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Dynamically Constructed (PO)MDPs for Adaptive Robot Planning

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Abstract

To operate in human-robot coexisting environments, intelligent robots need to simultaneously reason with commonsense knowledge and plan under uncertainty. Markov decision processes (MDPs) and partially observable MDPs (POMDPs), are good at planning under uncertainty toward maximizing long-term rewards; P-LOG, a declarative programming language under *Answer Set* semantics, is strong in commonsense reasoning. In this paper, we present a novel algorithm called iCORPP to dynamically reason about, and construct (PO)MDPs using P-LOG. iCORPP successfully shields exogenous domain attributes from (PO)MDPs, which limits computational complexity and enables (PO)MDPs to adapt to the value changes these attributes produce. We conduct a number of experimental trials using two example problems in simulation and demonstrate iCORPP on a real robot. Results show significant improvements compared to competitive baselines.

1 Introduction

In order to be fully robust and responsive in real-world environments, intelligent robots need a variety of simultaneous reasoning modalities that were separately developed in the past. In this paper, we focus on robots' needs for: i) commonsense reasoning (both logical and probabilistic), ii) modeling quantitative uncertainties from action outcomes and observations, and iii) planning under such uncertainties toward maximizing long-term rewards. This work uses (logical and probabilistic) commonsense reasoning techniques to dynamically construct probabilistic graphical models (such as MDPs and POMDPs). While traditional hand-coded models implicitly assume the acting agent is the only one that can make changes to the world, we introduce the *interleaved commonsense reasoning and probabilistic planning* (iCORPP) algorithm to leverage dynamically constructed (PO)MDPs to enable probabilistic planning to be adaptive to exogenous world changes.

An MDP describes a probabilistic transition system under the assumption of full observability. A POMDP extends an MDP by assuming partial observability of underlying states (Kaelbling, Littman, and Cassandra 1998), and hence models the quantitative uncertainties from robot observations and action outcomes well. (PO)MDP algorithms, e.g., value iteration (Sutton and Barto 1998), Monte Carlo tree search (Kocsis and Szepesvári 2006) and SARSOP (Kurniawati, Hsu, and Lee 2008), help compute a *policy* that enables planning toward maximizing long-term rewards. MDPs and POMDPs have been used in a variety of robot applications (Khandelwal, Barrett, and Stone 2015; Young et al. 2013; Goldhoorn et al. 2014). However, (PO)MDP models are not designed to reason about commonsense knowledge, e.g., *office doors are* normally *closed on holidays* and typically have a strong assumption that the acting agent to be the only one that can make changes to the world.

Existing work has investigated modeling exogenous events, e.g., sunlight reduces success rate of a robot navigating through an area (due to the limitations of range-finder sensors), *within* decision-theoretic models (Boutilier, Dean, and Hanks 1999; Hoey et al. 2005). However, it is often difficult to predict how an exogenous change will affect the system state, and what the distribution for the occurrence of these exogenous events will be. Doing so also presents a trade-off between model correctness and computational tractability (as more domain variables are modeled). Although it is possible to implement domain-specific planners to efficiently handle the exogenous events, we argue that, from a practical perspective, using commonsense reasoning to shield exogenous domain attributes from (PO)MDPs is relatively a much more easy-to-use approach than directly manipulating (PO)MDPs' graphical representations.

Answer set programming (ASP) is a logic programming language that is good at representing and reasoning with logical commonsense knowledge (Baral 2003; Gelfond and Kahl 2014) and has been used in robot applications (Chen et al. 2012; Erdem, Patoglu, and Saribatur 2015). Probabilistic extensions of ASP (Baral, Gelfond, and Rushton 2009; Lee and Wang 2015) further enable reasoning with probabilistic commonsense knowledge. As a result, ASP's probabilistic extensions can easily represent facts such as *office doors are normally closed on holidays* and probabilistic models such as *a robot has a lower success rate of navigating through an area under sunlight*. However, ASP and its extensions do not support probabilistic planning toward maximizing long-term rewards, e.g., techniques in the ASP family are not suitable for the robot navigation problem (§ 3.2), whereas (PO)MDPs are.

Contemporaneously with ASP, another family of pro-

gramming languages for probabilistic reasoning are built under First-order logic (FOL) semantics, including BLOG (Milch et al. 2007) and MLNs (Richardson and Domingos 2006), but the FOL-based languages are not good at representing or reasoning with commonsense knowledge that is *normally* true but not always – more detailed comparisons by Baral, Gelfond, and Rushton (2009). As a result, the FOL-based planning methods, such as (Srivastava et al. 2014), are not good for domains where the robot's world model (including its transition and reward systems) can be frequently changed by external factors. Similar weakness is shared by RDDL (Sanner 2010) that was developed for the ICAPS International Probabilistic Planning Competition.

Different methods have been developed to combine commonsense reasoning and probabilistic planning. ASP and POMDPs have been integrated for mobile robots, where the reasoning results were used for generating *prior* beliefs for POMDPs (Zhang, Sridharan, and Wyatt 2015). A switching planner was used for deterministic and probabilistic planning while commonsense knowledge was used for diagnostic tasks and generating explanations (Hanheide et al. 2015). An action language was used to interact with and build POMDPs (Sridharan and Gelfond 2016). In these algorithms, bridging the gap between logical knowledge and probabilistic beliefs requires considerable domain-dependent heuristics. The use of P-LOG and POMDPs in this work enables a principled algorithm that simultaneously allows (logical and probabilistic) commonsense reasoning and probabilistic planning. Learning and planning with commonsense knowledge have been integrated in POMDPs (Juba 2016). That work is restricted to goal-oriented planning and noise-free POMDP observations, whereas iCORPP is not.

