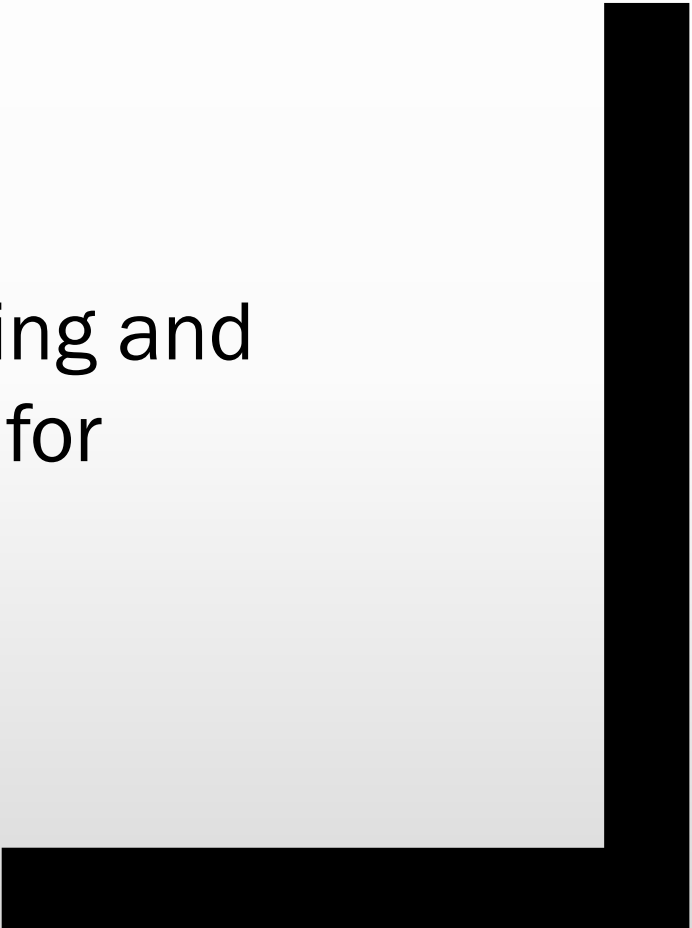




RePReL

Integrating Relational Planning and
Reinforcement Learning for
Effective Abstraction





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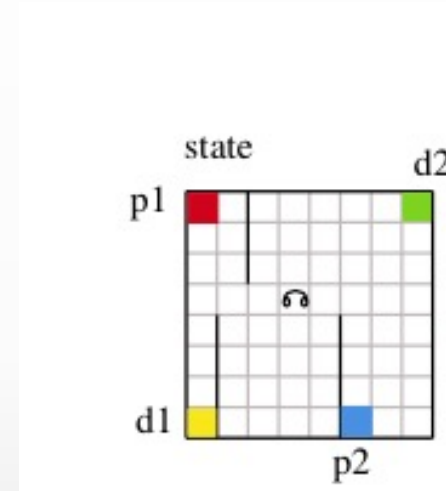
Overview

Goal:

Learning to act in relational domains with varying number of tasks and interacting objects

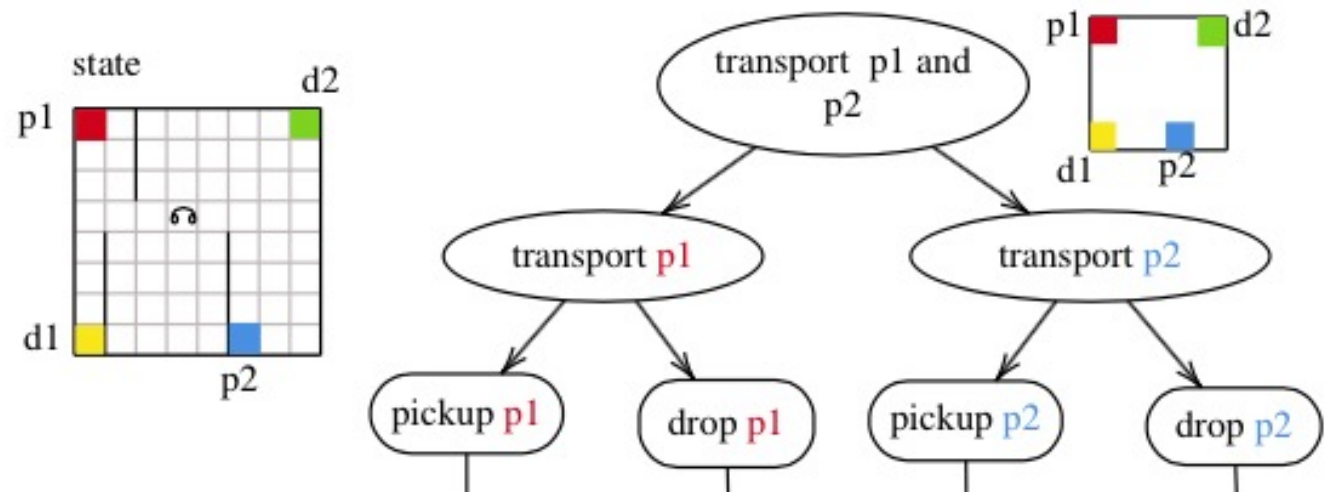
Proposed Solution:

