Order Matters: Generating Progressive Explanations for Planning Tasks in Human-Robot Teaming

Mehrdad Zakershahrak, Shashank Rao Marpally*, Akshay Sharma*, Ze Gong and Yu Zhang
Arizona State University
{mzakersh, smarpall, ashar204, zgong11, yu.Zhang.442}@asu.edu

Abstract

Prior work on generating explanations has been focused on providing the rationale behind the robot’s decision making. While these approaches provide the right explanations from the explainer’s perspective, they fail to heed the cognitive requirement of understanding an explanation from the explainee’s perspective. In this work, we set out to address this issue from a planning context by considering the order of information provided in an explanation, which is referred to as the progressiveness of explanations. Progressive explanations contribute to a better understanding by minimizing the cumulative cognitive effort required for understanding all the information in an explanation. As a result, such explanations are easier to understand. Given the sequential nature of communicating information, a general formulation based on goal-based Markov Decision Processes for generating progressive explanation is presented. The reward function of this MDP is learned via inverse reinforcement learning based on explanations that are provided by human subjects. Our method is evaluated in an escape-room domain. The results show that our progressive explanation generation method reduces the cognitive load over two baselines.

1 Introduction

As robotic applications start to benefit a diverse set of domains, human-robot interaction has evolved to be an increasingly important subject. In human-robot teaming, it is desired that the interaction occurs in a coherent manner that is observed in human-human teaming [Chakraborti et al., 2017a; Cooke, 2015]. Similar to a human teammate, a robotic agent is required to not only understand its human peers, but also explain its own decision or behaviors when necessary.

Explanations in a teaming context provide the rationale behind an individual agent’s decision making [Lombrozo, 2006], and help with building a shared situation awareness and maintaining trust between teammates [Endsley, 1988; Cooke, 2015]. Although there exists prior work on generating explanations, the focus has been on generating the right explanations from the explainer’s perspective rather than good explanations for the explainee [Göbelbecker et al., 2010; Hanheide et al., 2017; Sohrabi et al., 2011].

Unsurprisingly, the right explanation may not necessarily be a good explanation—anyone with parental experience would share the sympathy. Such dissonance between the explainer and explainee may be a result of various inconsistencies, such as information asymmetry or different cognitive capabilities, just to name a few. These inconsistencies may be summarized as model differences—the differences between the cognitive models that govern the generation and interpretation of an explanation, respectively, for the explainer and explainee [Chakraborti et al., 2019]. When these two models are the same, as is assumed in most prior work, an explanation from the perspective of the explainer would be not only right but also perfectly understandable to the explainee, that is, as if the explanation were made to the explainer himself. The more general case when the models differ has also been investigated [Chakraborti et al., 2017b; Zakershahrak et al., 2019] under the model reconciliation setting, where the focus is on explaining domain model differences such that the two models become more compatible. One remaining challenge in explanation generation, however, is to account for the differences in the cognitive capabilities to understand an explanation.

In this work, we take a step further by generating explanations while considering the differences between the cognitive capabilities that may be present between the explainer and explainee. This is especially relevant to human-robot teaming since robots are frequently deployed to situations that require high cognitive and computational abilities that humans do not have. To accommodate this, the motivation here is to generate explanations that reduce the cognitive effort required for understanding them. In particular, in this work, we focus on the influence of the order of information on the cognitive effort of the explainee in planning tasks. First, we note that making an explanation is normally not an instantaneous effort; instead, information must be conveyed in a sequential order; furthermore, given the characterizations of our cognitive systems [Ericsson and Smith, 1991; Kahneman, 2011], we often could not (or would not) wait until all the information has been conveyed before processing it. As a result, the order of presenting information matters. Hence, one of the keys to reducing cognitive effort is to minimize the cumulative effort required for processing all the
information progressively in an explanation. Consequently, we term our approach *progressive explanation generation*, to capture that aspect. Consider the following example of a conversation between two friends, which illustrates the importance of providing information in the right order when making an explanation:

Amy: Let’s go to the outlet today.
Monica: My car is ready.
Amy: Great!
Monica: The rain will stop soon.
Amy: Wonderful!
Monica: By the way, today is a holiday (shops closed).
Amy: You are telling me now!
Monica: Let us go to the central park!
Amy: ...

