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

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Harsha Kokel

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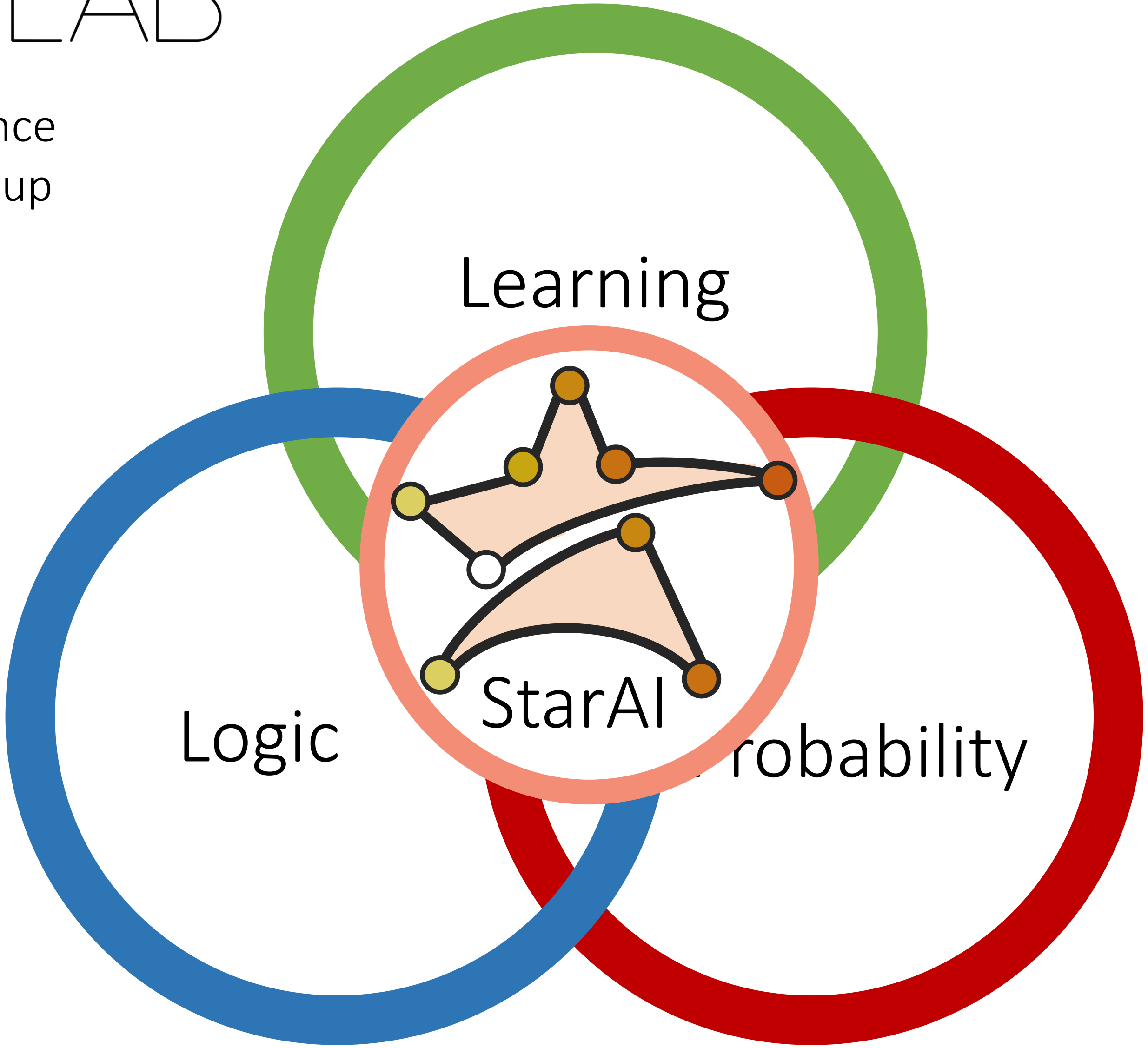
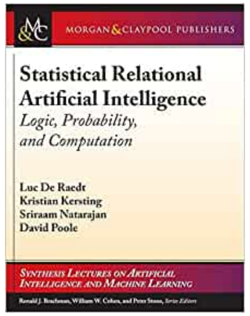
# StARLinG LAB

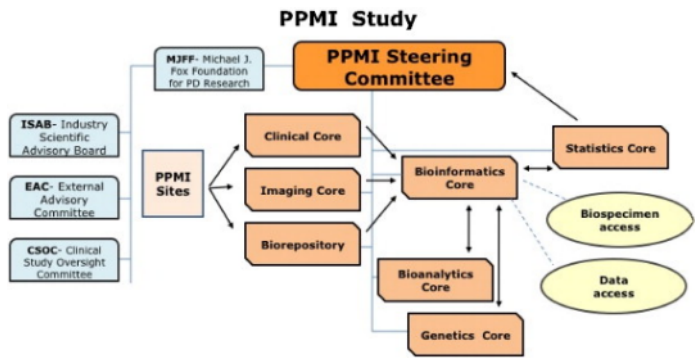
Statistical Artificial Intelligence
and Relational Learning Group



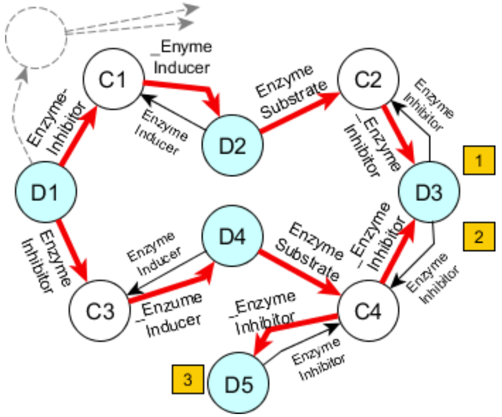




Raedt et al. 2016; Raedt et al. 2020

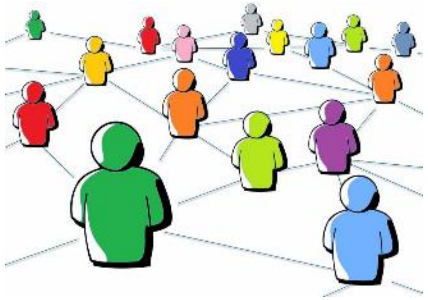
# StARLinG LAB



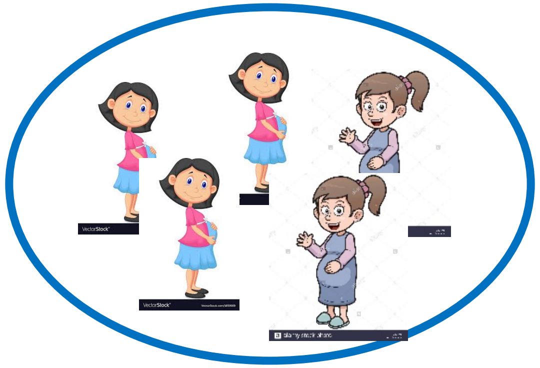

Parkinson's disease prediction



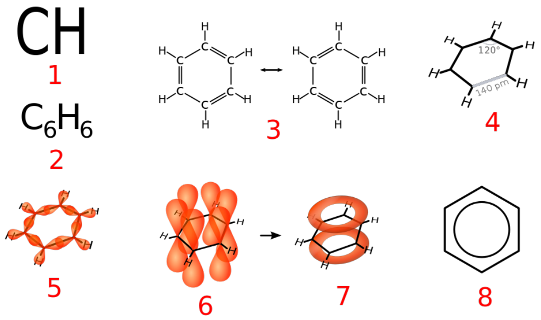

Drug-Drug Interactions



Social Networks



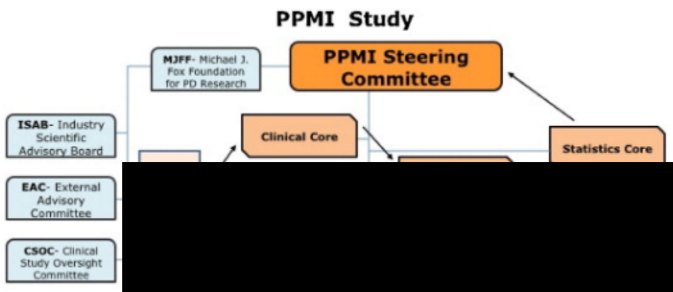
Cohort of Pregnant Women (nuMoM2b)

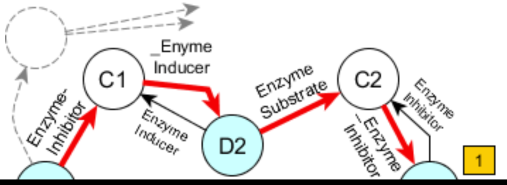


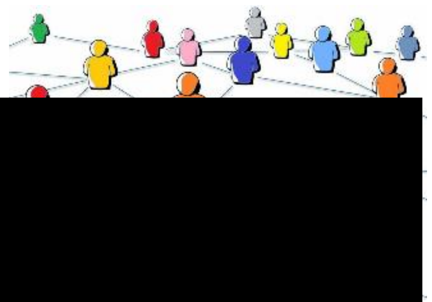

Chemical Entities of Biological Interest (ChEBI)


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

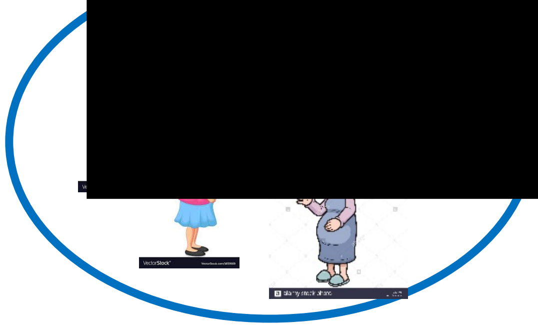


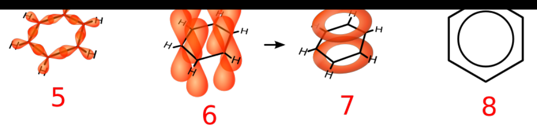



Park

# Relational and Human-Allied



Cohort of Pregnant Women (nuMoM2b)