This work extends our previous research on a algorithm called CORPP that unifies the strengths of POMDPs and P-LOG by reasoning with P-LOG to specify the state space of and compute informative priors for POMDP-based planning (Zhang and Stone 2015). However, a limitation of CORPP is that the reward and transition systems have to be hand-coded, making it incapable of adapting to exogenous world changes. This paper addresses this limitation by introducing iCORPP that dynamically constructs (PO)MDPs using P-LOG, and, for the first time, shields exogenous attributes from (PO)MDPs while still enabling probabilistic planning to adapt to the exogenous events. To evaluate iCORPP's performance, we have conducted a large number of trials in simulation and demonstrated its effectiveness on a real robot using tasks in an office domain. We observed significant improvements in efficiency and accuracy compared to CORPP.

2 Background

This work builds on the existing techniques of P-LOG (Baral, Gelfond, and Rushton 2009) and POMDPs (Kaelbling, Littman, and Cassandra 1998). Since POMDPs are currently more common in the literature, we do not discuss the general POMDP framework, but focus on introducing P-LOG, the other key technique this work builds on.

A P-LOG program typically includes both logical and probabilistic rules, where the syntax and semantics of the logical rules are inherited from ASP and the probabilistic reasoning algorithm is based on a causal Bayesian network. An ASP program consists of a set of logical rules, separated by the symbol "←" (as shown below). The left side is called the *head* and the right is called the *body*. A rule is read as "head is true if body is true", and specifically, a rule with an empty body is referred to as a *fact*.

$$\mathtt{l}_0 \text{ or } \cdots \text{ or } \mathtt{l}_k \leftarrow \mathtt{l}_{k+1}, \cdots, \mathtt{l}_m, \text{ not } \mathtt{l}_{m+1}, \cdots, \text{ not } \mathtt{l}_n.$$

The `l`'s in ASP rules are literals, i.e., an expression of `p` or $\neg$`p`, where `p` is an object constant or a variable. Symbol `not` is a logical connective called *default negation*; `not l` is read as "it is not believed that `l` is true", which does not imply `l` is believed to be false, e.g., `not prof(alice)` means it is unknown that `alice` is a professor. Using default negation, ASP can represent default knowledge with exceptions.

Traditionally, ASP does not explicitly quantify degrees of uncertainty: a literal is either true, false or unknown. P-LOG is an extension to ASP that allows *random functions*, saying that if `B`, a collection of extended literals (i.e., `l` or `not l`) holds, the value of $\mathtt{a}(\bar{\mathtt{t}})$ is selected randomly from the set $\{\mathtt{X} : \mathtt{q}(\mathtt{X})\} \cap \mathtt{range}(\mathtt{a})$, unless this value is fixed elsewhere, where `q` is a predicate:

$$\mathtt{random}(\mathtt{a}(\bar{\mathtt{t}}) : \{\mathtt{X} : \mathtt{q}(\mathtt{X})\}) \leftarrow \mathtt{B}.$$

Finally, a *probability atom* (or *pr-atom*) states that, if `B` holds, the probability of $\mathtt{a}(\bar{\mathtt{t}}) = \mathtt{y}$ is θ:

$$\mathtt{pr}(\mathtt{a}(\bar{\mathtt{t}}) = \mathtt{y} | \mathtt{B}) = \theta, \text{where, } \theta \in [0, 1].$$

As a result, we can easily use P-LOG's default negation for logical commonsense reasoning such as *office doors are normally closed on holidays* and use its probability atom for probabilistic commonsense reasoning such as *sunlight reduces the success rate of a robot navigating through an area*. Although P-LOG is good at commonsense reasoning, it does not support planning under uncertainty toward maximizing long-term rewards, which motivates the use of P-LOG for dynamically constructing (PO)MDPs in this work.

3 Algorithm

A global state space $\mathcal{S}^G$ can be specified using a set of *endogenous* attributes $\mathcal{V}^{en}$ (whose values can be changed by robot actions) and a set of *exogenous* attributes $\mathcal{V}^{ex}$ (whose values are changed by external factors).

$$\mathcal{S}^G : \mathtt{v}_1^{en} \times \cdots \times \mathtt{v}_n^{en} \times \mathtt{v}_1^{ex} \times \cdots \times \mathtt{v}_m^{ex}$$

where $\mathtt{v}^{en}$'s and $\mathtt{v}^{ex}$'s are *endogenous* and *exogenous* attributes respectively: $\mathtt{v}^{en} \in \mathcal{V}^{en}$ and $\mathtt{v}^{ex} \in \mathcal{V}^{ex}$.

In principle, all of these domain attributes, both endogenous and exogenous, can be modeled within a (PO)MDP. However, in practice there are often too many exogenous events to model all of them. Therefore, we take defaults and facts as the input to reason about all domain attributes in $\mathcal{S}^G$, and then compute a much lower-dimensional state space $\mathcal{S}$ for a (PO)MDP that focuses on a specific task, $\mathcal{S} : \mathtt{v}_1^{en} \times \cdots \times \mathtt{v}_n^{en}$. In POMDPs, reasoning with probabilistic commonsense rules associates a probability to each state $s \in \mathcal{S}$ and the probabilities together form a prior belief distribution, so the POMDP-based planning starts with this informative prior when interacting with the environment (similar

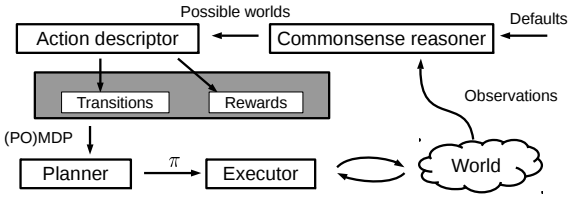


Figure 1: Overview of iCORPP

to CORPP (Zhang and Stone 2015)). We focus on constructing other components of (PO)MDPs in this paper, especially the state transition system $\mathcal{T}: \mathcal{S}\times\mathcal{A}\times\mathcal{S}\rightarrow[0,1]$ and reward system $\mathcal{R}: \mathcal{S}\times\mathcal{A}\rightarrow\mathbb{R}$ (§ 3.1), which were both treated as static by CORPP. We use example problems to present the whole process of constructing (PO)MDPs (§ 3.2).

