Dynamic Probabilistic Logic Models for Effective Abstractions in RL

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Objective

Humans are quite natural at creating an abstract representation for efficient planning. They use different abstractions for different tasks. Can we leverage their domain knowledge?

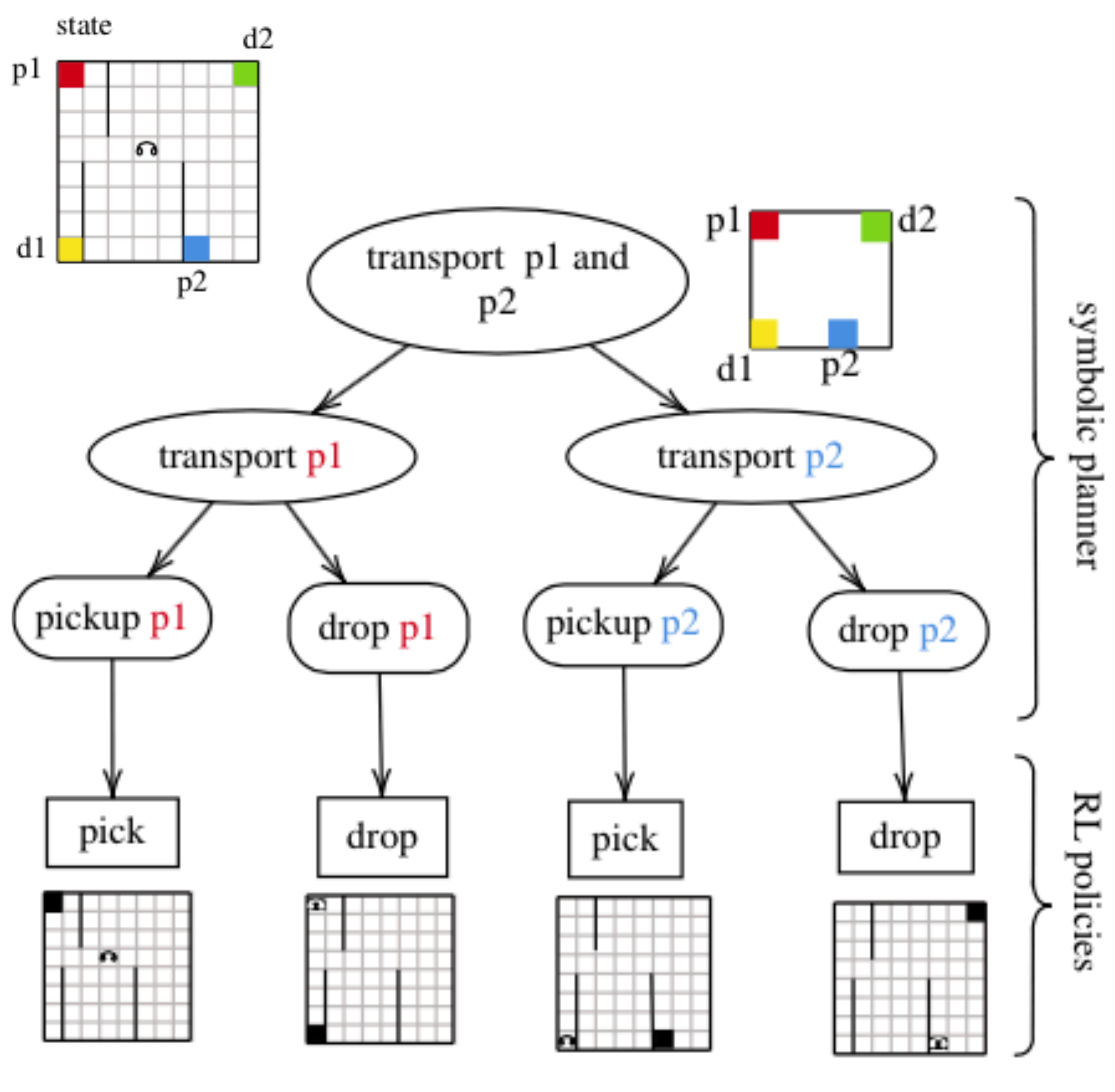
Here, we obtain task-specific state abstraction from humans in first-order statements to improve sample efficiency and generalization in RL.

