Dynamic probabilistic logic models for effective task-specific abstractions in RL

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Harsha Kokel

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Nikhilesh Prabhakar
Sriraam Natarajan
Arjun Manoharan
Balaraman Ravindran
Erik Blasch
Prasad Tadepalli

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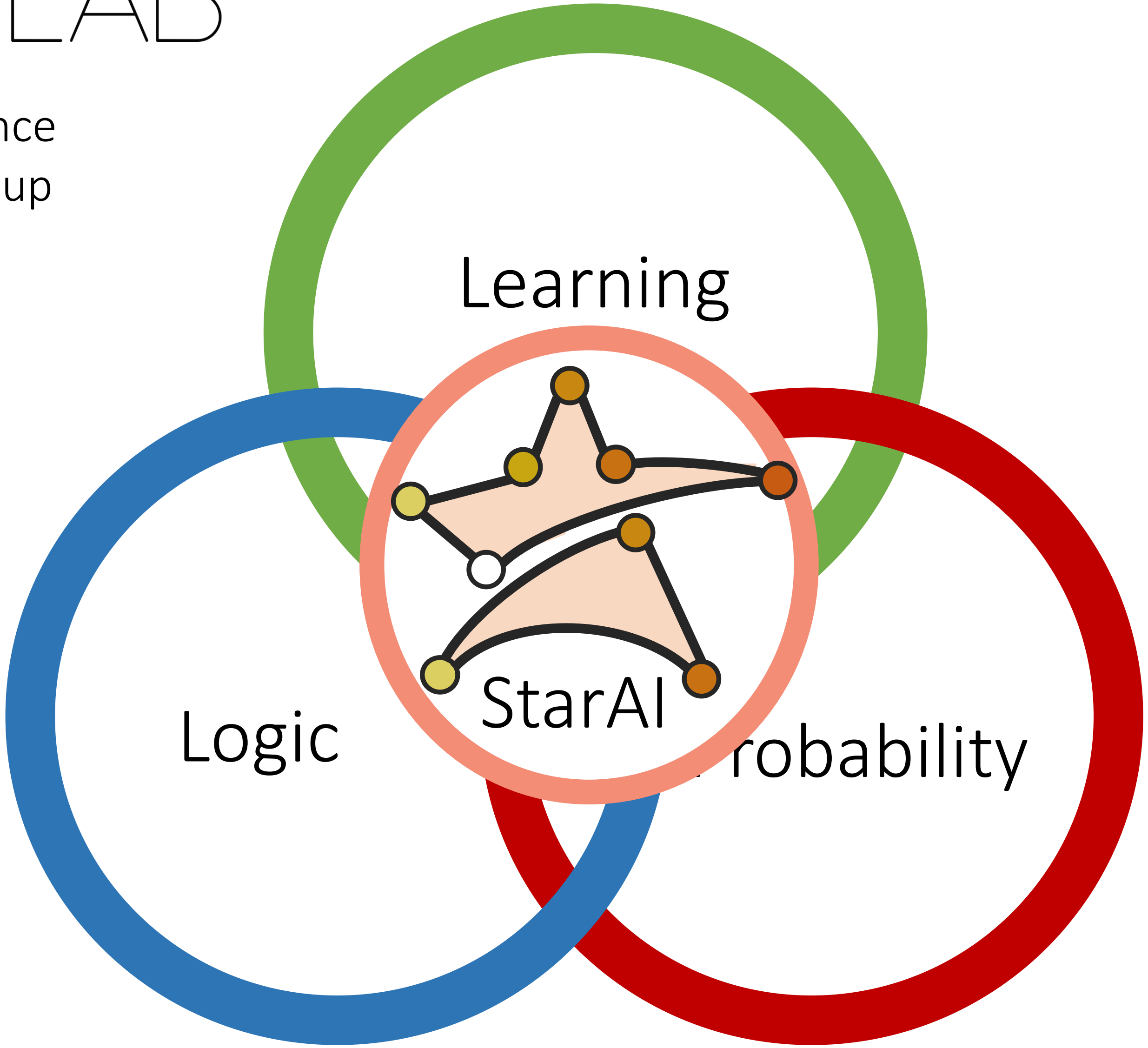
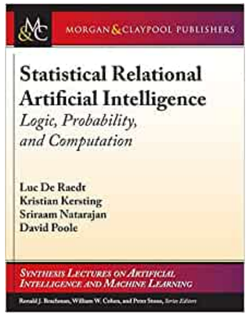
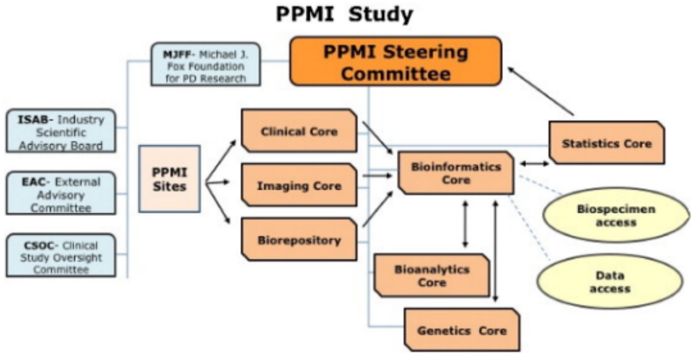
Statistical Artificial Intelligence
and Relational Learning Group



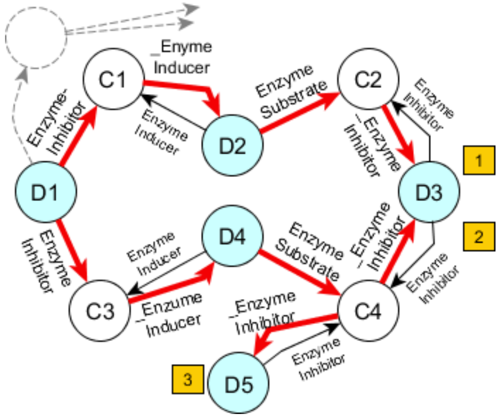


Raedt et al. 2016; Raedt et al. 2020

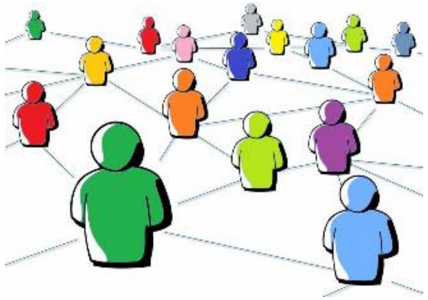
StARLinG LAB



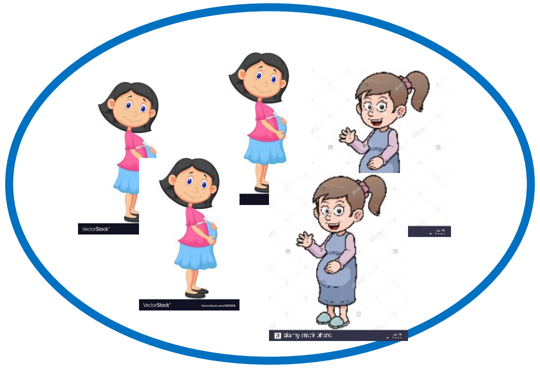
Parkinson's disease prediction



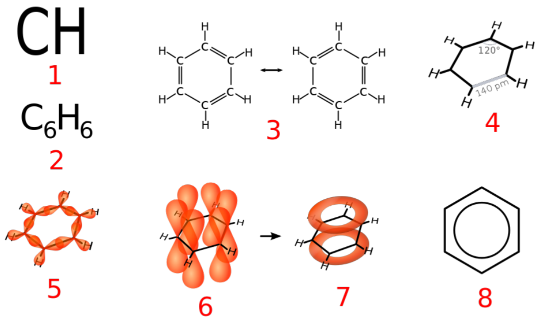
Drug-Drug Interactions



Social Networks



Cohort of Pregnant Women (nuMoM2b)

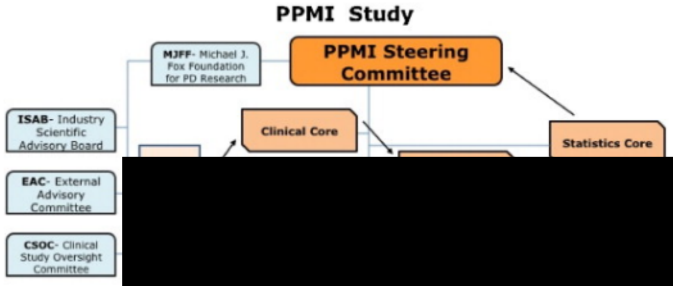


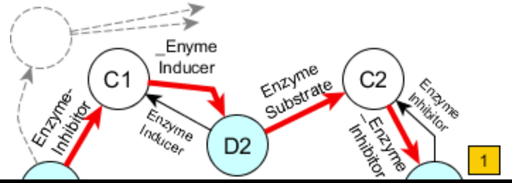
Chemical Entities of Biological Interest (ChEBI)

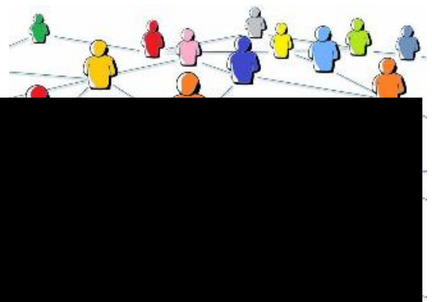
Collaborative Problem Solving

Dhami et al. 2017; Dhami et al. 2022; Karanam et al. 2022; Mathur et al. 2023; Dhami et al. 2017; Das et al. 2022; Ramanan et al. 2021; Kaur et al. 2020; Kokel et al. 2021

StARLinG LAB

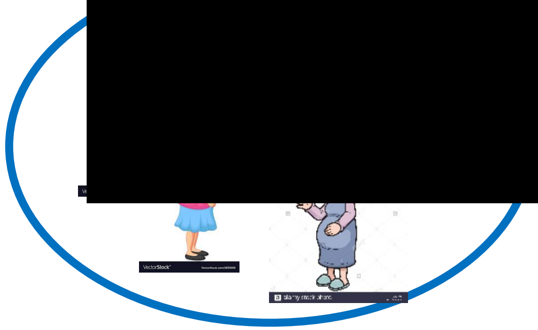




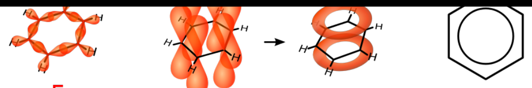


Park

Relational and Human-Allied



Cohort of Pregnant Women (nuMoM2b)



Chemical Entities of Biological Interest (ChEBI)

