Robot Representation and Reasoning with Knowledge from Reinforcement Learning

Keting Lu\textsuperscript{1}, Shiqi Zhang\textsuperscript{2}, Peter Stone\textsuperscript{3}, Xiaoping Chen\textsuperscript{1}

\textsuperscript{1}University of Science and Technology of China, \textsuperscript{2}SUNY Binghamton, \textsuperscript{3}UT Austin

ktlu@mail.ustc.edu.cn; szhang@cs.binghamton.edu; pstone@cs.utexas.edu; xpchen@ustc.edu.cn

Abstract—Reinforcement learning (RL) agents aim at learning by interacting with an environment, and are not designed for representing or reasoning with declarative knowledge. Knowledge representation and reasoning (KRR) paradigms are strong in declarative KRR tasks, but are ill-equipped to learn from such experiences. In this work, we integrate logical-probabilistic KRR with model-based RL, enabling agents to simultaneously reason with declarative knowledge and learn from interaction experiences. The knowledge from humans and RL is unified and used for dynamically computing task-specific planning models under potentially new environments. Experiments were conducted using a mobile robot working on dialog, navigation, and delivery tasks. Results show significant improvements, in comparison to existing model-based RL methods.

I. INTRODUCTION

Knowledge representation and reasoning (KRR) and reinforcement learning (RL) are two important research areas in artificial intelligence (AI) and have been applied to a variety of problems in robotics. On the one hand, KRR research aims to concisely represent knowledge, and robustly draw conclusions with the knowledge (or generate new knowledge). Knowledge in KRR is typically provided by human experts in the form of declarative rules. Although KRR paradigms are strong in representing and reasoning with knowledge in a variety of forms, they are not designed for (and hence not good at) learning from experiences of accomplishing the tasks. On the other hand, RL algorithms enable agents to learn by interacting with an environment, and RL agents are good at learning action policies from trial-and-error experiences toward maximizing long-term rewards under uncertainty, but they are ill-equipped to utilize declarative knowledge from human experts. Motivated by the complementary features of KRR and RL, we aim at a framework that integrates both paradigms to enable agents (robots in our case) to simultaneously reason with declarative knowledge and learn by interacting with an environment.

Most KRR paradigms support the representation and reasoning of knowledge in logical form, e.g., the Prolog-style. More recently, researchers have developed KRR paradigms that support both logical and probabilistic knowledge. Examples include Markov Logic Network (MLN) [19], P-log [4], and Probabilistic Soft Logic (PSL) [2]. Such logical-probabilistic KRR paradigms can be used for a variety of reasoning tasks. We use P-log in this work to represent and reason with both human knowledge and the knowledge from RL. When a task becomes available, our robot reasons at runtime to produce probabilistic transition systems for action policy generation.

Reinforcement learning (RL) algorithms can be used to help robots learn action policies from the experience of interacting with the real world [22]. There are at least two types of RL algorithms, namely model-based RL and model-free RL, depending on whether a world model is computed or not. Model-free RL aims at directly computing the “value” of a state (or state-action pair), whereas the output of model-based RL includes a world model, and one can use planning algorithms to compute action policies with the world model. We use model-based RL in this work, because the learned world model can be used to update the robot’s declarative knowledge base and combined with human knowledge.

In this paper, we develop a framework (KRR-RL) that integrates logical-probabilistic KRR and model-based RL. Transition probabilities that result from actions are learned via model-based RL, and then incorporated into the probabilistic reasoning module, which in turn (together with human knowledge) enables dynamic construction of efficient run-time task-specific planning models. Our KRR-RL framework, for the first time, enables a robot to: i) represent the probabilistic knowledge (i.e., world dynamics) learned from RL in declarative form; ii) unify and reason with both human knowledge and the knowledge from RL; and iii) compute policies at runtime by dynamically constructing task-oriented partial world models. The above advantages are backed with experiments both in simulation and using real mobile robots conducting navigation, dialog, and delivery tasks.

II. RELATED WORK

This work is on integrating logical-probabilistic knowledge representation and reasoning (KRR) and model-based reinforcement learning (RL). Related research areas include integrated logical KRR and RL, relational RL, and integrated KRR and probabilistic planning.