RePReL

- Hierarchical Framework with Planner and RL
- Plan sequence of sub-tasks at high level using planner and learn to execute each subtask at lower level using RL
- Advantages
  - Planner provides compositionality
  - Different RL agent for execution allows separate state representations
- Use D-FOCI statements to identify relevant objects and relations for a given task.

Toy Example

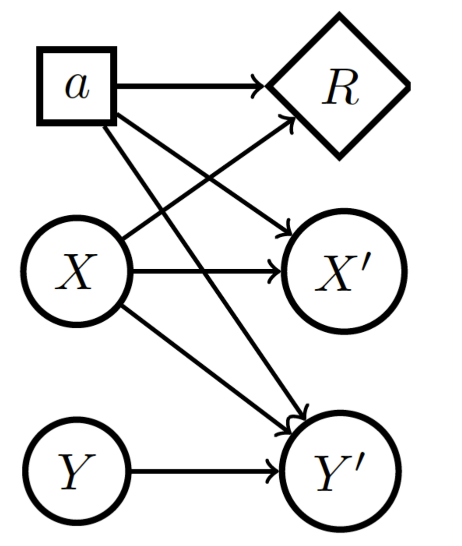
- Taxi domain with multiple passengers
- Acquire the sequence of passenger pickup and drop sub-tasks from planner
- Learn to execute the sub-task using RL
- Use different goal-conditioned RL for each sub-task
- Pickup subtask only needs pickup location, drop location is irrelevant
- Similarly, drop only needs destination, pickup location becomes irrelevant



Model-agnostic Abstraction

Definition: State variables Y are irrelevant in an MDP, if state variables can be partitioned into two disjoint subsets X and Y such that

$$P(x', y' \mid x, y, a) = P(x' \mid x, a) P(y' \mid x, y, a)$$
$$R(s, a, s') = R(x, a, x')$$



D-FOCI Statements

- First Order Conditional Influence (FOCI) statement is of the form
  "if *condition* then *X1* influence *X2*"
- FOCI statements encode the information that literal X2 is influenced only by the literals in X1 when the stated condition is satisfied
- We present Dynamic FOCI (D-FOCI) statements,

$$\text{sub-task} : \{\mathrm{p}(X_1), q(X_1)\} \xrightarrow{+1} \mathrm{q}(X_1)$$

- With +1, the D-FOCI encode the influence of literals in current time step on the literal in next time-step
- With sub-task, D-FOCI statement constraints the task being executed
- Given the current state and sub-task being executed we can obtain complete set of relevant state variables by grounding and rolling out the D-FOCI statements. This forms our abstract state
- Guarantees safe model-agnostic abstraction, if MDP satisfies the D-FOCI statement with fixed-depth unrolling

state : $\{\mathrm{at(p1, r), taxi\text{-}at(13), dest(p1, y), \neg\, at\text{-}dest(p1), \neg\, in\text{-}taxi(p1), at(p2, b), dest(p2, g), \neg\, at\text{-}dest(p2), \neg\, in\text{-}taxi(p1)}\}$

[at-p1 dest-p1, in-taxi-p1, at-dest-p2, at-p2, dest-p2, in-taxi-p2, at-dest-p2, taxi-at, move]