Such cognitive dissonance illustrated above occurs frequently in our lives and it is our aim in this work to address it in order to improve human-robot interaction. To this end, a general formulation based on goal-based Markov Decision Processes for generating progressive explanation is presented given the sequential nature of communicating information in an explanation. We propose to learn a quantification of the cognitive effort of each step as the reward function in an inverse reinforcement framework [Ng and Russell, 2000; Abbeel and Ng, 2004; Ziebart et al., 2008], as an explanation is being made. Both domain-dependent and domain-independent features are used in learning based on explanations provided by human subjects. It is part of our goal to identify which features play an important role in the progressiveness of an explanation. We evaluate our approach in an escape-room domain. The results show that the domain-independent features play a comparative (if not more important) role than domain dependent features. This observation has two important implications for explanations in planning tasks: 1) given that the domain independent feature is closely related to the cost of replanning, it verifies our hypothesis that humans replan during an explanation (not just after everything is explained) in complex tasks; 2) domain independent features may be used for generating progressive explanations for domains that have similar characterizations to ours—this allows our method to not only generalize to different scenarios but also different domains. Comparison with baseline methods show that our method reduces the cognitive load.

2 Related Work

Explainable AI [Gunning, 2017] is increasingly considered to be an important paradigm for designing future intelligent agents, especially as such systems begin to constitute an important part of our lives. The key requirement of explainable agency [Langley et al., 2017] is to be “explainable” to the human partners. To be explainable, an agent must not only provide a solution to achieve a goal, but also make sure that the solution is perceived as such by its human peers. A determinant here is the human’s interpretation of the agent’s behavior. It is critical to take careful steps to avoid situations where the agent’s assistance would be interpreted as no more than an interruption, which resulted in the pitfall of earlier effort in designing intelligent assistants, such as the loss of situation awareness and trust [Endsley, 2016; Langfred, 2004].

The key challenge to explainable agency hence is the ability to model the human cognitive model that is responsible for interpreting the behaviors of other agents [Chakraborti et al., 2017a]. With such a model, there are different ways to make the robot’s behavior explainable. One way is to bias the robot’s behavior towards the human’s expectation of it based on the human’s cognitive model. Under this framework, a robot can generate legible motions [Dragan and Srinivasa, 2013] or explicable plans [Zhang et al., 2017; Zakershahrak et al., 2018]. Essentially, the robot sacrifices the plan quality to respect the human’s expectation—the resulting plan is often a more costly plan. Another way is to provide a forewarning of the robot’s intention before execution, such as for persuasion [Petty and Cacioppo, 1979]. In [Gong and Zhang, 2018], the approach there is to provide additional context to help explain the robot’s decision. The third way, which is the most relevant to ours, is for the robot to explain its decision via explanations [Göbelbecker et al., 2010; Hanheide et al., 2017; Sohrabi et al., 2011]. The benefit of generating explanations, compared to generating explainable plans, is that the robot can keep its original (and optimal) plan. However, as mentioned earlier, the focus there is often on providing the rationale behind the explainer’s decision making, while largely ignoring the explainee. In [Chakraborti et al., 2017b], this gap is addressed by considering explanation generation as a model reconciliation problem, which takes into account the explainee’s model. Although the cognitive requirement is implicitly considered, the aim there is to reconcile (i.e., reduce) the differences in domain models, so that the robot’s plan would be interpretable also in the model of the explainee.

The idea of progressive explanation generation is based on the hypothesis that reducing replanning effort also reduces the cognitive load, which is anticipated but never empirically verified [Fox et al., 2006]. Generating progressive explanations also bears some similarities to the idea of nudging the human towards a new path [Lien et al., 2004] or providing constant and non-intrusive reminders for performing various tasks [Maxwell et al., 1999]. The general idea is to facilitate “smooth” or socially acceptable [Miller, 2018] interactions, whether physical or cognitive.

3 Model Reconciliation

We base our work on a general model reconciliation setting for explanation generation that considers both the models of the explainer and explainee, which is introduced in [Chakraborti et al., 2017b]. As shown in Fig. 1, the human uses $M^H$ to generate her expectation of the robot’s behavior, while the robot’s actual behavior is being created using the robot’s model $M^R$, which is different from $M^H$. Therefore, $\pi_M^R$, which is the plan created from $M^R$, could also be different with $\pi_M^H$, which is the plan created from $M^H$. Whenever these two plans differ, the robot’s plan must be explained.

**Definition 1** (Model Reconciliation). Model reconciliation [Chakraborti et al., 2017b] is a tuple $(\pi_{M^G}^1, (M^R, M^H))$. 

where $\text{cost}(\pi_{1,G}, M^R) = \text{cost}^*_{M^R}(I,G)$.

where $\pi_{1,G}^*$ is the robot’s optimal plan to be explained. $\text{cost}(\pi_{1,G}, M^R)$ is the cost of the robot’s plan under the model $M^R$. $\text{cost}^*_{M^R}(I,G)$ returns the optimal plan given the initial state and goal state pair using $M^R$. Therefore, the constraint in the Definition 1 ensures that the robot’s plan is optimal in its own model.