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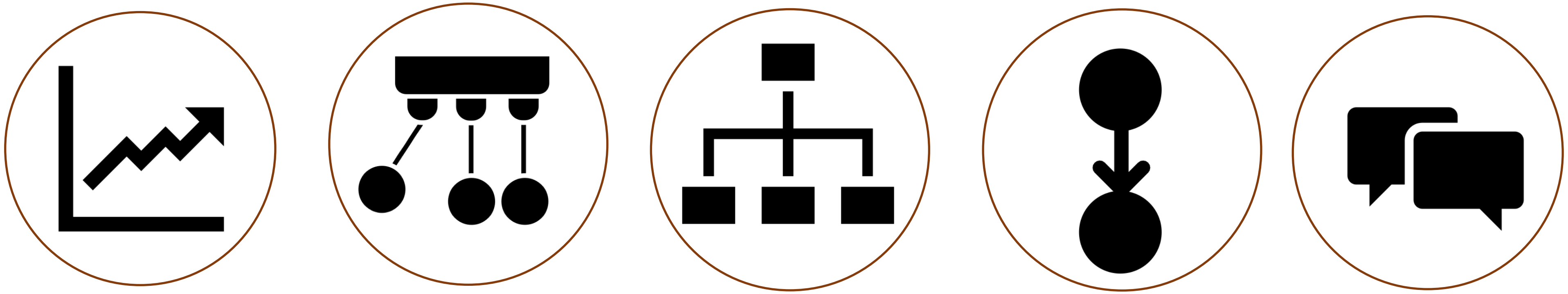
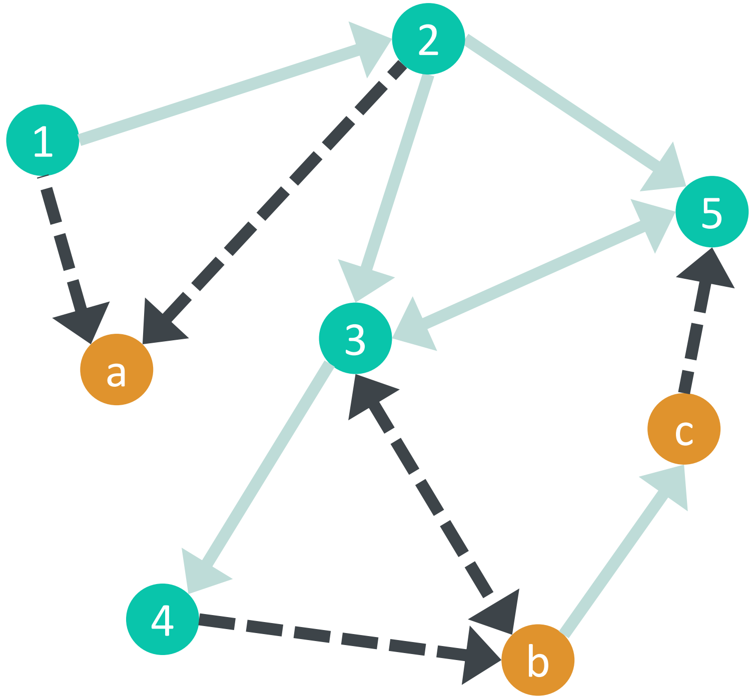
How to facilitate generalizable, effective and efficient learning with human guidance?

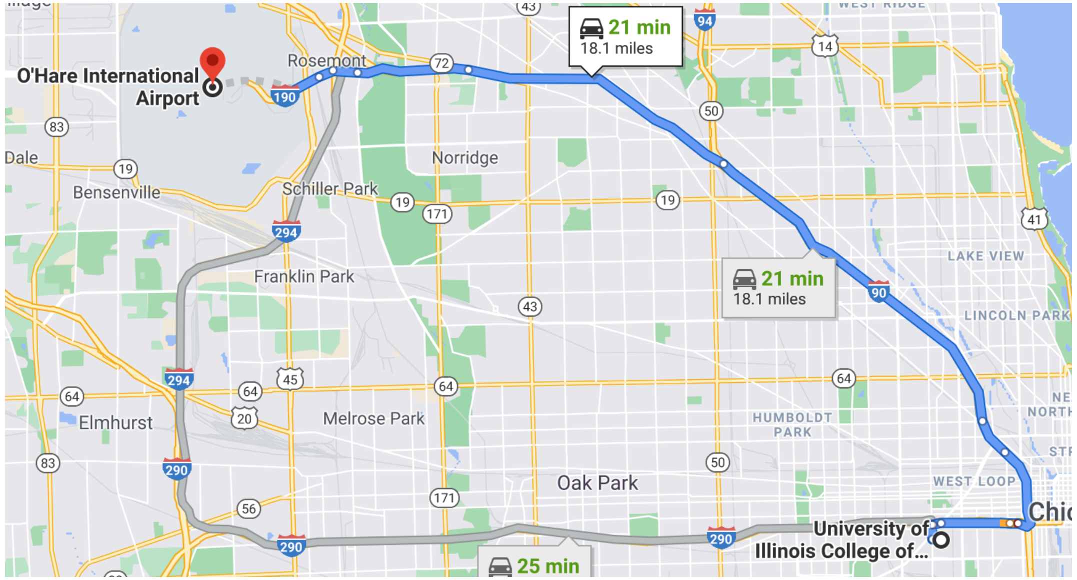


Relational domains

Non-IID domains with varying # objects and heterogeneous relations.



Abstract Representations



Planning

Execution

Konidaris, G., 2019; Li et al 2006

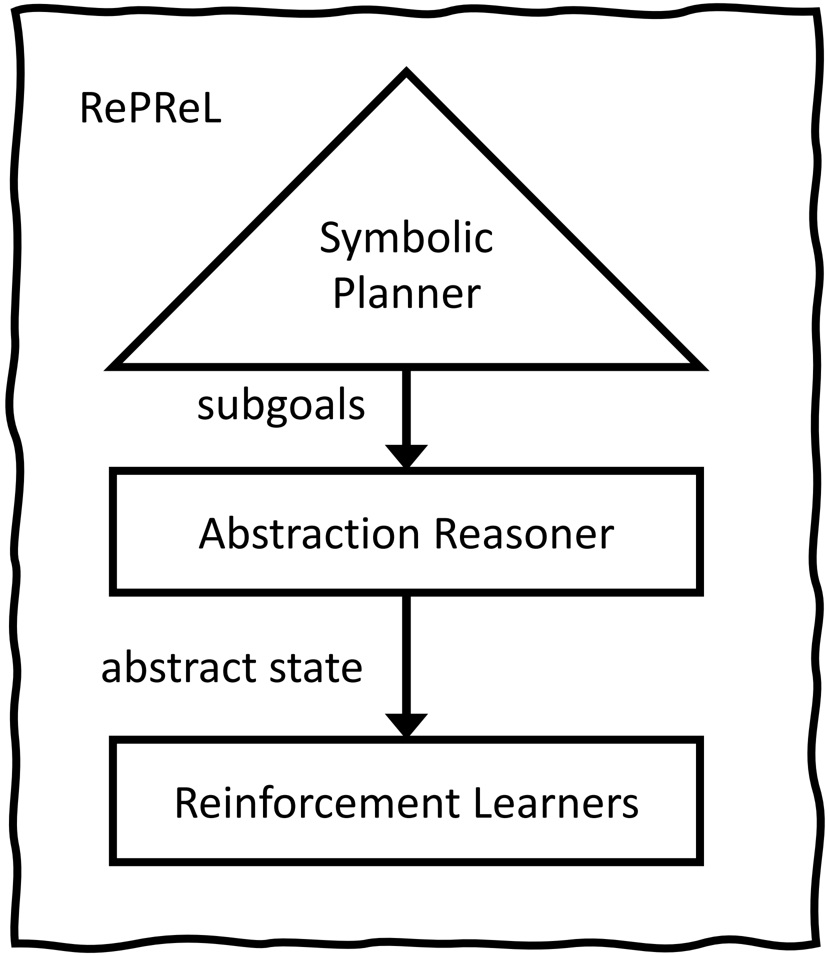
Given: Relational sequential decision-making domain

To do: Learn an efficient agent that

- is compositional
- can handle varying # of objects
- can generalize to different tasks
- can support task-specific representations
- can handle multi-modal data

RePReL

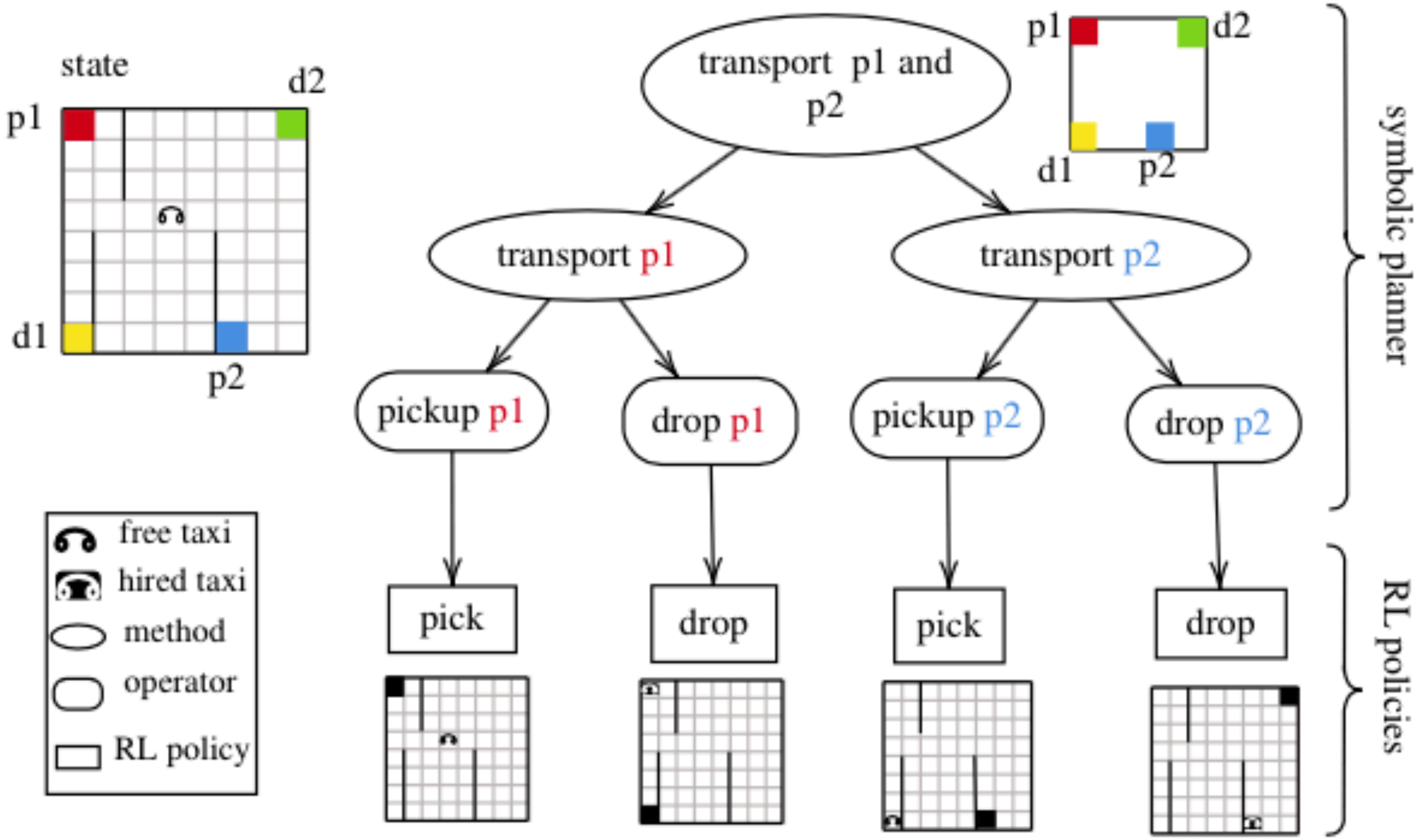
- Plan the sequence of high level subgoals and learn to execute each subgoal at lower level



Grounds and Kudenko 2008; Yang et al. 2018; Jiang et al. 2019; Eppe et al. 2019; Illanes et al. 2020; Lee et al. 2020; Mitchener et al. 2022; Lyu et al. 2019; Goel et al. 2022; Planning and RL workshop

RePReL

Goal directed relational MDP:
<S, A, P, R, γ, **G**>



Dietterich 1999

RePReL

Definition 3. *The subgoal RMDP M_o for each operator o is defined by the tuple $\langle S, A, P_o, R_o, \gamma \rangle$ consisting of states S, actions A, transition function P_o, reward function R_o, and discount factor γ. State and Actions remain same as the original RMDP. The reward function R_o and transition probability distribution function P_o are defined as follows:*