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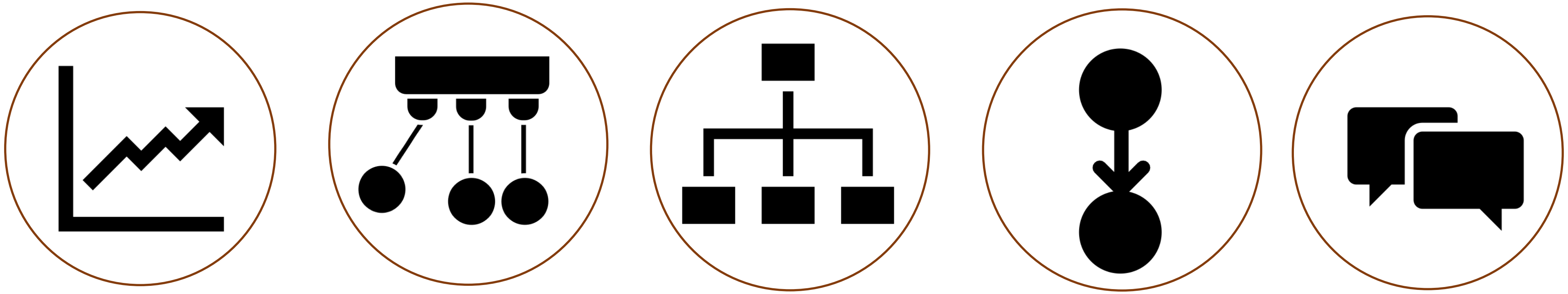
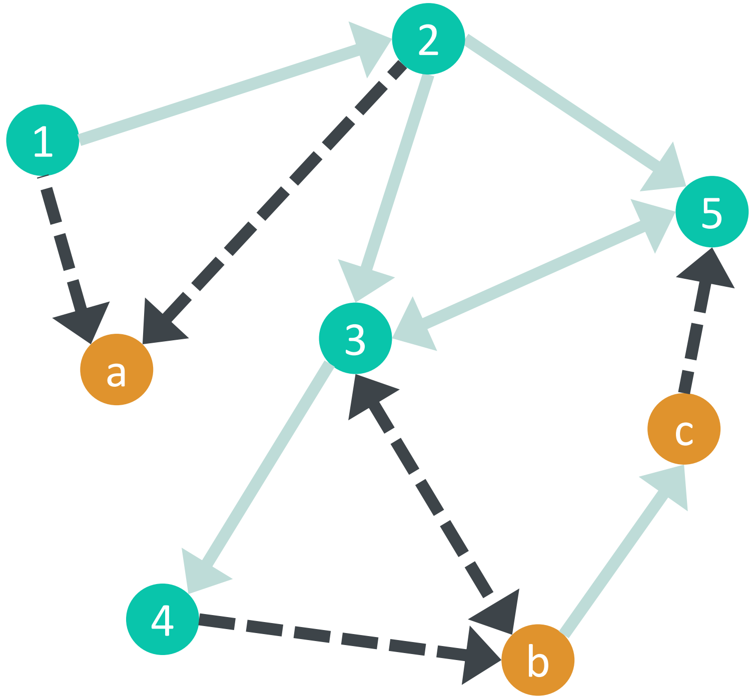
How to facilitate generalizable, effective and efficient learning with human guidance?

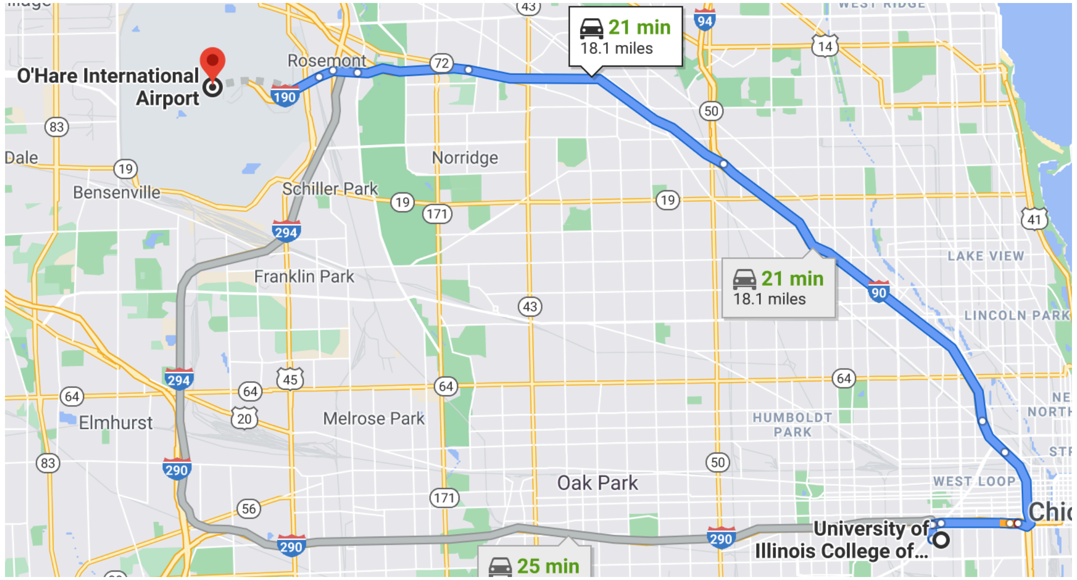


# Relational domains




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

# Abstract Representations




Planning

Execution

Konidaris, G., 2019; Li et al 2006

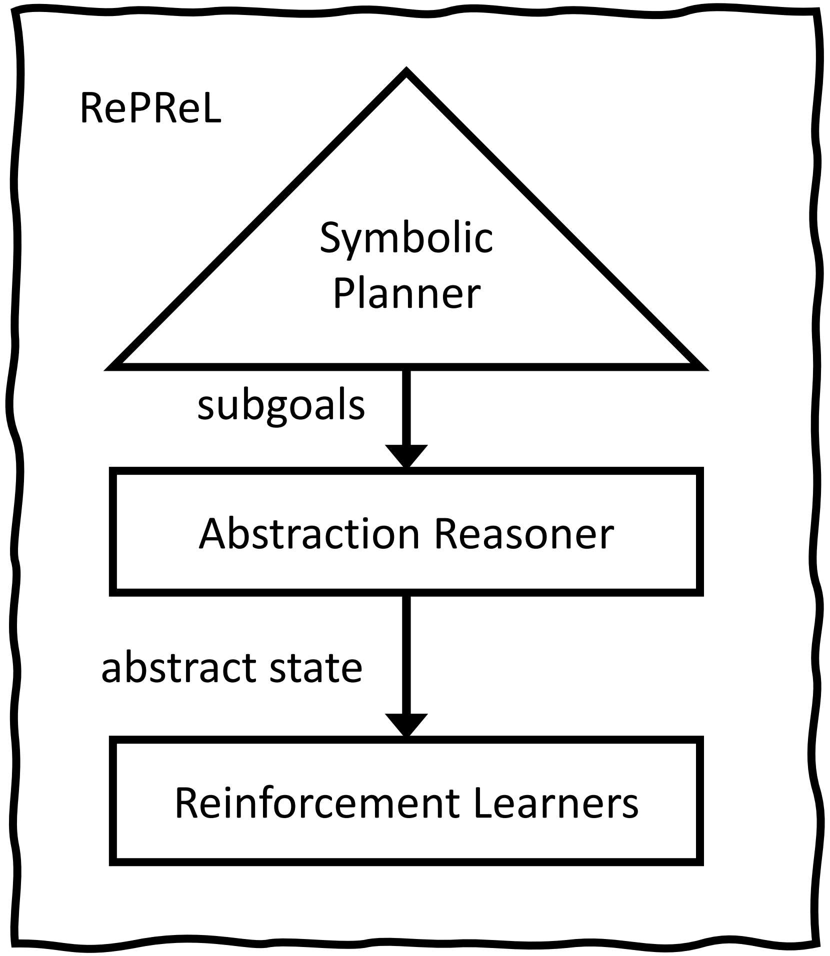
Given: Relational sequential decision-making domain

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

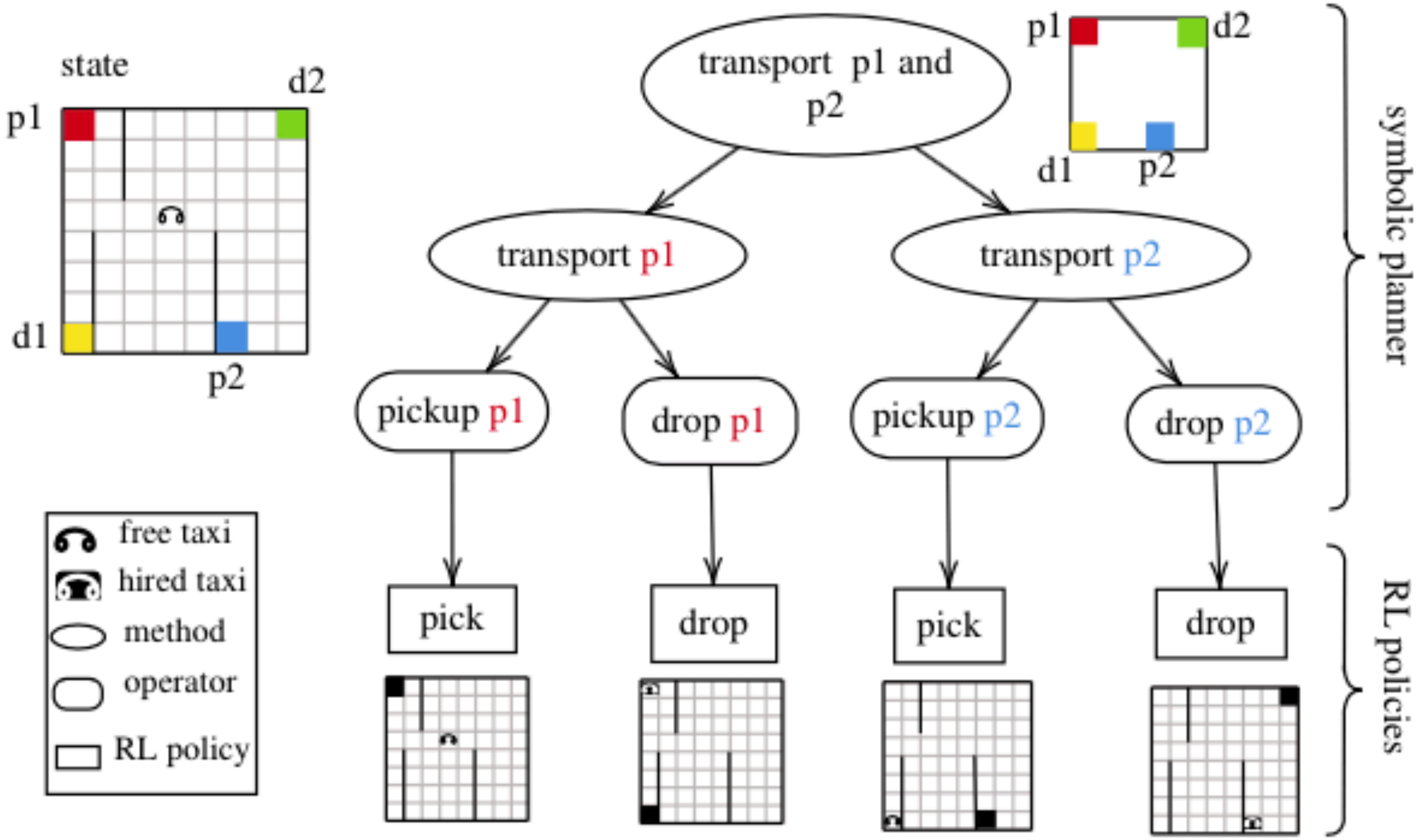
- Plan the sequence of high level subgoals and learn to execute each subgoal at lower level