For example, logical KRR has previously been integrated with RL. Action knowledge [15], [11] has been used to reason about action sequences and help an RL agent explore only the states that can potentially contribute to achieving the ultimate goal [14]. As a result, their agents learn faster by avoiding choosing “unreasonable” actions. A similar idea has been applied to domains with non-stationary dynamics [9]. More recently, task planning was used to interact with the high level of a hierarchical RL framework [24]. The
Declarative structs a partial world model (excluding unrelated factors), on becomes available, the KRR component dynamically con-

success rates and costs of navigation actions. When a task 

robot arbitrarily selects goals (different navigation goals in 

learned from model-based RL. When the robot is free, the 

KRR includes both human knowledge and the knowledge 

representation and reasoning (KRR) and model-based re-

component supports the representation of and reasoning with 

the first work on a tightly coupled integration of logical-

and RL capabilities. To the best of our knowledge, this is 

parison, we aim at a concise representation for robot KRR 

complex, and support a variety of functionalities. In com-

architectures [23], [17], [10], [13], which are relatively 

models must be provided to these methods, where learning 

provided information has been incorporated into belief state 

of actions for robots, where individual actions are then imple-

reasoning has been used to compute informative priors [28] 

planning is also related to this research. Logical-probabilistic 

representations, e.g., time 

the KRR of factors beyond the ones in state and action 

(in only) current tasks. In this research, our framework supports 

KRR paradigm that can directly reason with probabilities 

learned from RL.

Relational RL (RRL) combines RL with relational rea-

[8]. Action models have been incorporated into 

RL, resulting in a relational temporal difference learning method [1]. Recently, RRL has been deployed for learning 

affordance relations that forbid the execution of specific actions [21]. These RRL methods, including deep RRL [26], 

exploit structural representations over states and actions in 

(only) current tasks. In this research, our framework supports 

the KRR of factors beyond the ones in state and action 

representations, e.g., time in navigation tasks (Section III 

[B]).

The research area of integrated KRR and probabilistic 

planning is also related to this research. Logical-probabilistic 

reasoning has been used to compute informative priors [28] 

and world dynamics [27] for probabilistic planning. An ac-

tion language was used to compute a deterministic sequence of 

actions for robots, where individual actions are then imple-

mented using probabilistic controllers [20]. Recently, human-

provided information has been incorporated into belief state 

representations to guide robot action selection [7]. World 

models must be provided to these methods, where learning 

was not involved.

Finally, there are a number of robot reasoning and learning 

architectures [23], [17], [10], [13], which are relatively 

complex, and support a variety of functionalities. In compar-

ison, we aim at a concise representation for robot KRR 

and RL capabilities. To the best of our knowledge, this is 

the first work on a tightly coupled integration of logical-

probabilistic KRR with model-based RL, where the KRR 

component supports the representation of and reasoning with 

the knowledge both from a human and from RL.

III. INTEGRATED KRR-RL FRAMEWORK

Our unified framework for logical-probabilistic knowledge 

representation and reasoning (KRR) and model-based re-

forcement learning (RL) is illustrated in Figure [1]. The 

KRR includes both human knowledge and the knowledge 

learned from model-based RL. When the robot is free, the 

robot arbitrarily selects goals (different navigation goals in 

our case) to work on, and learns the world dynamics, e.g., 

success rates and costs of navigation actions. When a task 

becomes available, the KRR component dynamically con-

structs a partial world model (excluding unrelated factors), on 

which a task-oriented controller is computed using planning 

algorithms. Human knowledge is on environment variables 

and their dependencies, e.g., navigation actions’ success 

rates depend on current time and weather (laser sensors 

can be blinded in areas near east-facing windows in sunny 
mornings), while the robot must learn specific probabilities 

by interacting with the environment.

Why integrated KRR-RL is needed? Consider an indoor 

robot navigation domain, where a robot wants to maxi-

mize the success rate of moving to goal positions through 

navigation actions. Shall we include factors, such as time, 

weather, positions of human walkers, etc, into the state 

space? On the one hand, to ensure model completeness, 

the answer should be “yes” (11). Human walkers and sunlight 

reduce the success rates of the robot’s navigation actions, 

and both can cause the robot irrecoverably lost. On the other 

hand, to ensure computational feasibility, the answer is “no”.