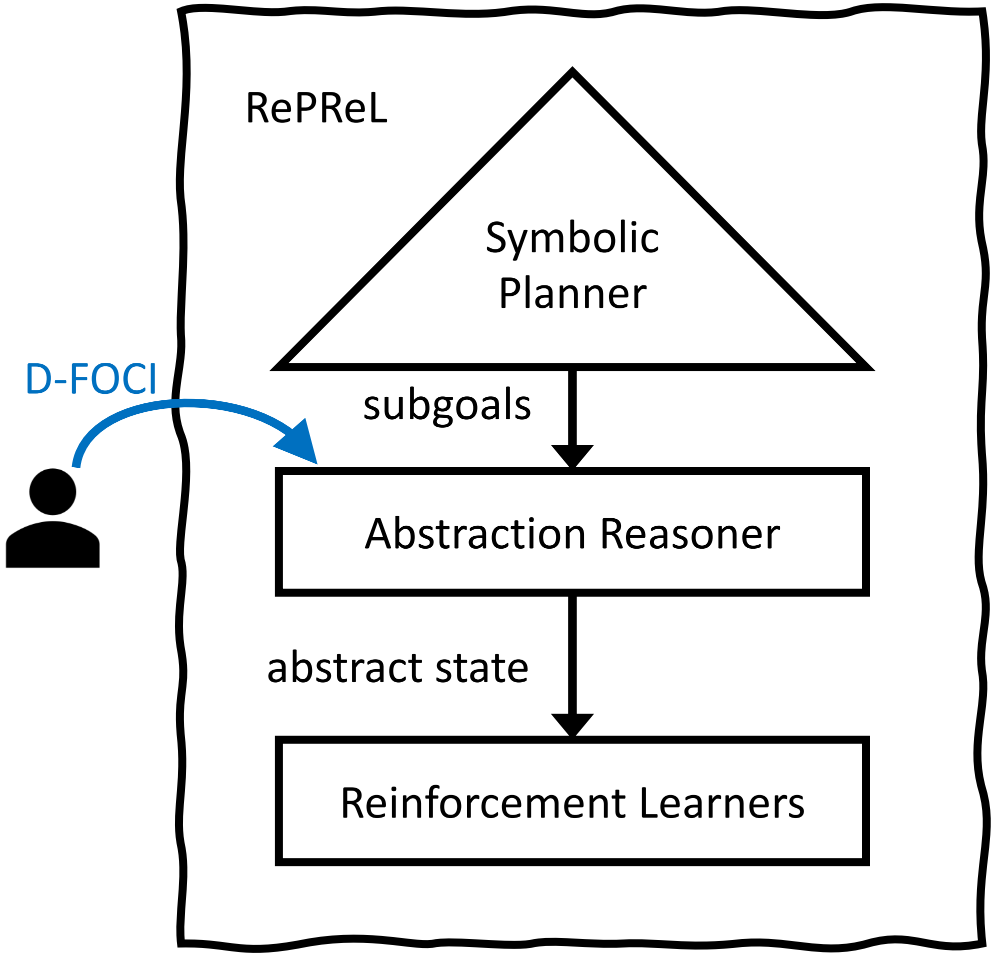
$$R_o(s,a,s') = \begin{cases} t_R + R(s,a,s') & \textit{if } s' \in \beta(o) \textit{ and } s \notin \beta(o) \\ 0 & \textit{if } s' \in \beta(o) \textit{ and } s \in \beta(o) \\ R(s,a,s') & \textit{otherwise} \end{cases}$$

$$P_o(s,a,s') = \begin{cases} 0 & \textit{if } s \in \beta(o) \textit{ and } s' \notin \beta(o) \\ 1 & \textit{if } s \in \beta(o) \textit{ and } s' \in \beta(o) \\ P(s,a,s') & \textit{otherwise} \end{cases}$$

with $R(s,a,s')$ indicating the reward function from the original GRMDP definition. t_R is a fixed terminal reward.

RePReL

- Plan the sequence of high level subgoals and learn to execute each subgoal at lower level
- Advantage:
  - Compositionality
  - Task specific state representations
- Dynamic First Order Conditional Influence (D-FOCI) statements to obtain task-specific abstract representations



Kokel et al ICAPS 2021

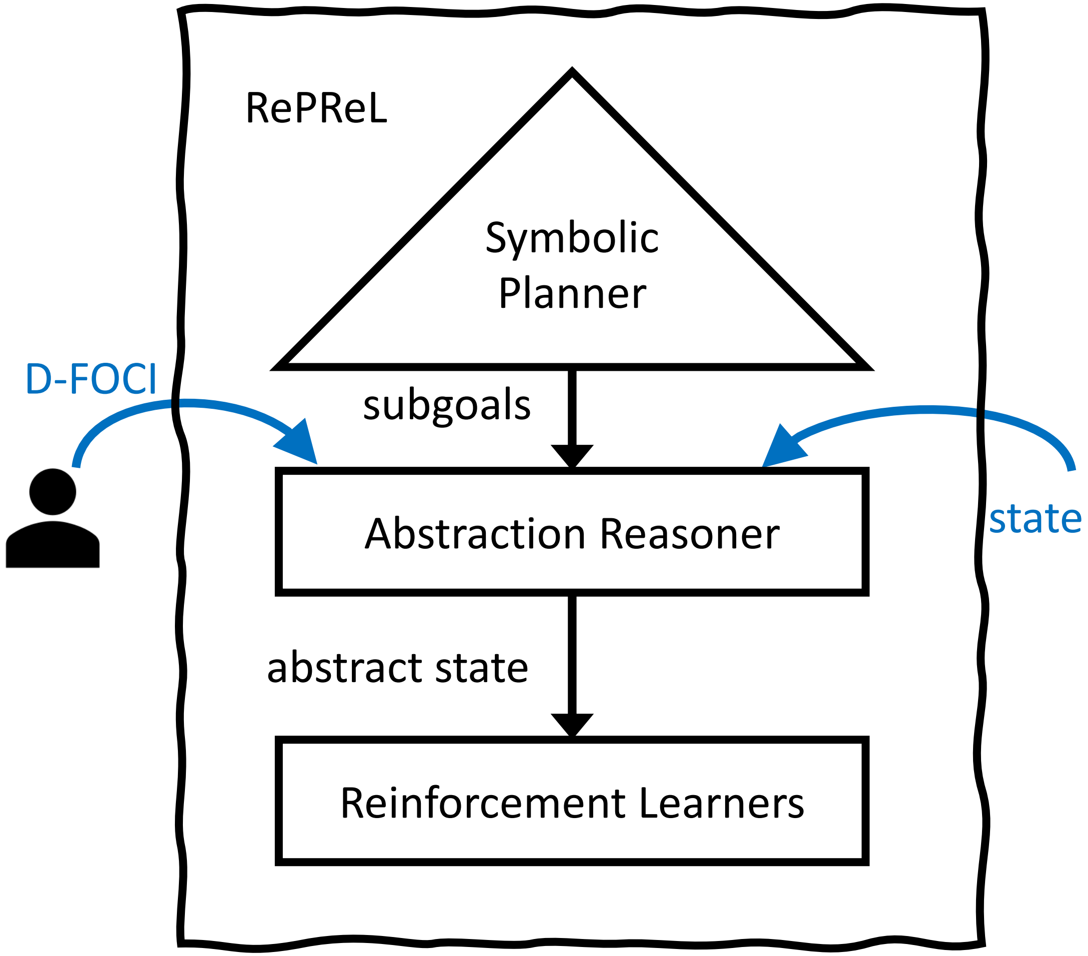
D-FOCI

First Order Conditional Influence (FOCI) statements

$$\text{if } \langle condition \rangle$$
$$\text{then } \langle influent \rangle \text{ QINF } \langle resultant \rangle$$

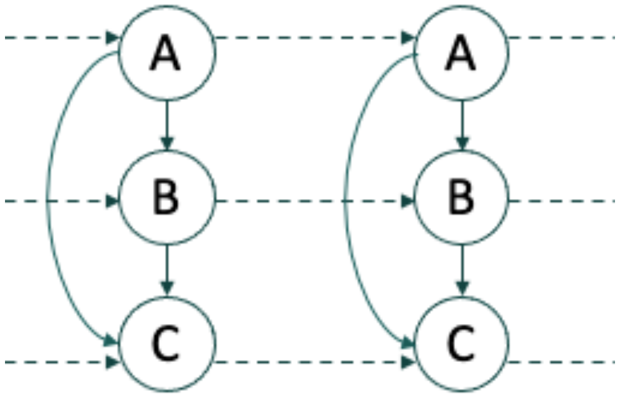
Dynamic FOCI statements

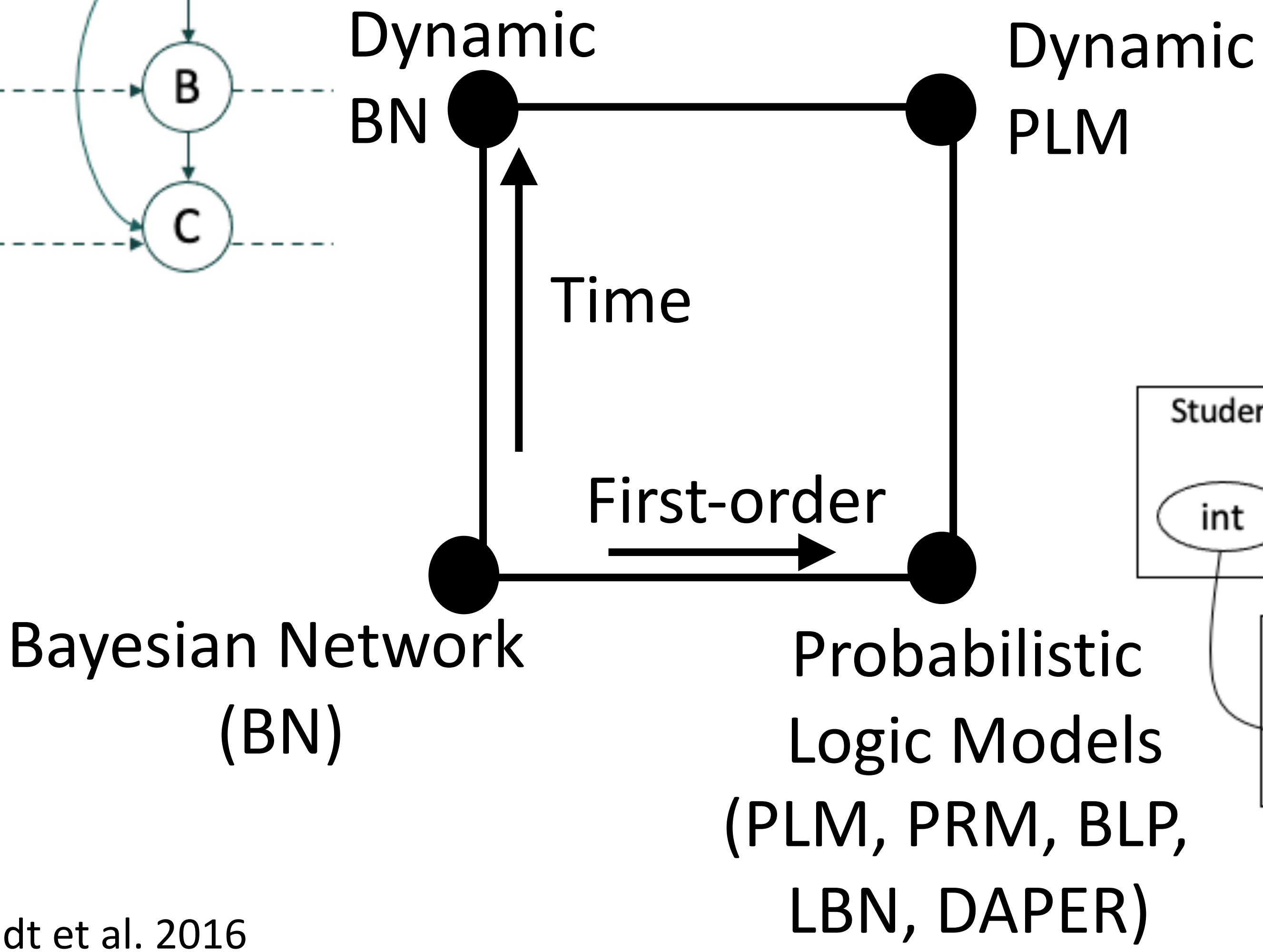
$$[\text{subgoal:}] \;\; \langle influent \rangle \xrightarrow{[+1]} \langle resultant \rangle$$

