A Simple Approach to Continual Learning By Transferring Skill Parameters

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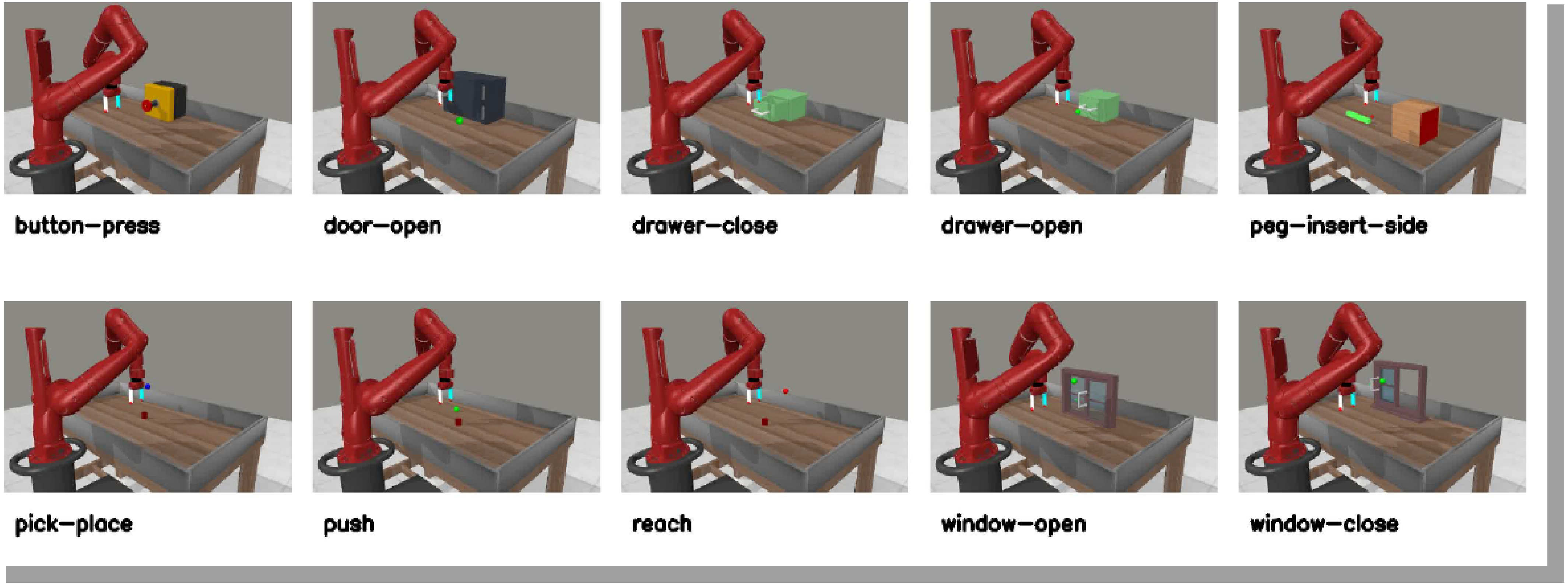
Introduction

- Problem:
  - existing transfer learning methods are too inefficient for vision-motor tasks (robotic manipulation)
  - Storing past experiences entirely, takes too much space and recall time
- Proposed:
  - Store previous knowledge only in terms of skill policies (parameters)
  - Use general purpose latent state skill representations for decomposed skills
  - Construct more complex skills based on simpler and prior skills
  - Use the propose optimal curriculum learning method for efficient transfer

Meta-World

› Web-based simulation environment for training DRL models for robotic tasks by OpenAI



Transfer Learning

- Defined as learning by transferring knowledge (known skills) from another agent
- Problems:
  - Traceability problem
  - Reward function estimation and tuning problem
  - Bad transfer

Continual Learning

- Defined as learning new skills either through real-world experimentation or transferring and re-tuning in simulation
- Problems:
  - Multi-task learning: could destroy prior skill (pessimal example)
  - Catastrophic forgetting
  - Current methods are too inefficient