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 $\gamma$. 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:*

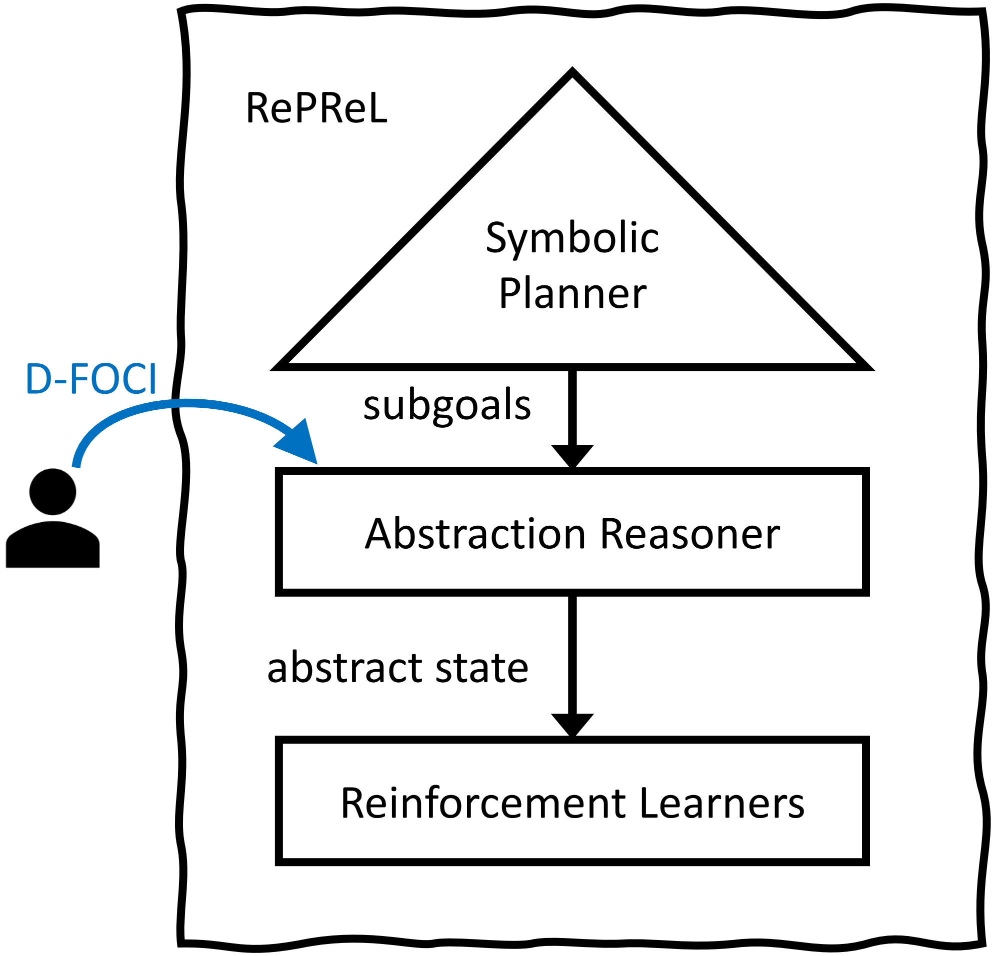
$$R_o(s, a, s') = \begin{cases} t_R + R(s, a, s') & \text{if } s' \in \beta(o) \text{ and } s \notin \beta(o) \\ 0 & \text{if } s' \in \beta(o) \text{ and } s \in \beta(o) \\ R(s, a, s') & \text{otherwise} \end{cases}$$

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

*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

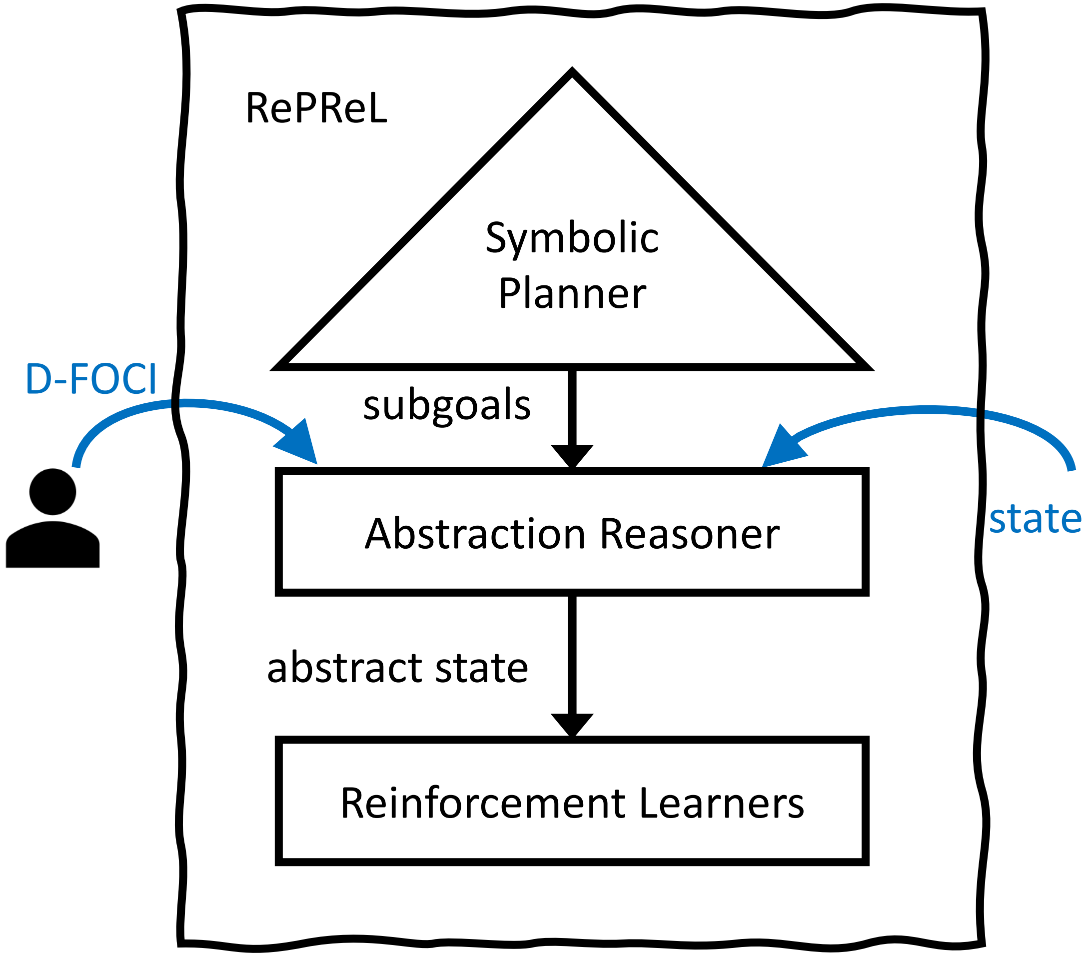
# D-FOCI

First Order Conditional Influence (FOCI) statements

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

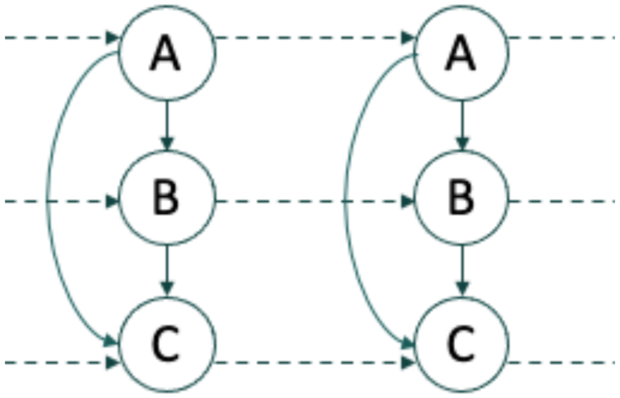
Dynamic FOCI statements

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



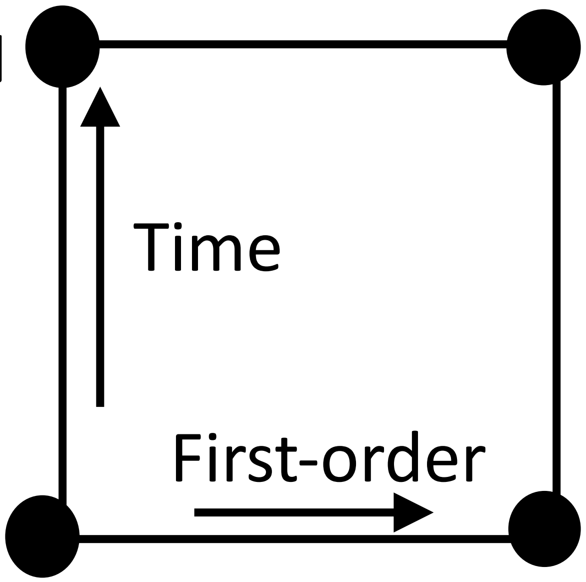

Natarajan, Tadepalli, Dietterich, and Fern 2008

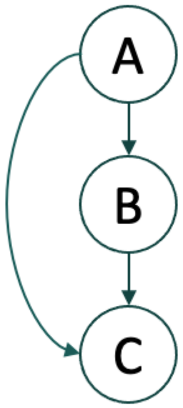
# D-FOCI as Dynamic PLMs




Dynamic BN

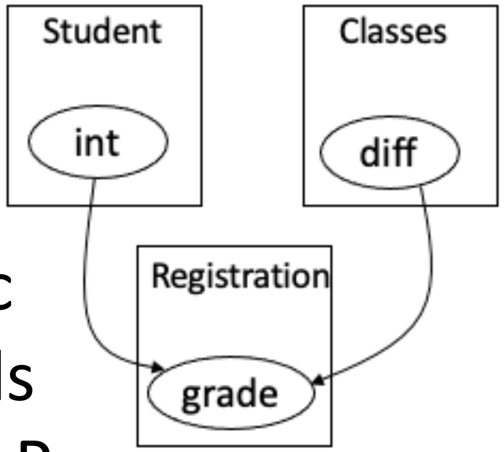
Dynamic PLM




Bayesian Network (BN)

Probabilistic Logic Models (PLM, PRM, BLP, LBN, DAPER)





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

# D-FOCI example

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

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

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

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

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

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

# Abstraction

**Given:**
a. D-FOCI statements from Equation 3
b. state $s = \{$ **at**(p1,r), **taxi_at**(l3), **dest**(p1,d1), $\neg$**at_dest**(p1) $\neg$**in_taxi**(p1), **at**(p2,b), $\neg$**at_dest**(p2), $\neg$**in_taxi**(p2)$\}$
c. grounded option$o\theta$: **pick**$(P)$ $\{P/\mathrm{p1}\}$
**Output:** A set of relevant state literals: $\hat{s}$