Use a (relational) hierarchical planner to provide abstractions for the RL agents



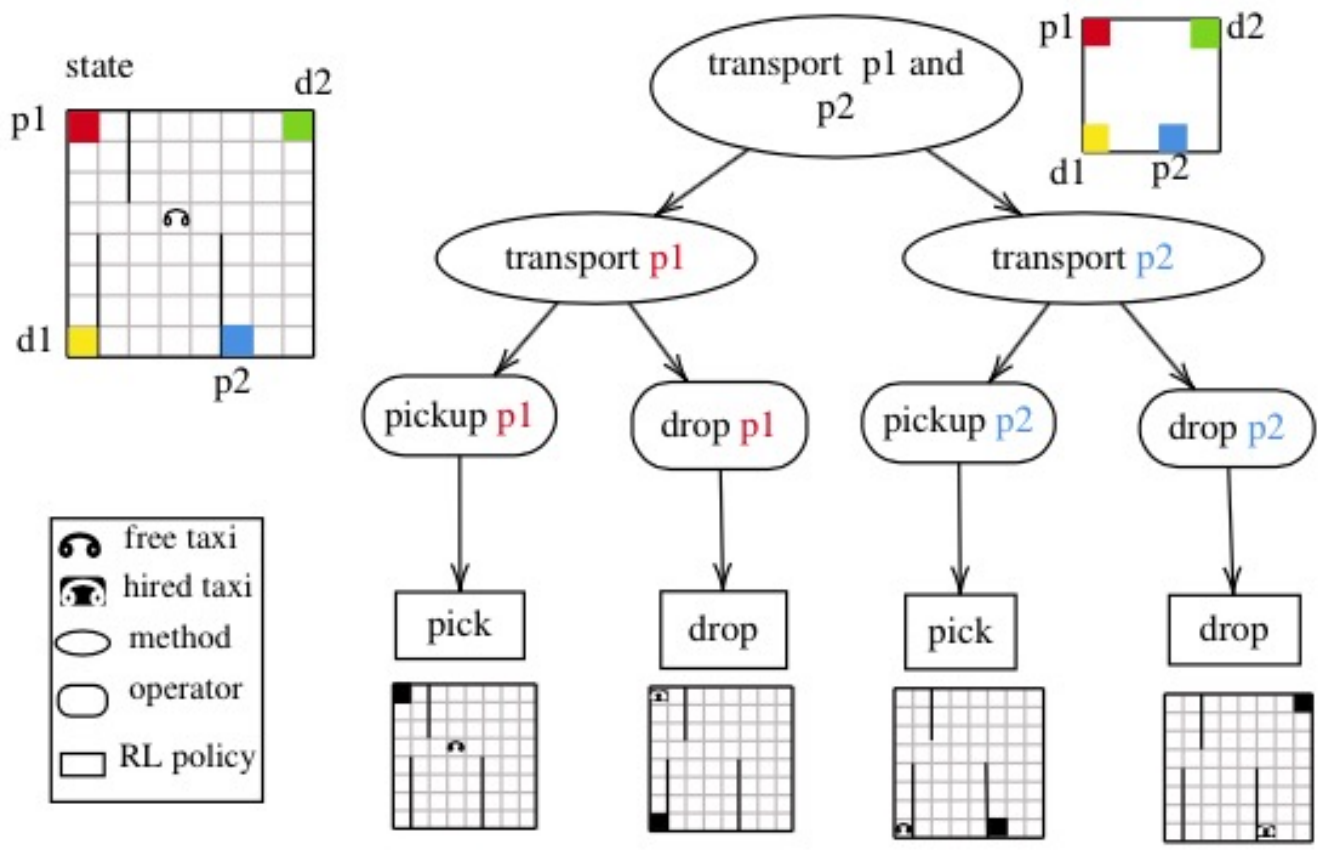
Toy Example

- Extended Taxi domain
- Planner provides sequence of passenger pickup and drop



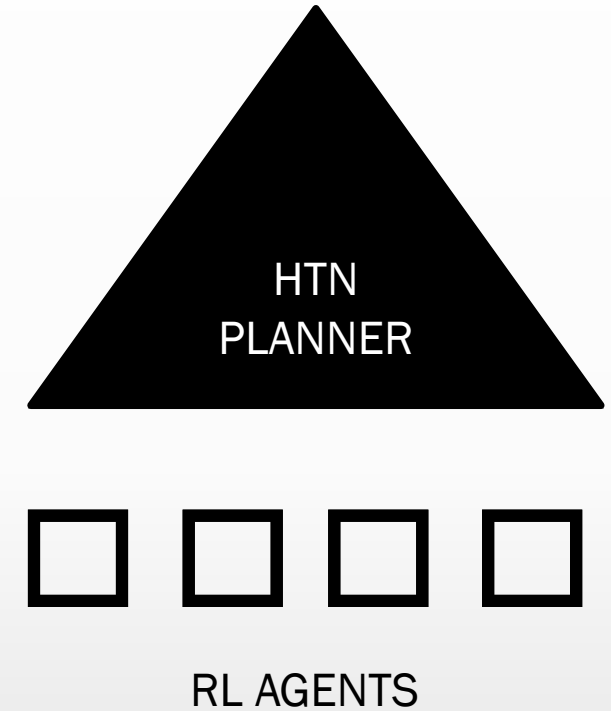
Toy Example

- Extended Taxi domain
- Planner provides sequence of passenger pickup and drop
- Learn driving route



RePReL