Reusable Skill Libraries (DRL-Based Models)

- Associative Skill Memories
- Probabilistic Movement Primitive
- Latent space parameter decomposition

Continual Learning with Skill Libraries and Curricula

- Learn skills in form of factorized policy model classes
- Train an online model-based planner for reusing skills with high level action space (domain) for hierarchical RL
- Use on-policy RL to directly update skills

Setting

- T: a possibly-unbounded discrete space of tasks.
- S: a single continuous state space shared among all tasks T.
- A: a single continuous action space shared among all tasks T.
- The MTRL problem: (T , S, A), and each task τ ∈ T is an infinite-horizon Markov decision process (MDP)

$$\tau = (S, A, M_i, p_{\tau_i}(s, a, s'), r_{\tau_i}(s, a, s')) \,,$$

- M_i: represents the set is manipulation skills the robot is initialized or pre-trained with
- i: ith the epoch number

Simple Continual Learning with Skill Transfer

Algorithm 1 Proposed Continual Learning Framework

Input: Initial skill library $\mathcal{M}_0$, target task space $\mathcal{T}$, RL algorithm $\mathcal{F} \rightarrow (\pi, \rho)$, target task rule `ChooseTargetTask`, base skill rule `ChooseBaseSkill`

$i \leftarrow 1$

while not done **do**

  $\tau \leftarrow \texttt{ChooseTargetTask}(\mathcal{T}, \mathcal{M}_{i-1})$

  while π_{target} not solved **do**

    $\pi_{base} \leftarrow \texttt{ChooseBaseSkill}(\mathcal{T}, \mathcal{M}_{i-1})$

    $\pi_{target}, \cdot \leftarrow \mathcal{F}(\tau, \texttt{clone}(\pi_{base}))$

  end while

  $\mathcal{M}_i \leftarrow \{\pi_{target}\} \cup \mathcal{M}_{i-1}$

  $i \leftarrow i + 1$

end while

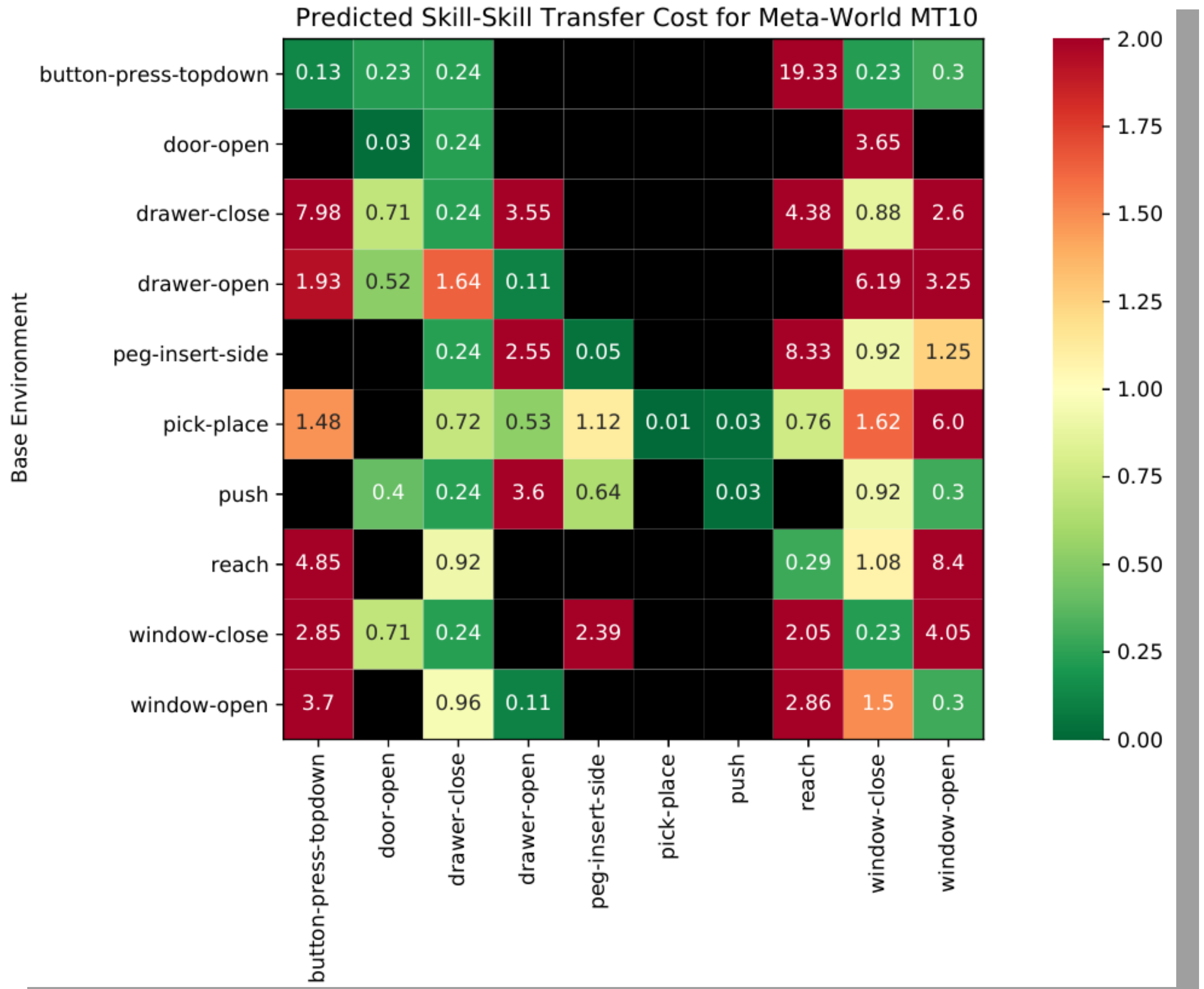
Output: Skill library $\mathcal{M}_i$

Other Techniques

- Warm-up procedure for value function transfer
- Rejecting bad transfers
- Skill-skill transfer cost
  - Number of samples needed to acquire target skill
- Predicted skill-skill transfer cost

$$A_{base \rightarrow target} = \frac{C_{base \rightarrow target}}{C_{scratch \rightarrow target}}$$

