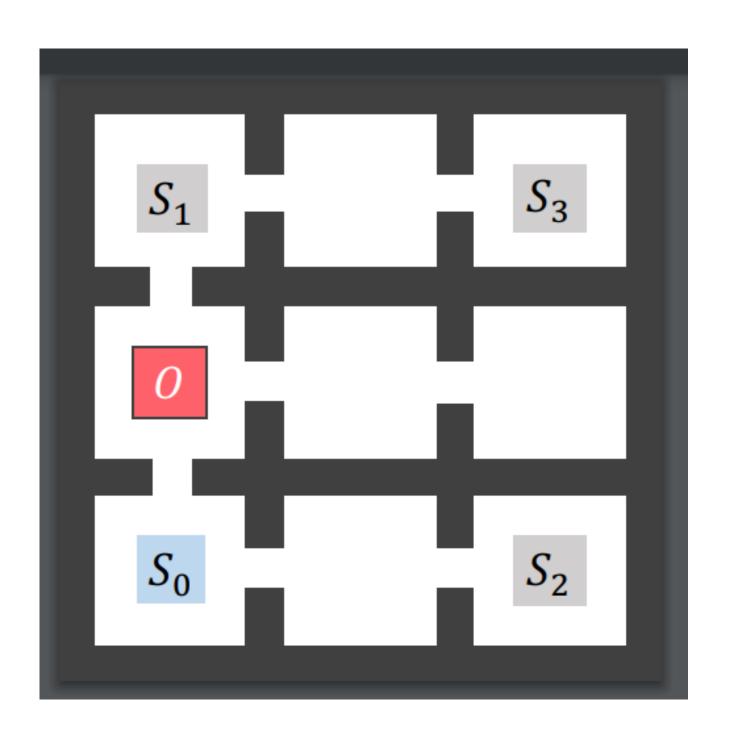
## Compositional Reinforcement Learning from Logical Specifications Kishor Jothimurugan, Suguman Bansal, Osbert Bastani and Rajeev Alur



#### Task

Visit  $S_1$  or  $S_2$ then visit  $S_3$ Always avoid *O* 

## **Logical Specifications**

- Hard to write well-shaped reward functions for complex tasks
  - We instead use logical specifications

## $\phi = (choose (reach S_1, reach S_2); reach S_3)$ **ensuring** avoid *O*

#### **Problem Statement**

Given an MDP *M* with unknown transition probabilities and a specification  $\phi$  we want to compute a policy  $\pi^*$  such that

# $\pi^* \in \arg\max_{\pi} \Pr_{\zeta \sim D_{\pi}^{M}}[\zeta \vDash \phi]$

#### **Drawbacks of Existing Approaches**

- Poor scalability w.r.t. complexity of specification
- Not designed to solve tasks that require high-level planning

#### Contributions

1. Compositional algorithm that interleaves high-level planning with low-level RL 2. Theoretical analysis showing that our algorithm's objective is a lower bound on satisfaction probability **3.** *Experimental evaluation* on challenging benchmarks

## **Compositional Algorithm**

#### Phase I: Construct Abstract Graph

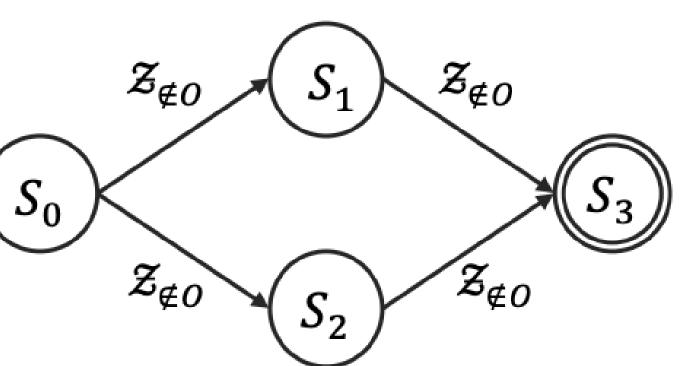
An *abstract graph* is a DAG-like structure derived from the given specification (automatically)