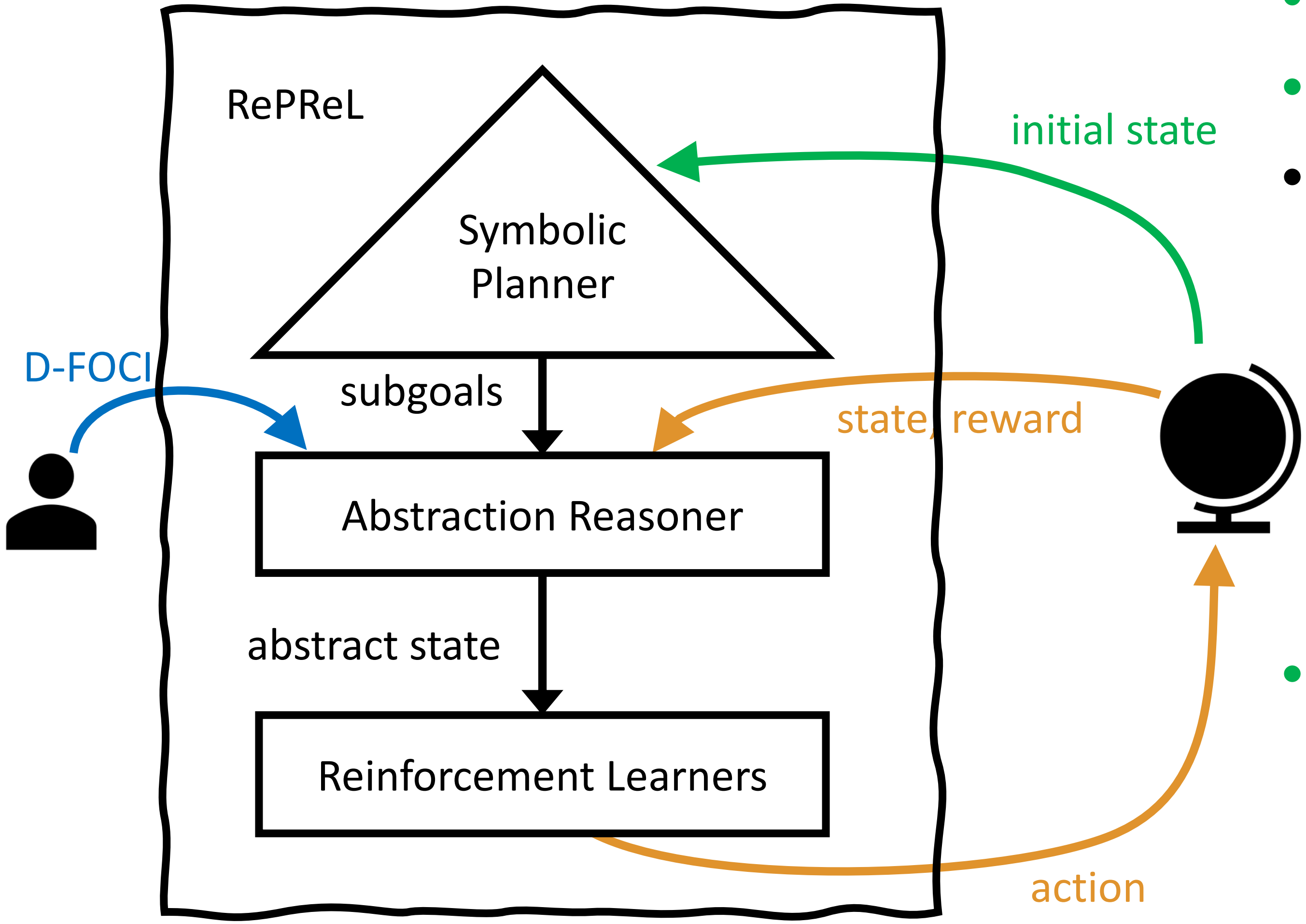
**Depth 1 unrolling**:
1. Find a substitution that grounds relevant D-FOCI statements that have reward on RHS
   **pick**(p1): **in_taxi**(p1) $\longrightarrow$ *Reward*
   $\theta = \{\mathrm{P/p1}\}$
2. Collect LHS in relevant literals set $\hat{s}$
   $\hat{s} \leftarrow \{$**in_taxi**(p1)$\}$

**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)
   $\theta = \{\mathrm{P/p1,\ X/l3,\ Y/r}\}$
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)
   $\theta = \{\mathrm{P/p1,\ X/l3,\ Y/r}\}$
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

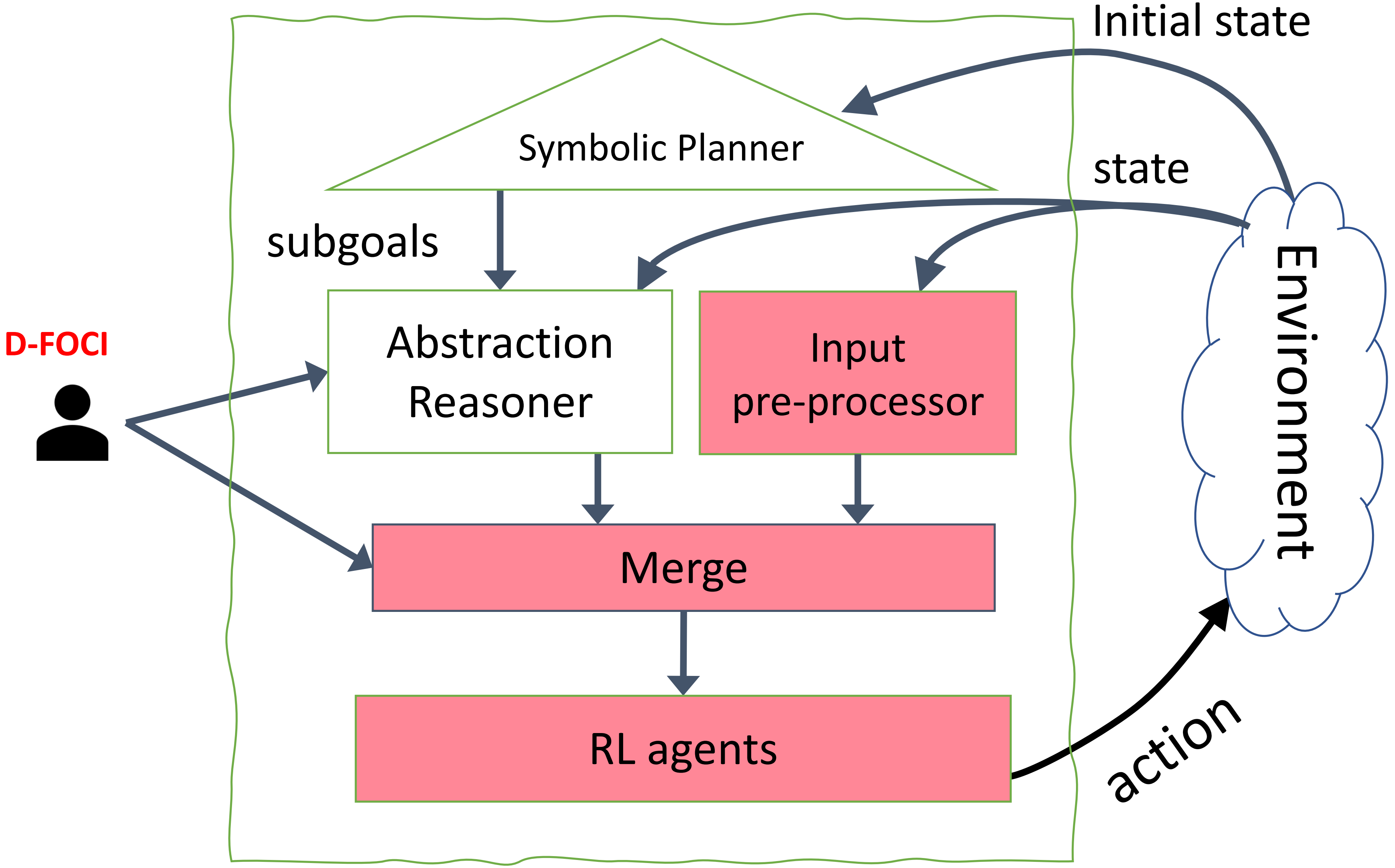
# RePReL Learning




- 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

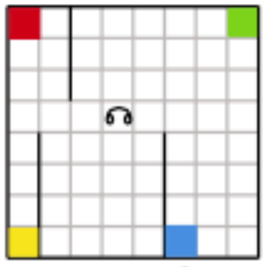
Given: Relational sequential decision-making domain

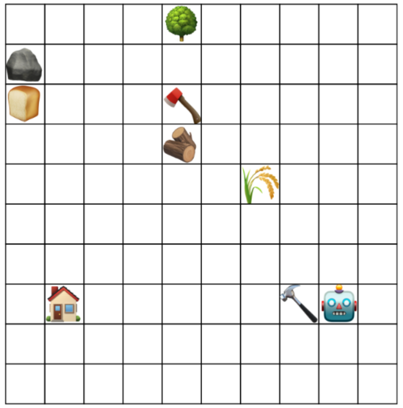
To do: Learn an efficient agent that

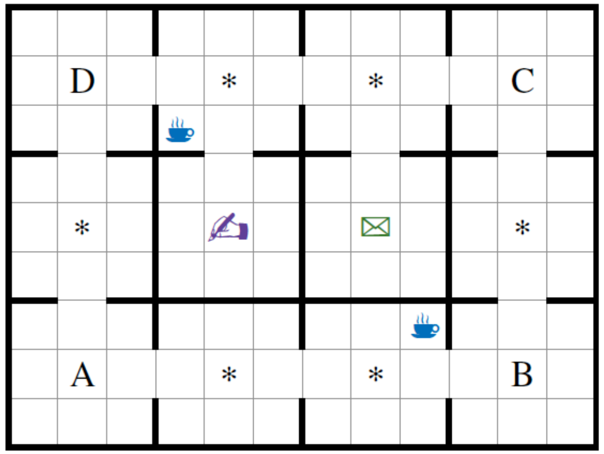
- is compositional
- can handle varying # of objects
- can generalize to different tasks
- can support task-specific representations
- can handle multi-modal data

