( M \) is a goal-based MDP model of the environment.

To capture the mindset changes, the model function \( \Lambda : \mathcal{M} \rightarrow 2^F \) is defined to convert a mindset to a set of mindset features [Chakraborti et al. 2017b], where \( \mathcal{M} \) is the mindset space and \( F \) the feature space. In this way, one mindset can be adapted to another mindset using editing functions that changes multiple features at a time. The set of feature changes is denoted as \( \Delta(M_1, M_2) \) and the distance between two mindsets as the number of such feature changes is denoted as \( \delta(M_1, M_2) \). In this work, we assume that the mindset is defined in PDDL (Fox and Long 2003), an extension of STRIPS [Fikes and Nilsson 1971] as explained in planning section under related work.

Definition 4 (Mindset Adaptation). We define the mindset adaptation as a tuple: \( \langle (\mathcal{M}^R, \mathcal{M}^H), \Lambda \rangle \), where \( \Lambda \) modifies the goal-based MDP of the human (\( \mathcal{M}^H \)) to robot (\( \mathcal{M}^R \)) using \( \Omega \) s.t. the robot’s optimal plausible plan \( \rho_R \) becomes optimally plausible for human as well with respect to Definition 2.

At each adaptation step, the robot introduces an option, \( o \in O \), uses \( \Lambda \) to modify the features present at the current state of the mindset and eventually gets to \( T_o \). Therefore, the adaptation process solves an optimization problem utilizing reinforcement learning, which we call providing the robot’s intent on the intent-level while solves a planning problem on the action-level. This process is illustrated in Fig. 2.

Mindset adaptation introduces new partitioning on the action-level by providing a new option on the intent level. Each new tree-like structure, option on the intent level, and states on the action level is similar to belief distribution. Therefore, the cost of adaptation, w.r.t. Equation 2 is defined as \( \Gamma \) in the following Equation:

\[
\Gamma(J_{\mathcal{M}^H}, J_{\mathcal{M}^R}) = \left| J(s) - J(\hat{s}) \right|_{s \in \mathcal{M}^H \atop \hat{s} \in \mathcal{M}^R}
\]

(13)

As a result, introducing new options can be viewed as changing the posterior belief distribution, which is different from a human’s prior belief distribution. Consequently, performing the mindset adaptation, the robot does not explain the details of planning proactively to maintain the human teammate’s cognitive load.

The optimal cost of adaptation, w.r.t. Equation 3 is calculated in the following Equation:

\[
\Gamma^* = \Gamma(J_{\mathcal{M}^H}^*, J_{\mathcal{M}^R}^*) = \left| J^*(s) - J^*(\hat{s}) \right|_{s \in \mathcal{M}^H \atop \hat{s} \in \mathcal{M}^R}
\]

(14)

Definition 5 (Concise Mindset Adaptation). We define concise mindset adaptation as a tuple \( \langle (\mathcal{M}^R, \mathcal{M}^H), \Lambda \rangle \), where \( \Lambda \) has the optimal cost of adaptation with respect to Equation 14.

Leveraging the mindset adaptation, the agent creates a hierarchical representation of the domain [Konidaris, Kaelbling, and Lozano-Perez 2018]. Generating explanations employing this representation is helpful toward maintaining

\[
\Delta(M_1, M_2) = \delta(M_1, M_2)
\]
Figure 2: Hierarchical explanation generation. The agent learns/employs options on the intent-level while at the action-level, explanations are features added/deleted to each state. On the intent-level, explanations about options are intents, while explanations about action-level provide transparency. Intent-level options are correlated with action-level states. While the agent finds an optimal policy on the intent-level, it provides planning on the action-level.

Learn Abstract Explanations from Experience

The agent constructed a planning representation by searching through possible combinations of action-level states within each classification of the option’s precondition mask. To compute the policy’s probability at the intent-level, correlated with action-level states, we calculate the conjunction of the options, distributional beliefs. However, without the loss of generality, we set the options to be deterministic to be compatible with PDDL (Fox and Long 2003). Therefore, in this paper, we used deterministic policies reinforcement learning to calculate the optimal policy.

Definition 6 (Concise Explanation Generation by Mindset Adaptation). Given $(\mathcal{M}^R, \mathcal{M}^H)$, the objective of concise explanation generation is to find the $\Lambda$, where the cardinality of changes required, $|\Lambda| \leq \Delta(M_1, M_2)$, are minimum subject to the Definition 5.

Following Equation 14 and consecutive to Theorem 2, the concise mindset adaptation process has the minimum adaptation cost while maximizing the discounted reward of reaching a goal state. The expected reward model of executing the optimal policy, at intent-level, learned assuming that expertly provides minimum adaptation cost to amend the original plan employing the human’s expert traces. The mindset adaptation process to generate the concise explanations ($\Lambda$) are presented at Algorithm 1.