3.1 Algorithm Description

The main idea of iCORPP is to dynamically construct probabilistic graphical models, e.g., (PO)MDPs, using a declarative language that is strong in both logical and probabilistic commonsense reasoning, e.g., P-LOG, and compute policies that are adaptive to exogenous domain changes at runtime. Figure 1 shows an overview, where this section focuses on the commonsense reasoner and the action descriptor.

Commonsense reasoner (CR) CR includes both logical and probabilistic reasoning rules in P-LOG, and models both exogenous and endogenous domain attributes. Informally, the aim of CR is to understand the parts of the world that may have effects on the robot working on the current task.

Since real-world domains are dynamically changing all the time and robots' observations are partial and unreliable, robots frequently need to reason with *incomplete* domain knowledge[1]. ASP, on which P-LOG is based, well supports CR to take a set of defaults as input and smoothly revise their values using observed "facts" when available, and hence supports reasoning with incomplete domain knowledge well. As an example, a robot using an MDP for indoor navigation may have default knowledge: "area A is under sunlight in the mornings". A fact of "no sunlight is observed in area A" can smoothly defeat the default. The set of possible worlds, $\mathcal{W}$, is described by a set of n endogenous attributes and their values.

To represent state transitions, we define two identical state spaces using predicates `curr_s` and `next_s` in P-LOG:

$$\texttt{curr\_s}(\texttt{V}_1,\cdots,\texttt{V}_\texttt{n}) \leftarrow \texttt{v}_1=\texttt{V}_1,\cdots,\texttt{v}_\texttt{n}=\texttt{V}_\texttt{n}.$$
$$\texttt{next\_s}(\texttt{V}_1,\cdots,\texttt{V}_\texttt{n}) \leftarrow \texttt{v}'_1=\texttt{V}_1,\cdots,\texttt{v}'_\texttt{n}=\texttt{V}_\texttt{n}.$$

where `curr_s` and `next_s` specify the current and next states and the `v`'s and `V`'s are endogenous attributes and their variables respectively.

If there is at least one endogenous attribute whose value is not directly observable to the robot, the corresponding task needs to be modeled as a POMDP (otherwise, an MDP).

[1]When we solve an MDP problem, we simply assume the endogenous attributes are fully observable. Robots face a partially observable world in general.

Algorithm 1 Algorithm iCORPP

Require: a set of defaults $\mathcal{D}$; (PO)MDP and P-LOG solvers
1: collect facts $\mathcal{F}^{ex}$ for exogenous attributes $\mathcal{V}^{ex}$
2: **repeat**
3: add $\mathcal{F}^{ex}$ and $\mathcal{D}$ into commonsense reasoner, CR
4: calculate possible worlds $\mathcal{W}$ (each corresponds to a state s)
5: **if** $\exists \texttt{v}^{en} \in \mathcal{V}^{en}$, whose value is not directly observable **then**
6: calculate a prior belief distribution b over $\mathcal{W}$
7: **end if**
8: generate $\mathcal{T}$ and $\mathcal{R}$ by reasoning with $\mathcal{W}$ in AD
9: compute policy π for the (PO)MDP specified by $\mathcal{T}$ and $\mathcal{R}$
10: **while** s **is not** *term* **and** $\mathcal{F}^{ex}$ is consistent with $\mathcal{W}$ **do**
11: make an observation z about endogenous attributes $\mathcal{V}^{en}$
12: update state s (or belief state b) using z
13: select action a with π, execute a, and update $\mathcal{F}^{ex}$
14: **end while**
15: **until** s **is** *term*

Action descriptor (AD) We introduce sort `action` and explicitly list a set of i actions, $\mathcal{A}$, as a set of *objects* in P-LOG. Random function `curr_a` maps to one of the actions.

$$\texttt{action}=\{\texttt{a}_0,\texttt{a}_1,\cdots,\texttt{a}_\texttt{i}\}.\ \ \texttt{curr\_a}:\texttt{action}.\ \ \texttt{random}(\texttt{curr\_a}).$$

The probabilistic state transitions, $\mathcal{T}(s,a,s')$, can be described using a set of pr-atoms in P-LOG. For instance, the rule below states that the probability of action `A` changing the value of attribute `v` from $\texttt{V}_1$ to $\texttt{V}_2$ is 0.9.

$$\texttt{pr}(\texttt{v}'=\texttt{V}_2 \mid \texttt{v}=\texttt{V}_1,\ \texttt{curr\_a}=\texttt{A})=0.9.$$

For MDPs, the values of endogenous attributes are fully observable to the robot, whereas POMDPs need to model a set of observations, Z, for estimating the underlying state. We define `obser` as a sort, and `curr_o` as a random function that maps to an observation object `o`.

$$\texttt{obser}=\{\texttt{o}_0,\texttt{o}_1,\cdots,\texttt{o}_\texttt{j}\}.\ \ \texttt{curr\_o}:\texttt{obser}.\ \ \texttt{random}(\texttt{curr\_o}).$$

The observation function, $\mathcal{O}$, defines the probability of observing `O` given the current state being `s` and current action being `a`. For instance, the rule below states that, if attribute `v`'s current value is `V`, the probability of observing `O` after taking action `A` is 0.8.

$$\texttt{pr}(\texttt{curr\_o}=\texttt{O} \mid \texttt{curr\_a}=\texttt{A},\ \texttt{v}=\texttt{V})=0.8.$$

The reward function R maps a state-action pair to a numeric value. For instance, this rule states that taking action `A` given attribute `v`'s value being `V` yields a reward of 10.0.

$$\texttt{reward}(10.0,\texttt{A},\texttt{V}_1,\cdots,\texttt{V}_\texttt{n}) \leftarrow \texttt{curr\_a}=\texttt{A},\ \texttt{curr\_s}(\texttt{V}_1,\cdots,\texttt{V}_\texttt{n}).$$

Algorithm 1 specifies the iCORPP algorithm. The robot first makes observations to collect facts $\mathcal{F}^{ex}$ for exogenous attributes $\mathcal{V}^{ex}$. In Steps 3-4, CR takes defaults $\mathcal{D}$ and facts $\mathcal{F}^{ex}$ as input and computes a set of possible worlds $\mathcal{W}$, where each $w\in\mathcal{W}$ is described by a set of endogenous attributes (and their values). In Steps 5-7, we compute a prior belief b over $\mathcal{W}$ for POMDPs. AD takes $\mathcal{W}$ as input and computes transition probabilities $\mathcal{T}$ and reward function $\mathcal{R}$. The planner can compute a policy $\pi: s\rightarrow a$ using algorithms such as SARSOP (for POMDPs) and value iteration or Monte Carlo tree search (for MDPs). Finally, the action executor uses π for interacting with the environment by making observations and taking actions, until a terminal state is reached or exoge-

nous facts lead to inconsistency. In case of inconsistency, we return to Step 3 to recompute the possible worlds.