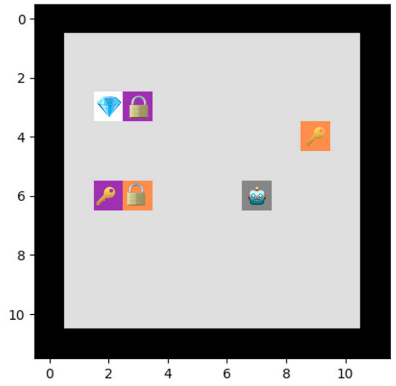
# Experiments

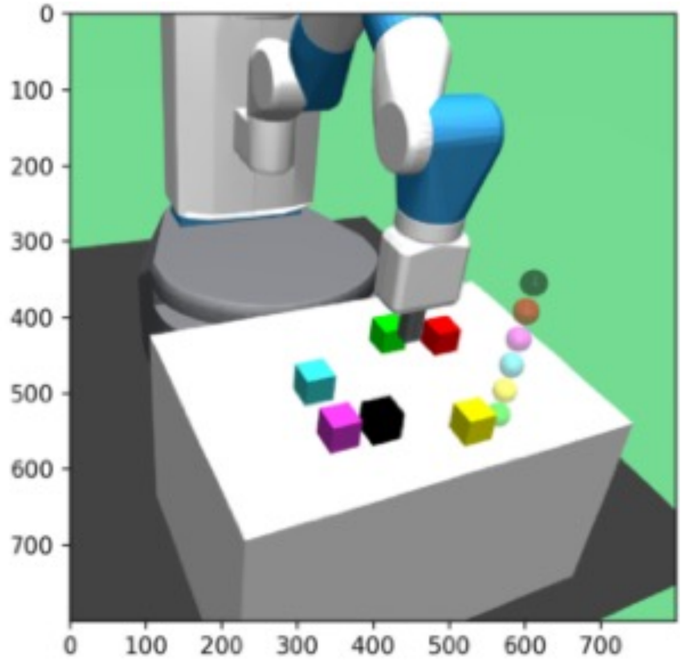
- Domains
  - Office World
  - Craft World
  - Relational Taxi
  - Relational Box World
  - Fetch Pick and Place
- Baselines
  - Tabular RL
  - Deep RL (DDQN, PPO, SAC)
  - Hierarchical RL (options framework)
  - Planner + RL (Taskable RL)
  - Deep Relational RL  (ReNN)





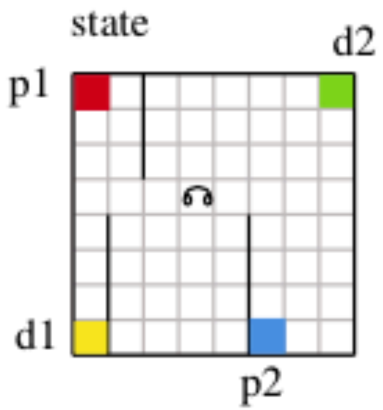


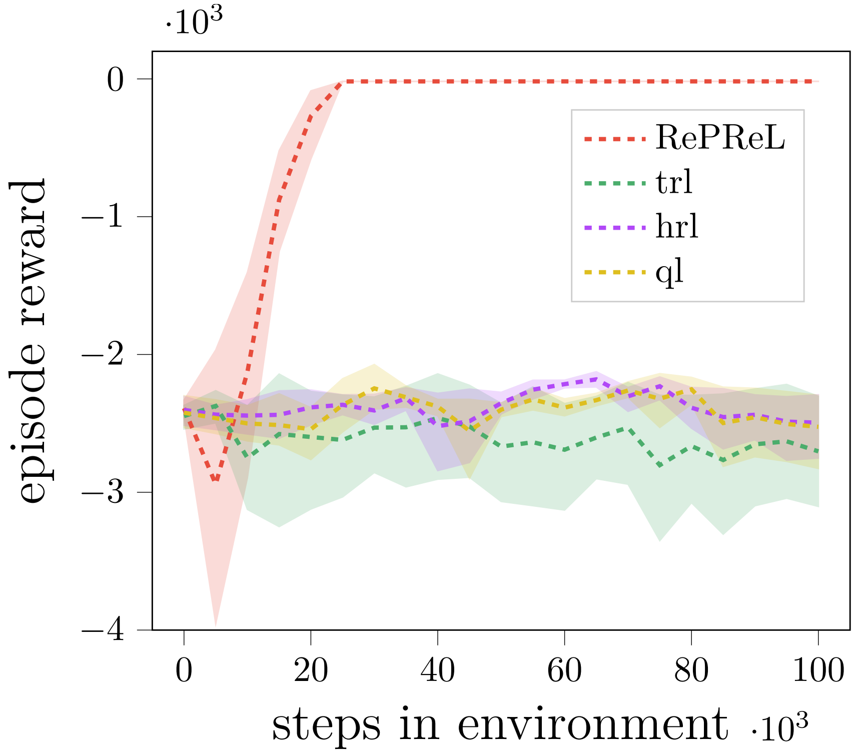



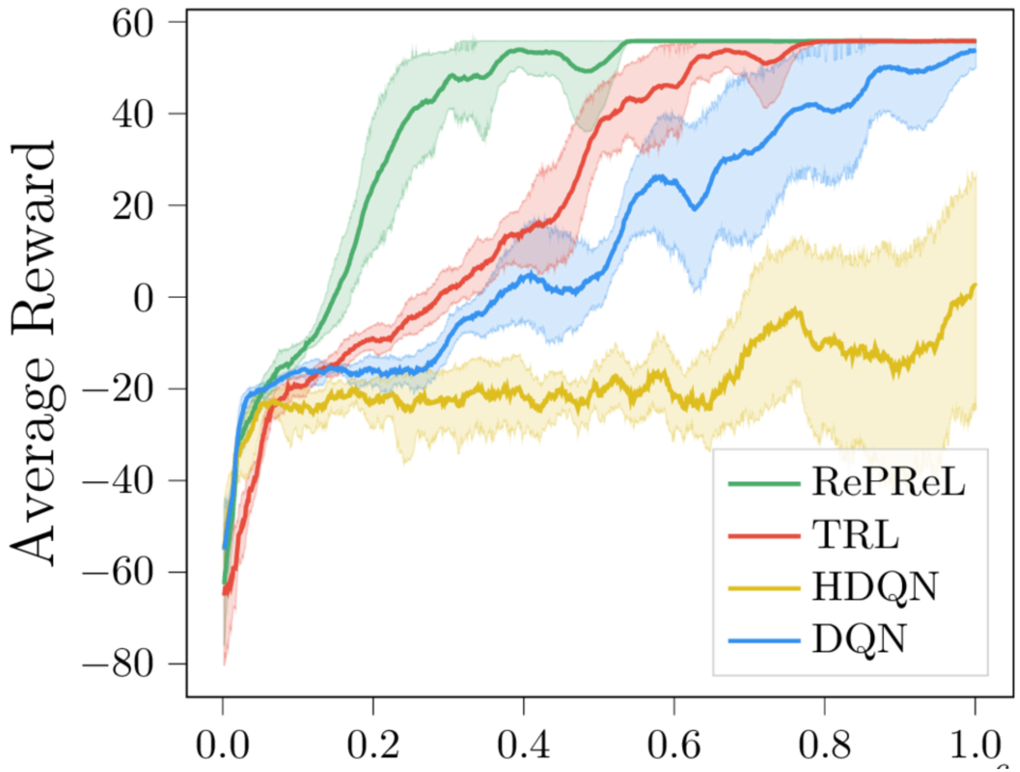




Illanes et al. 2020; Li et al 2020;

# Sample Efficiency



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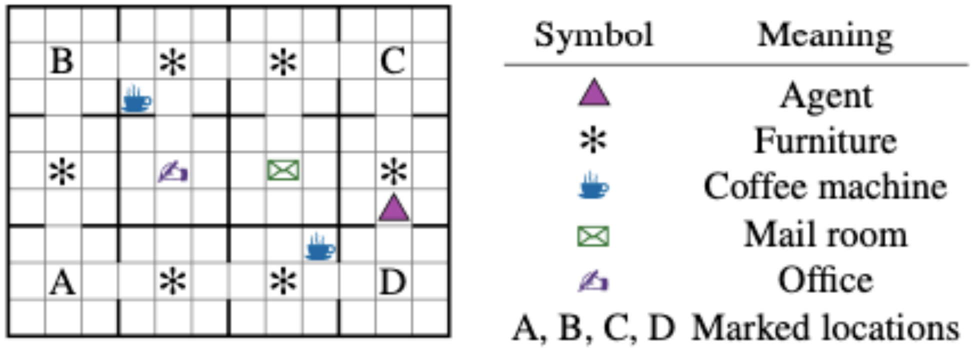
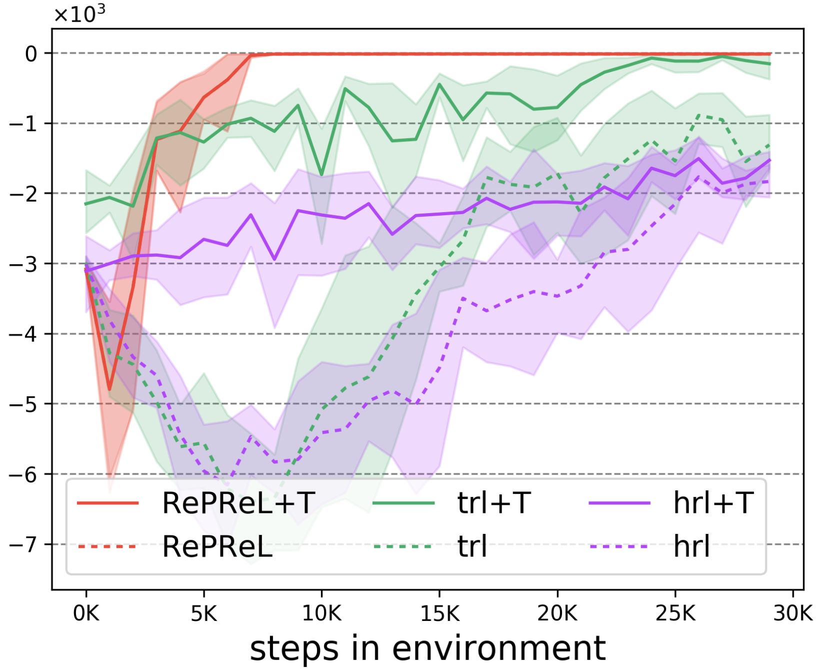
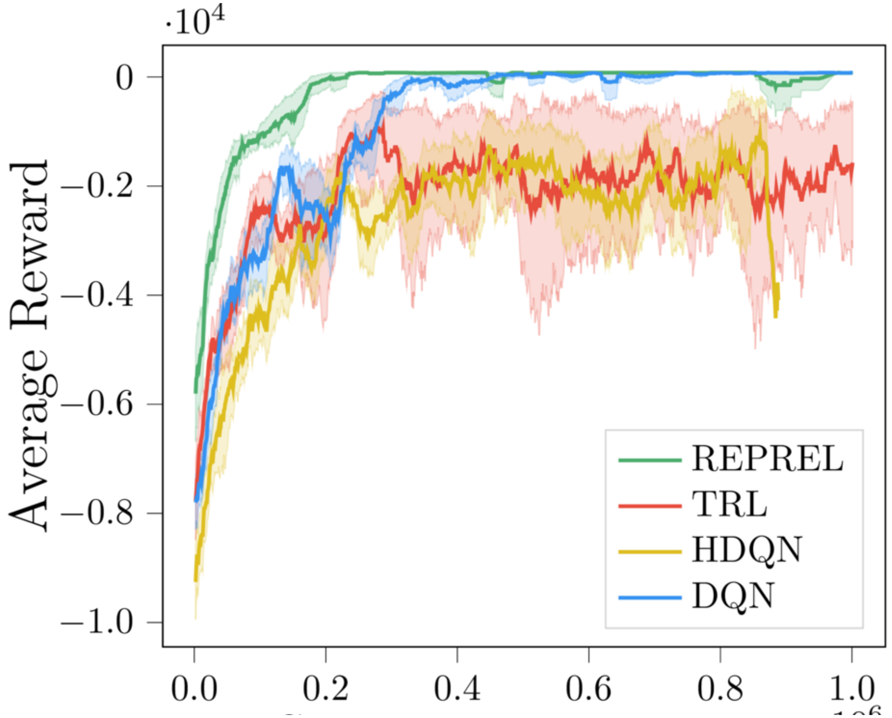
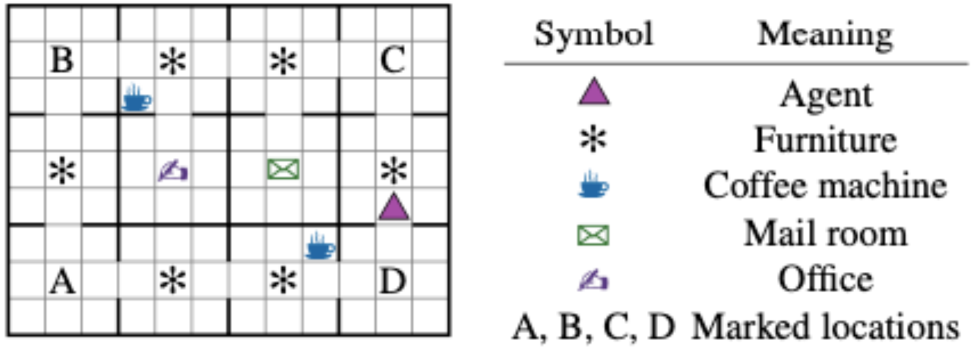
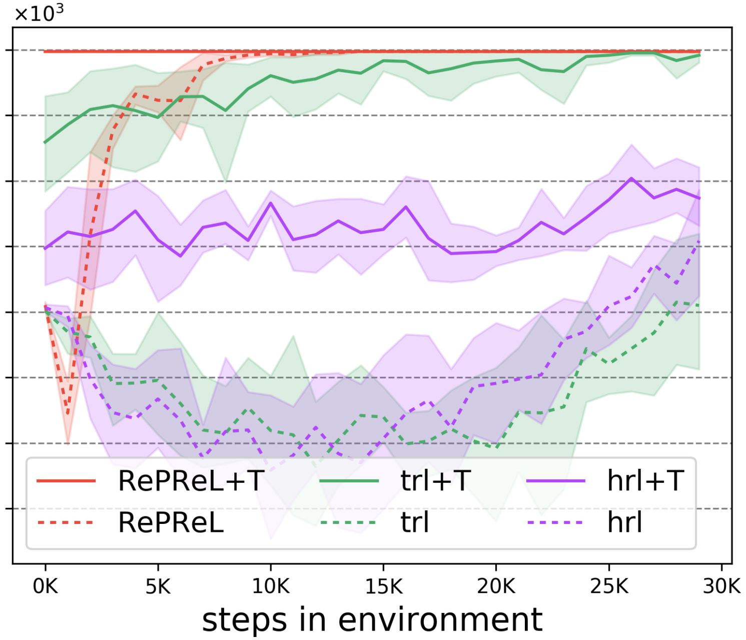