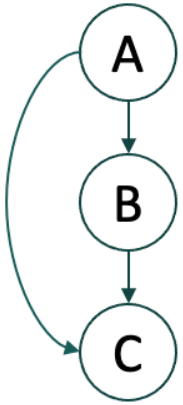


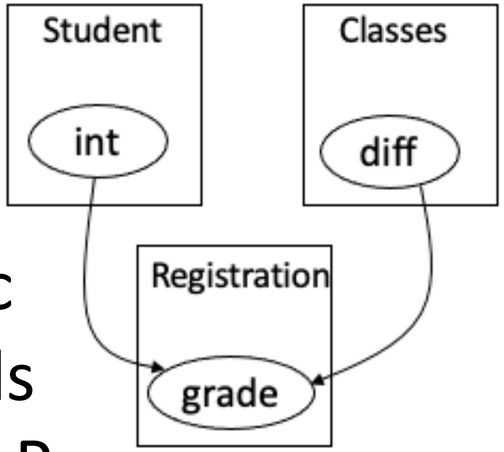
Natarajan, Tadepalli, Dietterich, and Fern 2008

D-FOCI as Dynamic PLMs









Koller and Friedman 2009;
Getoor and tasker 2007; Raedt et al. 2016

D-FOCI example

$$\{\texttt{action}, \texttt{taxi\_at}(X)\} \xrightarrow{+1} \texttt{taxi\_at}(X) \quad (3a)$$

$$\texttt{pick}(P) : \{\texttt{action}, \texttt{taxi\_at}(X), \texttt{at}(P, Y), \texttt{in\_taxi}(P)\} \xrightarrow{+1} \texttt{in\_taxi}(P) \quad (3b)$$

$$\texttt{pick}(P) : \{\texttt{in\_taxi}(P)\} \longrightarrow \mathit{Reward} \quad (3c)$$

$$\texttt{drop}(P) : \{\texttt{at\_dest}(P)\} \longrightarrow \mathit{Reward} \quad (3d)$$

$$\texttt{drop}(P) : \{\texttt{at}(P, X), \texttt{dest}(P, D), \texttt{at\_dest}(P)\} \longrightarrow \texttt{at\_dest}(P) \quad (3e)$$

$$\texttt{drop}(P) : \{\texttt{action}, \texttt{taxi\_at}(X), \texttt{at}(P, Y), \texttt{in\_taxi}(P)\} \xrightarrow{+1} \texttt{at}(P, K) \quad (3f)$$

Abstraction

Given:

a. D-FOCI statements from Equation 3

b. state $s = \{$ at(p1,r), taxi_at(l3), dest(p1,d1), ¬at_dest(p1) ¬in_taxi(p1), at(p2,b), ¬at_dest(p2), ¬in_taxi(p2)$\}$

c. grounded option$o\theta$: pick(P) $\{P/\text{p1}\}$

Output: A set of relevant state literals: $\hat{s}$

Depth 1 unrolling:

1. Find a substitution that grounds relevant D-FOCI statements that have reward on RHS

   pick(p1): in_taxi(p1) $\longrightarrow$ *Reward*

   $\theta = \{\text{P/p1}\}$

2. Collect LHS in relevant literals set $\hat{s}$

   $\hat{s} \leftarrow \{$in_taxi(p1)$\}$

Depth 2 unrolling:

1. Find a substitution that grounds relevant D-FOCI statements that have a relevant literal on RHS

   pick(P): $\{$ action, taxi_at(l3), at(p1, r), in_taxi(p1) $\}$ $\longrightarrow$ in_taxi(p1)

   $\theta = \{\text{P/p1, X/l3, Y/r}\}$

2. Collect LHS in set $\hat{s}$

   $\hat{s} \leftarrow \{$in_taxi(p1), action, taxi_at(l3), at(p1, r)$\}$

Depth 3 unrolling:

1. Ground applicable D-FOCI statements that have a relevant literal ($\hat{s}$) on RHS

   $\{$action, taxi_at(l3) $\}$ $\xrightarrow{+1}$ taxi_at(l3)

   pick(p1): $\{$ action, taxi_at(l3), at(p1, r), in_taxi(p1) $\}$ $\longrightarrow$ in_taxi(p1)

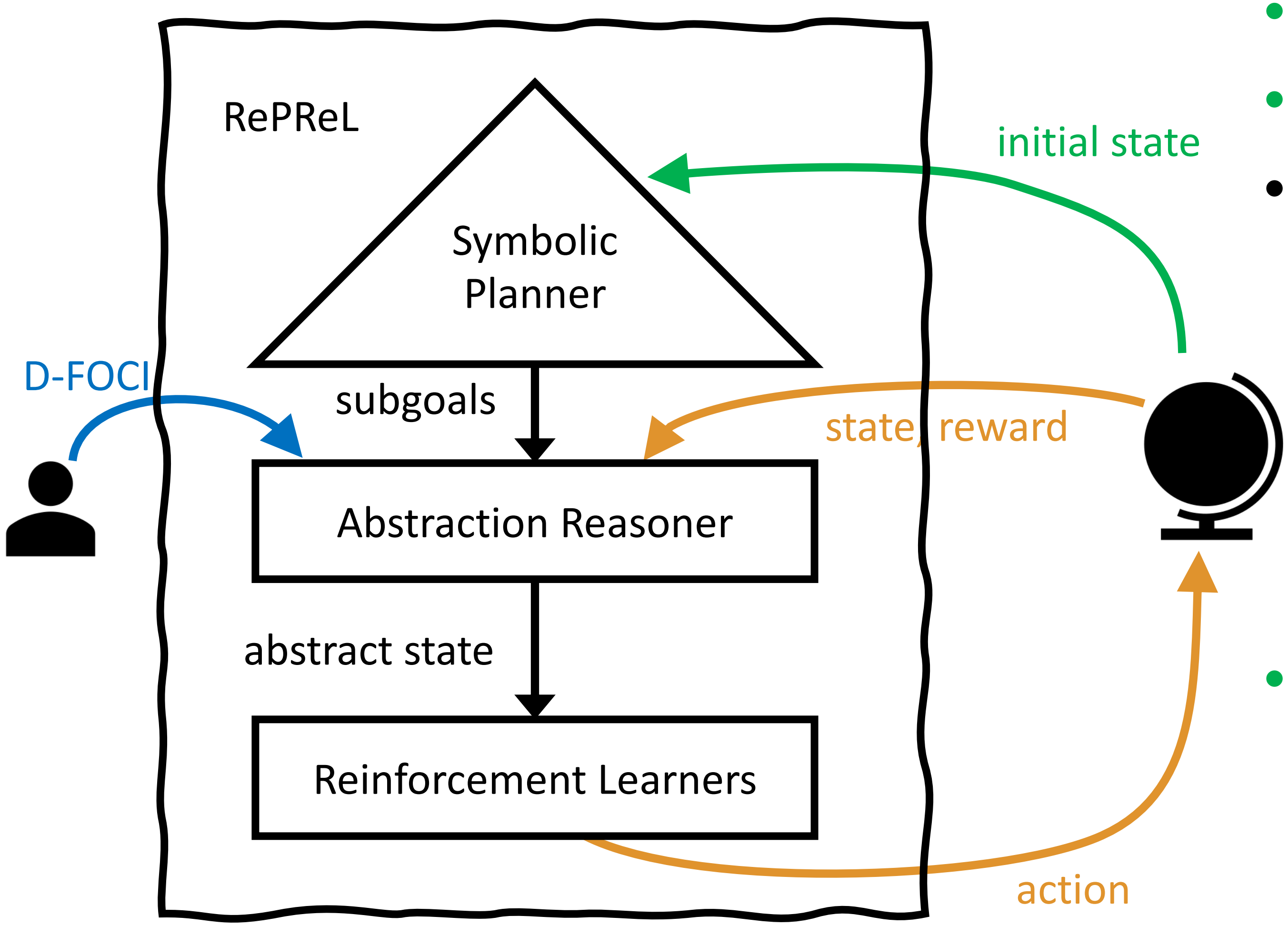
   $\theta = \{\text{P/p1, X/l3, Y/r}\}$

2. Collect LHS in set $\hat{s}$

   $\hat{s} \leftarrow \{$in_taxi(p1), action, taxi_at(l3), at(p1, r)$\}$

recursive grounding and unrolling process

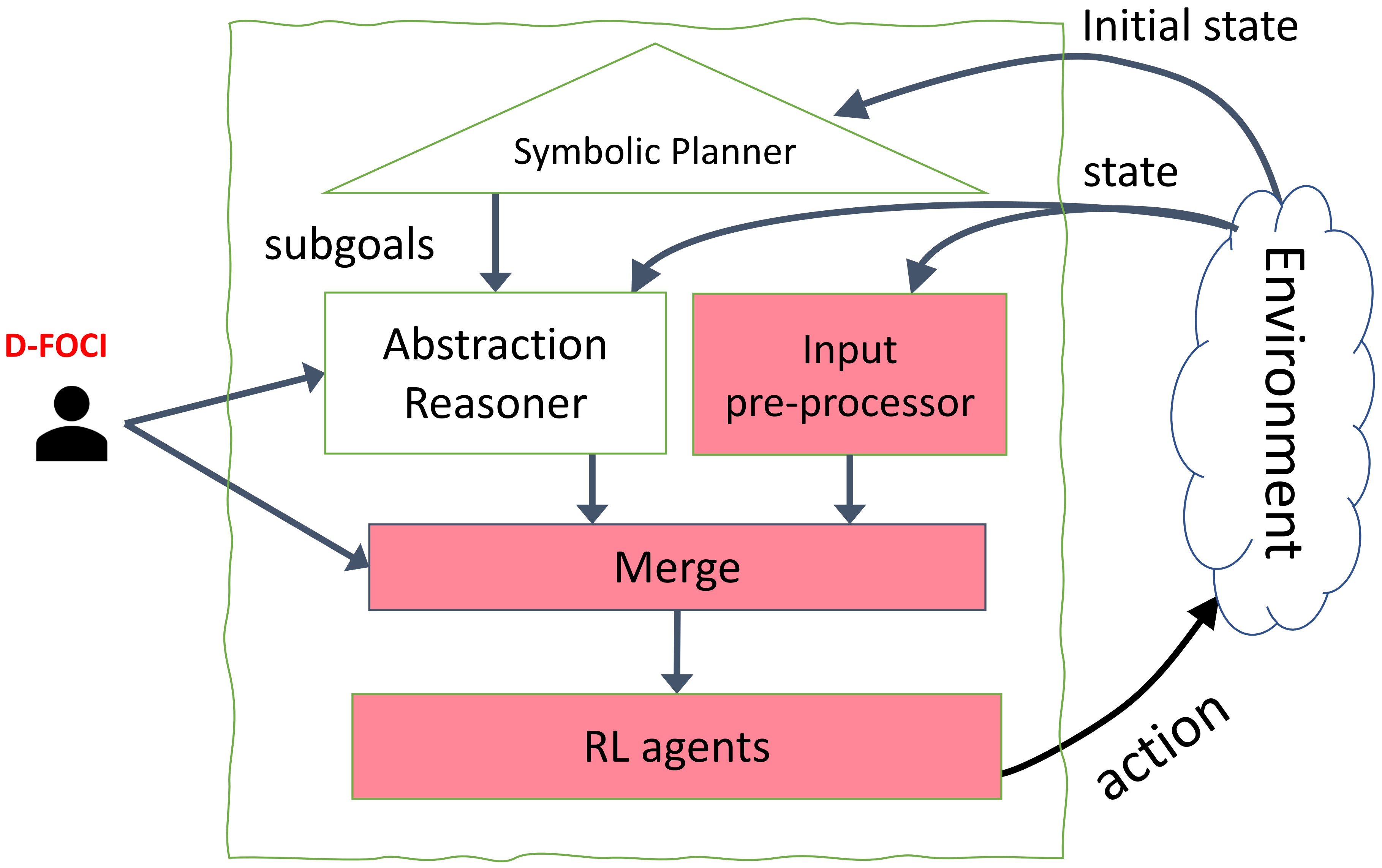
RePReL Learning



- Initialize buffers
- Get high level plan
- For each subgoal
  - Loop till the subgoal is achieved or # steps exceeds
    - Get the abstract state
    - Get the policy for that subgoal
    - Take a step and observe reward, next state
    - Add <S, A, R, S> to the buffer
- Update the subgoal policy using samples from the buffers