In this setting, the robot must generate an explanation to modify the human’s model $M^H$ such that $\pi_{1,G}^*$ becomes explainable in the human’s modified model (denoted as $\hat{M}^H$) after the reconciliation. As a result, an explanation for a model reconciliation setting can be considered as requesting changes to the model of the human. Note that making an explanation may also lead to an error report if it is identified that the robot’s model was incorrect.

To capture the model changes, a model function $\Gamma : M \rightarrow 2^P$ is defined to convert a model to a set of model features [Chakraborti et al., 2017b], where $M$ is the model space and $P$ the feature space. In this way, one model can be updated to another model with editing functions that change one feature at a time. The set of feature changes is denoted as $\Delta(M_1, M_2)$ and the distance between two models as the number of such feature changes is denoted as $\delta(M_1, M_2)$. In this work, we assume that the model is defined in PDDL [Fox and Long, 2003], an extension of STRIPS [Fikes and Nilsson, 1971], where a model is specified as a tuple $M = (D, I, G)$. The domain $D = (F, A)$ is comprised of a set of predicates, $F$, and a set of actions, $A$. $F$ is used to specify the state of the world. Each action $a \in A$ changes the state of the world by adding or deleting predicates. Therefore, an action can be represented as $a = (pre(a), eff^+(a), eff^-(a), c_a)$; where $pre(a)$ denotes the preconditions of the action $a$, and $eff^+(a), eff^-(a)$ indicate add and delete effects, respectively, and $c_a$ is the cost of the action. For example, a very simple model for Amy in our motivating example would be:

**Initial state:** not-holiday
**Goal state:** happy
**Actions:**

- OUTLET-SHOPPING
  - pre: not-holiday (car-ready is-sunny)
  - eff\+: happy
- VISIT-PARK
  - pre: (car-ready is-sunny)

For simplicity, we use only boolean variables above. The variables in parenthesis are optional predicates that are preferred but not required. The goal is to achieve the effect of happy. In this example, the model, denoted as $M_{\text{Amy}}$, will be converted by the model function $\Gamma$ to:

$$\Gamma(M_{\text{Amy}}) = \{ \text{init-has-not-holiday, goal-has-happy, OS-has-precondition-not-holiday, OS-has-add-effect-happy, ...} \}$$

where $OS$ above is short for OUTLET-SHOPPING. The function essentially turns a model into a set of features that fully specifies the model. Hence, changing the set of features will also change the model.

**Definition 2** (Explanation Generation as Model Reconciliation). The explanation generation [Chakraborti et al., 2017b] problem is a tuple $(\pi_{1,G}^*, (M^R, \hat{M}^H))$ where an explanation is a subset of $\Delta(M^R, \hat{M}^H)$ such that:

1. $\Gamma(\hat{M}^H) \cap \Gamma(M^R) \subseteq \Gamma(M^H)$, and
2. $\text{cost}(\pi_{1,G}, \hat{M}^H) - \text{cost}^*_{M^R}(I,G) < \text{cost}(\pi_{1,G}^*, \hat{M}^H) - \text{cost}^*_{\hat{M}^H}(I,G)$.

where $\hat{M}^H$ denotes the model after the changes. The first condition requires the changes to the human’s model to be consistent with the robot’s model. The second condition states that the robot’s plan must be closer (in terms of cost) to the optimal plan after the model changes than the situation before—an explanation should have the effect of moving the expected plan closer to the robot’s optimal plan.

**Definition 3** (Complete Explanation). A complete explanation [Chakraborti et al., 2017b] is an explanation that additionally satisfies $\text{cost}(\pi_{1,G}^*, \hat{M}^H) = \text{cost}^*_{\hat{M}^H}(I,G)$.

A complete explanation requires the model changes to modify the robot’s plan also optimal in the changed human model, so that the robot’s plan becomes interpretable in the human’s model as well. A minimally complete explanation (MCE) is also defined in [Chakraborti et al., 2017b], which is a complete explanation with the minimum number of unit feature changes. An example of $M_{\text{Amy}}$ (corresponds to $\hat{M}^H$) after a minimally complete explanation is:

**Initial state:** not-holiday (corresponds to $\hat{M}^H$)
**Goal state:** happy
**Actions:**

- OUTLET-SHOPPING
  - pre: not-holiday (car-ready is-sunny)
  - eff\+: happy
- VISIT-PARK
  - pre: (car-ready is-sunny)
  - eff\+: happy

where the strikeout denotes the feature removed and +’s denote additions. These changes correspond to the explanation made in our motivating example. In this case, the robot model, $M^H$, corresponds to $\hat{M}_{\text{Amy}}$ is the same as $\hat{M}_{\text{Amy}}$ after the explanation (with the model changes incorporated).
4 Progressive Explanation Generation

We first present the hypotheses that we intend to verify in this work:

- **H1:** Cognitive load is correlated with replanning cost.
- **H2:** Progressive explanations reduces cognitive load.