Modeling whether one specific grid cell being occupied by 

humans or not introduces one extra dimension in the state 

space, and doubles the state space size. If we consider (only) 
ten such grid cells, the state space becomes \(2^{10} \approx 1000 \) times 
bigger. As a result, RL practitioners frequently have to make 

a trade-off between model completeness and computational 

feasibility. In this work, we aim at a framework that retains 

both model scalability and computational feasibility, i.e., the 

agent is able to learn within relatively small spaces while 

computing action policies accounting for a large number of 

domain variables.

A. A General Procedure

In factored spaces, state variables \( V = \{V_0, V_1, ..., V_{n-1}\} \) 

can be split into two categories, namely endogenous vari-

ables \( V^{en} \) and exogenous variables \( V^{ex} \) [6], where \( V^{en} = \{V^{en}_0, V^{en}_1, ..., V^{en}_{p-1}\} \) and \( V^{ex} = \{V^{ex}_0, V^{ex}_1, ..., V^{ex}_{q-1}\} \). In our 
inegrated KRR-RL context, \( V^{en} \) is goal-oriented and in-

cludes the variables whose values the robot wants to actively 

change so as to achieve the goal; and \( V^{ex} \) corresponds to the 

variables whose values affect the robot’s action outcomes, 

but the robot cannot (or does not want to) change their 

values. Therefore, \( V^{en} \) and \( V^{ex} \) are both functions of task 

\( \tau \). Continuing the navigation example, robot position is 
an endogenous variable, and current time is an exogenous 

variable. For each task, \( V = V^{en} \cup V^{ex} \) and \( n = p + q \), and RL 

agents learn in spaces specified by \( V^{en} \).

The KRR component models \( V \), their dependencies from 

human knowledge, and conditional probabilities on how 

actions change their values, as learned through model-based 

RL. When a task arrives, the KRR component uses prob-

abilistic rules to generate a task-oriented Markov decision 

process (MDP) [18], which only contains a subset of \( V \) that 

are relevant to the current task, i.e., \( V^{en} \), and their transition 

probabilities. Given this task-oriented MDP, a corresponding 

action policy is computed using value iteration or policy 

iteration.

Our KRR-RL agent learns by interacting with an envi-

ronment when there is no task assigned (Procedure [1]). As 

soon as a task arrives, it uses the probabilities that are marked
to figure out the delivery request and conduct navigation tasks to physically fulfill the request. Specifically, a delivery task requires the robot to deliver item \( i \) to room \( R \) for person \( P \), resulting in services in the form of \( \langle I , R , P \rangle \). The challenges come from unreliable human language understanding (e.g., speech recognition) and unforeseen obstacles that probabilistically block the robot in navigation.

Next, we present complete world models constructed using P-log [4], [3], a logical-probabilistic KRR paradigm, and describe the process of constructing task-oriented controllers.

\textbf{a) Representing Rigid Knowledge:} Rigid knowledge includes information that does not depend upon the passage of time. We introduce a set of \textbf{sorts} including \textit{time, person, item, }and \textit{room, }so as to specify a complete space of service requests. For instance, we can use \textit{time}={morning, noon, afternoon, ...} to specify possible values of \textit{time}.

To model navigation domains, we introduce \( N \) grid cells using \textit{cell}={0, ..., \( N - 1 \)}, where the robot can travel. The geometric organization of these cells can be specified using predicates of \textit{leftof} \( (m_i, m_j) \) and \textit{belowof} \( (m_i, m_j) \), where \( n_i \) and \( m_j \) are cells, \( i, j \in \{0, \ldots, N - 1 \} \).