Kokel et al. 2021a; Kokel et al. 2021b

Hybrid Deep RePReL



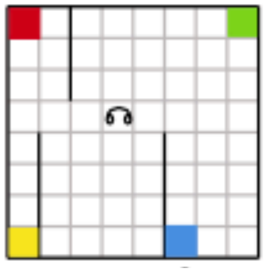
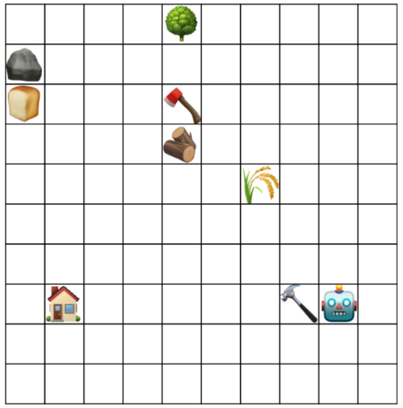
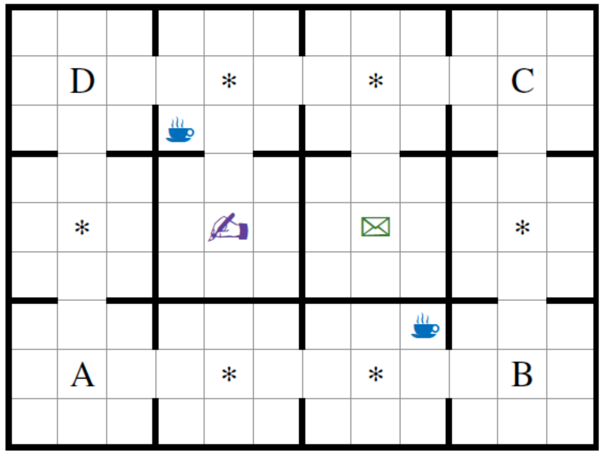
Manhaeve et al. 2018; Kokel et al. 2022

Given: Relational sequential decision-making domain

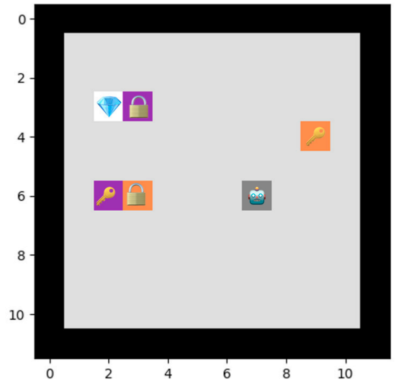
To do: Learn an efficient agent that

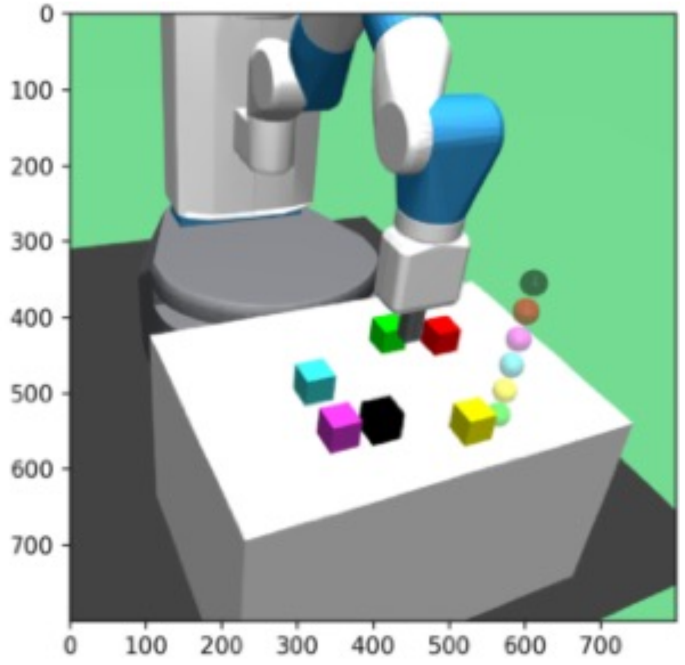
- is compositional
- can handle varying # of objects
- can generalize to different tasks
- can support task-specific representations
- can handle multi-modal data

Experiments

- Domains
  - Office World
  - Craft World
  - Relational Taxi
  - Relational Box World
  - Fetch Pick and Place

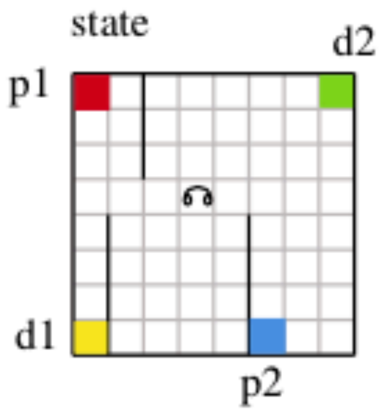


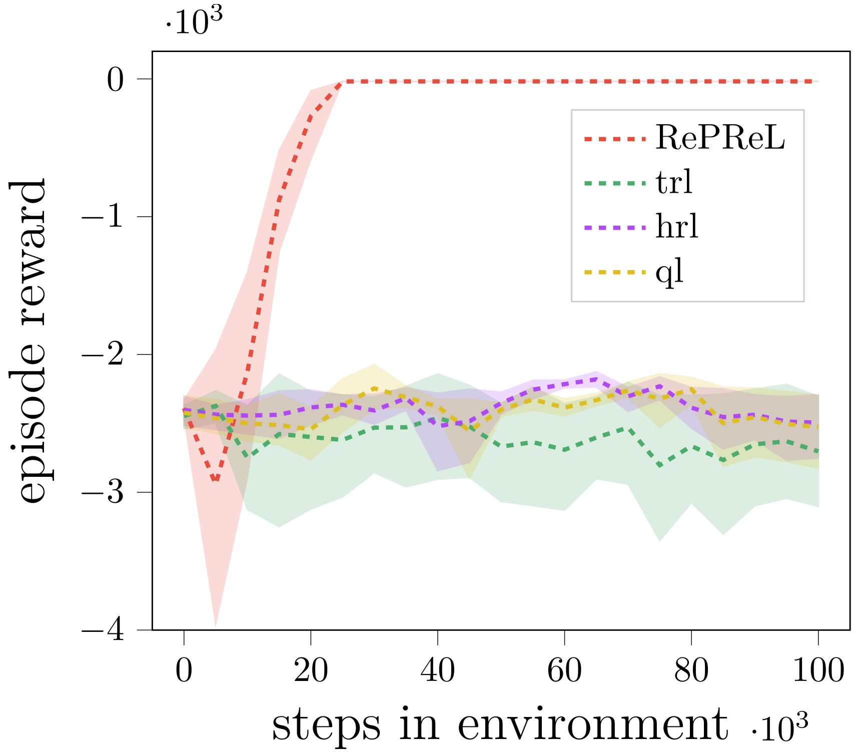


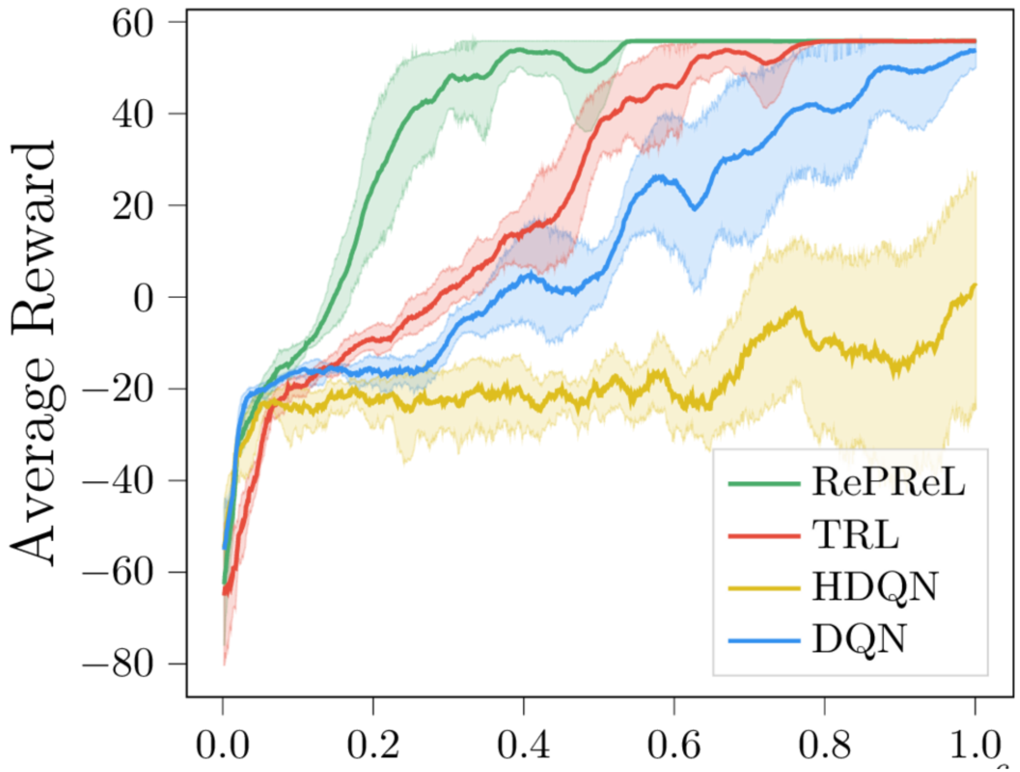
- Baselines
  - Tabular RL
  - Deep RL (DDQN, PPO, SAC)
  - Hierarchical RL (options framework)
  - Planner + RL (Taskable RL)
  - Deep Relational RL (ReNN)

Illanes et al. 2020; Li et al 2020;