As an example of exogenous facts causing inconsistency, consider a robot that plans to avoid the area under sunlight (which blinds the sensors) when it was started. Should clouds appear (an exogenous event) and the area previously under sunlight no longer poses a problem to the robot, all possible words are rendered inconsistent and the robot reactivates CR (Step 3) to recompute the MDP state space (and recompute the acting policy). Therefore, iCORPP enables the robot's behavior to adapt to the fact of a weather change.

3.2 Algorithm Instantiations on a Mobile Robot

In §3.1, we describe the transition and reward systems by *enumerating* all the probabilities and rewards, which can be very inefficient. In practice, we use domain-dependent attributes for much more efficient representations. To demonstrate such representations, we apply iCORPP to the following two tasks. Both task domains have exogenous changes at runtime. Figure 2(a) shows our simulation environment that is constructed using GAZEBO (Koenig and Howard 2004) and shared by the two tasks.

Task 1: shopping request identification

In this task, a robot attempts to identify a shopping request, $\langle item, room, person \rangle$, via spoken dialog in the presence of noisy speech recognition (Zhang and Stone 2015). We add more details including distances between rooms and ontology of items (Figure 2) and use this task to evaluate how iCORPP enables the robot to adapt to exogenous domain changes and fine-tune its behaviors. This domain has the following *sorts*, Θ, and each sort has a set of objects.

$\texttt{time} = \{\texttt{morning}, \texttt{noon}, \cdots\}$. $\texttt{room} = \{\texttt{r0}, \texttt{r1}, \cdots, \texttt{shop}, \cdots\}$.
$\texttt{person} = \{\texttt{alice}, \texttt{bob}, \cdots\}$. $\texttt{item} = \{\texttt{regular}, \texttt{decaf}, \cdots\}$.
$\texttt{class} = \{\texttt{item}, \texttt{drink}, \texttt{food}, \texttt{coffee}, \texttt{soda}\}$.

We then define predicate set $\mathcal{P}$:$\{\texttt{request}, \texttt{subcls}\}$, where $\texttt{request(I,R,P)}$ specifies a shopping request of delivering item $\texttt{I}$ to room $\texttt{R}$ for person $\texttt{P}$, and $\texttt{subcls}(\texttt{C}_1, \texttt{C}_2)$ claims class $\texttt{C}_1$ to be a subclass of class $\texttt{C}_2$. Figure 2(c) shows the categorical tree that can be represented using rules:

$\texttt{subcls}(\texttt{C}_1, \texttt{C}_3) \leftarrow \texttt{subcls}(\texttt{C}_1, \texttt{C}_2), \texttt{subcls}(\texttt{C}_2, \texttt{C}_3).$
$\texttt{is}(\texttt{I}, \texttt{C}_1) \leftarrow \texttt{is}(\texttt{I}, \texttt{C}_2), \texttt{subcls}(\texttt{C}_2, \texttt{C}_1).$

A set of random functions describes the possible values of random variables: $\texttt{curr\_time}$, $\texttt{req\_item(P)}$, $\texttt{req\_room(P)}$, and $\texttt{req\_person}$. E.g., the two rules below state that if the delivery is for person $\texttt{P}$, the value of $\texttt{req\_item}$ is randomly selected from the range of $\texttt{item}$, unless fixed elsewhere:

$\texttt{random}(\texttt{req\_item}(\texttt{P}))$. $\texttt{req\_item} : \texttt{person} \rightarrow \texttt{item}$.

We can then use a *pr-atom* to specify a probability. For instance, the rule below states that the probability of delivering $\texttt{coffee}$ in the morning is 0.8.

$\texttt{pr}(\texttt{req\_item}(\texttt{P}) = \texttt{coffee} | \texttt{curr\_time} = \texttt{morning}) = 0.8.$

Such random functions and pr-atoms allow us to represent and reason with probabilistic commonsense knowledge. Finally, the current state (a shopping request) is specified as follows: $\texttt{curr\_s(I,R,P,term)} \leftarrow \texttt{request(I,R,P)}, \texttt{term}.$, where predicate $\texttt{term}$ identifies the terminal state. The action set is explicitly defined as below.

$$\texttt{action} = \{\texttt{ask\_i}, \texttt{ask\_r}, \texttt{ask\_p}, \texttt{conf\_i0}, \texttt{conf\_i1} \cdots, \texttt{conf\_r0}, \texttt{conf\_r1}, \cdots, \texttt{conf\_p0}, \texttt{conf\_p1} \cdots, \texttt{del\_i0\_r0\_p0}, \cdots\}$$

where, $\texttt{ask\_}$'s are general questions (e.g., $\texttt{ask\_r}$ corresponds to "which room to deliver?"), $\texttt{conf\_}$'s are confirming questions (e.g., $\texttt{conf\_r0}$ corresponds to "is this delivery to $\texttt{room0}$?"), and $\texttt{del\_}$'s are actions of deliveries.