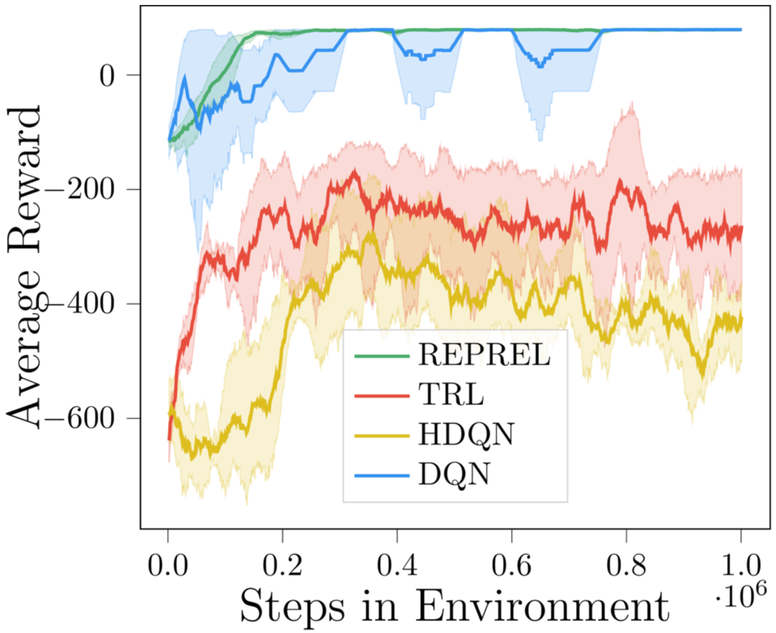



# Task Transfer

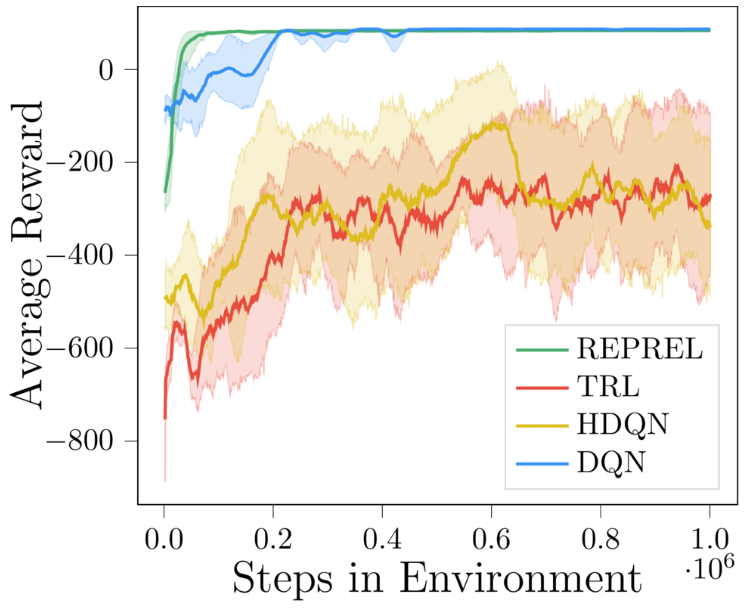



Tabular



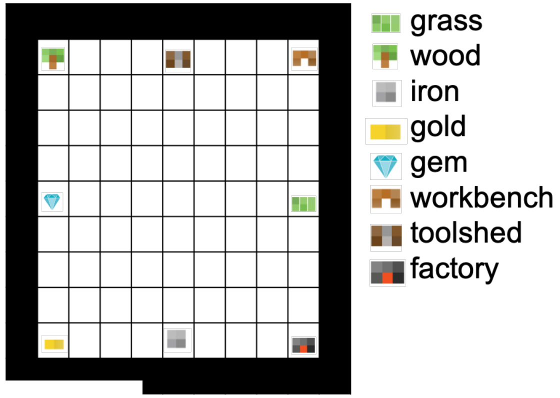

Deliver coffee

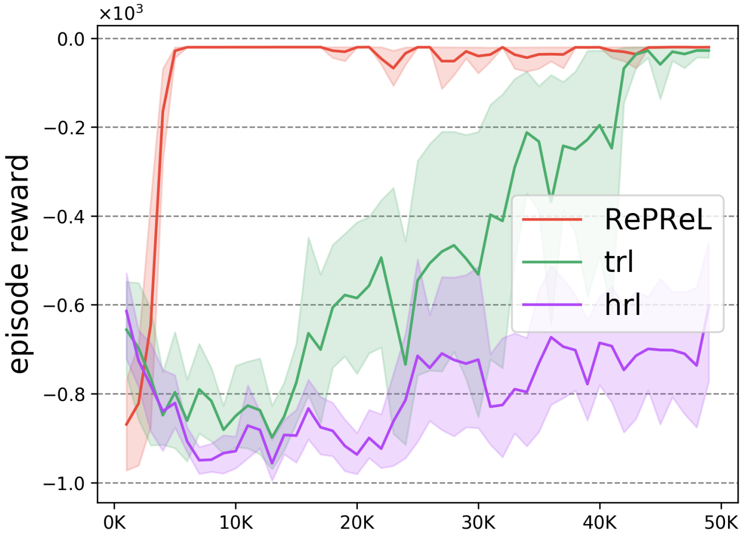



Deliver  mail

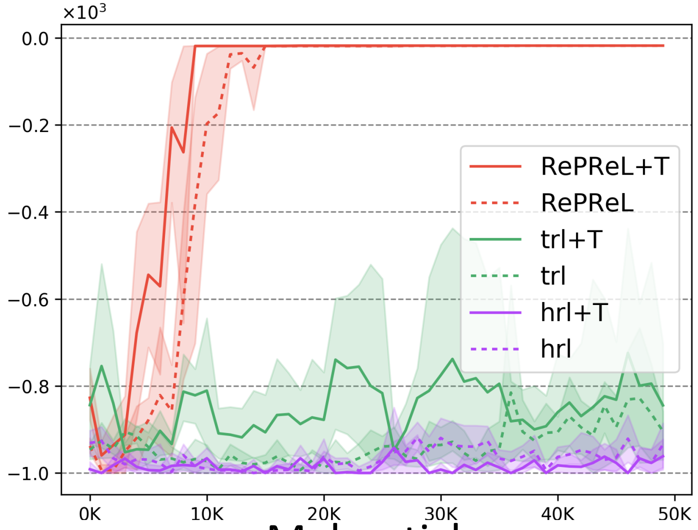
# Task Transfer

## CRAFT WORLD



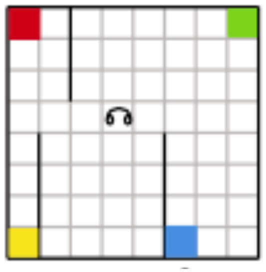



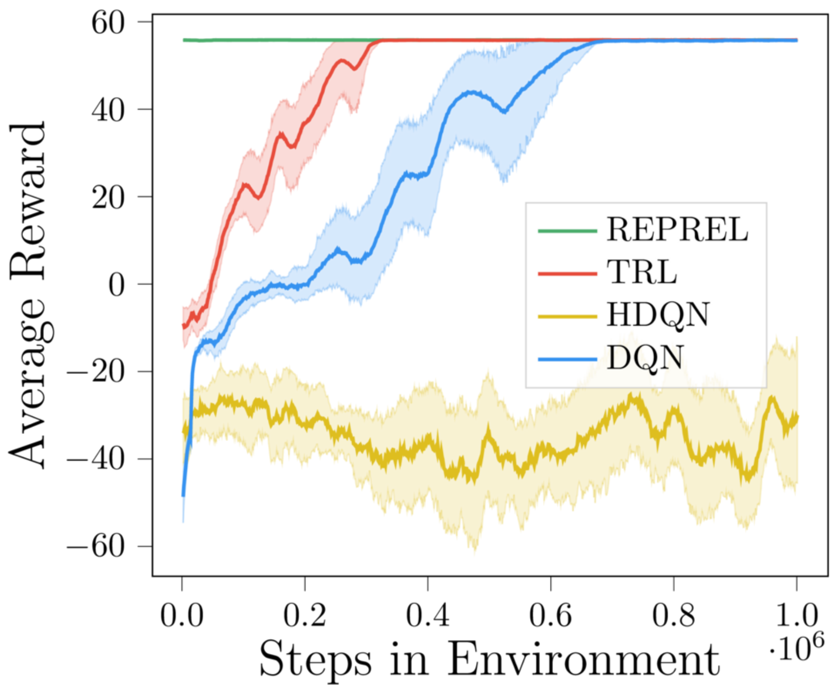

Get wood and iron



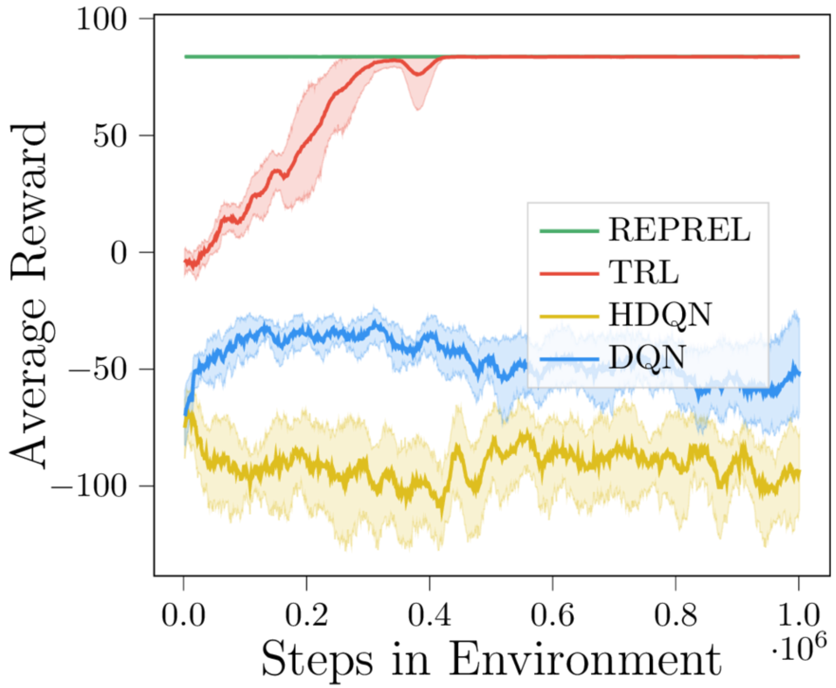

Make stick
(at workbench, needs wood)