- Plan the sequence of operators at high level and learn to execute each operator at lower level
- Advantage:
 - *Compositionality*
 - *Task specific abstract representations*
- Relational MDP which is deterministic and fully observable
- Adapt First Order Conditional Influence statements to specify bisimulation conditions of MDPs for ‘safe’ abstractions.



Abstraction

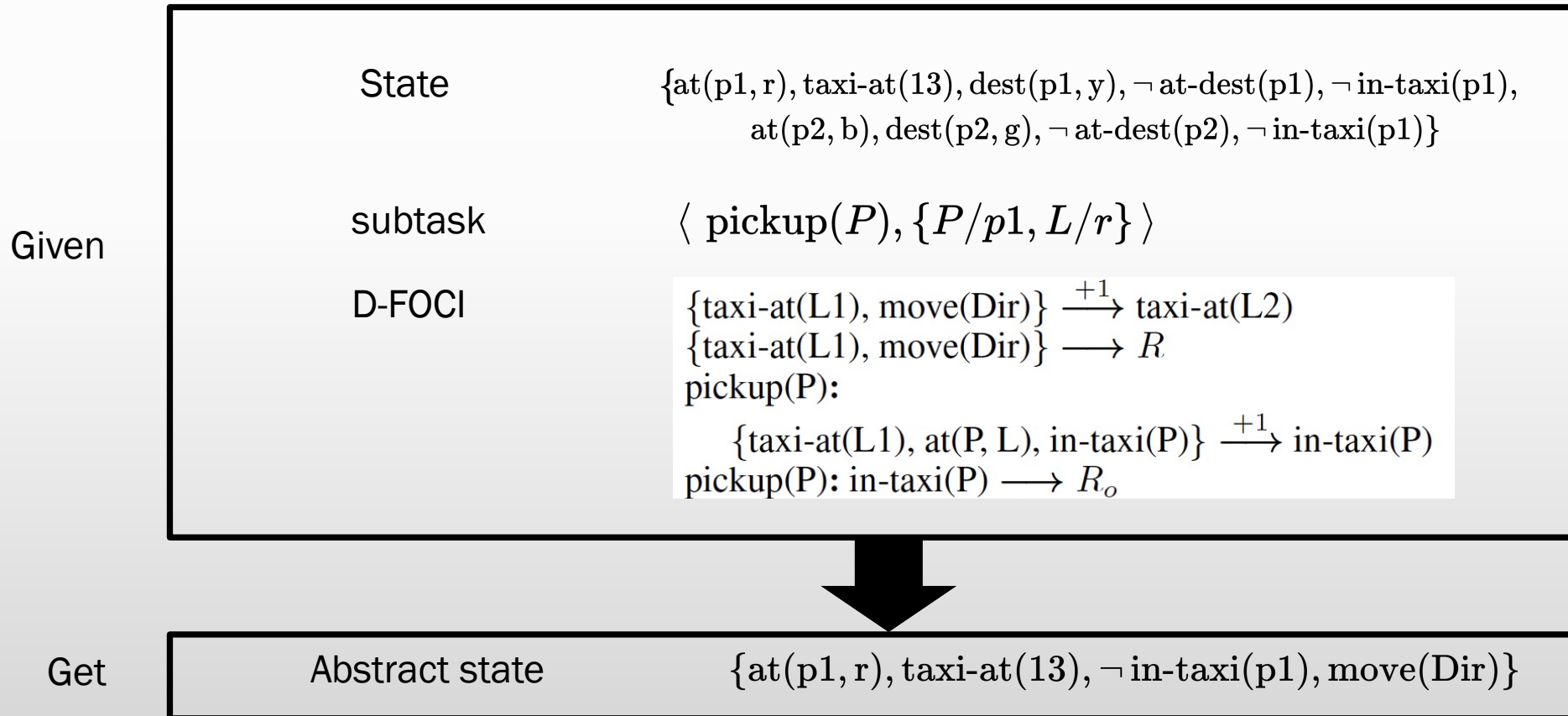
First Order Conditional Influence (FOCI) statements