We use a set of random variables to model the space of world states. For instance, \textit{curr-cell} is a cell that the robot’s position \textit{curr-cell}, as a random variable, must be in. \textit{curr-room} is a room that a person’s current room must be in. \textit{curr-success} identifies the request being fulfilled or not. We can then use \textit{random} to state that the robot’s current position follows a uniform distribution over \textit{cell}, unless specified elsewhere; and use the following \textit{pr-atom} (a form of declarative probabilistic rule in P-log) to state that, in probability 0.8, people request deliveries to their own rooms.

\begin{verbatim}
pr(curr_room(P)=R | place(P,R)=true)=8/10.
\end{verbatim}

\textbf{b) Representing Action Knowledge:} We use a set of random variables in P-log to specify the set of delivery actions available to the robot. For instance, \textit{serve(coffee,lab,alice)} indicates that the current service request is to deliver \textit{coffee} to \textit{lab} for \textit{alice}.

\textit{serve(I,R,P) :- act_item=I, act_room=lab, act_person=P.}

where predicates with prefix \textit{act.} are random variables for modeling actions.

To model probabilistic transitions, we need to look one step forward, modeling how actions lead state transitions. We introduce two identical state spaces using predicates \textit{curr-cell} and \textit{curr-cell}.
and next_s. The following shows the specification of the current state using curr_s.

\[
curr_s(I,R,P) := curr_{item}(P) = I, curr_{room}(P) = R, curr_{person} = P, curr_{cell} = C, curr_{success} = S.\]

Given the current and next state spaces, we can use pr-atoms to specify the transition probabilities led by delivery actions. For instance, to model physical movements, we introduce random variable act_move:move and sort move=[up, down, left, right]. Then we can use act_move=right to indicate the robot attempting to move rightward by one cell, and use the following pr-atom

\[
pr(\text{next} \_\text{cell} = C | \text{curr} \_\text{cell} = C, \text{leftof} (C, C1), \text{act} \_\text{move} = \text{right}) = 8/10.\]

to state that, after taking action right, the probability of the robot successfully navigating to the cell on the right is 0.8 (otherwise, it ends up with one of the nearby cells). Such probabilities are learned through model-based RL.

It should be noted that, even if a request is correctly identified in dialog, the robot still cannot always succeed in delivery, because there are obstacles that can probabilistically trap the robot in navigation. When the request is misidentified, delivery success rate drops, because the robot has to conduct multiple navigation tasks to figure out the correct request and redo the delivery. We use \( s \odot a \) and \( s \odot \overline{a} \) to represent delivery action \( a \) matches to request component of \( s \) or not (i.e., service request is correctly identified in dialog or not).

c) Constructing (PO)MDP Controllers: To fulfill a delivery request, the robot needs spoken dialog to identify the request under unreliable speech recognition, and navigation controllers for physically making the delivery.

The service request is not directly observable to the robot, and has to be estimated by asking questions, such as “What item do you want?” and “Is this delivery for Alice?” Once the robot is confident about the request, it takes a delivery action (i.e., serve\( (I,R,P) \)). We follow a standard way to use partially observable MDPs (POMDPs) [12] to build our dialog manager, as reviewed in [25]. The state set \( S \) is specified using \( \text{curr} \_s \). The action set \( A \) is specified using serve and question-asking actions. Question-asking actions do not change the current state, and delivery actions lead to one of the terminal states (success or failure).

After the robot becomes confident about the request via dialog, it will take a delivery action serve\( (I,R,P) \). This delivery action is then implemented with a sequence of act_move actions. When the request identification is incorrect, the robot needs to come back to the shop, figure out the correct request, and redeliver, where we assume the robot will correctly identify the request in the second dialog. We use an MDP to model this robot navigation task, where the states and actions are specified using sorts cell and move. We use pr-atoms to define the unreliable movements. Figure 2 shows the probabilistic transitions in delivery tasks.

d) Knowledge from Model-based RL: We use R-Max [5], a model-based RL algorithm, to help our robot learn the success rate of navigation actions in different positions. The agent first initializes an MDP, from which it uses R-Max to learn the partial world model (of navigation tasks). There is a fixed small cost for each navigation action. The robot receives a big bonus if it successfully achieves the goal \( R_{\text{max}} \), whereas it receives a big penalty otherwise \( (\neg R_{\text{max}}) \). A transition probability in navigation, \( T^N(s,a,s') \), is not computed until there are a minimum number \( M \) of transition samples visiting \( s' \). We recompute the action policy after \( E \) action steps.