For delivery actions, the reward function $\mathcal{R}$ maps a state-action pair to a real number, and is defined as:

$$\mathcal{R}(a^{del}, s) = \begin{cases} R^+, \text{ if } a_i \odot s_i \text{ and } a_p \odot s_p \text{ and } a_r \odot s_r \\ \big(1 - \lambda_i(a_i, s_i) \cdot \lambda_p(a_p, s_p) \cdot \lambda_r(a_r, s_r)\big) R^-, \text{ otherwise} \end{cases}$$

where operator $\odot$ returns true if the action on the left matches the state on the right in the given dimension (subscript). λ in the range of (0, 1] measures the closeness between actual delivery (action) and underlying request (state) in item, person, and room, respectively. R^+ and R^- are the reward and penalty that a robot can get in extreme cases (completely correct or completely incorrect deliveries).

We compute the closeness of two items, $\lambda(I_1, I_2)$ by post-processing the resulting answer set. Specifically, the heuristic closeness function of two items is defined as:

$$\lambda_i(I_1, I_2) = 1 - \frac{max\big(dep(LCA, I_1), dep(LCA, I_2)\big) - 1}{max\big(dep(root, I_1), dep(root, I_2)\big)} \quad (1)$$

where *LCA* is the lowest common ancestor of I_1 and I_2 and *dep(C,I)* is the number of nodes (inclusive) between C and I.

Informally, the closeness of room R_1 to room R_2 is inversely proportional to the effort needed to recover from a delivery to R_1 given the request being to R_2. In Figure 2(a), for instance, a wrong delivery to $r0$ given the request being to $r1$ requires the robot to go back to shop, learn the delivery room being $r1$, and then move to room $r1$. Therefore, the *asymmetric* room closeness function is defined as below:

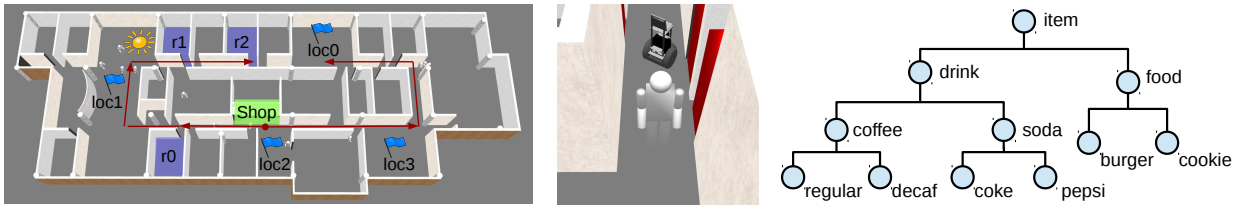
$$\lambda_r(R_1, R_2) = \frac{dis(shop, R_2)}{2 \cdot dis(shop, R_1) + dis(shop, R_2)} \quad (2)$$

We simply set λ_p to 1. The costs of question-asking actions are stationary: $\mathcal{R}(a^{ask}, s)$=-1, and $\mathcal{R}(a^{conf}, s)$=-2.

Task 2: robot navigation

In this task, the state is fully observable (MDP is used). The robot navigates in a domain shown in Figure 2(a), where moving people can (probabilistically) block its way—Figure 2(b), and sunlight can (probabilistically) blind the robot's laser range-finder, making the robot unrecoverably lost. Planning is done by mapping the domain to a grid, which is defined using sorts $\texttt{row}$ and $\texttt{col}$, and predicates $\texttt{belowof}$ and $\texttt{leftof}$. We then introduce predicates $\texttt{near\_row}$ and $\texttt{near\_col}$ used for specifying if two grid cells are next to each other, where $\texttt{R}$'s ($\texttt{C}$'s) are variables of row (column).

$\texttt{near\_row}(\texttt{RW}_1, \texttt{RW}_2) \leftarrow \texttt{belowof}(\texttt{RW}_1, \texttt{RW}_2).$
$\texttt{near\_row}(\texttt{RW}_1, \texttt{RW}_2) \leftarrow \texttt{near\_row}(\texttt{RW}_2, \texttt{RW}_1).$
$\texttt{near\_col}(\texttt{CL}_1, \texttt{CL}_2) \leftarrow \texttt{leftof}(\texttt{CL}_1, \texttt{CL}_2).$
$\texttt{near\_col}(\texttt{CL}_1, \texttt{CL}_2) \leftarrow \texttt{near\_col}(\texttt{CL}_2, \texttt{CL}_1).$



(a) (b) (c)

Figure 2: (a) Simulation environment used in experiments, where the red arrows indicate the delivery routes from the shop to individual rooms; (b) A human walker blocking the way of the robot; and (c) An ontology of available items used in the "shopping" task (Task 1).

To model the nondeterministic action outcomes, we define random functions `curr_row` and `next_row` that map to the current and next rows, and `curr_col` and `next_col` that map to the current and next columns.

$$\texttt{random}(\texttt{next\_row} : \{\texttt{R\_} : \texttt{near\_row}(\texttt{R\_}, \texttt{RW})\}) \leftarrow \texttt{curr\_row} = \texttt{RW}.$$
$$\texttt{random}(\texttt{next\_col} : \{\texttt{C\_} : \texttt{near\_col}(\texttt{C\_}, \texttt{CL})\}) \leftarrow \texttt{curr\_col} = \texttt{CL}.$$

We use predicates `near_window` and `sunny` to define the cells that are near to window and the cells that are actually under sunlight. The rule below is a default stating that: in the mornings, a cell near window is believed to be under sunlight, unless defeated elsewhere.

$$\texttt{sunny}(\texttt{RW}, \texttt{CL}) \leftarrow \texttt{near\_window}(\texttt{RW}, \texttt{CL}),\ \texttt{not}\ \neg\texttt{sunny}(\texttt{RW}, \texttt{CL}),\ \texttt{curr\_time} = \texttt{morning}.$$

While navigating in areas under sunlight, there is a large probability of becoming lost (0.9), which deterministically leads to the end of an episode.