if *condition* then X1 influence X2

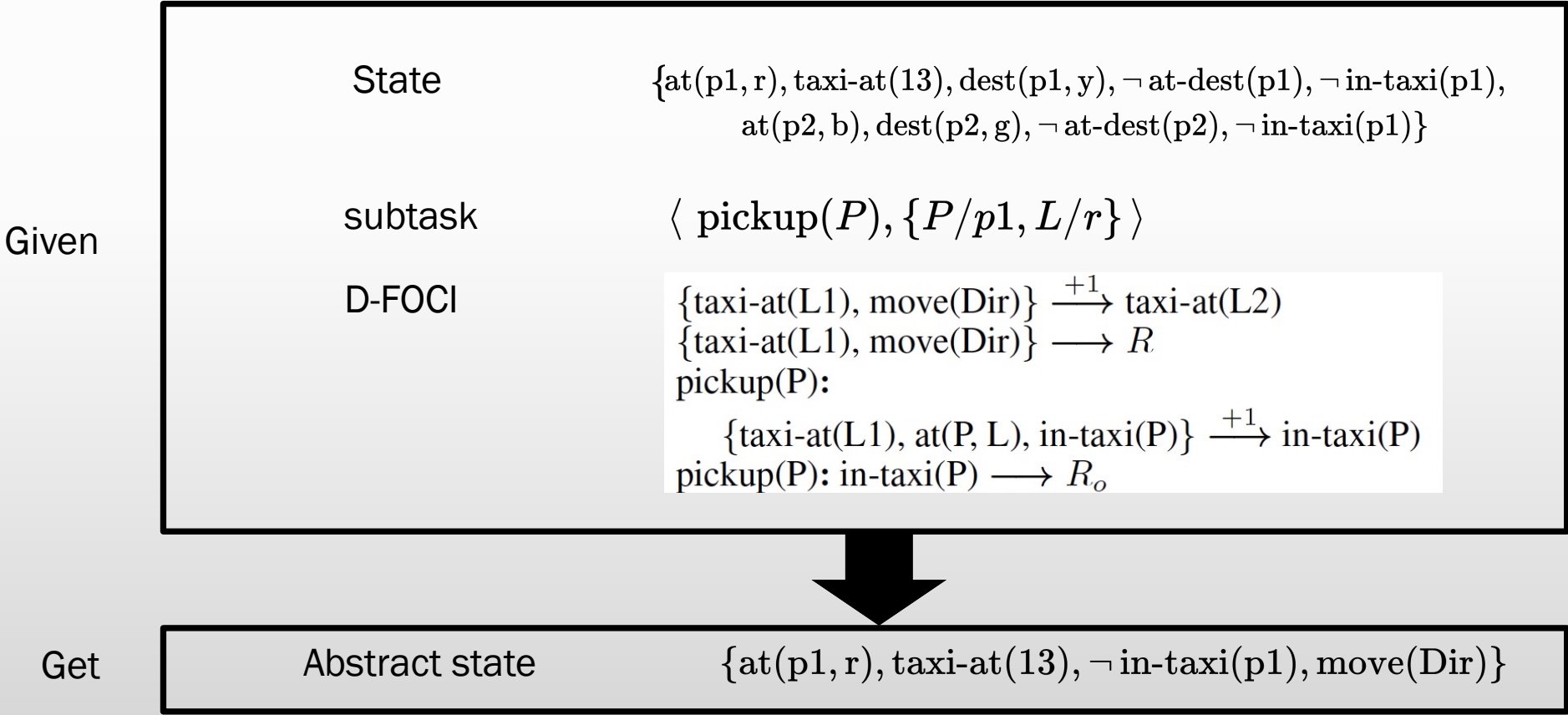
Dynamic FOCI statements

operator : $X1 \xrightarrow{+1} X2$

Abstraction



Abstraction



safe
model-agnostic
abstraction
(Theorem 1)

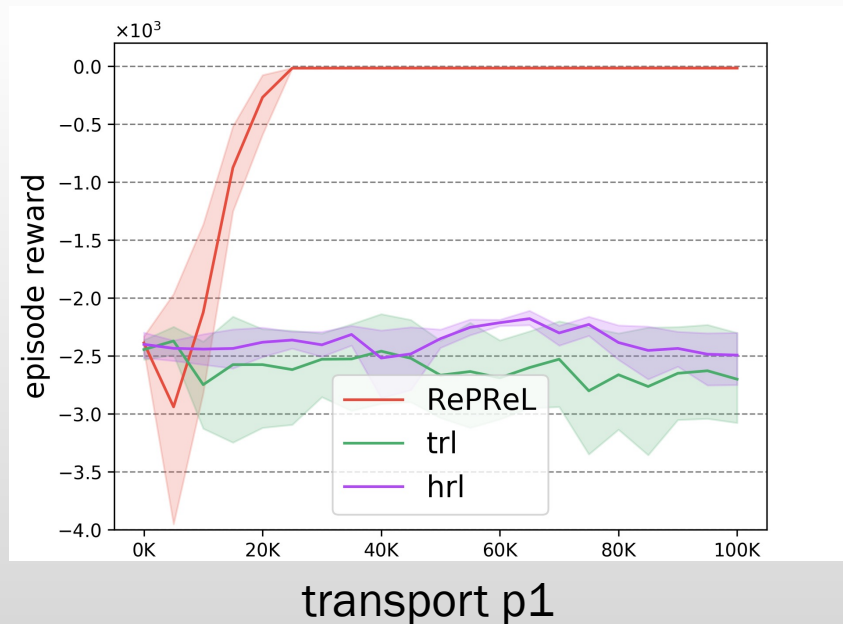
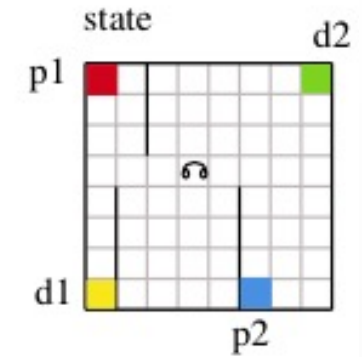
RePReL Learning Algorithm

- Get high level plan
- For each sub-task
 - *Get resp. policy π*
 - *Loop till the sub-task is achieved*
 - Get the abstract state s
 - Get action a from the policy π
 - Step in env observe reward $\langle s, a, r, s' \rangle$
 - Update the policy π