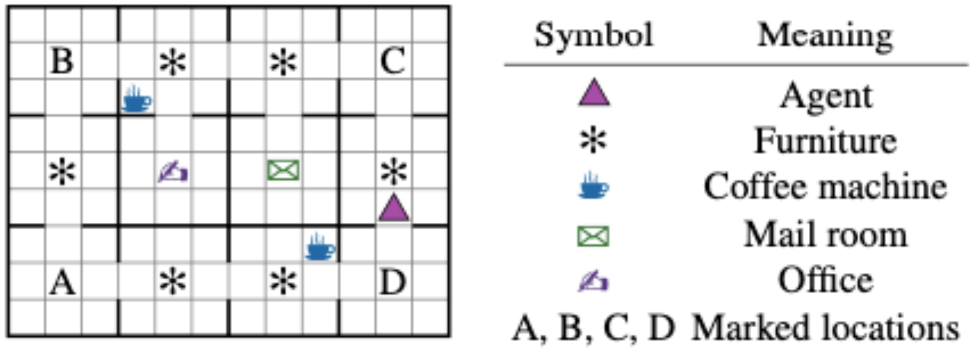
Sample Efficiency

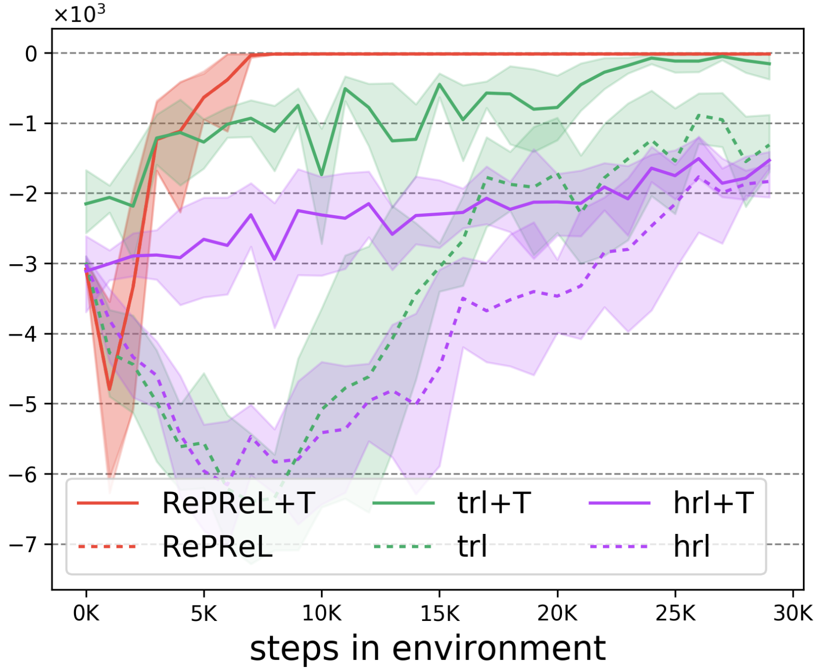


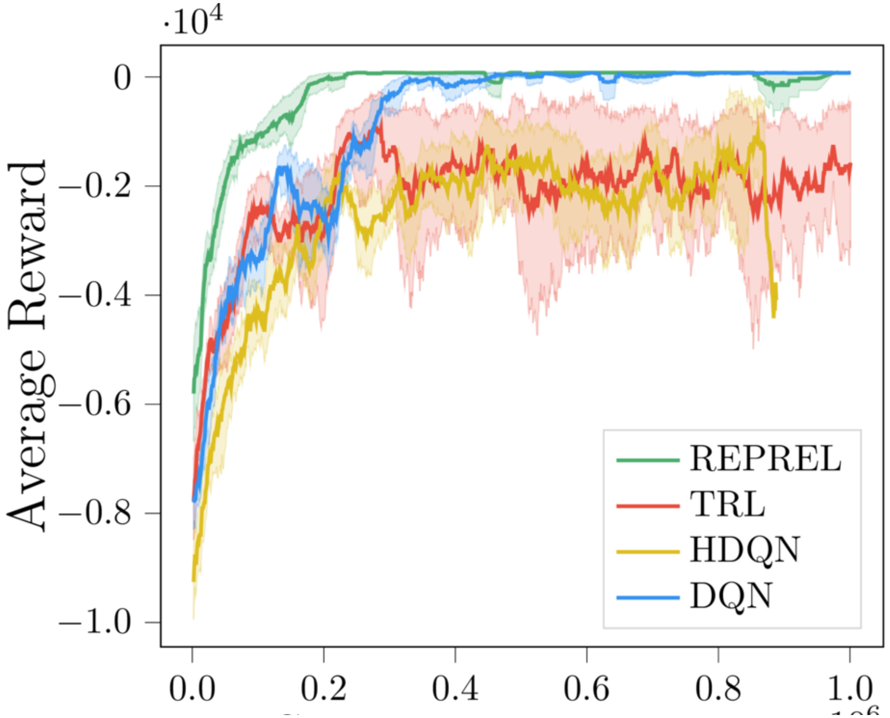




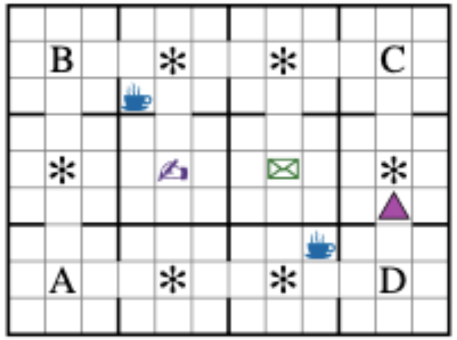
Sample Efficiency



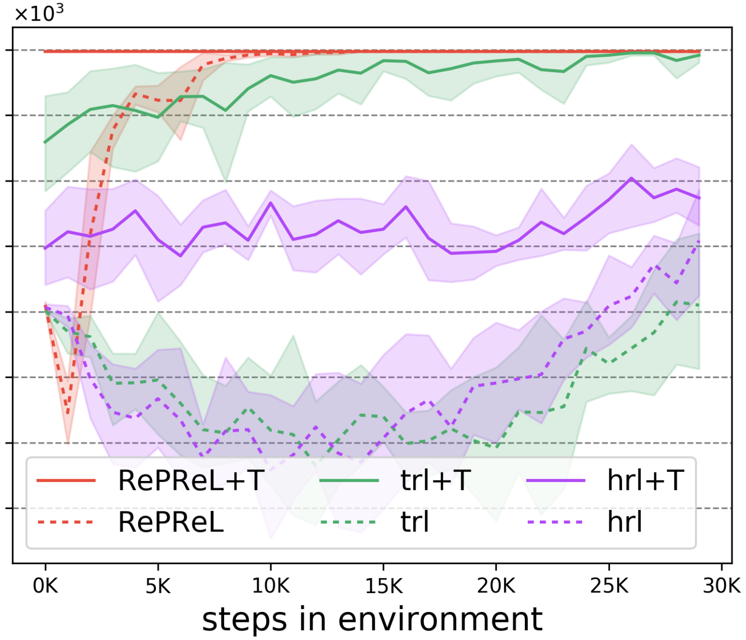




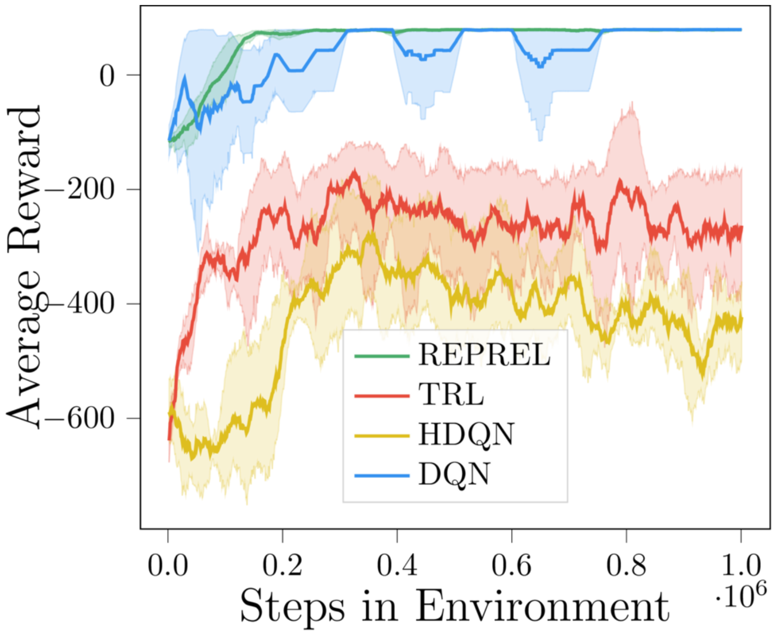
Task Transfer



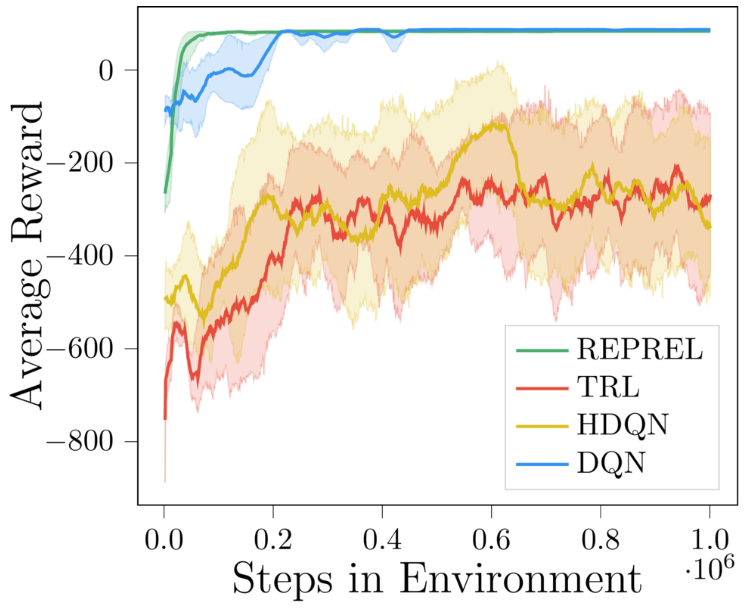
Symbol	Meaning
▲	Agent
*	Furniture
☕	Coffee machine
✉	Mail room
✍	Office
A, B, C, D	Marked locations