In progressive explanation generation, our focus is on how the ordering of presenting information in an explanation may affect its understanding. An explanation in our setting is naturally specified as a sequence of feature changes. Since we process information as it is received, the cumulative cognitive effort can then be considered as the sum of effort associated with understanding each feature change in a sequential order. We couple the cognitive effort for each change with a model distance metric, denoted as \( \rho(M_i, M_{i+1}) \) for the \( i \)-th feature change, where \( M_i \) is the model before the \( i \)-th feature change and \( M_{i+1} \) is the model after that change. Thereby, progressive explanation generation can be defined as the following optimization problem:

**Definition 4** (Progressive Explanation Generation (PEG)).

A progressive explanation is a complete explanation with an ordered sequence of unit feature changes that minimize the sum of the model distance metric:

\[
\arg\min_{\Psi} \sum_{i=1}^{n} \rho(M_i, M_{i+1}) \]

where \( \rho_i \) is short for \( \rho(M_i, M_{i+1}) \), \( i \) is the index of unit feature changes, and \( f_i \) denotes the \( i \)-th unit feature change.

The angle brackets above convert a set to an ordered set and the summation is over every unit feature change in an explanation, which is computed for before and after each unit feature change is made in a progressive fashion. The goal of PEG is to minimize the cumulative model distance metric, and thereby minimize the cognitive effort required from the explainer to understand the explanation.

4.1 Learning the Model Distance Metric

To learn the model distance metric for PEG, we formulate the problem as an inverse reinforcement learning (IRL) [Ng and Russell, 2000; Abbeel and Ng, 2004; Ziebart et al., 2008] framework, where we assume the task of generating explanations can be expressed as a goal-based Markov Decision Processes (MDP). A goal-based MDP is defined by a 6-element tuple \((S, A, T, R, \gamma, G)\), where \( S \) is the state space and \( A \) is the action space. 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., \( T(s'|s,a) \)). \( R \) is the reward function and the goal of the agent is to maximize the expected cumulative reward. \( \gamma \) is the discount factor that encodes the agent’s preference of current rewards over future rewards. \( G \) is a set of goal states where for each \( g \in G \), \( T(g,a,g) = 1, \forall a \in A \). We chose goal-based MDP since in each scenario, although the start state could be the same, the goal could be different and therefore the policy would be different.

Fig. 2 demonstrates the MDP that underlies PEG. In our work, the state space \( S \) is the set of all possible human models and the action space \( A \) is the set of all possible unit feature changes. The transition function \( T \) captures the probability that the human model would be updated to \( M' \) when the human model is \( M \) and the robot explains \( f \) to her (i.e., \( P(M'|M,f) \)). The model distance metric \( \rho \) serves as the reward function, which depends on both the current and updated human models.

4.2 Applying IRL

Following prior work on IRL [Ng and Russell, 2000; Abbeel and Ng, 2004; Ziebart et al., 2008], we define the distance metric as a linear combination of a set of weighted features:

\[
\rho(M, M') = \sum_{i} \theta_i \cdot \psi_i(M, M') = \Theta^T \Psi(M, M')
\]

where \( \Psi = \{\psi_1, \psi_2, \ldots, \psi_k\} \) is the set of features with respect to state pair \((M, M')\), \( \Theta = \{\theta_1, \theta_2, \ldots, \theta_k\} \) is the set of weights corresponding to the features.

Given a set of traces in a domain as a set of explanations (each is a sequence of unit features changes), which are obtained from human subjects, our goal is to learn the model distance metric \( \rho \), which in turn requires us to learn the weights \( \Theta \) given a set of features. Since noise is expected in the traces, we learn the weights by maximizing the likelihood of the traces using MaxEnt-IRL [Ziebart et al., 2008] as follows:

\[
\Theta^* = \arg\max_{\Theta} L(D) = \arg\max_{\Theta} \frac{1}{|D|} \log P(D|\Theta)
\]

\[
= \arg\max_{\Theta} \frac{1}{|D|} \sum_{G \in \mathcal{G}} \sum_{\zeta_G \in D_G} \log P(\zeta_G|\Theta)
\]

where \( D \) is the training data set, \( \mathcal{G} \) the collection of goal functions \( G \) for different scenarios. \( \zeta_G = (M_0, f_1, M_1, \ldots, f_n, M_n) \) is an explanation for achieving \( G \) with ordered feature changes provided by human subjects in a subset \( D_G \). It consists of the initial human model (i.e., \( M_0 = M^H \)), unit feature change and the updated model at each time step. To mitigate the ambiguity that the distribution of the traces may introduce preference for some traces over others, the principle of maximum entropy [Ziebart et al., 2008] is employed to define the distribution over all the possible traces for a specific goal (i.e., \( G \)):