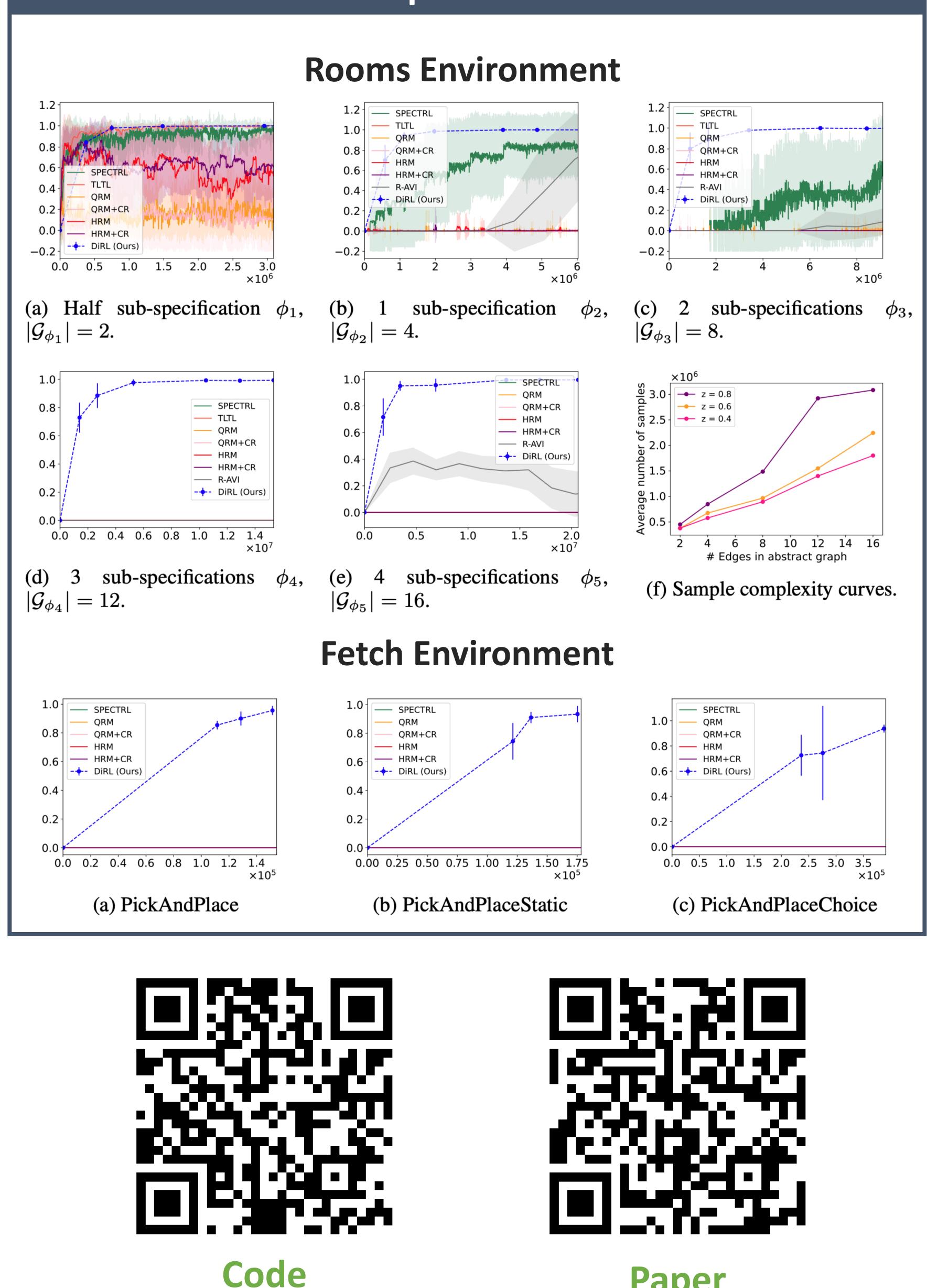
- Vertices are *sets of states*
- Edges are *subtasks*
- Edge labels denote *constraints*

### Phase II: Plan and Learn

Run *Dijkstra's algorithm* on the abstract graph

- Learn *policy for an edge* when Dijkstra's algorithm requires cost of edge
- Assign cost  $-log(p_e)$  for edge e where  $p_e$  is the probability that subtask is completed successfully Initial state distribution chosen heuristically







## Experiments

Paper