*Q learning

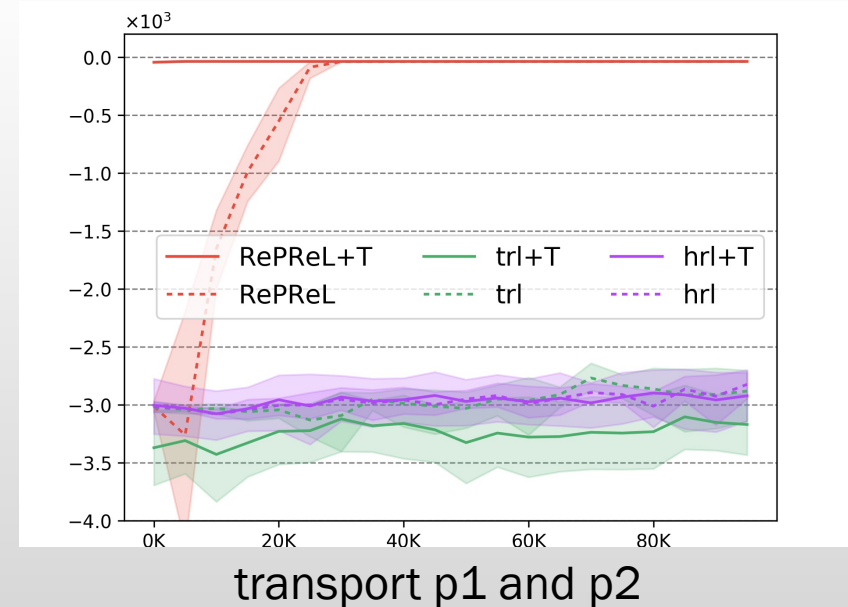
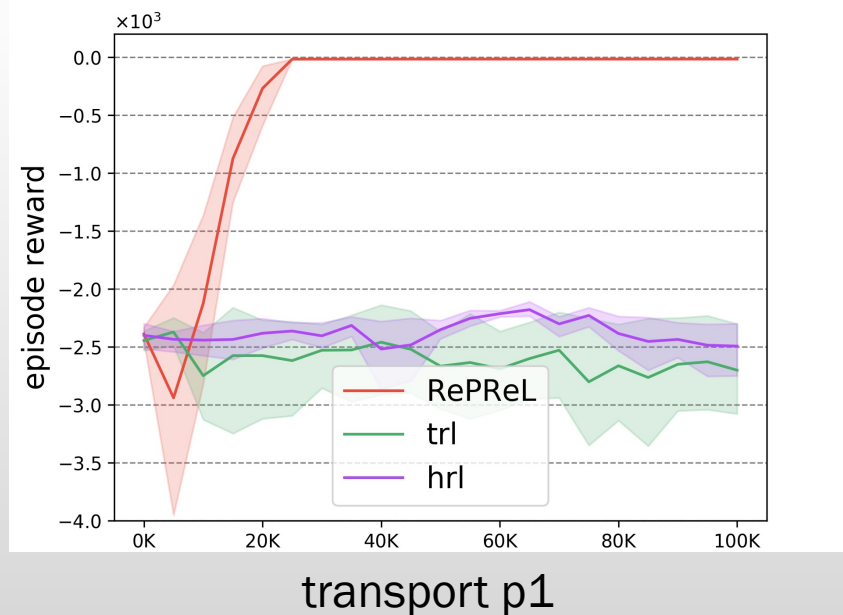
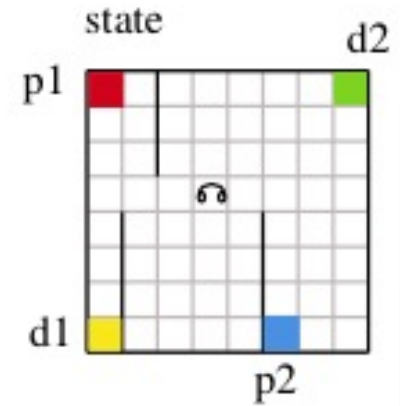
Experiments

- Evaluate for
 - *Sample efficiency*
 - *Transfer across task*
 - *Generalization across objects*