\[
P(\zeta_G|\Theta) = \frac{e^{\rho(\zeta_G)}}{\sum_{\zeta_G} e^{\rho(\zeta_G)}}
\]

where

\[
\rho(\zeta_G) = \Theta^T \Psi(\zeta_G) = \sum_{(M, M') \in \zeta_G} \Theta^T \Psi(M, M')
\]
Take Equation 2 into Equation 1, the optimization becomes:

$$\Theta^* = \arg\max_\Theta \frac{1}{|D|} \sum_{G \in \mathcal{G}} \sum_{G_i \in \mathcal{G}_D} \left( \Theta^T \Psi(G_i) - \log \sum_{G \in \mathcal{G}} e^{\Theta^T \Psi(G)} \right)$$  \hspace{1cm} (3)

Note that $G_i \in \mathcal{G}_D$ in the first term above represents a trace in the training data set while $G$ in the second term above refers to any possible trace of the domain. Since Equation 3 is convex, we use a gradient-based method to learn $\Theta$ and divide the traces into pairs of human models as in [Ziebart et al., 2008]:

$$\nabla_\Theta \mathcal{L} = \frac{1}{|D|} \sum_{G \in \mathcal{G}} \left( \sum_{(M, M') \in \mathcal{D}_G} \Psi(M, M') - \sum_{(M, M') \in \mathcal{D}_G} P(M, M' | \Theta) \Psi(M, M') \right)$$

Different from traditional applications of MaxEnt-IRL [Ziebart et al., 2008], the model distance metric in our work depends on both the current and next human model. As a result, $P(M, M' | \Theta)$ above represents the model pair occurrence frequency (MPOF) for a pair $(M, M')$, which can be computed using dynamic programming. If we denote the probability of occurrence of $(M, M')$ at time $t$ as $\mu_t(M, M')$, we then have $P(M, M' | \Theta) = \sum_{t} \mu_t(M, M')$.

The updating rules for $\mu_t$ is as follows:

$$\mu_1(M, M') = P((M_1, M_2) = (M', M'))$$

$$\mu_{t+1}(M, M') = \sum_f \mu_t(M'', M) P(f | M) P(M' | M, f)$$

The values for $\mu_1$ are initialized to the probability of the state pair $(M, M')$ being the first pair of a trace. The probability of the occurrence of $(M, M')$ at a certain time step then is calculated based on the occurrence frequency of the previous state pair, which has $M$ as the second entry in the pair, any unit feature change $f$ that the robot would explain to the human while in state $M$ (i.e., according to a stochastic policy), and the probability that the human model would end up in $M'$ when explaining $f$ in state $M$ (i.e., the transition function).

The stochastic policy $P(f | M)$ specifies the probability of explaining $f$ when the human model, which is computed as $P(f | M) = \frac{P(M, f, M')}{P(M, M')}$. Similarly, they can be calculated using dynamic programming as in [Ziebart et al., 2008]. $\mu_1(M, M')$ can then be approximated using sampled traces generated by the stochastic policy and transition function in each iteration. After learning the parameters for the model distance metric, we utilize uniform cost search for a specific goal to retrieve the best sequence of $f_i$ from a common initial state by maximizing the reward of each state:

$$\zeta_G^* = \arg\max_{G \in \mathcal{G}} \sum_{(M, M') \in \mathcal{G}_D} \Theta^T \Psi(M, M')$$  \hspace{1cm} (4)

### 4.3 Features Selection

The features used in our learning algorithm for the model distance metric belong in general to two categories: domain dependent and domain independent features.

The domain dependent features in our study are chosen to be the ones that we consider to have an impact on the cognitive load. These features should be fully specifiable by $M$ and $M'$ only given our IRL formulation. Although this imposes a restriction on the set features we can select, it still allows for a rich set of possibilities for any given domain. In our future work, we will further investigate the impact of this restriction on the learned model distance metric.

Domain independent features are chosen to reflect replanning cost. We consider two types of domain independent features: (1) action distance [Fox et al., 2006], and (2) cost distance. Each of them represents a type of plan distances. The motivation to use plan distances is that, as the information is communicated progressively for an explanation (as unit model changes), humans process it as it is received (i.e., replan based on the current information). Intuitively, the effort involved in the replanning process is correlated to how many changes must be made to a plan, which is often captured by a distance metric. For any model $M_i$, we denote the plan as $\pi_i$.

The following distance metrics are considered:

**Action Distance:** The action distance feature represents the difference between two plans $\pi_i$ and $\pi_j$ obtained from $M_i$ and $M_j$ respectively, as $\text{distance}(\pi_i, \pi_j) = 1 - \frac{\left| \pi_i \cap \pi_j \right|}{\left| \pi_i \cup \pi_j \right|}$.