The update of knowledge base is achieved through updating the success rate of delivery actions serve\( (I,R,P) \) (in dialog task) using the success rate of navigation actions act_move\( =M \) in different positions (in navigation task).

\[
T^D(s',a^d,s') = \begin{cases} P^N(s'p,s'^d), & \text{if } s' \odot a^d \\ P^N(s'p,s'^m) \times P^N(s^m,s'^p) \times P^N(s'^p,s'^d), & \text{if } s' \odot \overline{a}^d \end{cases} \tag{1}
\]

where \( T^D(s',a^d,s') \) is the probability of fulfilling request \( s' \) using delivery action \( a^d \); \( s' \) is the “success” terminal state; \( s'^p, s'^m \) and \( s'^d \) are states of the robot being in the shop, a misidentified goal position, and real goal position respectively; and \( P^N(s,s') \) is the probability of the robot successfully navigating from \( s \) to \( s' \) positions. In practice, \( P^N(s,s') \) is approximated by running a number of navigation tasks in simulation using the learned partial world model, while following an action policy computed using value iteration.

When \( s' \) and \( a^d \) are aligned in all three dimensions (i.e., \( s' \odot a^d \)), the robot needs to navigate once from the shop \( (s'^p) \) to the requested navigation goal \( (s'^d) \). \( P^N(s'^p,s'^d) \) is the probability of the corresponding navigation task. When the request and delivery action are not aligned in at least one dimension (i.e., \( s' \odot \overline{a}^d \)), the robot has to navigate back to the shop to figure out the correct request, and then redeliver, resulting in three navigation tasks.

IV. EXPERIMENTS

In this section, the goal is to evaluate our hypothesis that our KRR-RL framework enables a robot to learn from model-
based RL, reason with both the learned knowledge and human knowledge, and dynamically construct task-oriented controllers. Specifically, our robot learns from navigation tasks, and applied the learned knowledge (through KRR) to navigation, dialog, and delivery tasks. We also evaluated whether the learned knowledge can be represented and applied to tasks under different world settings. In addition to simulation experiments, we have used a real robot to demonstrate how our robot learns from navigation to perform better in dialog. Figure 3 shows the map of the working environment (generated using a real robot) used in both simulation and real-robot experiments. Human walkers in the blocking areas (“BA”) can probabilistically impede the robot, resulting in different success rates in navigation tasks.

a) Learn from and applied to navigation tasks: Focusing on navigation tasks, in this experiment, the robot learns in the shop-room1 navigation task, and extracts the learned partial world model to the shop-room2 task. It should be noted that navigation from shop to room2 requires traveling in areas that are unnecessary in the shop-room1 task. The results are shown in Figure 4, where each data point corresponds to an average of 1000 trials. Each episode allows at most 200 (300) steps in small (large) domain. The curves are smoothed using a window of 10 episodes. The results suggest that with knowledge extraction (the dashed line) the robot learns faster than without extraction, and this performance improvement is more significant in a larger domain (the Right subfigure).

b) Learn from navigation and applied to delivery: Robot delivering objects requires both tasks: dialog management for specifying service request (under unreliable speech recognition) and navigation for physically delivering objects (under unforeseen obstacles). Our office domain includes five rooms, two persons, and three items, resulting in 30 possible service requests. In the dialog manager, the reward function gives delivery actions

- a big bonus (80) given a request being fulfilled, and
- a big penalty (-80) otherwise.

General questions and confirming questions cost 2.0 and 1.5 respectively. In case a dialog does not end after 20 turns, the robot is forced to work on the most likely delivery.

Data II reports the robot’s overall performance in fulfilling delivery requests, which requires the robot accurately identifying the request in dialog and then safely delivering the item in navigation. We conduct 10,000 simulation trials under each blocking rate. Without learning from RL, the robot uses an outdated world model that was learned under \( br = 0.3 \). With learning, the robot updates its world model in domains with different blocking rates. We can see, when learning is enabled, our KRR-RL framework produces higher overall reward, higher request fulfillment rate, and lower question-asking cost. The improvement is statistically significant, e.g., the \( p \)-values are 0.028, 0.035, and 0.049 for overall reward, when \( br = 0.1 \), 0.5, and 0.7 respectively (100 randomly selected trials with/without extraction).