$$\texttt{pr}(\texttt{next\_term} = \texttt{true} \mid \texttt{curr\_row} = \texttt{RW},\ \texttt{curr\_col} = \texttt{CL},\ \texttt{sunny}(\texttt{RW}, \texttt{CL})) = 0.9.$$
$$\texttt{pr}(\texttt{next\_term} = \texttt{true} \mid \texttt{curr\_term} = \texttt{true}) = 1.0.$$

The robot can take actions to move to a grid cell next to its current one: $\texttt{action} = \{\texttt{left}, \texttt{right}, \texttt{up}, \texttt{down}\}$. For instance, given action `up`, the probability of successfully moving to the above grid cell is 0.9, given no obstacle in the above cell.

$$\texttt{pr}(\texttt{next\_row} = \texttt{RW}_2 \mid \texttt{curr\_row} = \texttt{RW}_1,\ \texttt{curr\_col} = \texttt{CL}_1,\ \texttt{belowof}(\texttt{RW}_1, \texttt{RW}_2),\ \neg\texttt{sunny}(\texttt{RW}_2, \texttt{CL}_1),\ \neg\texttt{blocked}(\texttt{RW}_2, \texttt{CL}_1),\ \texttt{curr\_a} = \texttt{up}) = 0.9.$$

Finally, the current state is specified by endogenous attributes `curr_row`, `curr_col`, and `curr_term`:

$$\texttt{curr\_state}(\texttt{RW}, \texttt{CL}, \texttt{TM}) \leftarrow \texttt{curr\_row} = \texttt{RW},\ \texttt{curr\_col} = \texttt{CL},\ \texttt{curr\_term} = \texttt{TM}.$$

The goal of visiting room $(\texttt{r0}, \texttt{c3})$ can be defined as below, where an early termination has a penalty of -100.0.

$$\texttt{pr}(\texttt{next\_term} = \texttt{true} \mid \texttt{curr\_row} = \texttt{r0}, \texttt{curr\_col} = \texttt{c3}) = 1.0.$$
$$\texttt{reward}(50.0, \texttt{A}, \texttt{r0}, \texttt{c3}, \texttt{true}) \leftarrow \texttt{curr\_state}(\texttt{r0}, \texttt{c3}, \texttt{true}).$$
$$\texttt{reward}(-100.0, \texttt{A}, \texttt{RW}, \texttt{CL}, \texttt{true}) \leftarrow \texttt{curr\_state}(\texttt{RW}, \texttt{CL}, \texttt{true}),\ \texttt{RW} <> \texttt{r0}.$$
$$\texttt{reward}(-100.0, \texttt{A}, \texttt{RW}, \texttt{CL}, \texttt{true}) \leftarrow \texttt{curr\_state}(\texttt{RW}, \texttt{CL}, \texttt{true}),\ \texttt{CL} <> \texttt{c3}.$$

Informally, iCORPP decomposes a (PO)MDP problem into two subproblems, commonsense reasoning and probabilistic planning, that respectively focus on "curse of dimensionality" and "curse of history" – elaborated in (Kurniawati et al. 2010). Therefore, iCORPP significantly reduces the complexity of (PO)MDP planning compared to its one-shot solution, while enabling robot behaviors to adapt to exogenous changes. As an example on complexity, the MDP constructed by iCORPP in Task 2 (thirty positions, five weather conditions and three times) includes only 60 states, whereas the traditional way of enumerating all combinations of attribute values (Boutilier, Dean, and Hanks 1999), produces more than 2^69 states, which cannot be solved (accurately or approximately) in practice.

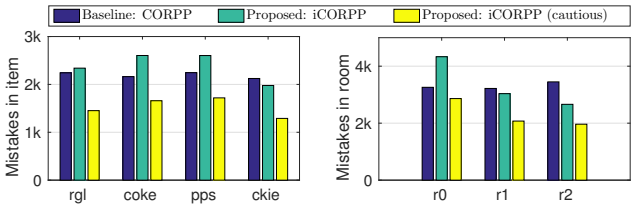


Figure 3: iCORPP enables the robot to fine-tune its behavior in delivering different items to different rooms. The x-axis and y-axis correspond to the *incorrect* deliveries and the number of mistakes (over 100k trials). For instance, `r0` in the right bars corresponds to the numbers of deliveries to `r0` given `r1` or `r2` being requested.

4 Experimental Results

iCORPP has been implemented both in simulation and on real robots. Focusing on the robot behavior using iCORPP, we evaluate two hypotheses that iCORPP enables the robot to (I) adaptively produce behaviors to a fine-tuned level that is impossible for handcoded (PO)MDP models; and (II) adapt to exogenous domain changes at runtime, without modeling these exogenous attributes in its (PO)MDPs. We take CORPP as the baseline algorithm unless specified otherwise. Note that CORPP is more competitive than standard (PO)MDP methods, as it reasons about domain attributes to specify the *initial* state set (Zhang and Stone 2015).

Experiments in simulation were conducted using GAZEBO (Koenig and Howard 2004). We used a solver introduced in (Zhu 2012) for P-LOG programs (except that reasoning about reward was manually conducted), the APPL solver for POMDPs (Kurniawati, Hsu, and Lee 2008), and value iteration for MDPs (Sutton and Barto 1998).

Hypothesis-I (Task 1) We use Task 1 with four items, three rooms and two persons for comparing iCORPP to CORPP (the baseline). The hidden shopping request was randomly selected in each trial. Speech recognition errors are modeled, e.g., 0.8 accuracy in recognizing answers of confirming questions and a lower accuracy for general questions (depending on the number of that sort's objects).

Figure 3 shows the numbers of mistakes made by the

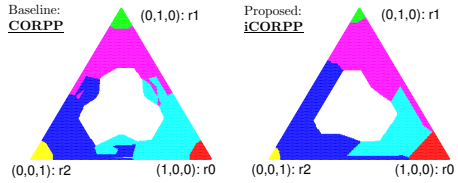


Figure 4: A visualization of CORPP and iCORPP policies, where the person wants to deliver to one of the three rooms. Each point corresponds to a belief. Each color corresponds to an action: white corresponds to the general question of "which room to deliver"; the colors in the corners correspond to delivery actions; and the remaining three colors correspond to confirming questions.