The action distance value is lower when two plans have more actions in common.

**Cost Distance:** Similarly, the cost distance is the difference between the cost of plans $\pi_i$ and $\pi_j$ obtained from $M_i$ and $M_j$ respectively: $C(\pi_i, \pi_j) = |\text{cost}^*_M(I, G) - \text{cost}^*_M(I, G)|$. Due to the associative property of the cost, we have used the square of the cost as a feature.

### 5 Evaluation

![Figure 3: Illustration of the escape-room domain.](image)

#### 5.1 The Escape-Room Domain

To evaluate our approach, we conducted a human subject study using Amazon Mechanical Turk (MTurk) with different scenarios in an escape-room domain. This domain is designed to expose the subjects to complex situations that require substantial cognitive effort in a short amount of time. The task is situated in a damaged nuclear plant represented as a maze-like environment in Fig. 3. Your goal is to navigate from the starting location $S$ to the goal location $G$ without going through dangerous zones as fast as you can with the help of an external agent. The set of actions in this domain are going to each of gateway cells from $S$, and get to the cell $G$ from there. For instance, go to cell $E$, go to $G$ from $E$, ...
assuming cell E is not a dangerous passage. Although you know all non-wall locations are initially traversable but a few marked locations (see Fig. 3) may be affected by the disaster, the accurate information is only communicated to you by the external agent. Due to the limited communication bandwidth, the external agent can only convey one piece of information at a time (e.g., $D$ is a danger zone). The states of the 7 marked locations correspond to 7 contingencies (modeled as unit feature changes in the domain) that may have affected your plan. This means that the original MDP has $2^7$ states. In training, the subjects performed the role of the external agent who communicates the information to you. In testing, after the explanation (similarly with one piece of information at a time) from the external agent (this time automatically generated by our algorithm running on a robot), you were asked to provide the best path which passes from $S$ to $G$ while avoiding the danger zones. The experimental framework is elaborated more in Sec. 5.2.

5.2 Experimental Design
We designed 8 different scenarios for the escape-room domain. We used 5 scenarios for training and 3 for testing. Each scenario involves a different set of contingencies and we ensure that there are contingencies in the testing scenarios that did not appear in the training scenarios. During training, the human subjects are at first introduced to the domain and informed that they are supposed to act as the external agent to communicate the contingencies to the internal person in the scenario. They are explained that the internal person is desperate to escape soon to give them a sense of urgency as well as an incentive to elucidate the situation. We asked them at the beginning about what path the internal person would take assuming no danger zones are present. We use the answer to this question later to make sure that they understand the task so as to sift the data. Then, they are explained that they are to guide the internal agent out by communicating one piece of information at a time, due to the limited communication bandwidth. The ordered sequences of contingencies that the subjects provided in each scenario are used as “expert” traces to learn the model distance metric.

In the testing phase, we test the subject performance with our progressive explanation generation method and two baselines. In particular, we provided the subjects the contingencies that are ordered 1) by our method, 2) by a random order, and 3) by the Manhattan distance relative to the starting location $S$. This time, a new set of subjects are recruited who are told that they are the internal agent and must get out of the nuclear plant as soon as they can. To create a highly cognitive demanding situation, the subjects are pushed to complete the task within 4 minutes. Responses that failed the sanity check question or ran over 4 minutes are not used. Again, they are given the contingencies one at a time but this time ordered by different methods. After the task, the subjects were provided the NASA Task Load standard questionnaire (TLX) [NASA, 2020] to evaluate the efficiency of the different methods.

5.3 Results & Analysis
To improve the quality of the responses, we set the criteria that the worker’s HIT acceptance rate must be greater than 99% and has been granted MTurk Masters. In the training phase, we created the surveys using Qualtrics and recruited 35 human subjects on MTurk, out of which 21 responses were used. For testing, we have recruited 163 human subjects out of which 87 responses were used. 58 of our subjects were male and 29 were female. The average of age of our subjects was 38.17 with a standard deviation of 11.13. For domain dependent features, we chose 4 features related to relative position of the contingency being explained with respect to the contingencies that have already been explained. We refer to these features as $x_{\text{min}}, x_{\text{max}}, y_{\text{max}}$, and $y_{\text{min}}$. Table 1 shows the normalized weights $\Theta$ for each feature after learning via IRL as explained in Sec. 4.2.

| Feature Category | Feature Name | Weights |
|------------------|--------------|---------|
| Domain dependent | $x_{\text{min}}, x_{\text{max}}$ | 0.75, 0.81 |
| Domain dependent | $x_{\text{max}}, y_{\text{max}}$ | 0.79, 0.87 |
| Domain independent | Cost$^2$ Distance | -0.02 |
| Domain independent | Action Distance | 1.00 |

Table 1: Normalized feature weights

As Table 1 shows, both domain dependent and domain independent features play an important role in generating the explanations, which is expected. Interestingly, the action distance, as a domain independent feature obtained the maximum weight. This shows that the domain independent features have a significant influence on the order of the explanation being made by humans in our domain.