To better analyze robot dialog behaviors, we generate cumulative distribution function (CDF) plots showing the percentage of dialog completions (y-axis) given different QA costs (x-axis). Figure 5 shows the results when the request are deliveries to room2 (left) and room4 (right). Comparing the two curves in each subfigure, we find our KRR-RL framework reduces the QA cost in dialogs (consistent to Table II). Comparing the two subfigures, we find a smaller QA cost is needed, when the request is a delivery to room4 (c.f., room2). This observation makes sense, because room4 is closer to the shop (see Figure 3) and deliveries to room4 is easier.

In the last experiment, we quantify the information collected in dialog in terms of entropy reduction. The hypothesis is that, using our KRR-RL framework, the dialog manager wants to collect more information before physically working on more challenging tasks. In each trial, we randomly generate a belief distribution over all possible service requests,
evaluate the entropy of this belief, and record the suggested action given this belief. We then statistically analyze the entropy values of beliefs, under which delivery actions are suggested.

Table II shows that, when $br$ grows from 0.1 to 0.7, the means of belief entropy decreases (i.e., belief is more converged). This suggests that the robot collected more information in dialog in environments that are more challenging for navigation, which is consistent with Table I (Right). Comparing the three columns of results, we find the robot collects the most information before it delivers to room5. This is because such delivery tasks are the most difficult due to the location of room5. The results support our hypothesis that learning from navigation tasks enables the robot to adjust its information gathering strategy in dialog given tasks of different difficulties.

c) Generate controllers for new circumstances: The knowledge learned through model-based RL is contributed to a knowledge base that can be used for many tasks. So our KRR-RL framework enables a robot to dynamically generate partial world models for tasks under settings that were never experienced. For example, an agent does not know the current time is morning or noon, there are two possible values for variable “time”. Consider that our agent has learned world dynamics under the times of morning and noon. Our KRR-RL framework enables the robot to reason about the two transition systems under the two settings and generate a new transition system for this “morning-or-noon” setting. Without our framework, an agent would have to randomly select one between the “morning” and “noon” policies.

To evaluate our policies dynamically constructed via KRR, we let an agent learn three controllers under three different environment settings – the navigation actions have decreasing success rates under the settings. In this experiment, the robot does not know which setting it is in (out of two that are randomly selected). The baseline agent does not have the KRR capability of merging knowledge learned from different settings, and can only randomly select a policy from the two (each corresponding to a setting). Experimental results show that the baseline agent received an average of 26.8% in success rate in navigation tasks. In comparison, our KRR-RL agent achieved 83.8% success rate on average. Thus, our KRR-RL framework enables a robot to effectively apply the learned knowledge to tasks under new settings.

d) An Illustrative Trial on a Robot: We have implemented our KRR-RL framework on a mobile robot in an office environment, the robot is shown in Figure 3 (Right). Figure 6 shows the belief changes (in the dimensions of item, person, and room) as the robot interacts with a human user. The robot started with a uniform distribution in all three categories. It should be noted that, although the marginal distributions are uniform, the joint belief distribution is not, as the robot has prior knowledge such as Bob’s office is office2 and people prefer deliveries to their own offices.

After hearing “a coke for Bob to office2”, the three sub-beliefs are updated (turn1). Since the robot is aware of its unreliable speech recognition, it asked about the item, “Which item is it?” After hearing “a coke”, the belief is updated (turn2), and the robot further confirmed on the item by asking “Should I deliver a coke?” It received a positive response (turn3), and decided to move on to ask about the delivery room: “Should I deliver to office 2?” The robot did not confirm the delivery room, because it learned through model-based RL that navigating to office2 is relatively easy and it decided that it is more worth risking an error and having to replan than it is to ask the person another question. The robot became confident in three dimensions of the service request (item <coke,Bob,office2> in turn4) without asking about person, because of the prior knowledge (encoded in P-log) about Bob’s office.

