Cooperative Exploration for Multi-Agent Deep Reinforcement Learning

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1. Introduction

Problem:

- Multi-agent deep reinforcement learning (MARL)
- Learning policies in sparse-reward settings is challenging
- Efficient exploration strategies are needed

Challenges for Multi-Agent Exploration:

Identify states that are worth exploring:

- > Number of states grow exponentially with number of agents
- Infeasible to explore all states
- \succ Example: N-agent push-box task in $L \times L$ grid
- $(L^2)^{1+N}$ states to explore

Coordinate agents' exploration efforts:

- Uncoordinated exploration is inefficient
- \succ Example: two-agent push-box task in $L \times L$ grid
- Agents need to push the box toward same direction to move the box

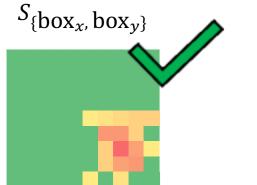
3. Restricted Space

Why Restricted Space?

- **Observation:** Reward function typically depends on a low-dimensional subspace of the state space
- **Example:** N-agent push-box task in $L \times L$ grid.
 - Size of state space: $(L^2)^{1+N}$
 - Reward function depends only on the box location L^2

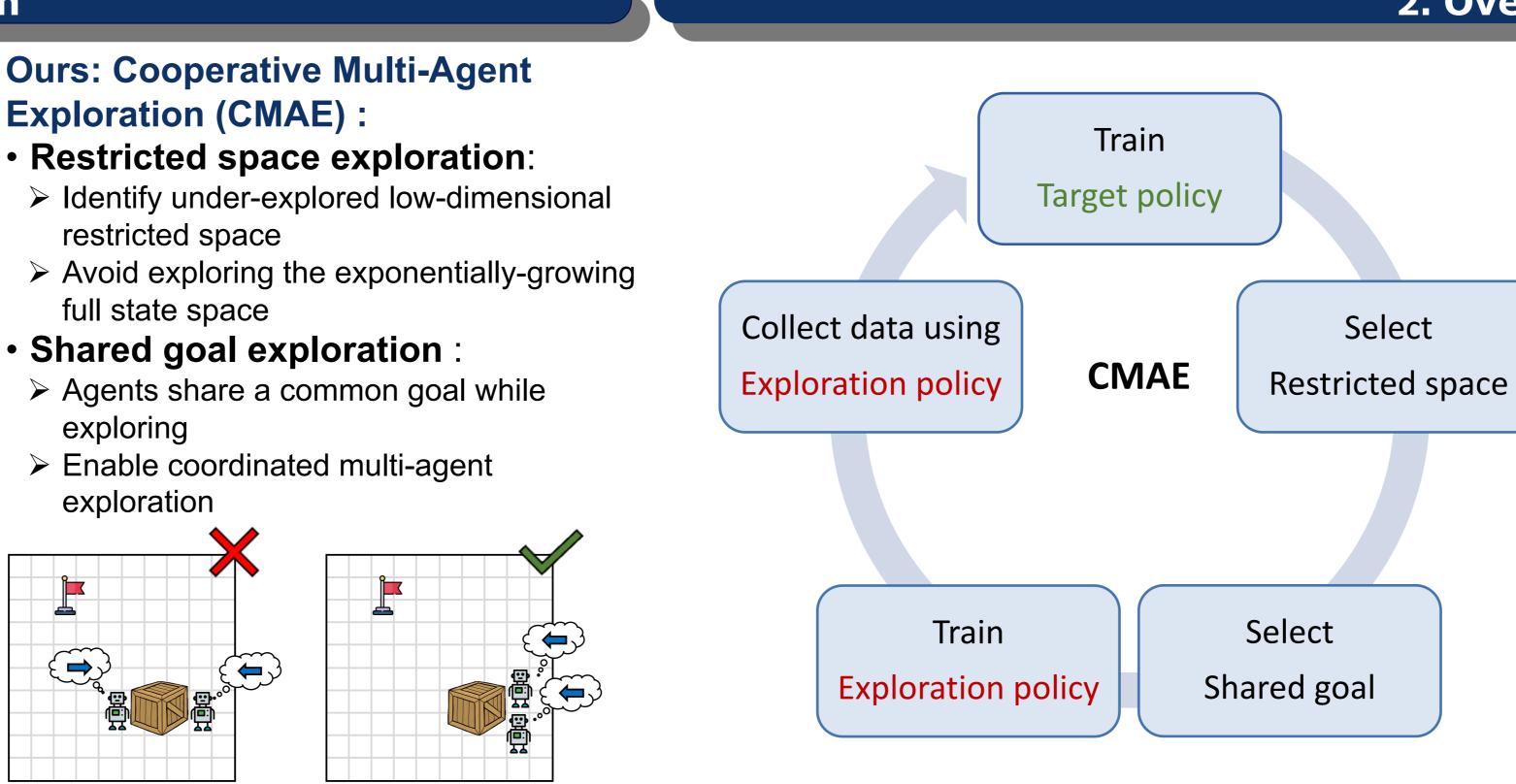
How to find under-explored restricted space?