# Varying # of objects



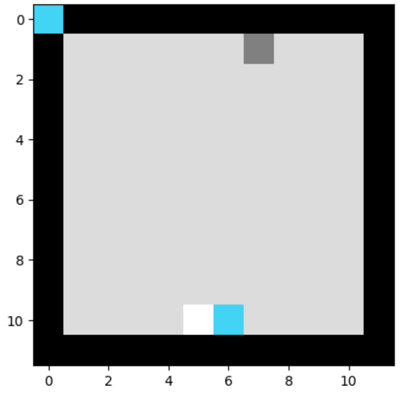



Transport 2 passengers

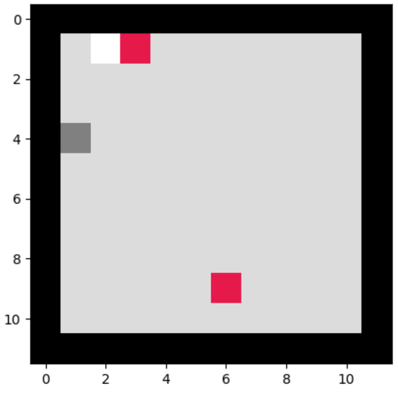



Transport 3 passengers

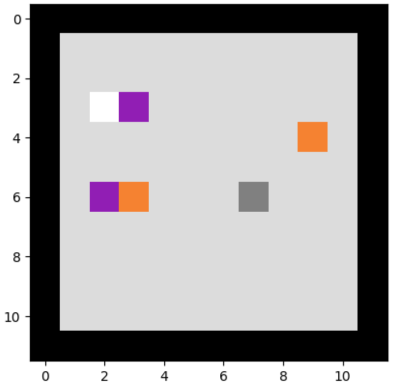
# Varying # of objects



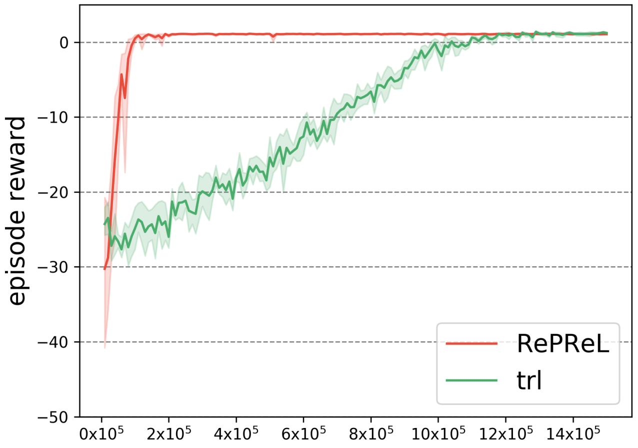

Open lock

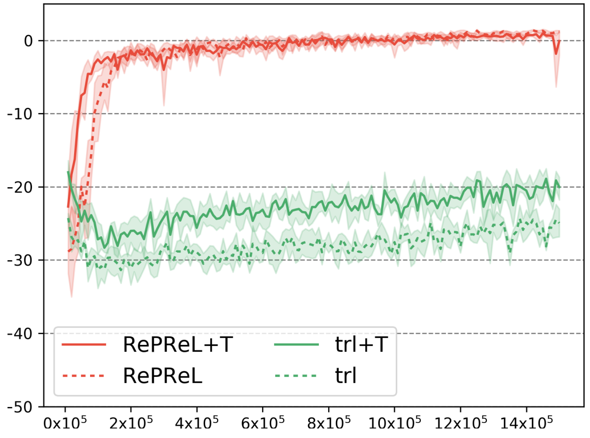


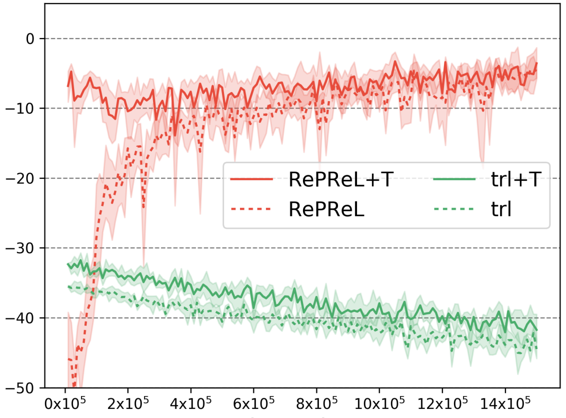

Collect key and open lock



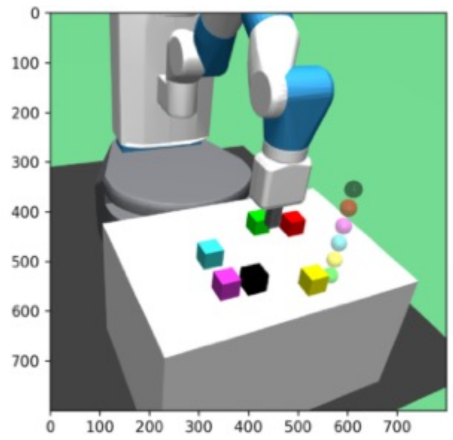

Collect key and
open 2 locks

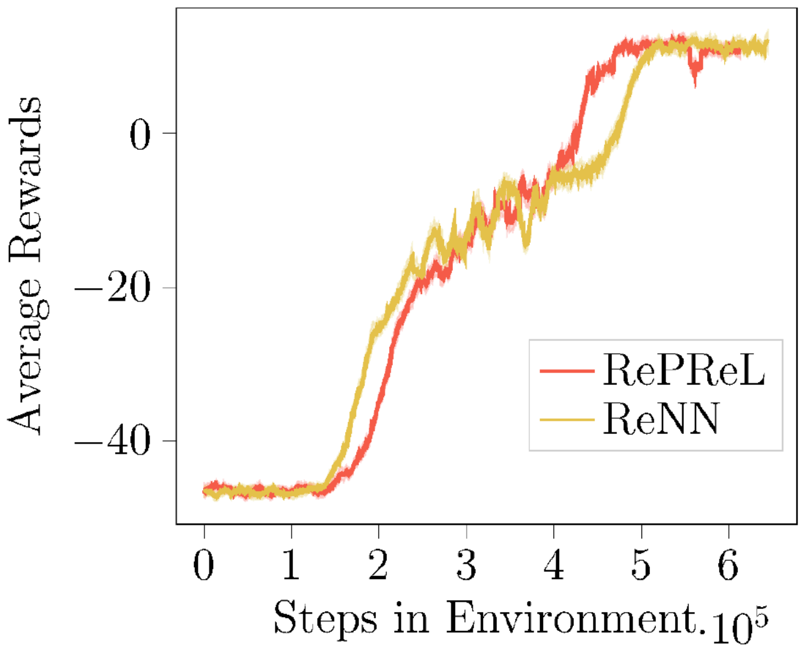


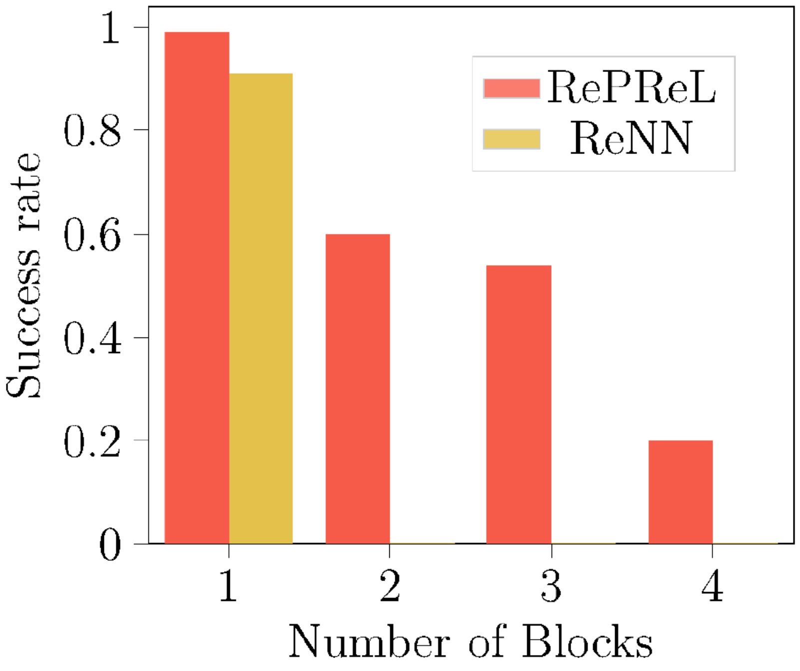