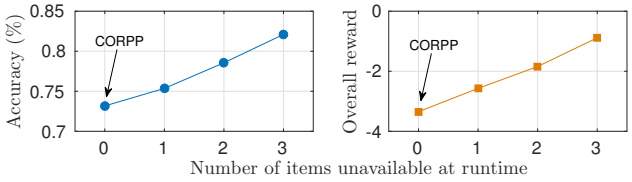


Figure 5: iCORPP performs increasingly better in accuracy and overall reward in the shopping task when more items are known to be unavailable: CORPP corresponds to the left ends of the two curves (CORPP uses a static model so it has to include all items).

robot. In the default and cautious versions of iCORPP, the values of $[R^+, R^-]$ are $[20, -20]$ and $[30, -30]$ respectively. The first observation is that CORPP makes no difference in either item (**Left**) or room (**Right**), because it does not reason about the reward system—incorrect deliveries are not differentiated and all receive the same penalty. In contrast, both versions of iCORPP enable the robot to behave in such a way that the robot makes the fewest mistakes in `cookie` (**Left**) and room `r2` (**Right**). Such behaviors match our expectations: `cookie` is "very different" from the other three items and `r2` has the greatest distance from the shop, so the robot should make effort to avoid delivering `cookie` (or delivering to `r2`) when that is not requested. The second (side) observation from comparing the default and cautious versions of iCORPP is that, to adjust the robot's "cautious level", we can simply change the value of $[R^+, R^-]$. Without iCORPP, to achieve such fine-tuned behaviors, there will be 600 parameters in the reward function need to be handcoded, which is impossible from a practical point of view.

To better understand the robot's behavior (specifically, the **Right** of Figure 3), we manually remove the uncertainties in `item` and `person` in the initial belief, and visualize which action the POMDP policy suggests given different initial beliefs in `room`. In the **Right** of Figure 4, we see the robot is relatively more cautious in delivering to `r1` and `r2` (the green and yellow areas in the top and left corners are smaller than the red one in the right). It is very difficult to achieve such fine-tuned behaviors from hand-coded models.

Hypothesis-II (Task 1) Figure 5 shows the results of the shopping task when exogenous changes are added: items can be temporarily unavailable. iCORPP dynamically constructs POMDPs: when items are known to be unavailable, states of these items being requested and actions of delivering these items are removed from the POMDP. For instance, when three items are unavailable, the numbers of states and

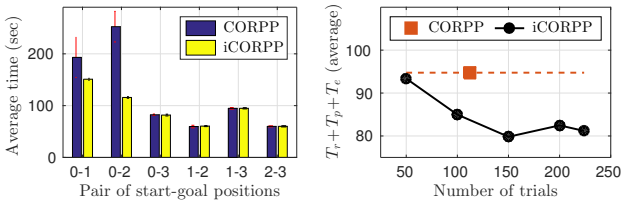


Figure 6: (Left) Average time (with standard deviations) consumed in navigating between location pairs when a walker moves near the door of room $r1$; **(Right)** iCORPP enables the robot to adapt to exogenous domain changes (the walker's position). Results are processed in batches (each has 50 trials, when available).

actions are reduced from $(37, 50)$ to $(18, 29)$. As a result, iCORPP performs increasingly better in both accuracy and overall reward (y-axes in Figure 5) when more items are known to be unavailable (x-axes in Figure 5). In contrast, CORPP has to use a static POMDP that includes all items (assuming no item unavailable), because it cannot adapt to exogenous changes. So CORPP's performance corresponds to the left ends of the two curves. Results shown in Figure 5 support that iCORPP enables the robot to adapt to exogenous domain changes, whereas CORPP does not.

Hypothesis-II (Task 2) We further evaluate Hypothesis-II using the navigation task: the testing environment and the robot are shown in Figure 2(a) and 2(b). We limit the number of random walkers to be 1 and its speed to be one fifth of the robot's. A goal room is randomly selected from the four flag rooms. Reasoning happens only after the current episode is terminated (goal room is reached). The walker's position is the only exogenous domain change (by temporarily setting the time to be "evening"). We cached policies for both CORPP (4 policies) and iCORPP (56 policies).

Figure 6 (Left) shows the robot's traveling time given start-goal pairs: once the robot arrives at its current goal, the next one is randomly selected. The walker moves slowly near the door of room $r1$. Without adaptive planning developed in this work, the robot follows the "optimal" path and keeps trying to bypass the walker for a fixed length of time. If the low-level motion planner does not find a way to bypass the walker within the time, the robot will take the other way to navigate to the other side of the walker and continues executing the "optimal" plan generated by the outdated model. We can see when the robot navigates between $loc0$ and $loc2$, iCORPP reduces the traveling time from about 250 seconds to about 110 seconds, producing a significant improvement. We do not see a significant difference for position pairs other than "0-1" and "0-2", because the walking human is constrained to be near the door of room $r1$.

Results over 8.5 hours of experiments are shown in Figure 6 (Right): 224 trials using iCORPP and 112 trials using CORPP. Without caching, we find the time consumed by iCORPP (over 54 trials) is distributed over P-LOG reasoning (T_r, 28%), MDP planning (T_p, $<$1%), and execution (T_e, 72%). Compared to CORPP, iCORPP enables the robot to spend much less time in execution (T_e) in all phases. At the beginning phase, iCORPP requires more reasoning time for dynamically constructing MDPs, which together with the less execution time makes the overall time comparable to CORPP (left ends of Figure 6-Right). Eventually, the low

execution time (T_e) dominates the long-term performance (right ends of Figure 6-Right), supporting that iCORPP enables the robot to adapt to exogenous domain changes, whereas CORPP does not.

Hypothesis-II (Task 2 on a robot) Experiments on a real robot (including demo videos) can be found in Appendix *A* that is available in an extended version of this paper (`http://eecs.csuohio.edu/~szhang/corpp`).