- Each restricted space S_k has a counter
- Under-explored restricted space has smaller entropy

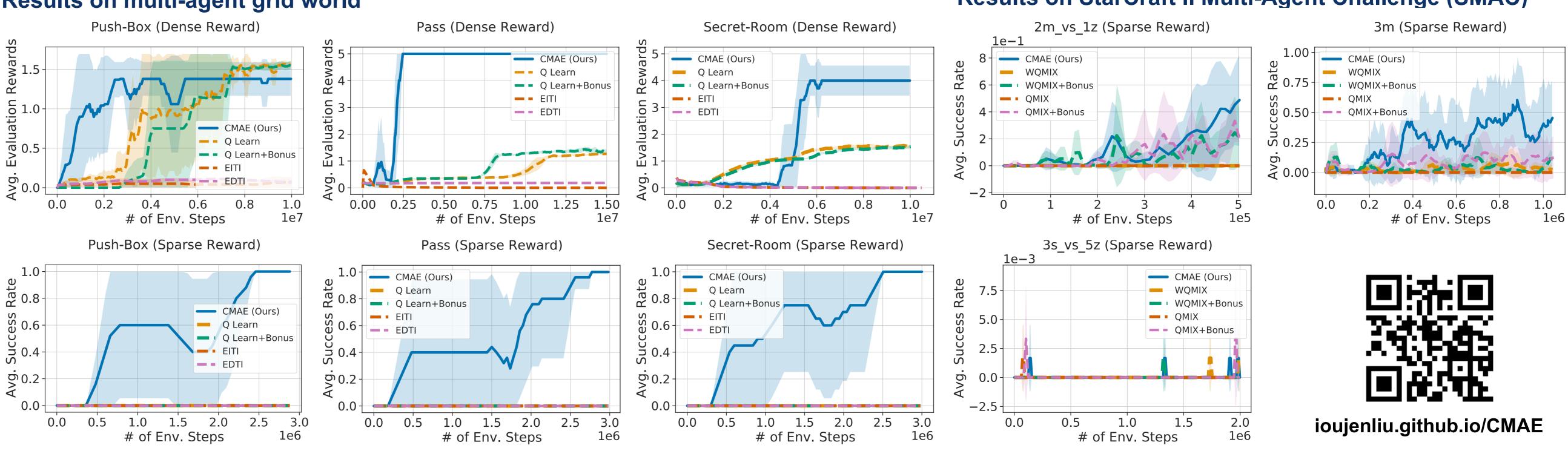


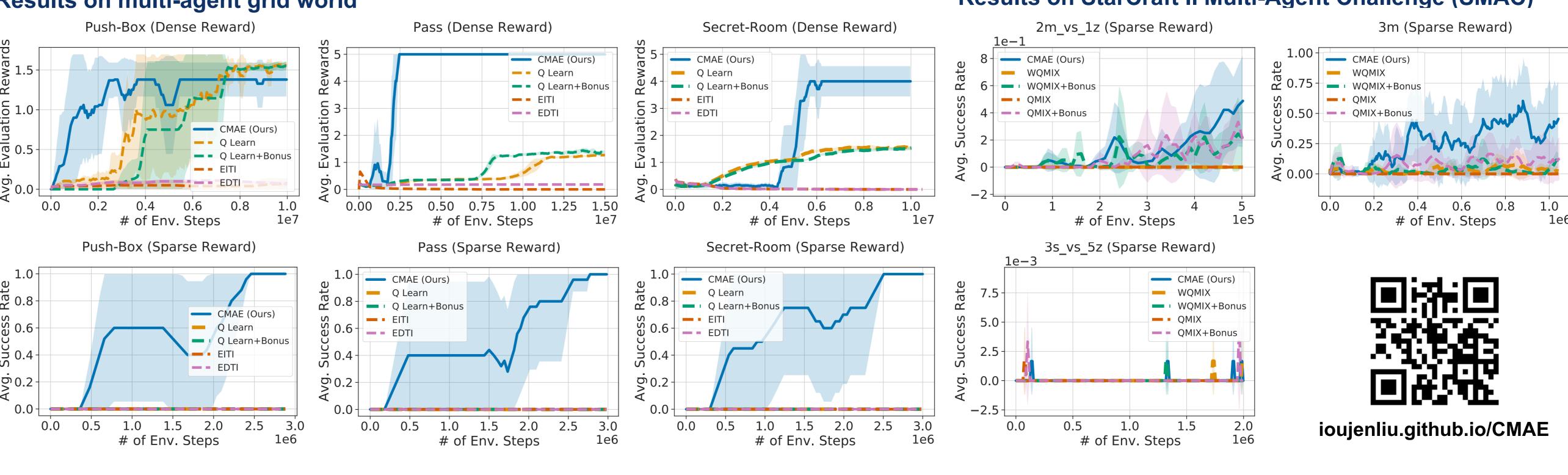
 $S_{\{\text{agent1}_x, \text{agent1}_y\}}$

- exploring
- exploration



Results on multi-agent grid world





4. Experimental Results



2. Overview

Approach:

Decouple exploration and target policy

- Train target policy: Maximize the external environment reward using off-policy RL algorithms
- Collect data using exploration policy: Data contains under-explored states
- Train exploration policy: Positive reward when reaching a shared goal
- Select shared goal: Select a rarely visited state as shared goal
- Select restricted space: Select lowdimensional and under explored subspace as restricted space

Please see paper for details

Results on StarCraft II Multi-Agent Challenge (SMAC)