Tabular



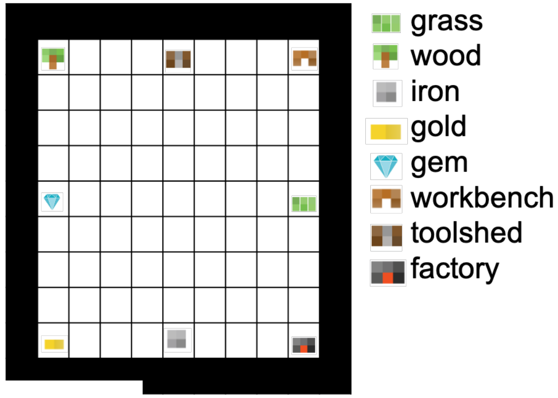
Deliver coffee

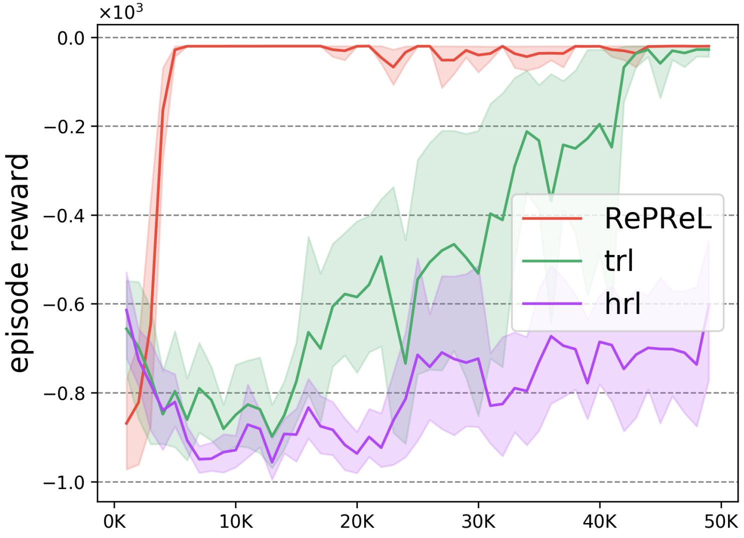


Deliver mail

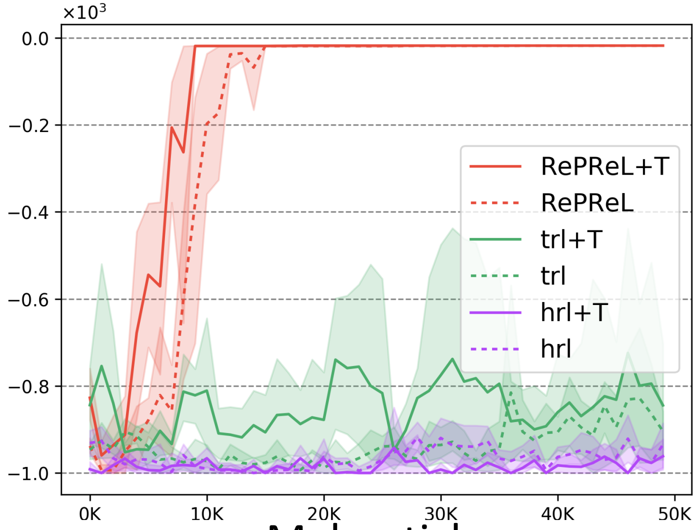
Task Transfer

CRAFT WORLD



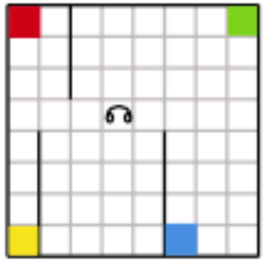


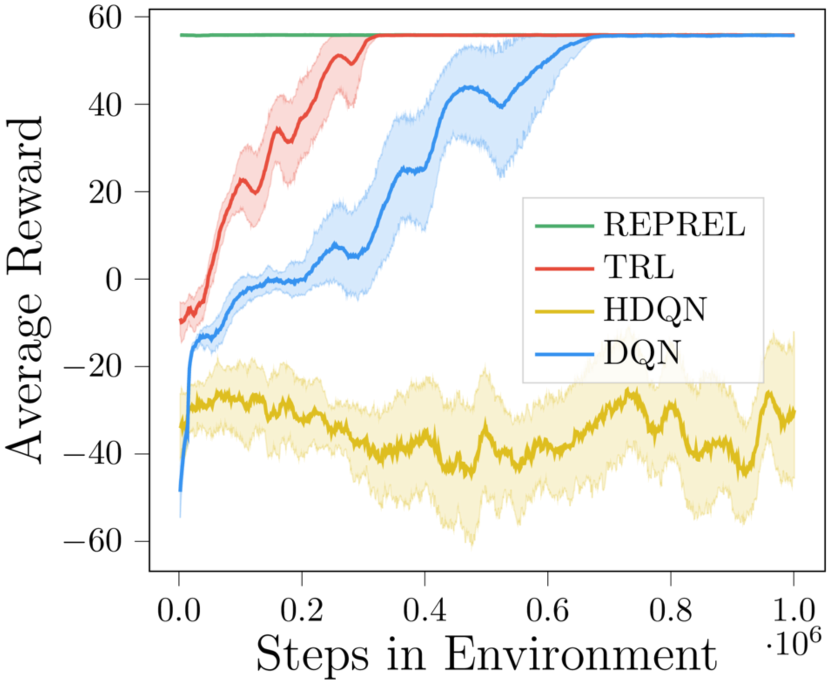
Get wood and iron



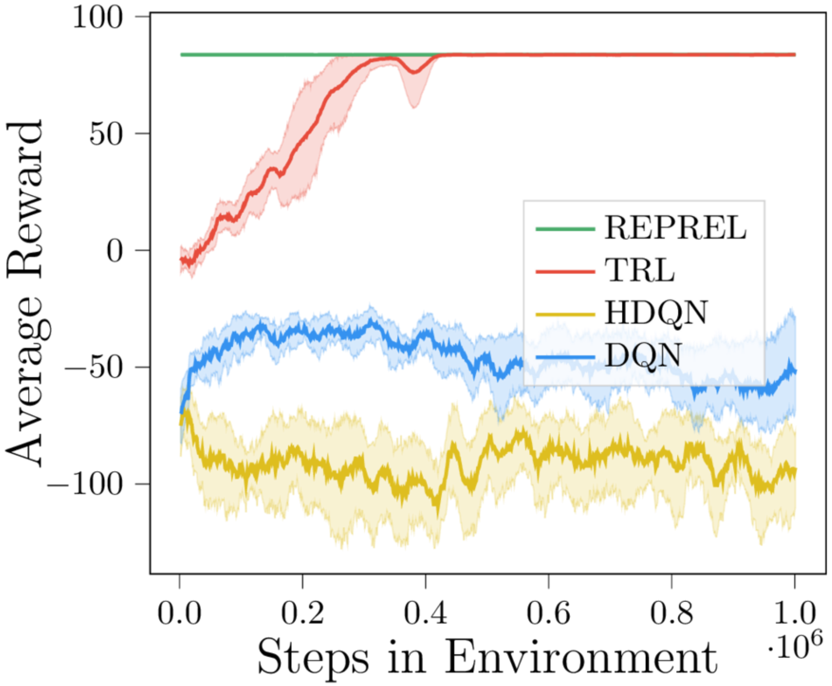
Make stick
(at workbench, needs wood)