operator $\langle\ \mathrm{pickup}(P), \{P/\mathrm{p1}, L/r\}\ \rangle$

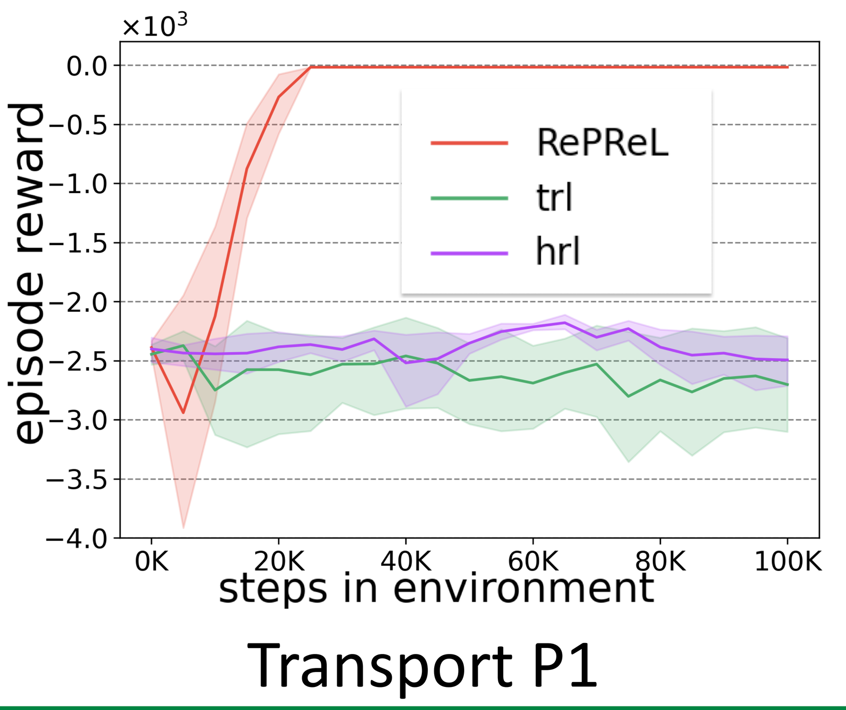
D-FOCI : $\{\text{taxi-at(L1), move(Dir)}\} \xrightarrow{+1} \text{taxi-at(L2)}$
$\{\text{taxi-at(L1), move(Dir)}\} \longrightarrow R$
pickup(P):
$\{\text{taxi-at(L1), at(P, L), in-taxi(P)}\} \xrightarrow{+1} \text{in-taxi(P)}$
pickup(P): in-taxi(P) $\longrightarrow R_o$

abstract state: $\{\mathrm{at(p1, r), taxi\text{-}at(13), \neg\, in\text{-}taxi(p1), move(Dir)}\}$

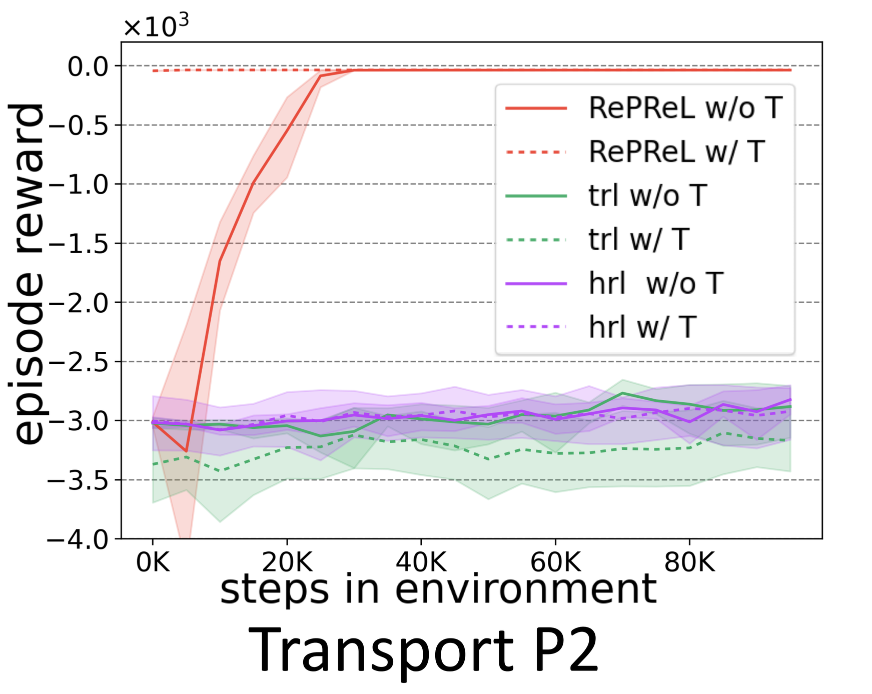
[at, taxi-at, in-taxi, move]

Experiments

Taxi domain



Transport P1



Transport P2

Human knowledge can help provide effective abstractions that enable efficient learning and effective generalization across tasks and objects.

More details on http://starling.utdallas.edu/papers/RePReL

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