Algorithm 1: Mindset Adaptation

\begin{algorithm}
\begin{algorithmic}
\STATE \textbf{input} : $(\mathcal{M}^H, \mathcal{M}^R, I, G)$
\STATE \textbf{output}: $\Lambda$
\STATE Compute $\Delta(\mathcal{M}^H, \mathcal{M}^R)$ as the difference between the two mindsets;
\STATE Compute $\pi^*_{\mathcal{H}}$ using $\mathcal{M}^H$;
\STATE Compute $\pi^*$ using $\mathcal{M}^R$;
\STATE initialize $\Lambda$, $q = \{\}$;
\WHILE{$\pi^*_{\mathcal{H}} \neq \pi^*$}
\FOR{each $\delta \in \Delta$}
\STATE $q \leftarrow Q(\delta, e)$;
\ENDFOR
\STATE $\mathcal{M}^H' \leftarrow$ Modify $\mathcal{M}^H$ using $\arg\max(q)$;
\STATE $\Lambda$.append() $\leftarrow \forall o \in \arg\max(q)$;
\STATE Update $\pi^*_{\mathcal{H}}$ using $\mathcal{M}^H'$;
\ENDWHILE
\RETURN $\Lambda$;
\end{algorithmic}
\end{algorithm}

Scavenger-Hunt Domain

The domain portrays a damaged office building after an earthquake, showed by a floor-plan in Fig. 3. Typically, the human uses the doors to exit each room and eventually exit the building via the elevator from his office. However, an earthquake may interrupt the human’s original path in different ways. The first response team sent an autonomous robot to the damaged building to find and help the trapped human navigate through the building. The robot’s goal is to explain to the human whenever the robot’s plan (optimal plan) becomes less interpretable according to the human’s model of the environment. Therefore, the robot provides its intent to the human to verify the legibility of the synthesized plan. At complex situations that requires subjects to invest a significant amount of cognitive effort quickly.

Evaluation

We evaluated our approach by conducting human-subject studies using Amazon Mechanical Turk (MTurk) in the scavenger-hunt domain. This domain designed to create the cognitive load of the human teammate. Throughout the mindset adaptation, there are options that the agent requires to explain in more detail by going down the hierarchy. Similarly, there are options that the human teammate would be notified about the high-level option, and no further details are required.

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Evaluate...

Figure 2: Hierarchical explanation generation.
Figure 3: Left: Illustration of the scavenger-hunt domain. Right: The hierarchical planning task representation of the domain. The green circles, intent-level options, are local optimas for the policy based on q-learning, and the small blue circles are action-level states for each option. The numbers in each local optima represent the number of action-level explanations the agent has to provide, depending on the scenario, upon learning an option.

any step, the robot can explain multiple correlated changes illustrated in red boxes, as an intent-level explanation or a unique feature change, action-level explanation. As shown in Fig. 4, a power outage caused the second door PIN pad to be activated and the elevator to be out of service is an intent level explanation; and You need a fire extinguisher to put out the fire blocking the door is an action-level explanation.

The participants are given a map that contains all the possible changes. These are also shown on the left side of Fig. 3. A total of 10 possible changes has changed the trapped human's domain, which resulted in 13 changes in the action-level, classified in 5 intent level options. However, for any given scenario, only a few selected changes will be present.

Algorithm 2: Q-learning for mindset adaptation

| input  | \( \delta, \epsilon \) |
|--------|-------------------|
| output | \( Q(s, o), \forall o \in \delta \) |
| initialize | \( Q(s, o) \) arbitrarily; |
| for each episode do |
| initialize s as \( i \in I \); |
| \( p_1 \leftarrow \text{Random(seed)} \); |
| while \( s \notin G \) do |
| if \( (p_1 < \epsilon) \) then |
| \( o \leftarrow \text{Maximum value using } \pi \text{ of } Q(s, o) \); |
| else |
| \( o \leftarrow \text{Choose randomly} \); |
| end |
| for each episode do |
| \( r, s' \leftarrow \text{Perform}(o) \); |
| \( p_2 \leftarrow \text{Random(seed)} \); |
| if \( (p_2 < \epsilon) \) then |
| \( o' \leftarrow \text{Maximum value using } \pi \text{ of } Q(s', o') \); |
| else |
| \( o' \leftarrow \text{Choose randomly} \); |
| end |
| \( s \leftarrow s' \); |
| \( o \leftarrow a' \); |
| end |
| end |
| return \( Q(s, o) \); |

Experiment Design First, we explained the search and rescue domain to participants and tasked them to play the trapped person’s role. We asked the participants to determine the next action of the plan after each robot’s explanation. This was meant to encourage the participants to clearly understand the situation in a way the robot aimed to unfold the plan. We then asked the participants to explain if the robot is performing according to their expectations or not. Therefore, we purposely inserted random actions after some of the explanations to make sure that the subject questions some of the robot’s actions. Moreover, to ensure the data’s quality, we implemented a sanity check question to make sure the participants understood the task. We removed the responses with wrong answers to the sanity questions or took them
over 4 minutes to finish the task.