Varying # of objects



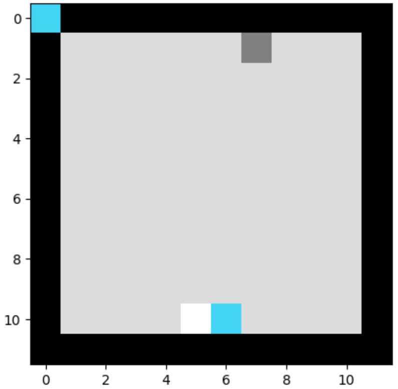


Transport 2 passengers

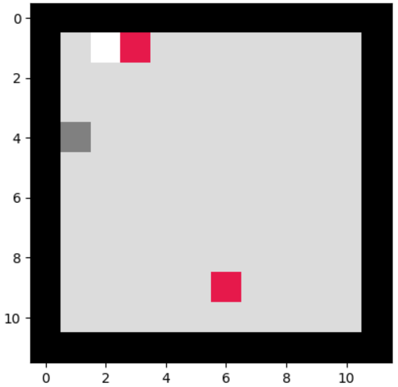


Transport 3 passengers

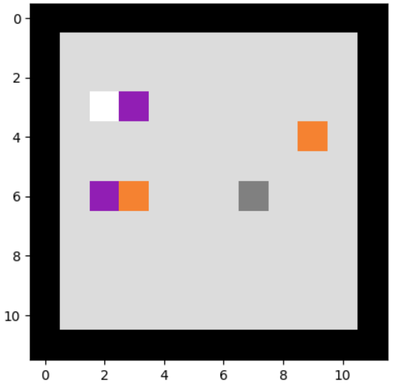
Varying # of objects



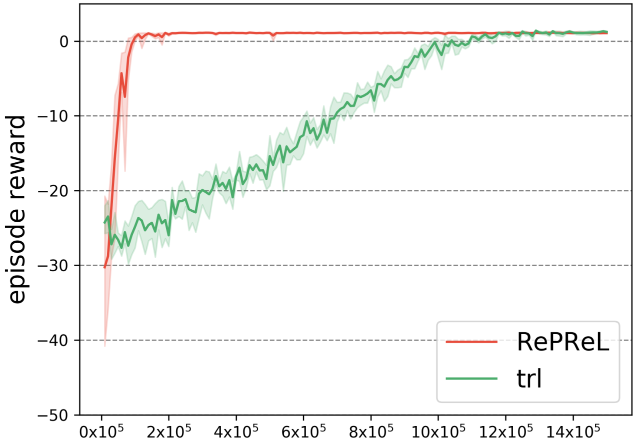
Open lock

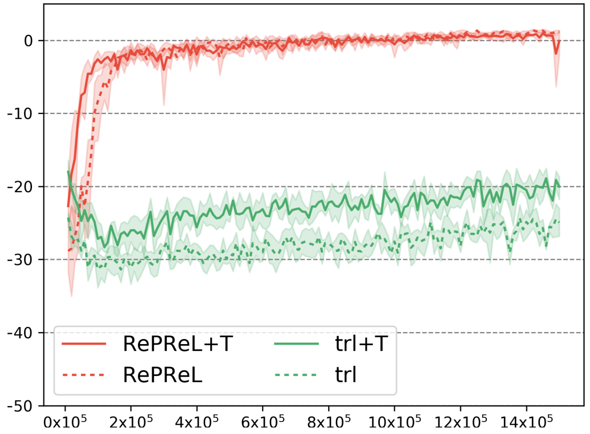


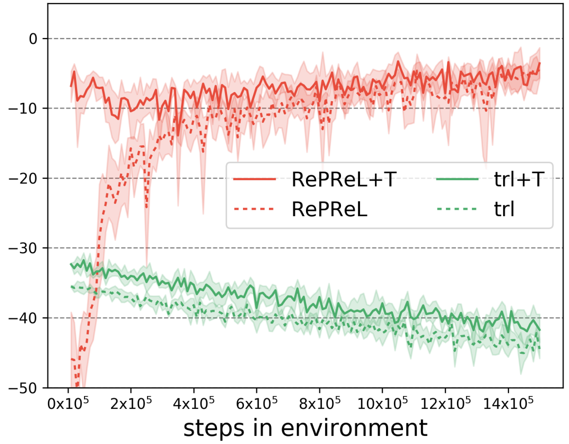
Collect key and open lock



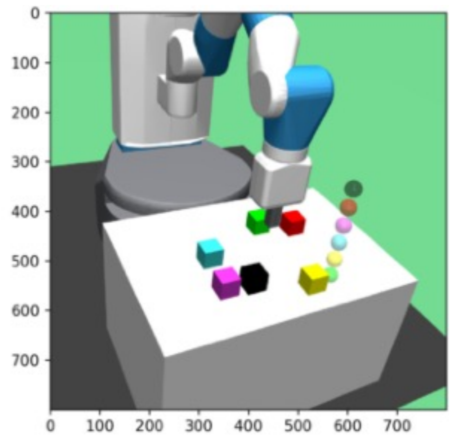
Collect key and
open 2 locks

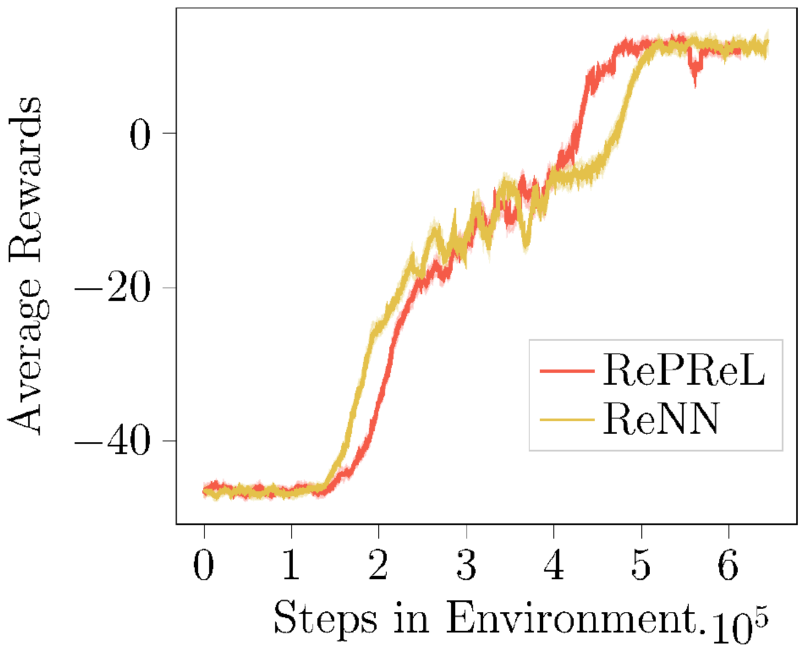




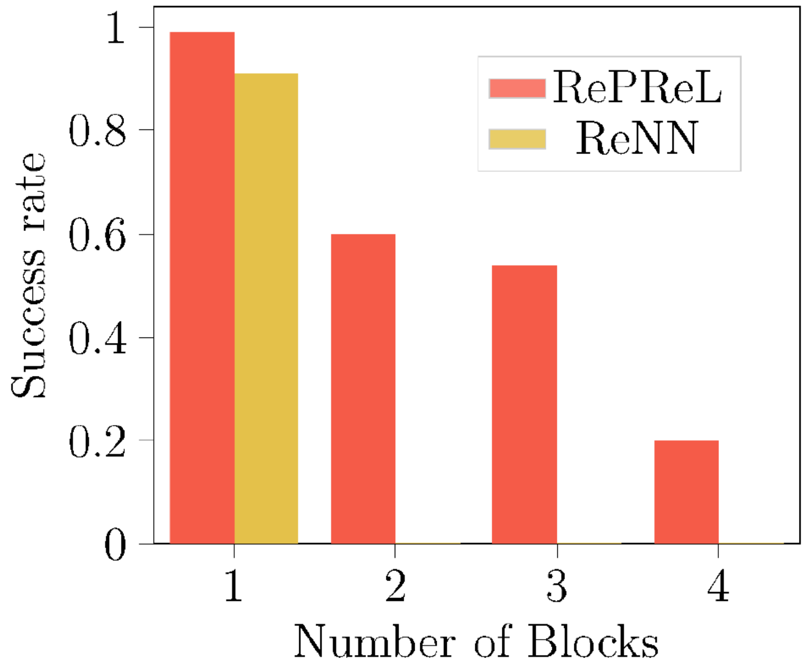


Varying # of objects



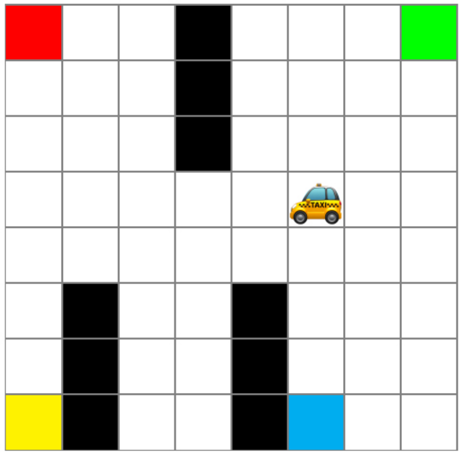


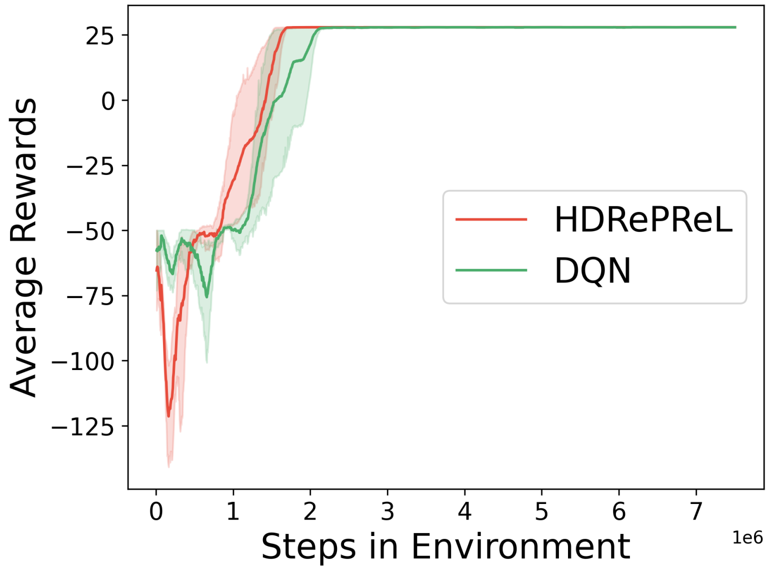
(a)



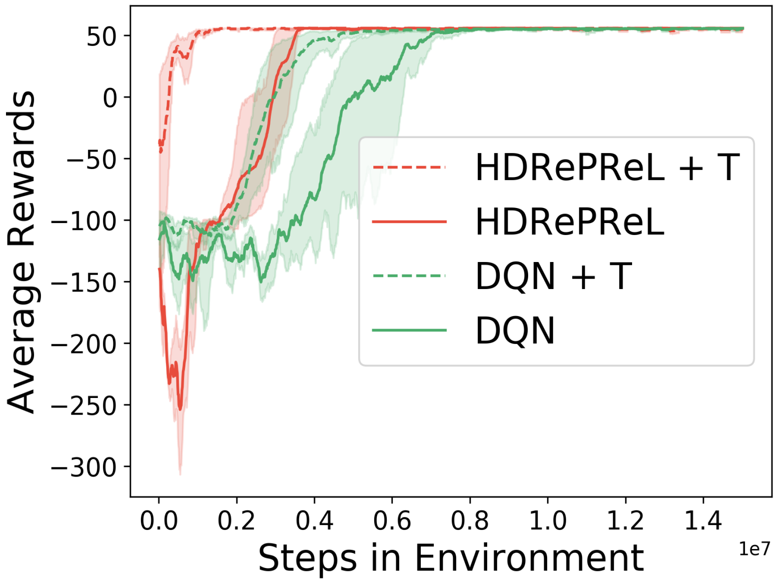
(b)

Multi modal

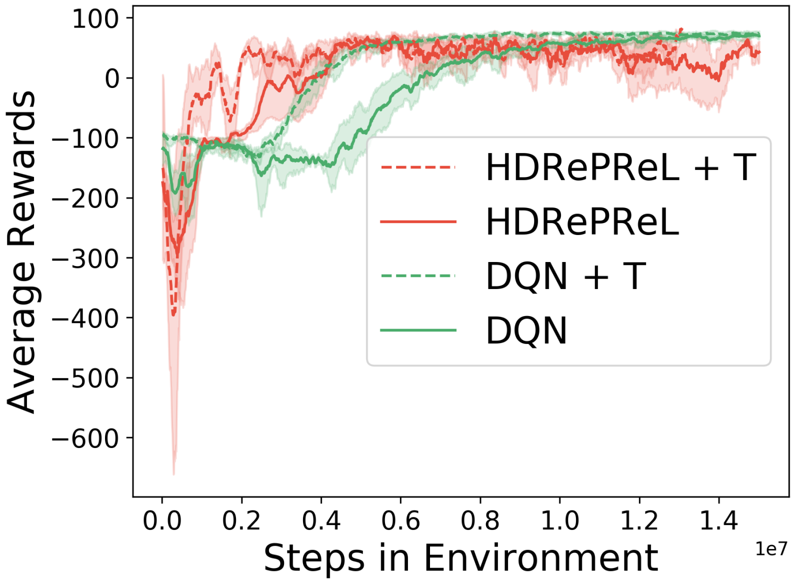




transport one passenger

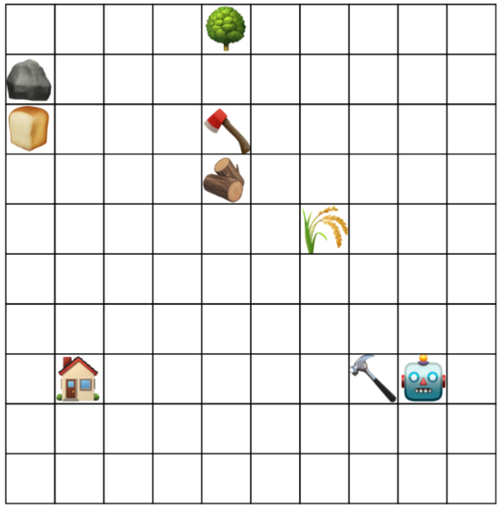


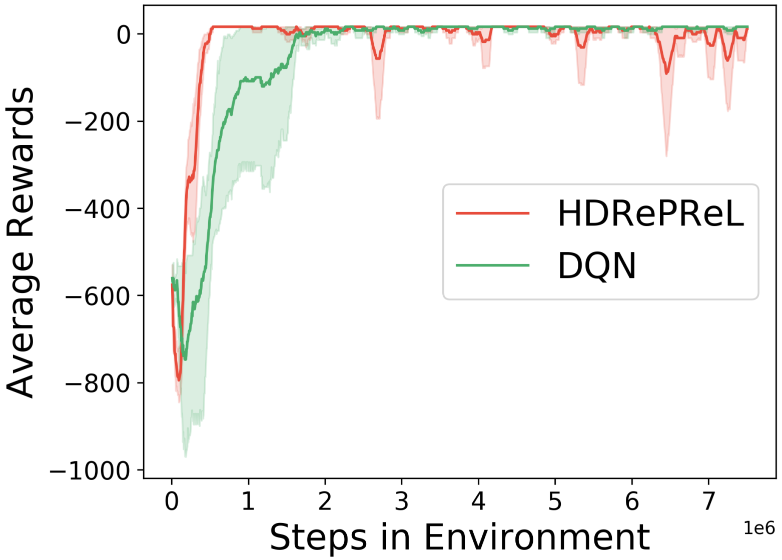
Transport two passengers



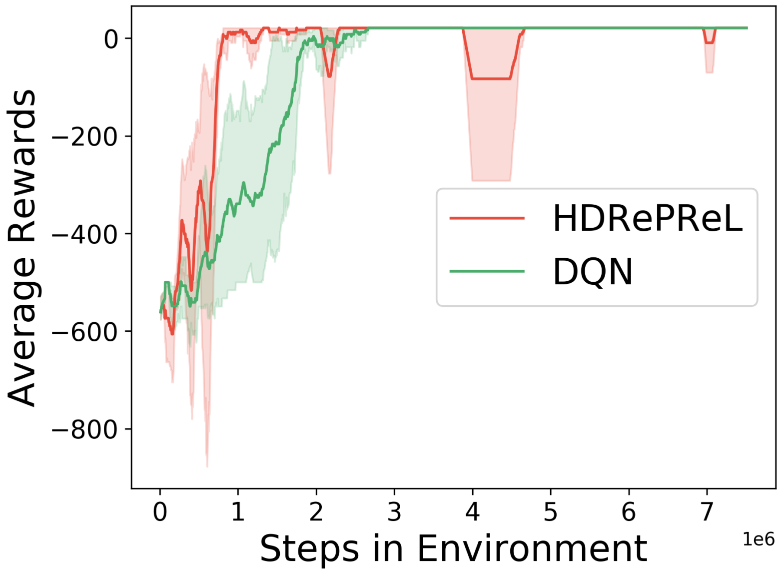
Transport three passengers

Multi modal

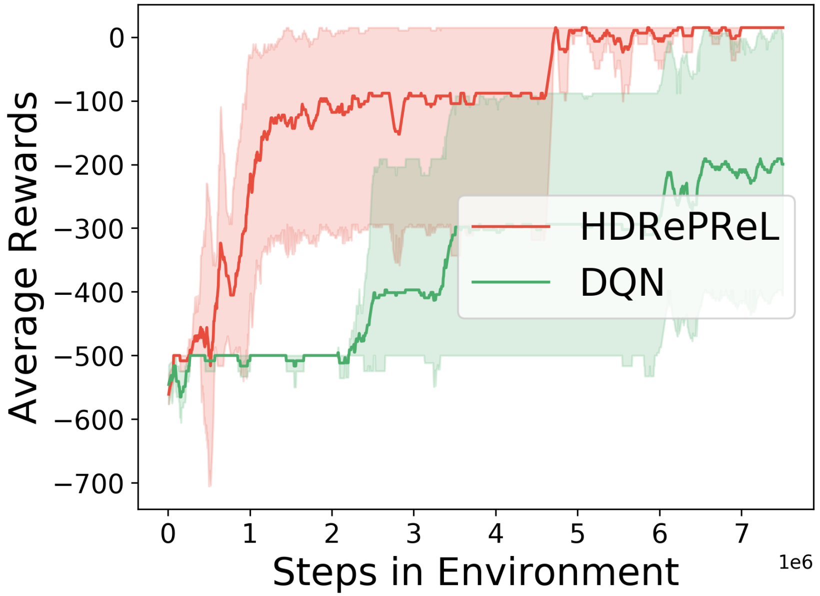




Make Bread



Build a house



Break a rock

Given: Relational sequential decision-making domain

To do: Learn an efficient agent that

- is compositional
- can handle varying # of objects
- can generalize to different tasks
- can support task-specific representations
- can handle multi-modal data

Summary

- Combined a symbolic planner with RL agents
- Provide a batch learning algorithm
- Demonstrate **sample efficiency**, that is significant reduction in the number of steps required for the model to learn an optimal policy for the task
- Demonstrate **efficient generalization** over number of objects
- Provide hybrid approach for structured and unstructured data
- Most importantly, the framework is planner agnostic and RL algorithm agnostic

Future work

- Refine the D-FOCI statements
- Relax downward refinement
- Partial observability and uncertainty over states
- Boolean task algebra style compositions

Questions?

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THANKS

starling.utdallas.edu
harshakokel.com

StaRLinG LAB

@starling_lab
@harsha_kokel