V. Conclusions and Future Work

In this work, we develop a KRR-RL framework that, for the first time, integrates computational paradigms of logical-probabilistic knowledge representation and reasoning (KRR), and model-based reinforcement learning (RL). Our KRR-RL agent learns world dynamics (in the form of transition probabilities) via model-based RL, and then incorporates the learned dynamics into the logical-probabilistic reasoning module, which is used for dynamic construction of efficient run-time task-specific planning models. Experiments were conducted using a mobile robot (simulated and physical) working on delivery tasks that involve both navigation and dialog. Results suggested that the learned knowledge from RL can be represented and used for reasoning by the KRR component, enabling the robot to dynamically generate task-oriented action policies.

The integration of a KRR paradigm and model-based RL paves the way for at least the following research directions. We plan to study how to sequence source tasks to help the robot perform the best in the target task (i.e., a curriculum learning problem [16]). Balancing the efficiencies between service task completion and RL is another topic for further study – currently the robot optimizes for task completions (without considering the potential knowledge learned in this process) once a task becomes available.

| Entropy (room1) | Entropy (room2) | Entropy (room5) |
|-----------------|-----------------|-----------------|
| Mean (std)      | Max             | Mean (std)      | Max             | Mean (std)      | Max             |
| $br = 0.1$      | .274 (.090)     | .419            | .221 (.075)     | .334            | .177 (.063)     | .269            |
| $br = 0.5$      | .154 (.056)     | .233            | .111 (.044)     | .176            | .100 (.041)     | .156            |
| $br = 0.7$      | .132 (.050)     | .207            | .104 (.042)     | .166            | .100 (.041)     | .156            |
REFERENCES

[1] Nima Agharbayegi, David Stracuzzi, and Pat Langley. Relational
temporal difference learning. In *Proceedings of the 23rd international
conference on Machine learning*, pages 49–56. ACM, 2006.

[2] Stephen H. Bach, Matthias Broecheler, Bert Huang, and Lise Getoor.
Hinge-loss markov random fields and probabilistic soft logic. *Journal of
Machine Learning Research*, 18(1):3846–3912, 2017.

[3] Evgenii Balai and Michael Gelfond. Refining and generalizing p-log:
Preliminary report. In *Proceedings of the 10th Workshop on Answer
Set Programming and Other Computing Paradigms*, 2017.

[4] Chitta Baral, Michael Gelfond, and Nelson Rushion. Probabilistic rea-
soning with answer sets. *Theory and Practice of Logic Programming*,
9(1):57–144, 2009.

[5] Ronen I Brafman and Moshe Tennenholtz. R-max—a general poly-
nomial time algorithm for near-optimal reinforcement learning. *Journal of
Machine Learning Research*, 3(Oct):213–231, 2002.

[6] Thomas J Chermack. Improving decision-making with scenario
planning. *Futures*, 36(3):295–309, 2004.

[7] Rohan Chitnis, Leslie Pack Kaelbling, and Tomás Lozano-Pérez.
Integrating human-provided information into belief state representation
using dynamic factorization. *arXiv preprint arXiv:1803.01119*, 2018.

[8] Saô Džeroski, Luc De Raedt, and Kurt Driessens. Relational
reinforcement learning. *Machine learning*, 43(1-2):7–52, 2001.

[9] Leonardo A Ferreira, Reinaldo AC Bianchi, Paulo E Santos, and
Ramon Lopez de Mantaras. Answer set programming for non-
stationary markov decision processes. *Applied Intelligence*, 47(4):993–
1007, 2017.

[10] Marc Hanheide, Moritz Göbelbecker, Graham S Horn, Andrzej Prono-
bis, Kristoffer Sjöblom, Patric Jensfelt, Charles Gretton, Richard
Dearden, Miroslav Janicek, et al. Robot task planning and explanation in open
and uncertain worlds. *Artificial Intelligence*, 247:119–150, 2017.

[11] Yuqian Jiang, Shiqi Zhang, Piuysh Khandelwal, and Peter Stone.
An empirical comparison of pddl-based and asp-based task planners.
*arXiv preprint arXiv:1804.08229*, 2018.

[12] Leslie Pack Kaelbling, Michael L Littman, and Anthony R Cassan-
dra. Planning and acting in partially observable stochastic domains.
*Artificial Intelligence*, 101(1):99–134, 1998.