The results for testing are presented in Fig. 4. We can see that our method (PEG) performs better than the baselines for all NASA TLX metrics, a statistically significant difference was observed between PEG and other methods for a weighted sum of TLX metrics, as shown in Table 2. Objective metrics further confirmed that our method improved task performance as presented in Table 3 which represents the percentage in which the human subject came up with the correct plan after the respective explanations. This result verifies H2.

Fig. 5 shows the action distance per explanation step for testing scenarios. The curve of PEG is smoother, i.e. the first four sub explanations change the plan for PEG while they might or might not change the plan for the other approaches. This entails that our approach sorts the important explanations to be shared at the beginning of the communication. A
Figure 5: Changes of action distance per explanation step

|                  | Mental Demand | Temporal Demand | Performance | Effort | Frustration | Weighted TLX (excluding Performance) |
|------------------|---------------|-----------------|-------------|--------|-------------|--------------------------------------|
| Random           | 63.10         | 61.96           | 89.06       | 59.04  | 33.96       | 52.47                                |
| PEG              | 56.19         | 55.37           | 90.74       | 54.11  | 25.89       | 41.93                                |
| Manhattan        | 57.43         | 69.93           | 85.00       | 66.86  | 43.93       | 58.35                                |

Table 2: Subjective results for each NASA TLX category

deep analysis of the Fig. 5 shows that progressive explanation creates a smoother connected to replanning cost which is expected to contribute to a better understanding of the explanation which has been conjectured in prior work [Zhang and Zakershahrak, 2019] but never formally established. Furthermore, Table 4 demonstrates the $p$-value comparison between PEG and two other baselines, which proves the statistical significance of the results.

|                  | Random | PEG     | Manhattan |
|------------------|--------|---------|-----------|
| Accuracy         | 85.4 (41/48) | 96.3 (26/27) | 66.7 (8/12) |

Table 3: Objective performance in terms of task accuracy

6 Conclusions

In this paper, we studied the problem of PEG. We took a step further from the prior work by considering not only the right explanation for the explaine, but also the underlying cognitive effort required from the explaine for understanding the explanation, resulting in a general framework for PEG. An observation was that making explanation is an incremental process that constitutes of multiple steps. As a result, the mental workload can be computed as a sum of the mental workload required at each step. The goal then becomes minimizing the sum of such effort. This converts our explanation generation problem to a sequential decision making problem. The mental workload at each step is associated with a model distance metric, which was then learned using inverse reinforcement learning based on both domain dependent and independent features. Our approach is evaluated with an escape-room domain with human subjects. Results show that domain independent features play a significant role in quantifying the cognitive load, which suggests that human cognitive load is directly correlated with replanning cost, thus verifying H1. We compared progressive explanation with two baselines. Results show that PEG reduced cognitive load, which verified H2.

References

[Abbeel and Ng, 2004] P. Abbeel and A. Y Ng. Apprentice-like learning via inverse reinforcement learning. In Proceedings of the twenty-first ICML, page 1. ACM, 2004.

[Chakraborti et al., 2017a] T. Chakraborti, S.Kambhampati, M.Scheutz, and Yu Zhang. Ai challenges in human-robot cognitive teaming. 2017.

[Chakraborti et al., 2017b] T. Chakraborti, S. Sreedharan, Yu Zhang, and S. Kambhampati. Plan explanations as model reconciliation: Moving beyond explanation as soliloquy. ijcai (2017), 156–163, 2017.

[Chakraborti et al., 2019] T. Chakraborti, A. Kulkarni, S. Sreedharan, David E Smith, and S. Kambhampati. Explicability? legibility? predictability? transparency? privacy? security? the emerging landscape of interpretable agent behavior. In ICAPS, volume 29, pages 86–96, 2019.

[Cooke, 2015] N. J Cooke. Team cognition as interaction. Current directions in psychological science, 24(6):415–419, 2015.

[Dragan and Srinivasa, 2013] A. Dragan and S. Srinivasa. Generating legible motion. 2013.

[Endsley, 1988] M. R Endsley. Design and evaluation for situation awareness enhancement. In Proceedings of the Human Factors Society annual meeting, volume 32, pages 97–101. SAGE Publications Sage CA: Los Angeles, CA, 1988.

[Endsley, 2016] M. R Endsley. Designing for situation awareness: An approach to user-centered design. CRC press, 2016.