Predicted Skill-Skill Transfer Cost

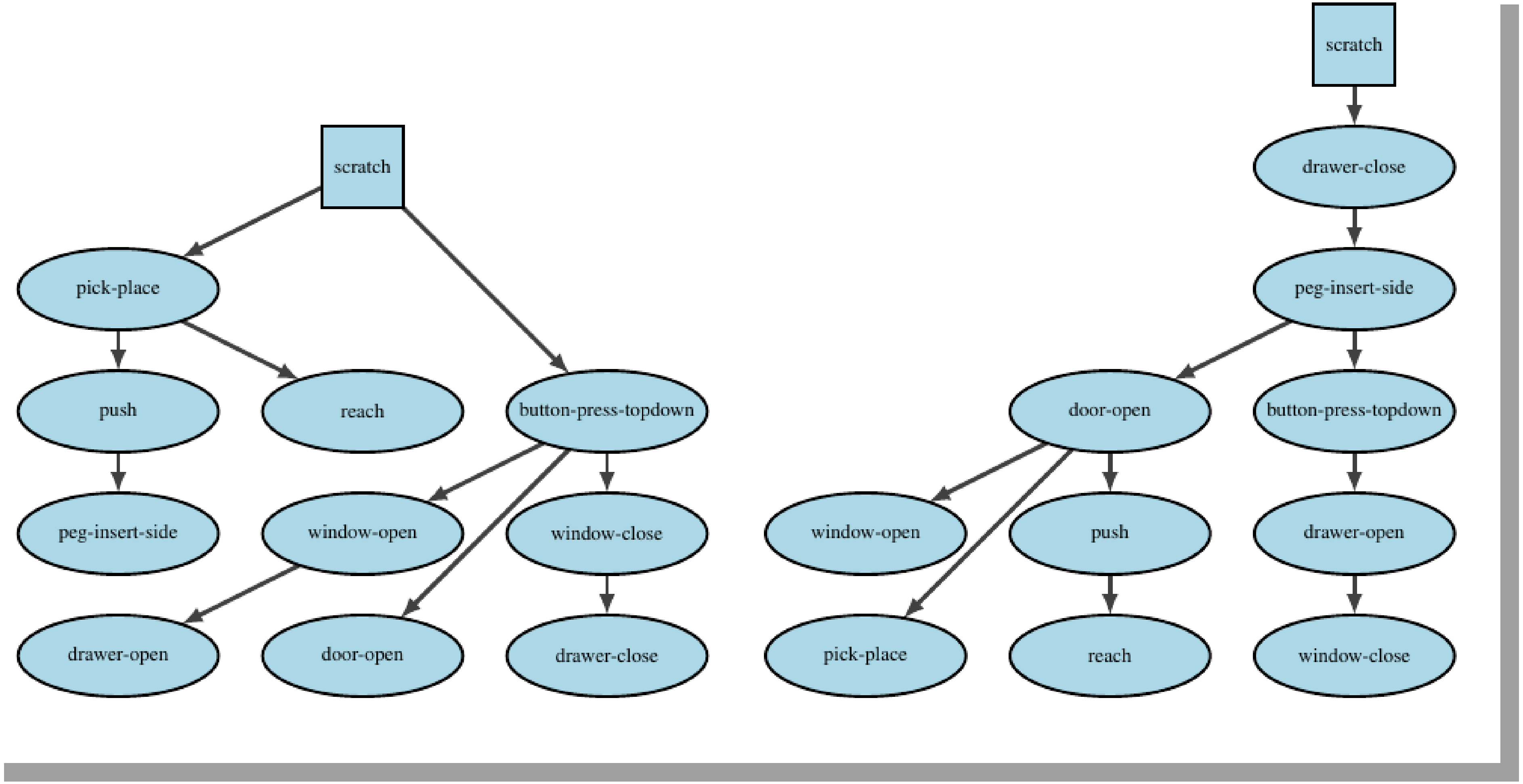


Curriculum Selection Algorithm

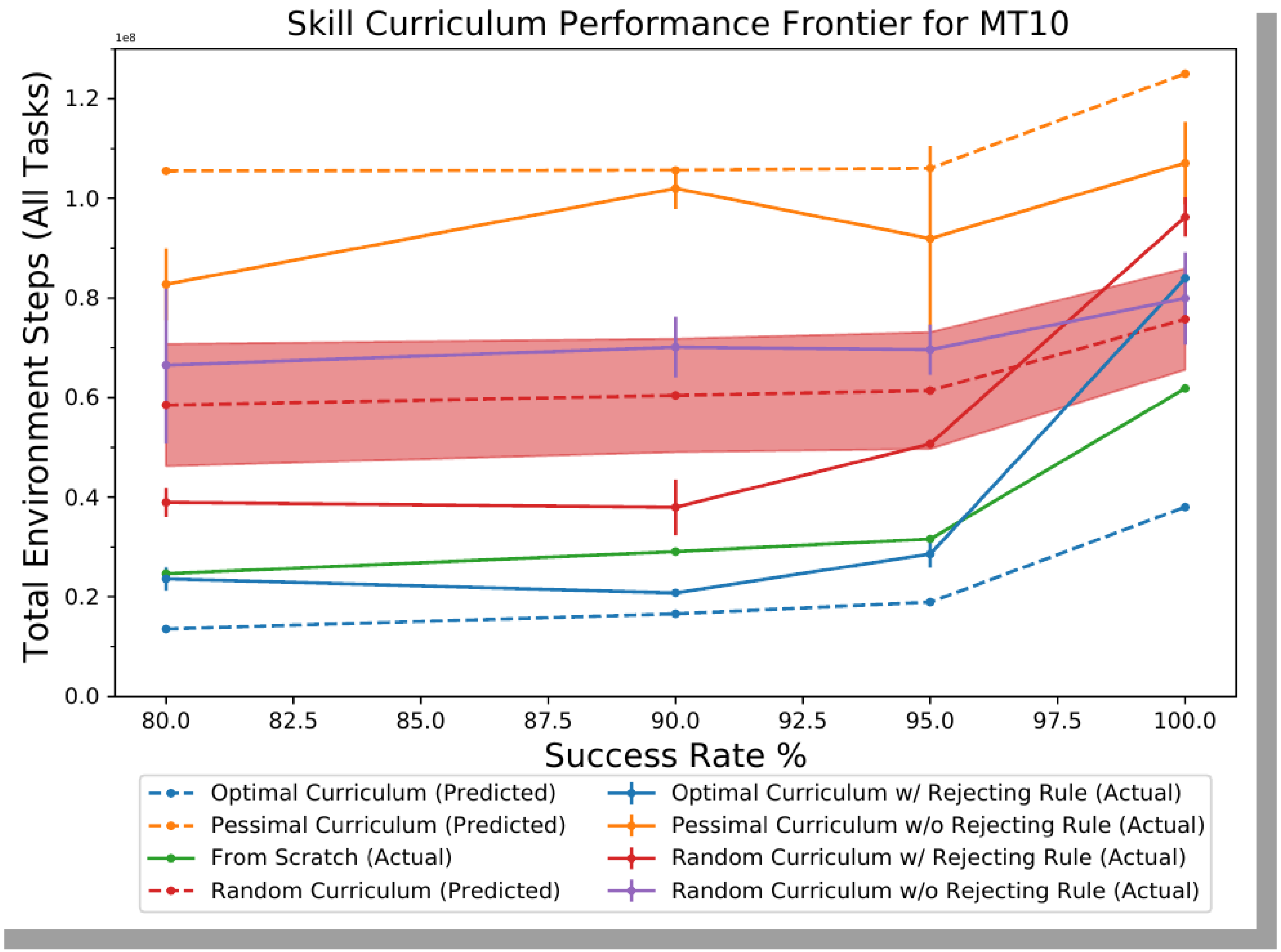
Algorithm 2 DMST-Based Curriculum Transfer

Input: Initial skill library $\mathcal{M}_0$, target task space $\mathcal{T}$, RL algorithm $\mathcal{F} \rightarrow (\pi, C)$
$V \leftarrow \mathcal{T} \cup scratch$
$E \leftarrow \{\}$
for $\tau_{base} \in \mathcal{T}$ **do**
    $E \leftarrow (scratch, \tau_{base}, -1.0)$
    $\pi_{base}, C_{scratch \rightarrow target} \leftarrow \mathcal{F}(\tau_{base}, \pi_{random})$
    for $\tau_{target} \in \mathcal{T}$ **do**
        $\cdot, C_{base \rightarrow target} = \mathcal{F}(\tau_{target}, \pi_{base})$
        $E \leftarrow E(\tau_{base}, \tau_{target}, C_{base \rightarrow target}) \cup E$
    end for
end for
$T_{optimal} \leftarrow \texttt{kruskal}((V, E))$
$i \leftarrow 1$
$\pi_{base} \leftarrow \pi_{random}$
for $\tau_{target} \in \texttt{traverse}(T_{optimal})$ **do**
    while τ_{target} not solved **do**
        $\pi_{target}, \cdot \leftarrow \mathcal{F}(\tau_{target}, \texttt{clone}(\pi_{base}))$
        if τ_{target} not solved **then**
            $E \leftarrow E \setminus (\tau_{base}, \tau_{target})$
            $T_{optimal} \leftarrow \texttt{kruskal}((V, E))$
        end if
    end while
    $\mathcal{M}_i \leftarrow \{\pi_{target}\} \cup \mathcal{M}_{i-1}$
    $i \leftarrow i + 1$
end for
Output: Skill library $\mathcal{M}$

Optimal and Pessimal Curricula



Experiments



- Thank you!