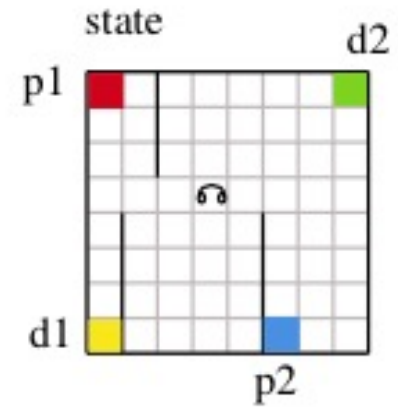


Experiments

- Sample efficiency
- Transfer across task
- Generalization across objects

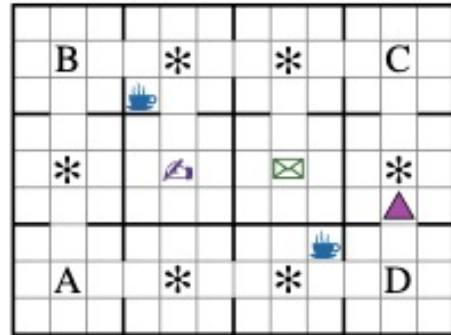


Experiments



	state	abstract state (pick-up)
Relational {s}	$at(p1, r), taxi-at(13), dest(p1, y), \neg at-dest(p1), \neg in-taxi(p1),$ $at(p2, b), dest(p2, g), \neg at-dest(p2), \neg in-taxi(p1)$	$\{at(p1, r), taxi-at(13), \neg in-taxi(p1), move(Dir)\}$
Vector [s,a]	$[at-p1, dest-p1, in-taxi-p1, at-dest-p2, at-p2, dest-p2,$ $in-taxi-p2, at-dest-p2, taxi-at, move]$	$[at, taxi-at, in-taxi, move]$

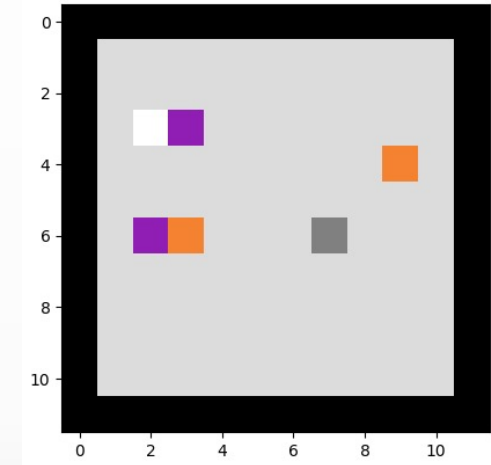
Experiments



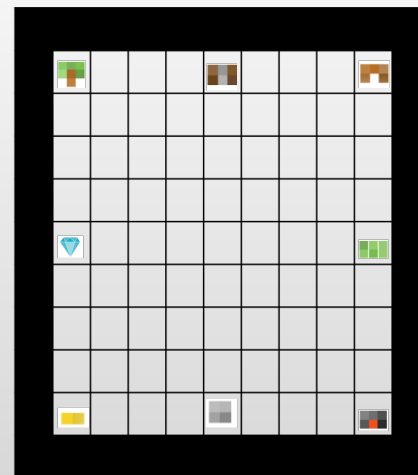
Symbol	Meaning
▲	Agent
*	Furniture
☕	Coffee machine
✉	Mail room
🪑	Office

A, B, C, D Marked locations

Office world

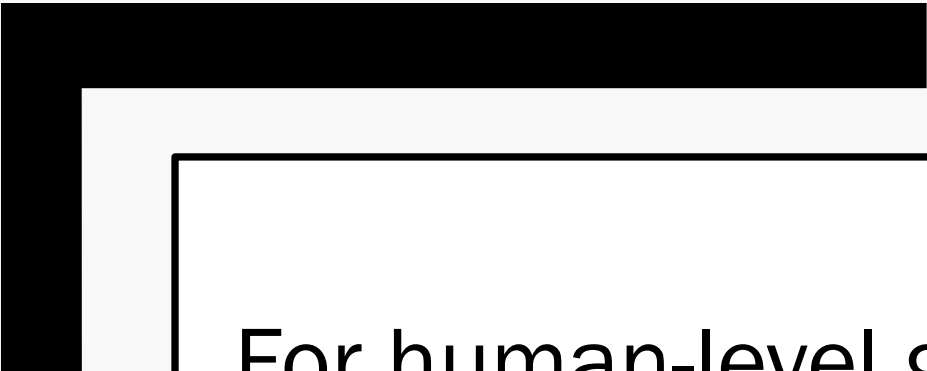


Box world




Craft world

- grass
- wood
- iron
- gold
- gem
- workbench
- toolshed
- factory



For human-level general intelligence, the ability to detect compositional structure in the domain and form task-specific abstractions are necessary.



THANKS