[Ericsson and Smith, 1991] K Anders Ericsson and Jacqui Smith. Toward a general theory of expertise: Prospects and limits. Cambridge University Press, 1991.

[Fikes and Nilsson, 1971] Richard E Fikes and Nils J Nilsson. Strips: A new approach to the application of theorem proving to problem solving. AIJ, 2(3-4):189–208, 1971.

[Fox and Long, 2003] M. Fox and D. Long. Pddl2. 1: An extension to pddl for expressing temporal planning domains. JAIR, 20:61–124, 2003.

[Fox et al., 2006] M. Fox, A. Gerevini, D. Long, and I. Serina. Plan stability: Replanning versus plan repair. In ICAPS, volume 6, pages 212–221, 2006.

[Göbelbecker et al., 2010] M. Göbelbecker, T. Keller, P. Eyerich, M. Brenner, and B. Nebel. Coming up with good excuses: What to do when no plan can be found. In ICAPS, 2010.
[Gong and Zhang, 2018] Ze Gong and Y. Zhang. Behavior explanation as intention signaling in human-robot teaming. In RO-MAN, pages 1005–1011. IEEE, 2018.

[Gunning, 2017] D. Gunning. Explainable artificial intelligence (xai). Defense Advanced Research Projects Agency (DARPA), nd Web, 2, 2017.

[Hanheide et al., 2017] M. Hanheide, M. Göbelbecker, G. S Horn, A. Pronobis, K. Sjöö, A. Aydemir, P. Jensfelt, Charles Gretton, R. Dearden, M. Janicek, et al. Robot task planning and explanation in open and uncertain worlds. AIJ, 247:119–150, 2017.

[Kahneman, 2011] D. Kahneman. Thinking, fast and slow. Macmillan, 2011.

[Langfred, 2004] C. W Langfred. Too much of a good thing? negative effects of high trust and individual autonomy in self-managing teams. Academy of management journal, 47(3):385–399, 2004.

[Langlee et al., 2017] P. Langley, B. Meadows, M. Sridharan, and D. Choi. Explainable agency for intelligent autonomous systems. In IAAI, 2017.

[Lien et al., 2004] J. Lien, O Burchan Bayazit, R. T Sowell, S. Rodriguez, and N. M Amato. Shepherding behaviors. In ICRA. IEEE, 2004.

[Lombrozo, 2006] T. Lombrozo. The structure and function of explanations. Trends in cognitive sciences, 10(10):464–470, 2006.

[Maxwell et al., 1999] B. A Maxwell, L. A Meeden, N. Addo, L. Brown, P. Dickson, J. Ng, S. Olshfski, E. Silk, and J. Wales. Alfred: The robot waiter who remembers you. In Proceedings of AAAI workshop on robotics. AAAI Press, 1999.

[Miller, 2018] T. Miller. Explanation in artificial intelligence: Insights from the social sciences. AJJ, 2018.

[NASA, 2020] NASA. Nasa task load index. https://humansystems.arc.nasa.gov/groups/TLX/, January 2020.

[Ng and Russell, 2000] A. Y Ng and S. J Russell. Algorithms for inverse reinforcement learning. In ICML, pages 663–670. Morgan Kaufmann Publishers Inc., 2000.

[Petty and Cacioppo, 1979] Richard E Petty and John T Cacioppo. Effects of forwarning of persuasive intent and involvement on cognitive responses and persuasion. Personality and Social Psychology Bulletin, 5(2):173–176, 1979.

[Sohrabi et al., 2011] S. Sohrabi, J. A Baier, and S. A McIraith. Preferred explanations: Theory and generation via planning. In AAAI, 2011.

[Zakershahrak et al., 2018] M. Zakershahrak, Akshay Sonawane, Z. Gong, and Y. Zhang. Interactive plan explicability in human-robot teaming. In RO-MAN), pages 1012–1017. IEEE, 2018.

[Zakershahrak et al., 2019] M. Zakershahrak, Z. Gong, N. Sadassivam, and Y. Zhang. Online explanation generation for human-robot teaming, 2019.

[Zhang and Zakershahrak, 2019] Yu Zhang and Mehrdad Zakershahrak. Progressive explanation generation for human-robot teaming. arXiv preprint arXiv:1902.00604, 2019.

[Zhang et al., 2017] Y. Zhang, S. Sreedharan, A. Kulkarni, T. Chakraborti, H. Hankui Zhuo, and S. Kambhampati. Plan explicability and predictability for robot task planning. In ICRA. IEEE, 2017.

[Ziebart et al., 2008] B. D Ziebart, A. Maas, J A. Bagnell, and A. K Dey. Maximum entropy inverse reinforcement learning. 2008.