**Results**

We conducted a survey using Qualtrics and recruited 68 human subjects using Mturk, with a HIT acceptance rate of 99%. After sifting through the responses described in the previous section, we used 54 responses over 10 scenarios. We compared the outputs of our explanation generation algorithm (H-RL) based on the reward policy learned by hierarchical RL algorithm with the subjects’ responses for two other baselines: Online Explanation Generation (OEG) (Zakershahrak et al. 2019) and Progressive Explanation Generation (PEG) (Zakershahrak et al. 2020). These baselines are state of the art for maintaining cognitive demand for explanation generation in planning tasks in a human-robot teaming scheme. OEG focuses on dividing the explanation generation process and tangle them with plan execution concerning plan prefix, plan optimality, and the clarity of the next executed action (Zakershahrak et al. 2019). PEG focuses on the progression of the comprehension of a sequence of explanations as a cognitive demand to amend the original plan (Zakershahrak et al. 2020).

This evaluation aimed to analyze if we could learn the human preferences from training scenarios and apply them to the scenarios (H1). Our method’s accuracy was 94.4%: our approach successfully matched 51 out of the 54 human responses across 10 scenarios as illustrated in Table 1. This result showed that humans indeed had particular preferences for information hierarchy in such situations and that our method could capture these preferences. Moreover, this Table reveals that sharing all of the detailed information, even in a preferred progressive sequence (PEG), is not as useful as abstraction since the accuracy is considerably lower in PEG compared to the two other methods. Furthermore, although dividing the explanations and entwining them with plan execution helps increase the accuracy in OEG, the results confirm that our approach’s effectiveness is mostly due to the hierarchical context of the explanations. These results verify H1.

Table 2 demonstrates the comparison results of the time taken to calculate explanations using different approaches in the scavenger-hunt domain across different scenarios. As shown in this Table, the time for H-RL is considerably lower than the other two methods. One reason is, the choice of deterministic policies for RL helped to reduce the search space. Moreover, this Table illustrates that the total number of explanations in H-RL is lower than other approaches, which contributes to lowering the cognitive demand required to understand the changes (H2).

The subjective measures in Fig. 5 reaffirm the conclusions. H-RL has the best performance and the lowest mental and temporal demand. Due to intertwining explanations with plan execution, OEG is expected to create more temporal demand. The p-values for the subjective measures are presented in Fig. 6. The results indicate statistically significant differences between H-RL, OEG and PEG. Thus, these subjective results with results of Table 2 confirm H2.

**Conclusion & Future Work**

In this paper, we studied hierarchical explanation generation employing reinforcement learning to maintain the cognitive
predictability and legibility of different plans. As a result, realistic assumptions for human cognition in correlation with this is well suited for probabilistic planning and it is more appropriate to use Boltzmann machines as an energy-based model instead, since MDP is quite restrictive for modeling human preferences of the information order, considering the right abstraction level explanation for the explainee, assuming the underlying cognitive effort required to understand the explainee’s perspective, resulting in a general framework for hierarchical explanation generation. One interesting observation was making an explanation is an incremental cognitive process based on the shared information’s details’ scale. To address the challenge with modeling human preferences of the information order, we adopted a goal-based MDP and applied RL to learn the explanation process as a policy based on traces. Our first contribution is that we show that humans indeed demonstrate preferences for the information ranking to scale based on its detail level, and we can indeed learn about such preferences using our framework. This verified H1. Results from this domain validated H2. Finally, we showed that H-RL did improve task performance and reduce cognitive load.

One interesting future direction is to generalize the MDP model and use Boltzmann machines as an energy-based model instead, since MDP is quite restrictive for modeling human cognition. Moreover, it enables the use of continuous stochastic cognition distributions over all possible plans. This is well suited for probabilistic planning and it is more realistic assumption for human cognition in correlation with predictability and legibility of different plans. As a result, they create more robust plans that are less likely to overfit.

| Pr. | H-RL | OEG | PEG |
|-----|------|-----|-----|
|     | |     |     |
| P1  | 3    | 18.2| 7   |
| P2  | 5    | 21.8| 8   |
| P3  | 5    | 23.7| 12  |
| P4  | 5    | 28.0| 11  |
| P5  | 4    | 25.4| 10  |
| P6  | 5    | 34.3| 10  |
| P7  | 5    | 30.5| 9   |
| P8  | 4    | 26.2| 10  |
| P9  | 3    | 19.7| 8   |
| P10 | 4    | 25.9| 8   |
| Average | 4.3 | 25.37 | 9.3 |

Table 2: Comparison of explanation size, and time (in seconds) taken to generate the explanations using the different methods across 10 scenarios of the scavenger-hunt domain.

Table 1: Objective performance in terms of plan accuracy and number of questionable actions based on the subjects’ feedback for the three settings. The ground truth for questionable actions is 3 out of 36 in total.

| Accurac y | OEG | PEG | H-RL | Random |
|-----------|-----|-----|------|--------|
| 0.866     | 0.775 | 0.944 |       |
| # Actions | 4.714 | 7.161 | **3.170** | 3/36   |

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