5 Conclusions

This paper introduces a novel algorithm called iCORPP that uses commonsense reasoning to dynamically construct (PO)MDPs for adaptive robot planning. We use declarative language P-LOG, a probabilistic extension of answer set programming, for reasoning with logical and probabilistic commonsense knowledge, and use probabilistic graphical models, such as (PO)MDPs, for probabilistic planning. This paper, for the first time, enables robot behaviors to adapt to exogenous domain changes without including these exogenous attributes in probabilistic planning models. iCORPP has been evaluated both in simulation and on a real robot. We observed significant improvements comparing to competitive baselines (including CORPP), based on experiments on two tasks in an office environment.

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Appendix *A*

iCORPP has been implemented on a Segway-based robot. The robot uses the RMP 110 base, Xtion sensor for RGB-D sensing, and the Velodyne VLP-16 for navigation. A semantic map was hand-coded to map each symbolic position into a pair of x-y coordinates in the real-world environment.

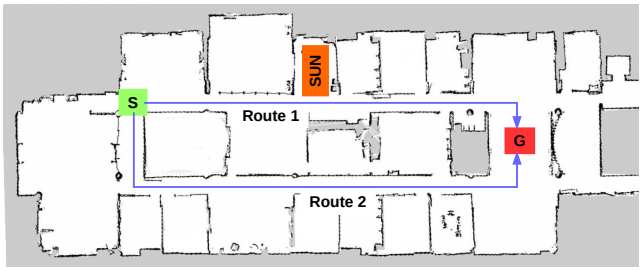

Figure 1: iCORPP enables the robot to select "Route 1", successfully avoiding the "sunlight" area along "Route 2".

Figure 1 shows the office environment where real-robot experiments were conducted. It includes ten offices, two meeting rooms, and three research labs. The occupancy-grid map of the environment was generated using a simultaneous localization and mapping (SLAM) algorithm. The "SUN" area is an area that is subject to strong sunlight in the mornings given the current weather being sunny. The *default reasoning* capability of P-LOG supports that a fact of "under sunlight" (or not) can defeat the default belief about sunlight. Such sunlight can blind the robot's laser range-finder, and makes the robot unrecoverably lost. Therefore, the robot needs to reason about the knowledge of current time and weather to dynamically construct its MDP-based probabilistic transition system, including the success rate of navigating through the "SUN" area given the current condition.

Figure 1 also shows two routes in a demonstration trial where the robot needs to navigate from its start point ("S" in the green box) to the goal ("G" in the red box). To test the robot's behavior adapting to sunlight change, we left the robot two routes that lead to the goal. For instance, Route 1 is shorter, but it goes through the area that is currently under sunlight. Figure 2 shows screenshots of two trials in which the baseline (CORPP) and iCORPP were used respectively. iCORPP enables the robot to select the safer route (Route 2), even though it is longer. CORPP cannot adapt to the exogenous change of current time being morning and current weather being sunny, letting the robot still believe the shorter path is safe. In experiments, we directly encode such exogenous knowledge to the robot. [1]

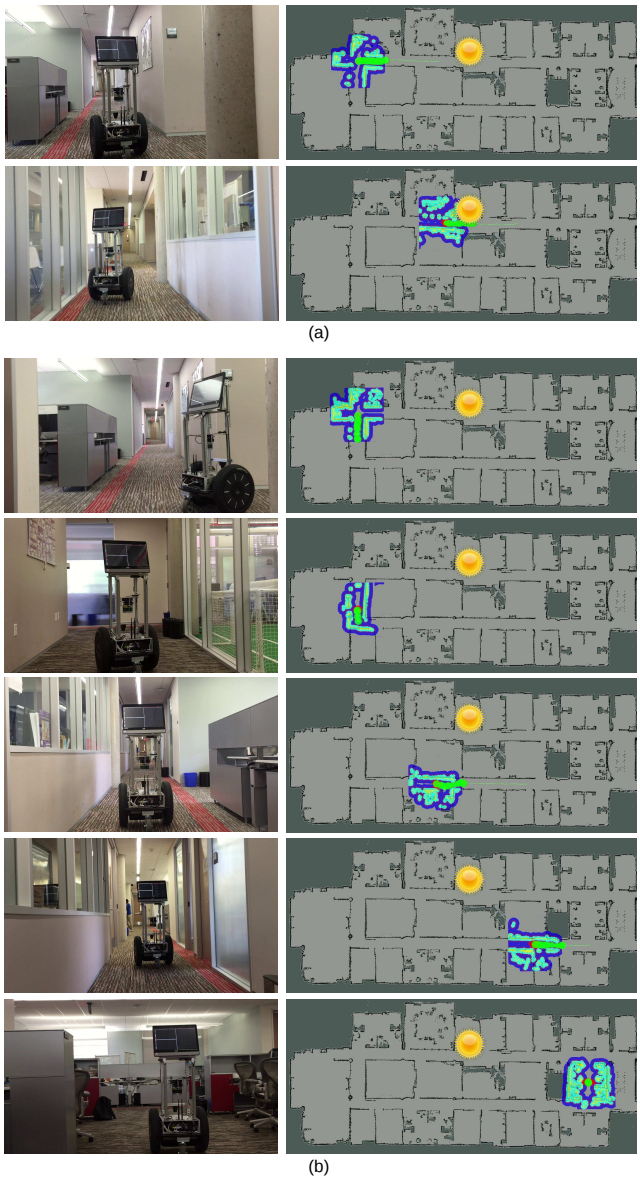

Figure 2: Screen shots of two illustrative trials: (a) Using the baseline approach (CORPP), the robot chose Route 1 that is dangerous but shorter, causing the robot to become unrecoverably lost in the "sunny" area; (b) By reasoning about current time (morning) and weather (sunny), iCORPP successfully helps the robot take Route 2 to avoid being trapped in the "sunlight" area, even though the route is longer.

[1] Demo videos of simulated and real-robot trials are available at: http://eecs.csuohio.edu/~szhang/corpp