[13] Piuysh Khandelwal, Shiqi Zhang, Jivko Sinapov, Matteo Leonetti,
Jesse Thomason, Fangkai Yang, Ilaria Gori, Maxwell Svetlik, Priyanka
Khante, Vladimir Lifshitz, J. K. Aggarwal, Raymond Mooney, and
Peter Stone. Bbwots: A platform for bridging the gap between ai
and humanrobot interaction research. *The International Journal of
Robotics Research*, 36(5-7):635–659, 2017.

[14] Matteo Leonetti, Luca Iocchi, and Peter Stone. A synthesis of
automated planning and reinforcement learning for efficient, robust
decision-making. *Artificial Intelligence*, 241:103–130, 2016.

[15] Drew McDermott, Malik Ghallab, Adele Howe, Craig Knoblock,
Ashwin Ram, Manuela Veloso, Daniel Weld, and David Wilkins. Pddl-
lite: A planning domain definition language. 1998.

[16] Samnit Narvekar, Jivko Sinapov, and Peter Stone. Autonomous
task sequencing for customized curriculum design in reinforcement
learning. In *Proceedings of the 26th International Joint Conference on
Artificial Intelligence (IJCAI)*, volume 147, page 149, 2017.

[17] Jean H Oh, Arne Suppé, Felix Duvallet, Abdesslam Boularias, Luis E
Navarro-Serment, Martial Hebert, Anthony Stentz, Jerry Vinokurov,
Oscar J Romero, Christian Leibiere, et al. Toward mobile robots
reasoning like humans. In *AAAI*, pages 1371–1379, 2015.

[18] Martin L Puterman. *Markov decision processes: discrete stochastic
dynamic programming*. John Wiley & Sons, 1994.

[19] Matthew Richardson and Pedro Domingos. Markov logic networks.
*Machine learning*, 62(1):107–136, 2006.

[20] Mohan Sridharan, Michael Gelfond, Shiqi Zhang, and Jeremy Wyatt.
A refinement-based architecture for knowledge representation and
reasoning in robotics. *arXiv preprint arXiv:1508.03891*, 2015.

[21] Mohan Sridharan, Ben Meadows, and Rocío Gomez. What can i
not do? towards an architecture for reasoning about and learning
affordances. In *International Conference on Automated Planning and
Scheduling (ICAPS)*, Pittsburgh, USA, pages 18–23, 2017.

[22] Richard S Sutton and Andrew G Barto. *Reinforcement learning: An
introduction*. MIT press Cambridge, 1998.

[23] Moritz Tenorth and Michael Beetz. Knowrob: A knowledge processing
infrastructure for cognition-enabled robots. *The International Journal of
Robotics Research*, 32(5):566–590, 2013.

[24] Fangkai Yang, Daoming Lyu, Bo Liu, and Steven Gustafson. Peorf:
Integrating symbolic planning and hierarchical reinforcement learning for
robust decision-making. *arXiv preprint arXiv:1804.07779*, 2018.

[25] Steve Young, Milica Gai, Blaise Thomson, and Jason D. Williams.
Pomdp-based statistical spoken dialog systems: A review. *Proceedings of
the IEEE*, 101(5):1160–1179, 2013.

[26] Vinicius Zambaldi, David Raposo, Adam Santoro, Victor Bapst, Yuja
Li, Igor Babuschkin, Karl Tuyls, David Reichert, Timothy Lillicrap,
Edward Lockhart, et al. Relational deep reinforcement learning. *arXiv
preprint arXiv:1806.01830*, 2018.

[27] Shiqi Zhang, Piuysh Khandelwal, and Peter Stone. Dynamically
constructed (PO)MDPs for adaptive robot planning. In *Proceedings of
the Thirty-First AAAI Conference on Artificial Intelligence*, pages
3855–3863, 2017.

[28] Shiqi Zhang and Peter Stone. corpp: Commonsense reasoning and
probabilistic planning, as applied to dialog with a mobile robot. In *Twenty-Ninth AAAI Conference on Artificial Intelligence*, 2015.