# Varying # of objects



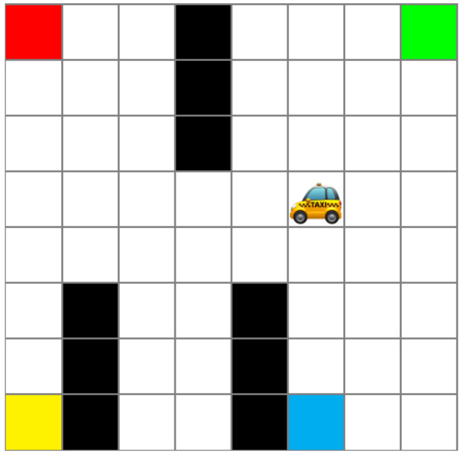



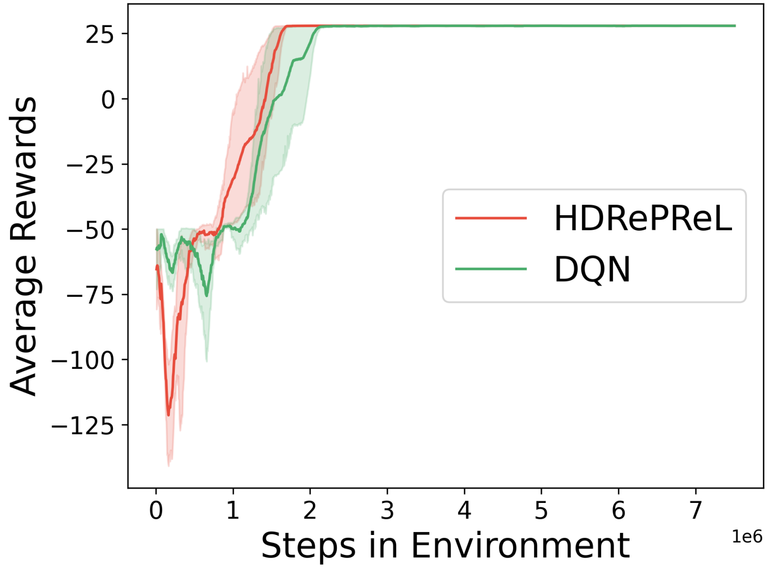

(a)



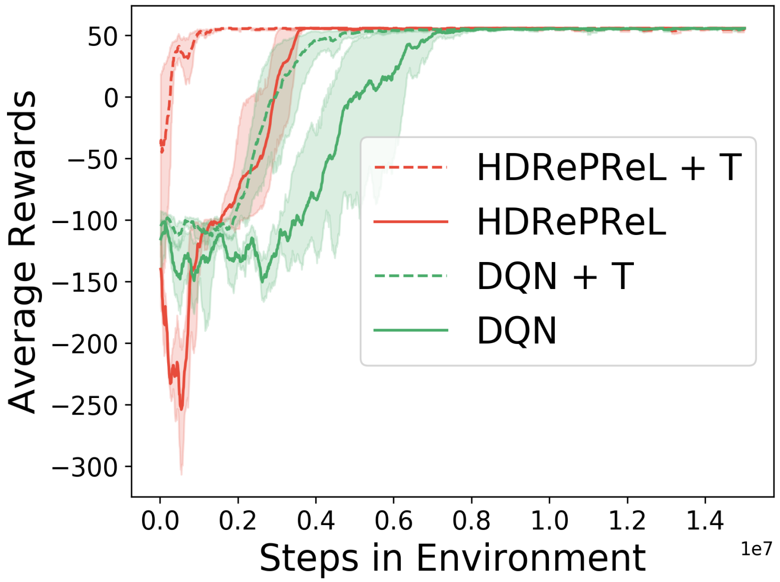

(b)

# Multi modal

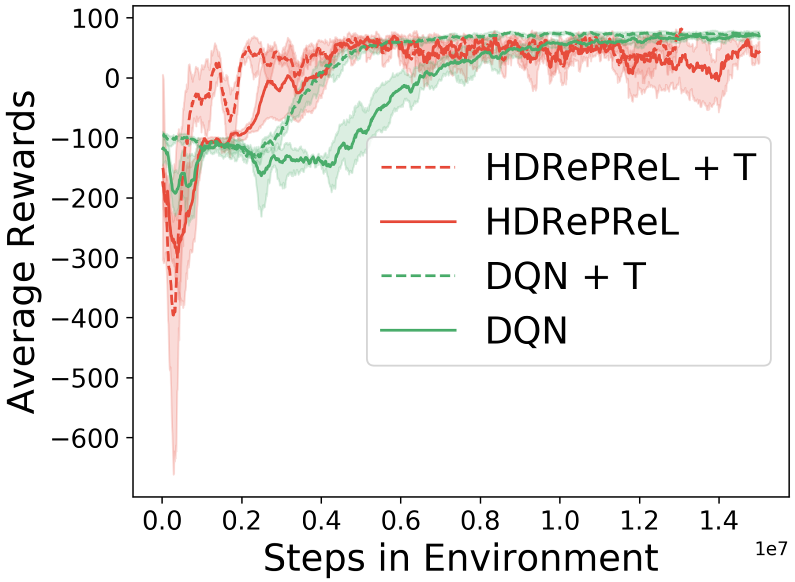





transport one passenger

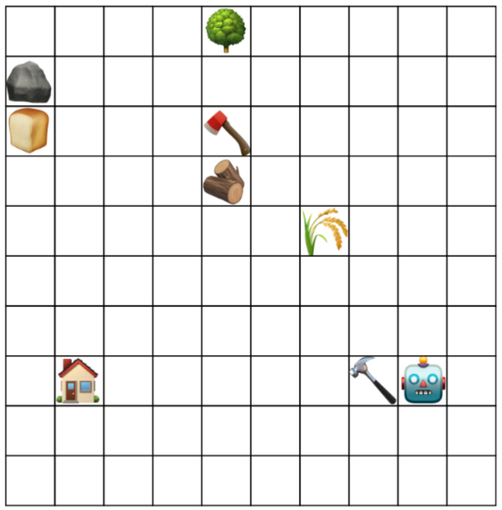


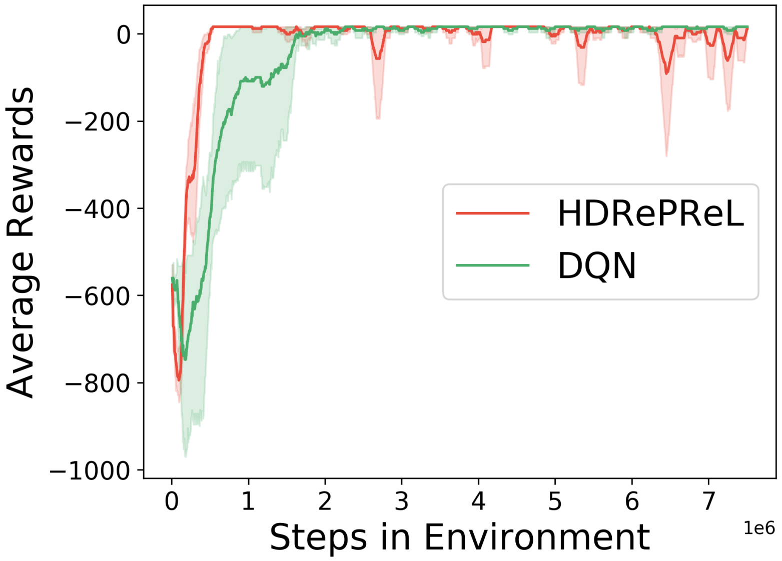

Transport two passengers



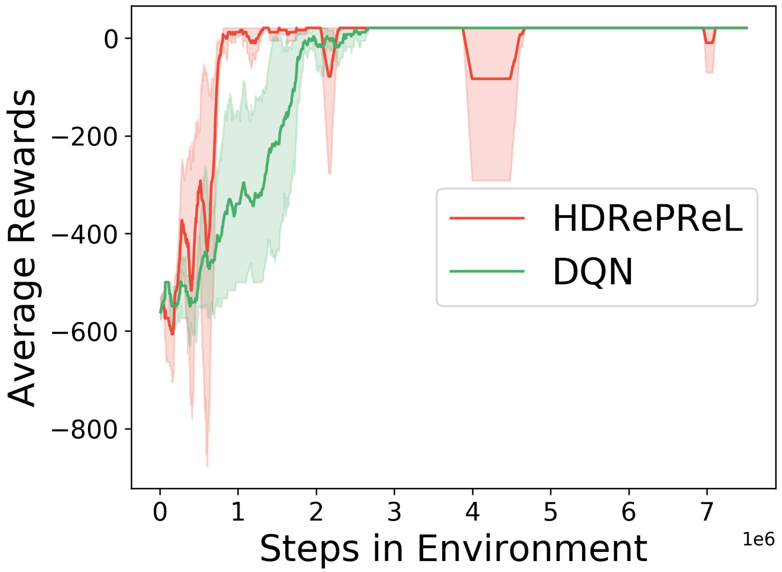

Transport three passengers

# Multi modal

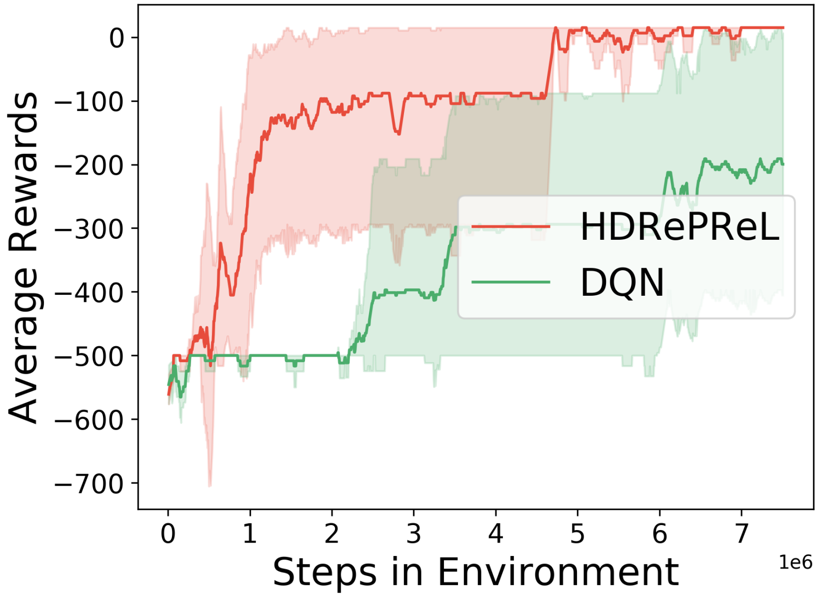





Make Bread




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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